Data Science Toolbox

DECAP792

Edited by:
Ajay Kumar Bansal

LOVELY PROFESSIONAL UNIVERSITY

Data Science Toolbox

Edited By
Ajay Kumar Bansal

Title: DATA SCIENCE TOOLBOX

Author's Name: Dr. Divya

Published By : Lovely Professional University

Publisher Address: Lovely Professional University, Jalandhar Delhi GT road, Phagwara - 144411

Printer Detail: Lovely Professional University

Edition Detail: (I)

ISBN: 978-81-19334-46-9

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Unit 01: Introduction to Data Science

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Objectives:

After studying this unit, you will be able to

- understand the concept of data science,
- understand the need of data science,
- understand the life cycle of data analytic,
- understand the types of data analytic,
- understand the pros and cons of data science.

Introduction

Data science is the task of scrutinizing and processing raw data to reach a meaningful conclusion.A lot of data is mined and classified to detect and study the behavioral data and patterns. Every year the data is growing exponentially in zettabytes which requires processing. The below image shows the tentative increase in data in coming years. This image shows the demand of data science tools for the processing of data so that meaningful conclusions can be drawn. There are a number of tools available for processing the raw data like Weka, RapidMiner, R tool, Excel, Python, Tableau, KNIME, PowerBI and DataRobot etc.

1.1 Data Classification

The data available is nominal, ordinal, interval, and ratio data.

Nominal Data: It contains a set of items that can be distinguished by the name of category.

Ordinal Data: It contains the items that can be ordered, such as military rank, or units of government, but whose degree of difference can't be measured.

Interval Data: It contains the items that have a measurable distance between them, but no meaningful zero point, such as Fahrenheit and Celsius temperatures.

Ratio Data: The measurements that have a meaningful zero and can be divided meaningfully, such as the Kelvin temperature scale.

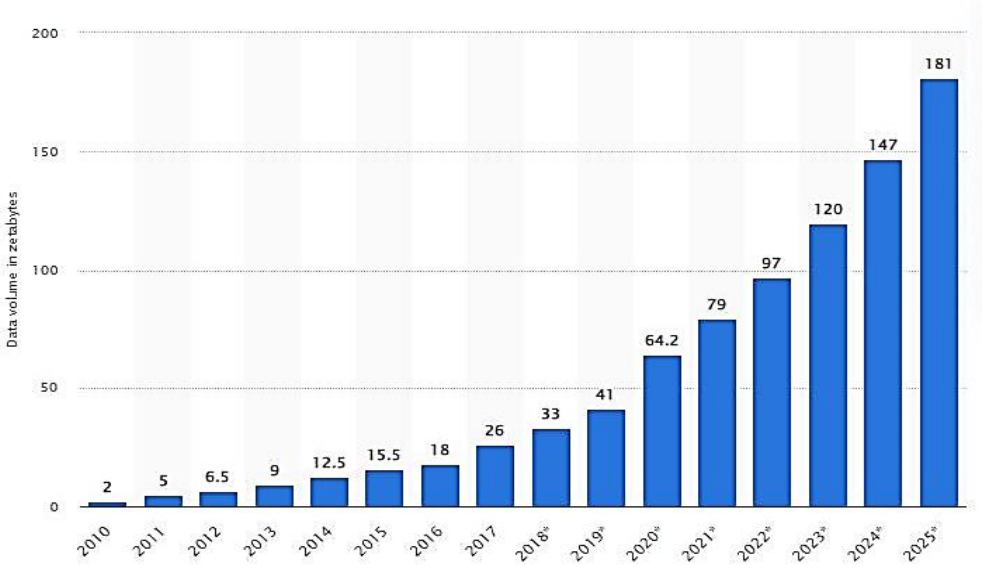

Figure 1: Increase in data

1.2 Data Collection

Two major sources of data are:

Primary data:

A primary data source is an original data source, that is, one in which the data are collected first-hand by the researcher for a specific research purpose or project. It can be collected in a number of ways. The most common techniques are surveys, interviews, observations and experiments. The primary data collection is quite expensive and time-consuming as compared to secondary data collection.

Secondary data:

The secondary data is the data that has been already collected through primary sources and made readily available for researchers to use for their own research. It is a type of data that has already been collected in the past.Sources of secondary data include books, personal sources, journals, newspapers, websites, government records etc. Secondary data are known to be readily available compared to that of primary data. It requires very little research and needs for manpower to use these sources.

The popular websites for data downloading are UCI machine learning repository, Kaggle datasets, IMDB datasets, Stanford Large Network Dataset Collections.

1.3 Why Learn Data Science?

The data scientists use the tools of data science in various sectors like ecommerce, finance, retail, healthcare, education, human resource, sports and various others. The use in every field is described below.

- **Ecommerce**: In ecommerce, the tools of data science are used for maximizing revenue and profitability.
- **Finance**: In finance, the different tools are available to take care of risk analysis, fraud detection, working capital management.

- **Retail**: For optimal pricing, better marketing strategies, stock management, the data science toolbox can be used.
- **Healthcare**: For patient quality care, classification of the type of symptoms of patients and predicted health deficiencies, we can use data science tools.
- **Education**: In academic institutions the data science toolbox can be deployed for better admission scenario, empowerment of students for successful examination results and all-round student performance.
- **Human resource**: For building strong leadership, employee acquisition, employee retention and performance management, we can use data science toolbox.
- **Sports**: To analyse the performance of players, the predicted scores, prevention of injuries and the possibility of winning or losing a match by a particular team. In sports, the data science tools can be used for all these tasks.

1.4 Data Analytic Lifecycle

Data science is an umbrella term, and the data analytics is a subset of data science.Data analytics is comprised of six phases that are carried out in a cycle.All these phases of data analytic lifecycle proceed one by one in line.

1) Data discovery
2) Data preparation
3) Planning of data models
4) Building of data models
5) Communication of results
6) Operationalization

Data Discovery

The stakeholders regularly perform the following tasks: examine the business trends, make case studies of similar data analytics, and study the domain of business industry.The team assesses in-house resources, in-house infrastructure, technology requirements and total time involved.After evaluations and assessments, stakeholders start formulating the initial hypotheses for resolving all business challenges in terms of current market scenario.

Data Preparation

Data is prepared by transforming it from a legacy system into a data analytics form by using any kind of platform.Example: IBM Netezza 1000 is one such Sandbox platform used by IBM Company for handling data marts.

Model Planning

Proper planning of methods to be adopted and the various workflows to be followed during the next phase is done in model planning phase. The various division of work among the team is decided.Feature selection is performed for applying it to the model.

Model Building

Building a model in which team works for deploying datasets for training and testing as well as for production purposes.The model is executed.

Figure 2: Data Analytic Lifecycle

Communicate Results

Checks the results of project to find whether it is a success or failure.The inferences are drawn on key insights, the entire work is summarized and the elaborate narrative on the key findings is prepared.

Operationalization

A final report is made by the team along with the briefings, source codes and related documents.It involves running the pilot project in real time and test the project in real time environment.

1.5 Types of Data Analysis

Descriptive analysis

It is the simplest and most common type of data analysis. The main emphasis is on "What has happened?" by analysing valuable information found from the available past data. The data dealt with are large in volume and often includes the entire population.Mostly used in businesses to generate monthly revenue reports, sales leads and KPI indicators.For example: A data analyst will be able to generate the statistical results of the performance of the cricket players of team India.

Diagnostic analysis

The emphases are not only on 'what has happened?' but also on 'why it happened?'.Deeper insights on reasons behind the pattern of data found in the past.For example: A data analyst will be able to find why the performance of each cricket player of India has risen/degraded in recent past six months. The major task forthe analyst must be correct enough to find the reason behind a particular change or cause of occurrence to make a gain or profit in various fields.Machine learning techniques are used very often for this.

Predictive analysis

It deals with the prediction of future based upon the available current and past data. The emphasis is given on 'what is likely to happen?'.For example: A data analyst will be able to predict the performance of each player of Indian cricket team.Predictive analysis is applied in many domains such as risk management, weather forecasting, sales forecasting and prediction of the performance of each team.Usually, prediction is made by dividing the available dataset in training and testing sets.The predicted solution provides an approximated forecast results and may vary from the actual results.

Prescriptive analysis

It is highest in terms of complexity.The insights gain from other three types of analysis are combined to determine the kind of action to be taken to solve a certain situation.It involves a high degree of responsibility, time and complicacy to reach to informed decision making. It can be summarised as

1) Descriptive analysis – what has happened till date.
2) Diagnostic analysis – Why it has happened in a particular way.
3) Predictive analysis – what might happen in near future.
4) Prescriptive analysis – recommendations based on forecast.

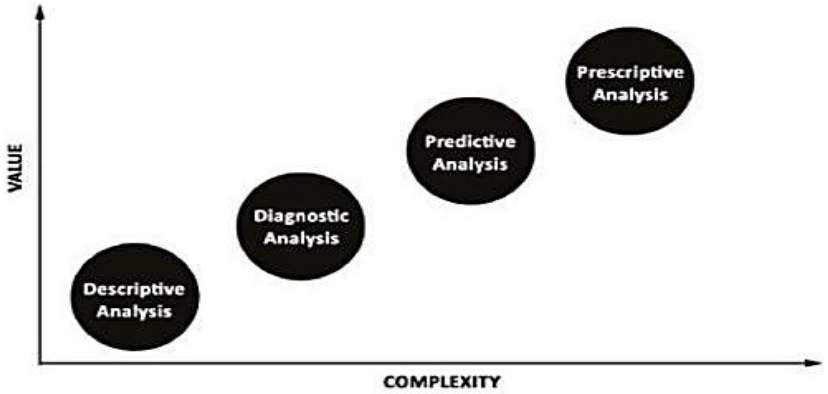

Figure 3: Data Analytic Types

1.6 Some of the Key Stakeholders

Figure 4: Stakeholders

Each of the stakeholder has a clear role to play for a business problem

- understanding the essentials of the problem,
- proper planning,
- implementation of the project,
- analysing various outcomes of the project,
- solving bottlenecks visible in the outcomes,
- generating reports by drawing inferences about the success of the project.

1.7 Types of Jobs in Data Analytics

Various stakeholders in data analytics are:

1) Data analyst

2) Data scientist

3) Data engineer

4) Database administrator

5) Analytics manager

Data analyst

The main role is to extract data and interpret the information attained from the data for analysing the outcome of a given problem in business.The analyst also discovers the various bottlenecks that are found in the results and provides possible solutions for the same.Information is extracted from given existing data is done using one or more standard methodologies such as data cleaning, data transformation, data visualization and data modelling.Major skills required to be data analyst:

1) Python

2) R programming

3) Structured Query Language

4) Statistical Analysis Software

5) SAS Miner

6) Microsoft Excel

7) Tableu.

Key areas and techniques for data analyst:

1) Data pre-processing: It involves data cleaning, data integration, data transformation and data reduction.

2) Data visualization: It involves graphical representation of data for easier analysis and better understanding.

3) Statistical modelling: It involves descriptive statistics and inferential statistics.

4) Programming skills: R and/or python programming.

5) Communication and presentation skills: Required for communicating with the team

Data Scientist

A data scientist incurs all the skills of a data analyst with the additional skills of data wrangling, complex machine learning, Big Data tools and software engineering.Both data analysts and data scientists use same tools and practices. However, the scope and nature of the problem discussed are different.The scope and nature of the problem addressed by a data scientist differ from data analyst.Data scientist deal with large and complex data that can be of high dimension, and carry out appropriate machine learning and visualization tools to convert the complex data into easily interpretable meaningful information. The fundamentals prerequisites for a data scientist

1) Statistics – Descriptive statistics and inferential statistics.

2) Mathematics – Linear algebra and calculus.

3) Computer programming – Pyhton or R.

4) Database handling – SQL.

Data Engineer

The role of data engineer is not to analyse data but rather to prepare, manage and convert data into a form that can be readily used by a data scientist or data analyst.So, the job of data engineer comes first and then the data is handed over to data analyst or data scientist for analysis.With special training a data engineer can design, build, integrate and maintain data from multiple sources.The prominent work of data engineer:

1) Developing and maintaining data architectures.

2) Aligning data architectures with business or project requirements.

3) Improving data quality and raising data efficiency.

4) Performing predictive and prescriptive modelling for given input data.

5) Determining activities that can be automated.

Database Administrator

DBA administers and operates the database.The technical skills required by DBA are:

1) SQL
2) Scripting
3) Database performance tuning
4) System and network design
5) Backup and recovery of databases

Few prominent works done by DBA are:

1) Database designing as per end user requirements.
2) Providing/or revoking rights to/or from database end users.
3) Enable efficient data backup and data recovery mechanisms.
4) Database related training to end users.
5) Ensuring data privacy and security.
6) Managing data integrity for end users.
7) Monitoring the performances of the database.

Data Architect

Data architect provides the support of various tools and platforms that are required by data engineers to carry out various tests with precision. The skills required by data architects:

1) Data modelling
2) Data warehousing
3) Extraction, transformation and load (ETL)
4) Knowledge of Hive, Pig and Spark.

The prominent works of data architect are:

1) Design and implement database systems
2) Design and implement data models
3) Design and implement components of data architecture
4) Management of data warehouses and ETL operations
5) Knowledge of data available

Analytic Manager

The analytic manager is involved in overall management of various data analytics operations.The analytics manager deals with the team leader of each group and monitors and manages the work of each team. The major skills required to be an analytics manager are:

1) Python/R programming language
2) SQL
3) SAS

The prominent works of analytics manager are:

1) Leading data analysts' team
2) Having a thorough understanding of business requirements and objectives
3) Configuring and implementing data analytics solution
4) Ensuring the quality results of the reports developed by every team
5) Keeping an eye on recent industry and business trends.

1.8 Pros and Cons of Data Science

Pros	Cons
A highly demanding course in terms of job prospects.	Data science is blurry and there are no learning limits in this career.
Multi-variety of positions which makes data science course less saturated.	A data scientist requires diverse domain knowledge to become an expert.
A highly paid job in terms of career choice.	Need to be over careful about the preservation of data privacy.
Data science is versatile and is widely used in various sectors.	Data scientists need to be very careful about the inferences drawn from the analysis as wrong output may lead to failure in businesses or other sectors.
The job of data scientist is highly prestigious.	NA
The nature of job of data scientist is very interesting.	NA

Summary

- It is the task of scrutinizing and processing raw data to reach a meaningful conclusion.
- Data science is umbrella term and data analytics is a subset of data science.
- In descriptive analysis, main emphasis is on "What has happened?" by analyzing valuable information found from the available past data.
- In diagnostic analysis, the main emphasis is not only on 'what has happened?' but also on 'why it happened?'.
- In predictive analysis, the main emphasis is on what might happen in near future.
- In prescriptive analysis, the recommendations are based on forecast.

Keywords

- **Nominal Data**: It contains a set of items that can be distinguished by the name of category.
- **Ordinal Data**: It contains the items that can be ordered, such as military rank, or units of government, but whose degree of difference can't be measured.
- **Interval Data**: It contains the items that have a measurable distance between them, but no meaningful zero point, such as Fahrenheit and Celsius temperatures.
- **Ratio Data*:*** The measurements that have a meaningful zero and can be divided meaningfully, such as the Kelvin temperature scale.
- **Model Building:**Building a model in which team works for deploying datasets for training and testing as well as for production purposes.
- **Data visualization**: It involves graphical representation of data for easier analysis and better understanding.

SelfAssessment

1. Which of these is the simplest type of data analysis?
A. Descriptive analysis
B. Diagnostic analysis
C. Prescriptive analysis
D. Predictive analysis

2. Not only on 'what has happened?' but also on 'why it happened?'. This describes
A. Descriptive analysis
B. Diagnostic analysis
C. Prescriptive analysis
D. Predictive analysis

3. It deals with the prediction of future based upon the available current and past data.
A. Descriptive analysis
B. Diagnostic analysis
C. Prescriptive analysis
D. Predictive analysis

4. Which one is the most complex in this?
A. Descriptive analysis
B. Diagnostic analysis
C. Prescriptive analysis
D. Predictive analysis

5. Which skills are required to be an analytics manager?
A. Python
B. SQL
C. SAS
D. All of the above

6. Data science is
A. Scrutinizing of raw data
B. Processing of raw data
C. Both of the above
D. None of the above

7. What are the major sources of data for studying data science?
A. Primary data
B. Secondary data
C. Both of the above
D. None of the above

8. The popular websites for data downloading are
A. Kaggle datasets
B. UCI machine learning repositories
C. IMDB datasets
D. All of the above

9. In which areas, data science can be applied?
A. E-commerce
B. Healthcare
C. Human resource management
D. All of the above

10. Data science is ……. and data analytics is its …….
A. Umbrella term, subset
B. Subset, umbrella
C. Umbrella term, umbrella term
D. Subset, subset

11. Which of these is the simplest type of data analysis?
A. Descriptive analysis
B. Diagnostic analysis
C. Prescriptive analysis
D. Predictive analysis

12. Not only on 'what has happened?' but also on 'why it happened?'. This describes
A. Descriptive analysis
B. Diagnostic analysis
C. Prescriptive analysis
D. Predictive analysis

13. It deals with the prediction of future based upon the available current and past data.
A. Descriptive analysis
B. Diagnostic analysis
C. Prescriptive analysis
D. Predictive analysis

14. Which one is the most complex in this?
A. Descriptive analysis
B. Diagnostic analysis
C. Prescriptive analysis
D. Predictive analysis

15. Which skills are required to be an analytics manager?
A. Python
B. SQL
C. SAS
D. All of the above

Answer for Self Assessment

1.	A	2.	B	3.	C	4.	D	5.	D
6.	D	7.	D	8.	D	9.	D	10.	A
11.	A	12.	C	13.	A	14.	C	15.	B

Review Questions

1. What is data science? Explain its need. What are two major sources of data?
2. Explain the reasons why one should learn data science? Explain its use in different areas.
3. What is data analytics lifecycle? Explain its phases.
4. What are the types of data analysis? Explain.
5. What are the types of jobs in data analytics? Explain.
6. What are the pros and cons of data science? Explain in detail.

Further Readings

https://www.geeksforgeeks.org/life-cycle-phases-of-data-analytics/

Web Links

https://www.simplilearn.com/tutorials/data-science-tutorial/what-is-data-science

Unit 02: Data Pre-Processing

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2.1 Phases of Data Preparation

2.2 Data Types and Forms

2.3 Categorical Data

2.4 Numerical Data

2.5 Hierarchy of Data Types

2.6 Possible Error Data Types

Summary

Keywords

Self Assessment

Answer for Self Assessment

Review Questions:

Further Readings

Objectives

After studying this unit, you will be able to

- understand the first concept of data science,
- understand the concept of data pre-processing,
- understand the various types of data,
- understand the possible types of errors.

Introduction

The data is often incomplete, unreliable, error prone and deficient in certain trends. The data can be

- Incomplete: Values of some attributes in data are missing.
- Noisy: Data contains error or outliers.
- Inconsistent: Data containing discrepancies in codes or names.

The data pre-processing is an essential step that needs to be considered before any analysis of data.The raw data collected from various sources needs to be pre-processed for converting it to a form that can be used for analysis.Data preparation takes place in usually two phases for any data science or data analysis project. The data preparation process phases are data pre-processing and data wrangling.

2.1 Phases of Data Preparation

Data Pre-processing: It is the task of transforming raw data to be ready to be fed into an algorithm. It is a time consuming yet important step that cannot be avoided for the accuracy of results in data analysis.

Data Wrangling: It is the task of converting data into a feasible format that is suitable for the consumption of the data. It is also known as data munging and it typically follows a set of common

steps such as extracting data from various data sources, parsing data into predefined data structures and storing the converted data int a data sink for further analysis.

2.2 Data Types and Forms

It is important to know the type of data that needs to be dealt with.There are two main types of data – categorical data and numerical data.Categorical data can be further classified into two types – Nominal and Ordinal data.Numerical data can be further classified into two types – Interval and Ratio data.Interval and ratio data are parametric; and nominal and ordinal data are non-parametric.The categorization of data types can be seen in figure 1.

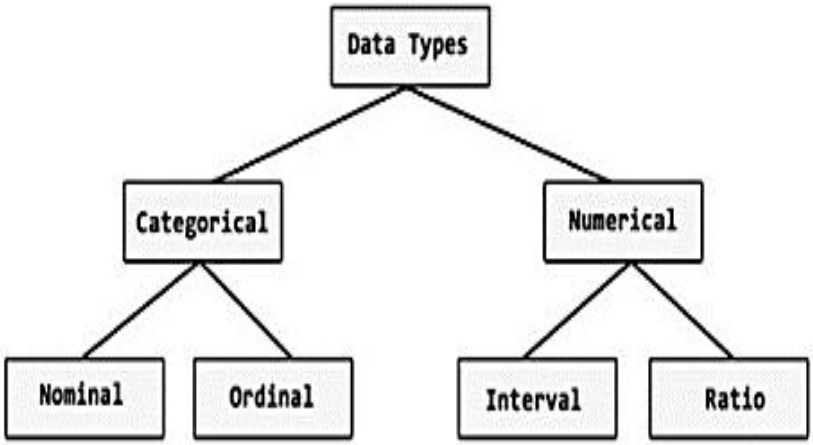

Figure 1: Categorization of data types

2.3 Categorical Data

This type of data is non-numeric and consists of text that can be coded as numeric. However, these numbers do not represent any fixed mathematical notation or meaning for the text and are simply assigned as labels or codes. It is of two types.

Nominal data:This type of data is used to label variables without providing any quantitative value. For example, gender can be labelled as 1 for Male, 2 for Female and 3 for Others. However, in real the assigned numbers for gender are not fixed and are simply assigned for labelling. Nominal scales are mutually exclusive, that is, the values don't overlap, and the labels assigned do not bear any numerical significance.

Ordinal data: This type of data is used to label variables that need to follow some order. For example: A company may take the feedback about the quality of their service. In such a case, the possible answers could be labelled as 1 (very unsatisfied), 2 (somewhat unsatisfied), 3 (neutral), 4(somewhat satisfied), and 5 (very satisfied). Thus, each categorical value is classified on a rating scale of 1 to 5.

2.4 Numerical Data

This type of data is numeric, and it usually follows an order of values. These quantitative data represent fixed values and can be of two types.

Interval data: This type of data follows numeric scales in which the order and exact differences between the values is considered. The interval data can be measured along a scale in which each position is equidistant from one another.The distances between each value on the interval scale are always kept equal. For example, age can be measured on an interval sale as 1, 2, 3, 4, 5 years etc.Also, income can be measured on an interval scale as Rs. 0 – 20,000, Rs. 20,001 – 40,000, Rs. 40,001 – 60,000, Rs. 60,001 – 80,000 and Rs. 80,001 – 1,00,000.

Ratio data: This type of data also follows numeric scales and has an equal and definitive ratio between each data. It is measured as multiple of one another and unlike interval data, can be multiple or divided. No negative numerical value if considered in ratio data and zero is considered as a point of origin. For instance, measurement of height and weight is an example of ratio data.

2.5 Hierarchy of Data Types

The hierarchy of data types can be seen in figure 2.

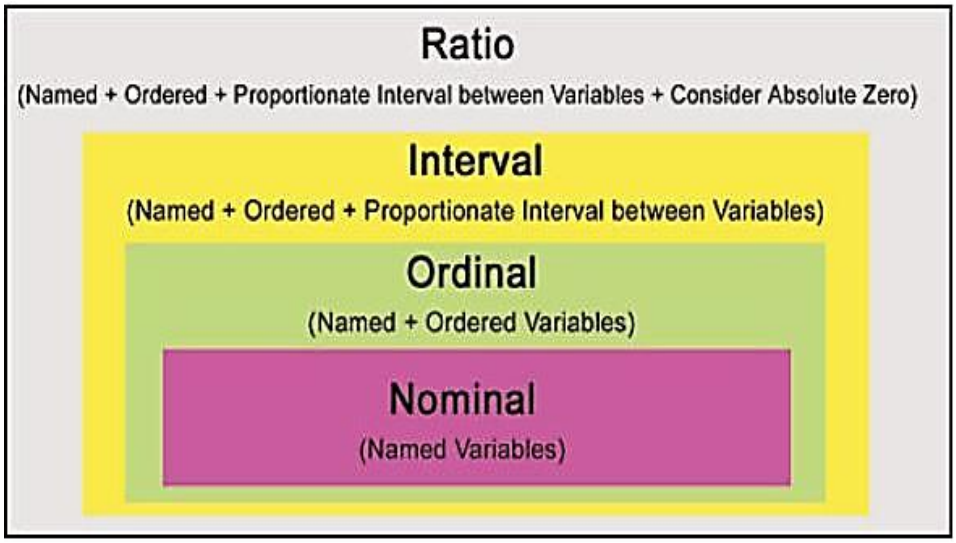

Figure 2: Hierarchy of data types

2.6 Possible Error Data Types

1) **Missing data**: Data is not to be filled up for various reasons. There can be various reasons for which the data can be missed. There are three types of this:

- Missing completely at random: Forgetting to fill in the value or lost the information.
- Missing at random data: Due to the privacy issues.
- Missing not at random: Data may not be available.

2) **Manual input**: There is an error which is made in data when we are manually inputting the values that is why it is called as human made error.

3) **Data inconsistency**: Data may be stored in various formats.Due to different formats, the issue of data inconsistency arises.

4) **Wrong data types**: The data type for values is different, so the error occurs. It is different for 3 and three.

5) **Numerical units**: Due to varying considerations of data units. For example: weight in pounds and kilograms.

6) **File manipulation**: Data may be stored in CSV or text formats. Due to the varying formats, the error occurs.

Summary

- The data is often incomplete, unreliable, error prone and deficient in certain trends.
- There are two main types of data – categorical data and numerical data.
- Categorical data can be further classified into two types – Nominal and Ordinal data.

- Numerical data can be further classified into two types – Interval and Ratio data.
- The data is incomplete as thevalues of some attributes in data are missing, noisy as thedata contains error or outliers; and inconsistent as thedata containing discrepancies in codes or names.

Keywords

- **Data pre-processing**: It is the task of transforming raw data to be ready to be fed into an algorithm.
- **Data Wrangling**: It is the task of converting data into a feasible format that is suitable for the consumption of the data.
- **Categorical data**: This type of data is non-numeric and consists of text that can be coded as numeric.
- **Nominal data**: This type of data is used to label variables without providing any quantitative value.
- **Ordinal data**: This type of data is used to label variables that need to follow some order.
- **Interval data**: This type of data follows numeric scales in which the order and exact differences between the values is considered.
- **Ratio data**: This type of data also follows numeric scales and has an equal and definitive ratio between each data.

SelfAssessment

1. Nominal values are

A. Mutual exclusive
B. Can be same
C. Not mutually exclusive
D. None of the above

2. Which of these techniques follows a set of common steps such as data extraction, parsing data and storing of converted data?

A. Data Discovery
B. Data Preparation
C. Data Wrangling
D. None of the above

3. Which of these types of data is non-numeric and consists of text that can be coded as numeric?

A. Categorical data
B. Numerical data
C. Both of the above
D. None of the above

4. The task of transforming raw data to be ready to be fed into an algorithm is known as

A. Data pre-processing
B. Model building
C. Data Wrangling
D. Operationalization

5. The task of converting data into a feasible format that is suitable for the consumption of the data is known as

A. Data pre-processing
B. Model building
C. Data Wrangling
D. Operationalization

6. The possible errors in missing data can be
A. Missing completely at random
B. Missing at random data
C. Missing not at random
D. All of the above

7. The data of type Named + Ordered + Proportionate Interval between Variables + Consider Absolute zero is
A. Ratio data
B. Interval data
C. Ordinal data
D. Nominal data

8. The data of Named + Ordered variables is a type of
A. Ratio data
B. Interval data
C. Ordinal data
D. Nominal data

9. Which of the following is a type of non-parametric data?
A. Nominal data
B. Ordinal data
C. Both of the above
D. None of the above

10. Which of the following is a type of parametric data?
A. Interval data
B. Ratio data
C. Both of the above
D. None of the above

11. The data preprocessing deals with
A. Incomplete
B. Noisy
C. Inconsistent
D. All of the above

12. The data preparation consists of
A. Data preprocessing
B. Data wrangling
C. Both of the above
D. None of the above

13. Which of the following is also known as data munging?
A. Data wrangling
B. Data preprocessing
C. Data discovery
D. None of the above

14. The task of converting data into a feasible format that is suitable for the consumption of the data is also known as _____.
A. Data Discovery
B. Data Preparation
C. Data Wrangling
D. None of the above

15. The data type for 5 and five will be same. This statement is
A. True
B. False

Answer for Self Assessment

1.	A	2.	C	3.	A	4.	A	5.	C
6.	D	7.	A	8.	C	9.	C	10.	C
11.	D	12.	C	13.	A	14.	C	15.	B

Review Questions:

1. What is data pre-processing? Explain its two phases.
2. What are two main types of data? Also explain its further categorization.
3. What are the possible error data types? Explain with example.
4. What is the hierarchy of data types? Explain with examples.
5. What is data pre-processing and data wrangling? Explain in detail.

Further Readings

https://byjus.com/maths/types-of-data-in-statistics/

Web links

https://www.asiapremierbpo.com/insights/4-common-data-entry-errors-and-how-to-fix-them/

Unit 03: Various Data Pre-processing Operations

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Keywords

Self Assessment

Answer for Self Assessment

Review Questions:

Further Readings

Objectives

After studying this unit, you will be able to

- understand the concept of data preprocessing,
- understand the process and methods of data cleaning,
- understand the concept of data integration,
- understand the data integration framework and tools,
- understand the concept, need and techniquesof data transformation,
- understand the concept, need and strategies of data reduction
- understand the concept of data discretization.

Introduction

The raw data collected are prone to several errors and thus need to go through a series of steps for preprocessing. There are various data pre-processing operations like data cleaning, data integration, data transformation, data reduction and data discretization.

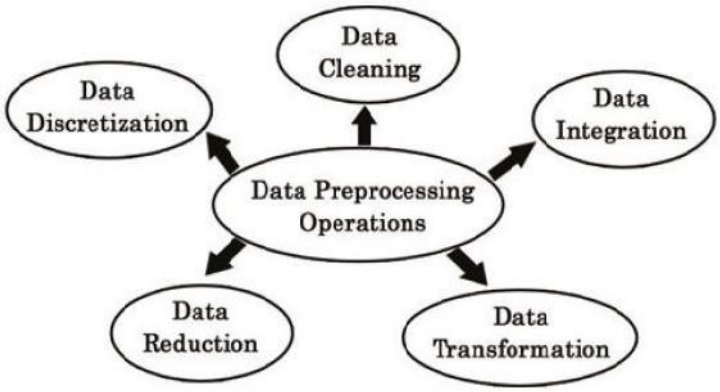

Figure 1: Data Pre-processing Operations

3.1 Data Cleaning

Dirty data can cause an error while doing data analysis. Data cleaning is done to handle irrelevant or missing data.Data is cleaned by:

1) Filling in the missing values.
2) Smoothing noisy data
3) Detecting and removing outliers

Filling the missing values

Filling up the missing values in data is known as the imputation of missing data.Sometimes, this imputation process becomes time-consuming.The method to be adapted for filling up the missing values depends on the pattern of data used and the nature of analysis to be performed with the data.The simplest methods used for handling missing values are:

1) Replace Missing Values with Zeroes
2) Dropping Rows with Missing Values
3) Replace Missing Values with Mean/Median/Mode
4) Filling every missing value with the previous value
5) Filling every missing value with the next value

Smoothing the noisy data

It is an important technique for data preprocessing.It is intended to identify trends in the presence of noisy data when the pattern of the trend is unknown.Two main methods used for smoothing noisy data are: binning and regression.

Binning

The method of binning is mainly applied to improve the accuracy of a predictive model by reducing the noise from data. It also helps in easy identification of outliers or invalid values for numerical data.It is a discretization method that performs local smoothing of data by transforming numerical values into categorical counterparts. This method smoothens sorted data values by referring to the values around it.The sorted values are distributed into a number of bins or buckets.For instance, values of age can be categorized into groups to make it fall into separate bins. One bin consists of age 10-19, another bin consists of age 20-29, the third bin consists of age 30-39; another bin consists of age 40-49, and so on. Thus, all the numerical values are discretized to form a frequency table.Distributing of values into bins can be done in two ways:

1) **Equal width binning**: The data is divided into n intervals of equal size. The width w of the interval is calculated as w = (maxvalue – minvalue) / n .
2) **Equal frequency binning**: The data is divided into n groups and each group contains approximately the same number of values.

Example: Data Values: 0, 3, 13, 17, 17, 19, 23, 28, 29

Equal Width Binning:

Bin 1: 0, 3 [-, 10]

Bin 2: 13, 17, 17, 19 [10,20]

Bin 3: 23, 28, 29 [20, +]

Equal Frequency Binning:

Bin 1: 0, 3, 13 [-, 14]

Bin 2: 17, 17, 19 [14,21]

	Bin 3: 23, 28, 29 [21, +]

Binning is often used as a standard method of data smoothing to predict trends and to make a quick analysis of the ranges of the entire data. In the binning method, the bins are formed by consulting the neighborhood values. For this reason, the binning method is considered to perform local smoothing.

Regression

This method smoothens data by fitting the data to a function. The simplest type of regression is the linear regression which works by finding the "best fitted " line to fit two attributes so that the values of the independent attribute can be used to predict the values of the dependent attribute.There are various regression techniques such as linear regression, logistic regression, decision tree regression, polynomial regression, and lasso regression. For each of these types of regression, the main concept is the same, that is, to establish the nature of the functional relationship between two or more variables for future prediction or forecasting.

Detecting and removing outliers

An outlier is a data point that is far away from other related data points. Outliers may occur due to several reasons such as measurement error, data entry error, experimental error, intentional inclusion of outliers, sampling error or natural occurrence of outliers. For data analysis, outliers should be excluded from the dataset as much as possible as these outliers may mislead the analysis process resulting in incorrect results and longer training time. In turn, the model developed will be less accurate that provides comparatively poorer results.

There are several ways to detect outliers in each dataset. Few such popular methods of outlier detection are listed below:

1) Probabilistic and Statistical Modelling (parametric)
2) Z-Score or Extreme Value Analysis (parametric)
3) Proximity Based Models (non-parametric)
4) Linear Regression Models (PCA, LMS)
5) High Dimensional Outlier Detection Methods (high dimensional sparse data)

Statistical method of outlier detection

1) Standard deviation method
2) Interquartile range method

Standard deviation method:

This method of outlier detection initially calculates the mean and standard deviation of the data points. Each value is then compared by checking whether the value is a certain number of standard deviations away from the mean. If so, the data point is identified as an outlier. The specified number of standard deviations is considered as the threshold value for which the default value is 3.

Interquartile range method:

This method of outlier detection initially calculates the interquartile range (IQR) for the given data points. Each value is then compared with the value (1.5 x IQR). If the data point is more than (1.5 x IQR) above the third quartile or below the first quartile, the data point is identified as an outlier. This can be mathematically represented as low outliers are less than Q1 - (1.5 x IQR), and high outliers are more than Q3 + (1.5 x IQR), where Q1 is the first quartile and Q3 is the third quartile.

3.2 Data Integration

The technique of data integration allows merging data from various disparate sources to maintain a unified view of the data. It is an important technique used mainly for merging varying data of a company in a common unified format or for combining data of more than one company tomaintain

common data assets. The task is complex as the data sources in real life are heterogeneous and this raises the complexity of assimilating the data of different formats into a common format to be stored in a unified data source.

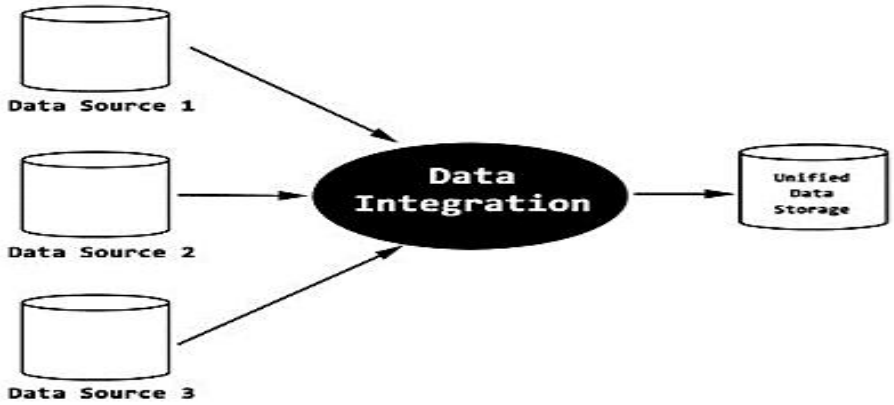

Figure 2: Data Integration

Data integration is carried out in many areas such as data warehousing, data migration, information integration, and enterprise management. It is a challenging work as a lot of understanding of the system is required prior to integrating data from multiple sources, such as:

1) What is the main objective of the integration of data for the company?
2) What kind of data assets are to be integrated?
3) What are the various sources of data?
4) What are the various business rules to be followed?
5) What is the support model for the new system?
6) Who will be the owner of the entire system?

One important aspect to consider for data integration is to handle redundancy. Redundant data can be detected using the concept of correlation analysis. There are several methods used in correlation analysis to find the correlation coefficient (a value between 0 and 1), which measures the strength and the direction of a linear relationship between two variables.One of the standard methods of finding the correlation coefficient is called Karl Pearson's Coefficient of Correlation (denoted by r), which can be mathematically represented as:

$$r = \frac{\sum xy}{N\sigma_x\sigma_y}$$

Standard Data Integration Techniques

Virtual integration

This technique, also called Uniform Data Access, lets the data be viewed from a single source system, but the entire data is not stored in a single location. Data virtualization can provide a unified view of data to customers across a platform without maintaining a separate store for the consolidated data. However, if this method is used, there is a limited possibility of accessing data history and version management.

Physical data integration

This technique, also called Common Data Storage, maintains a copy of the data from the source to a new system. Here, the collected integrated data from several sources is stored and managed by the new system instead of the source system. This approach is typically followed by data warehouse systems.

Application-based integration

This technique takes the help of application(s) to implement the integration process of collecting and storing data in a unified single storage system. This technique has limited use compared to physical data integration.

Manual integration

This technique, also called as Common User Interface, is largely used for accessing information that is available on the Internet. Here, the entire data is not stored in a single location for unified data access; rather the source system is used to access the required web pages.

Middleware data integration

This technique handovers the integration process from particular applications to a new middleware layer. The applications do not fully implement the integration logic but partially participate in the data integration.

Data integration framework

The data integration framework (DIF) involves two categories of processes as given below:

1) The first category involves the process of determining the data requirements and solutions. Data requirements can be –studying business requirements, determining data and quality needs, data profiling, performing a data quality assessment based on business requirements, and so on.

2) The second category involves the process used to physically accumulate the data from multiple sources and transform it into meaningful information to be used for analysis and decision making.

For carrying out this process, the various steps involved are:

- **Data preparation**: This includes gathering, reformatting, combining, transforming, cleansing and storing data for further analysis.
- **Data franchising** : This involves reconstructing data into information that can be used for reporting and analysis.
- **Data and metadata management** : This involves managing both the data and metadata between the several processes.

Data Integration Tools

Data Integration Tool	Data Integration Capabilities/Services	Main feature(s)
Informatica	Provides advanced hybrid data integration	Integrated codeless environment
Microsoft	Provides hybrid data integration, provides its own Server Integration Services	Fully managed ETL service in the cloud.
Talend	Integrates data with unified development and management tools	Open, scalable architectures; Five times faster than MapReduce
Oracle	Cloud-based data integration	Machine learning and AI capabilities; data migration across hybrid environments; data profiling and governance
IBM	Data integration for structured and unstructured data	Massive parallel processing capabilities; data profiling, standardization, machine enrichment.

Other standard integration tools

- SAP
- Information builders
- SAS
- Adeptia
- Actian
- Dell Bhoomi
- Syncsort

These integration tools are mainly involved in solving various complex data integration processes such as ingestion, cleansing, ETL mapping and transformation.

3.3 Data Transformation

Once the data is cleaned and integrated, it is transformed into a range of values that are easier to be analyzed. This is done as the values for different information are found to be in a varied range of scales. For example, for a company, age values for employee scan be within the range of 20-55 years whereas salary values for employees can be within the range of Rs. 10,000 – Rs. 1,00,000.This indicates one column in a dataset can be more weighted compared to others due to the varying range of values. In such cases, applying statistical measures for data analysis across this dataset may lead to unnatural or incorrect results. Data transformation is hence required to solve this issue before applying any analysis of data.

Various data transformation techniques

1) Rescaling data
2) Normalizing data
3) Binarizing data
4) Standardizing data
5) Label encoding
6) One hot encoding

Rescaling data

When the data encompasses attributes with varying scales, many statistical or machine learning techniques prefer rescaling the attributes to fall within a given scale. Rescaling of data allows scaling all data values to lie between a specified minimum and maximum value (say, between 0 and 1). Data rescaling is done prior to data analysis in many cases such as, in algorithms that weight inputs like regression and neural networks, in optimization algorithms used in machine learning, and in algorithms that use distance measures like K-Nearest Neighbors.

Normalizing data

Normalizing rescales data in such a way that each row of observation equals to a length of 1 (called a unit norm in linear algebra). Data normalization is done prior to data analysis in many cases such as for sparse data having lots of zeroes or for attributes having high varying ranges of data values.

Binarizing data

Binarizing is the process of converting data to either 0 or 1 based on a threshold value. All the data values above the threshold value are marked 1 whereas all the data values equal to or below the threshold value are marked as 0. Data binarizing is done prior to data analysis in many cases such as, dealing with crisp values for the handling of probabilities and adding new meaningful features in the dataset.

Standardizing data

Standardization, also called mean removal, is the process of transforming attributes having a Gaussian distribution with differing mean and standard deviation values into a standard Gaussian distribution with a mean of 0 and a standard deviation of 1. Standardization of data is done prior to

data analysis in many cases such as, in the case of linear discriminate analysis, linear regression, and logistic regression.

Label encoding

The process of label encoding is used to convert textual labels into numeric form in order to prepare it to be used in a machine-readable form. The labels are assigned a value of 0 to (n-1) where n is the number of distinct values for a particular categorical feature. The numeric values are repeated for the same label of that attribute. For instance, let us consider the feature 'gender' having two values – male and female. Using label encoding, each gender value will be marked with unique numerical values starting with 0. Thus, males will be marked 0, females will be marked 1.

One hot encoding

It refers to splitting the column which contains numerical categorical data to many columns depending on the number of categories present in that column. Each column contains "0" or "1" corresponding to which column it has been placed.For instance, let us consider a feature X has two distinct values A and B as follows: X: A A B. If one hot encoding is applied to the above feature, the matrix that will be formed as follows:

1 [1,0]

2 [1,0]

3[0,1]

3.4 Data Reduction

An essential step of data preprocessing is data reduction. To reduce the unimportant or unwanted features from a dataset.

Strategies for data reduction

1) Dimensionality reduction
2) Data cube aggregation
3) Numerosity reduction

Dimensionality Reduction

For classification and clustering, features are studied to obtain the analysis output.The higher the number of features, the more difficult it is for the training process for output analysis.There may be many features that are correlated or redundant.The main aim is to obtain a set of principal variables.There are two main components:

1) Feature selection
2) Feature extraction

Feature selection

The main aim is to obtain a smaller subset that can be used to model a given problem.It usually involves three ways – filter, wrapper, and embedded. The standard techniques for feature selection are:

1) Univariate selection: This method works by inspecting each feature and then finding the best feature based on statistical tests. It also analyses the capability of these features in accordance with the response variable.
2) Recursive feature elimination: This method works by performing a greedy search to acquire the best feature subset from a given dataset. This is done in an iterative process by determining the best or the worst feature at each iteration.
3) Stepwise forward selection : This method initially starts with an empty set of attributes which is considered as the minimal set. In each iteration, the most relevant attribute is then added to the minimal set until the stopping rule is satisfied.One of the stopping rules is to stop when all remaining variables have a p-value above some threshold.
4) Stepwise backward elimination: This method initially starts with all the sets of attributes that are considered as the initial set. In each iteration, the most irrelevant attribute is then removed from the minimal set until the stopping rule is satisfied. One of the stopping rules is to stop when all remaining variables have a significant p-value defined by some significance threshold.

5) Combination of forward selection and backward elimination: This method is commonly used for attribute subset selection and works by combining both the methods of forward selection and backward elimination.
6) Decision tree induction: This method uses the concept of decision trees for attribute selection. A decision tree consists of several nodes that have branches. The nodes of a decision tree indicate a test applied on an attribute while the branch indicates the outcome of the test. The decision tree helps in discarding the irrelevant attributes by considering those attributes that are not a part of the tree.

Feature extraction

This process is used to reduce the data in a high dimensional space to a lower dimension space. While feature selection chooses the most relevant features from among a set of given features, feature extraction creates a new, smaller set of features that consists of the most useful information.Few methods of dimensionality reduction

1) PCA
2) LDA

Principal Component Analysis

It is an unsupervised method of feature extraction that creates linear combinations of the original features.The features are uncorrelated and are ranked in order of variance. The data has to be normalized before performing PCA. PCA has several variations of it such as sparse PCA, kernel PCA, and so on.

Linear Discriminant Analysis

It is a supervised method of feature extraction that also creates linear combinations of the original features.However, it can be used for only labeled data and can be thus used only in certain situations. The data has to be normalized before performing LDA.This helps in removing redundant features, reducing computation time, as well as in reducing storage space.However, dimensionality reduction results in loss of data and should be used with proper understanding to effectively carry out data preprocessing before performing analysis of data.

Data Cube Aggregation

Data cubes store multidimensional aggregated information. For example, a sales report has been prepared to analyze the number of sales of mobile phones per brand in each branch for the year 2009 to 2019.

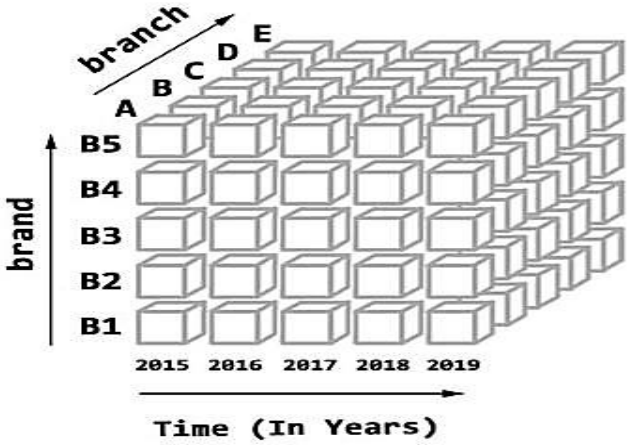

Figure 3: Data cube

This has three dimensions – time, brand and branch. All the dimensions together help to solve queries.Thus, OLAP cubes are designed using business logic and understanding. They are optimized for analytical purposes so that they can report on millions of records at a time.

Cell in Data Cube

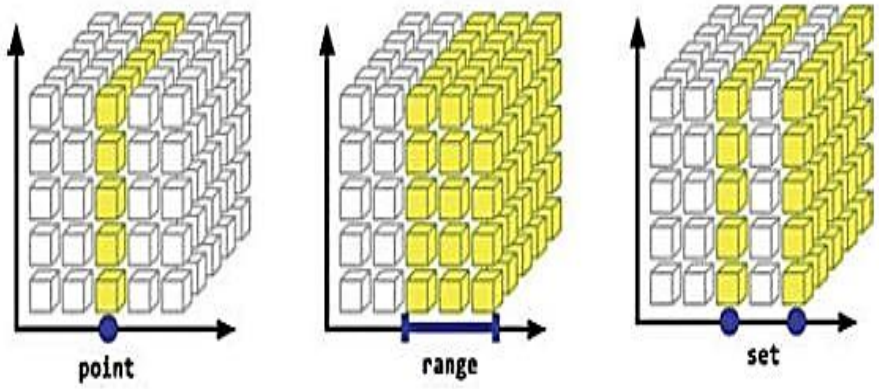

Figure 4: A point, range and set

Cubes are used in many ways for several tasks, such as:

- Model preparation
- Measure aggregation
- Drill-down through dimensions
- Slice-and-dice

Numerosity Reduction

This method is used for converting the data to smaller forms to reduce the volume of data. Numerosity reduction may be either parametric or non-parametric. Parametric methods use a model to represent data in which parameters of the data are stored, rather than the data itself. Examples of parametric models include regression and log-linear models. Non-parametric methods are used for storing reduced representations of the data. Examples of non-parametric models include clustering, histograms, sampling, and data cube aggregation.

3.5 Data Discretization

The data discretization method is used to partition the range of continuous attributes into intervals. By doing so, several continuous attribute values are replaced by lesser interval labels. Data discretization can be of two types - top-down discretization and bottom-up discretization:

- Top-down discretization: This process, also called splitting , works by first finding one or a few split points to divide the entire attribute range. This process is repeated on the resulting intervals until the stopping condition is found to be true.
- Bottom-up discretization: This process, also called as merging , works by first considering all the continuous values as potential split-points. The process then further removes some continuous values by merging neighborhood values to form intervals.

Concept hierarchy: If an attribute is taken into consideration and the technique of discretization is performed recursively on the attribute to provide a hierarchical partitioning of its values, it is known as a concept hierarchy.Often the clustering technique is used to generate a concept hierarchy by considering either splitting process or the merging process. Clustering using the splitting process initially decomposes each cluster or partition into subclusters.This forms a lower level of the hierarchy of clusters. In the merging process of clustering for discretization, clusters are created by recurrently grouping neighboring clusters to form higher-level concepts.

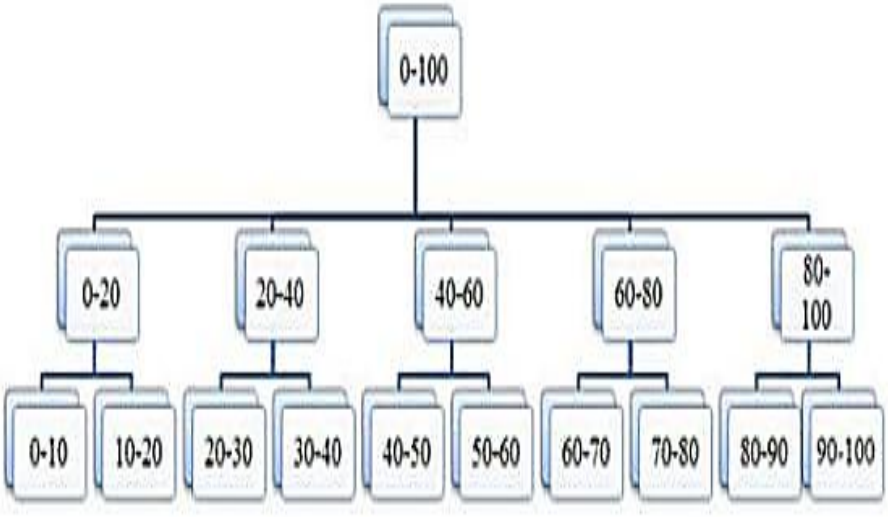

Figure 5: Concept hierarchy

Summary

- Data cleaning is done to handle irrelevant or missing data.
- Data is cleaned by filling in the missing values, smoothing noisy data and detecting and removing outliers.
- Binning is often used as a standard method of data smoothing to predict trends and to make a quick analysis of the ranges of the entire data.
- In Karl Pearson Coefficient, the value of r = +1 indicates a perfect positive relationship between two variables; r = -1 indicates a perfect negative relationship between two variables, and r=0 indicates that there is no relationship between the two variables.
- Once the data is cleaned and integrated, it is transformed into a range of values that are easier to be analyzed. This is done as the values for different information are found to be in a varied range of scales.
- If an attribute is taken into consideration and the technique of discretization is performed recursively on the attribute to provide a hierarchical partitioning of its values, it is known as a concept hierarchy.

Keywords

- **Imputation of missing data**: Filling up the missing values in data is known as the imputation of missing data.
- **Binning:**It is a discretization method that performs local smoothing of data by transforming numerical values into categorical counterparts.
- **Equal width binning**: The data is divided into n intervals of equal size. The width w of the interval is calculated as w = (maxvalue – minvalue) / n .
- **Equal frequency binning**: The data is divided into n groups and each group contains approximately the same number of values.
- **Outlier:**An outlier is a data point that is far away from other related data points.
- **Interquartile range method**: It initially calculates the interquartile range (IQR) for the given data points. Each value is then compared with the value (1.5 x IQR). If the data point is more than (1.5 x IQR) above the third quartile or below the first quartile, the data point is identified as an outlier
- **Data Integration:** The technique of data integration allows merging data from various disparate sources so as to maintain a unified view of the data.
- **Data franchising :** This involves reconstructing data into information that can be used for reporting and analysis.

- **Data and metadata management :** This involves managing both the data and metadata between the several processes.
- **Rescaling:**Rescaling of data allows scaling all data values to lie between a specified minimum and maximum value (say, between 0 and 1).
- **Binarizing:** Binarizing is the process of converting data to either 0 or 1 based on a threshold value.
- **Standardization:** Standardization, also called mean removal, is the process of transforming attributes having a Gaussian distribution with differing mean and standard deviation values into a standard Gaussian distribution with a mean of 0 and a standard deviation of 1.
- **Label encoding:** The process of label encoding is used to convert textual labels into numeric form to prepare it to be used in a machine-readable form.
- **Feature Selection:** The main aim is to obtain a smaller subset that can be used to model a given problem. It usually involves three ways – filter, wrapper, and embedded.
- **Data Discretization**: The data discretization method is used to partition the range of continuous attributes into intervals. By doing so, several continuous attribute values are replaced by lesser interval labels. Data discretization can be of two types - top-down discretization and bottom-up discretization.

SelfAssessment

1. Which of these represents the techniques of data transformation?

A. Binarizing data
B. Label encoding
C. One hot encoding
D. All of the above

2. _____ is the process of converting data to either 0 or 1 based on a threshold value.

A. Binarizing data
B. Label encoding
C. One hot encoding
D. Standardizing data

3. The process of _____ is used to convert textual labels into numeric form in order to prepare it to be used in a machine-readable form.

A. Binarizing data
B. Label encoding
C. One hot encoding
D. Standardizing data

4. Where is the data integration carried out?

A. Data warehousing
B. Data migration
C. Information integration
D. All of the above

5. The redundant data can be detected using

A. Concept of correlation analysis
B. Concept of regression analysis
C. Concept of classification analysis
D. Concept of clustering analysis

6. The value +1 of correlation coefficient indicates

A. No relationship
B. A perfect positive relationship
C. A perfect negative relationship
D. Just a number

7. The value -1 of correlation coefficient indicates

A. No relationship
B. A perfect positive relationship
C. A perfect negative relationship

D. Just a number

8. Which of these techniques of data integration is also known as Uniform Data Access?
A. Virtual integration
B. Physical data integration
C. Application based integration
D. Manual integration

9. Which of these are data integration tools?
A. Microsoft
B. Talend
C. IBM
D. All of the above

10. Which of the following are data pre-processing operations?
A. Data reduction
B. Data cleaning
C. Data transformation
D. All of the above

11. The data is cleaned by:
A. Filling in the missing values
B. Smoothing noisy data
C. Detecting and removing outliers
D. All of the above

12. The methods for smoothing noisy data are:
A. Regression
B. Binning
C. Both of the above
D. None of the above

13. Which of these can be used for smoothing of noisy data?
A. Equal width binning
B. Equal frequency binning
C. Both of the above
D. None of the above

14. _____ works by performing a greedy search to acquire the best feature subset from a given dataset.
A. Recursive feature elimination
B. Univariate selection
C. Stepwise forward selection
D. Stepwise backward elimination

15. Which process of discretization is also known as splitting?
A. Top-down discretization
B. Bottom-up discretization
C. Left-right discretization
D. Right-left discretization

Answer for Self Assessment

1.	D	2.	A	3.	B	4.	D	5.	A
6.	B	7.	C	8.	A	9.	D	10.	D
11.	D	12.	C	13.	C	14.	A	15.	A

Review Questions

1. What is data pre-processing? Explain its different operations in detail.
2. What is data cleaning? What is the need of data cleaning? Explain the strategies by which we can clean the data.
3. In data cleaning, explain how can we detect and remove the outliers?
4. What is data integration? How can we handle redundancies?
5. What are standard data integration techniques? Explain.
6. What is data integration framework? Explain its phases.
7. What is data transformation? Explain various data transformation techniques.
8. What is data reduction? What are different strategies for data reduction?
9. What are two main strategies for dimensionality reduction? Explain.

Further Readings

https://www.javatpoint.com/data-preprocessing-machine-learning

Web Links

https://www.geeksforgeeks.org/data-cleansing-introduction/

Unit 04: Data Plotting and Visualization

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4.8 Advanced Data Visualization using Seaborn Library

4.9 Visualization Libraries

Summary

Keywords

Self Assessment

Answers for Self Assessment

Review Questions

Further Readings

Objectives

Afterthis unit, you will be able to:

- Understand the concept of data visualization
- Understand the importance of data visualization
- Understand the data visualization softwares and libraries
- Understand the advanced visualization using Seaborn library
- Understand the types of data visualization

Introduction

To make the information easy to understand and analyze, we use the concept of visualization which is a graphical way to represent the data. Data visualization has the capacity of demonstrating the complex data relationships and patterns with the help of simple designs consisting of lines, shapes, and colors.

4.1 Data visualization

It is considered as an evolving blend of art and science that has brought a revolutionary change in the corporate sectors and will also continue to do so over the next few years. It plays a major role in the decision making of the analytics world. Is the process of presenting data in the form of graphs or charts?

- **Visualize:**To form a mental vision, image, or picture of something to make visible to the mind or imagination.

- **Visualization**: Itis the use of computer graphics to createvisual images which aid in the understanding of complex, often massive representations of data.
- **Visual Data Mining**: It is the process of discovering implicit but useful knowledge from large data sets using visualization techniques.

Table vs Graph

- A table is best when you need to look up specific values. A graph is best when the message is contained in the shape of the values.
- A table is best when users need precise values and there is a need to precisely compare related values. A graph is best when you want to reveal relationships among multiple values (similarities and differences)

Data Visualization can help in

- **Identify outliers in data:**An outlier is a data point that is aloof or far away from other related data points. Outliers may occur due to several reasons such as measurement error, data entry error, experimental error, intentional inclusion of outliers, sampling error or natural occurrence of outliers.For data analysis, outliers may mislead the analysis process resulting in abruptly different, incorrect results and longer training time.
- **Improve response time:**Data visualization gives a quick glance of the entire data and, in turn, allows analysts or scientists to quickly identify issues, thereby improving response time. This contrasts with huge chunks of information that may be displayed in textual or tabular format covering multiple lines or records.
- **Greater simplicity:**Data, when displayed graphically in a concise format, allows analysts or scientists to examine the picture easily. The data to be concentrated on gets simplified as analysts or scientists interact only with relevant data.
- **Easier visualization of patterns**: Data presented graphically permits analysts to effortlessly understand the content for identifying new patterns and trends that are otherwise almost impossible to analyze. Trend analysis or time-series analysis are in huge demand in the market for a continuous study of trends in the stock market, companies, or business sectors.
- **Business analysis made easy**: Business analysts can deal with various important decision-making such as sales prediction, product promotion, and customer behavior using correct data visualization techniques.
- **Enhanced collaboration**: Advanced visualization tools make it easier for teams to collaboratively go through the reports for instant decision-making.

Advantages of Data Visualization

- It helps to understand large and complex amounts of data very easily.
- It allows the decision-makers to make decisions very efficiently and also allows them in identifying new trends and patterns very easily.
- It is also used in high-level data analysis for Machine Learning and Exploratory Data Analysis (EDA).

4.2 Visual Encoding

Visual encoding is the approach used to map data into visual structures, thereby building an image on the screen.This is an important consideration to be made as one visualization tool can be more effective than the other visualization tool due to the easy perception of information conveyed by the former visualization graph than the latter.The attribute values signify important data characteristics such as numerical data, categorical data, or ordinal data.Spatiotemporal data contains special attributes such as geographical location (spatial dimension) and/or time (temporal dimension).Mapping of data is based on the visual cues (also called retinal variables) such as location, size, color value, color hue, color saturation, transparency, shape, structure, orientation, and so on.

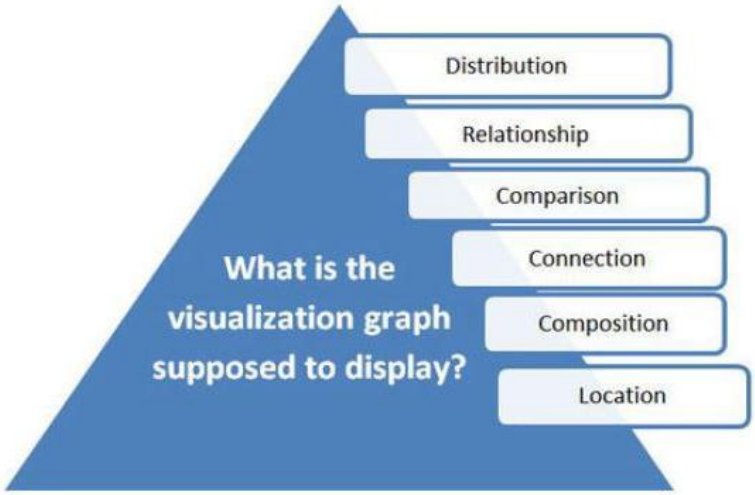
Retinal Variables

To represent data that involves three or more variables, these retinal variables play a major role.

- **Size:** Itis an important visualize for quantitative data as a smaller size indicates less value while bigger size indicates more value.
- **Color hue:** It plays an important role in data visualization as for instance, the red color signifies something alarming, the blue color signifies something serene and peaceful, while the yellow color signifies something bright and attractive.
- **Shape**: Such as circle, oval, diamond and rectangle, may signify different types of data and is easily recognized by the eye for the distinguished look.
- **Orientation**:Such as vertical, horizontal and slanted, help in signifying data trends such as an upward trend or a downward trend.
- **Color Saturation:** Thisdecides the intensity of color and can be used to differentiate visual elements from their surroundings by displaying different scales of values.
- **Length:** Itdecides the proportion of data and is a good visualization parameter for comparing data of varying values.

4.3 Concepts of Visualization Graph

The main question for visual encoding lies in the fact ' What do we want to portray with the given data?'



4.4 Role of Data Visualization and its Corresponding Visualization Tool

Role of Data Visualization	Data Visualization Graph
Distribution	Scatter Chart
	3D Area Chart
	Histogram
Relationship	Bubble Chart
	Scatter Chart

Comparison	Bar Chart
	Column Chart
	Line Chart
	Area Chart
Composition	Pie Chart
	Waterfall Chart
	Stacked Column Chart
	Stacked Area Chart
Location	Bubble Map
	Choropleth Map
	Connection Map
Connection	Matrix Chart
	Node-link Diagram
	Word Cloud
	Alluvial Diagram
	Tube Map

4.5 Data Visualization Softwares

These software applications differ in their ability to use various types of graphs and visuals, simplified user interface, accurate trend tracking capability, level of security, ease of use in mobile and friendly report generation.

Data Visualization Software	**Description**	**Key Features**
Tableau	Easily connects, visualizes, and shares data with effective seamless experience from desktop to mobile	Flexible data analysis methods Mobile friendly Manageable permission access
Qlikview	Allows users to create default and custom data connectors and templates, depending on one's need	Personalized data search Script building Role-based access
Sisense	Uses agile analysis software with a variety of data visualization options. Can create dashboards and graphics with drag and drop user	Easy setup and use, Data exporting range, Interactive dashboards

	interface.	
Looker	It provides an efficient business intelligence platform for users to utilize SQL for organizing unstructured data.	Ease of use Strong collaboration features Handy and compact visualization.
Zoho Analytics	Uses a variety of tools, such as pivot tables, KPI widgets, and tabular view components. Can generate reports with valuable business insights.	Insightful reports, Robust security, Integration and app development
Domo	Generates real time data in a single dashboard. Can generate various creative data displays such as multi-part widgets and trend indicators	Free trial, Socialization, Dashboard creation
Microsoft Power BI	Comes with unlimited access to on-site and in-cloud data that gives a centralized data access hub.	Unlimited connective options, Affordability, Web publishing
IBM Waston Analytics	Can type in various questions which the intelligence software can interpret and answer accordingly	File Upload Public forum support On-site data
SAP Analytics Cloud	Can generate focused reports and collaborative tools for online discussion. Provides import and export features for spreadsheets and visuals	Easy Forecasting Set up important events Cloud-based protection
Plotly	Provides a vast variety of colorful designs for data visualization. Can use the chart studio to create web-based reporting templates	2D and 3D Chart options, Open-source coding, Designer input

Few Other Softwares

Few other softwares available for plotting visualization graphs:

1. MATLAB
2. FusionCharts
3. Datawrapper
4. Periscope Data
5. Klipfolio
6. Kibana
7. Chartio
8. Highcharts
9. Infogram

4.6 Data Visualization Libraries

The libraries which are very important for data visualization are:

1. The matplotlib library
2. The seaborn library
3. The ggplot library
4. The Bokeh library
5. The plotly library
6. The pygal library
7. The geoplotlib library
8. The Gleam library
9. The missingno library
10. The Leather library

The matplotlib library

It is the most common and standard Python library used for plotting 2D data visualizations.This library was created by John D. Hunter and is currently maintained by a team of Python developers.The matplotlib library is mainly used for creating plots that can be zoomed in on a section of the plot and pan around the plot using the toolbar in the plot window. It is the first data visualization library to be developed in Python, and later many other libraries were built on top of it for various other ways of visualizations. This library is used to create a variety of visualization graphs such as line plots, pie charts, scatter plots, bar charts, histograms, stem plots, and spectrograms. The matplotlib allows easy use of labels, axes titles, grids, legends, and other graphic requirements with customizable values and text.Matplotlib is a low-level library of Python which is used for data visualization. It is easy to use and emulates MATLAB like graphs and visualization. This library is built on the top of NumPy arrays and consist of several plots like line chart, bar chart, histogram, etc.It provides a lot of flexibility but at the cost of writing more code.

The sea born library

The sea born library couples the power of the matplotlib library to create artistic charts with very few lines of code. The sea born library follows creative styles and rich color palettes, that allows to create visualization plots to be more attractive and modern. Today's visualization graph is mainly plotted in sea born rather than matplotlib , primarily because of the sea born library's rich color palettes and graphic styles that is much more stylish and sophisticated than matplotlib.As sea born is considered to be a higher-level library, there are certain special visualization tools such as, violin plots, heat maps and time series plots that can be created using this library.

The ggplot library

The ggplot library is based on the ggplot2 library which is an R plotting system and concepts are based on the Grammar of Graphics. The ggplot library creates a layer of components for creating plots which makes it different from matplotlib based on the operations of plotting graph. It is integrated with pandas and is mainly used for creating very simple graphics. This library sacrifices the complexity of plotting complex graphs as its primary focus is on building basic graphs that are often required for analyzing simple data distribution.

The Bokeh library

The Bokeh library is native to Python and is mainly used to create interactive, web-ready plots, which can be easily output as HTML documents, JSON objects, or interactive web applications. Like ggplot , its concepts are also based on the Grammar of Graphics. It has an added advantage of managing real-time data and streaming. This library can be used for creating common charts such as histograms, bar plots, and box plots.It can also handle very minute points of a graph such as handling a dot of a scatter plot.Using Bokeh, it is easy for a user to control and define every element of the chart without using any default values and designs.There are three varying interfaces supported by Bokeh for being used by different types of users. The topmost level interface allows building simple, common charts and graphs very easily. The middle-level interface allows designing visualization graphs with a provision to control the basic building blocks of each graph. Lastly, the bottom level interface is used mainly by software engineers and developers as this

interface provides full support for controlling and customizing each and every component of a graph to deal with complex graphics.

The Plotly library

The plotly library is an online platform for data visualization and it can be used in making interactive plots that are not possible using other Python libraries. Few such plots include dendrograms, contour plots, and 3D charts. Other than these graphics, some basic visualization graphs such as area charts, bar charts, box plots, histograms, polar charts, and bubble charts can also be created using the plotly library. One interesting fact about plotly is that the graphs are not saved as images but rather serialized as JSON, because of which the graphs can be opened and viewed with other applications such as R, Julia, and MATLAB.

The Pygal library

The pygal library creates interactive plots that can be embedded in the web browser. It also has the ability to output charts as Scalable Vector Graphics (SVGs). All the chart types created using pygalare packaged into a method that makes it easy to create an artistic chart in a few lines of code. For instance, to create a bar chart, simply import the pygal library and then create a variable to assign the value of pygal. Bar ().The graph created can finally be saved in . svg extension to get a stylized CSS formatting.

The Geoplotlib library

The geoplotlib is a toolbox for designing maps and plotting geographical data. Few of the map-types that can be created are heat maps, dotdensity maps, and choropleths. In order to use geoplotlib , one has to also install Pyglet , an object-oriented programming interface. This library is mainly used for drawing maps as no other Python libraries are meant for creating graphics for maps.

The Gleam library

The Gleam library is like the R's Shiny package. It converts analyses into interactive web apps using Python scripts. It creates a web interface that lets anyone play with the data in real-time. One interesting capability of this library is that fields can be created on top of the graphic and users can filter and sort data by choosing appropriate field.

The missing no library

The missingno library can deal with missing data and can quickly measure the wholeness of a dataset with a visual summary, instead of managing through a table. The data can be filtered and arranged based on completion or spot correlations with a dendrogram or heatmap.

The leather library

Christopher Groskopf, the Creator of Leather, has stated that Leather is the Python charting library for those who need charts now and don't care if they're perfect. This library is designed to work with all data types and create charts as SVGs. This library is relatively new and the charts that can be made using this library are the very basics.

4.7 Matplotlib Library

Pyplot

Pyplot is a Matplotlib module that provides a MATLAB-like interface. Matplotlib is designed to be as usable as MATLAB, with the ability to use Python and the advantage of being free and open source.Each pyplot function makes some change to a figure: e.g., creates a figure, creates a plotting area in a figure, plots some lines in a plotting area, decorates the plot with labels, etc. The various plots we can utilize using Pyplot are Line Plot, Histogram, Scatter, 3D Plot, Image, Contour, and Polar.

Create a simple plot

```
importmatplotlib.pyplot as plt

# Initializing the data

x =[10, 20, 30, 40]
```

```
y =[20, 25, 35, 55]
 # plotting the data
plt.plot(x, y)
plt.show()
```

Adding title

The title() method in matplotlib module is used to specify the title of the visualization depicted and displays the title using various attributes.

- SYNTAX: matplotlib.pyplot.title(label, fontdict=None, loc='center', pad=None, **kwargs)
- CODE: plt.title("Linear Graph")

Changing of appearance

We can also change the appearance of the title by using the parameters of this function.

- CODE: plt.title("Linear Graph", fontsize=25, color="green")

Adding xlabel and ylabel

In layman's terms, the X label and the Y label are the titles given to X-axis and Y-axis respectively. These can be added to the graph by using the xlabel()and ylabel()methods.

- SYNTAX:matplotlib.pyplot.xlabel(xlabel, fontdict=None, labelpad=None, **kwargs)
  matplotlib.pyplot.ylabel(ylabel, fontdict=None, labelpad=None, **kwargs)
- CODE: plt.xlabel('X-Axis')
  plt.ylabel('Y-Axis')

Setting limits and tick labels

Matplotlib automatically sets the values and the markers(points) of the X and Y axis, however, it is possible to set the limit and markers manually. xlim() and ylim() functions are used to set the limits of the X-axis and Y-axis respectively. Similarly, xticks() and yticks() functions are used to set tick labels.

- CODE: plt.ylim(0, 80)

  plt.xticks(x, labels=["one", "two", "three", "four"])

Adding legends

A legend is an area describing the elements of the graph. In simple terms, it reflects the data displayed in the graph's Y-axis. It generally appears as the box containing a small sample of each color on the graph and a small description of what this data means.The attribute bbox_to_anchor=(x, y) of legend() function is used to specify the coordinates of the legend, and the attribute ncol represents the number of columns that the legend has. Its default value is 1.

- SYNTAX:matplotlib.pyplot.legend(["name1", "name2"], bbox_to_anchor=(x, y), ncol=1)
- CODE:plt.legend(["GFG"])

Classes in matplotlib

The important classes in matplotlib are:

1. Figure class
2. Axes class

Figure class

Considerthe figure class as the overall window or page on which everything is drawn. It is a top-level container that contains one or more axes. A figure can be created using the figure() method.

- SYNTAX:class matplotlib.figure.Figure(figsize=None, dpi=None, facecolor=None, edgecolor=None, linewidth=0.0, frameon=None, subplotpars=None, tight_layout=None, constrained_layout=None)

```
# Python program to show pyplot module

import matplotlib.pyplot as plt

from matplotlib.figure import Figure

# initializing the data

x = [10, 20, 30, 40]

y = [20, 25, 35, 55]

# Creating a new figure with width = 7 inches and height = 5 inches with face color as green, edgecolor as red and the line width of the edge as 7

fig = plt.figure(figsize =(7, 5), facecolor='g', edgecolor='b', linewidth=7)

# Creating a new axes for the figure

ax = fig.add_axes([1, 1, 1, 1])

# Adding the data to be plotted

ax.plot(x, y)

# Adding title to the plot

plt.title("Linear graph", fontsize=25, color="yellow")

# Adding label on the y-axis

plt.ylabel('Y-Axis')

# Adding label on the x-axis

plt.xlabel('X-Axis')

# Setting the limit of y-axis

plt.ylim(0, 80)

# setting the labels of x-axis

plt.xticks(x, labels=["one", "two", "three", "four"])

# Adding legends

plt.legend(["GFG"])

plt.show()
```

Axes Class

Axes classis the most basic and flexible unit for creating sub-plots. A given figure may contain many axes, but a given axes can only be present in one figure. The axes() function creates the axes object.

- SYNTAX: axes([left, bottom, width, height])

Just like pyplot class, axes class also provides methods for adding titles, legends, limits, labels, etc.

- Adding Title – ax.set_title()
- Adding X Label and Y label – ax.set_xlabel(), ax.set_ylabel()
- Setting Limits – ax.set_xlim(), ax.set_ylim()
- Tick labels – ax.set_xticklabels(), ax.set_yticklabels()
- Adding Legends – ax.legend()

```
# Python program to show pyplot module

import matplotlib.pyplot as plt

from matplotlib.figure import Figure

# initializing the data

x = [10, 20, 30, 40]
```

```
y = [20, 25, 35, 55]
fig = plt.figure(figsize = (5, 4))
# Adding the axes to the figure
ax = fig.add_axes([1, 1, 1, 1])
# plotting 1st dataset to the figure
ax1 = ax.plot(x, y)
# plotting 2nd dataset to the figure
ax2 = ax.plot(y, x)
# Setting Title
ax.set_title("Linear Graph")
# Setting Label
ax.set_xlabel("X-Axis")
ax.set_ylabel("Y-Axis")
# Adding Legend
ax.legend(labels = ('line 1', 'line 2'))
plt.show()
```

Different types of matplotlib plots

Matplotlib supports a variety of plots including line charts, bar charts, histograms, scatter plots, etc.

Line Chart: It is one of the basic plots and can be created using the**plot()**function. It is used to represent a relationship between two data X and Y on a different axis.

SYNTAX: matplotlib.pyplot.plot(*args, scalex=True, scaley=True, data=None, **kwargs)

```
import matplotlib.pyplot as plt
# initializing the data
x = [10, 20, 30, 40]
y = [20, 25, 35, 55]
# plotting the data
plt.plot(x, y)
# Adding title to the plot
plt.title("Line Chart")
# Adding label on the y-axis
plt.ylabel('Y-Axis')
# Adding label on the x-axis
plt.xlabel('X-Axis')
plt.show()
```

Properties of Line Chart

- **color:** Changing the color of the line
- **line width:** Customizing the width of the line
- **marker:** For changing the style of actual plotted point
- **marker size:** For changing the size of the markers
- **line style:** For defining the style of the plotted line

```
import matplotlib.pyplot as plt
# initializing the data
x = [10, 20, 30, 40]
y = [20, 25, 35, 55]
# plotting the data
plt.plot(x, y, color='green', linewidth=3, marker='o',  markersize=15, linestyle='--')
# Adding title to the plot
plt.title("Line Chart")
# Adding label on the y-axis
plt.ylabel('Y-Axis')
# Adding label on the x-axis
plt.xlabel('X-Axis')
plt.show()
```

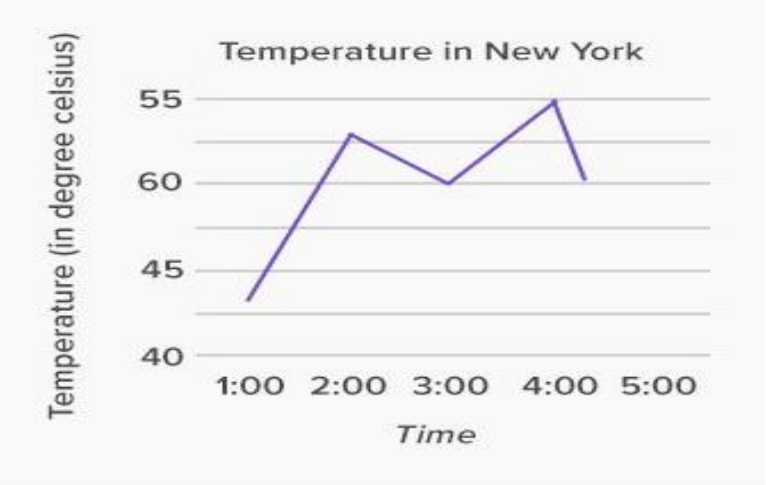
When to use line graph

The line graph is good at:

1)Showing specific values

2)Trends

3)Trends in groups (using multiple line graphs)



Bar Chart

A **bar** chart is a graph that represents the category of data with rectangular bars with lengths and heights that is proportional to the values which they represent. The bar plots can be plotted horizontally or vertically. A bar chart describes the comparisons between the discrete categories. It can be created using the bar() method.e will use the tips dataset. Tips database is the record of the tip given by the customers in a restaurant for two and a half months in the early 1990s.It contains 6 columns as total_bill, tip, sex, smoker, day, time, size.

```
import matplotlib.pyplot as plt
import pandas as pd
# Reading the tips.csv file
data = pd.read_csv('tips.csv')
# initializing the data
x = data['day']
```

```
y = data['total_bill']
# plotting the data
plt.bar(x, y)
# Adding title to the plot
plt.title("Tips Dataset")
# Adding label on the y-axis
plt.ylabel('Total Bill')
# Adding label on the x-axis
plt.xlabel('Day')
plt.show()
```

Bar Chart Customization

Customization that is available for the Bar Chart –

- **color:** For the bar faces
- **edgecolor:** Color of edges of the bar
- **linewidth:** Width of the bar edges
- **width:** Width of the bar

```
import matplotlib.pyplot as plt
import pandas as pd
# Reading the tips.csv file
data = pd.read_csv('tips.csv')
# initializing the data
x = data['day']
y = data['total_bill']
# plotting the data
plt.bar(x, y, color='green', edgecolor='blue', linewidth=2)
# Adding title to the plot
plt.title("Tips Dataset")
# Adding label on the y-axis
plt.ylabel('Total Bill')
# Adding label on the x-axis
plt.xlabel('Day')
plt.show()
```

When to use bar chart

Bar charts are best suited when there is a need of comparison of relative point values.

Histograms

A **histogram**is basically used to represent data provided in a form of some groups. It is a type of bar plot where the X-axis represents the bin ranges while the Y-axis gives information about frequency. The hist() function is used to compute and create histogram of x.

SYNTAX: matplotlib.pyplot.hist(x, bins=None, range=None, density=False, weights=None, cumulative=False, bottom=None, histtype='bar', align='mid', orientation='vertical', rwidth=None, log=False, color=None, label=None, stacked=False, *, data=None, **kwargs)

```
import matplotlib.pyplot as plt
import pandas as pd
# Reading the tips.csv file
data = pd.read_csv('tips.csv')
# initializing the data
x = data['total_bill']
# plotting the data
plt.hist(x)
# Adding title to the plot
plt.title("Tips Dataset")
# Adding label on the y-axis
plt.ylabel('Frequency')
# Adding label on the x-axis
plt.xlabel('Total Bill')
plt.show()
```

Histogram Customization

Customization that is available for the Histogram –

- **bins:** Number of equal-width bins
- **color:** For changing the face color
- **edgecolor:** Color of the edges
- **linestyle:** For the edgelines
- **alpha:** blending value, between 0 (transparent) and 1 (opaque)

```
import matplotlib.pyplot as plt
import pandas as pd
# Reading the tips.csv file
data = pd.read_csv('tips.csv')
# Initializing the data
x = data['total_bill']
# Plotting the data
plt.hist(x, bins=25, color='green', edgecolor='blue', linestyle='--', alpha=0.5)
# Adding title to the plot
plt.title("Tips Dataset")
# Adding label on the y-axis
plt.ylabel('Frequency')
# Adding label on the x-axis
plt.xlabel('Total Bill')
plt.show()
```

Scatter Plots

Scatter plotsare used to observe relationships between variables. The scatter() method in the matplotlib library is used to draw a scatter plot.

SYNTAX:matplotlib.pyplot.scatter(x_axis_data, y_axis_data, s=None, c=None, marker=None, cmap=None, vmin=None, vmax=None, alpha=None, linewidths=None, edgecolors=None

```
import matplotlib.pyplot as plt
import pandas as pd
# Reading the tips.csv file
data = pd.read_csv('tips.csv')
# Initializing the data
x = data['day']
y = data['total_bill']
# Plotting the data
plt.scatter(x, y)
# Adding title to the plot
plt.title("Tips Dataset")
# Adding label on the y-axis
plt.ylabel('Total Bill')
# Adding label on the x-axis
plt.xlabel('Day')
plt.show()
```

Scatter plot customization

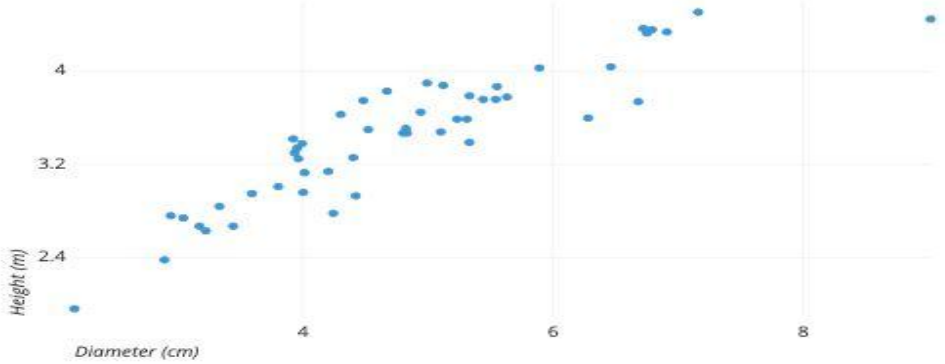
Customizations that are available for the scatter plot are –

- **s:** marker size (can be scalar or array of size equal to size of x or y)
- **c:** color of sequence of colors for markers
- **marker:** marker style
- **linewidths:** width of marker border
- **edgecolor:** marker border color
- **alpha:** blending value, between 0 (transparent) and 1 (opaque)

```
import matplotlib.pyplot as plt
import pandas as pd
# Reading the tips.csv file
data = pd.read_csv('tips.csv')
# initializing the data
x = data['day']
y = data['total_bill']
# plotting the data
plt.scatter(x, y, c=data['size'], s=data['total_bill'],  marker='D', alpha=0.5)
# Adding title to the plot
plt.title("Tips Dataset")
# Adding label on the y-axis
plt.ylabel('Total Bill')
# Adding label on the x-axis
plt.xlabel('Day')
plt.show()
```

When to use scatter plot?

Scatter plots are needed to convey overall impression of relationship between two variables. It is effective if a relationship exists between the two variables.



Pie chart

A Pie chart is a circular chart used to display only one series of data. The area of slices of the pie represents the percentage of the parts of the data. The slices of pie are called wedges. It can be created using the pie() method.

SYNTAX:matplotlib.pyplot.pie(data, explode=None, labels=None, colors=None, autopct=None, shadow=False)

```
import matplotlib.pyplot as plt

import pandas as pd

# Reading the tips.csv file

data = pd.read_csv('tips.csv')

# Initializing the data

cars = ['AUDI', 'BMW', 'FORD', 'TESLA', 'JAGUAR',]

data = [23, 10, 35, 15, 12]

# Plotting the data

plt.pie(data, labels=cars)

# Adding title to the plot

plt.title("Car data")

plt.show()
```

Pie chart customization

Customizations that are available for the Pie chart are

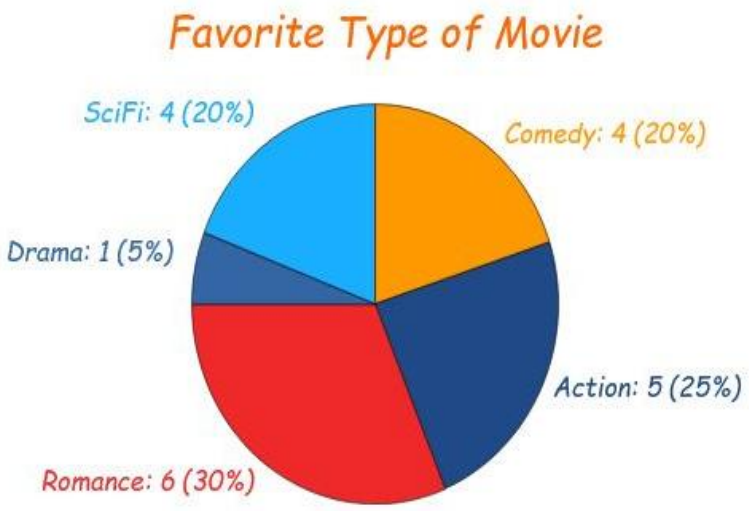
- **explode:** Moving the wedges of the plot
- **autopct:** Label the wedge with their numerical value.
- **color:** Attribute is used to provide color to the wedges.
- **shadow:** Used to create shadow of wedge.

```
import matplotlib.pyplot as plt

import pandas as pd

# Reading the tips.csv file

data = pd.read_csv('tips.csv')

# Initializing the data
```

```
cars = ['AUDI', 'BMW', 'FORD', 'TESLA', 'JAGUAR',]
data = [23, 13, 35, 15, 12]
explode = [0.1, 0.5, 0, 0, 0]
colors = ( "orange", "cyan", "yellow", "grey", "green",)
# Plotting the data
plt.pie(data, labels=cars, explode=explode, autopct='%1.2f%%', colors=colors, shadow=True)
plt.show()
```

When to use pie chart

It is for emphasizing differences in proportion among a few numbers



Saving a plot

For saving a plot in a file on storage disk, savefig() method is used. A file can be saved in many formats like .png, .jpg, .pdf, etc.

SYNTAX:pyplot.savefig(fname, dpi=None, facecolor='w', edgecolor='w', orientation='portrait', papertype=None, format=None, transparent=False, bbox_inches=None, pad_inches=0.1, frameon=None, metadata=None)

```
import matplotlib.pyplot as plt
# Creating data
year = ['2010', '2002', '2004', '2006', '2008']
production = [25, 15, 35, 30, 10]
# Plotting barchart
plt.bar(year, production)
# Saving the figure.
plt.savefig("output.jpg")
```

4.8 Advanced Data Visualization using Seaborn Library

Seaborn is an amazing visualization library for statistical graphics plotting in Python. It is built on the top of matplotlib library and closely integrated into the data structures from pandas.**Pandas** offer tools for cleaning and process your data. It is the most popular Python library that is used for data analysis. In pandas, a data table is called a data frame. Sea born helps to visualize the statistical relationships. To understand how variables in a dataset are related to one another and how that relationship is dependent on other variables, we perform statistical analysis. This Statistical analysis helps to visualize the trends and identify various patterns in the dataset.

Creating Pandas dataframe

```
# Python code demonstrate creating
import pandas as pd
# Initialise data of lists.
data = {'Name':[ 'Mohe' , 'Karnal' , 'Yrik' , 'jack' ],'Age':[ 30 , 21 , 29 , 28 ]}
# Create DataFrame
df = pd.DataFrame( data )
# Print the output.
df
```

4.9 Visualization Libraries

- Line Plot
- Scatter Plot
- Box plot
- Point plot
- Count plot
- Violin plot
- Swarm plot
- Bar plot
- KDE Plot

Line Plot

Line plot Is the most popular plot to draw a relationship between x and y with the possibility of several semantic groupings.

Syntax: sns.lineplot(x=None, y=None)

Parameters: x, y: Input data variables; must be numeric. Can pass data directly or reference columns in data.

```
# import module
import seaborn as sns
import pandas
# loading csv
data = pandas.read_csv("nba.csv")
# plotting lineplot
sns.lineplot( data['Age'], data['Weight'])
```

Hue Parameter

```
# import module
import seaborn as sns
import pandas
# read the csv data
data = pandas.read_csv("nba.csv")
# plot
sns.lineplot(data['Age'],data['Weight'], hue =data["Position"])
```

Scatter Plot

Scatterplot Can be used with several semantic groupings which can help to understand well in a graph against continuous/categorical data. It can draw a two-dimensional graph.

Syntax: seaborn.scatterplot(x=None, y=None)

Parameters: x, y: Input data variables that should be numeric.

Returns: This method returns the Axes object with the plot drawn onto it.

```
# import module
import seaborn
import pandas
# load csv
data = pandas.read_csv("nba.csv")
# plotting
seaborn.scatterplot(data['Age'],data['Weight'])
```

Hue Parameter

```
import seaborn
import pandas
data = pandas.read_csv("nba.csv")
seaborn.scatterplot( data['Age'], data['Weight'], hue =data["Position"])
```

Box Plot

A box plot (or box-and-whisker plot) is the visual representation of the depicting groups of numerical data through their quartiles against continuous/categorical data.A box plot consists of 5 things.

- Minimum
- First Quartile or 25%
- Median (Second Quartile) or 50%
- Third Quartile or 75%
- Maximum

Syntax: seaborn.boxplot(x=None, y=None, hue=None, data=None)

Parameters: x, y, hue: Inputs for plotting long-form data.

Data: Dataset for plotting. If x and y are absent, this is interpreted as wide form.

Returns: It returns the Axes object with the plot drawn onto it.

```
# import module
import seaborn as sns
import pandas
# read csv and plotting
data = pandas.read_csv( "nba.csv" )
sns.boxplot( data['Age'] )
```

Violin Plot

A violin plot is like a boxplot. It shows several quantitative data across one or more categorical variables such that those distributions can be compared.

Syntax: seaborn.violinplot(x=None, y=None, hue=None, data=None)

Parameters: x, y, hue: Inputs for plotting long-form data.

Data: Dataset for plotting.

```
# import module
import seaborn as sns
import pandas
# read csv and plot
data = pandas.read_csv("nba.csv")
sns.violinplot(data['Age'])
```

Swarm plot

A swarm plot is similar to a strip plot, we can draw a swarm plot with non-overlapping points against categorical data.

Syntax: seaborn.swarmplot(x=None, y=None, hue=None, data=None)

Parameters: x, y, hue: Inputs for plotting long-form data.

Data: Dataset for plotting.

```
# import module
import seaborn
seaborn.set(style = 'whitegrid')
# read csv and plot
data = pandas.read_csv( "nba.csv" )
seaborn.swarmplot(x = data["Age"])
```

Bar Plot

Bar plot represents an estimate of central tendency for a numeric variable with the height of each rectangle and provides some indication of the uncertainty around that estimate using error bars.

Syntax:seaborn.barplot(x=None, y=None, hue=None, data=None)

Parameters: x, y: This parameter take names of variables in data or vector data, Inputs for plotting long-form data.

Hue: (optional) This parameter takes column name for color encoding.

Data: (optional) This parameter take DataFrame, array, or list of arrays, Dataset for plotting. If x and y are absent, this is interpreted as wide form. Otherwise, it is expected to be long form.

Returns: Returns the Axes object with the plot drawn onto it.

```
# import module
import seaborn
seaborn.set(style = 'whitegrid')
# read csv and plot
data = pandas.read_csv("nba.csv")
seaborn.barplot(x =data["Age"])
```

Point plot

Point plot used to show point estimates and confidence intervals using scatter plot glyphs. A point plot represents an estimate of central tendency for a numeric variable by the position of scatter plot points and provides some indication of the uncertainty around that estimate using error bars.

Syntax: seaborn.pointplot(x=None, y=None, hue=None, data=None)

Parameters: x, y: Inputs for plotting long-form data.

Hue: (optional) column name for color encoding.

Data: dataframe as a Dataset for plotting.

Return: The Axes object with the plot drawn onto it.

```
# import module
import seaborn
seaborn.set(style = 'whitegrid')
# read csv and plot
data = pandas.read_csv("nba.csv")
seaborn.pointplot(x = "Age", y = "Weight", data = data)
```

Count Plot

Count plot used to Show the counts of observations in each categorical bin using bars.

Syntax: seaborn.countplot(x=None, y=None, hue=None, data=None)

Parameters:x, y: This parameter take names of variables in data or vector data, optional, Inputs for plotting long-form data.

Hue: (optional) This parameter takes column name for color encoding.

Data: (optional) This parameter take DataFrame, array, or list of arrays, Dataset for plotting. If x and y are absent, this is interpreted as wide form. Otherwise, it is expected to be long form.

Returns: Returns the Axes object with the plot drawn onto it.

```
# import module
import seaborn
seaborn.set(style = 'whitegrid')
# read csv and plot
data = pandas.read_csv("nba.csv")
seaborn.countplot(data["Age"])
```

KDE Plot

KDE Plot described as **Kernel Density Estimate** is used for visualizing the Probability Density of a continuous variable. It depicts the probability density at different values in a continuous variable. We can also plot a single graph for multiple samples which helps in more efficient data visualization.

Syntax: seaborn.kdeplot(x=None, *, y=None, vertical=False, palette=None, **kwargs)

Parameters: x, y: vectors or keys in data

Vertical: boolean (True or False)

Data: pandas.DataFrame, numpy.ndarray, mapping, or sequence

```
# import module
import seaborn as sns
import pandas
# read top 5 column
data = pandas.read_csv("nba.csv").head()
sns.kdeplot( data['Age'], data['Number'])
```

Summary

- Visualization is the graphical representation of data that can make information easy to analyze and understand.

- The data visualization software applications differ in their ability to use various types of graphs and visuals, simplified user interface, accurate trend tracking capability, level of security, ease of use in mobile and friendly report generation.
- Zoho Analytics uses a variety of tools, such as pivot tables, KPI widgets, and tabular view components. It can generate reports with valuable business insights.
- Microsoft Power BI comes with unlimited access to on-site and in-cloud data that gives a centralized data access hub.
- The matplotlib library was created by John D. Hunter and is currently maintained by a team of Python developers.
- The matplotlib allows easy use of labels, axes titles, grids, legends, and other graphic requirements with customizable values and text.
- The seaborn library follows creative styles and rich color palettes, that allows to create visualization plots to be more attractive and modern.
- It is integrated with pandas and is mainly used for creating very simple graphics. This library sacrifices the complexity of plotting complex graphs as its primary focus is on building basic graphs that are often required for analyzing simple data distribution.
- One interesting fact about plotly is that the graphs are not saved as images but rather serialized as JSON, because of which the graphs can be opened and viewed with other applications such as R, Julia, and MATLAB.

Keywords

- **Data visualization**: It is the graphical representation of data that can make information easy to analyze and understand.
- **Visual encoding**: Itis the approach used to map data into visual structures, thereby building an image on the screen.
- **Qlikview:** It allows users to create default and custom data connectors and templates, depending on one's need.
- **Sisense:** It uses agile analysis software with a variety of data visualization options. It can create dashboards and graphics with drag and drop user interface.
- **Seaborn library**: Seaborn library is considered to be a higher-level library, there are certain special visualization tools such as, violin plots, heat maps and time series plots that can be created using this library.
- **Ggplot library:** The ggplot library is based on the ggplot2 library which is an R plotting system and concepts are based on the Grammar of Graphics.
- **Bokeh library:** The Bokeh library is native to Python and is mainly used to create interactive, web-ready plots, which can be easily output as HTML documents, JSON objects, or interactive web applications.
- **Plotly library:** The plotly library is an online platform for data visualization and it can be used in making interactive plots that are not possible using other Python libraries.
- **Pygal library:** The pygal library creates interactive plots that can be embedded in the web browser.
- **Geoplotlib library:** The geoplotlib is a toolbox for designing maps and plotting geographical data. Few of the map-types that can be created are heatmaps, dotdensity maps, and choropleths.

SelfAssessment

1. How can we illustrate the complex data relationship and patterns?

A. Lines

B. Graphs

C. Colours

D. All of the above

2. Data visualization can help in

A. Identifying outliers

B. Improve response time

C. Easier visualization of patterns

D. All of the above

3. Which approach used to map data into visual structures, thereby building an image on the screen?

A. Visual Encoding

B. Audio Encoding

C. Redirecting

D. None of the above

4. What is the visualization graph supposed to display?

A. Comparison

B. Composition

C. Connection

D. All of the above

5. Which of the following can be used to show the composition?

A. Pie chart

B. Waterfall chart

C. Stacked column chart

D. All of the above

6. The Tableau data visualization software is

A. A flexible data analysis method

B. Mobile friendly

C. Manageable

D. All of the above

7. The plotly supports

A. 2D and 3D chart options

B. Designer input

C. Open source coding

D. All of the above mentioned

8. Which is the first data visualization library developed in Python?
A. Matplotlib library
B. Seaborn library
C. Bokeh library
D. None of the above

9. Which library supports the three varying interfaces used by different types of users?
A. Matplotlib library
B. Seaborn library
C. Bokeh library
D. None of the above

10. What is a Matplotlib module that provides a MATLAB-like interface?
A. Ayplot
B. Pyplot
C. Syplot
D. Typlot

11. Which of these are the important classes of matplotlib library?
A. Axes class
B. Figure class
C. Both of the above
D. None of the above

12. How many components are required to make a box plot?
A. 4
B. 5
C. 6
D. 7

13. Which of the following is used to show the comparison of relative data points?
A. Line graph
B. Scatter graph
C. Bar graph
D. Pie graph

14. Which of these if most effective if a relationship exists between the two variables
A. Line graph
B. Scatter plot
C. Bar graph
D. Pie plot

15. Which of the following emphasizes differences in proportion among a few numbers

A. Line graph

B. Scatter plot

C. Bar graph

D. Pie plot

Answers for Self Assessment

1.	D	2.	D	3.	A	4.	D	5.	D
6.	D	7.	D	8.	A	9.	C	10.	C
11.	C	12.	B	13.	C	14.	B	15.	D

Review Questions

1. What is data visualization? Explain its need and importance.
2. Explain the need of data visualization for different purposes. Also explain its advantages.
3. What is visual encoding? Also explain few retinal variables.
4. Explain the role of data visualization in different areas andtell the corresponding data visualization graph.
5. Describe few data visualization softwares. Also tell its important key features.
6. Name few important data visualization libraries. Also explain in detail about matplotlib library.
7. What is Pyplot module? How can we create a simple plot using it? Also tell how to add different things to the plot?
8. Which type of plots can be created using matplotlib library? Also explain its syntax.
9. What is advanced data visualization? How can we do it using seaborn library?

Further Readings

https://www.geeksforgeeks.org/life-cycle-phases-of-data-analytics/

Web Links

https://www.simplilearn.com/tutorials/data-science-tutorial/what-is-data-science

Unit 05: Role of Statistics in Data Science

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Summary

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Objectives

After studying this unit, you will be able to

- understand what is hypothesis testing,
- understand the steps of hypothesis testing,
- understand two types of hypotheses,
- understand Type – I and Type –II errors,
- understand what P-value is,
- understand ANOVA,
- understand chi-square test.

Introduction

Hypothesis testing is an act in statistics whereby an analyst tests an assumption regarding a population parameter. The methodology employed by the analyst depends on the nature of the data used and the reason for the analysis.Hypothesis testing is used to assess the plausibility of a hypothesis by using sample data. Such data may come from a larger population, or from a data-generating process.

5.1 Key Features in Hypothesis Testing

- Hypothesis testing is used to assess the plausibility of a hypothesis by using sample data.
- The test provides evidence concerning the plausibility of the hypothesis, given the data.
- Statistical analysts test a hypothesis by measuring and examining a random sample of the population being analyzed.

Statistical analysts test a hypothesis by measuring and examining a random sample of the population being analyzed. All analysts use a random population sample to test two different

hypotheses: the null hypothesis and the alternative hypothesis.In hypothesis testing, an analyst tests a statistical sample, with the goal of providing evidence on the plausibility of the null hypothesis.

5.2 Null and Alternative Hypothesis

- **Null Hypothesis**: The null hypothesis is usually a hypothesis of equality between population parameters; e.g., a null hypothesis may state that the population mean return is equal to zero.
- **Alternate Hypothesis**: The alternative hypothesis is effectively the opposite of a null hypothesis (e.g., the population mean return is not equal to zero).

The null and alternative hypothesis are mutually exclusive, and only one can be true. However, one of the two hypotheses will always be true.

Steps of hypothesis testing

1. The first step is for the analyst to state the two hypotheses so that only one can be right.
2. The second step is to collect data.
3. The third step is to perform a statistical test.
4. The fourth is to reject the null hypothesis, or state that the null hypothesis is plausible, given the data.
5. The fifth step is to present your findings.

Step 1: Null and alternate hypothesis

The alternate hypothesis is usually your initial hypothesis that predicts a relationship between variables. The null hypothesis is a prediction of no relationship between the variables you are interested in.

Step 2: Collect data

For a statistical test to be valid, it is important to perform sampling and collect data in a way that is designed to test your hypothesis. If your data are not representative, then you cannot make statistical inferences about the population you are interested in.

Step 3: Perform a statistical test

There are a variety of statistical tests available, but they are all based on the comparison of within-group variance (how spread out the data is within a category) versus between-group variance (how different the categories are from one another).

Step 4: Decide whether to reject or fail to reject you null hypothesis

Based on the outcome of your statistical test, you will have to decide whether to reject or fail to reject your null hypothesis.In most cases you will use the p-value generated by your statistical test to guide your decision.

Step 5: Present your findings

Present your findings by either any article or by the means of a research publications of by any form of IPR.

Example: You want to test whether there is a relationship between gender and height. Based on your knowledge of human physiology, you formulate a hypothesis that men are,

on average, taller than women.

Step 1: State null hypothesis and alternative hypothesis.

Ho: Men are, on average, not taller than women.

Ha: Men are, on average, taller than women.

Step 2: Collection of data.Your sample should have an equal proportion of men and women and cover a variety of socio-economic classes and any other control variables that might influence average height.

Step 3: Perform a statistical test

Step 4: Decide whether to reject or fail to reject your null hypothesis. In your analysis of the difference in average height between men and women, you find that the p-value of 0.002 is below your cutoff of 0.05, so you decide to reject your null hypothesis of no difference.

Step 5: Present your findings.

Example: A person wants to test that a penny has exactly a 50% chance of landing on heads, the null hypothesis would be that 50% is correct, and the alternative hypothesis would be that 50% is not correct.

Mathematically, the null hypothesis would be represented as Ho: P = 0.5. The alternative hypothesis would be denoted as "Ha" and be identical to the null hypothesis, except with the equal sign struck-through, meaning that it does not equal 50%. A random sample of 100-coin flips is taken, and the null hypothesis is then tested.

If it is found that the 100-coin flips were distributed as 40 heads and 60 tails, the analyst would assume that a penny does not have a 50% chance of landing on heads and would reject the null hypothesis and accept the alternative hypothesis.

If, on the other hand, there were 48 heads and 52 tails, then it is plausible that the coin could be fair and still produce such a result.

In cases such as this where the null hypothesis is "accepted," the analyst states that the difference between the expected results (50 heads and 50 tails) and the observed results (48 heads and 52 tails) is "explainable by chance alone."

5.3 Type 1 and Type 2 Errors

In statistics, a Type I error is a false positive conclusion, while a Type II error is a false negative conclusion.You decide to get tested for COVID-19 based on mild symptoms. There are two errors that could potentially occur:

- **Type I error (false positive):** the test result says you have coronavirus, but you actually don't.
- **Type II error (false negative):** the test result says you don't have coronavirus, but you actually do.

Making a statistical decision always involves uncertainties, so the risks of making these errors are unavoidable in hypothesis testing.

Alpha and Beta

The probability of making a Type I error is the significance level, or alpha (α), while the probability of making a Type II error is beta (β). These risks can be minimized through careful planning in your study design.

Using hypothesis testing, you can make decisions about whether your data support or refute your research predictions.Hypothesis testing starts with the assumption of no difference between groups or no relationship between variables in the population—this is the **null hypothesis**. It's always paired with an **alternative hypothesis**, which is your research prediction of an actual difference between groups or a true relationship between variables.

Example: To test whether a new drug intervention can alleviate symptoms of an autoimmune disease.

Null hypothesis (H_0) is that the new drug has no effect on symptoms of the disease.

Alternative hypothesis (H_1) is that the drug is effective for alleviating symptoms of the disease.

A **Type I error** happens when you get false positive results: you conclude that the drug intervention improved symptoms when it didn't. These improvements could have arisen from other random factors or measurement errors.

A **Type II error** happens when you get false negative results: you conclude that the drug intervention didn't improve symptoms when it did. Your study may have missed key indicators of improvements or attributed any improvements to other factors instead.

Type I and Type II Error

Null hypothesis is ...	True	False
Rejected	Type I error False positive Probability = α	Correct decision True positive Probability = 1 – β
Not rejected	Correct decision True negative Probability = 1 – α	Type II error False negative Probability = β

Type 1 error and its statistical significance

A Type I error means rejecting the null hypothesis when it's true. It means concluding that results are **statistically significant** when they came about purely by chance or because of unrelated factors.The risk of committing this error is the significance level (alpha or α) you choose. That's a value that you set at the beginning of your study to assess the statistical probability of obtaining your results. The significance level is usually set at 0.05 or 5%. This means that your results only have a 5% chance of occurring, or less, if the null hypothesis is true.

In your clinical study, you compare the symptoms of patients who received the new drug intervention or a control treatment. Using a t test, you obtain a *p* value of .035. This *p* value is lower than your alpha of .05, so you consider your results statistically significant and reject the null hypothesis.However, the *p* value means that there is a 3.5% chance of your results occurring if the null hypothesis is true. Therefore, there is still a risk of making a Type I error.Power is the extent to which a test can correctly detect a real effect when there is one. A power level of 80% or higher is usually considered acceptable.

Type 2 error and its statistical significance

A Type II error means not rejecting the null hypothesis when it's actually false. This is not quite the same as "accepting" the null hypothesis, because hypothesis testing can only tell you whether to reject the null hypothesis.Instead, a Type II error means failing to conclude there was an effect when there actually was. In reality, your study may not have had enough **statistical power** to detect an effect of a certain size.When preparing your clinical study, you complete a power analysis and determine that with your sample size, you have an 80% chance of detecting an effect size of 20% or greater. An effect size of 20% means that the drug intervention reduces symptoms by 20% more than the control treatment.However, a Type II may occur if an effect that's smaller than this size. A smaller effect size is unlikely to be detected in your study due to inadequate statistical power.

Statistical power is determined by:

- Size of the effect: Larger effects are more easily detected.
- Measurement error: Systematic and random errors in recorded data reduce power.
- Sample size: Larger samples reduce sampling error and increase power.
- Significance level: Increasing the significance level increases power.

Trade-off between Type I and Type II errors

The Type I and Type II error rates influence each other. That's because the significance level (the Type I error rate) affects statistical power, which is inversely related to the Type II error rate.This means there's an important tradeoff between Type I and Type II errors:

- Setting a lower significance level decreases a Type I error risk but increases a Type II error risk.
- Increasing the power of a test decreases a Type II error risk but increases a Type I error risk.

5.4 P-Value/ Probability Value

The *p*-value is a number, calculated from a statistical test, that describes how likely you are to have found a particular set of observations if the null hypothesis were true.P-values are used in hypothesis testing to help decide whether to reject the null hypothesis.The smaller the p-value, the more likely you are to reject the null hypothesis.

All statistical tests have a null hypothesis. For most tests, the null hypothesis is that there is no relationship between your variables of interest or that there is no difference among groups.For example, in a two-tailed t-test, the null hypothesis is that the difference between two groups is zero.

- You want to know whether there is a difference in longevity between two groups of mice fed on different diets, diet A and diet B. You can statistically test the difference between these two diets using a two-tailed t test.
- Null hypothesis: there is no difference in longevity between the two groups.
- Alternative hypothesis: there is a difference in longevity between the two groups.

The p-value tells you how likely it is that your data could have occurred under the null hypothesis. It does this by calculating the likelihood of your test statistic, which is the number calculated by a statistical test using your data.The p-value tells you how often you would expect to see a test statistic as extreme or more extreme than the one calculated by your statistical test if the null hypothesis of that test was true.The p-value gets smaller as the test statistic calculated from your data gets further away from the range of test statistics predicted by the null hypothesis.The p-value is a proportion: if your p-value is 0.05, that means that 5% of the time you would see a test statistic at least as extreme as the one you found if the null hypothesis was true.

Calculation of p-value

P-values are usually automatically calculated by your statistical program (R, SPSS, etc.).You can also find tables for estimating the p-value of your test statistic online. These tables show, based on the test statistic and degrees of freedom (number of observations minus number of independent variables) of your test, how frequently you would expect to see that test statistic under the null hypothesis.The calculation of the p-value depends on the statistical test you are using to test yourhypothesis:Different statistical tests have different assumptions and generate different test statistics. You should choose the statistical test that best fits your data and matches the effect or relationship you want to test.The number of independent variables you include in your test changes how large or small the test statistic needs to be to generate the same p-value.

Choosing a statistical test

If you are comparing only two different diets, then a two-sample t-test is a good way to compare the groups. To compare three different diets, use an ANOVA instead – doing multiple pairwise comparisons will result in artificially low p-values and lets you overestimate the significance of the difference between groups.

P-values are most often used by researchers to say whether a certain pattern they have measured is statistically significant.Statistical significance is another way of saying that the p-value of a statistical test is small enough to reject the null hypothesis of the test.

5.5 ANOVA

Analysis of variance (ANOVA) is a collection of statistical models and their associated estimation procedures (such as the "variation" among and between groups) used to analyze the differences among means.ANOVA was developed by the statistician Ronald Fisher. ANOVA is based on the law of total variance, where the observed variance in a particular variable is partitioned into components attributable to different sources of variation.In its simplest form, ANOVA provides a statistical test of whether two or more population means are equal, and therefore generalizes the t-test beyond two means. In other words, the ANOVA is used to test the difference between two or more means. Due to its nature, it can only test general differences only. A non-parametric alternative is PERMANOVA.

Classes of models

There are three classes of models used in analysis of variance:

1) Fixed effects models
2) Random effects models
3) Mixed effects models

Fixed-effects models:The fixed-effects model (class I) of analysis of variance applies to situations in which the experimenter applies one or more treatments to the subjects of the experiment to see whether the response variable values change. This allows the experimenter to estimate the ranges of response variable values that the treatment would generate in the population.

Random-effects model:Random-effects model (class II) is used when the treatments are not fixed. This occurs when the various factor levels are sampled from a larger population. Because the levels themselves are random variables, some assumptions, and the method of contrasting the treatments (a multi-variable generalization of simple differences) differ from the fixed-effects model.

Mixed-effects model:A mixed-effects model (class III) contains experimental factors of both fixed and random-effect types, with appropriately different interpretations and analysis for the two types.

ANOVA Test

An ANOVA test is a way to find out if survey or experiment results are significant. In other words, they help you to figure out if you need to reject the null hypothesis or accept the alternate hypothesis.Basically, you're testing groups to see if there's a difference between them. Examples of when you might want to test different groups:

1) A group of psychiatric patients are trying three different therapies: counseling, medication and biofeedback. You want to see if one therapy is better than the others.

2) A manufacturer has two different processes to make light bulbs. They want to know if one process is better than the other.

3) Students from different colleges take the same exam. You want to see if one college outperforms the other.

What does "one-way" or "two-way" mean?

One-way or two-way refers to the number of independent variables (IVs) in your Analysis of Variance test.One-way has one independent variable (with 2 levels). For example: brand of cereal, two-way has two independent variables (it can have multiple levels). For example: brand of cereal, calories.

"Levels" or "groups"

Groups or levels are different groups within the same independent variable. Your levels for "brand of cereal" might be Lucky Charms, Raisin Bran, Cornflakes — a total of three levels. Your levels for "Calories" might be sweetened, unsweetened — a total of two levels.Let's say you are studying if an alcoholic support group and individual counseling combined is the most effective treatment for lowering alcohol consumption. You might split the study participants into three groups or levels:

- Medication only,
- Medication and counseling,
- Counseling only.

Your dependent variable would be the number of alcoholic beverages consumed per day. If your groups or levels have a hierarchical structure (each level has unique subgroups), then use a nested ANOVA for the analysis.

Replication

It's whether you are replicating (i.e., duplicating) your test(s) with multiple groups. With a two way ANOVA with replication , you have two groups and individuals within that group are doing more than one thing (i.e., two groups of students from two colleges taking two tests). If you only have one group taking two tests, you will use without replication.

Types of Tests

There are two main types: one-way and two-way. Two-way tests can be with or without replication.

One-way ANOVA between groups: It is used when you want to test two groups to see if there's a difference between them.

Two-way ANOVA without replication: It is used when you have one group and you're double testing that same group. For example, you're testing one set of individuals before and after they take a medication to see if it works or not.

Two-way ANOVA with replication: Two groups, and the members of those groups are doing more than one thing. For example, two groups of patients from different hospitals trying two different therapies.

One way ANOVA

A one-way ANOVA is used to compare two means from two independent (unrelated) groups using the F-distribution. The null hypothesis for the test is that the two means are equal. Therefore, a significant result means that the two means are unequal.

When to use One Way ANOVA?

Situation 1: You have a group of individuals randomly split into smaller groups and completing different tasks. For example, you might be studying the effects of tea on weight loss and form three groups: green tea, black tea, and no tea.

Situation 2: Like situation 1, but in this case the individuals are split into groups based on an attribute they possess. For example, you might be studying leg strength of people according to weight.

You could split participants into weight categories (obese, overweight, and normal) and measure their leg strength on a weight machine.

Limitations of One-way ANOVA

A one-way ANOVA will tell you that at least two groups were different from each other.But it won't tell you which groups were different. If your test returns a significant f-statistic, you may need to run an ad hoc test (like the Least Significant Difference test) to tell you exactly which groups had a difference in means.

Two Way ANOVA

A Two Way ANOVA is an extension of the One Way ANOVA. With a One Way, you have one independent variable affecting a dependent variable. With a Two Way ANOVA, there are two independents. Use a two-way ANOVA when you have one measurement variable (i.e., a quantitative variable) and two nominal variables. In other words, if your experiment has a quantitative outcome and you have two categorical explanatory variables, a two-way ANOVA is appropriate.For example, you might want to find out if there is an interaction between income and gender for anxiety level at job interviews. The anxiety level is the outcome, or the variable that can be measured. Gender and Income are the two categorical variables. These categorical variables are also the independent variables, which are called factors in a Two Way ANOVA.The factors can be split into levels. In the above example, income level could be split into three levels: low, middle and high income. Gender could be split into three levels: male, female, and transgender. Treatment groups are all possible combinations of the factors. In this example there would be 3 x 3 = 9 treatment groups.

The results from a Two Way ANOVA will calculate a main effect and an interaction effect. The main effect is like a One Way ANOVA: each factor's effect is considered separately. With the interaction effect, all factors are considered at the same time. Interaction effects between factors are easier to test if there is more than one observation in each cell.Two null hypotheses are tested if you are placing one observation in each cell. For this example, those hypotheses would be: H01: All the income groups have equal mean stress.

H02: All the gender groups have equal mean stress.

For multiple observations in cells, you would also be testing a third hypothesis: H03: The factors are independent, or the interaction effect does not exist.

Assumptions for Two-way ANOVA

1. The population must be close to a normal distribution.
2. Samples must be independent.
3. Population variances must be equal (i.e., homoscedastic).
4. Groups must have equal sample sizes.

MANOVA

MANOVA is just an ANOVA with several dependent variables. It's similar to many other tests and experiments in that its purpose is to find out if the response variable (i.e., your dependent variable) is changed by manipulating the independent variable. The test helps to answer many research questions, including:

- Do changes to the independent variables have statistically significant effects on dependent variables?
- What are the interactions among dependent variables?
- What are the interactions among independent variables?

Suppose you wanted to find out if a difference in textbooks affected students' scores in math and science. Improvements in math and science means that there are two dependent variables, so a MANOVA is appropriate.An ANOVA will give you a single (univariate) f-value while a MANOVA will give you a multivariate F value.MANOVA tests the multiple dependent variables by creating new, artificial, dependent variables that maximize group

differences.These new dependent variables are linear combinations of the measured dependent variables.

Advantages and Disadvantages of MANOVA vs ANOVA

Advantages

1. MANOVA enables you to test multiple dependent variables.
2. MANOVA can protect against Type I errors.

Disadvantages

1. MANOVA is many times more complicated than ANOVA, making it a challenge to see which independent variables are affecting dependent variables.
2. One degree of freedom is lost with the addition of each new variable.
3. The dependent variables should be uncorrelated as much as possible.

Factorial ANOVA

A factorial ANOVA is an Analysis of Variance test with more than one independent variable, or "factor".It can also refer to more than one Level of Independent Variable. For example, an experiment with a treatment group and a control group has one factor (the treatment) but two levels (the treatment and the control).The terms "two-way" and "three-way" refer to the number of factors or the number of levels in your test.Four-way ANOVA and above are rarely used because the results of the test are complex and difficult to interpret. A two-way ANOVA has two factors (independent variables) and one dependent variable. For example, time spent studying and prior knowledge are factors that affect how well you do on a test.A three-way ANOVA has three factors (independent variables) and one dependent variable. For example, time spent studying, prior knowledge, and hours of sleep are factors that affect how well you do on a test. Factorial ANOVA is an efficient way of conducting a test. Instead of performing a series of experiments where you test one independent variable against one dependent variable, you can test all independent variables at the same time.

Variability

In a one-way ANOVA, variability is due to the differences between groups and the differences within groups. In factorial ANOVA, each level and factor are paired up with each other ("crossed"). This helps you to see what interactions are going on between the levels and factors. If there is an interaction, then the differences in one factor depend on the differences in another.

Assumptions of factorial ANOVA

- Normality: the dependent variable is normally distributed.
- Independence: Observations and groups are independent from each other.
- Equality of Variance: the population variances are equal across factors/levels.

Steps

1. Find the mean for each of the groups.
2. Find the overall mean (the mean of the groups combined).
3. Find the Within Group Variation; the total deviation of each member's score from the Group Mean.
4. Find the Between Group Variation: the deviation of each Group Mean from the Overall Mean.
5. Find the F statistic: the ratio of Between Group Variation to Within Group Variation.

ANOVA vs T Test

- A Student's t-test will tell you if there is a significant variation between groups.
- A t-test compares means, while the ANOVA compares variances between populations.
- You could technically perform a series of t-tests on your data.
- However, as the groups grow in number, you may end up with a lot of pair comparisons that you need to run. ANOVA will give you a single number (the f-statistic) and one p-value to help you support or reject the null hypothesis.

5.6 Chi-Square Test

A chi-square (χ^2) statistic is a test that measures how a model compares to actual observed data. The data used in calculating a chi-square statistic must be random, raw, mutually exclusive, drawn from independent variables, and drawn from a large enough sample. For example, the results of tossing a fair coin meet these criteria.Chi-square tests are often used in hypothesis testing.The chi-square statistic compares the size of any discrepancies between the expected results and the actual results, given the size of the sample and the number of variables in the relationship.For these tests, degrees of freedom are utilized to determine if a certain null hypothesis can be rejected based on the total number of variables and samples within the experiment. As with any statistic, the larger the sample size, the more reliable the results.

Formula for Chi-Square is

$$X_c^2 = \sum \frac{(Oi - Ei)2}{Ei}$$

where:

C = Degrees of freedom

O = Observed value(s)

E = Expected value(s)

What does a Chi-Square Statistic Tell You?

There are two main kinds of chi-square tests: the test of independence, which asks a question of relationship, such as, "Is there a relationship between student sex and course choice?The goodness-of-fit test, which asks something like "How well does the coin in my hand match a theoretically fair coin?"

Independence

When considering student type and course choice, a χ^2 test for independence could be used. To do this test, the researcher would collect data on the two chosen variables (type and courses picked) and then compare the frequencies at which male and female students select among the offered classes.If there is no relationship between type and course selection (that is, if they are independent), then the actual frequencies at which male and female students select each offered course should be expected to be approximately equal, or conversely, the proportion of male and female students in any selected course should be approximately equal to the proportion of male and female students in the sample.A χ^2 test for independence can tell us how likely it is that random chance can explain any observed difference between the actual frequencies in the data and these theoretical expectations.

Goodness of fit

χ2 provides a way to test how well a sample of data matches the (known or assumed) characteristics of the larger population that the sample is intended to represent. This is known as goodness of fit. If the sample data do not fit the expected properties of the population that we are interested in, then we would not want to use this sample to draw conclusions about the larger population.

Example:

Consider an imaginary coin with exactly a 50/50 chance of landing heads or tails and a real coin that you toss 100 times. If this coin is fair, then it will also have an equal probability of landing on either side, and the expected result of tossing the coin 100 times is that heads will come up 50 times and tails will come up 50 times.In this case, χ^2 can tell us how well the actual results of 100-coin flips compare to the theoretical model that a fair coin will give 50/50 results. The actual toss could come up 50/50, or 60/40, or even 90/10. The farther away the actual results of the 100 tosses is from 50/50, the less good the fit of this set of tosses is to the theoretical expectation of 50/50, and the more likely we might conclude that this coin is not actually a fair coin.

When to use a chi-square test?

A chi-square test is used to help determine if observed results are in line with expected results, and to rule out that observations are due to chance. A chi-square test is appropriate for this when the data being analyzed is from a random sample, and when the variable in question is a categorical variable. A categorical variable is one that consists of selections such as type of car, race, educational attainment, male vs. female, how much somebody likes a political candidate (from very much to very little), etc.These types of data are often collected via survey responses or questionnaires. Therefore, chi-square analysis is often most useful in analyzing this type of data.

What is a chi-square test used for?

Chi-square is a statistical test used to examine the differences between categorical variables from a random sample in order to judge goodness of fit between expected and observed results. Is chi-square analysis used when the independent variable is nominal or ordinal?A nominal variable is a categorical variable that differs by quality, but whose numerical order could be irrelevant. For instance, asking somebody their favorite color would produce a nominal variable. Asking somebody's age, on the other hand, would produce an ordinal set of data. Chi-square can be best applied to nominal data.

Summary

- Hypothesis testing is used to assess the plausibility of a hypothesis by using sample data.
- The null and alternative hypothesis are mutually exclusive, and only one can be true.
- In statistics, a Type I error is a false positive conclusion, while a Type II error is a false negative conclusion.
- The probability of making a Type I error is the significance level, or alpha (α), while the probability of making a Type II error is beta (β).
- P-values are used in hypothesis testing to help decide whether to reject the null hypothesis. The smaller the p-value, the more likely you are to reject the null hypothesis.
- ANOVA provides a statistical test of whether two or more population means are equal, and therefore generalizes the t-test beyond two means.
- A non-parametric alternative of ANOVA is PERMANOVA.
- There are three classes of models used in analysis of variance: Fixed effects models, random effects models and mixed effects models.
- One-way or two-way refers to the number of independent variables (IVs) in your Analysis of Variance test.
- MANOVA is just an ANOVA with several dependent variables.
- Chi-square tests are often used in hypothesis testing.

Keywords

- **Hypothesis testing**: It is an act in statistics whereby an analyst tests an assumption regarding a population parameter.

- **Null Hypothesis**: The null hypothesis is usually a hypothesis of equality between population parameters, e.g., a null hypothesis may state that the population mean return is equal to zero.
- **Alternate Hypothesis**: The alternative hypothesis is effectively the opposite of a null hypothesis (e.g., the population mean return is not equal to zero).
- **Type I error**: A Type I error means rejecting the null hypothesis when it's true.
- **Type II error:**A Type II error means not rejecting the null hypothesis when it's false.
- **P-value**: P-values are used in hypothesis testing to help decide whether to reject the null hypothesis.
- **ANOVA:** Analysis of variance (ANOVA) is a collection of statistical models and their associated estimation procedures (such as the "variation" among and between groups) used to analyze the differences among means.
- **Fixed-effects models:** The fixed-effects model (class I) of analysis of variance applies to situations in which the experimenter applies one or more treatments to the subjects of the experiment to see whether the response variable values change.
- **Random-effects model**: Random-effects model (class II) is used when the treatments are not fixed. This occurs when the various factor levels are sampled from a larger population.
- **Mixed-effects models**: A mixed-effects model (class III) contains experimental factors of both fixed and random-effect types, with appropriately different interpretations and analysis for the two types.
- **One-way ANOVA between groups**: It is used when you want to test two groups to see if there's a difference between them.
- **Two-way ANOVA without replication**: It is used when you have one group and you're double testing that same group.
- **Two-way ANOVA with replication**: Two groups, and the members of those groups are doing more than one thing.
- **Factorial ANOVA:** A factorial ANOVA is an Analysis of Variance test with more than one independent variable, or "factor".
- **Chi-square test:** A chi-square (χ^2) statistic is a test that measures how a model compares to actual observed data.

SelfAssessment

1. The smaller the p-value, the more likely you are to …… the null hypothesis.

A. Accept
B. Reject
C. Can't say
D. None of the above

2. If we are comparing just two things, then which test is more applicable?

A. T-test
B. ANOVA
C. P-Test
D. None of the above

3. Which test compares the size of any discrepancies between the expected results and the actual results?

A. Chi-square test
B. T-test
C. ANOVA
D. None of the above

4. Asking somebody their favorite color would produce a …… variable.
A. Nominal
B. Ordinal
C. Can't say
D. None of the above

5. Which of the following leads to false positive conclusion?
A. Type I error
B. Type II error
C. Type III error
D. None of the above

6. Which of the following leads to false negative conclusion?
A. Type I error
B. Type II error
C. Type III error
D. None of the above

7. The result says that "You have a fever, but actually you don't have". Then this is
A. Type I error
B. Type II error
C. Type III error
D. None of the above

8. The probability of making Type I error is
A. Alpha
B. Beta
C. Gamma
D. Lamda

9. The probability of making Type II error is
A. Alpha
B. Beta
C. Gamma
D. Lamda

10. The "one-way" or "two-way" ANOVA refers to
A. Number of dependent variables
B. Number of independent variables
C. Number of total variables
D. None of the above

11. What is nonparametric alternative of ANOVA?
A. PERMANOVA
B. NONPERMANOVA
C. ANOVANONPERM
D. None of the above

12. "You have a group of individuals randomly split into smaller groups and completing different tasks". You have this situation, in this case what will be applied?
A. One way ANOVA
B. Two-way ANOVA
C. Three-way ANOVA
D. None of the above

13. Which of the following usually represents the equality between the population parameters?
A. Null hypothesis
B. Alternate hypothesis

14. Can alternate hypothesis and null hypothesis be same at one time?
A. Yes
B. No

15. Which of the classes of models are used in analysis of variance?
A. Fixed effects models
B. Random effects models
C. Mixed effects models
D. All of the above

Answer for Self Assessment

1.	B	2.	A	3.	A	4.	A	5.	A
6.	B	7.	A	8.	A	9.	B	10.	B
11.	A	12.	A	13.	A	14.	B	15.	D

Review Questions

1. What is hypothesis testing? What are two types of hypotheses?
2. What are the steps of hypothesis testing? Explain with example and its mathematical representation.
3. What are type I and type II errors? Explain its probabilities also. How can we find the trade off between Type I and Type II error?
4. What is a P-value? How can we calculate the p-value? Write its importance.
5. What is ANOVA? What are the classes of models used in ANOVA?
6. What is ANOVA test? What does "one-way" or "two-way" ANOVA mean?
7. Write the limitations of one-way ANOVA? Explain two-way ANOVA. Write the assumptions for two-way ANOVA.
8. What is factorial ANOVA? Write the assumptions for factorial ANOVA. Also write its steps.
9. What is chi-square test? Also write its formula. What does a Chi-Square Statistic Tell You?
10. When to use a chi-square test? What is a chi-square test used for?

Further Readings

- https://www.statisticshowto.com/probability-and-statistics/hypothesis-testing/
- https://byjus.com/maths/type-i-and-type-ii-errors/

Web Links

- https://www.statisticshowto.com/probability-and-statistics/hypothesis-testing/anova/
- https://www.statisticshowto.com/probability-and-statistics/chi-square/

Unit 06: Machine Learning

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Objectives

After studying this unit, you will be able to

- understand the concept of machine learning,
- know the types of machine learning,
- understand the process of designing a learning system,
- understand the concept of learning task,
- understand the challenges in learning problems.

Introduction

Machine learning is a branch of artificial intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy. Machine learning is an important component of the growing field of data science.When machines assist humans, then machines should have a minimum level of intelligence.The challenge here is how machines could be incorporated with the level of intelligence required. Humans either learned through the hit and trial method or in the presence of some supervisors.Example: A child takes his finger to touch the fire of a candle that is lit.So, in a simple sense it is stated that the way a machine could learn about its tasks and objectives is called a machine learning.

Using statistical methods, algorithms are trained to make classifications or predictions, uncovering key insights within data mining projects. These insights subsequently drive decision making within applications and businesses, ideally impacting key growth metrics. As big data continues to expand and grow, the market demand for data scientists will increase, requiring them to assist in the identification of the most relevant business questions and subsequently the data to answer them.

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks T, as measured by P, improves with experience E. A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks T, as measured by P, improves with experience E.

1) Handwriting recognition learning problem
   - Task T: Recognizing and classifying handwritten words within images
   - Performance P: Percent of words correctly classified
   - Training experience E: A dataset of handwritten words with given classifications

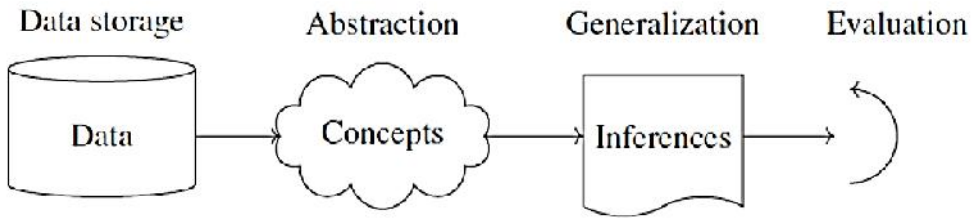
2) A robot driving learning problem
   - Task T: Driving on highways using vision sensor
   - Performance measure P: Average distance traveled before an error
   - Training experience: A sequence of images and steering commands recorded while observing a human driver

3) A chess learning problem
   - Task T: Playing chess
   - Performance measure P: Percent of games won against opponents
   - Training experience E: Playing practice games against itself

A computer program which learns from experience is called a machine learning program or simply a learning program. Such a program is sometimes also referred to as a learner.

6.1 Components of Learning

The learning process, whether by a human or a machine, can be divided into four components, namely, data storage, abstraction, generalization, and evaluation.



1. ***Data storage:***Facilities for storing and retrieving huge amounts of data are an important component of the learning process. Humans and computers alike utilize data storage as a foundation for advanced reasoning. • In a human being, the data is stored in the brain and data is retrieved using electrochemical signals. • Computers use hard disk drives, flash memory, random access memory and similar devices to store data and use cables and other technology to retrieve data.
2. ***Abstraction:***The second component of the learning process is known as abstraction. Abstraction is the process of extracting knowledge about stored data. This involves creating general concepts about the data. The creation of knowledge involves application of known models and creation of new models. The process of fitting a model to a dataset is known as training. When the model has been trained, the data is transformed into an abstract form that summarizes the original information.
3. ***Generalization:***The third component of the learning process is known as generalization. The term generalization describes the process of turning the knowledge about stored data into a form that can be utilized for future action. These actions are to be carried out on tasks that are similar, but not identical, to those what have been seen before. In

generalization, the goal is to discover those properties of the data that will be most relevant to future tasks.

4. *Evaluation:*Evaluation is the last component of the learning process. It is the process of giving feedback to the user to measure the utility of the learned knowledge. This feedback is then utilized to effect improvements in the whole learning process.

6.2 How Machine Learning Works

The learning system of a machine learning algorithm is broken into three main parts.

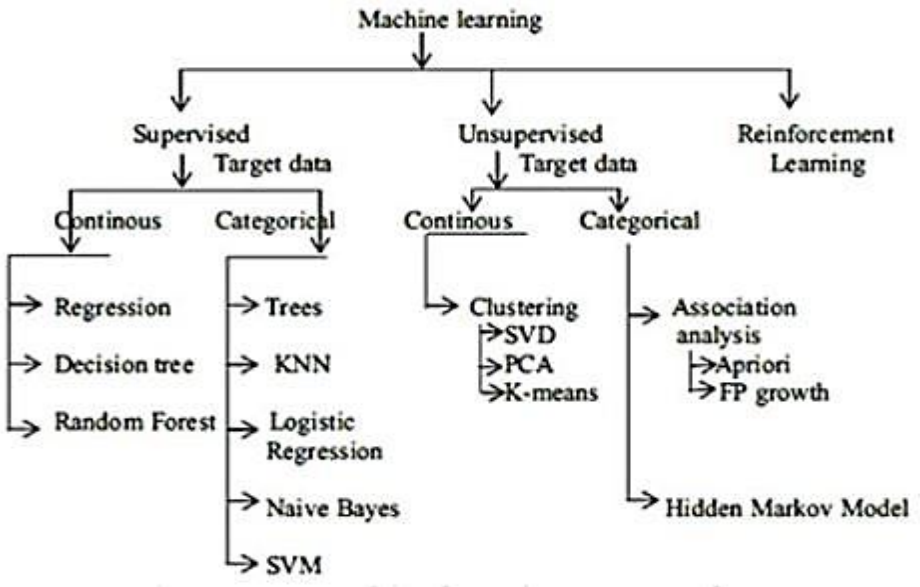
A Decision Process: In general, machine learning algorithms are used to make a prediction or classification. Based on some input data, which can be labelled or unlabeled, your algorithm will produce an estimate about a pattern in the data.

An Error Function: An error function serves to evaluate the prediction of the model. If there are known examples, an error function can make a comparison to assess the accuracy of the model.

An Model Optimization Process: If the model can fit better to the data points in the training set, then weights are adjusted to reduce the discrepancy between the known example and the model estimate. The algorithm will repeat this evaluate and optimize process, updating weights autonomously until a threshold of accuracy has been met.

6.3 Machine Learning Methods

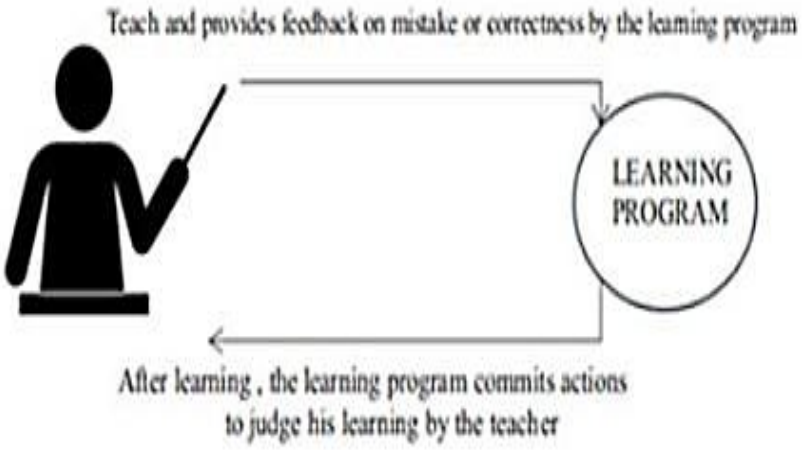
The machine learning methods are divided into three categories: supervised learning, unsupervised learning and reinforcement learning.



Supervised Learning

It is the field of learning where the machine learns with the help of a supervisor and instructor.A training set of examples with the correct responses (targets) is provided and, based on this training set, the algorithm generalises to respond correctly to all possible inputs. This is also called learning from exemplars. Supervised learning is the machine learning task of learning a function that maps an input to an output based on example input-output pairs. In supervised learning, each example in the training set is a pair consisting of an input object (typically a vector) and an output value. A supervised learning algorithm analyses the training data and produces a function, which can be used for mapping new examples. In the optimal case, the function will correctly determine the class labels for unseen instances. Both classification and regression problems are supervised learning problems. A wide range of supervised learning algorithms are available, each with its strengths and weaknesses. There is no single learning algorithm that works best on all supervised learning problems.

Example: Welcome Robot in home



Unsupervised Learning

Correct responses are not provided, but instead the algorithm tries to identify similarities between the inputs so that inputs that have something in common are categorised together. The statistical approach to unsupervised learning is known as density estimation. Unsupervised learning is a type of machine learning algorithm used to draw inferences from datasets consisting of input data without labelled responses. In unsupervised learning algorithms, a classification or categorization is not included in the observations. There are no output values and so there is no estimation of functions. Since the examples given to the learner are unlabelled, the accuracy of the structure that is output by the algorithm cannot be evaluated. The most common unsupervised learning method is cluster analysis, which is used for exploratory data analysis to find hidden patterns or grouping in data.

Example: Clustering of different objects

Reinforcement Learning

This is somewhere between supervised and unsupervised learning. The algorithm gets told when the answer is wrong but does not get told how to correct it. It must explore and try out different possibilities until it works out how to get the answer right. Reinforcement learning is sometime called learning with a critic because of this monitor that scores the answer but does not suggest improvements. Reinforcement learning is the problem of getting an agent to act in the world to maximize its rewards. A learner (the program) is not told what actions to take as in most forms of machine learning, but instead must discover which actions yield the most reward by trying them. In the most interesting and challenging cases, actions may affect not only the immediate reward but also the next situations and, through that, all subsequent rewards.Every state and action have a reward: positive and negative.The reinforcement process is accomplished by an agent called a reinforcement agent.

Example: Learning of four-wheel vehicle

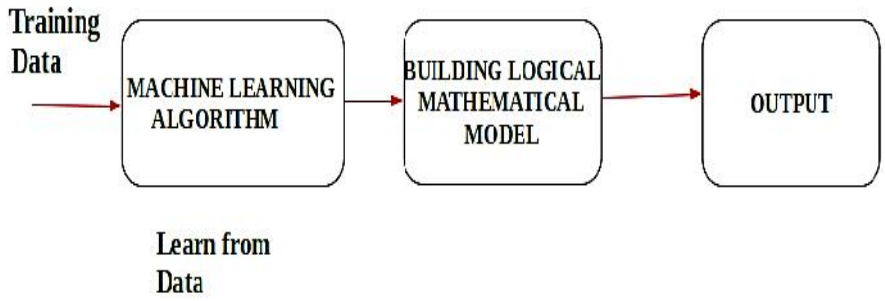
6.4 Learning Problems

1) Identification of spams
2) Recommending Products
3) Customer segmentation

4) Image and video recognition
5) Fraudulent Transactions
6) Demand Forecasting
7) Virtual Personal Assistant
8) Sentiment Analysis
9) Customer Service Automation

6.5 Designing a Learning System

According to Arthur Samuel "Machine Learning enables a Machine to Automatically learn from Data, improve performance from an Experience and predict things without explicitly programmed."When we fed the Training Data to Machine Learning Algorithm, this algorithm will produce a mathematical model and with the help of the mathematical model, the machine will make a prediction and take a decision without being explicitly programmed.Also, during training data, the more machine will work with it the more it will get experience and the more it will get experience the more efficient result is produced.



Choose training experience

The very important and first task is to choose the training data or training experience which will be fed to the Machine Learning Algorithm. It is important to note that the data or experience that we fed to the algorithm must have a significant impact on the Success or Failure of the Model. So, training data or experience should be chosen wisely.

Choose target function

It means according to the knowledge fed to the algorithm the machine learning will choose NextMove function which will describe what type of legal moves should be taken.

Choosing representation of a target function

When the machine algorithm will know all the possible legal moves the next step is to choose the optimized move using any representation, i.e., using linear Equations, Hierarchical Graph Representation, Tabular form etc. The NextMove function will move the Target move like out of these moves which will provide more success rate.

Choosing function approximation algorithm

An optimized move cannot be chosen just with the training data. The training data had to go through with set of examples and through these examples the training data will approximates which steps are chosen and after that machine will provide feedback on it.

Final design

The final design is created at last when system goes from number of examples , failures and success, correct and incorrect decision and what will be the next step etc.

6.6 Challenges in Machine Learning

1) Poor quality of data
2) Underfitting of training data
3) Overfitting of training data
4) Machine learning is a complex process
5) Lack of training data
6) Slow implementation

Summary

- Machine learning is programming computers to optimize a performance criterion using example data or experience.
- A computer program which learns from experience is called a machine learning program.
- The learning process, whether by a human or a machine, can be divided into four components, namely, data storage, abstraction, generalization, and evaluation.
- For any learning system, we must be knowing the three elements — **T (Task)**, **P (Performance Measure)**, and **E (Training Experience)**.
- Reinforcement learning is somewhere between supervised and unsupervised learning.

Keywords

- **Abstraction**: Abstraction is the process of extracting knowledge about stored data. This involves creating general concepts about the data as a whole.
- **Generalization**: The term generalization describes the process of turning the knowledge about stored data into a form that can be utilized for future action.
- **Evaluation**: It is the process of giving feedback to the user to measure the utility of the learned knowledge. This feedback is then utilized to effect improvements in the whole learning process.
- **Supervised Learning:** Supervised learning is the machine learning task of learning a function that maps an input to an output based on example input-output pairs.
- **Unsupervised Learning:**Unsupervised learning is a type of machine learning algorithm used to draw inferences from datasets consisting of input data without labeled responses.

Self Assessment

1. Which of the following supervised machine learning algorithms is not applicable on continuous data?

A. Regression
B. Decision tree
C. Random Forest
D. KNN

2. Find the odd one out.

A. K-means
B. SVM
C. Naïve Bayes
D. Random Forest

3. For association analysis, the techniques can be

A. Apriori algorithm
B. FP growth
C. Both of the above
D. None of the above

4. Which of the following supervised machine learning algorithms is not applicable on categorical data?

A. Trees
B. KNN
C. SVM
D. Random forest

5. Find the odd one out.

A. SVD
B. PCA
C. K-means
D. SVM

6. In which type of machine learning, the column of label is not provided along with data?

A. Supervised
B. Unsupervised
C. Can't say
D. None of the above

7. Reinforcement learning works best with … environment.

A. Static
B. Dynamic
C. Can't say
D. None of the above

8. In unsupervised machine learning, for target data which techniques can be applied?

A. Clustering
B. Association rule mining
C. Hidden Markov model
D. All of the above

9. In which case, the feedback is provided on mistake, and it is corrected by learning process?

A. Supervised
B. Unsupervised
C. Can't say
D. None of the above

10. Which of the following usually interacts with the environment?

A. Supervised machine learning
B. Unsupervised machine learning
C. Reinforcement learning

D. None of the above

11. What are the challenges for machine learning algorithms?
A. Lack of training data
B. Slow implementation
C. Poor quality of data
D. All of the above

12. The field of learning where the machine learns with the help of an instructor is known as
A. Supervised machine learning
B. Unsupervised machine learning
C. Non supervised machine learning
D. None of the above

13. In this kind of learning, the learning happens with an interaction with the environment. This is known as
A. Supervised machine learning
B. Unsupervised machine learning
C. Reinforcement learning
D. None of the above

14. On which learning problem, the machine learning algorithms can be applied?
A. Sentiment analysis
B. Image and video recognition
C. Identification of spams
D. All of the above

15. The machine learning type can be
A. Supervised machine learning
B. Unsupervised machine learning
C. Reinforcement learning
D. All of the above

Answer for Self Assessment

1.	D	2.	A	3.	C	4.	D	5.	D
6.	B	7.	B	8.	D	9.	A	10.	C
11.	D	12.	A	13.	C	14.	D	15.	D

Review Questions

1. What is machine learning? Explain the concept of learning with an example.
2. What are the types of machine learning? Explain with example.
3. Explain the components of learning process in detail. Also explain how machine learning works.
4. Give few examples of learning problems. Also explain how to design a learning system.
5. What are the challenges in machine learning? Also explain how we can overcome these challenges.

Further Readings

https://www.ibm.com/in-en/cloud/learn/machine-learning

Web Links

https://www.techtarget.com/searchenterpriseai/definition/machine-learning-ML

Unit 07: Unsupervised Learning

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Objectives

After this lecture, students will:

- Understand the unsupervised learning
- Understanding the clustering algorithms
- Understanding k-means algorithm
- Understand k-mode algorithm
- Understand k-median algorithm
- Know the performance metrics of clustering

Introduction

Unsupervised learning is a machine learning technique in which models are not supervised using training dataset. Instead, models itself find the hidden patterns and insights from the given data.

7.1 Unsupervised Learning

Unsupervised learning cannot be directly applied to a regression or classification problem because unlike supervised learning, we have the input data but no corresponding output data. The goal of unsupervised learning is to find the underlying structure of dataset, group that data according to similarities, and represent that dataset in a compressed format.

Why use unsupervised learning?

There are various benefits to use unsupervised learning. These are:

- Unsupervised learning is helpful for finding useful insights from the data.
- Unsupervised learning is much similar as a human learns to think by their own experiences, which makes it closer to the real AI.
- Unsupervised learning works on unlabeled and uncategorized data which make unsupervised learning more important.

- In real-world, we do not always have input data with the corresponding output so to solve such cases, we need unsupervised learning.

Advantages of Unsupervised Learning

The unsupervised learning is advantageous in many ways. These are:

- Unsupervised learning is used for more complex tasks as compared to supervised learning because, in unsupervised learning, we don't have labeled input data.
- Unsupervised learning is preferable as it is easy to get unlabeled data in comparison to labeled data.

Disadvantages of Unsupervised learning

Along with many advantages, it provides few disadvantages as well:

- Unsupervised learning is intrinsically more difficult than supervised learning as it does not have corresponding output.
- The result of the unsupervised learning algorithm might be less accurate as input data is not labeled, and algorithms do not know the exact output in advance.

Types of unsupervised learning

There are two main types of unsupervised learning. These are: clustering and association.

Clustering

Clustering is a method of grouping the objects into clusters such that objects with most similarities remains into a group and has less or no similarities with the objects of another group. Cluster analysis finds the commonalities between the data objects and categorizes them as per the presence and absence of those commonalities.

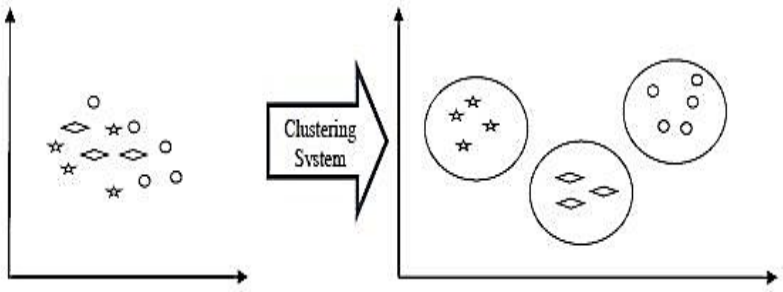
Association

An association rule is an unsupervised learning method which is used for finding the relationships between variables in the large database. It determines the set of items that occurs together in the dataset. Association rule makes marketing strategy more effective. Such as people who buy X item (suppose a bread) also tend to purchase Y (Butter/Jam) item. A typical example of Association rule is Market Basket Analysis.

7.2 Clustering

Clustering methods are one of the most useful unsupervised ML methods. Clustering is the task of grouping a set of customers in such a way that customers in the same group (called a cluster) are more similar (in some sense) to each other than to those in other groups (clusters).These methods are used to find similarity as well as the relationship of patterns among data samples and then cluster those samples into groups having similarity based on features.Cluster analysis uses mathematical models to discover groups of similar customers based on the smallest variations among customers within each group. A Clustering Algorithm tries to analyze natural groups of data based on some similarity.Clustering is important because it determines the intrinsic grouping among the present unlabeled data.They basically make some assumptions about data points to constitute their similarity. Clustering is dividing data points into homogeneous classes or clusters:

- Points in the same group are as similar as possible
- Points in different group are as dissimilar as possible



Applications of Clustering

1) **Data summarization and compression** − Clustering is widely used in the areas where we require data summarization, compression, and reduction as well. The examples are image processing and vector quantization.

2) **Collaborative systems and customer segmentation** − Since clustering can be used to find similar products or same kind of users, it can be used in collaborative systems and customer segmentation.

3) **Serve as a key intermediate step for other data mining tasks** − Cluster analysis can generate a compact summary of data for classification, testing, hypothesis generation; hence, it serves as a key intermediate step for other data mining tasks also.

4) T**rend detection in dynamic data** − Clustering can also be used for trend detection in dynamic data by making various clusters of similar trends.

5) **Social network analysis** − Clustering can be used in social network analysis. The examples are generating sequences in images, videos, or audios.

6) **Biological data analysis** − Clustering can also be used to make clusters of images, videos hence it can successfully be used in biological data analysis.

7.3 Partitioning Clustering

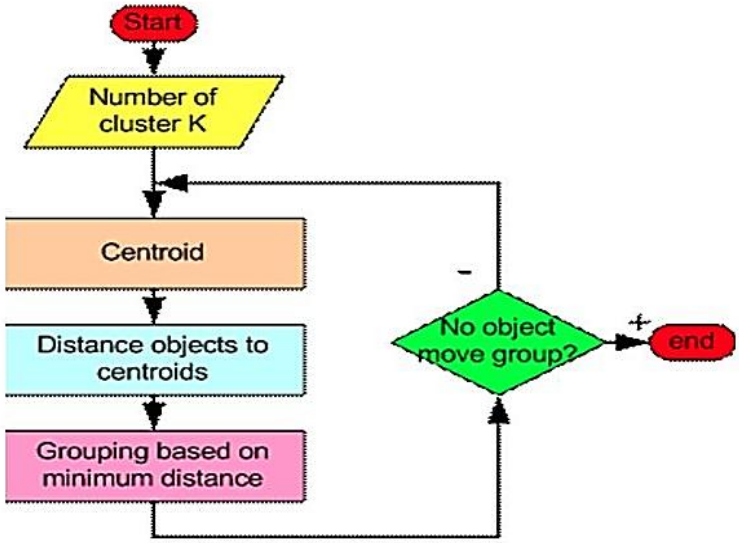
The most popular class of clustering algorithms that we have is the iterative relocation algorithms. These algorithms minimize a given clustering criterion by iteratively relocating data points between clusters until a (locally) optimal partition is attained.

K-Means algorithm

It is one of the most used algorithms for partitioning a given data set into a set of k groups (i.e., k clusters), where k represents the number of groups.It classifies objects in multiple groups (i.e., clusters), such that objects within the same cluster are as similar as possible (i.e., high intra-class similarity), whereas objects from different clusters are as dissimilar as possible (i.e., low inter-class similarity).In k-means clustering, each cluster is represented by its center (i.e., centroid) which corresponds to the mean of points assigned to the cluster. The basic idea behind k-means clustering consists of defining clusters so that the total intra-cluster variation (known as total within-cluster variation) is minimized.

Basic Phenomenon

Given a set of observations ($\mathbf{x}_1$, $\mathbf{x}_2$, ..., $\mathbf{x}_n$), where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k ($\leq$ n) sets $\mathbf{S}$ = {S_1, S_2, ..., S_k} to minimize the within-cluster sum of squares (WCSS) (i.e., variance).



- Step – 1

The first step when using k-means clustering is to indicate the number of clusters (k) that will be generated in the final solution.

- Step – 2

The algorithm starts by randomly selecting k objects from the data set to serve as the initial centers for the clusters. The selected objects are also known as cluster means or centroids.

- Step – 3

Next, each of the remaining objects is assigned to its closest centroid, where closest is defined using the Euclidean distance between the object and the cluster mean. This step is called "cluster assignment step".

- Step – 4

After the assignment step, the algorithm computes the new mean value of each cluster. The term cluster "centroid update" is used to design this step. Now that the centers have been recalculated, every observation is checked again to see if it might be closer to a different cluster. All the objects are reassigned again using the updated cluster means.

- Step – 5

The cluster assignment and centroid update steps are iteratively repeated until the cluster assignments stop changing (i.e., until convergence is achieved). That is, the clusters formed in the current iteration are the same as those obtained in the previous iteration.

- Given an initial set of k means $m_1^{(1)}...,m_k^{(1)}$, the algorithm proceeds by alternating between two steps:

1) **Assignment step**: Assign each observation to the cluster with the nearest mean: that with the least squared Euclidean distance.

2) **Update step**: Recalculate means (centroids) for observations assigned to each cluster.

Specific features of k-means algorithm

- It is an efficient algorithm for clustering data items, i.e., theEuclidean distance is used as a metric and variance is used as a measure of cluster scatter.
- It is very sensitive to outliers.
- In k-means algorithm, the number of clusters need to be specified in advance.The number of clusters k is an input parameter: an inappropriate choice of k may yield poor results. That is

why, when performing k-means, it is important to run diagnostic checks for determining the number of clusters in the data set.

- The convergence to a local minimum may produce wrong results.

Applications of k-means algorithm

- K-means clustering is rather easy to apply to even large data sets.
- It has been successfully used in market segmentation, computer vision, and astronomy among many other domains.
- It often is used as a preprocessing step for other algorithms, for example to find a starting configuration.
- K-means originates from signal processing, and still finds use in this domain. For example, in computer graphics, color quantization is the task of reducing the color palette of an image to a fixed number of colors k. The K-means algorithm can easily be used for this task and produces competitive results
- In cluster analysis, the k-means algorithm can be used to partition the input data set into k partitions (clusters).

K-Mode algorithm

K-Modes clustering is one of the unsupervised Machine Learning algorithms that is used to cluster categorical variables.

Why not k-means algorithm?

- K-Means uses mathematical measures (distance) to cluster continuous data.
- The lesser the distance, the more similar our data points are.
- Centroids are updated by Means.
- But for categorical data points, we cannot calculate the distance. So, we go for K Modes algorithm. It uses the dissimilarities(total mismatches) between the data points.
- The lesser the dissimilarities the more similar our data points are. It uses Modes instead of means.

Algorithm

1. Pick K observations at random and use them as leaders/clusters
2. Calculate the dissimilarities and assign each observation to its closest cluster
3. Define new modes for the clusters
4. Repeat 2–3 steps until there is no re-assignment required

Example

Imagine we have a dataset that has the information about hair color, eye color, and skin color of persons. We aim to group them based on the available information. Hair color, eye color, and skin color are all categorical variables.

Person	Hair Color	Eye Color	Skin Color
P1	Blonde	Amber	Fair

P2	Brunette	Gray	Brown
P3	Red	Green	Brown
P4	Black	Hazel	Brown
P5	Brunette	Amber	Fair
P6	Black	Gray	Brown
P7	Red	Green	Fair
P8	Black	Hazel	Fair

Step 1: Pick k observations at random

Leaders			
P1	Blonde	Amber	Fair
P7	Red	Green	Fair
P8	Black	Hazel	Fair

Step 2: Calculate the dissimilarities

Iteratively compare the cluster data points to each of the observations. In the first iteration, compare P1 of leaders with P1 of data given. Similar data points give 0, dissimilar data points give 1.

Leaders			
P1	Blonde	Amber	Fair
P7	Red	Green	Fair
P8	Black	Hazel	Fair
Person	Hair Color	Eye Color	Skin Color
P1	Blonde	Amber	Fair
P2	Brunette	Gray	Brown
P3	Red	Green	Brown
P4	Black	Hazel	Brown
P5	Brunette	Amber	Fair
P6	Black	Gray	Brown
P7	Red	Green	Fair
P8	Black	Hazel	Fair

Comparing leader/Cluster P1 to the observation P1 gives 0 dissimilarities. In next iteration, compare P1 of leaders table with the table data given. Comparing leader/cluster P1 to the

observation P2 gives 3(1+1+1) dissimilarities.Likewise, calculate all the dissimilarities and put them in a matrix and assign the observations to their closest cluster(cluster that has the least dissimilarity). So, with this we will calculate the matrix for cluster 1, 2 and 3 which is shown below.

Person	Cluster 1 (P1)
P1	0
P2	3
P3	3
P4	3
P5	1
P6	3
P7	2
P8	2

Person	Cluster 2 (P7)
P1	2
P2	3
P3	1
P4	3
P5	2
P6	3
P7	0
P8	2

Person	**Cluster 3 (P8)**
P1	2

P2	3
P3	0
P4	1
P5	2
P6	2
P7	2
P8	0

- After step 2, the observations P1, P2, P5 are assigned to cluster 1; P3, P7 are assigned to Cluster 2; and P4, P6, P8 are assigned to cluster 3.
- If all the clusters have the same dissimilarity with an observation, assign to any cluster randomly. In our case, the observation P2 has 3 dissimilarities with all the leaders. I randomly assigned it to Cluster 1.

Dissimilarity Matrix

	Cluster 1 (P1)	**Cluster 2 (P7)**	**Cluster 3 (P8)**	Cluster
P1	0	2	2	Cluster 1
P2	3	3	3	Cluster 1
P3	3	1	3	Cluster 2
P4	3	3	1	Cluster 3
P5	1	2	2	Cluster 1
P6	3	3	2	Cluster 3
P7	2	0	2	Cluster 2
P8	2	2	0	Cluster 3

Step 3: Define new modes for the clusters

- Mode is simply the **most observed value**.
- Mark the observations according to the cluster they belong to. Observations of Cluster 1 are marked in Yellow, Cluster 2 are marked in Brick red, and Cluster 3 are marked in Purple.
- Cluster 1 observations(P1, P2, P5) has brunette as the most observed hair color, amber as the most observed eye color, and fair as the most observed skin color.

person	hair color	eye color	skin color
P1	blonde	amber	fair
P2	brunette	gray	brown
P3	red	green	brown
P4	black	hazel	brown
P5	brunette	amber	fair
P6	black	gray	brown
P7	red	green	fair
P8	black	hazel	fair

New Leaders			
	Hair Color	Eye Color	Skin Color
Cluster 1	Brunette	Amber	Fair
Cluster 2	Red	Green	Fair
Cluster 3	Black	Hazel	Brown

Repeat steps 2-4

- After obtaining the new leaders, again calculate the dissimilarities between the observations and the newly obtained leaders.

New Leaders			
	hair color	eye color	skin color
Cluster 1	brunette	amber	fair
Cluster 2	red	green	fair
Cluster 3	black	hazel	brown

person	hair color	eye color	skin color
P1	blonde	amber	fair
P2	brunette	gray	brown
P3	red	green	brown
P4	black	hazel	brown
P5	brunette	amber	fair
P6	black	gray	brown
P7	red	green	fair
P8	black	hazel	fair

- Comparing Cluster 1 to the observation P1 gives 1 dissimilarity.

New Leaders			
	hair color	eye color	skin color
Cluster 1	brunette	amber	fair
Cluster 2	red	green	fair
Cluster 3	black	hazel	brown

person	hair color	eye color	skin color
P1	blonde	amber	fair
P2	brunette	gray	brown
P3	red	green	brown
P4	black	hazel	brown
P5	brunette	amber	fair
P6	black	gray	brown
P7	red	green	fair
P8	black	hazel	fair

- Comparing Cluster 1 to the observation P2 gives 2 dissimilarities.
- Likewise, calculate all the dissimilarities and put them in a matrix. Assign each observation to its closest cluster.

	Cluster 1	Cluster 2	Cluster 3	Cluster
P1	1 ✓	2	3	Cluster 1
P2	2 ✓	3	2	Cluster 1
P3	3	1 ✓	2	Cluster 2
P4	3	3	0 ✓	Cluster 3
P5	0 ✓	2	3	Cluster 1
P6	3	3	1 ✓	Cluster 3
P7	2	0 ✓	3	Cluster 2
P8	2	2	1 ✓	Cluster 3

K-Median Algorithm

It is a variation of k-means clustering where instead of calculating the mean for each cluster to determine its centroid, one instead calculates the median.In this, we use L1 norm as the distance measure. The k-medians approach to clustering data attempts to minimize the 1-norm distances between each point and its closest cluster center. This minimization of distances is obtained by setting the center of each cluster to be the median of all points in that cluster.

Benefits over k-means

- The mean is a measurement that is highly vulnerable to outliers. Even just one drastic outlier can pull the value of the mean away from the majority of the data set, which can be a high concern when operating on very large data sets.
- The median, on the other hand, is a statistic incredibly resistant to outliers, for in order to deter the median away from the bulk of the information, it requires at least 50% of the data to be contaminated

Criterion function

- The criterion function for k-median algorithm is:

$$S = \sum_{k=1}^{k} \sum_{x} |xij - medkj|$$

Algorithm

1. Select K points as the initial representative objects (i.e., as initial k medians).
2. Repeat
    1. Assign each point to its nearest median
    2. Re-compute the median using the median of each individual feature
3. Until convergence criterion is satisfied

7.4 Performance Measures

The most popular metrics evaluation metrics for clustering algorithms are the Silhouette coefficient, Dunn's Index and Rand Index.

Silhoutte Coefficient

$$S = \frac{b - a}{\max(a, b)}$$

The Silhoutte Coefficient is defined for each sample and is composed of two scores:

a: The mean distance between a sample and all other points in the same cluster.

b: The mean distance between a sample and all other points in the next nearest cluster.

Score -1: Incorrect clustering

Score +1: Highly dense clustering

Score around 0: Overlapping clustering

The score is higher when clusters are dense and well separated, which relates to a standard concept of a cluster.

Dunn's Index

Dunn's Index is equal to the minimum inter-cluster distance divided by the maximum cluster size. The large inter-cluster distances (better separation) and smaller cluster sizes (more compact clusters) lead to a higher DI value. A higher DI implies better clustering.It assumes that better clustering means that clusters are compact and well-separated from other clusters.

Rand Index

It computes a similarity measure between two clusters by considering all pairs of samples and counting pairs that are assigned in the same or different clusters in the predicted and true clustering.

Summary

- Unsupervised learning is a machine learning technique in which models are not supervised using training dataset.
- Unsupervised learning cannot be directly applied to a regression or classification problem because unlike supervised learning, we have the input data but no corresponding output data.
- Unsupervised learning is much similar as a human learns to think by their own experiences, which makes it closer to the real AI.
- The result of the unsupervised learning algorithm might be less accurate as input data is not labeled, and algorithms do not know the exact output in advance.
- Clustering methods are one of the most useful unsupervised ML methods.
- Clustering is dividing data points into homogeneous classes or clusters with the condition: The points in the same group are as similar as possible and points in different group are as dissimilar as possible.

- The basic idea behind k-means clustering consists of defining clusters so that the total intra-cluster variation (known as total within-cluster variation) is minimized.
- We use L1 norm as the distance measure for k-median algorithm.
- The most popular metrics evaluation metrics for clustering algorithms are the Silhouette coefficient, Dunn's Index and Rand Index.

Keywords

- **Unsupervised learning**: The goal of unsupervised learning is to find the underlying structure of dataset, group that data according to similarities, and represent that dataset in a compressed format.
- **Clustering**: Clustering is a method of grouping the objects into clusters such that objects with most similarities remains into a group and has less or no similarities with the objects of another group.
- **Cluster analysis**: Cluster analysis finds the commonalities between the data objects and categorizes them as per the presence and absence of those commonalities.
- **Association Rule:**An association rule is an unsupervised learning method which is used for finding the relationships between variables in the large database.
- **K-means algorithm**: It classifies objects in multiple groups (i.e., clusters), such that objects within the same cluster are as similar as possible (i.e., high intra-class similarity), whereas objects from different clusters are as dissimilar as possible (i.e., low inter-class similarity).
- **K-mode algorithm**: It is one of the unsupervised Machine Learning algorithms that is used to cluster **categorical variables.**
- **K-median algorithm**: It is a variation of k-means clustering where instead of calculating the mean for each cluster to determine its centroid, one instead calculates the median.

SelfAssessment

1. A machine learning technique in which models are not supervised using training dataset is known as:

A. Unsupervised learning
B. Supervised learning
C. Non defined learning
D. None of the above

2. Unsupervised learning cannot be directly applied to

A. Classification problems
B. Regression problems
C. Both of the above
D. None of the above

3. The important types of unsupervised algorithms are:

A. Association rule
B. Clustering
C. Both of the above
D. None of the above

4. ……. is an unsupervised learning method which is used for finding the relationships between variables in the large database.

A. Association rule
B. Clustering
C. Both of the above
D. None of the above

5. What is the task of grouping a set of customers in such a way that customers in the same group are more like each other than to those in other groups?

A. Association rule
B. Clustering
C. Both of the above
D. None of the above

6. What are the applications of clustering?

A. Data summarization and compression
B. Trend detection in dynamic data.
C. Biological data analysis
D. All of the above

7. The basic idea behind k-means clustering consists of defining clusters so that the total intra-cluster variation (known as total within-cluster variation) is …...

A. Minimized
B. Maximized
C. Remains same
D. None of the above

8. The basic idea behind …. clustering consists of defining clusters so that the total intra-cluster variation (known as total within-cluster variation) is minimized.

A. K-means algorithm
B. K-mode algorithm
C. K-median algorithm
D. None of the above

9. The first step in k-means algorithm is to define the value of k. This statement is

A. True
B. False

10. …… clustering is one of the unsupervised Machine Learning algorithms that is used to cluster categorical variables.

A. K-means algorithm
B. K-mode algorithm

C. K-median algorithm
D. None of the above

11. In k-modes algorithm, the …. Between the data points are used.
A. Similarities
B. Dissimilarities
C. Half of the oiginal points
D. None of the above

12. In k-median algorithm, what is used as a distance measure?
A. L1 norm
B. L2 norm
C. L0 norm
D. None of the above

13. Which algorithm is more resistant to outliers in data?
A. K-means algorithm
B. K-mode algorithm
C. K-median algorithm
D. None of the above

14. Which of the following are the performance measures for clustering algorithms?
A. Silhouette coefficient
B. Dunn's Index
C. Rand Index
D. All of the above

15. In Silhouette coefficient, if the score is +1. Then it represents
A. Incorrect clustering
B. Highly dense clustering
C. Overlapping clustering
D. None of the above

Answers for Self Assessment

1.	A	2.	C	3.	C	4.	A	5.	B
6.	D	7.	A	8.	A	9.	A	10.	B
11.	B	12.	A	13.	C	14.	D	15.	B

Review Questions

1. What is unsupervised learning? Write down its advantages and disadvantages.
2. What are the applications of unsupervised learning? Also explain what the benefits are of using unsupervised learning.
3. What are the types of clustering? Explain all in detail.
4. What is k-means algorithm? Explain its basic phenomenon and specific features.
5. What is k-mode algorithm? Why is it preferred more over k-means algorithm? Explain with one example.
6. What is k-median algorithm? Explain its criterion function and algorithm.
7. What are the performance measures of clustering algorithms?

Further Readings

https://www.geeksforgeeks.org/life-cycle-phases-of-data-analytics/

Web Links

https://www.simplilearn.com/tutorials/data-science-tutorial/what-is-data-science

Unit 08: Supervised Learning

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Objectives

After this unit, you will be able to understand:

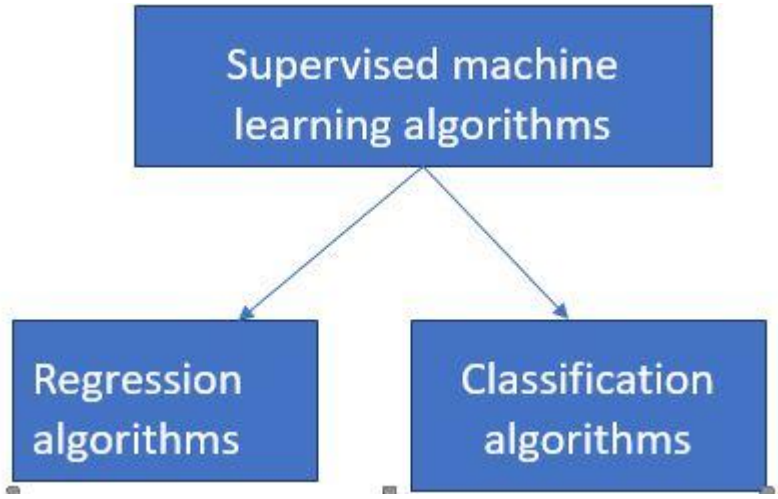
- Understand the meaning of classification
- Understand the KNN algorithm
- Understand the Naïve Bayes algorithm
- Understand the cross-validation
- Understand the performance metrics of classification algorithms

Introduction

Supervised learning is the types of machine learning in which machines are trained using well "labeled" training data, and on basis of that data, machines predict the output. The labeled data means some input data is already tagged with the correct output.

8.1 Supervised Learning

In supervised learning, the training data provided to the machines work as the supervisor that teaches the machines to predict the output correctly. It applies the same concept as a student learns in the supervision of the teacher. Supervised learning is a process of providing input data as well as correct output data to the machine learning model. The aim of a supervised learning algorithm is to find a mapping function to map the input variable(x) with the output variable(y). In the real-world, supervised learning can be used for Risk Assessment, Image classification, Fraud Detection, spam filtering, etc.



8.2 Classification

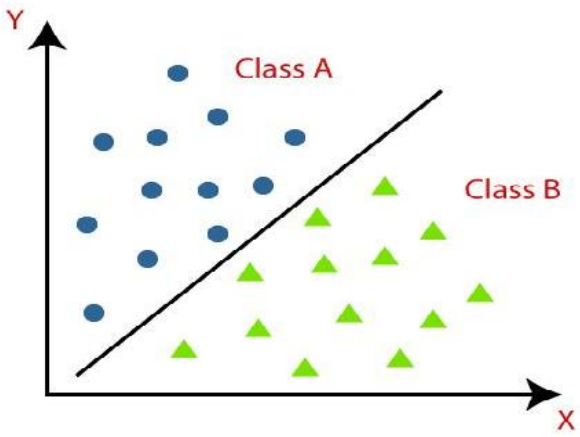
Classification: It is the operation of separating various entities into several classes.

Classification algorithm: The Classification algorithm is a supervised learning technique that is used to identify the category of new observations based on training data.

In Classification, a program learns from the given dataset or observations and then classifies new observation into several classes or groups such as, Yes or No, 0 or 1, Spam or Not Spam, cat or dog, etc. Classes can be called as targets/labels or categories.The output variable of Classification is a category, not a value, such as "Green or Blue", "fruit or animal", etc.Since the Classification algorithm is a supervised learning technique, hence it takes labeled input data, which means it contains input with the corresponding output.

Output function: In classification algorithm, a discrete output function(y) is mapped to input variable(x).y=f(x), where y = categorical output.

Example



Types of classification

- **Binary Classifier**: If the classification problem has only two possible outcomes, then it is called as Binary Classifier.Examples: YES or NO, MALE or FEMALE, SPAM or NOT SPAM, CAT or DOG, etc.
- **Multi-class Classifier**: If a classification problem has more than two outcomes, then it is called as Multi-class Classifier.Example: Classifications of types of crops, Classification of types of music.

Learning in classification problems

- **Lazy Learners**: Lazy Learner firstly stores the training dataset and wait until it receives the test dataset. In Lazy learner case, classification is done on the basis of the most related data stored in the training dataset. It takes less time in training but more time for predictions. Example: K-NN algorithm, Case-based reasoning.
- **Eager Learners**: Eager Learners develop a classification model based on a training dataset before receiving a test dataset. Opposite to Lazy learners, Eager Learner takes more time in learning, and less time in prediction. Example: Decision Trees, Naïve Bayes, ANN.

Types of ML classification algorithms

- Linear Models
    - Logistic Regression
    - Support Vector Machines
- Non-linear Models
    - K-Nearest Neighbors
    - Kernel SVM
    - Naïve Bayes
    - Decision Tree Classification
    - Random Forest Classification

Basic terminologies

- **Classifier:** An algorithm that maps the input data to a specific category.
- **Classification model:** It tries to draw some conclusion from the input values given for training. It will predict the class labels/categories for the new data.
- **Feature:** It is an individual measurable property of a phenomenon being observed.
- **Binary Classification:** Yes/No
- **Multi-class classification:** An animal can be a cat or dog but not both at the same time.
- **Multi-label classification:** A news article can be about sports, a person, and location at the same time.

Steps in building a classification model

1. Initialize
2. Train the classifier
3. Predict the target
4. Evaluate

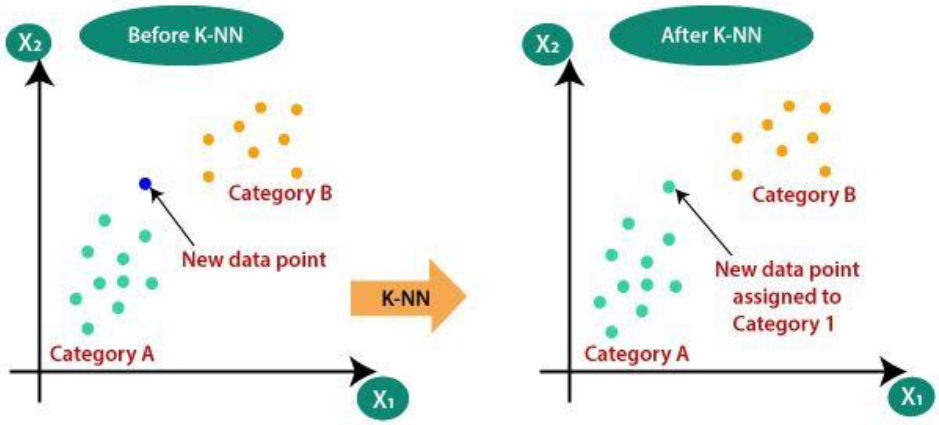
Applications of classification algorithms

1. Sentiment analysis – It is a machine learning text analysis technique that assigns sentiment (opinion, feeling, or emotion) to words within a text, or an entire text, on a polarity scale of Positive, Negative, or Neutral.
2. Email spam classification - Email applications use the above algorithms to calculate the likelihood that an email is either not intended for the recipient or unwanted spam.
3. Document classification - Document classification is the ordering of documents into categories according to their content.
4. Image classification - Image classification assigns previously trained categories to a given image.
5. Diagnosis of disease – Based upon the gene/values, detects a person is suffering from the disease or not.

8.3 K-NN Algorithm

It is a supervised learning technique. It works on similarity measure.K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most like the available categories.K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.K-NN is a **non-parametric algorithm**, which means it does not make any assumption on underlying data.It is also called a **lazy learner algorithm** because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset.KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much like the new data.

Need



Working

Step-1: Select the number K of the neighbors

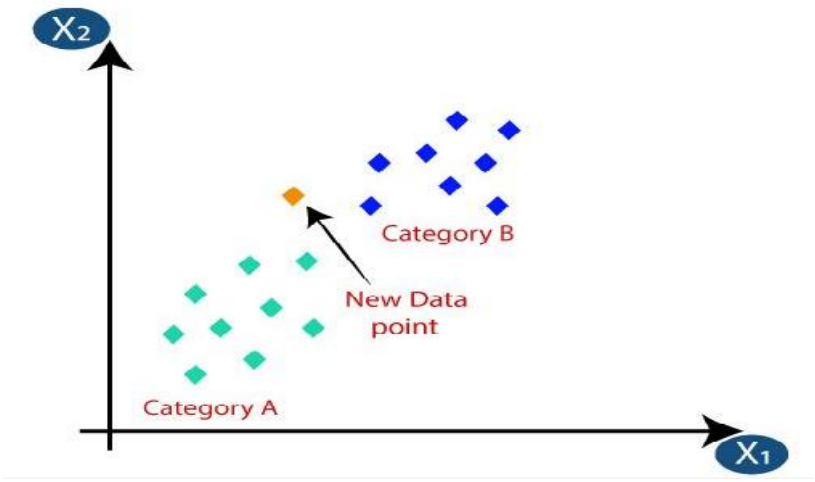
Step-2: Calculate the Euclidean distance of **K number of neighbors**

Step-3: Take the K nearest neighbors as per the calculated Euclidean distance.

Step-4: Among these k neighbors, count the number of the data points in each category.

Step-5: Assign the new data points to that category for which the number of the neighbor is maximum.

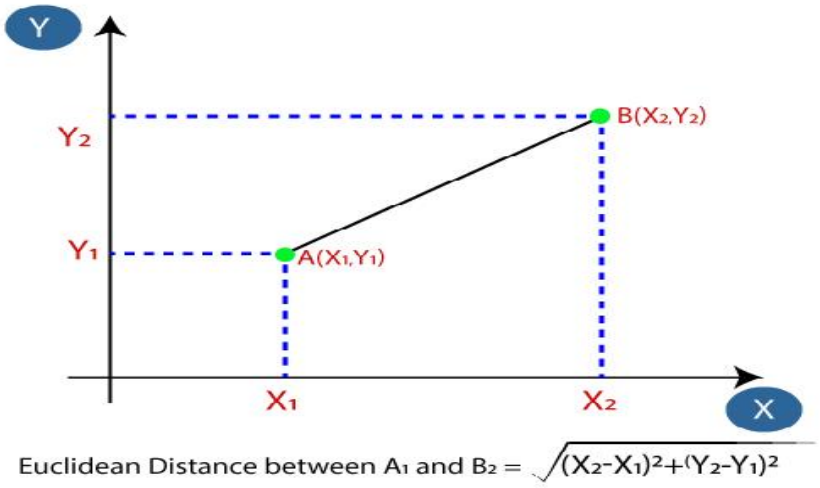
Step-6: The model is ready.



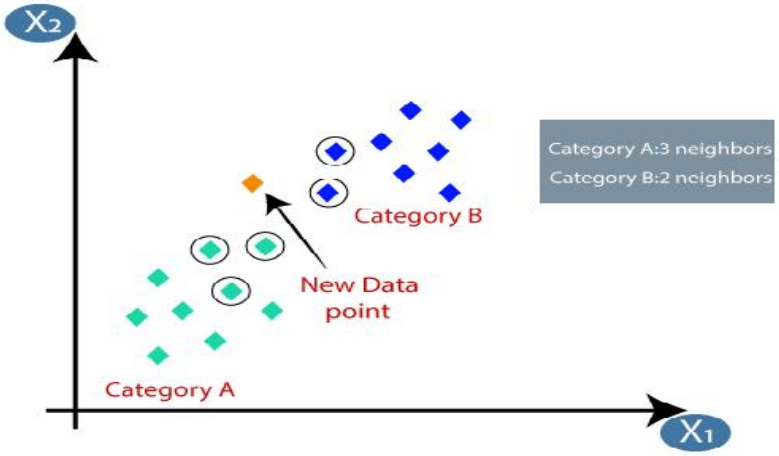
- Firstly, we will choose the number of neighbors,

Let us suppose k=5.

- Next, we will calculate the **Euclidean distance** between the data points. The Euclidean distance is the distance between two points. It can be calculated as:



- By calculating the Euclidean distance, we got the nearest neighbors, as three nearest neighbors in category A and two nearest neighbors in category B.



- 3 nearest neighbors are from category A, hence this new data point must belong to category A.

Selection of K

- There is no way to determine the best value for "K", so we need to try some values to find the best out of them.
- A very low value for K such as K=1 or K=2, can be noisy and lead to the effects of outliers in the model.

Advantages of KNN algorithms

- It is simple to implement.
- It is robust to the noisy training data
- It can be more effective if the training data is large.

Disadvantages of KNN algorithm

- Always needs to determine the value of K which may be complex some time.
- The computation cost is high because of calculating the distance between the data points for all the training samples.

8.4 Naïve Bayes

It is a supervised learning algorithm. The naïve Bayes algorithm for classification is based on Bayes theorem.It is mainly used in text classification that includes a high-dimensional training dataset.Naïve Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast machine learning models that can make quick predictions.It is a probabilistic classifier, which means it predicts based on the probability of an object. The popular examplesare spam filtration, sentiment analysis and classifying articles. It is composed of two words – Naïve and Bayes.Naïve: It is called Naïve because it assumes that the occurrence of a certain feature is independent of the occurrence of other features. Such as if the fruit is identified on the bases of color, shape, and taste, then red, spherical, and sweet fruit is recognized as an apple. Hence each feature individually contributes to identify that it is an apple without depending on each other.

Bayes Theorem

Thisis called Bayes because it depends on the principle of Bayes' Theorem.Bayes' theorem is also known as **Bayes' Rule** or **Bayes' law**.It is used to determine the probability of a hypothesis with prior knowledge. It depends on the conditional probability.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

P(A | B) is Posterior probability: Probability of hypothesis A on the observed event B.

P(B | A) is Likelihood probability: Probability of the evidence given that the probability of a hypothesis is true.

P(A) is Prior Probability: Probability of hypothesis before observing the evidence.

P(B) is Marginal Probability: Probability of Evidence.

Steps of Naïve Bayes

1. Convert the given dataset into frequency tables.
2. Generate Likelihood table by finding the probabilities of given features.
3. Now, use Bayes theorem to calculate the posterior probability.

Example

Suppose we have a dataset of **weather conditions** and corresponding target variable "**Play**".

Dataset given is

	Outlook	Play
0	Rainy	Yes
1	Sunny	Yes
2	Overcast	Yes
3	Overcast	Yes
4	Sunny	No
5	Rainy	Yes
6	Sunny	Yes
7	Overcast	Yes
8	Rainy	No
9	Sunny	No
10	Sunny	Yes
11	Rainy	No
12	Overcast	Yes
13	Overcast	Yes

Frequency table

Weather	Yes	No
Overcast	5	0
Rainy	2	2
Sunny	3	2
Total	10	5

Likelihood table

Weather	No	Yes	
Overcast	0	5	5/14 = 0.35
Rainy	2	2	4/14 = 0.29
Sunny	2	3	5/14 = 0.35
All	4/14 = 0.29	10/4 = 0/71	

Applying Bayes theorem

P(Yes | Sunny)= P(Sunny | Yes)*P(Yes)/P(Sunny)

P(Sunny | Yes)= 3/10= 0.3

P(Sunny)= 0.35

P(Yes)=0.71

So, P(Yes|Sunny) = 0.3*0.71/0.35= **0.60**

P(No|Sunny)= P(Sunny|No)*P(No)/P(Sunny)

P(Sunny|NO)= 2/4=0.5

P(No)= 0.29

P(Sunny)= 0.35

So, P(No|Sunny)= 0.5*0.29/0.35 = **0.41**

So, as we can see from the above calculation that **P(Yes|Sunny)>P(No|Sunny).**

Hence on a Sunny day, Player can play the game.

Advantages

- Naïve Bayes is one of the fast and easy ML algorithms to predict a class of datasets.
- It can be used for Binary as well as Multi-class Classifications.
- It performs well in multi-class predictions as compared to the other Algorithms.
- It is the most popular choice for **text classification problems**.

Disadvantages

- Naive Bayes assumes that all features are independent or unrelated, so it cannot learn the relationship between features.

Applications

- It is used for **Credit Scoring**.
- It is used in **medical data classification**.
- It can be used in **real-time predictions** because Naïve Bayes Classifier is an eager learner.
- It is used in Text classification such as **Spam filtering** and **Sentiment analysis**.

8.5 Cross-Validation

Cross validation is a model evaluation method. It is one of the most widely used data resampling methods to assess the generalization ability of a predictive model. The objective is to not use the entire data set when training a learner. Some of the data is removed before training begins.Then when training is done, the data that was removed can be used to test the performance of the learned model on "new" data. There are three main types of cross validation. These are holdout validation, k-fold cross validation and LOOCV.

Holdout validation: The holdout technique is an exhaustive cross-validation method that randomly splits the dataset into train and test data depending on data analysis. (Image by Author), 70:30 split of Data into training and validation data respectively.

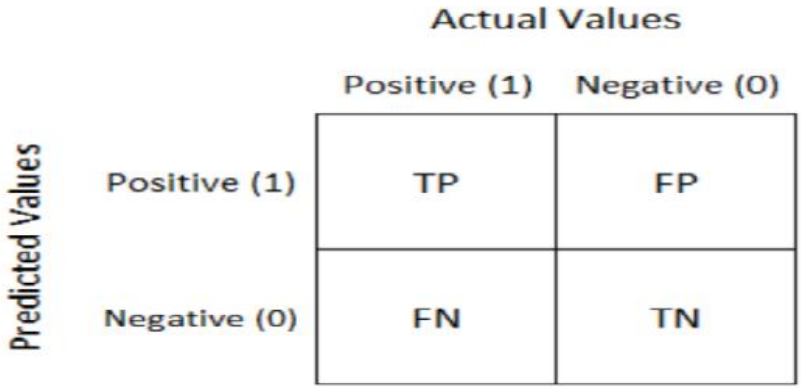
K-Fold cross validation: K-fold Cross-Validation is when the dataset is split into a K number of folds and is used to evaluate the model's ability when given new data. K refers to the number of groups the data sample is split into. For example, if you see that the k-value is 5, we can call this a 5-fold cross-validation.

LOOCV: LOOCV(Leave One Out Cross-Validation) is a type of cross-validation approach in which each observation is considered as the validation set and the rest (N-1) observations are considered as the training set. In LOOCV, fitting of the model is done and predicting using one observation validation set.

8.6 Metrics of Classification Algorithms

There are various measures of classification algorithms. The important measures are accuracy, precision, recall, F1 score AUC-ROC. These all measures can be easily calculated using confusion matrix.

Confusion matrix



From confusion matrix we can calculate accuracy, precision, sensitivity, specificity, recall and AUC-ROC.

Accuracy: Accuracy is the fraction of predictions our model got right. Formally, accuracy has the following definition: Accuracy = Number of correct predictions/ Total number of predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

Precision is one indicator of a machine learning model's performance – the quality of a positive prediction made by the model. Precision refers to the number of true positives divided by the total number of positive predictions (i.e., the number of true positives plus the number of false positives).

$$Precision = True\ positive/(True\ positive + False\ positive)$$

Recall

The recall is calculated as **the ratio between the numbers of Positive samples correctly classified as Positive to the total number of Positive samples**. The recall measures the model's ability to detect positive samples. The higher the recall, the more positive samples detected.

$$Recall = True\ positive/(True\ positive + False\ negative$$

F1 Score

F1-score is **one of the most important evaluation metrics in machine learning**. It elegantly sums up the predictive performance of a model by combining two otherwise competing metrics — precision and recall.

$$F1 = 2.\ (Precision * Recall)/Precision + Recall$$

AUC – ROC

The Receiver Operator Characteristic (ROC) is a probability curve that plots the TPR(True Positive Rate) against the FPR(False Positive Rate) at various threshold values and separates the 'signal' from the 'noise'. The **Area Under the Curve (AUC)** is the measure of the ability of a classifier to distinguish between classes.

Summary

- The output variable of Classification is a category, not a value, such as "Green or Blue", "fruit or animal", etc.
- In Classification, a program learns from the given dataset or observations and then classifies new observation into several classes or groups.
- Classes can be called as targets/labels or categories.
- Since the Classification algorithm is a supervised learning technique, hence it takes labeled input data, which means it contains input with the corresponding output.
- Linear models of classification are logistic regression and SVM.
- Nonlinear models are KNN, Kernel SVM, Naïve Bayes, Decision tree, Random Forest.
- K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.
- Naïve Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast machine learning models that can make quick predictions.
- Naïve Bayes performs well in multi-class predictions as compared to the other Algorithms.
- Naive Bayes assumes that all features are independent or unrelated, so it cannot learn the relationship between features.

Keywords

- **Classification:** It is the operation of separating various entities into several classes.
- **Classification algorithm:** The Classification algorithm is a supervised learning technique that is used to identify the category of new observations on the basis of training data.
- **Binary Classifier**: If the classification problem has only two possible outcomes, then it is called as Binary Classifier.
- **Multi-class Classifier**: If a classification problem has more than two outcomes, then it is called as Multi-class Classifier.
- **Lazy Learners**: Lazy Learner firstly stores the training dataset and wait until it receives the test dataset. In Lazy learner case, classification is done on the basis of the most related data stored in the training dataset. It takes less time in training but more time for predictions.
- **Eager Learners**: Eager Learners develop a classification model based on a training dataset before receiving a test dataset. Opposite to Lazy learners, Eager Learner takes more time in learning, and less time in prediction.
- **Feature:** It is an individual measurable property of a phenomenon being observed.
- **Naïve Bayes**: It is a supervised learning algorithm. It is based on Bayes theorem.It is mainly used in text classification that includes a high-dimensional training dataset.
- **Cross validation**: Cross-validation is one of the most widely used data resampling methods to assess the generalization ability of a predictive model
- **AUC-ROC**: The Receiver Operator Characteristic (ROC) is a probability curve that plots the TPR(True Positive Rate) against the FPR(False Positive Rate) at various threshold values and separates the 'signal' from the 'noise'. The **Area Under the Curve (AUC)** is the measure of the ability of a classifier to distinguish between classes.

SelfAssessment

1. The supervised machine learning algorithms are

A. Classification algorithms
B. Regression algorithms
C. Both of the above
D. None of the above

2. Which learner firstly stores the training dataset and wait until it receives the test dataset?

A. Lazy learner
B. Eager learner
C. Either of the above
D. None of the above

3. Which learners develop a classification model based on a training dataset before receiving a test dataset?

A. Lazy learner
B. Eager learner
C. Either of the above
D. None of the above

4. Eager Learner takes ……. time in learning, and …… time in prediction.

A. More, less
B. Less, more
C. Less, less
D. More, more

5. Lazy learners take …… time in training but ……. time for predictions

A. More, less
B. Less, more
C. Less, less
D. More, more

6. Which of the following is not a nonlinear model for classification?

A. KNN
B. Kernel SVM
C. Logistic Regression
D. Decision Tree

7. K-NN is a …….., which means it does not make any assumption on underlying data.

A. Parametric
B. Non-parametric
C. Functional

D. None of the above

8. KNN is a
A. Eager learner
B. Lazy learner
C. Not a learner
D. None of the above

9. Which of the following is the advantage of KNN algorithm?
A. Simple to implement
B. Robust to noisy training data
C. Effective if the training data is large
D. All of the above

10. Which of the following is the disadvantage of KNN algorithm?
A. Determining the value of k in advance
B. High computational cost
C. Both of the above
D. None of the above

11. The Naïve Bayes algorithm
A. Is a supervised learning algorithm
B. Is based upon Bayes theorem
C. Mainly used for text classifications
D. All of the above

12. P(A | B) in Bayes theorem is
A. Posterior probability
B. Prior probability
C. Likelihood probability
D. Marginal probability

13. What is marginal probability?
A. Probability of evidence
B. Probability of hypothesis
C. Both of the above
D. None of the above

14. Naïve Bayes works for
A. Binary classes
B. Multi-classes
C. Both of the above

D. None of the above

15. Naïve Bayes algorithm assumes that all features are
A. Independent
B. Unrelated
C. Both of the above
D. None of the above

Answers for Self Assessment

1.	C	2.	A	3.	B	4.	A	5.	B
6.	C	7.	B	8.	B	9.	D	10.	C
11.	D	12.	A	13.	A	14.	C	15.	C

Review Questions

1. What is supervised learning? Explain its types and give few examples.
2. What is classification and classification algorithm? What are the types of classification?
3. State the difference between classification and regression.
4. What is learning in classification problems? Explain its types.
5. What are linear and non-linear models in classification algorithms. Give examples of both.
6. What are the applications of classification algorithms? Tell any 5 in detail.
7. What is K-NN algorithm? What is its need? Also explain its working.
8. In KNN algorithm, how do we select the value of K? What are the advantages and disadvantages of KNN algorithm?
9. What is Naïve Bayes algorithm? Also explain the Bayes theorem.
10. What are the steps of Naive Bayes algorithm? Explain it with an example.
11. What are the advantages, disadvantages, and applications of Naïve Bayes algorithm?
12. What is cross validation? Explain its types.
13. What isthe performance metrices of classification algorithms? Explain.

Further Readings

https://www.geeksforgeeks.org/life-cycle-phases-of-data-analytics/

Web Links

https://www.simplilearn.com/tutorials/data-science-tutorial/what-is-data-science

Unit 09: Regression Models

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Objectives

Afterthis unit, you will be able to:

- Understand the meaning of regression
- Know the types of regression
- Understand machine linear regression and machine logistic regression
- Understand the concept of regularization
- Understand the performance metrics of regression

Introduction

Regression is also one of the supervised learning techniques. It is different from the concept of classification. It is a task of predicting the continuous quantity. Regression is known as a process of finding a model that predicts a continuous value based on its input variables.

9.1 Regression

In regression problems, the goal is to mathematically estimate a mapping function (f) from the input variables (x) to the output variables (y).

Example:

- Consider a dataset that contains information about all the students in a university. An example of a regression task would be to predict the height of any student based on their gender, weight, major, and diet. We can do this because height is a continuous quantity, i.e., there are an infinite number of possible values for a person's height.

Formal definition of regression

Regression analysis is a way of predicting future happenings between a dependent (target) and one or more independent variables (also known as a predictor).

Example 1: To predict the relationship between reckless driving and the total number of road accidents caused by a driver.

Example2: The effect on sales and spending a certain amount of money on advertising.

Regression vs Classification

Undoubtedly, both regression and classification are supervised learning techniques. But still there is a major difference in classification and regression.

Regression	Classification
Predicting the continuous quantity.	Predicting the categorical value

Applicability

The concept of regression is applied to many areas for solving different kinds of problems. These are:

- Financial forecasting (like house price estimates, or stock prices)
- Sales and promotions forecasting
- Testing automobiles
- Weather analysis and prediction
- Time series forecasting

Related terms

- **Dependent Variable**: The main factor in Regression analysis which we want to predict or understand is called the dependent variable. It is also called target variable.
- **Independent Variable**: The factors which affect the dependent variables, or which are used to predict the values of the dependent variables are called independent variable, also called as a predictor.
- **Outliers**: Outlier is an observation which contains either very low value or very high value in comparison to other observed values. An outlier may hamper the result, so it should be avoided.
- **Multicollinearity**: If the independent variables are highly correlated with each other than other variables, then such condition is called Multicollinearity. It should not be present in the dataset, because it creates problem while ranking the most affecting variable.
- **Underfitting and Overfitting**: If our algorithm works well with the training dataset but not well with test dataset, then such problem is called Overfitting. And if our algorithm does not perform well even with training dataset, then such problem is called underfitting.

Reasons of using regression analysis

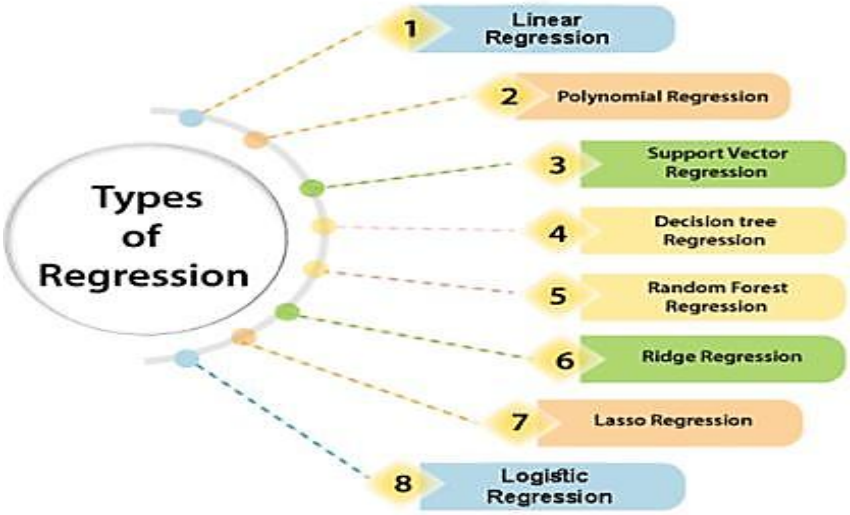
Regression estimates the relationship between the target and the independent variable.It is used to find the trends in data.It helps to predict real/continuous values.By performing the regression, we can confidently determine the most important factor, the least important factor, and how each factor is affecting the other factors.

Types of Regression

There are various types of regression. These are:

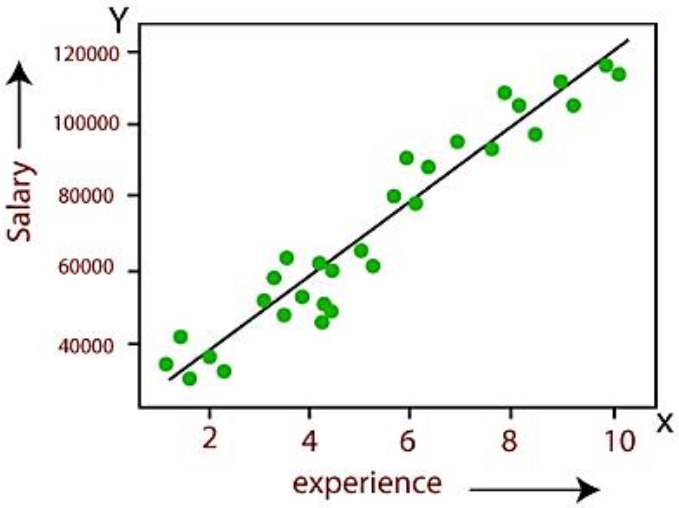
1. Linear regression

2. Polynomial regression
3. Support vector regression
4. Decision tree regression
5. Random forest regression
6. Lasso regression
7. Logistic regression



9.2 Machine Linear Regression

Linear regression is a statistical regression method which is used for predictive analysis.It is one of the very simple and easy algorithms which works on regression and shows the relationship between the continuous variables.It is used for solving the regression problem in machine learning.Linear regression shows the linear relationship between the independent variable (X-axis) and the dependent variable (Y-axis), hence called linear regression.If there is only one input variable (x), then such linear regression is called simple linear regression. And if there is more than one input variable, then such linear regression is called multiple linear regression.The relationship between variables in the linear regression model can be explained using the below image. Here we are predicting the salary of an employee based on the year of experience.



Mathematical equation for Linear regression: Y= aX+b

Here, Y = dependent variables (target variables),X= Independent variables (predictor variables), a and b are the linear coefficients

Applications of linear regression

Some popular applications of linear regression are:

- Analyzing trends and sales estimates
- Salary forecasting
- Real estate prediction
- Arriving at ETAs in traffic.

9.3 Machine Logistic Regression

Logistic regression is a type of regression, but it is different from the linear regression algorithm in the term how they are used.Logistic regression is another supervised learning algorithm which is used to solve the classification problems. In **classification problems**, we have dependent variables in a binary or discrete format such as 0 or 1.Logistic regression algorithm works with the categorical variable such as 0 or 1, Yes or No, True or False, Spam or not spam, etc.It is a predictive analysis algorithm which works on the concept of probability.

Use of Function in Machine Logistic Regression

Logistic regression uses **sigmoid function** or logistic function which is a complex cost function. This sigmoid function is used to model the data in logistic regression. The function can be represented as: $f(x) = 1/(1 + e^{-x})$

- f(x)= Output between the 0 and 1 value.
- x= input to the function
- e= base of natural logarithm.

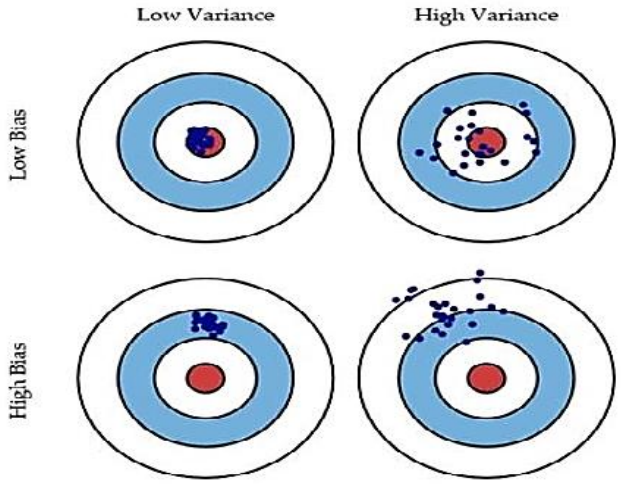
Types of machine logistic regression

There are three types of logistic regression:

- Binary(0/1, pass/fail)
- Multi(cats, dogs, lions)
- Ordinal(low, medium, high)

Bias and variance in regression models

- Bias is the simplifying assumptions made by a model to make the target function easier to learn.
- Variance is the amount that the estimate of the target function will change if different training data was used.



1. Very Accurate Model — therefore the error of our model will be low, meaning a **low bias and low variance** as shown in the first part of the figure.
2. As variance increases, the spread of our data point increases which result in less accurate prediction.
3. As Bias increases the error between our predicted value and the observed values increases. A high bias assumes a strong assumption or strong restrictions on the model.

There are two major issues which comes under consideration are:

- **Under fitting —** under fitting model performs poorly on training data. This happens because the model is unable to capture the relationship between the input example and the target variable.To overcome under fitting or high bias, we can basically add new parameters to our model so that the model complexity increases, and thus reducing high bias.
- **Over fitting —** As we add more and more parameters to our model, its complexity increases, which results in increasing variance and decreasing bias? To overcome over fitting there are two ways —

1. Reduce the model complexity
2. Regularization

9.4 Regularization

Regularization Techniques is an unavoidable and important step to improve the model prediction and reduce errors. One of the major aspects of training your machine learning model is avoiding over fitting. The model will have a low accuracy if it is over fitting. This happens because your model is trying too hard to capture the noise in your training dataset. By noise we mean the data points that don't really represent the true properties of your data, but random chance.Learning such data points, makes your model more flexible, at the risk of over fitting.Regularization is a technique that helps in avoiding over fittingand increasing model interpretability.This is a form of regression that constrains / regularizes or shrinks the coefficient estimates towards zero. In other words, this technique discourages learning a more complex or flexible model, to avoid the risk of over fitting.

9.5 Performance Metric of Regression

There are various performance metrics of regression. These are

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- R-Squared
- Adjusted R-squared

Mean Absolute Error

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - y_i'|$$

y_i = Actual expected output

$\hat{y}_i$ = Model's prediction

Mean Squared Error

$$MSE = \frac{1}{N}\sum_{i=1}^{n} (y_i - y_i')^2$$

Here, the error term is squared and thus more sensitive to outliers as compared to Mean Absolute Error (MAE).

Root Mean Squared Error

$$RMSE = \frac{\sqrt{1}}{n}\sum_{j=1}^{n}\left(y_j - y_j'\right)^2$$

MSE includes squared error terms, we take the square root of MSE which gives the RMSE

R-Sqaured

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = 1 - \sum_i (y_i - y_i')^2 / \sum_i (y_i - y')^2$$

R-squared is also known as the **Coefficient of Determination**. It explains the degree to which the input variables explain the variation of the output / predicted variable.

Adjusted R Square

$$AdjustedR^2 = 1 - \frac{(1 - R^2)(N - 1)}{N - p - 1}$$

Here, **N**- total sample size (number of rows) and **p**- number of predictors (number of columns). The **limitation of R-squared** is that it will *either stay the same or increases with the addition of more variables, even if they do not have any relationship with the output variables.

Summary

- Regression is a task of predicting the continuous quantity.It is the process of finding a model that predicts a continuous value based on its input variables.
- In regression problems, the goal is to mathematically estimate a mapping function (f) from the input variables (x) to the output variables (y).
- If our algorithm works well with the training dataset but not well with test dataset, then such problem is called over fitting. And if our algorithm does not perform well even with training dataset, then such problem is called under fitting.
- Linear regression shows the linear relationship between the independent variable (X-axis) and the dependent variable (Y-axis), hence called linear regression.
- If there is only one input variable (x), then such linear regression is called simple linear regression. And if there is more than one input variable, then such linear regression is called multiple linear regression.
- Logistic regression uses sigmoid function or logistic function which is a complex cost function.
- To overcome over fitting there are two ways – reduce the model complexity and Regularization
- The **limitation of R-squared** is that it will *either stay the same or increases with the addition of more variables, even if they do not have any relationship with the output variables.

Keywords

- **Regression:**It is the process of finding a model that predicts a continuous value based on its input variables.
- **Regression analysis**: It is a way of predicting future happenings between a dependent (target) and one or more independent variables (also known as a predictor).
- **Dependent Variable**: The main factor in Regression analysis which we want to predict or understand is called the dependent variable. It is also called target variable.

- **Independent Variable**: The factors which affect the dependent variables, or which are used to predict the values of the dependent variables are called independent variable, also called as a predictor.
- **Outliers**: Outlier is an observation which contains either very low value or very high value in comparison to other observed values. An outlier may hamper the result, so it should be avoided.
- **Multicollinearity**: If the independent variables are highly correlated with each other than other variables, then such condition is called Multicollinearity. It should not be present in the dataset, because it creates problem while ranking the most affecting variable.
- **Linear Regression**: Linear regression is a statistical regression method which is used for predictive analysis.
- **Logistic regression**: It is another supervised learning algorithm which is used to solve the classification problems. In **classification problems**, we have dependent variables in a binary or discrete format such as 0 or 1.
- **Bias:** Itis the simplifying assumptions made by a model to make the target function easier to learn.
- **Variance:**variance is the amount that the estimate of the target function will change if different training data was used.
- **Under fitting –** under fitting model performs poorly on training data. This happens because the model is unable to capture the relationship between the input example and the target variable.
- **Over fitting –** As we add more and more parameters to our model, its complexity increases, which results in increasing variance and decreasing bias.

SelfAssessment

1. Regression is the task of predicting

A. Continuous quantities
B. Categorical values
C. Both of these
D. None of the above

2. Using supervised machine learning techniques, we can

A. Predict the continuous quantities
B. Predict the categorical values
C. Both of the above
D. None of the above

3. Which of the following are the applications of regression?

A. Sales and promotion forecasting
B. Testing automobiles
C. Time series forecasting
D. All of the above

4. The factor which we want to predict or understand in regression is

A. Dependent variable
B. Independent variable
C. Non-dependent variable

D. None of the above

5. The factors which are used to predict the values are known as
A. Dependent variable
B. Independent variables
C. Pending variables
D. None of the above

6. What is an outlier?
A. A value much lesser than other values
B. A value much greater than other values
C. Either of the above
D. None of the above

7. The concept of multicollinearity should be avoided for ranking the most affecting variable.
A. True
B. False

8. What kind of issue occurs if the algorithm does not even work well with training data?
A. Overfitting
B. Underfitting
C. Any of these
D. None of the above

9. If an algorithm works well with training data, but not with testing data. Then what kind of issue can occur?
A. Overfitting
B. Underfitting
C. Any of these
D. None of the above

10. By performing regression, we can determine
A. Most important factor
B. Least important factor
C. Reason of one factor affecting the another
D. All of the above

11. Which of these are the types of regression?
A. Lasso regression
B. Decision tree regression
C. Support vector regression
D. All of the above

12. Which of the following is used to solve the classification problem?
A. K-means clustering
B. Linear regression
C. Logistic regression
D. Hierarchical clustering

13. Which of the following are types of logistic regression?
A. Binary
B. Multi
C. Ordinal
D. All of the above

14. Why is regularization techniques used?
A. To reduce error
B. To improve the model prediction
C. To make a good model
D. All of the above

15. The performance metrics of regression are
A. Mean absolute error
B. Mean Squared error
C. Root mean squared error
D. All of the above

Answers for Self Assessment

1.	A	2.	C	3.	D	4.	A	5.	B
6.	C	7.	A	8.	B	9,	A	10.	D
11.	D	12.	C	13.	D	14.	D	15.	D

Review Questions

1. What is regression? Give its formal definition. Also tell how it is different from classification?
2. What is the goal of regression in machine learning? Also tell what are the applications of regression?
3. What are the types of regression? Explain linear regression and logistic regression.
4. What is machine linear regression? Also give few applications of it.
5. What is machine logistic regression? Also give the use of function in it. Explain its types as well.
6. Explain the performance metrics of regression in detail.

Further Readings

https://www.geeksforgeeks.org/life-cycle-phases-of-data-analytics/

Web Links

https://www.simplilearn.com/tutorials/data-science-tutorial/what-is-data-science

Chapter 10: Weka

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Objectives

After this unit, you will be able to

- Understand Weka tool
- Understand how to import data in Weka
- Understand how to cluster and classify the data in Weka

Introduction

WEKA was developed at the University of Waikato in New Zealand; the name stands for Waikato Environment for Knowledge Analysis.

10.1 WEKA

It has a great collection of machine learning algorithms and data preprocessing tools.It provides extensive support for the whole process of experimental data mining, including preparing the input data, evaluating learning schemes statistically, and visualizing the input data and the result of learning.It also includes a variety of tools for transforming datasets, such as the algorithms for discretization and sampling.You can preprocess a dataset, feed it into a learning scheme, and analyze the resulting classifier and its performance.The workbench includes methods for the main data mining problems: regression, classification, clustering, association rule mining, and attribute selection.All algorithms take their input in the form of a single relational table that can be read from a file or generated by a database query.One way of using WEKA is to apply a learning method to a dataset and analyze its output to learn more about the data. Another is to use learned models to generate predictions on new instances. A third is to apply several different learners and compare their performance in order to choose one for prediction.

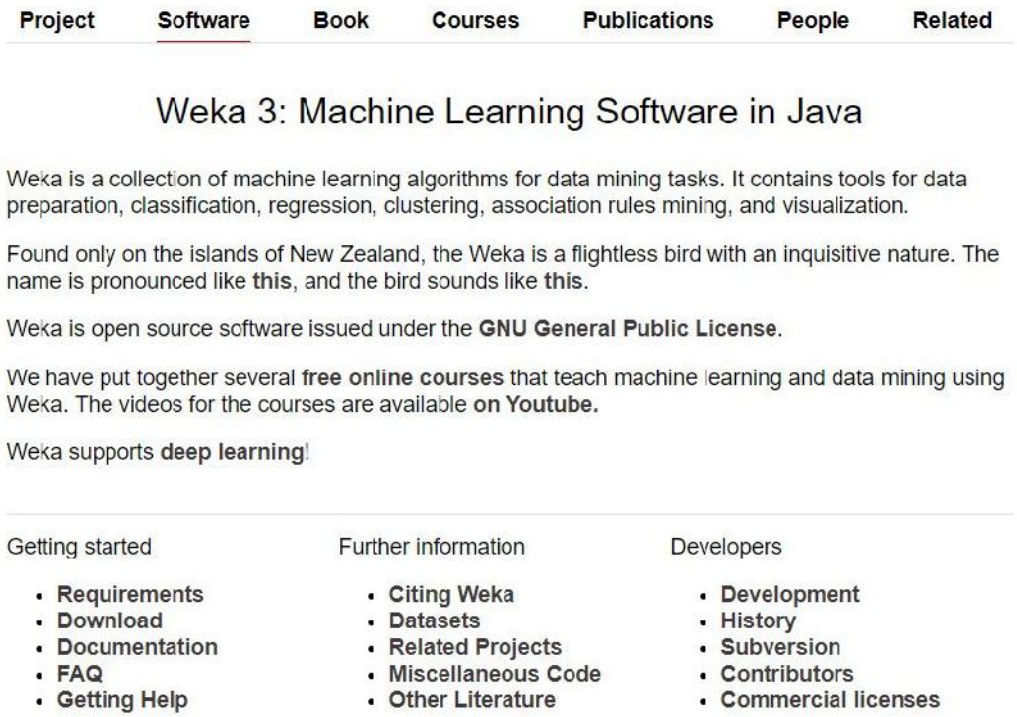
How to use?

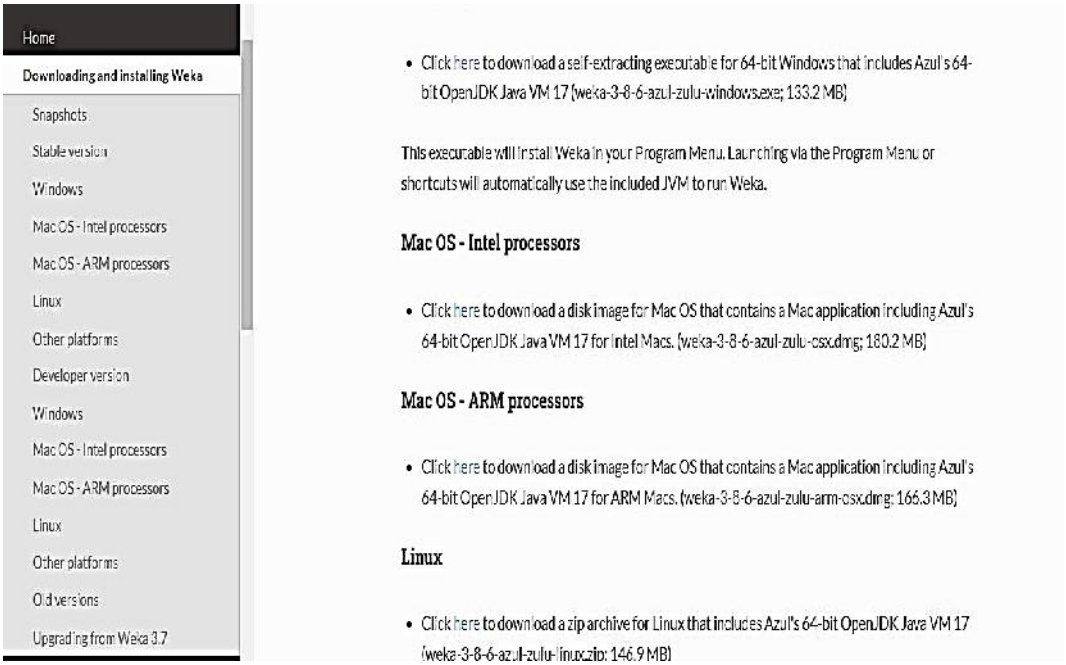
- The easiest way to use WEKA is through a graphical user interface called the Explorer.
- The Knowledge Flow interface allows you to design configurations for streamed data processing.

- WEKA's third interface, the Experimenter, is designed to help you answer a basic practical question when applying classification and regression techniques: Which methods and parameter values work best for the given problem?
- The fourth interface, called the Workbench, is a unified graphical user interface that combines the other three (and any plugins that the user has installed) into one application.

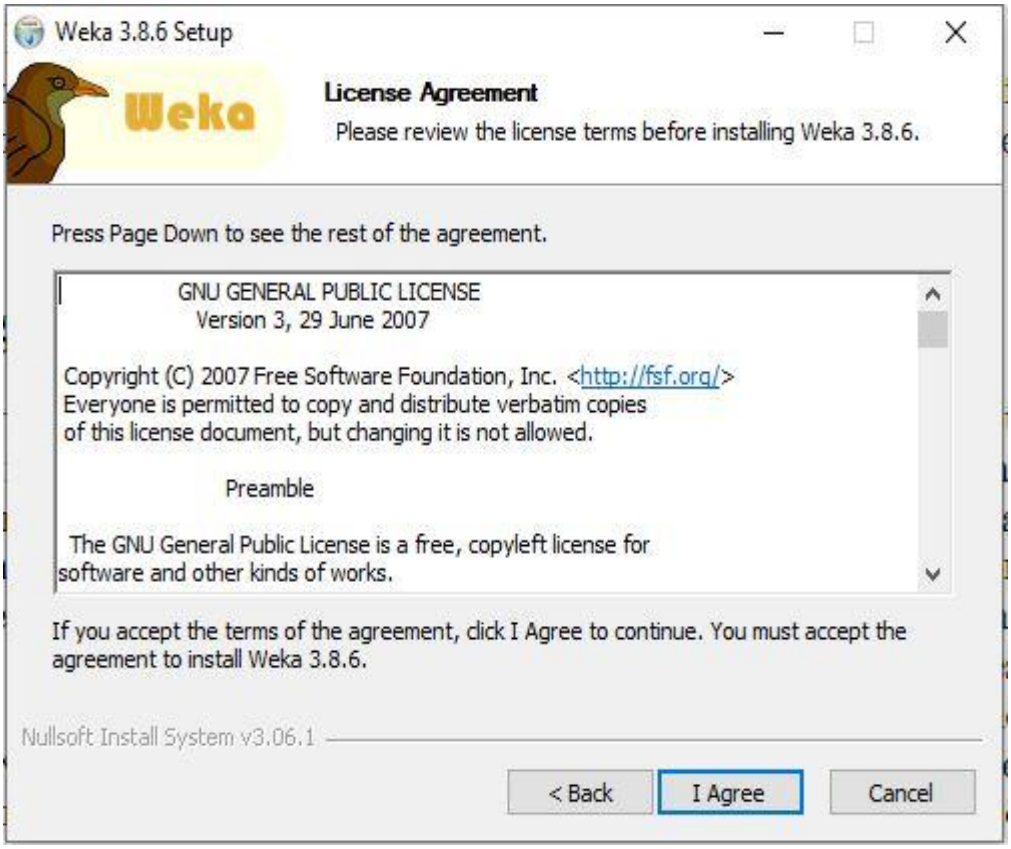
10.2 Download Weka

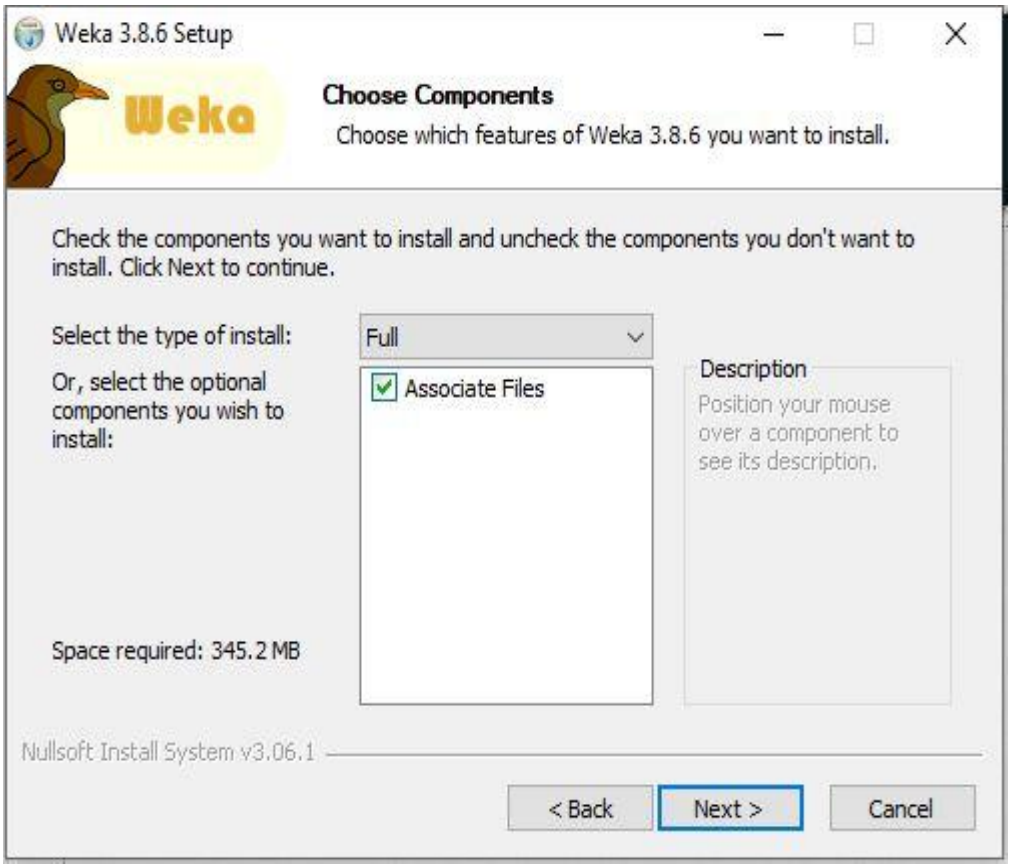
WEKA is available from http://www.cs.waikato.ac.nz/ml/weka. When you open this website, click on softwares. Under softwares, click on Download tab. It will ask you to choose the operating system of your computer. So, choose the appropriate option of operating system and download it. After downloading, double click on .exe file to start installation. Then click next. Then agree to the terms of service by checking the box. Then after that select the components that you want to install and unselect the components that you want to uninstall. After that it will ask you to choose the installation location and start folder. The installation will begin, and it will be completed in few seconds.

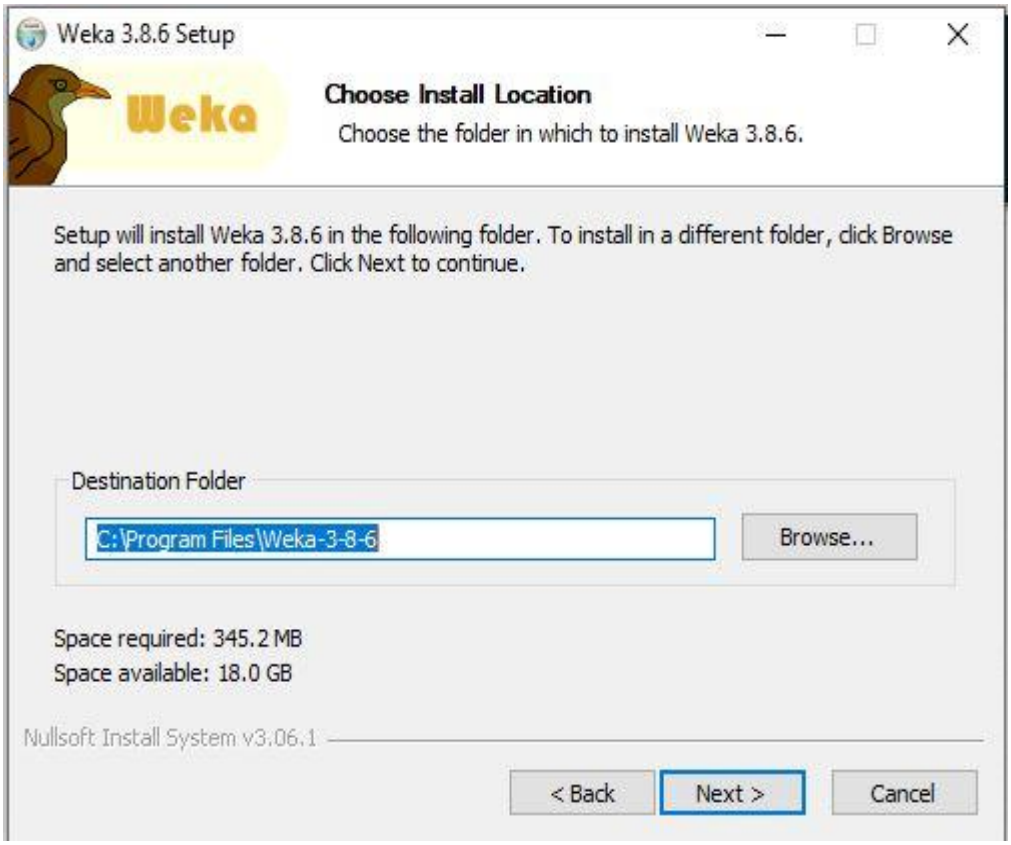


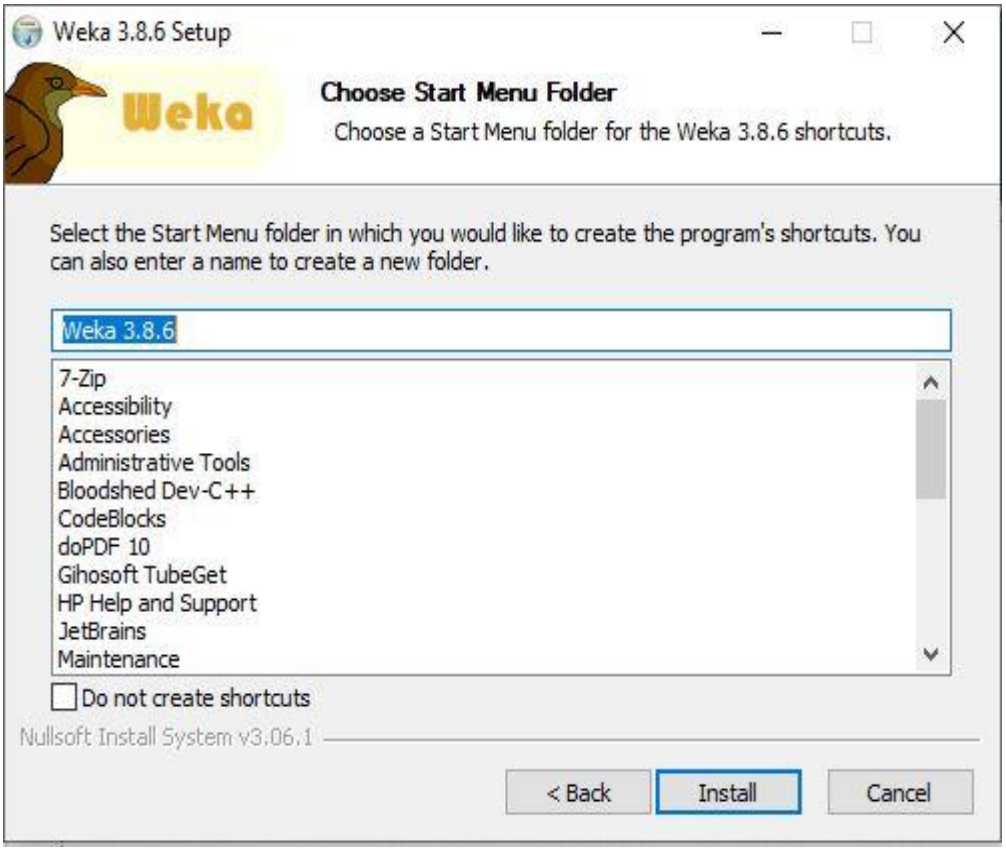

Home
Downloading and installing Weka
Snapshots
Stable version
Windows
Mac OS - Intel processors
Mac OS - ARM processors
Linux
Other platforms
Developer version
Windows
Mac OS - Intel processors
Mac OS - ARM processors
Linux
Other platforms
Old versions
Upgrading from Weka 3.7
Click here to download a self-extracting executable for 64-bit Windows that includes Azul's 64-bit OpenJDK Java VM 17 (weka-3-8-6-azul-zulu-windows.exe; 133.2 MB)
This executable will install Weka in your Program Menu. Launching via the Program Menu or shortcuts will automatically use the included JVM to run Weka.
Mac OS - Intel processors
Click here to download a disk image for Mac OS that contains a Mac application including Azul's 64-bit OpenJDK Java VM 17 for Intel Macs. (weka-3-8-6-azul-zulu-osx.dmg; 180.2 MB)
Mac OS - ARM processors
Click here to download a disk image for Mac OS that contains a Mac application including Azul's 64-bit OpenJDK Java VM 17 for ARM Macs. (weka-3-8-6-azul-zulu-arm-osx.dmg; 166.3 MB)
Linux
Click here to download a zip archive for Linux that includes Azul's 64-bit OpenJDK Java VM 17 (weka-3-8-6-azul-zulu-linux.zip; 146.9 MB)

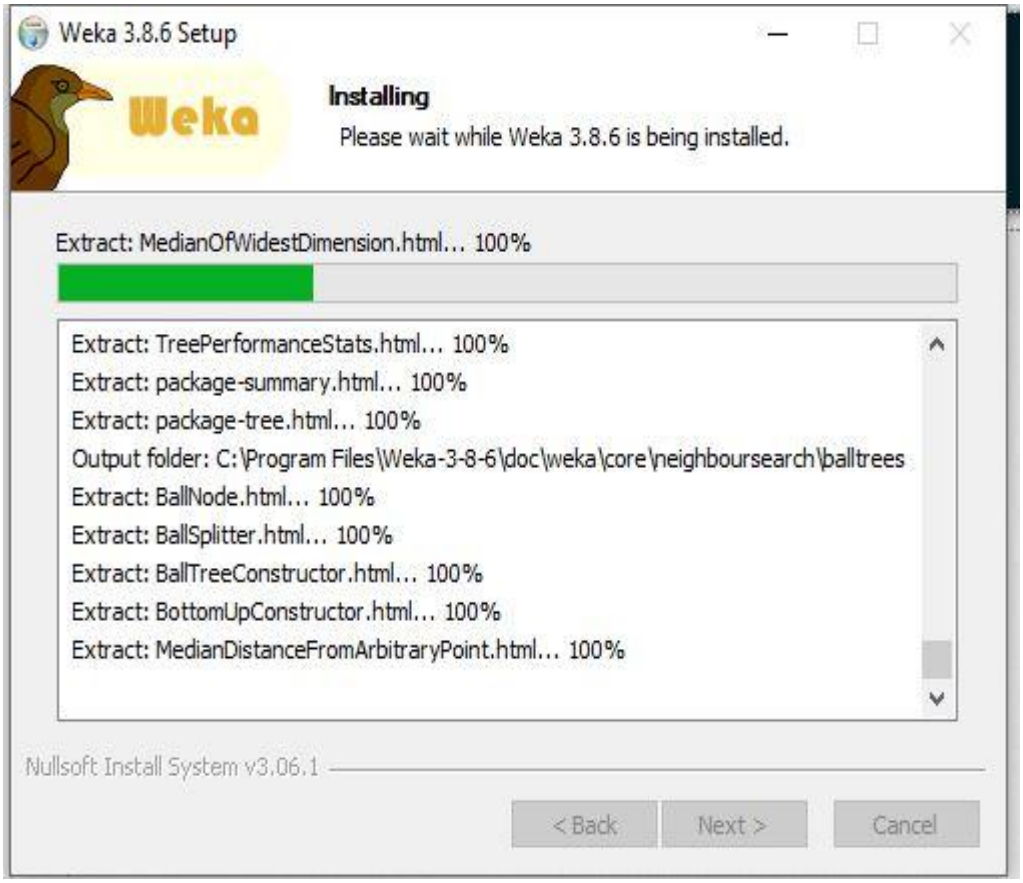
Weka 3.8.6 Setup
Welcome to the Weka 3.8.6 Setup Wizard
Setup will guide you through the installation of Weka 3.8.6.
It is recommended that you close all other applications before starting Setup. This will make it possible to update relevant system files without having to reboot your computer.
Click Next to continue.
Next >
Cancel

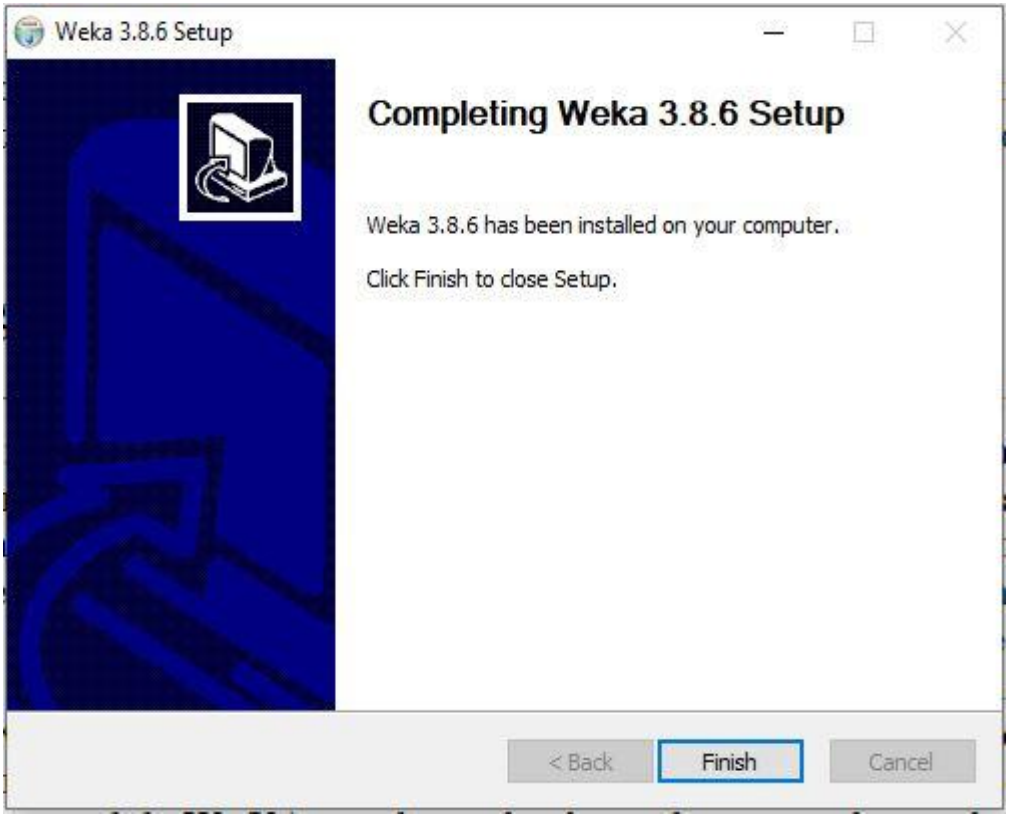

Weka 3.8.6 Setup
Weka
License Agreement
Please review the license terms before installing Weka 3.8.6.
Press Page Down to see the rest of the agreement.
GNU GENERAL PUBLIC LICENSE
Version 3, 29 June 2007
Copyright (C) 2007 Free Software Foundation, Inc. <http://fsf.org/>
Everyone is permitted to copy and distribute verbatim copies
of this license document, but changing it is not allowed.
Preamble
The GNU General Public License is a free, copyleft license for
software and other kinds of works.
If you accept the terms of the agreement, click I Agree to continue. You must accept the agreement to install Weka 3.8.6.
Nullsoft Install System v3.06.1
< Back
I Agree
Cancel


Weka 3.8.6 Setup
Weka
Choose Components
Choose which features of Weka 3.8.6 you want to install.
Check the components you want to install and uncheck the components you don't want to install. Click Next to continue.
Select the type of install:
Full
Or, select the optional components you wish to install:
Associate Files
Description
Position your mouse over a component to see its description.
Space required: 345.2 MB
Nullsoft Install System v3.06.1
< Back
Next >
Cancel


Weka 3.8.6 Setup
Weka
Choose Install Location
Choose the folder in which to install Weka 3.8.6.
Setup will install Weka 3.8.6 in the following folder. To install in a different folder, click Browse and select another folder. Click Next to continue.
Destination Folder
C:\Program Files\Weka-3-8-6
Browse...
Space required: 345.2 MB
Space available: 18.0 GB
Nullsoft Install System v3.06.1
< Back
Next >
Cancel


Weka 3.8.6 Setup
Weka
Choose Start Menu Folder
Choose a Start Menu folder for the Weka 3.8.6 shortcuts.
Select the Start Menu folder in which you would like to create the program's shortcuts. You can also enter a name to create a new folder.
Weka 3.8.6
7-Zip
Accessibility
Accessories
Administrative Tools
Bloodshed Dev-C++
CodeBlocks
doPDF 10
Gihosoft TubeGet
HP Help and Support
JetBrains
Maintenance
Do not create shortcuts
Nullsoft Install System v3.06.1
< Back
Install
Cancel


Weka 3.8.6 Setup
Weka
Installing
Please wait while Weka 3.8.6 is being installed.
Extract: MedianOfWidestDimension.html... 100%
Extract: TreePerformanceStats.html... 100%
Extract: package-summary.html... 100%
Extract: package-tree.html... 100%
Output folder: C:\Program Files\Weka-3-8-6\doc\weka\core\neighboursearch\balltrees
Extract: BallNode.html... 100%
Extract: BallSplitter.html... 100%
Extract: BallTreeConstructor.html... 100%
Extract: BottomUpConstructor.html... 100%
Extract: MedianDistanceFromArbitraryPoint.html... 100%
Nullsoft Install System v3.06.1
< Back
Next >
Cancel

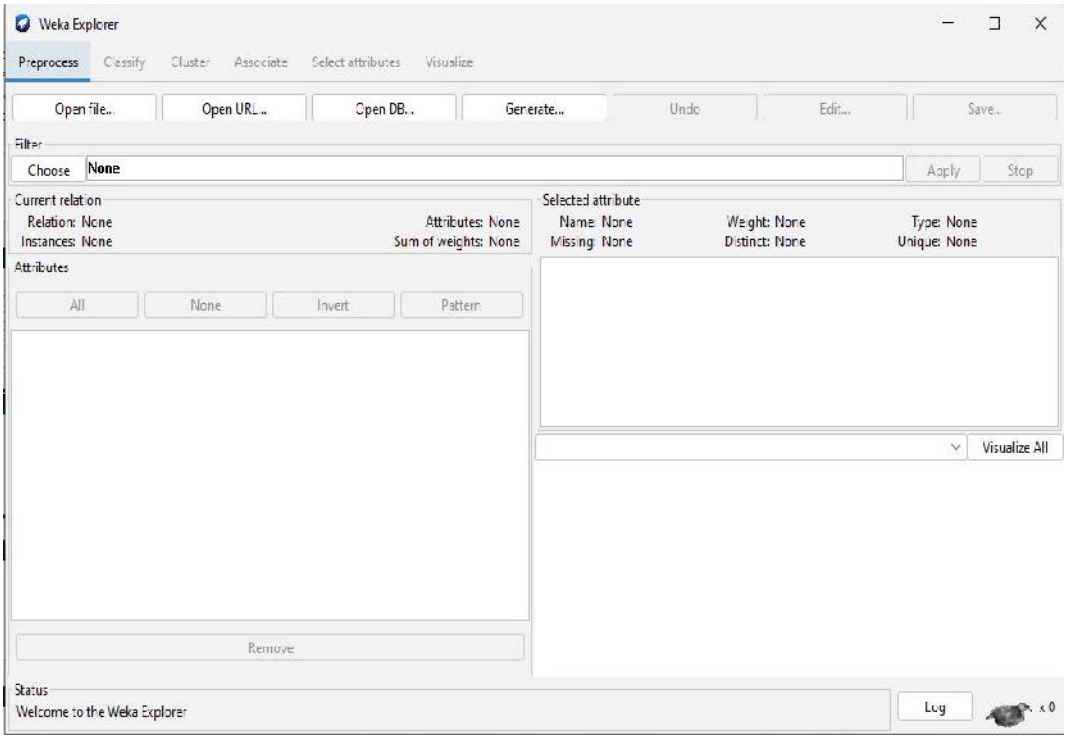

Weka 3.8.6 Setup
Completing Weka 3.8.6 Setup
Weka 3.8.6 has been installed on your computer.
Click Finish to close Setup.
< Back
Finish
Cancel

10.3 GUI Selector

When the Weka is installed, the first screen that will be visible to you is GUI selector. There are a total of 5 applications available. These are: Explorer, Experimenter, Knowledge Flow, Workbench and Simple CLI. Click on any application to start with it.

This image below shows the Explorer application. Under this, we have various panels. These are

- Pre-process:
- Classify
- Cluster
- Associate
- Select Attributes
- Visualize



Preparing the Data

The data is often presented in a spreadsheet or database. However, WEKA's native data storage

method is ARFF format. You can easily convert from a spreadsheet to ARFF. The bulk of an ARFF file consists of a list of the instances, and the attribute values for each instance are separated by commas. Most spreadsheet and database programs allow you to export data into a file in comma-separated value (CSV) format as a list of records with commas between items.

Load the data

Click the Open file button to bring up a standard dialog through which you can select a file. Choose the file. If you have it in CSV format, change from *ARFF data files* to *CSV data*

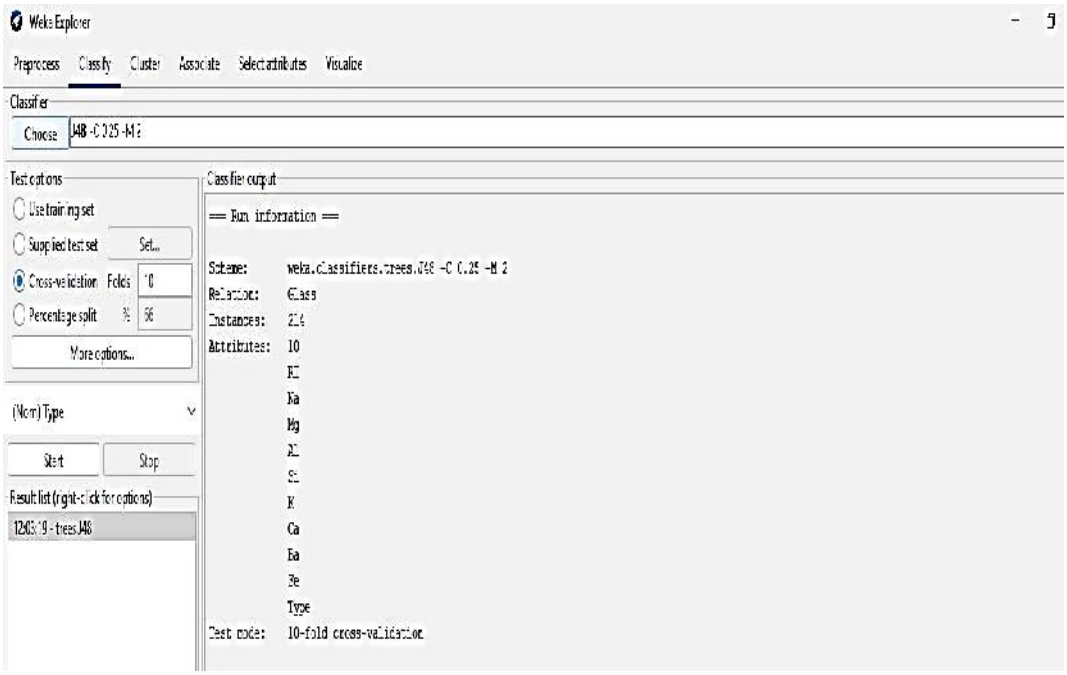
files. When you specify a .csv file it is automatically converted into ARFF format.

Building a decision tree model

Click the *Classify* tab to get a screen for classification. First select the classifier by clicking the *Choose* button at the top left, opening the trees section of the hierarchical menu and finding *J48*.

Estimate the model

See the confusion matrix to find out the results.

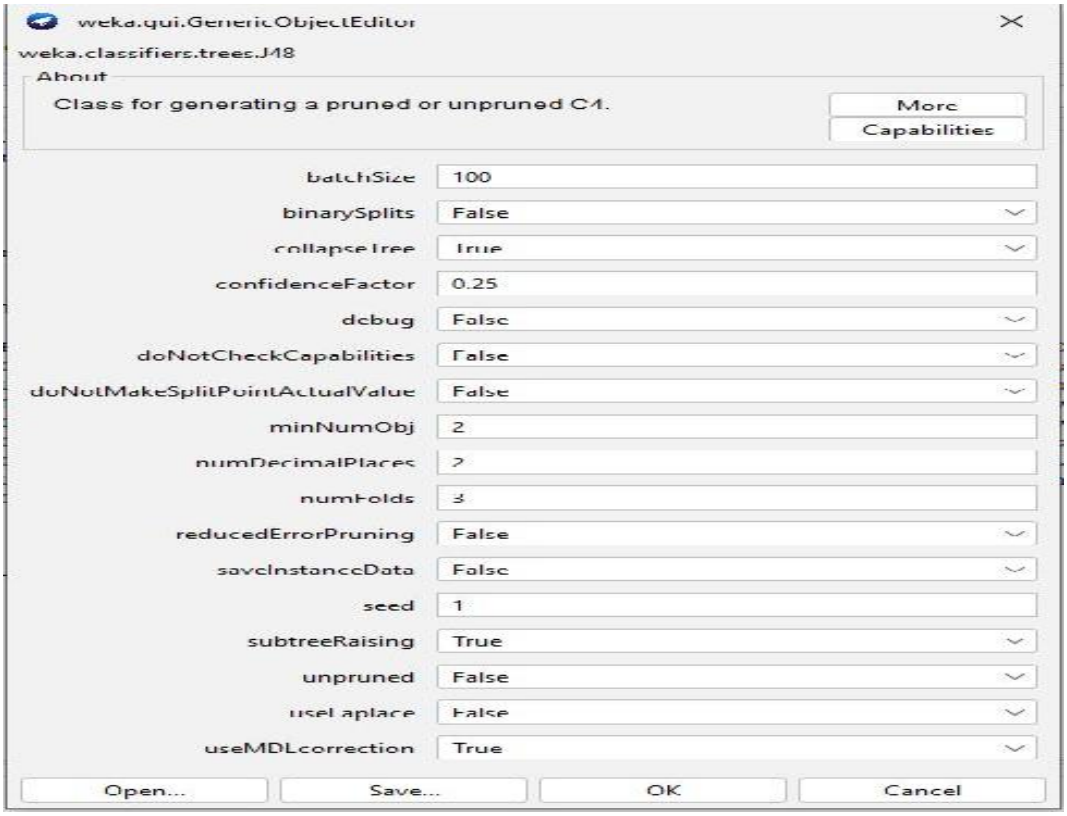



```
J48 pruned tree
------------------

Ba <= 0.27
|   Mg <= 2.41
|   |   K <= 0.03
|   |   |   Na <= 13.75: build wind non-float (3.0)
|   |   |   Na > 13.75: tableware (9.0)
|   |   K > 0.03
|   |   |   Na <= 13.49
|   |   |   |   RI <= 1.5241: containers (13.0/1.0)
|   |   |   |   RI > 1.5241: build wind non-float (3.0)
|   |   |   Na > 13.49: build wind non-float (7.0/1.0)
|   Mg > 2.41
|   |   Al <= 1.41
|   |   |   RI <= 1.51707
|   |   |   |   RI <= 1.51596: build wind float (3.0)
|   |   |   |   RI > 1.51596
|   |   |   |   |   Fe <= 0.12
|   |   |   |   |   |   Mg <= 3.54: vehic wind float (5.0)
|   |   |   |   |   |   Mg > 3.54
|   |   |   |   |   |   |   RI <= 1.51667: build wind non-float (2.0)
|   |   |   |   |   |   |   RI > 1.51667: vehic wind float (2.0)
|   |   |   |   |   Fe > 0.12: build wind non-float (2.0)
|   |   |   RI > 1.51707
|   |   |   |   K <= 0.23
|   |   |   |   |   Mg <= 3.34: build wind non-float (2.0)
|   |   |   |   |   Mg > 3.34
|   |   |   |   |   |   Si <= 72.64
|   |   |   |   |   |   |   Na <= 14.01: build wind float (14.0)
```

```
Number of Leaves  :     30

Size of the tree :      59


Time taken to build model: 0.06 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         143               66.8224 %
Incorrectly Classified Instances        71               33.1776 %
Kappa statistic                          0.55
Mean absolute error                      0.1026
Root mean squared error                  0.2897
Relative absolute error                 48.4507 %
Root relative squared error             89.2727 %
Total Number of Instances              214

=== Detailed Accuracy By Class ===

               TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
               0.714    0.174    0.667      0.714    0.690      0.532    0.806     0.667     build wind float
               0.618    0.181    0.653      0.618    0.635      0.443    0.768     0.606     build wind non-float
               0.353    0.046    0.400      0.353    0.375      0.325    0.766     0.251     vehic wind float
               ?        0.000    ?          ?        ?          ?        ?         ?         vehic wind non-float
               0.769    0.010    0.833      0.769    0.800      0.788    0.872     0.575     containers
               0.778    0.029    0.538      0.778    0.636      0.629    0.930     0.527     tableware
               0.793    0.022    0.852      0.793    0.821      0.795    0.869     0.738     headlamps
Weighted Avg.  0.668    0.130    0.670      0.668    0.668      0.539    0.807     0.611
```

```
=== Confusion Matrix ===

  a  b  c  d  e  f  g   <-- classified as
 50 15  3  0  0  1  1 |  a = build wind float
 16 47  6  0  2  3  2 |  b = build wind non-float
  5  5  6  0  0  1  0 |  c = vehic wind float
  0  0  0  0  0  0  0 |  d = vehic wind non-float
  0  2  0  0 10  0  1 |  e = containers
  1  1  0  0  0  7  0 |  f = tableware
  3  2  0  0  0  1 23 |  g = headlamps
```

The image shown below is the configuration panel of classifier which we have implemented. We can change the value of any parameter here. For example: unpruned → False to true or we can change the batch size as well. Once the parameters are changed, we can see the results using the confusion matrix.



The result after changing the configuration

```
Correctly Classified Instances         144               67.2897 %
Incorrectly Classified Instances        70               32.7103 %
Kappa statistic                          0.5571
Mean absolute error                      0.1001
Root mean squared error                  0.2854
Relative absolute error                 47.2665 %
Root relative squared error             87.9232 %
Total Number of Instances              214
```

Visualization of tree

The Visualize panel helps you visualize a dataset—not the result of a classification or clusteringmodel, but the dataset itself. It displays a matrix of two-dimensional scatter plots of every pairof attributes.

Use of filter

These areaccessible from the Explorer, and also from the Knowledge Flow and Experimenter interfaces. All filters transform the input dataset in some way. When a filter is selectedusing the Choose button, its name appears in the line beside that button. Click that line to geta generic object editor to specify its properties. What appears in the line is the command-lineversion of the filter, and the parameters are specified with minus signs. This is a good way oflearning how to use the WEKA commands directly. There are two kinds of filter: unsupervised and supervised. This

seemingly innocuous distinctionmasks a rather fundamental issue. Filters are often applied to a training dataset andthen also applied to the test file. If the filter is supervised—for example, if it uses class valuesto derive good intervals for discretization—applying it to the test data will bias the results. It isthe discretization intervals derived from the training data that must be applied to the test data.

10.4 Clustering of Data

Use the Cluster and Associate panels to invoke clustering algorithms and methods for findingassociation rules. When clustering, WEKA shows the number of clusters and how many instanceseach cluster contains. For some algorithms the number of clusters can be specified by setting aparameter in the object editor. For probabilistic clustering methods, WEKA measures theloglikelihoodof the clusters on the training data: the larger this quantity, the better the model fitsthe data. Increasing the number of clusters normally increases the likelihood but may overfit.The controls on the Cluster panel are like those for Classify. You can specify some ofthe same evaluation methods—use training set, supplied test set, and percentage split (the lasttwo are used with the log-likelihood). A further method, classes to clusters evaluation, compareshow well the chosen clusters match a preassigned class in the data. You select an attribute(which must be nominal) that represents the "true" class. Having clustered the data, WEKAdetermines the majority class in each cluster and prints a confusion matrix showing how manyerrors there would be if the clusters were used instead of the true class. If your dataset has a classattribute, you can ignore it during clustering by selecting it from a pull-down list of attributes and see how well the clusters correspond to actual class values. Finally, you can choose whether to store the clusters for visualization

Summary

- WEKA was developed at the University of Waikato in New Zealand; the name stands for Waikato Environment for Knowledge Analysis.
- It also includes a variety of tools for transforming datasets, such as the algorithms for discretization and sampling.
- The workbench includes methods for the main data mining problems: regression, classification, clustering, association rule mining, and attribute selection.
- One way of using WEKA is to apply a learning method to a dataset and analyze its output to learn more about the data. Another is to use learned models to generate predictions on new instances. A third is to apply several different learners and compare their performance in order to choose one for prediction.
- The panels in Explorer arePre-process, classify, cluster, associate, select Attributes and visualize.

Keywords

- **WEKA**: It is a collection of machine learning algorithms and data preprocessing tools.
- **Knowledge Flow:**The Knowledge Flow interface allows you to design configurations for streamed data processing.
- **Workbench**: It is a unified graphical user interface that combines the other three (and any plugins that the user has installed) into one application.
- **Clustering:** It is the task of dividing the population or data points into a number of groups such that data points in the same groups are more similar to other data points in the same group and dissimilar to the data points in other groups. It is basically a collection of objects on the basis of similarity and dissimilarity between them.
- **Classification:**The definition of classifying is categorizing something or someone into a certain group or system based on certain characteristics. An example of classifying is assigning plants or animals into a kingdom and species.

SelfAssessment

1. What is WEKA?

A. Waikato Environment for Known Analysis
B. Waikato Environment for Knowledge Analysis
C. Waste Environment for Knowledge Analysis
D. None of the above

2. Weka was developed in?

A. New Zealand
B. New York
C. India
D. None of the above

3. Weka has a great collection of

A. Data mining tools
B. Clustering algorithm
C. Classification algorithms
D. All of the above

4. With Weka, we can

A. Preprocess a dataset
B. Feed it into a learning scheme
C. Analyze the classifier and corresponding performance
D. All of the above

5. The easiest interface of WEKA is

A. Explorer
B. Knowledge Flow
C. Experimenter
D. Workbench

6. Which of the following GUI combines the other three applications?

A. Explorer
B. Knowledge Flow
C. Experimenter
D. Workbench

7. Under Weka Explorer which tabs are available?

A. Pre-process
B. Classify
C. Cluster
D. All of the above

8. Which filters are available in Weka?
A. Supervised
B. Unsupervised
C. Both of the above
D. None of the above

9. Which of the following algorithms are available for classification in Weka?
A. Decision Tree
B. Random Forest
C. Naïve Bayes
D. All of the above

10. Under cluster tab, which options are available?
A. Simple K means
B. Filtered clusterer
C. Hierarchical cluster
D. All of the above

11. In loading data in Weka, the data can be loaded from
A. Local file system
B. Web
C. Database
D. Either of the above

12. Which of the following file formats are supported in Weka?
A. csv
B. arff
C. json
D. All of the above

13. Which of the following is used for creating association rules?
A. Naïve Bayes
B. Hierarchical clustering
C. Random forest
D. Apriori algorithm

14. Which of the following can be performed in Weka?
A. Associate
B. Attribute selection
C. Cluster
D. All of the above

15. Weka was developed in?

A. New Zealand
B. New York
C. India
D. None of the above

Answers for Self Assessment

l.	B	2.	A	3.	D	4.	D	5.	A
6.	D	7.	D	8.	C	9.	D	10.	D
11.	D	12.	D	13.	D	14.	D	15.	A

Review Questions

1. What is Weka? How to use it?
2. Summarize the tasks done by Weka using a diagram.
3. How to install Weka? Also tell how to use it?
4. Under Weka, we have several tabs for different tasks. Explain each tab.
5. How to pre-process the data in Weka?

Further Readings

https://www.geeksforgeeks.org/life-cycle-phases-of-data-analytics/

Web Links

https://www.simplilearn.com/tutorials/data-science-tutorial/what-is-data-science

Unit 11: Excel Data Analysis

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Objectives

After studying this unit, you will be able to

- Understand how to analyze data using excel
- Understand some data analysis functions
- Understand the working of data analysis toolpak
- Understand about the descriptive statistics
- Understand how to perform ANOVA

Introduction

Data analysis is the process of cleansing, transforming, and analyzing raw data to obtain usable, relevant information that can assist businesses in making educated decisions.Data analysis is a valuable skill that can help you make better judgments. Microsoft Excel is one of the most used data analysis programs, with the built-in pivot tables being the most popular analytic tool.

11.1 Data Analysis Functions

There are various functions which are used for data analysis. These are shown below:

1. Concatenate()
2. Len()
3. Days()
4. Networkdays()
5. Sumifs()
6. Averageifs()
7. Countsifs()
8. Counta()
9. Vlookup()
10. Hlookup()

11. If()
12. Iferror()
13. Find()/Search()
14. Left()/Right()
15. Rank()

Concatenate()

The concatenate function is used to concatenate the text one after the another.

SYNTAX = CONCATENATE (text1, text2, [text3], …)

Len()

LEN is used to show the number of characters in each cell.

SYNTAX = LEN (text)

Days()

The number of calendar days between two dates is calculated using this function = DAYS.

SYNTAX =DAYS (end_date, start_date)

Networkdays()

The number of weekends is automatically excluded when using the function. It's classified as a Date/Time Function in Excel.

SYNTAX = NETWORKDAYS (start_date, end_date, [holidays])

Sumifs()

SUM is a familiar formula, but what if you need to sum data based on numerous criteria? It's SUMIFS.

SYNTAX = SUMIFS (sum_range, range1, criteria1, [range2], [criteria2], …)

Averageifs()

AVERAGEIFS is like SUMIFS.

SYNTAX = AVERAGEIFS (avg_rng, range1, criteria1, [range2], [criteria2], …)

Countifs()

The COUNTIFS function counts the number of values that satisfy a set of conditions. As a result, it doesn't need a sum range like SUMIFS.

SYNTAX = COUNTIFS (range, criteria)

Counta()

COUNTA determines whether a cell is empty or not. You'll come across incomplete data sets daily as a data analyst. Without needing to restructure the data, COUNTA will allow you to examine any gaps in the dataset.

SYNTAX = COUNTA (value1, [value2], …)

Vlookup()

The acronym VLOOKUP stands for 'Vertical Lookup.' It's a function that tells Excel to look for a specific value in a column (the so-called 'table array') to return a value from another column in the same row.

SYNTAX = VLOOKUP (lookup_value, table_array, column_index_num, [range_lookup])

Hlookup()

"Horizontal" is represented by the letter H in HLOOKUP. It looks for a value in the top row of a table or an array of values, then returns a value from a row you specify in the table or array in the same column. When your comparison values are in a row across the top of a data table and you wish to look down a specific number of rows, use HLOOKUP. When your comparison values are in a column to the left of the data you wish to find, use VLOOKUP.

SYNTAX = HLOOKUP (lookup_value, table_array, row_index, [range_lookup])

If()

The IF function comes in handy a lot. We can use this function to automate decision-making in our spreadsheets. We could use IF to make Excel conduct a different computation or show a different value based on the results of a logical test (a decision). The IF function will ask you to run a logical test, as well as what action to take if the test is true and what action to take if the test is false.

SYNTAX = IF (logical_test, [value_if_true], [value_if_false])

Iferror()

Two things are required for the IFERROR function to work. What value should be checked for an error and what action should be taken instead.

SYNTAX = IFERROR (value, value_if_error)

Find()/Search()

The FIND function in Excel returns the position of one text string within another (as a number). FIND delivers a #VALUE error if the text cannot be located.However, a =SEARCH for "Bigger" will return results for Bigger or bigger, broadening the scope of the query. This is very helpful when searching for anomalies or unique identifiers.SYNTAX = FIND (find_text, within_text, [start_num]).

SYNTAX = SEARCH (find_text, within_text, [start_num])

Left()/Right()

LEFT and RIGHT are simple and efficient ways for retrieving static data from cells. =RIGHT returns the "x" number of characters from the cell's end, while LEFT returns the "x" number of characters from the cell's beginning.

SYNTAX = LEFT (text, [num_chars])

SYNTAX = RIGHT (text, [num_chars])

Rank()

Even though RANK is an old Excel function, it is nevertheless useful for data analysis. =RANK is a quick way to show how values in a dataset rank in ascending or descending order. RANK is being utilized in this case to determine which clients order the most stuff.

SYNTAX = RANK (number, ref, [order])

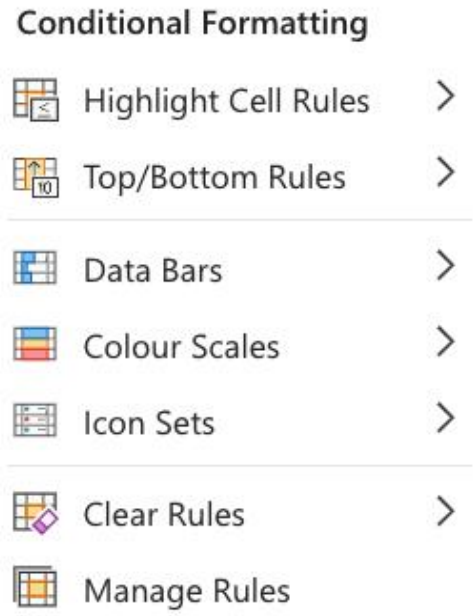
11.2 Methods for Data Analysis

1) Conditional formatting
2) Sorting and filtering
3) Pivot tables
4) Data visualization in excel

1) Conditional Formatting

Conditional formatting is used to change the appearance of cells in a range based on your specified **conditions**. The conditions are rules based on specified numerical values or matching text.Changing the appearance of cells can visually highlight interesting data points for analysis.

Number of built-in conditions



Example:

	A	B	C	D
1	Name	Type 1	Speed	
2	Bulbasaur	Grass	45	
3	Ivysaur	Grass	60	
4	Venusaur	Grass	80	
5	Charmander	Fire	65	
6	Charmeleon	Fire	80	
7	Charizard	Fire	100	
8	Squirtle	Water	43	
9	Wartortle	Water	58	
10				

Steps to follow for conditional formatting

- Select the range of values. For example, in the above table shown select the range C2:C9.
- Click on the Conditional Formatting icon in the ribbon, from the **Home** menu.
- Select the **Color Scales** from the drop-down menu. There are 12 Color Scale options with different color variations.
- Click on the "Green - Yellow - Red Colour Scale" icon.

Highlight cell rules

Highlight Cell Rules is a premade type of conditional formatting in Excel used to change the appearance of cells in a range based on your specified **conditions**. The conditions are rules based on specified numerical values, matching text, calendar dates, or duplicated and unique values.

Appearance options

- Light Red Fill with Dark Red Text
- Yellow Fill with Dark Yellow Text
- Green Fill with Dark Green Text
- Light Red Fill
- Red Text
- Red Border

Cell Rule Types

- Greater Than...
- Less Than...
- Between...
- Equal To...
- Text That Contains...
- A Date Occurring...
- Duplicate/Unique Values

2) Sorting and filtering

There are many options for sorting data. You can sort data on common attributes, such as:

- text (A to Z, or Z to A)
- numbers (low to high, or high to low)
- dates and times (newest to oldest, or oldest to newest)
- format (e.g. cell colour).

As well as sorting by individual properties, you can sort data over multiple columns or rows. For example, the following table is initially sorted by ID.

id	title	season	imdb_rating
10	Homer's Night Out	1	7.4
12	Krusty Gets Busted	1	8.3
14	Bart Gets an 'F'	2	8.2
17	Two Cars in Every Garage and Three Eyes on Every Fish	2	8.1
19	Dead Putting Society	2	8.0
35	Blood Feud	2	8.0
37	Mr. Lisa Goes to Washington	3	7.7
39	Bart the Murderer	3	8.7
41	Like Father, Like Clown	3	7.7
44	Saturdays of Thunder	3	7.9

Process of sorting data in Excel:

1. Select a cell in the column you want to sort.
2. In the **Data** tab, go to the **Sort & Filter** group. Then you have two options.
    - To sort values in ascending or descending order based on Excel's interpretation of the column, click the **Sort A to Z** or **Sort Z to A** icons.
    - For more sorting options, click the **Sort** button. You can then specify the **Column**, what to **Sort On**, and **Order**. With the **Add Level** option, you can perform a secondary level of sorting if needed.

Filtering data in excel

You can use filters to temporarily hide some of the data in a table, so you can focus on the data you want to see. When filtering, you can specify exact matches or comparisons ('more than', 'less than') or data that doesn't match specific criteria. The following comparison operators are available in Excel. You can compare two values by using the following operators. When you use these operators to compare two values, the result is a logical value—it's either TRUE or FALSE.

Comparison operator	Meaning	Example	Result (A1=1, B1=2)
=	Equal to	A1=B1	FALSE
>	Greater than	A1>B1	FALSE
<	Less than	A1<B1	TRUE
>=	Greater than or equal to	A1>=B1	FALSE
<=	Less than or equal to	A1<=B1	TRUE
<>	Not equal to	A1<>B1	TRUE

To create a filter in Excel:

1. Select the data you want to work with.
2. Select **Data > Filter** from the ribbon menu.
3. At the top of your selection, select the column header arrow (grey box with downwards arrow).
4. Select **Text Filters** or **Number Filters**, and then select a comparison.
5. Enter the filter criteria and select OK.

3) Pivot Table

Pivot tables are built into Excel. They allow you to group and summarise large quantities of data quickly and easily. If you have an input table with tens, hundreds, or even thousands of rows, pivot tables allow you to extract answers to a series of basic questions about your data with minimal effort. For example: if you have typical sales data, you can use a pivot table to:

- find the sum of total sales per customer
- count the total number of orders by customer
- find the sum total of sales by item type
- create a summary of sales by customer and item type
- find the average amount of sales to a particular customer in a quarter
- create a summary showing the maximum order value by customer and month
- create a breakout summary of orders by customer, month, and item type.

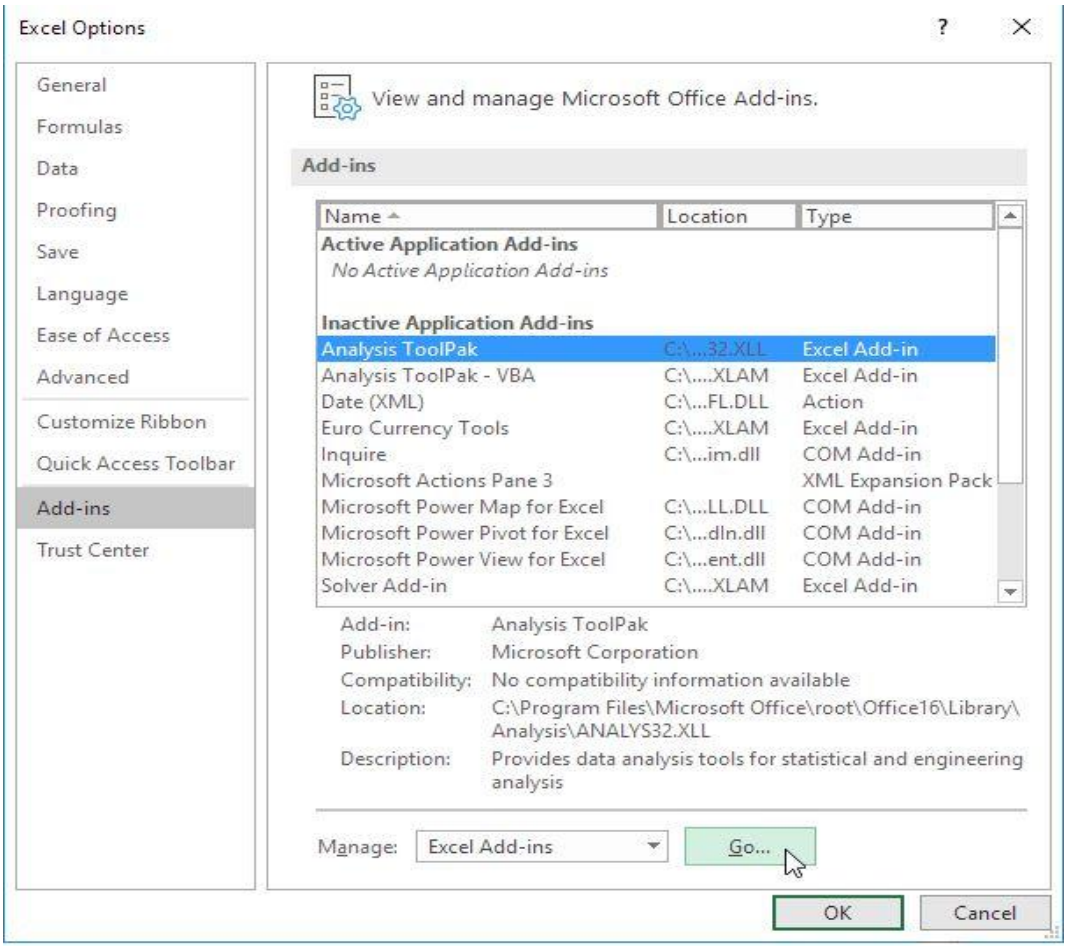
Data Analysis Toolpak

The Analysis ToolPak is an Excel add-in program that provides data analysis tools for financial, statistical and engineering data analysis.

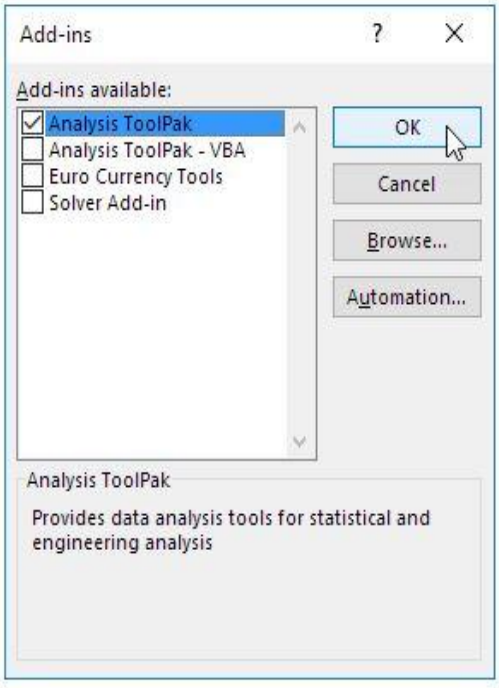
Load the data analysis ToolPak

1) On the File tab, click Options.

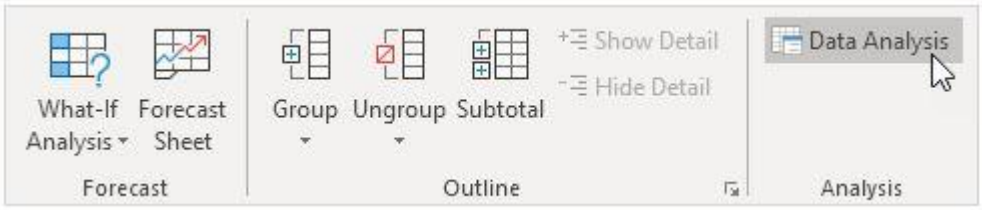
2) Under Add-ins, select Analysis ToolPak and click on the Go button.



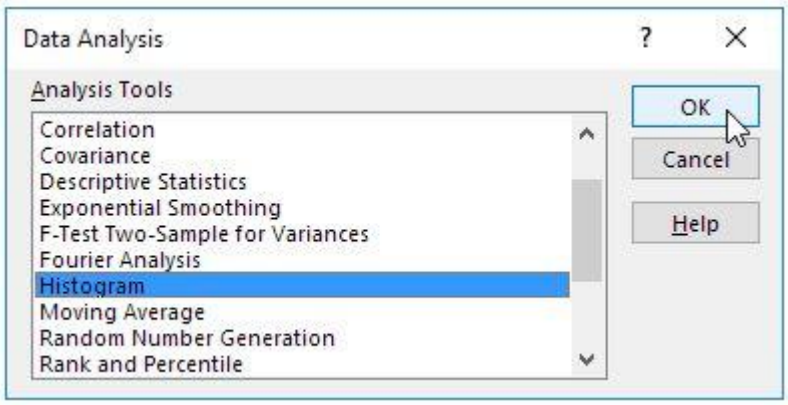
3) Check Analysis ToolPak and click on OK



4) On the Data tab, in the Analysis group, you can now click on Data Analysis.



5) For example, select Histogram and click OK to create a Histogram in Excel.



Descriptive Statistics

The Descriptive Statistics analysis tool generates a report of univariate statistics for data in the input range, providing information about the central tendency and variability of your data.

ANOVA

The ANOVA analysis tools provide different types of variance analysis. The tool that you should use depends on the number of factors and the number of samples that you have from the populations that you want to test.

Regression

The Regression analysis tool performs linear regression analysis by using the "least squares" method to fit a line through a set of observations. You can analyze how a single dependent variable is affected by the values of one or more independent variables.

Histogram

The Histogram analysis tool calculates individual and cumulative frequencies for a cell range of data and data bins. This tool generates data for the number of occurrences of a value in a data set.

Summary

- Data analysis is a valuable skill that can help you make better judgments. Microsoft Excel is one of the most used data analysis programs, with the built-in pivot tables being the most popular analytic tool.
- The data analysis functions are: Concatenate(), Len(), Days(), Networkdays(), Sumifs(), Averageifs(), Countsifs(), Counta(), Vlookup(), Hlookup(), If(), Iferror(), Find()/Search(), Left()/Right() and Rank().

- "Horizontal" is represented by the letter H in HLOOKUP. It looks for a value in the top row of a table or an array of values, then returns a value from a row you specify in the table or array in the same column
- The syntax of if function is IF (logical_test, [value_if_true], [value_if_false])
- The FIND function in Excel returns the position of one text string within another (as a number). FIND delivers a #VALUE error if the text cannot be located.

Keywords:

- Data analysis: Data analysis is the process of cleansing, transforming, and analyzing raw data to obtain usable, relevant information that can assist businesses in making educated decisions.
- Len(): LEN is used to show the number of characters in each cell.
- COUNTIFS(): The COUNTIFS function counts the number of values that satisfy a set of conditions. As a result, it doesn't need a sum range like SUMIFS.
- COUNTA(): COUNTA determines whether a cell is empty or not. You'll come across incomplete data sets daily as a data analyst. Without needing to restructure the data, COUNTA will allow you to examine any gaps in the dataset.
- VLOOKUP(): The acronym VLOOKUP stands for 'Vertical Lookup.' It's a function that tells Excel to look for a specific value in a column (the so-called 'table array') to return a value from another column in the same row.

SelfAssessment

1. Data analysis is the process of

A. Cleansing

B. Transforming

C. Analyzing data

D. All of the above

2. Which of the following are data analysis functions?

A. Len()

B. Concatenate()

C. Count()

D. All of the above

3. Which of the following are data analysis functions?

A. Sumif()

B. Average ifs()

C. Countsifs()

D. All of the above

4. What is the syntax of concatenate function for data analysis?

A. CONCATENATE(text1, text2, [text3], …)

B. CAT(text1, text2, [text3], …)

C. CONCAT (text1, text2, [text3], …)

D. Any of the above

5. The syntax of days() function is
A. DAYS (end_date, start_date)
B. DAYS (start_date, end_date)
C. DAYS (start_date, start_date)
D. None of the above

6. What is the syntax of networkdays()?
A. NETWORKDAYS (end_date, start_date, [holidays])
B. NETWORKDAYS (start_date, end_date, [holidays])
C. NETWORKDAYS ([holidays], start_date, end_date)
D. NETWORKDAYS (start_date, [holidays], end_date)

7. The counta() function allows you to count any gaps in the dataset.
A. True
B. False

8. Which of the following are the methods for data analysis?
A. Pivot table
B. Conditional formatting
C. Data visualization
D. All of the above

9. Which of the following are the methods for data analysis?
A. Sorting and filtering
B. Pivot table
C. Conditional formatting
D. All of the above

10. The data analysis toolpak provides the tools for
A. Financial
B. Statistical
C. Engineering data analysis
D. All of the above

11. In data analysis toolpak, the tools are available for
A. Correlation
B. Histogram
C. Rank and percentile
D. All of the above

12. In data analysis toolpak, the tools are available for
A. Exponential smoothing
B. Covariance
C. Random number generation
D. All of the above

13. The descriptive analysis tool provides information about
A. Central tendency
B. Variability
C. Both of the above
D. None of the above

14. Which of the following are the data analysis functions?
A. If()
B. Vlookup()
C. Hlookup()
D. All of the above

15. Which function is used when the sum is required if a criteria is met?
A. SUMCRITERIA()
B. SUM()
C. SUMIF()
D. All of the above

Answers for Self Assessment

1.	D	2.	D	3.	D	4.	A	5.	A
6.	B	7.	A	8.	D	9.	D	10.	D
11.	D	12.	D	13.	C	14.	D	15.	D

Review Questions

1. What is data analysis? What are the different tools available for this?
2. Explain Concatenate(), Len(), Days(), Networkdays() and Sumifs() functions with their syntax.
3. Explain averageifs(), countsifs(), counta() and vlookup() functions with their syntax.
4. Explain hlookup() and vlookup() functions in detail with example and syntax.
5. What are the different methods for data analysis? Explain the use and importance of data analysis toolpak of excel.

Further Readings

https://www.geeksforgeeks.org/life-cycle-phases-of-data-analytics/

Web Links

https://www.simplilearn.com/tutorials/data-science-tutorial/what-is-data-science

Unit 12: R Tool

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Summary

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Objectives

After this unit, you will be able to

- Understand about R and RStudio
- Understand the R data types
- Understand variables and operators
- Understand the decision-making algorithms and loops
- Understand the functions
- Understand strings and string methods
- Understand R packages

Introduction

R is an open-source programming language mostly used for statistical computing and data analysis.It is available across widely used platforms like Windows, Linux, and MacOS.It generally comes with a command-line interface and provides a vast list of packages for performing tasks. R is an interpreted language that supports both procedural programming and object-oriented programming.

Development of R

- It was designed by Ross Ihaka and Robert Gentleman at the University of Auckland, New Zealand, and is currently developed by the R Development Core Team.
- R programming language is an implementation of the S programming language.

Why useR programming language?

- R programming is used as a leading tool for machine learning, statistics, and data analysis. Objects, functions, and packages can easily be created by R.
- It's a platform-independent language. This means it can be applied to all operating systems.
- It's an open-source free language. That means anyone can install it in any organization without purchasing a license.
- R programming language is not only a statistic package but also allows us to integrate with other languages (C, C++). Thus, you can easily interact with many data sources and statistical packages.
- The R programming language has a vast community of users and it's growing day by day.
- R is currently one of the most requested programming languages in the Data Science job market that makes it the hottest trend nowadays.

Features of R programming languages

- **Statistical Features of R**
- **Programming Features of R**

Statistical Features of R

- **Basic Statistics:** The most common basic statistical terms are the mean, mode, and median. These are all known as "Measures of Central Tendency." So, using the R language we can measure central tendency very easily.
- **Static graphics:** R is rich with facilities for creating and developing interesting static graphics. R contains functionality for many plot types including graphic maps, mosaic plots, biplots, and the list goes on.
- **Probability distributions:** Probability distributions play a vital role in statistics and by using R we can easily handle various types of probability distribution such as Binomial Distribution, Normal Distribution, Chi-squared Distribution and many more.
- **Data analysis:** It provides a large, coherent, and integrated collection of tools for data analysis

Programming Features of R

- **R Packages:** One of the major features of R is it has a wide availability of libraries. R has CRAN(Comprehensive R Archive Network), which is a repository holding more than 10, 0000 packages.
- **Distributed Computing:** Distributed computing is a model in which components of a software system are shared among multiple computers to improve efficiency and performance. Two new packages **ddR and multidplyr** used for distributed programming in R were released in November 2015.

Advantages of R

- R is the most comprehensive statistical analysis package. As new technology and concepts often appear first in R.
- As R programming language is an open source. Thus, you can run R anywhere and at any time.

- R programming language is suitable for GNU/Linux and Windows operating system.
- R programming is a cross-platform which runs on any operating system.
- In R, everyone is welcome to provide new packages, bug fixes, and code enhancements.

Disadvantages of R

- In the R programming language, the standard of some packages is less than perfect.
- Although, R commands put little pressure on memory management. So, R programming language may consume all available memory.
- In R basically, nobody complains if something doesn't work.
- R programming language is much slower than other programming languages such as Python and MATLAB.

Applications of R

- We use R for Data Science. It gives us a broad variety of libraries related to statistics. It also provides the environment for statistical computing and design.
- R is used by many quantitative analysts as its programming tool. Thus, it helps in data importing and cleaning.
- R is the most prevalent language. So many data analysts and research programmers use it. Hence, it is used as a fundamental tool for finance.
- Tech giants like Google, Facebook, bing, Twitter, Accenture, Wipro and many more use R nowadays.

Interesting facts about R

- R programming language is an implementation of the S programming language. It also combines with lexical scoping semantics inspired by Scheme. It is named partly after the first names of the first two R authors and partly as a play on the name of S.
- R supports both procedural programming and object-oriented programming. Procedural programming includes the procedure, records, modules, and procedure calls. While object-oriented programming language includes class, objects, and generic functions
- R language is an interpreted language instead of a compiled language. Therefore, it doesn't need a compiler to compile code into an executable program. This makes running an R script much less time-consuming.
- The number of R packages available either through CRAN or GitHub is 1, 00, 000 and they do epic stuff with just one line of code. It could range from Regression to Bayesian analysis.
- R is growing faster than any other data science language. It's the most-used data science language after SQL. It is used by 70% of data miners.
- One of the packages in R namely rmarkdown package helps you create reproducible Word documents and reproducible Powerpoint Presentations from your R markdown code just by changing one line in the YAML! ("YAML Ain't Markup Language!")
- It is really very easy in R to connect to almost any database using the dbplyer package. This makes it possible for an R user to work independently and pulling data from almost all common database types. You can also use packages like bigrquery to work directly with BigQuery and other high-performance data stores.
- You can build and host interactive web apps in just a few lines of code in R. Using the flexdashboard package in R you can create interactive web apps with a few lines of code. And using the rsconnect package you can also host your web apps on your own server or, even easier, host them on a cloud server.

- You can not only deploy web apps but also can make them into awesome video games in R. The nessy package helps you create NES(The Nintendo Entertainment System) looking Shiny apps and deploy them just like you would any other Shiny app.
- You can build APIs and serve them from R. The plumbr package in R helps you convert R functions to web APIs that can be integrated into downstream applications.

Environment in R

- The environment is a virtual space that is triggered when an interpreter of a programming language is launched.
- Simply, the environment is a collection of all the objects, variables, and functions. Or Environment can be assumed as a top-level object that contains the set of names/variables associated with some values.

Introduction to R studio

R Studio is an integrated development environment(IDE) for R. IDE is a GUI, where you can write your quotes, see the results,and see the variables that are generated during the course of programming. R Studio is available as both Open source and Commercial software.R Studio is also available as both Desktop and Server versions.R Studio is also available for various platforms such as Windows, Linux, and macOS.RStudio is an open-source tool that provides Ide to use R language, and enterprise-ready professional software for data science teams to develop share the work with their team.R Studio can be downloaded from its official website (https://rstudio.com/)

13.1 Data Types

Variables are nothing but reserved memory locations to store values. This means that, when you create a variable, you reserve some space in memory.You may like to store information of various data types like character, wide character, integer, floating point, double floating point, Boolean etc. Based on the data type of a variable, the operating system allocates memory and decides what can be stored in the reserved memory.In contrast to other programming languages like C and java in R, the variables are not declared as some data type. The variables are assigned with R-Objects and the data type of the R-object becomes the data type of the variable. There are many types of R-objects.

Various types of Data Types

- Vectors
- Lists
- Matrices
- Arrays
- Factors
- Data Frames

Vector object

The simplest of these objects is the **vector object** and there are six data types of these atomic vectors, also termed as six classes of vectors.

1) Logical – True, False
2) Numeric – 12.3, 5, 999
3) Integer – 2L, 3L, 0L
4) Complex – 3+2i
5) Character – ‘a’, “good”, “TRUE”, ‘23.4’

6) Raw - "Hello" is stored as 48 65 6c 6c 6f

When you want to create vector with more than one element, you should use **c()** function which means to combine the elements into a vector.

- # Create a vector

```
apple <- c('red', 'apple', 'yellow')
print(apple)
```

- # Get the class of a vector

```
print(class(apple))
```

Lists

A list is an R-object which can contain many different types of elements inside it like vectors, functions and even another list inside it.

- #Create a list

```
list1 <- list(c(2,5,3),21.3,sin)
```

- #Print the list

```
Print(list1)
```

Matrix

A matrix is a two-dimensional rectangular data set. It can be created using a vector input to the matrix function.

- #Create a matrix

```
M = matrix(c('a', 'a', 'b', 'c', 'b', 'a'), nrow=2, ncol=3, byrow=TRUE)
Print(M)
```

Arrays

While matrices are confined to two dimensions, arrays can be of any number of dimensions. The array function takes a dim attribute which creates the required number of dimensions.

- #Create an array

```
a <- array(c('green', 'yellow'), dim=c(3,3,2))
print(a)
```

Factors

Factors are the r-objects which are created using a vector. It stores the vector along with the distinct values of the elements in the vector as labels. The labels are always character irrespective of whether it is numeric or character or Boolean etc. in the input vector.They are useful in statistical modeling.Factors are created using the **factor()** function. The **nlevels** functions gives the count of levels.

- #Create a vector

```
apple_colors<- c('green', 'green', 'yellow', 'red', 'red', 'red', 'green')
```

- #Create a factor object

```
factor_apple<- factor(apple_colors)
```

- Print the factor

```
print(factor_apple)
print(nlevels(factor_apple))
```

Data Frames

Data frames are tabular data objects. Unlike a matrix in data frame each column can contain different modes of data. The first column can be numeric while the second column can be character and third column can be logical. It is a list of vectors of equal length.Data Frames are created using the **data.frame()** function.

- #Create the data frame

```
BMI <- data.frame(gender = c("Male", "Male", Female"),
                  height = c(152, 171.5, 165),
                  weight = c(81, 93, 78),
                  age = c(42, 38, 26) )
print(BMI)
```

13.2 Variables

A variable provides us with named storage that our programs can manipulate. A variable in R can store an atomic vector, group of atomic vectors or a combination of many Robjects.A valid variable name consists of letters, numbers and the dot or underline characters. The variable name starts with a letter, or the dot not followed by a number.

Valid variable names

- var_name2.
- .var_name,
- var.name

Invalid variable names

- var_name%
- 2var_name
- .2var_name
- _var_name

Variable assignment

The variables can be assigned values using leftward, rightward,and equal to operator. The values of the variables can be printed using **print()** or **cat()** function. The **cat()** function combines multiple items into a continuous print output.

Assignment with equal operator

- var.1 = c(0,1,2,3)

Assignment with leftward operator

- var.2 <- c("learn", "R")

Assignment with rightward operator

- C(TRUE,1) -> var.3

Printing of variables

cat(“var.1 is “, var.1, “\n”)

cat(“var.2 is “, var.2, “\n”)

cat(“var.3 is “, var.3, “\n”)

Data type of a variable

In R, a variable itself is not declared of any data type, rather it gets the data type of the R - object assigned to it. So, R is called a dynamically typed language, which means that we can change a variable’s data type of the same variable again and again when using it in a program.

```
var_x<- "Hello"
cat("The class of var_x is ",class(var_x),"\n")
var_x<- 34.5
cat("  Now the class of var_x is ",class(var_x),"\n")
var_x<- 27L
cat("   Next the class of var_x becomes ",class(var_x),"\n")
```

Finding variables

To know all the variables currently available in the workspace we use the **ls()** function. Also, the ls() function can use patterns to match the variable names.

- Print(ls())

Deleting variables

Variables can be deleted by using the **rm()** function. Below we delete the variable var.3. On printing the value of the variable error is thrown.

```
rm(var.3)
print(var.3)
```

13.3 R operators

An operator is a symbol that tells the compiler to perform specific mathematical or logical manipulations. R language is rich in built-in operators and provides the following types of operators.

Types of operators

- Arithmetic Operators
- Relational Operators
- Logical Operators
- Assignment Operators
- Miscellaneous Operators

Arithmetic operators

- + Addition

- - Subtraction
- * Multiplication
- / Division
- %% Remainder
- ^ Power

Relational Operators

- > Greater than
- < Less than
- == Equal to
- <= Less than or equal to
- >= Greater than or equal to
- != Not equal to

Logical Operators

- & Element wise Logical AND
- | Element wise Logical OR
- ! Element wise Logical NOT
- && Logical AND
- || Logical OR

Assignment operators

- <- or == or <<- Left assignment
- -> or ->> Right assignment

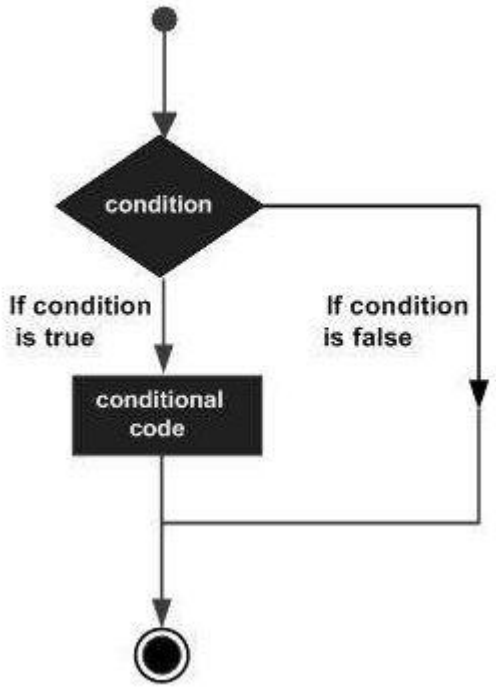
Miscellaneous operator

- : Colon operator
- %in% Identify an element belongs to a vector
- %*% Multiply a matrix with its transpose

13.4 Decision Making

Decision making structures require the programmer to specify one or more conditions to be evaluated or tested by the program, along with a statement or statements to be executed if the condition is determined to be **true**, and optionally, other statements to be executed if the condition is determined to be **false**.

General form



Types of decision-making statements

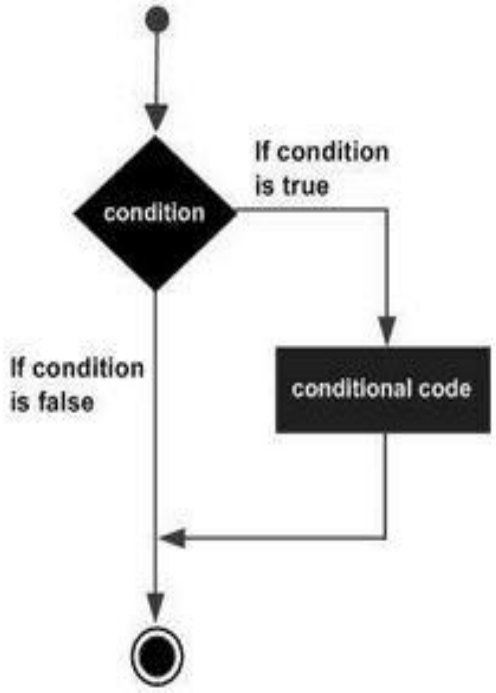
- If statement
- If……else statement
- Switch statement

If statement

An **if** statement consists of a Boolean expression followed by one or more statements.The syntax is:

```
if(boolean_expression) {
// statement(s) will execute if the boolean expression is true.
}
```

If the Boolean expression is evaluated to be **true**, then the block of code inside the if statement will be executed. If Boolean expression evaluates to be **false**, then the first set of code after the end of the if statement (after the closing curly brace) will be executed.




```
x <- 30L
if(is.integer(x)) {
  print("X is an Integer")
}
```

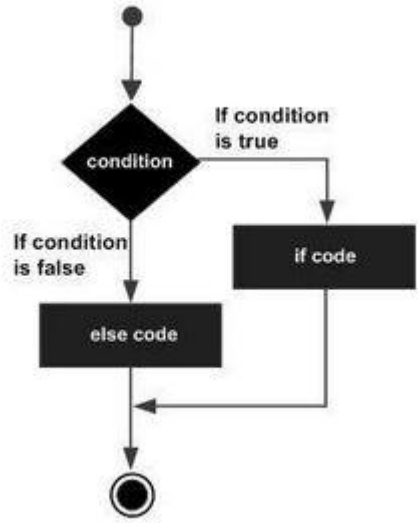
Output: [1] "X is an Integer"

If…Else statement

An **if** statement can be followed by an optional **else** statement which executes when the boolean expression is false. The syntax is:

```
if(boolean_expression) {
  // statement(s) will execute if the boolean expression is true.
} else {
  // statement(s) will execute if the boolean expression is false.
}
```

If the Boolean expression evaluates to be **true**, then the **if block** of code will be executed, otherwise **else block** of code will be executed.




```
x <- c("what","is","truth")
if("Truth" %in% x) {
  print("Truth is found")
} else {
  print("Truth is not found")
}
```

O/P: [1] "Truth is not found"

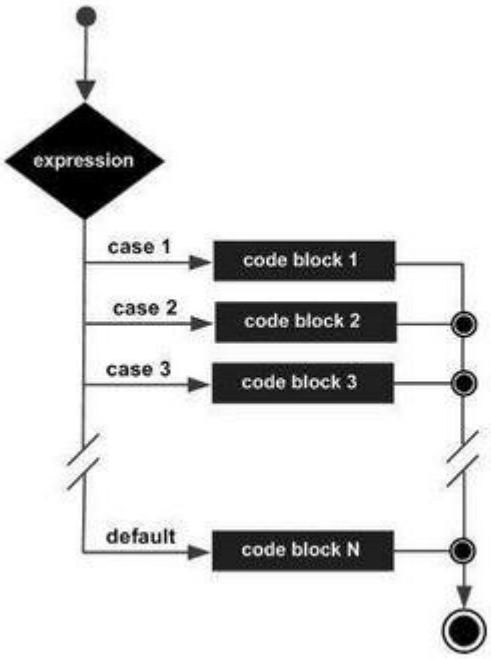
Switch statement

A **switch** statement allows a variable to be tested for equality against a list of values. Each value is called a case, and the variable being switched on is checked for each case. The syntax is:

switch(expression, case1, case2, case3....)

Rules apply to a switch statement −

- If the value of expression is not a character string it is coerced to integer.
- You can have any number of case statements within a switch. Each case is followed by the value to be compared to and a colon.
- If the value of the integer is between 1 and nargs()−1 (The max number of arguments)then the corresponding element of case condition is evaluated, and the result returned.
- If expression evaluates to a character string, then that string is matched (exactly) to the names of the elements.
- If there is more than one match, the first matching element is returned.
- No Default argument is available.
- In the case of no match, if there is an unnamed element of ... its value is returned. (If there is more than one such argument an error is returned.)



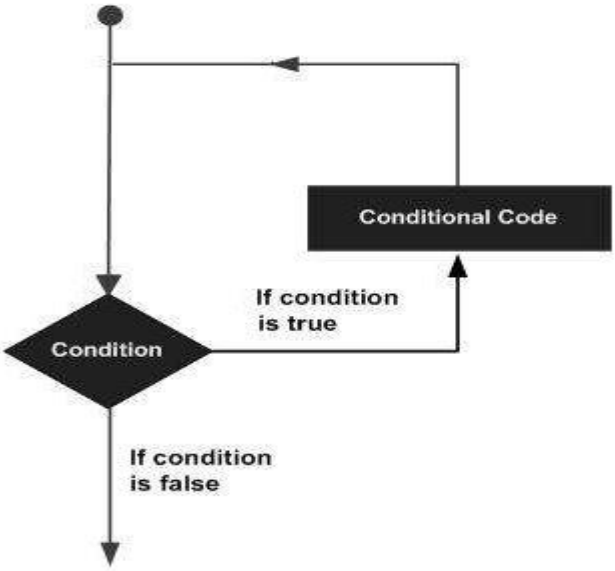
x <- switch(3, "first", "second", "third", "fourth“)

print(x)

O/P: [1] "third"

13.5 Loops

There may be a situation when you need to execute a block of code several number of times. In general, statements are executed sequentially. The first statement in a function is executed first, followed by the second, and so on.Programming languages provide various control structures that allow for more complicated execution paths.A loop statement allows us to execute a statement or group of statements multiple times and the following is the general form of a loop statement in most of the programming languages.



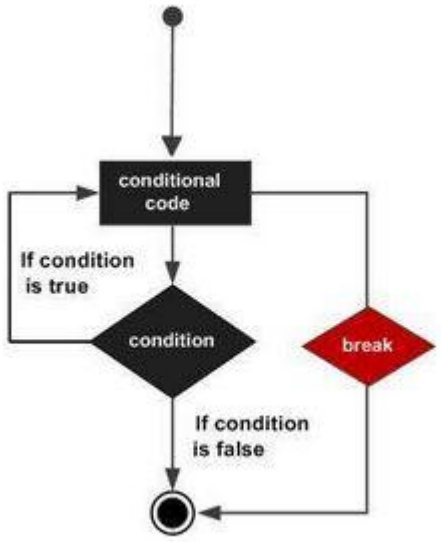
Kinds of Loops

- Repeat loop
- While loop
- For loop

Repeat Loop

The **Repeat loop** executes the same code again and again until a stop condition is met. The syntax is:

```
repeat {
  commands
  if(condition) {
    break
  }
}
```




```
v <- c("Hello","loop")
cnt<- 2
repeat {
  print(v)
cnt<- cnt+1
if(cnt> 5) {
    break
  }
}
```

O/P: [1] "Hello" "loop"

[1] "Hello" "loop"

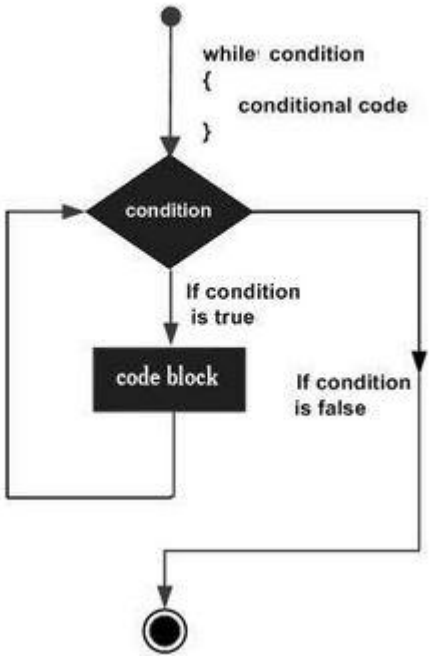
[1] "Hello" "loop"

[1] "Hello" "loop"

While Loop

The While loop executes the same code again and again until a stop condition is met. The syntax is:

```
while (test_expression) {
  statement
}
```



Here key point of the **while** loop is that the loop might not ever run. When the condition is tested and the result is false, the loop body will be skipped and the first statement after the while loop will be executed.

```
v <- c("Hello","while loop")
cnt<- 2
while (cnt< 7) {
  print(v)
cnt = cnt + 1
}
```

[1] "Hello" "while loop"

[1] "Hello" "while loop"

[1] "Hello" "while loop"

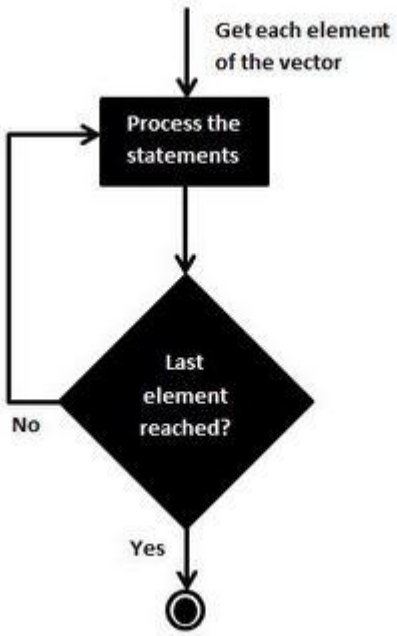
[1] "Hello" "while loop"

[1] "Hello" "while loop"

For loop

A **For loop** is a repetition control structure that allows you to efficiently write a loop that needs to execute a specific number of times.

```
for (value in vector) {
  statements
        }
```



R's for loops are particularly flexible in that they are not limited to integers, or even numbers in the input. We can pass character vectors, logical vectors, lists or expressions.

```
v <- LETTERS[1:4]
for ( i in v) {
  print(i)
}
```

O/P: [1] "A"

[1] "B"

[1] "C"

[1] "D"

13.6 Loop Control Statements

Loop control statements change execution from its normal sequence. When execution leaves a scope, all automatic objects that were created in that scope are destroyed. The loop control statements are:

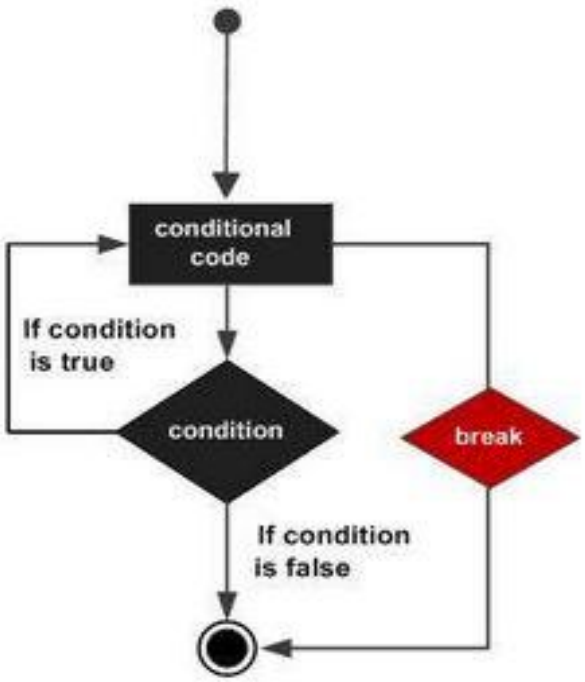
- Break statement
- Next statement

Break Statement

The break statement in R programming language has the following two usages.

1) When the break statement is encountered inside a loop, the loop is immediately terminated, and program control resumes at the next statement following the loop.

2) It can be used to terminate a case in the switch statement.




```
v <- c("Hello","loop")
cnt<- 2
repeat {
  print(v)
cnt<- cnt + 1
if(cnt> 5) {
     break
  }
}
```

O/P: [1] "Hello" "loop"

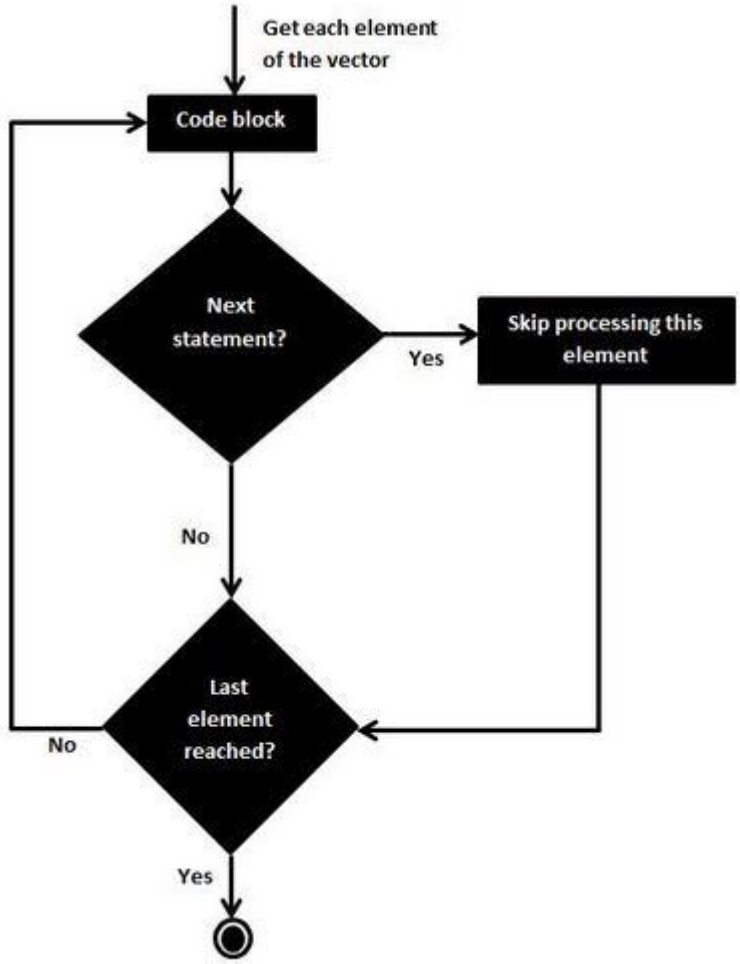
[1] "Hello" "loop"

[1] "Hello" "loop"

[1] "Hello" "loop"

Next Statement

The **next** statement in R programming language is useful when we want to skip the current iteration of a loop without terminating it. On encountering next, the R parser skips further evaluation and starts the next iteration of the loop.




```
v <- LETTERS[1:6]
for ( i in v) {
  if (i == "D") {
    next
  }
  print(i)
}
```

O/P: [1] "A"

[1] "B"

[1] "C"

[1] "E"

[1] "F"

13.7 Functions

A function is a set of statements organized together to perform a specific task. R has many in-built functions, and the user can create their own functions.In R, a function is an object so the R interpreter can pass control to the function, along with arguments that may be necessary for the function to accomplish the actions.The function in turn performs its task and returns control to the interpreter as well as any result which may be stored in other objects.

Function Definition

An R function is created by using the keyword **function**. The basic syntax of an R function definition is:

function_name<- function(arg_1, arg_2, ...) {

function body

}

Function Components

- **Function Name** − This is the actual name of the function. It is stored in an R environment as an object with this name.
- **Arguments** − An argument is a placeholder. When a function is invoked, you pass a value to the argument. Arguments are optional; that is, a function may contain no arguments. Also, arguments can have default values.
- **Function Body** − The function body contains a collection of statements that defines what the function does.
- **Return Value** − The return value of a function is the last expression in the function body to be evaluated

R has many **in-built** functions which can be directly called in the program without defining them first. We can also create and use our own functions referred to as **user defined** functions.

Built-in Functions

The simple examples of in-built functions are seq(), mean(), max(), sum(x) and paste(...) etc. They are directly called by user written programs.

- # Create a sequence of numbers from 32 to 44.

print(seq(32,44))

- # Find mean of numbers from 25 to 82.

print(mean(25:82))

- # Find sum of numbers frm 41 to 68.

print(sum(41:68))

O/P: [1] 32 33 34 35 36 37 38 39 40 41 42 43 44

[1] 53.5

[1] 1526

User Defined Functions

We can create user-defined functions in R.They are specific to what a user wants and once created they can be used like the built-in functions.

- # Create a function to print squares of numbers in sequence.

```
new.function<- function(a) {
  for(i in 1:a) {
    b <- i^2
    print(b)
  }
}
```

- Calling a function

```
# Call the function new.function supplying 6 as an argument.
new.function(6)
```

O/P: [1] 1

[1] 4

[1] 9

[1] 16

[1] 25

[1] 36

- Calling a function without an argument

```
# Create a function without an argument.
new.function<- function() {
  for(i in 1:5) {
    print(i^2)
  }
}
```

- # Call the function without supplying an argument.

```
new.function()
```

O/P: [1] 1

[1] 4

[1] 9

[1] 16

[1] 25

The arguments to a function call can be supplied in the same sequence as defined in the function or they can be supplied in a different sequence but assigned to the names of the arguments.

- # Create a function with arguments.

```
new.function<- function(a,b,c) {
  result <- a * b + c
  print(result)
}
```

- # Call the function by position of arguments.

```
new.function(5,3,11)
# Call the function by names of the arguments.
new.function(a = 11, b = 5, c = 3)
```

- Calling a function with default arguments

We can define the value of the arguments in the function definition and call the function without supplying any argument to get the default result. But we can also call such functions by supplying new values of the argument and get non default result.

- # Create a function with arguments.

```
new.function<- function(a = 3, b = 6) {
  result <- a * b
  print(result)
}
```

- # Call the function without giving any argument.

```
new.function()
```

- # Call the function giving new values of the argument.

```
new.function(9,5)
```

O/P: [1] 18

[1] 45

13.8 Strings

Any value written within a pair of single quotes or double quotes in R is treated as a string.Internally R stores every string within double quotes, even when you create them with single quote.

Rules applied in string construction

- The quotes at the beginning and end of a string should be both double quotes or both single quote. They cannot be mixed.
- Double quotes can be inserted into a string starting and ending with single quote.
- Single quotes can be inserted into a string starting and ending with double quotes.
- Double quotes cannot be inserted into a string starting and ending with double quotes.
- Single quotescannot be inserted into a string starting and ending with single quote.

Valid strings

a <- 'Start and end with single quote'

print(a)

b <- "Start and end with double quotes"

print(b)

c <- "single quote ' in between double quotes"

print(c)

d <- 'Double quotes " in between single quote'

print(d)

O/P: [1] "Start and end with single quote"

[1] "Start and end with double quotes"

[1] "single quote ' in between double quote"

[1] "Double quote \" in between single quote"

Invalid strings

e<- 'Mixed quotes"

print(e)

f <- 'Single quote ' inside single quote'

print(f)

g <- "Double quotes " inside double quotes"

print(g)

Error: unexpected symbol in:

"print(e)

f <- 'Single"

Execution halted

String manipulation

- Concatenating Strings - paste () function
- Formatting numbers & strings - format() function
- Counting number of characters in a string - nchar() function
- Changing the case - toupper() &tolower() functions
- Extracting parts of a string - substring () function

Concatenating Strings - paste() function

Many strings in R are combined using the **paste()** function. It can take any number of arguments to be combined.

paste (..., sep = " ", collapse = NULL)

- **...** represents any number of arguments to be combined.
- **sep** represents any separator between the arguments. It is optional.
- **collapse** is used to eliminate the space in between two strings. But not the space within two words of one string.

a <- "Hello"

b <- 'How'

c <- "are you? "

print(paste(a,b,c))

print(paste(a,b,c, sep = "-"))

print(paste(a,b,c, sep = "", collapse = ""))

O/P: [1] "Hello How are you? "

[1] "Hello-How-are you? "

[1] "HelloHoware you? "

Formatting numbers & strings - format() function

Numbers and strings can be formatted to a specific style using **format()** function.

format(x, digits, nsmall, scientific, width, justify = c("left", "right", "centre", "none"))

- **x** is the vector input.

- **digits**are the total number of digits displayed.
- **nsmall** is the minimum number of digits to the right of the decimal point.
- **scientific** is set to TRUE to display scientific notation.
- **width** indicates the minimum width to be displayed by padding blanks in the beginning.
- **Justify** is the display of the string to left, right or center.

```
# Total number of digits displayed. Last digit rounded off.
result <- format(23.123456789, digits = 9)
print(result)
```

- # Display numbers in scientific notation.

```
result <- format(c(6, 13.14521), scientific = TRUE)
print(result)
```

- # The minimum number of digits to the right of the decimal point.

```
result <- format(23.47, nsmall = 5)
print(result)
```

- # Format treats everything as a string.

```
result <- format(6)
print(result)
```

- # Numbers are padded with blank in the beginning for width.

```
result <- format (13.7, width = 6)
print(result)
```

- # Left justify strings.

```
result <- format ("Hello", width = 8, justify = "l")
print(result)
```

- # Justfy string with center.

```
result <- format ("Hello", width = 8, justify = "c")
print(result)
```

O/P: [1] "23.1234568"

[1] "6.000000e+00" "1.314521e+01"

[1] "23.47000"

[1] "6"

[1] " 13.7"

[1] "Hello   "

[1] " Hello "

Counting number of characters in a string - nchar() function

This function counts the number of characters including spaces in a string. The syntax is:

nchar(x)

x is the vector input.

result <- nchar("Count the number of characters")

print(result)

O/P: [1] 30

Changing the case - toupper() &tolower() functions

These functions change the case of characters of a string.

toupper(x)

tolower(x)

- x is the vector input.

- # Changing to Upper case.

result <- toupper("Changing to Upper")

print(result)

- # Changing to lower case.

result <- tolower("Changing to Lower")

print(result)

- O/P: [1] "CHANGING TO UPPER"

[1] "changing to lower"

Extracting parts of a string - substring() function

This function extracts parts of a String.

- substring(x,first,last)

Following is the description of the parameters used −

- x is the character vector input.
- first is the position of the first character to be extracted.
- last is the position of the last character to be extracted

- # Extract characters from 5th to 7th position.

result <- substring("Extract", 5, 7)

print(result)

O/P: [1] "act"

13.9 R Packages

R packages are a collection of R functions, complied code and sample data. They are stored under a directory called **"library"** in the R environment. By default, R installs a set of packages during installation. More packages are added later when they are needed for some specific purpose. When we start the R console, only the default packages are available by default. Other packages which are already installed must be loaded explicitly to be used by the R program that is going to use them.

Check available R packages

- Get library locations containing R packages: .libPaths()
- Get the list of all the packages installed: library()

Install a new package

There are two ways to add new R packages. One is installing directly from the CRAN directory, and another is downloading the package to your local system and installing it manually.

Install from CRAN

install.packages("Package Name")

Install the package named "XML".

install.packages("XML")

Install package manually

install.packages(file_name_with_path, repos = NULL, type = "source")

Install the package named "XML"

install.packages("E:/XML_3.98-1.3.zip", repos = NULL, type = "source")

Load package to library

Before a package can be used in the code, it must be loaded to the current R environment. You also need to load a package that is already installed previously but not available in the current environment.A package is loaded using the following command −

library ("package Name", lib.loc = "path to library")

Load the package named "XML"

install.packages("E:/XML_3.98-1.3.zip", repos = NULL, type = "source")

13.10 Data Reshaping

Data Reshaping in R is about changing the way data is organized into rows and columns. Most of the time data processing in R is done by taking the input data as a data frame. Data Reshaping in R is about changing the way data is organized into rows and columns. Most of the time data processing in R is done by taking the input data as a data frame.

Joining Columns and Rows in a Data Frame

We can join multiple vectors to create a data frame using the cbind()function. Also, we can merge two data frames using rbind() function.

Merging data frames

We can merge two data frames by using the **merge()** function. The data frames must have the same column names on which the merging happens.

Melting and casting

One of the most interesting aspects of R programming is about changing the shape of the data in multiple steps to get a desired shape. The functions used to do this are called **melt()** and **cast()**.

Summary

- R is an open-source programming language mostly used for statistical computing and data analysis.It is available across widely used platforms like Windows, Linux, and MacOS.
- R programming is used as a leading tool for machine learning, statistics, and data analysis. Objects, functions, and packages can easily be created by R.
- As R programming language is an open source. Thus, you can run R anywhere and at any time.
- Based on the data type of a variable, the operating system allocates memory and decides what can be stored in the reserved memory.
- The data types in R are: vectors, lists, matrices, arrays, factors and data frames.
- Factors are the r-objects which are created using a vector. It stores the vector along with the distinct values of the elements in the vector as labels.
- A valid variable name consists of letters, numbers and the dot or underline characters.
- The variables can be assigned values using leftward, rightward and equal to operator.
- An operator is a symbol that tells the compiler to perform specific mathematical or logical manipulations. R language is rich in built-in operators and provides the following types of operators.
- A function is a set of statements organized together to perform a specific task. R has many in-built functions, and the user can create their own functions.

Keywords

- **R**: R is an interpreted language that supports both procedural programming and object-oriented programming. This is an implementation of the S programming language.
- **RStudio**: R Studio is an integrated development environment(IDE) for R. IDE is a GUI, where you can write your quotes, see the results, and also see the variables that are generated during the course of programming.

- **R Objects**: The variables are assigned with R-Objects and the data type of the R-object becomes the data type of the variable. There are many types of R-objects.
- **Lists:**A list is an R-object which can contain many different types of elements inside it like vectors, functions and even another list inside it.
- **Variable in R:**A variable provides us with named storage that our programs can manipulate. A variable in R can store an atomic vector, group of atomic vectors or a combination of many Robjects.
- **Loops**: A loop statement allows us to execute a statement or group of statements multiple times and the following is the general form of a loop statement in most of the programming languages.

SelfAssessment

1. R language is used for
A. Statistical computing
B. Data analysis
C. Fixing the bugs
D. All of the above

2. R language is available across
A. Windows
B. MAC
C. Linux
D. All of the above

3. R is an interpreted language which supports
A. Only procedural programming
B. Object-oriented programming
C. Both procedural and object-oriented programming
D. None of the above

4. Which of the following are the data types in R programming language?
A. Vectors
B. Lists
C. Data frames
D. All of the above mentioned

5. Which attribute creates the required number of dimensions in arrays?
A. dimension
B. dim
C. sides
D. All of the above

6. The values of the variables can be printed using
A. Cat()
B. Print()
C. Both above mentioned
D. None of the above

7. The decision-making structures in R programming languages are
A. If statement
B. If-else statement
C. Switch statement
D. All the above

8. In switch statement, the number of cases allowed are:
A. 1
B. 2
C. 3
D. Any

9. Each case in switch statement is followed by the value to be compared to and a ……..
A. Colon
B. Comma
C. Semi-colon
D. Asterisk

10. The kinds of loops in R language are
A. While loop
B. Repeat loop
C. For loop
D. All of the above

11. Loop control statements in R are
A. Break statement
B. Next statement
C. Both of the above
D. None of the above

12. Which of the following are the function components?
A. Function body
B. Function name
C. Arguments
D. All of the above mentioned

13. The strings in R programming language can be written in
A. Single quotes
B. Double quotes
C. Either single of double quotes
D. None of the above

14. The concatenation of strings can be done using
A. paste()
B. format()
C. nchar()
D. substring()

15. The numbers and strings can be formatted to a specific style using
A. paste()
B. format()
C. nchar()
D. substring()

Answers for Self Assessment

l.	D	2.	D	3.	C	4.	D	5.	B
6.	D	7.	D	8.	D	9.	A	10.	D
11.	C	12.	D	13.	D	14.	A	15.	B

Review Questions

1. Why is R programming language used? Also explain the features of R programming language.
2. What are the advantages and disadvantages of R programming language?
3. What is a data type? Which data types exist in R programming language?
4. What is a vector object? How do we create a vector, and get the class of a vector?
5. What are operators? Explain its types.
6. What is decision making structures in R programming language? Explain.

Further Readings

https://www.r-project.org/about.html

https://www.geeksforgeeks.org/r-programming-language-introduction/

Unit 13: R Tool

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Summary

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Objectives

After this unit, you will be able to

- Understand about R and RStudio
- Understand the R data types
- Understand variables and operators
- Understand the decision-making algorithms and loops
- Understand the functions
- Understand strings and string methods
- Understand R packages

Introduction

R is an open-source programming language mostly used for statistical computing and data analysis.It is available across widely used platforms like Windows, Linux, and MacOS.It generally comes with a command-line interface and provides a vast list of packages for performing tasks. R is an interpreted language that supports both procedural programming and object-oriented programming.

Development of R

- It was designed by Ross Ihaka and Robert Gentleman at the University of Auckland, New Zealand, and is currently developed by the R Development Core Team.
- R programming language is an implementation of the S programming language.

Why useR programming language?

- R programming is used as a leading tool for machine learning, statistics, and data analysis. Objects, functions, and packages can easily be created by R.
- It's a platform-independent language. This means it can be applied to all operating systems.
- It's an open-source free language. That means anyone can install it in any organization without purchasing a license.
- R programming language is not only a statistic package but also allows us to integrate with other languages (C, C++). Thus, you can easily interact with many data sources and statistical packages.
- The R programming language has a vast community of users and it's growing day by day.
- R is currently one of the most requested programming languages in the Data Science job market that makes it the hottest trend nowadays.

Features of R programming languages

- **Statistical Features of R**
- **Programming Features of R**

Statistical Features of R

- **Basic Statistics:** The most common basic statistical terms are the mean, mode, and median. These are all known as "Measures of Central Tendency." So, using the R language we can measure central tendency very easily.
- **Static graphics:** R is rich with facilities for creating and developing interesting static graphics. R contains functionality for many plot types including graphic maps, mosaic plots, biplots, and the list goes on.
- **Probability distributions:** Probability distributions play a vital role in statistics and by using R we can easily handle various types of probability distribution such as Binomial Distribution, Normal Distribution, Chi-squared Distribution and many more.
- **Data analysis:** It provides a large, coherent, and integrated collection of tools for data analysis

Programming Features of R

- **R Packages:** One of the major features of R is it has a wide availability of libraries. R has CRAN(Comprehensive R Archive Network), which is a repository holding more than 10, 0000 packages.
- **Distributed Computing:** Distributed computing is a model in which components of a software system are shared among multiple computers to improve efficiency and performance. Two new packages **ddR and multidplyr** used for distributed programming in R were released in November 2015.

Advantages of R

- R is the most comprehensive statistical analysis package. As new technology and concepts often appear first in R.
- As R programming language is an open source. Thus, you can run R anywhere and at any time.

- R programming language is suitable for GNU/Linux and Windows operating system.
- R programming is a cross-platform which runs on any operating system.
- In R, everyone is welcome to provide new packages, bug fixes, and code enhancements.

Disadvantages of R

- In the R programming language, the standard of some packages is less than perfect.
- Although, R commands put little pressure on memory management. So, R programming language may consume all available memory.
- In R basically, nobody complains if something doesn't work.
- R programming language is much slower than other programming languages such as Python and MATLAB.

Applications of R

- We use R for Data Science. It gives us a broad variety of libraries related to statistics. It also provides the environment for statistical computing and design.
- R is used by many quantitative analysts as its programming tool. Thus, it helps in data importing and cleaning.
- R is the most prevalent language. So many data analysts and research programmers use it. Hence, it is used as a fundamental tool for finance.
- Tech giants like Google, Facebook, bing, Twitter, Accenture, Wipro and many more use R nowadays.

Interesting facts about R

- R programming language is an implementation of the S programming language. It also combines with lexical scoping semantics inspired by Scheme. It is named partly after the first names of the first two R authors and partly as a play on the name of S.
- R supports both procedural programming and object-oriented programming. Procedural programming includes the procedure, records, modules, and procedure calls. While object-oriented programming language includes class, objects, and generic functions
- R language is an interpreted language instead of a compiled language. Therefore, it doesn't need a compiler to compile code into an executable program. This makes running an R script much less time-consuming.
- The number of R packages available either through CRAN or GitHub is 1, 00, 000 and they do epic stuff with just one line of code. It could range from Regression to Bayesian analysis.
- R is growing faster than any other data science language. It's the most-used data science language after SQL. It is used by 70% of data miners.
- One of the packages in R namely rmarkdown package helps you create reproducible Word documents and reproducible Powerpoint Presentations from your R markdown code just by changing one line in the YAML! ("YAML Ain't Markup Language!")
- It is really very easy in R to connect to almost any database using the dbplyer package. This makes it possible for an R user to work independently and pulling data from almost all common database types. You can also use packages like bigrquery to work directly with BigQuery and other high-performance data stores.
- You can build and host interactive web apps in just a few lines of code in R. Using the flexdashboard package in R you can create interactive web apps with a few lines of code. And using the rsconnect package you can also host your web apps on your own server or, even easier, host them on a cloud server.

- You can not only deploy web apps but also can make them into awesome video games in R. The nessy package helps you create NES(The Nintendo Entertainment System) looking Shiny apps and deploy them just like you would any other Shiny app.
- You can build APIs and serve them from R. The plumbr package in R helps you convert R functions to web APIs that can be integrated into downstream applications.

Environment in R

- The environment is a virtual space that is triggered when an interpreter of a programming language is launched.
- Simply, the environment is a collection of all the objects, variables, and functions. Or Environment can be assumed as a top-level object that contains the set of names/variables associated with some values.

Introduction to R studio

R Studio is an integrated development environment(IDE) for R. IDE is a GUI, where you can write your quotes, see the results,and see the variables that are generated during the course of programming. R Studio is available as both Open source and Commercial software.R Studio is also available as both Desktop and Server versions.R Studio is also available for various platforms such as Windows, Linux, and macOS.RStudio is an open-source tool that provides Ide to use R language, and enterprise-ready professional software for data science teams to develop share the work with their team.R Studio can be downloaded from its official website (https://rstudio.com/)

13.1 Data Types

Variables are nothing but reserved memory locations to store values. This means that, when you create a variable, you reserve some space in memory.You may like to store information of various data types like character, wide character, integer, floating point, double floating point, Boolean etc. Based on the data type of a variable, the operating system allocates memory and decides what can be stored in the reserved memory.In contrast to other programming languages like C and java in R, the variables are not declared as some data type. The variables are assigned with R-Objects and the data type of the R-object becomes the data type of the variable. There are many types of R-objects.

Various types of Data Types

- Vectors
- Lists
- Matrices
- Arrays
- Factors
- Data Frames

Vector object

The simplest of these objects is the **vector object** and there are six data types of these atomic vectors, also termed as six classes of vectors.

1) Logical – True, False
2) Numeric – 12.3, 5, 999
3) Integer – 2L, 3L, 0L
4) Complex – 3+2i
5) Character – 'a', "good", "TRUE", '23.4'

6) Raw - "Hello" is stored as 48 65 6c 6c 6f

When you want to create vector with more than one element, you should use **c()** function which means to combine the elements into a vector.

- # Create a vector

```
apple <- c('red', 'apple', 'yellow')
print(apple)
```

- # Get the class of a vector

```
print(class(apple))
```

Lists

A list is an R-object which can contain many different types of elements inside it like vectors, functions and even another list inside it.

- #Create a list

```
list1 <- list(c(2,5,3),21.3,sin)
```

- #Print the list

```
Print(list1)
```

Matrix

A matrix is a two-dimensional rectangular data set. It can be created using a vector input to the matrix function.

- #Create a matrix

```
M = matrix(c('a', 'a', 'b', 'c', 'b', 'a'), nrow=2, ncol=3, byrow=TRUE)
Print(M)
```

Arrays

While matrices are confined to two dimensions, arrays can be of any number of dimensions. The array function takes a dim attribute which creates the required number of dimensions.

- #Create an array

```
a <- array(c('green', 'yellow'), dim=c(3,3,2))
print(a)
```

Factors

Factors are the r-objects which are created using a vector. It stores the vector along with the distinct values of the elements in the vector as labels. The labels are always character irrespective of whether it is numeric or character or Boolean etc. in the input vector.They are useful in statistical modeling.Factors are created using the **factor()** function. The **nlevels** functions gives the count of levels.

- #Create a vector

```
apple_colors<- c('green', 'green', 'yellow', 'red', 'red', 'red', 'green')
```

- #Create a factor object

```
factor_apple<- factor(apple_colors)
```

- Print the factor

```
print(factor_apple)
print(nlevels(factor_apple))
```

Data Frames

Data frames are tabular data objects. Unlike a matrix in data frame each column can contain different modes of data. The first column can be numeric while the second column can be character and third column can be logical. It is a list of vectors of equal length.Data Frames are created using the **data.frame()** function.

- #Create the data frame

```
BMI <- data.frame(gender = c("Male", "Male", Female"),
                  height = c(152, 171.5, 165),
                  weight = c(81, 93, 78),
                  age = c(42, 38, 26) )
print(BMI)
```

13.2 Variables

A variable provides us with named storage that our programs can manipulate. A variable in R can store an atomic vector, group of atomic vectors or a combination of many Robjects.A valid variable name consists of letters, numbers and the dot or underline characters. The variable name starts with a letter, or the dot not followed by a number.

Valid variable names

- var_name2.
- .var_name,
- var.name

Invalid variable names

- var_name%
- 2var_name
- .2var_name
- _var_name

Variable assignment

The variables can be assigned values using leftward, rightward,and equal to operator. The values of the variables can be printed using **print()** or **cat()** function. The **cat()** function combines multiple items into a continuous print output.

Assignment with equal operator

- var.1 = c(0,1,2,3)

Assignment with leftward operator

- var.2 <- c("learn", "R")

Assignment with rightward operator

- C(TRUE,1) -> var.3

Printing of variables

cat(“var.1 is “, var.1, “\n”)

cat(“var.2 is “, var.2, “\n”)

cat(“var.3 is “, var.3, “\n”)

Data type of a variable

In R, a variable itself is not declared of any data type, rather it gets the data type of the R - object assigned to it. So, R is called a dynamically typed language, which means that we can change a variable’s data type of the same variable again and again when using it in a program.

```
var_x<- "Hello"
cat("The class of var_x is ",class(var_x),"\n")
var_x<- 34.5
cat("  Now the class of var_x is ",class(var_x),"\n")
var_x<- 27L
cat("   Next the class of var_x becomes ",class(var_x),"\n")
```

Finding variables

To know all the variables currently available in the workspace we use the **ls()** function. Also, the ls() function can use patterns to match the variable names.

- Print(ls())

Deleting variables

Variables can be deleted by using the **rm()** function. Below we delete the variable var.3. On printing the value of the variable error is thrown.

```
rm(var.3)
print(var.3)
```

13.3 R operators

An operator is a symbol that tells the compiler to perform specific mathematical or logical manipulations. R language is rich in built-in operators and provides the following types of operators.

Types of operators

- Arithmetic Operators
- Relational Operators
- Logical Operators
- Assignment Operators
- Miscellaneous Operators

Arithmetic operators

- + Addition

- - Subtraction
- * Multiplication
- / Division
- %% Remainder
- ^ Power

Relational Operators

- > Greater than
- < Less than
- == Equal to
- <= Less than or equal to
- >= Greater than or equal to
- != Not equal to

Logical Operators

- & Element wise Logical AND
- | Element wise Logical OR
- ! Element wise Logical NOT
- && Logical AND
- || Logical OR

Assignment operators

- <- or == or <<- Left assignment
- -> or ->> Right assignment

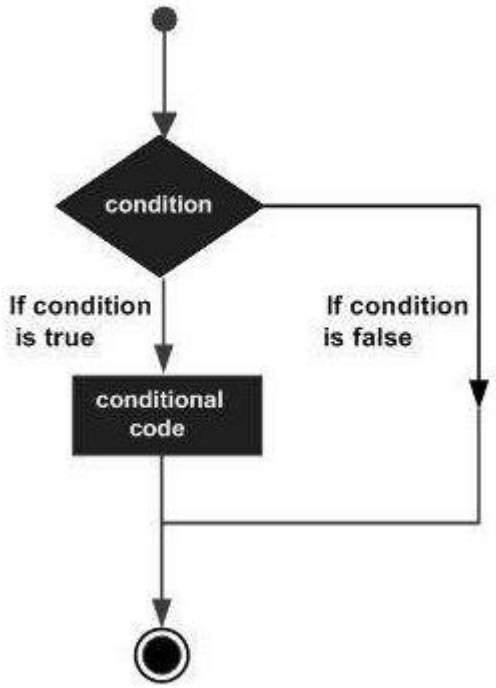
Miscellaneous operator

- : Colon operator
- %in% Identify an element belongs to a vector
- %*% Multiply a matrix with its transpose

13.4 Decision Making

Decision making structures require the programmer to specify one or more conditions to be evaluated or tested by the program, along with a statement or statements to be executed if the condition is determined to be **true**, and optionally, other statements to be executed if the condition is determined to be **false**.

General form



Types of decision-making statements

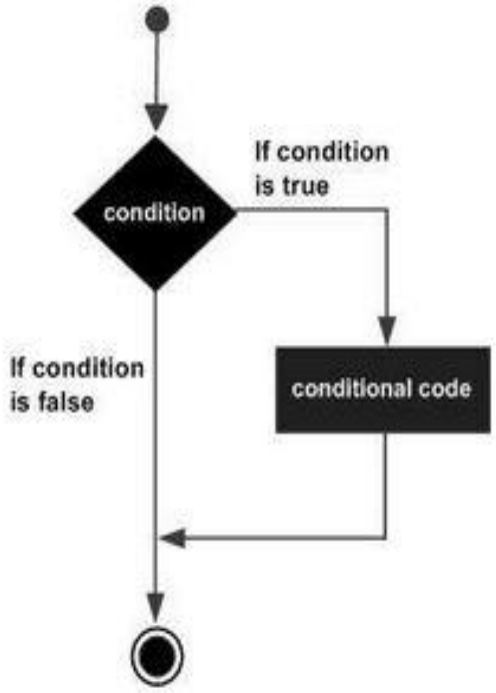
- If statement
- If……else statement
- Switch statement

If statement

An **if** statement consists of a Boolean expression followed by one or more statements.The syntax is:

```
if(boolean_expression) {
// statement(s) will execute if the boolean expression is true.
}
```

If the Boolean expression is evaluated to be **true**, then the block of code inside the if statement will be executed. If Boolean expression evaluates to be **false**, then the first set of code after the end of the if statement (after the closing curly brace) will be executed.




```
x <- 30L
if(is.integer(x)) {
  print("X is an Integer")
}
```

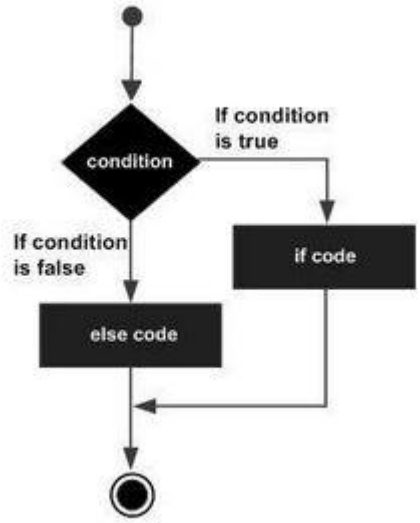
Output: [1] "X is an Integer"

If…Else statement

An **if** statement can be followed by an optional **else** statement which executes when the boolean expression is false. The syntax is:

```
if(boolean_expression) {
  // statement(s) will execute if the boolean expression is true.
} else {
  // statement(s) will execute if the boolean expression is false.
}
```

If the Boolean expression evaluates to be **true**, then the **if block** of code will be executed, otherwise **else block** of code will be executed.




```
x <- c("what","is","truth")
if("Truth" %in% x) {
  print("Truth is found")
} else {
  print("Truth is not found")
}
```

O/P: [1] "Truth is not found"

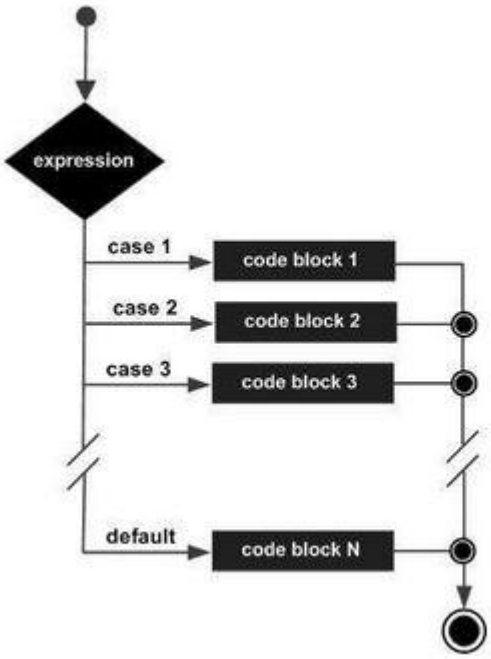
Switch statement

A **switch** statement allows a variable to be tested for equality against a list of values. Each value is called a case, and the variable being switched on is checked for each case. The syntax is:

switch(expression, case1, case2, case3....)

Rules apply to a switch statement −

- If the value of expression is not a character string it is coerced to integer.
- You can have any number of case statements within a switch. Each case is followed by the value to be compared to and a colon.
- If the value of the integer is between 1 and nargs()−1 (The max number of arguments)then the corresponding element of case condition is evaluated, and the result returned.
- If expression evaluates to a character string, then that string is matched (exactly) to the names of the elements.
- If there is more than one match, the first matching element is returned.
- No Default argument is available.
- In the case of no match, if there is an unnamed element of ... its value is returned. (If there is more than one such argument an error is returned.)



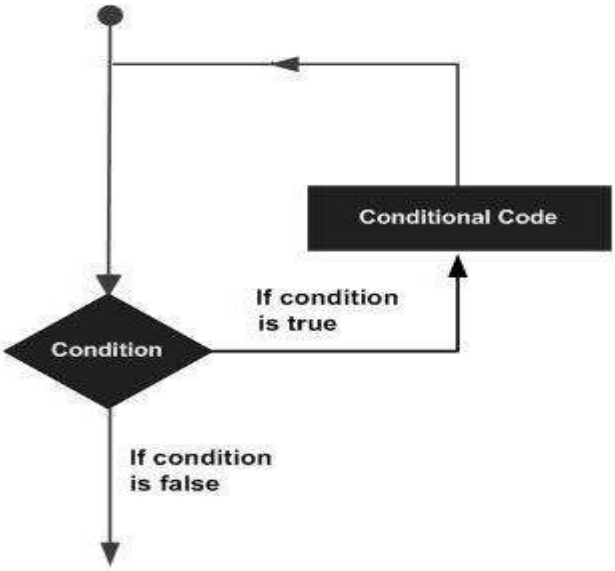
x <- switch(3, "first", "second", "third", "fourth")

print(x)

O/P: [1] "third"

13.5 Loops

There may be a situation when you need to execute a block of code several number of times. In general, statements are executed sequentially. The first statement in a function is executed first, followed by the second, and so on.Programming languages provide various control structures that allow for more complicated execution paths.A loop statement allows us to execute a statement or group of statements multiple times and the following is the general form of a loop statement in most of the programming languages.



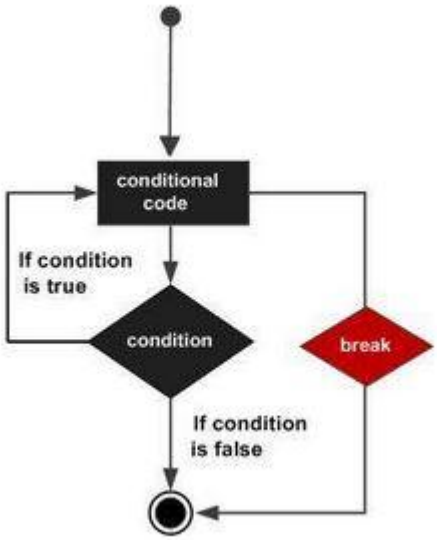
Kinds of Loops

- Repeat loop
- While loop
- For loop

Repeat Loop

The **Repeat loop** executes the same code again and again until a stop condition is met. The syntax is:

```
repeat {
  commands
  if(condition) {
    break
  }
}
```




```
v <- c("Hello","loop")
cnt<- 2
repeat {
  print(v)
cnt<- cnt+1
if(cnt> 5) {
    break
  }
}
```

O/P: [1] "Hello" "loop"

[1] "Hello" "loop"

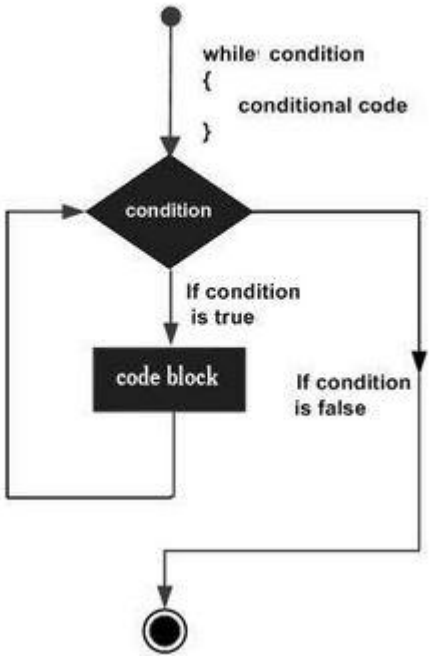
[1] "Hello" "loop"

[1] "Hello" "loop"

While Loop

The While loop executes the same code again and again until a stop condition is met. The syntax is:

```
while (test_expression) {
  statement
}
```



Here key point of the **while** loop is that the loop might not ever run. When the condition is tested and the result is false, the loop body will be skipped and the first statement after the while loop will be executed.

```
v <- c("Hello","while loop")
cnt<- 2
while (cnt< 7) {
  print(v)
cnt = cnt + 1
}
```

[1] "Hello" "while loop"

[1] "Hello" "while loop"

[1] "Hello" "while loop"

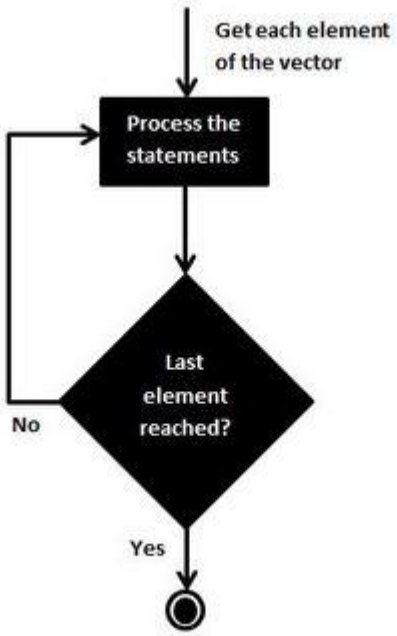
[1] "Hello" "while loop"

[1] "Hello" "while loop"

For loop

A **For loop** is a repetition control structure that allows you to efficiently write a loop that needs to execute a specific number of times.

```
for (value in vector) {
  statements
        }
```



R's for loops are particularly flexible in that they are not limited to integers, or even numbers in the input. We can pass character vectors, logical vectors, lists or expressions.

```
v <- LETTERS[1:4]
for ( i in v) {
  print(i)
}
```

O/P: [1] "A"

[1] "B"

[1] "C"

[1] "D"

13.6 Loop Control Statements

Loop control statements change execution from its normal sequence. When execution leaves a scope, all automatic objects that were created in that scope are destroyed. The loop control statements are:

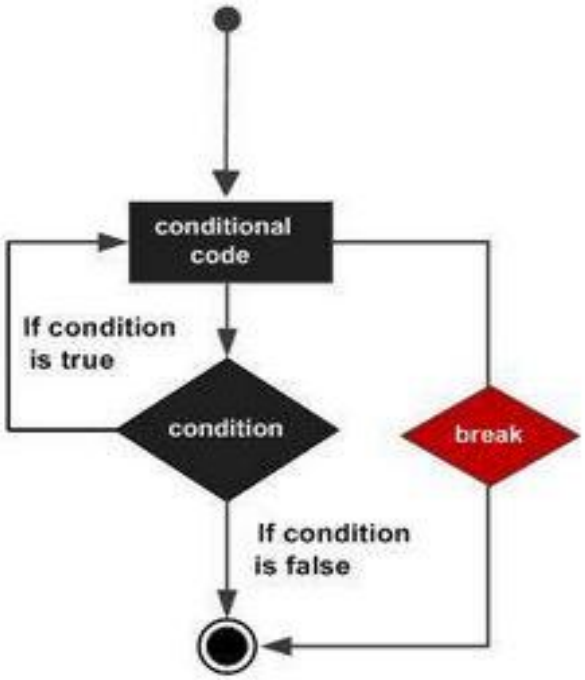
- Break statement
- Next statement

Break Statement

The break statement in R programming language has the following two usages.

1) When the break statement is encountered inside a loop, the loop is immediately terminated, and program control resumes at the next statement following the loop.

2) It can be used to terminate a case in the switch statement.




```
v <- c("Hello","loop")
cnt<- 2
repeat {
  print(v)
cnt<- cnt + 1
if(cnt> 5) {
     break
  }
}
```

O/P: [1] "Hello" "loop"

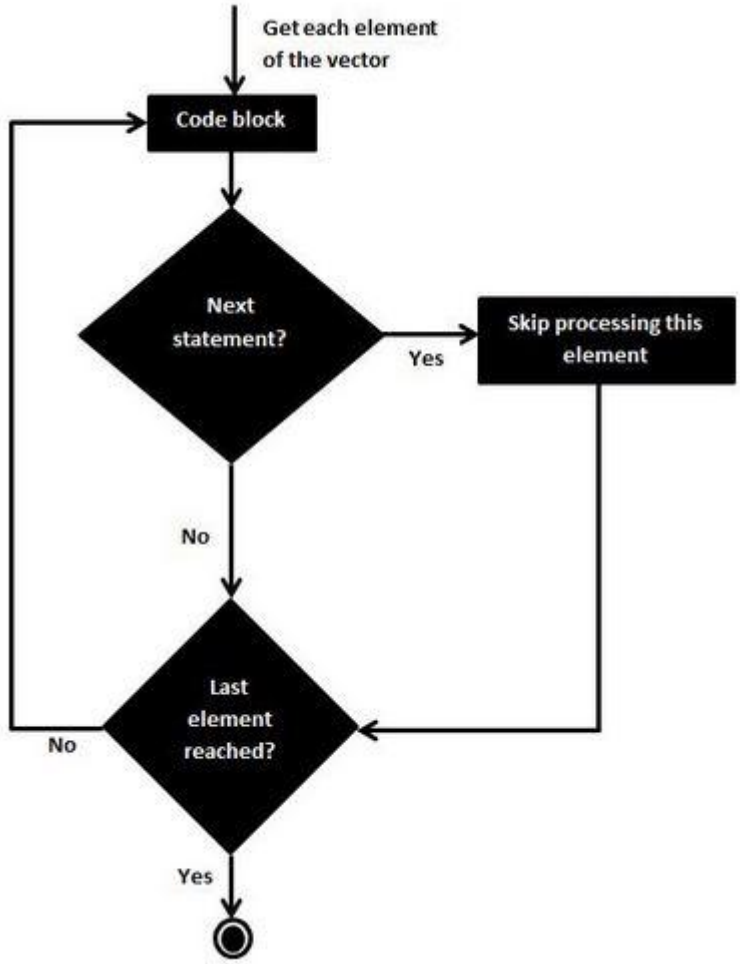
[1] "Hello" "loop"

[1] "Hello" "loop"

[1] "Hello" "loop"

Next Statement

The **next** statement in R programming language is useful when we want to skip the current iteration of a loop without terminating it. On encountering next, the R parser skips further evaluation and starts the next iteration of the loop.




```
v <- LETTERS[1:6]
for ( i in v) {
  if (i == "D") {
    next
  }
  print(i)
}
```

O/P: [1] "A"

[1] "B"

[1] "C"

[1] "E"

[1] "F"

13.7 Functions

A function is a set of statements organized together to perform a specific task. R has many in-built functions, and the user can create their own functions.In R, a function is an object so the R interpreter can pass control to the function, along with arguments that may be necessary for the function to accomplish the actions.The function in turn performs its task and returns control to the interpreter as well as any result which may be stored in other objects.

Function Definition

An R function is created by using the keyword **function**. The basic syntax of an R function definition is:

function_name<- function(arg_1, arg_2, ...) {

function body

}

Function Components

- **Function Name** − This is the actual name of the function. It is stored in an R environment as an object with this name.
- **Arguments** − An argument is a placeholder. When a function is invoked, you pass a value to the argument. Arguments are optional; that is, a function may contain no arguments. Also, arguments can have default values.
- **Function Body** − The function body contains a collection of statements that defines what the function does.
- **Return Value** − The return value of a function is the last expression in the function body to be evaluated

R has many **in-built** functions which can be directly called in the program without defining them first. We can also create and use our own functions referred to as **user defined** functions.

Built-in Functions

The simple examples of in-built functions are seq(), mean(), max(), sum(x) and paste(...) etc. They are directly called by user written programs.

- # Create a sequence of numbers from 32 to 44.

print(seq(32,44))

- # Find mean of numbers from 25 to 82.

print(mean(25:82))

- # Find sum of numbers frm 41 to 68.

print(sum(41:68))

O/P: [1] 32 33 34 35 36 37 38 39 40 41 42 43 44

[1] 53.5

[1] 1526

User Defined Functions

We can create user-defined functions in R.They are specific to what a user wants and once created they can be used like the built-in functions.

- # Create a function to print squares of numbers in sequence.

```
new.function<- function(a) {
  for(i in 1:a) {
    b <- i^2
    print(b)
  }
}
```

- Calling a function

```
# Call the function new.function supplying 6 as an argument.
new.function(6)
```

O/P: [1] 1

[1] 4

[1] 9

[1] 16

[1] 25

[1] 36

- Calling a function without an argument

```
# Create a function without an argument.
new.function<- function() {
  for(i in 1:5) {
    print(i^2)
  }
}
```

- # Call the function without supplying an argument.

```
new.function()
```

O/P: [1] 1

[1] 4

[1] 9

[1] 16

[1] 25

The arguments to a function call can be supplied in the same sequence as defined in the function or they can be supplied in a different sequence but assigned to the names of the arguments.

- # Create a function with arguments.

```
new.function<- function(a,b,c) {
  result <- a * b + c
  print(result)
}
```

- # Call the function by position of arguments.

```
new.function(5,3,11)
# Call the function by names of the arguments.
new.function(a = 11, b = 5, c = 3)
```

- Calling a function with default arguments

We can define the value of the arguments in the function definition and call the function without supplying any argument to get the default result. But we can also call such functions by supplying new values of the argument and get non default result.

- # Create a function with arguments.

```
new.function<- function(a = 3, b = 6) {
  result <- a * b
  print(result)
}
```

- # Call the function without giving any argument.

```
new.function()
```

- # Call the function giving new values of the argument.

```
new.function(9,5)
```

O/P: [1] 18

[1] 45

13.8 Strings

Any value written within a pair of single quotes or double quotes in R is treated as a string.Internally R stores every string within double quotes, even when you create them with single quote.

Rules applied in string construction

- The quotes at the beginning and end of a string should be both double quotes or both single quote. They cannot be mixed.
- Double quotes can be inserted into a string starting and ending with single quote.
- Single quotes can be inserted into a string starting and ending with double quotes.
- Double quotes cannot be inserted into a string starting and ending with double quotes.
- Single quotescannot be inserted into a string starting and ending with single quote.

Valid strings

a <- 'Start and end with single quote'

print(a)

b <- "Start and end with double quotes"

print(b)

c <- "single quote ' in between double quotes"

print(c)

d <- 'Double quotes " in between single quote'

print(d)

O/P: [1] "Start and end with single quote"

[1] "Start and end with double quotes"

[1] "single quote ' in between double quote"

[1] "Double quote \" in between single quote"

Invalid strings

e<- 'Mixed quotes"

print(e)

f <- 'Single quote ' inside single quote'

print(f)

g <- "Double quotes " inside double quotes"

```
print(g)

Error: unexpected symbol in:

"print(e)

f <- 'Single"

Execution halted
```

String manipulation

- Concatenating Strings - paste () function
- Formatting numbers & strings - format() function
- Counting number of characters in a string - nchar() function
- Changing the case - toupper() &tolower() functions
- Extracting parts of a string - substring () function

Concatenating Strings - paste() function

Many strings in R are combined using the **paste()** function. It can take any number of arguments to be combined.

paste (..., sep = " ", collapse = NULL)

- **...** represents any number of arguments to be combined.
- **sep** represents any separator between the arguments. It is optional.
- **collapse** is used to eliminate the space in between two strings. But not the space within two words of one string.

```
a <- "Hello"

b <- 'How'

c <- "are you? "

print(paste(a,b,c))

print(paste(a,b,c, sep = "-"))

print(paste(a,b,c, sep = "", collapse = ""))
```

O/P: [1] "Hello How are you? "

[1] "Hello-How-are you? "

[1] "HelloHoware you? "

Formatting numbers & strings - format() function

Numbers and strings can be formatted to a specific style using **format()** function.

format(x, digits, nsmall, scientific, width, justify = c("left", "right", "centre", "none"))

- **x** is the vector input.

- **digits**are the total number of digits displayed.
- **nsmall** is the minimum number of digits to the right of the decimal point.
- **scientific** is set to TRUE to display scientific notation.
- **width** indicates the minimum width to be displayed by padding blanks in the beginning.
- **Justify** is the display of the string to left, right or center.

```
# Total number of digits displayed. Last digit rounded off.
result <- format(23.123456789, digits = 9)
print(result)
```

- # Display numbers in scientific notation.

```
result <- format(c(6, 13.14521), scientific = TRUE)
print(result)
```

- # The minimum number of digits to the right of the decimal point.

```
result <- format(23.47, nsmall = 5)
print(result)
```

- # Format treats everything as a string.

```
result <- format(6)
print(result)
```

- # Numbers are padded with blank in the beginning for width.

```
result <- format (13.7, width = 6)
print(result)
```

- # Left justify strings.

```
result <- format ("Hello", width = 8, justify = "l")
print(result)
```

- # Justfy string with center.

```
result <- format ("Hello", width = 8, justify = "c")
print(result)
```

O/P: [1] "23.1234568"

[1] "6.000000e+00" "1.314521e+01"

[1] "23.47000"

[1] "6"

[1] " 13.7"

[1] "Hello   "

[1] " Hello "

Counting number of characters in a string - nchar() function

This function counts the number of characters including spaces in a string. The syntax is:

nchar(x)

x is the vector input.

result <- nchar("Count the number of characters")

print(result)

O/P: [1] 30

Changing the case - toupper() &tolower() functions

These functions change the case of characters of a string.

toupper(x)

tolower(x)

- x is the vector input.

- # Changing to Upper case.

result <- toupper("Changing to Upper")

print(result)

- # Changing to lower case.

result <- tolower("Changing to Lower")

print(result)

- O/P: [1] "CHANGING TO UPPER"

[1] "changing to lower"

Extracting parts of a string - substring() function

This function extracts parts of a String.

- substring(x,first,last)

Following is the description of the parameters used −

- x is the character vector input.
- first is the position of the first character to be extracted.
- last is the position of the last character to be extracted

- # Extract characters from 5th to 7th position.

result <- substring("Extract", 5, 7)

print(result)

O/P: [1] "act"

13.9 R Packages

R packages are a collection of R functions, complied code and sample data. They are stored under a directory called **"library"** in the R environment. By default, R installs a set of packages during installation. More packages are added later when they are needed for some specific purpose. When we start the R console, only the default packages are available by default. Other packages which are already installed must be loaded explicitly to be used by the R program that is going to use them.

Check available R packages

- Get library locations containing R packages: .libPaths()
- Get the list of all the packages installed: library()

Install a new package

There are two ways to add new R packages. One is installing directly from the CRAN directory, and another is downloading the package to your local system and installing it manually.

Install from CRAN

install.packages("Package Name")

Install the package named "XML".

install.packages("XML")

Install package manually

install.packages(file_name_with_path, repos = NULL, type = "source")

Install the package named "XML"

install.packages("E:/XML_3.98-1.3.zip", repos = NULL, type = "source")

Load package to library

Before a package can be used in the code, it must be loaded to the current R environment. You also need to load a package that is already installed previously but not available in the current environment.A package is loaded using the following command −

library ("package Name", lib.loc = "path to library")

Load the package named "XML"

install.packages("E:/XML_3.98-1.3.zip", repos = NULL, type = "source")

13.10 Data Reshaping

Data Reshaping in R is about changing the way data is organized into rows and columns. Most of the time data processing in R is done by taking the input data as a data frame. Data Reshaping in R is about changing the way data is organized into rows and columns. Most of the time data processing in R is done by taking the input data as a data frame.

Joining Columns and Rows in a Data Frame

We can join multiple vectors to create a data frame using the cbind()function. Also, we can merge two data frames using rbind() function.

Merging data frames

We can merge two data frames by using the **merge()** function. The data frames must have the same column names on which the merging happens.

Melting and casting

One of the most interesting aspects of R programming is about changing the shape of the data in multiple steps to get a desired shape. The functions used to do this are called **melt()** and **cast()**.

Summary

- R is an open-source programming language mostly used for statistical computing and data analysis.It is available across widely used platforms like Windows, Linux, and MacOS.
- R programming is used as a leading tool for machine learning, statistics, and data analysis. Objects, functions, and packages can easily be created by R.
- As R programming language is an open source. Thus, you can run R anywhere and at any time.
- Based on the data type of a variable, the operating system allocates memory and decides what can be stored in the reserved memory.
- The data types in R are: vectors, lists, matrices, arrays, factors and data frames.
- Factors are the r-objects which are created using a vector. It stores the vector along with the distinct values of the elements in the vector as labels.
- A valid variable name consists of letters, numbers and the dot or underline characters.
- The variables can be assigned values using leftward, rightward and equal to operator.
- An operator is a symbol that tells the compiler to perform specific mathematical or logical manipulations. R language is rich in built-in operators and provides the following types of operators.
- A function is a set of statements organized together to perform a specific task. R has many in-built functions, and the user can create their own functions.

Keywords

- **R**: R is an interpreted language that supports both procedural programming and object-oriented programming. This is an implementation of the S programming language.
- **RStudio**: R Studio is an integrated development environment(IDE) for R. IDE is a GUI, where you can write your quotes, see the results, and also see the variables that are generated during the course of programming.

- **R Objects**: The variables are assigned with R-Objects and the data type of the R-object becomes the data type of the variable. There are many types of R-objects.
- **Lists:**A list is an R-object which can contain many different types of elements inside it like vectors, functions and even another list inside it.
- **Variable in R:**A variable provides us with named storage that our programs can manipulate. A variable in R can store an atomic vector, group of atomic vectors or a combination of many Robjects.
- **Loops**: A loop statement allows us to execute a statement or group of statements multiple times and the following is the general form of a loop statement in most of the programming languages.

SelfAssessment

1. R language is used for

A. Statistical computing
B. Data analysis
C. Fixing the bugs
D. All of the above

2. R language is available across

A. Windows
B. MAC
C. Linux
D. All of the above

3. R is an interpreted language which supports

A. Only procedural programming
B. Object-oriented programming
C. Both procedural and object-oriented programming
D. None of the above

4. Which of the following are the data types in R programming language?

A. Vectors
B. Lists
C. Data frames
D. All of the above mentioned

5. Which attribute creates the required number of dimensions in arrays?

A. dimension
B. dim
C. sides
D. All of the above

6. The values of the variables can be printed using

A. Cat()
B. Print()
C. Both above mentioned
D. None of the above

7. The decision-making structures in R programming languages are
A. If statement
B. If-else statement
C. Switch statement
D. All the above

8. In switch statement, the number of cases allowed are:
A. 1
B. 2
C. 3
D. Any

9. Each case in switch statement is followed by the value to be compared to and a ……..
A. Colon
B. Comma
C. Semi-colon
D. Asterisk

10. The kinds of loops in R language are
A. While loop
B. Repeat loop
C. For loop
D. All of the above

11. Loop control statements in R are
A. Break statement
B. Next statement
C. Both of the above
D. None of the above

12. Which of the following are the function components?
A. Function body
B. Function name
C. Arguments
D. All of the above mentioned

13. The strings in R programming language can be written in
A. Single quotes
B. Double quotes
C. Either single of double quotes
D. None of the above

14. The concatenation of strings can be done using
A. paste()
B. format()
C. nchar()
D. substring()

15. The numbers and strings can be formatted to a specific style using
A. paste()
B. format()
C. nchar()
D. substring()

Answers for Self Assessment

l.	D	2.	D	3.	C	4.	D	5.	B
6.	D	7.	D	8.	D	9.	A	10.	D
11.	C	12.	D	13.	D	14.	A	15.	B

Review Questions

1. Why is R programming language used? Also explain the features of R programming language.
2. What are the advantages and disadvantages of R programming language?
3. What is a data type? Which data types exist in R programming language?
4. What is a vector object? How do we create a vector, and get the class of a vector?
5. What are operators? Explain its types.
6. What is decision making structures in R programming language? Explain.

Further Readings

https://www.r-project.org/about.html

https://www.geeksforgeeks.org/r-programming-language-introduction/

Unit 14: NumPy and Pandas

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Summary

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Objectives

After studying this unit, you will be able to:

- Understand the basics of Python
- Understand data types in python
- Understand NumPy and its data types
- Understand different NumPy operations
- Understand NumPy sorting and filter arrays
- Understand random numbers in NumPy
- Understand the basic concept of pandas and its data structures
- Understand how to clean the data and various preprocessing operations

Introduction

Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. These are the features of Python programming language.

14.1 Python

- Interpreted - An interpreted language is a programming language which are generally interpreted, without compiling a program into machine instructions. It is one where the instructions are not directly executed by the target machine, but instead read and executed by some other program.
- Object-oriented - Object-oriented language is a high-level computer programming language that implements objects and their associated procedures within the programming context to create software programs. Object-oriented language uses an object-oriented programming technique that binds related data and functions into an object and encourages reuse of these objects within the same and other programs.
- High-level - Python is a high-level language which just means that it's simpler for a human to use. Low-level languages such as C/C++ require a much more detailed understanding of how a computer works. With a high-level language, many of these details are abstracted away to make your life easier. Python uses dynamic semantics, meaning that its variables are dynamic objects.

Few Other Features of Python are

1. Popular
2. User-friendly
3. Simple
4. Highly powerful
5. Open source
6. General purpose

Comparison with other language

Python is often compared to other interpreted languages such as Java, JavaScript, Perl, Tcl, or Smalltalk.

1. Java - Python programs are generally expected to run slower than Java programs, but they also take much less time to develop. Python programs are typically 3-5 times shorter than equivalent Java programs. This difference can be attributed to Python's built-in high-level data types and its dynamic typing.
2. Javascript - Python's "object-based" subset is roughly equivalent to JavaScript. Like JavaScript (and unlike Java), Python supports a programming style that uses simple functions and variables without engaging in class definitions.
3. Perl - Perl emphasizes support for common application-oriented tasks, e.g., by having built-in regular expressions, file scanning and report generating features. Python emphasizes support for common programming methodologies such as data structure design and object-oriented programming and encourages programmers to write readable (and thus maintainable) code by providing an elegant but not overly cryptic notation.
4. C++ - Python code is typically 3-5 times shorter than equivalent Java code; it is often 5-10 times shorter than equivalent C++ code.

Uses of Python

Python is a very versatile language. Its uses are:

1.Web applications:Popular frameworks like the Django web application and Flask are written in Python.

2.Desktop applications:The Dropbox client is written in Python.

3.Scientific and numeric computing: Python is the top choice for data science and machine learning.

4.Cybersecurity: Python is excellent for data analysis, writing system scripts that interact with an operating system, and communicating over network sockets.

What can Python do?

1. Python can be used on a server to create web applications.
2. Python can be used alongside software to create workflows.
3. Python can connect to database systems. It can also read and modify files.
4. Python can be used to handle big data and perform complex mathematics.
5. Python can be used for rapid prototyping, or for production-ready software development.

Why to study Python?

1. Python works on different platforms (Windows, Mac, Linux, Raspberry Pi, etc).
2. Python has a simple syntax like the English language.
3. Python has syntax that allows developers to write programs with fewer lines than some other programming languages.
4. Python runs on an interpreter system, meaning that code can be executed as soon as it is written. This means that prototyping can be very quick.
5. Python can be treated in a procedural way, an object-oriented way or a functional way.

Download and install Python

- Open browser
- Open python.org
- Click on downloads
- Download the latest version

Download a Code Editor

- PyCharm
- www.jetbrains.com/pycharm

- Download pycharm
- Download Community edition (free)

14.2 First Python Program

- Open the project.
- Right click on it.
- Create a new python file.
- Save it with extension .py.
- Write the program.
  - Printing anything on screen

```
print('Data Science Toolbox')
```

OR

```
print("Data Science Toolbox")
```

- For printing a statement, single or double quotation marks can be used to print anything.

How to run?

1. Go to run →run.
2. Shortcut = Alt + Shift + F10.
3. See the result in the terminal window.

Python Indentation

Indentation refers to the spaces at the beginning of a code line.Where in other programming languages the indentation in code is for readability only, the indentation in Python is very important.Python uses indentation to indicate a block of code. For example

```
if 5 > 2:
print("Five is greater than two!")
```

But this will show the syntax error

```
if 5 > 2:
print("Five is greater than two!")
```

Python comments

Comments can be used to explain Python code.Comments can be used to make the code more readable.Comments can be used to prevent execution when testing code. Comments can be created using a specific way in Python. Comments start with # and Python will ignore them. For example:

```
#This is a comment
```

For multiline comments, the Python does not have a syntax for multiline comments. To add a multi-line comment, you need to insert # in every line.

14.3 Python Variables

Variables are containers for storing data values.Python has no command for declaring a variable.A variable is created the moment you first assign a value to it.For example:

```
x = 5
y = "John"
print(x)
print(y)
```

Variables do not need to be declared with any particular type, and can even change type after they have been set. For example:

```
x = 4       # x is of type int
x = "Sally" # x is now of type str
print(x)
```

Type Casting

If you want to specify the data type of a variable, this can be done with casting. For example:

```
x = str(3)    # x will be '3'
y = int(3)    # y will be 3
z = float(3)  # z will be 3.0
```

Gettingthe type of a variable

You can get the data type of a variable with the type () function.

```
x = 5
y = "John"
print(type(x))
print(type(y))
```

Declaration of variables

String variables can be declared either by using single or double quotes: For example:

```
x = "John"
# is the same as
x = 'John'
```

Case-sensitiveness

Variable names are case-sensitive in nature.

```
a = 4
A = "Sally"
#A will not overwrite a
```

Rules for variable names

A variable can have a short name (like x and y) or a more descriptive name (age, carname, total_volume). The rules for Python variables:

- A variable name must start with a letter or the underscore character
- A variable name cannot start with a number
- A variable name can only contain alpha-numeric characters and underscores (A-z, 0-9, and_)
- Variable names are case-sensitive (age, Age and AGE are three different variables)

Few Legal variable names are

```
myvar = "John"
my_var = "John"
_my_var = "John"
myVar = "John"
MYVAR = "John"
myvar2 = "John"
```

Few Illegal variable names are

```
2myvar = "John"
```

my-var = "John"

my var = "John"

Variable names with more than one word can be difficult to read. So, for multiword names, the declaration can be different types. These are:

1. Camel Case: Each word, except the first, starts with a capital letter:

myVariableName = "John"

2. Pascal Case: Each word starts with a capital letter:

MyVariableName = "John"

3. Snake case: Each word is separated by an underscore character:

my_variable_name = "John"

For assigning multiple values, there are different ways. These are

1. Many Values to Multiple Variables: Python allows you to assign values to multiple variables in one line:

x, y, z = "Orange", "Banana", "Cherry"

print(x)

print(y)

print(z)

2. One Value to Multiple Variables: You can assign the same value to multiple variables in one line:

x = y = z = "Orange"

print(x)

print(y)

print(z)

3. Unpack a Collection: If you have a collection of values in a list, tuple etc. Python allows you to extract the values into variables. This is called unpacking.

fruits = ["apple", "banana", "cherry"]

x, y, z = fruits

print(x)

print(y)

print(z)

Output variables

The python print () function is used to output variables.

- x = "Python is awesome"

  print(x)

In the print () function, you can output multiple variables separated by a comma

- x = "Python"

  y = "is"

  z = "awesome"

  print (x, y, z)

You can also use + operator to output multiple variables.

- x = "Python "

  y = "is "

  z = "awesome"

  print (x + y + z)

14.4 Python Data Types

In all programming languages, data types are used to classify one particular type of data.This is important because the specific data type you use will determine what values you can assign to it and what you can do to it (including what operations you can perform on it).

Numbers

Python's core objects set includes the usual suspects:

- Integers (numbers without a fractional part),
- Floating-point numbers (roughly, numbers with a decimal point in them),
- Exotic numeric types (complex numbers with imaginary parts, fixed-precision decimals, rational fractions with numerator and denominator, and full featured sets).

Numbers in Python support normal mathematical operations. For instance, the plus sign (+) performs addition, a star (*) is used for multiplication, and two stars (**) are used for exponentiation:

- >>>123 + 222 # *Integer addition*

  345

- >>>1.5 * 4 # *Floating-point multiplication*

  6.0

- >>>2 ** 100 # *2 to the power 100*

  1267650600228229401496703205376

Besides expressions, there are a handful of useful numeric modules that ship with Python—modules are just packages of additional tools that we import to use:

>>> import math

>>>math.pi

3.1415926535897931

>>>math.sqrt(85)

9.2195444572928871

Random module performs random number generation and random selections

>>> import random

>>>random.random()

0.59268735266273953

>>>random.choice([1, 2, 3, 4])

1

Strings

Strings are used to record textual information as well as arbitrary collections of bytes.A sequence in Python—that is, a positionally ordered collection of other objects. Sequences maintain a left-to-right order among the items they contain: their items are stored and fetched by their relative position.

Sequence Operations

1. Indexing:

As sequences, strings support operations that assume a positional ordering among items. For example, if we have a four-character string, we can verify its length with the built-in len function and fetch its components with indexing expressions:

```
>>> S = 'Spam'
>>>len(S)                    # Length
4
>>> S[0]                          # The first item in S, indexing by zero-based position
'S'
>>>S[1]                    # The second item from the left
'p'
```

In Python, indexes are coded as offsets from the front, and so start from 0: the first item is at index 0, the second is at index 1, and so on.Python variables never need to be declared ahead of time. A variable is created when you assign it a value, may be assigned any type of object, and is replaced with its value when it shows up in an expression. It must also have been previously assigned by the time you use its value.In Python, we can also index backward, from the end—positive indexes count from the left, and negative indexes count back from the right:

```
>>>S[-1]          # The last item from the end in S
'm'
>>>S[-2]          # The second to last item from the end
'a'
```

2. Slicing

In addition to simple positional indexing, sequences also support a more general form of indexing known as slicing, which is a way to extract an entire section (slice) in a single step. For example:

```
>>>S                    # A 4-character string
'Spam'
>>>S[1:3]               # Slice of S from offsets 1 through 2 (not 3)
'pa'
```

The easiest way to think of slices is that they are a way to extract an entire column from a string in a single step. Their general form, X [I: J], means "give me everything in X from offset I up to but not including offset J."In a slice, the left bound defaults to zero, and the right bound defaults to the length of the sequence being sliced. This leads to some common usage variations:

```
>>>S[1:]                 # Everything past the first (1:len(S))
'pam'
>>>S                          # S itself hasn't changed
'Spam'
>>>S[0:3]                     # Everything but the last
'Spa'
>>>S[:3]                 # Same as S[0:3]
'Spa'
>>>S[:-1]                # Everything but the last again, but simpler (0:-1)
'Spa'
>>>S[:]                  # All of S as a top-level copy (0:len(S))
'Spam'
```

3. Concatenation:

As sequences, strings also support concatenation with the plus sign (joining two strings into a new string) and repetition (making a new string by repeating another):

```
>>>S
Spam'
>>>S + 'xyz'                    # Concatenation
'Spamxyz'
>>>S                            # S is unchanged
'Spam'
>>>S * 8                        # Repetition
'SpamSpamSpamSpamSpamSpamSpamSpam'
```

4. Type specific methods

- Find

The string find method is the basic substring search operation (it returns the offset of the passed-in substring, or −1 if it is not present),

```
>>>S.find('pa')                 # Find the offset of a substring
1
>>>S
'Spam'
```

- Replace

The string replace method performs global searches and replacements:

```
>>>S.replace('pa', 'XYZ')       # Replace occurrences of a substring with another
'SXYZm'
>>>S
'Spam'
```

Despite the names of these string methods, we are not changing the original strings here, but creating new strings as the results—because strings are immutable, we have to do it this way. String methods are the first line of text-processing tools in Python. Other methods split a string into substrings on a delimiter (handy as a simple form of parsing), perform case conversions, test the content of the string (digits, letters, and so on), and strip whitespace characters off the ends of the string:

```
>>> line = 'aaa,bbb,ccccc,dd'
>>>line.split(',')             # Split on a delimiter into a list of substrings
['aaa', 'bbb', 'ccccc', 'dd']
>>> S = 'spam'
>>>S.upper()                   # Upper- and lowercase conversions
'SPAM'
>>>S.isalpha()                 # Content tests: isalpha, isdigit, etc.
True
>>> line = 'aaa,bbb,ccccc,dd\n'
>>> line = line.rstrip()       # Remove whitespace characters on the right side
>>> line
    'aaa,bbb,ccccc,dd'
```

14.5 Lists

The Python list object is the most general sequence provided by the language. The lists are positionally ordered collections of arbitrarily typed objects, and they have no fixed size. They are also mutable—unlike strings, lists can be modified in-place by assignment to offsets as well as a variety of list method calls.

Sequence operations

Because they are sequences, lists support all the sequence operations as strings; the only difference is that the results are usually lists instead of strings.

```
>>>L = [123, 'spam', 1.23]          # A list of three different-type objects
>>>len(L)                           # Number of items in the list
3
>>>L[0]                             # Indexing by position
123
>>>L[:-1]                           # Slicing a list returns a new list
[123, 'spam']
>>>L + [4, 5, 6]                    # Concatenation makes a new list too
[123, 'spam', 1.23, 4, 5, 6]
>>>L                                # We're not changing the original list
[123, 'spam', 1.23]
```

Type specific operations

Python's lists are related to arrays in other languages, but they tend to be more powerful. For one thing, they have no fixed type of constraint—the list we just looked at, for example, contains three objects of completely different types (an integer, a string, and a floating-point number). Further, lists have no fixed size. That is, they can grow and shrink on demand, in response to list-specific operations.

```
>>>L.append('NI')                   # Growing: add object at end of list
>>>L
[123, 'spam', 1.23, 'NI']
>>>L.pop(2)                         # Shrinking: delete an item in the middle
1.23
>>> L                               # "del L[2]" deletes from a list too
[123, 'spam', 'NI']
```

Because lists are mutable, most list methods also change the list object in-place, instead of creating a new one:

```
>>> M = ['bb', 'aa', 'cc']
>>>M.sort()
>>> M
['aa', 'bb', 'cc']
>>>M.reverse()
>>> M
['cc', 'bb', 'aa']
```

Although lists have no fixed size, Python still doesn't allow us to reference items that are not present. Indexing off the end of a list is always a mistake, but so is assigning off the end:

```
>>>L
```

[123, 'spam', 'NI']

>>>L [99]

...error text omitted...

IndexError: list index out of range

Nesting

One nice feature of Python's core data types is that they support arbitrary nesting—we can nest them in any combination, and as deeply as we like One immediate application of this feature is to represent matrixes, or "multidimensional arrays" in Python. A list with nested lists will do the job for basic applications:

>>>M = [[1, 2, 3], # A 3 × 3 matrix, as nested lists

[4, 5, 6], # Code can span lines if bracketed

[7, 8, 9]]

>>>M

[[1, 2, 3], [4, 5, 6], [7, 8, 9]]

Here, we've coded a list that contains three other lists. The effect is to represent a 3 × 3 matrix of numbers. Such a structure can be accessed in a variety of ways:

>>>M[1] # Get row 2

[4, 5, 6]

>>>M[1][2] # Get row 2, then get item 3 within the row

6

14.6 Dictionaries

Python dictionaries are something completely different they are not sequences at all, but are instead known as mappings. Mappings are also collections of other objects, but they store objects by key instead of by relative position. In fact, mappings don't maintain any reliable left-to-right order; they simply map keys to associated values. Dictionaries, the only mapping type in Python's core objects set, are also mutable: they may be changed in-place and can grow and shrink on demand, like lists.

Mapping Operations

1) When written as literals, dictionaries are coded in curly braces and consist of a series of "key: value" pairs. Dictionaries are useful anytime we need to associate a set of values with keys—to describe the properties of something, for instance. As an example, consider the following three-item dictionary (with keys "food," "quantity," and "color"):

>>> D = {'food': 'Spam', 'quantity': 4, 'color': 'pink'}

2) We can index this dictionary by key to fetch and change the keys' associated values. The dictionary index operation uses the same syntax as that used for sequences, but the item in the square brackets is a key, not a relative position:

>>>D['food'] # *Fetch value of key 'food'*

'Spam'

>>>D['quantity'] += 1 # *Add 1 to 'quantity' value*

>>>D

{'food': 'Spam', 'color': 'pink', 'quantity': 5}

The example starts with an empty dictionary and fills it out one key at a time. Unlike out-of-bounds assignments in lists, which are forbidden, assignments to new dictionary keys create those keys:

>>> D = {}

>>> D['name'] = 'Bob' # *Create keys by assignment*

```
>>> D['job'] = 'dev'
>>> D['age'] = 40
>>> D
{'age': 40, 'job': 'dev', 'name': 'Bob'}
>>> print(D['name'])
Bob
```

14.7 Tuples

The tuple object is roughly like a list that cannot be changed—tuples are sequences, like lists, but they are immutable, like strings. Syntactically, they are coded in parentheses instead of square brackets, and they support arbitrary types, arbitrary nesting, and the usual sequence operations.

```
>>> T = (1, 2, 3, 4)                    # A 4-item tuple
>>>len(T)                               # Length
4
>> T + (5, 6)                           # Concatenation
(1, 2, 3, 4, 5, 6)
>>> T[0]                                # Indexing, slicing, and more
1
```

Type Specific Methods

Tuples also have two type-specific callable methods in Python 3.0, but not nearly as many as lists:

```
>>>T.index(4)                          # Tuple methods: 4 appears at offset 3
3
>>>T.count(4)                          # 4 appears once
1
```

The primary distinction for tuples is that they cannot be changed once created. That is, they are immutable sequences:

```
>>> T[0] = 2                            # Tuples are immutable
...error text omitted...
    TypeError: 'tuple' object does not support item assignment
```

Like lists and dictionaries, tuples support mixed types and nesting, but they don't grow and shrink because they are immutable:

```
>>>T = ('spam', 3.0, [11, 22, 33])
>>>T[1]
3.0
>>>T[2][1]
22
>>>T.append(4)
AttributeError: 'tuple' object has no attribute 'append'
```

Frankly, tuples are not generally used as often as lists in practice, but their immutability is the whole point. If you pass a collection of objects around your program as a list, it can be changed anywhere; if you use a tuple, it cannot. That is, tuples provide a sort of integrity constraint that is convenient in programs.

14.8 Files

File objects are Python code's main interface to external files on your computer. Files are a core type, but they're something of an oddball—there is no specific literal syntax for creating them. Rather, to create a file object, you call the built-in open function, passing in an external filename and a processing mode as strings.To create a text output file, you would pass in its name and the 'w' processing mode string to write data:

```
>>>f = open('data.txt', 'w')          # Make a new file in output mode
>>>f.write('Hello\n')                 # Write strings of bytes to it
6
>>>f.write('world\n')                 # Returns number of bytes written in Python 3.0
6
>>>f.close()                          # Close to flush output buffers to disk
```

This creates a file in the current directory and writes text to it (the filename can be a full directory path if you need to access a file elsewhere on your computer). To read back what you just wrote, reopen the file in 'r' processing mode, for reading text input—this is the default if you omit the mode in the call. Then read the file's content into a string, and display it.A file's contents are always a string in your script, regardless of the type of data the file contains:

```
>>>f = open('data.txt')              # 'r' is the default processing mode
>>>text = f.read()                   # Read entire file into a string
>>>text
'Hello\nworld\n'
>>>print(text)                       # print interprets control characters
Hello
world
>>>text.split()                      # File content is always a string
['Hello', 'world']
```

14.9 Other Core Data Types

1.Sets

2.Booleans

1. Sets

Sets are neither mappings nor sequences; rather, they are unordered collections of unique and immutable objects. Sets are created by calling the built-in set function or using new set literals and expressions in 3.0, and they support the usual mathematical set operations (the choice of new {...} syntax for set literals in 3.0 makes sense, since sets are much like the keys of a valueless dictionary).

```
>>>X = set('spam')                   # Make a set out of a sequence in 2.6 and 3.0
>>>Y = {'h', 'a', 'm'}               # Make a set with new 3.0 set literals
>>>X, Y
({'a', 'p', 's', 'm'}, {'a', 'h', 'm'})
>>> X & Y                           # Intersection
{'a', 'm'}
>>> X | Y                           # Union
{'a', 'p', 's', 'h', 'm'}
>>>X – Y                           # Difference
```

{'p', 's'}

>>>{x ** 2 for x in [1, 2, 3, 4]} # *Set comprehensions in 3.0*

{16, 1, 4, 9}

2. Booleans

Python also comes with Booleans (with predefined True and False objects that are essentially just the integers 1 and 0 with custom display logic), and it has long supported a special placeholder object called None commonly used to initialize names and objects:

>>> 1 > 2, 1 < 2 # Booleans

(False, True)

>>> bool('spam')

True

>>> X = None # *None placeholder*

>>> print(X)

None

>>> L = [None] * 100 ` # *Initialize a list of 100 Nones*

>>> L

[None, ...a list of 100 Nones...]

14.10 NumPy

It is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays.NumPy is open-source software and has many contributors.

Why use NumPy?

- In Python we have lists that serve the purpose of arrays, but they are slow to process. NumPy aims to provide an array object that is up to 50x faster than traditional Python lists.
- The array object in numpy is called ndarray, it provides a lot of supporting functions that make working with ndarray very easy.
- Arrays are very frequently used in data science, where speed and resources are very important.

Why is numPy faster than lists?

NumPy arrays are stored at one continuous place in memory unlike lists, so processes can access and manipulate them very efficiently.This behavior is called locality of reference.

Language of numPy

NumPy is a Python library and is written partially in Python, but most of the parts that require fast computation are written in C or C++.

Installation of numpy

If you have Python and PIP already installed on a system, then installation of NumPy is very easy.

C:\Users\Your Name>pip install numpy

Import numPy

Once NumPy is installed, import it in your applications by adding the import keyword.

import numpy

Simple example

import numpy

arr = numpy.array([1, 2, 3, 4, 5])

print(arr)

Output: [1 2 3 4 5]

Creating Alias

Alias is an alternative name for referring the same thing.NumPy is usually imported under the np aliases.Use as here: import numpy as np. Now the numpy package can be referred to as np instead of numpy.

See the difference

- import numpy

  arr = numpy.array([1, 2, 3, 4, 5])

  print(arr)

- import numpy as np

  arr = np.array([1, 2, 3, 4, 5])

  print(arr)

ndarray data structure

The core functionality of NumPy is its "ndarray", for n-dimensional array, data structure. In contrast to Python's built-in list data structure, these arrays are homogeneously typed: all elements of a single array must be of the same type.

Creating arrays

NumPy is used to work with arrays. The array object in NumPy is called ndarray. We can create a NumPy ndarray object by using array() function.

import numpy as np

arr = np.array([1, 2, 3, 4, 5])

print(arr)

Output: [1 2 3 4 5]

To create an ndarray, we can pass a list, tuple or any array-like object into the array() method and it will be converted into an ndarray.

- Use a tuple to create a NumPy array:

import numpy as np

arr = np.array((1, 2, 3, 4, 5))

print(arr)

Output: [1 2 3 4 5]

Dimensions in Arrays

A dimension in arrays is one level of array depth. The nested arrays are the arrays that have arrays as their elements.

0-D arrays

0-D arrays, or Scalars, are the elements in an array. Each value in an array is a 0-D array.Example: Create a 0-D array with element 42.

import numpy as np

arr = np.array(42)

print(arr)

Output: 42

1-D arrays

An array that has 0-D arrays as its elements is called uni-dimensional or 1-D array. These are the most common and basic arrays.Example: Create a 1-D array containing the values 1,2,3,4,5:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5])

print(arr)
```

Output: [1 2 3 4 5]

2-D arrays

An array that has 1-D arrays as its elements is called a 2-D array. These are often used to represent matrix or 2nd order tensors.Example: Create a 2-D array containing two arrays with the values 1,2,3 and 4,5,6:

```
import numpy as np

arr = np.array([[1, 2, 3], [4, 5, 6]])

print(arr)
```

Output**:** [[1 2 3]

[4 5 6]]

3-D arrays

An array that has 2-D arrays (matrices) as its elements is called 3-D array. These are often used to represent a 3rd order tensor.Example: Create a 3-D array with two 2-D arrays, both containing two arrays with the values 1,2,3 and 4,5,6:

```
import numpy as np

arr = np.array([[[1, 2, 3], [4, 5, 6]], [[1, 2, 3], [4, 5, 6]]])

print(arr)
```

Output: [[[1 2 3]

[4 5 6]]

[[1 2 3]

[4 5 6]]]

Check the number of dimensions

NumPy Arrays provides the ndim attribute that returns an integer that tells us how many dimensions the array has.Example: Check how many dimensions the arrays have:

```
import numpy as np

a = np.array(42)

b = np.array([1, 2, 3, 4, 5])

c = np.array([[1, 2, 3], [4, 5, 6]])

d = np.array([[[1, 2, 3], [4, 5, 6]], [[1, 2, 3], [4, 5, 6]]])

print(a.ndim)

print(b.ndim)

print(c.ndim)

print(d.ndim)
```

Output:

0

1

2

3

Higher Dimensional Arrays

An array can have any number of dimensions. When the array is created, you can define the number of dimensions by using the ndmin argument.Example: Create an array with 5 dimensions and verify that it has 5 dimensions:

```
import numpy as np

arr = np.array([1, 2, 3, 4], ndmin=5)

print(arr)

print('number of dimensions :', arr.ndim)
```

Output: [[[[[1 2 3 4]]]]]

Number of dimensions : 5

14.11 Operations on NumPy Arrays

indexing

Array indexing is the same as accessing an array element.You can access an array element by referring to its index number.The indexes in NumPy arrays start with 0, meaning that the first element has index 0, and the second has index 1 etc.

- Example: Get the first element from the following array:

```
import numpy as np

arr = np.array([1, 2, 3, 4])

print(arr[0])
```

Output: 1

- Example: Get the second element from the following array:

```
import numpy as np

arr = np.array([1, 2, 3, 4])

print(arr[1])
```

Output: 2

- Example: Get third and fourth elements from the following array and add them.

```
import numpy as np

arr = np.array([1, 2, 3, 4])

print(arr[2] + arr[3])
```

Output: 7

Access 2-D arrays:

To access elements from 2-D arrays we can use comma separated integers representing the dimension and the index of the element.Think of 2-D arrays like a table with rows and columns, where the row represents the dimension, and the index represents the column.

- Example: Access the element on the first row, second column:

```
import numpy as np

arr = np.array([[1,2,3,4,5], [6,7,8,9,10]])

print ('2nd element on 1st row: ', arr[0, 1])
```

Output: 2nd element on 1st row: 2

- Example: Access the element on the 2nd row, 5th column:

```
import numpy as np

arr = np.array([[1,2,3,4,5], [6,7,8,9,10]])


print ('5th element on 2nd row: ', arr[1, 4])
```

Output: 5th element on 2nd row: 10

Access 3-D arrays:

To access elements from 3-D arrays we can use comma separated integers representing the dimensions and the index of the element.Example: Access the third element of the second array of the first array:

```
import numpy as np

arr = np.array([[[1, 2, 3], [4, 5, 6]], [[7, 8, 9], [10, 11, 12]]])

print (arr[0, 1, 2])
```

Output: 6

Slicing

Slicing in python means taking elements from one given index to another given index.We pass slice instead of index like this: [start:end]. We can also define the step, like this: [start:end:step]. If we don't pass start its considered 0, if we don't pass end its considered length of array in thatdimension and if we don't pass step its considered 1.Example: Slice elements from index 1 to index 5 from the following array:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5, 6, 7])

print(arr[1:5])
```

Output: [2 3 4 5]

- Example: Slice elements from index 4 to the end of the array:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5, 6, 7])

print(arr[4:])
```

Output: [5 6 7]

- Example: Slice elements from index 4 to the end of the array:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5, 6, 7])

print(arr[:4])
```

Output: [1 2 3 4]

Negative slicing: Use the minus operator to refer to an index from the end.

- Example: Slice from the index 3 from the end to index 1 from the end:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5, 6, 7])

print(arr[-3:-1])
```

Output: [5 6]

- Example: Return every other element from index 1 to index 5:

```
import numpy as np
arr = np.array([1, 2, 3, 4, 5, 6, 7])
print(arr[1:5:2])
```

Output: [2 4]

- Example: Return every other element from the entire array:

```
import numpy as np
arr = np.array([1, 2, 3, 4, 5, 6, 7])
print(arr[::2])
```

Output: [1 3 5 7]

Slicing 2-D arrays

Example: From the second element, slice elements from index 1 to index 4 (not included):

```
import numpy as np
arr = np.array([[1,2,3,4,5],[6,7,8,9,10]])
print (arr[1, 1:4])
```

Output: [7 8 9]

14.12 Data Types in NumPy

NumPy has some extra data types. It refers to data types with only one character, like I for integers, u for unsigned integers, etc. These are:

- i-integer
- b-boolean
- u-unsigned integer
- f-float
- c-complex float
- m-timedelta
- M-datetime
- O-object
- S-string
- U-Unicode string
- V-fixed chunk of memory for other type

Checking the data type of an array

The numPy array object has a property called dtype that return the data type of the array.

```
import numpy as np
arr = np.array([1, 2, 3, 4])
print(arr.dtype)
import numpy as np
arr = np.array(['apple', 'banana', 'cherry'])
print(arr.dtype)
```

14.13 Creating Arrays

We use the array () function to create arrays. The dtype() function is used to define the data type of the array elements. For example: Create an array with data type string:

```
import numpy as np

arr = np.array([1, 2, 3, 4], dtype='S')

print(arr)

print(arr.dtype)
```

For i, u, f, S and U we can define the size as well. For example: Create an array with data type 4 bytes' integer:

```
import numpy as np

arr = np.array([1, 2, 3, 4], dtype='i4')

print(arr)

print(arr.dtype)
```

If a type is given in which elements can't be casted then NumPy will raise a ValueError. ValueError: In Python ValueError is raised when the type of passed argument to a function is unexpected/incorrect. Example: A non-integer string like 'a' cannot be converted to integer (will raise an error):

```
import numpy as np
arr = np.array(['a', '2', '3'], dtype='i')
```

Converting data types on existing arrays

The best way to change the data type of an existing array, is to make a copy of the array with the astype() method. The astype() function creates a copy of the array and allows you to specify the data type as a parameter. The data type can be specified using a string, like 'f' for float, 'i' for integer etc. or you can use the data type directly like float for float and int for int. For example: Change data type from float to integer by using 'i' as parameter value:

```
import numpy as np

arr = np.array([1.1, 2.1, 3.1])

newarr = arr.astype('i')

print(newarr)

print(newarr.dtype)
```

Example: Change data type from float to integer by using int as parameter value:

```
import numpy as np

arr = np.array([1.1, 2.1, 3.1])

newarr = arr.astype(int)

print(newarr)

print(newarr.dtype)
```

Example: Change data type from integer to boolean:

```
import numpy as np

arr = np.array([1, 0, 3])

newarr = arr.astype(bool)

print(newarr)

print(newarr.dtype)
```

14.14 NumPy Operations

NumPy copy vs View

The main difference between a copy and a view of an array is that the copy is a new array, and the view is just a view of the original array.The copy owns the data and any changes made to the copy will not affect original array, and any changes made to the original array will not affect the copy.The view does not own the data and any changes made to the view will affect the original array, and any changes made to the original array will affect the view.

Example: Make a copy, change the original array, and display both arrays:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5])

x = arr.copy()

arr[0] = 42

print(arr)

print(x)
```

Example: Make a view, change the original array, and display both arrays:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5])

x = arr.view()

arr[0] = 42

print(arr)

print(x)
```

Make changes in view

Example: Make a view, change the view, and display both arrays:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5])

x = arr.view()

x[0] = 31

print(arr)

print(x)
```

Check if Array owns its data

Copies owns the data, and views does not own the data, but how can we check this? Every NumPy array has the attribute base that returns none if the array owns the data. Otherwise, the base attribute refers to the original object.

Example: Print the value of the base attribute to check if an array owns it's data or not:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5])

x = arr.copy()

y = arr.view()

print(x.base)

print(y.base)
```

14.15 NumPy Array Shape

The shape of an array is the number of elements in each dimension. NumPy arrays have an attribute called shape that returns a tuple with each index having the number of corresponding elements. Example: Print the shape of a 2D array

```
import numpy as np

arr = np.array([[1, 2, 3, 4], [5, 6, 7, 8]])

print(arr.shape)
```

Example: Create an array with 5 dimensions using ndim using a vector with values 1,2,3,4 and verify that last dimension has value 4:

```
import numpy as np

arr = np.array([1, 2, 3, 4], ndmin=5)

print(arr)

print ('shape of array :', arr.shape)
```

14.16 Reshaping NumPy arrays

Reshaping means changing the shape of an array. The shape of an array is the number of elements in each dimension. By reshaping we can add or remove dimensions or change number of elements in each dimension.

Reshape from 1-D to 2-D

Example: Convert the following 1-D array with 12 elements into a 2-D array. The outermost dimension will have 4 arrays, each with 3 elements:

```
import numpy as np

arr = np.array([1,2,3,4,5,6,7,8,9,10,11,12])

newarr = arr.reshape(4, 3)

print(newarr)
```

Reshape from 1-D to 3-D

Example: Convert the following 1-D array with 12 elements into a 3-D array. The outermost dimension will have 2 arrays that contains 3 arrays, each with 2 elements:

```
import numpy as np

arr = np.array([1,2,3,4,5,6,7,8,9,10,11,12])

newarr = arr.reshape(2, 3, 2)

print(newarr)
```

14.17 NumPy Array Iterating

Iterating means going through elements one by one. As we deal with multi-dimensional arrays in numpy, we can do this using basic for loop of python. If we iterate on a 1-D array it will go through each element one by one.

Example: Iterate on the elements of the following 1-D array:

```
import numpy as np

arr = np.array([1, 2, 3])

for x in arr:

print(x)
```

Example: Iterate on the elements of the following 2-D array:

```
import numpy as np
arr = np.array([[1, 2, 3], [4, 5, 6]])
for x in arr:
print(x)
```

Example: Iterate on the elements of the following 3-D array:

```
import numpy as np
arr = np.array([[[1, 2, 3], [4, 5, 6]], [[7, 8, 9], [10, 11, 12]]])
for x in arr:
print(x)
```

14.18 Joining NumPy Arrays

Joining means putting contents of two or more arrays in a single array.In SQL we join tables based on a key, whereas in NumPy we join arrays by axes.We pass a sequence of arrays that we want to join to the concatenate () function, along with the axis. If the axis is not explicitly passed, it is taken as 0.

- Example: Join two arrays

```
import numpy as np
arr1 = np.array([1, 2, 3])
arr2 = np.array([4, 5, 6])
arr = np.concatenate((arr1, arr2))
print(arr)
```

- Example: Join two 2-D arrays along rows (axis=1):

```
import numpy as np
arr1 = np.array([[1, 2], [3, 4]])
arr2 = np.array([[5, 6], [7, 8]])
arr = np.concatenate((arr1, arr2), axis=1)
print(arr)
```

Joining NumPy Arrays using Stack Functions

Stacking is same as concatenation; the only difference is that stacking is done along a new axis. We can concatenate two 1-D arrays along the second axis which would result in putting them one over the other, ie. stacking. We pass a sequence of arrays that we want to join to the stack () method along with the axis. If the axis is not explicitly passed it is taken as 0.

Example:

```
import numpy as np
arr1 = np.array([1, 2, 3])
arr2 = np.array([4, 5, 6])
arr = np.stack((arr1, arr2), axis=1)
print(arr)
```

1. Stacking Along Rows: NumPy provides a helper function hstack() to stack along rows.

```
import numpy as np
arr1 = np.array([1, 2, 3])
```

```
arr2 = np.array([4, 5, 6])
arr = np.hstack((arr1, arr2))
print(arr)
```

2. Stacking Along Columns: NumPy provides a helper function vstack() to stack along columns.

```
import numpy as np
arr1 = np.array([1, 2, 3])
arr2 = np.array([4, 5, 6])
arr = np.vstack((arr1, arr2))
print(arr)
```

3. Stacking Along Height (depth): NumPy provides a helper function dstack() to stack along height, which is the same as depth.

```
import numpy as np
arr1 = np.array([1, 2, 3])
arr2 = np.array([4, 5, 6])
arr = np.dstack((arr1, arr2))
print(arr)
```

14.19 NumPy Splitting Arrays

Splitting is the reverse operation of Joining. Joining merges multiple arrays into one and Splitting breaks one array into multiple. We use array_split () for splitting arrays, we pass it the array we want to split and the number of splits.

Example: Split the array in 3 parts:

```
import numpy as np
arr = np.array([1, 2, 3, 4, 5, 6])
newarr = np.array_split(arr, 3)
print(newarr)
```

The return value of the array_split() method is an array containing each of the split as an array. If you split an array into 3 arrays, you can access them from the result just like any array element:

14.20 NumPy Array Search

You can search an array for a certain value and return the indexes that get a match. To search an array, use the where () method.

Example: Find the indexes where the value is 4:

```
import numpy as np
arr = np.array([1, 2, 3, 4, 5, 4, 4])
x = np.where(arr == 4)
print(x)
```

There is a method called search sorted () which performs a binary search in the array and returns the index where the specified value would be inserted to maintain the search order.

14.21 NumPy Sorting arrays

Sorting means putting elements in an ordered sequence. Ordered sequence is any sequence that has an order corresponding to elements, like numeric or alphabetical, ascending or descending. The NumPy ndarray object has a function called sort () that will sort a specified array.

Example: Sort the array

```
import numpy as np

arr = np.array([3, 2, 0, 1])

print(np.sort(arr))
```

O/P: [0 1 2 3]

Sort (): This method returns a copy of the array, leaving the original array unchanged.You can also sort arrays of strings, or any other data type. Example: Sort the array alphabetically:

```
import numpy as np

arr = np.array(['banana', 'cherry', 'apple'])

print(np.sort(arr))
```

O/P: [‘apple’, ‘banana’, ‘cherry’]

Example: Sort a boolean array:

```
import numpy as np

arr = np.array([True, False, True])

print(np.sort(arr))
```

O/P: [False True True]

If you use the sort () method on a 2-D array, both arrays will be sorted.Example: Sort a 2-D array:

```
import numpy as np

arr = np.array([[3, 2, 4], [5, 0, 1]])

print(np.sort(arr))
```

O/P: [[2 3 4]

[0 1 5]]

14.22 NumPy Filter Arrays

Gettingsome elements out of an existing array and creating a new array out of them is called filtering.In NumPy, you filter an array using a boolean index list.A boolean index list is a list of booleans corresponding to indexes in the array.If the value at an index is True that element is contained in the filter array, if the element at that index is False that element is excluded from the filter array.Example: Create an array from the elements on index 0 and 2:

```
import numpy as np

arr = np.array([41, 42, 43, 44])

x = [True, False, True, False]

newarr = arr[x]

print(newarr)
```

O/P: [41 43]

Example: Create a filter array that will return only values higher than 42:

```
import numpy as np

arr = np.array([41, 42, 43, 44])

filter_arr = arr > 42

newarr = arr[filter_arr]

print(filter_arr)

print(newarr)
```

O/P: [43 44]

14.23 Random Number in NumPy

Random number does NOT mean a different number every time. Random means something that cannot be predicted logically.NumPy offers the random module to work with random numbers.

Example: Generate a random integer from 0 to 100:

```
from numpy import random

x = random.randint(100)

print(x)
```

The random module's rand method returns a random float between 0 and 1.Example: Generate a random float from 0 to 1:

```
from numpy import random

x = random.rand()

print(x)
```

14.24 Pandas

Pandas is one of the most famous data science tools and it is used for cleaning, manipulating, and analyzing data.The name "Pandas" has a reference to both "Panel Data", and "Python Data Analysis" and was created by Wes McKinney in 2008.Python has a powerful and most popular package 'Pandas' built on top of Numpy which has the implementation of many data objects and data operations.

14.25 Why Pandas?

- Pandas provide tools for reading and writing data into data structures and files.
- It also provides powerful aggregation functions to manipulate data.
- Pandas provide extended data structures to hold different types of labeled and relational data. This makes python highly flexible and extremely useful for data cleaning and manipulation.
- Pandas is highly flexible and provides functions for performing operations like merging, reshaping, joining, and concatenating data.
- Pandas allows us to analyze big data and make conclusions based on statistical theories. Pandas can clean messy data sets and make them readable and relevant. Relevant data is very important in data science.

14.26 Installing and ImportingPandas

File → Settings → python interpreter → + → search pandas → install package.

Once Pandas is installed, import it in your applications by adding the import keyword:import pandas. Pandas is usually imported under the pd alias.Create an alias with the as keyword while importing:

import pandas as pd

Now the Pandas package can be referred to as pd instead of pandas.

14.27 Data Structures of Pandas

There are two main data structures of Pandas. These are:

1. Series

2. Dataframes

1. Pandas Series

The Pandas Series is like a column in a table.It is a one-dimensional array holding data of any type.Example: Create a simple Pandas Series from a list:

import pandas as pd

a = [1, 7, 2]

myvar

= pd.Series(a)

print(myvar)

If nothing else is specified, the values are labeled with their index number. The first value has index 0, second value has index 1 etc.This label can be used to access a specified value.Example: Return the first value of the Series:

print(myvar[0])

With index argument, you can name your own labels.Example: Create your own labels.

import pandas as pd

a = [1, 7, 2]

myvar = pd.Series(a, index = ["x", "y", "z"])

print(myvar)

When you have created labels, you can access an item by referring to the label.Example: Return the value of "y":

print(myvar["y"])

Pandas Dataframes

Data sets in Pandas are usually multi-dimensional tables, called DataFrames. A Pandas DataFrame is a 2 dimensional data structure, like a 2 dimensional array, or a table with rows and columns.Series is like a column, a DataFrame is the whole table.

Example: Create a DataFrame from two Series:

import pandas as pd

data={"calories":[420,380,390],"duration":[50,40,45]}

myvar = pd.DataFrame(data)

print(myvar)

Example: Create a simple Pandas DataFrame:

```
import pandas as pd
data={"calories":[420,380,390],"duration":[50,40,45]}
#load data into a DataFrame object:
df = pd.DataFrame(data)
print(df)
```

Pandas can read CSV files

A simple way to store big data sets is to use CSV files (comma separated files).CSV files contains plain text and is a well know format that can be read by everyone including Pandas.Example: Load the CSV into a DataFrame:

```
import pandas as pd
df = pd.read_csv('data.csv')
print(df.to_string())
```

Use to_string to print the entire DataFrame.

14.28 Data Cleaning

Data cleaning means fixing bad data in your data set. The bad data could be:

1. Empty cells
2. Data in wrong format
3. Wrong data
4. Duplicates

There are various ways to deal with these different things. These are:

1. Cleaning Empty Cells

- Empty cells can potentially give you a wrong result when you analyze data.

A. Remove rows: One way to deal with empty cells is to remove rows that contain empty cells. This is usually OK, since data sets can be very big, and removing a few rows will not have a big impact on the result. Example: Return a new Data Frame with no empty cells:

```
import pandas as pd
df = pd.read_csv('data.csv')
new_df = df.dropna()
print(new_df.to_string())
```

The dropna() method returns a new DataFrame and will not change the original. If you want to change the original DataFrame, use the inplace = True argument.

B. Replace empty cells: Another way of dealing with empty cells is to insert a new value instead. This way you do not have to delete entire rows just because of some empty cells. The fillna() method allows us to replace empty cells with a value:

C. Replace only for specified columns: To only replace empty values for one column, specify the column name for the DataFrame. Example: Replace NULL values in the "Calories" columns with the number 130:

```
import pandas as pd
df = pd.read_csv('data.csv')
df["Calories"]. fillna(130, inplace = True)
```

D. Replace using mean, median or mode: A common way to replace empty cells, is to calculate the mean, median or mode value of the column. Pandas uses the mean (), median () and mode () methods to calculate the respective values for a specified column:

E. Cleaning data of wrong format

Cells with data of wrong format can make it difficult, or even impossible, to analyze data.

How to deal?

1. Convert into a correct format: Try to convert all cells in the 'Date' column into dates. Pandas has a to_datetime() method for this.
2. **Remove the rows:** We can remove the rows by using dropna() method. Example: Remove rows with a NULL value in the "Date" column: df.dropna(subset=['Date'], inplace = True)

3. Cleaning Wrong data

- "Wrong data" does not have to be "empty cells" or "wrong format", it can just be wrong, like if someone registered "199" instead of "1.99". Sometimes you can spot wrong data by looking at the data set, because you have an expectation of what it should be.

How to deal?

1. Replacing values: One way to fix wrong values is to replace them with something else. Example: Set "Duration" = 45 in row 7:

   df.loc[7, 'Duration'] = 45

2. Removing rows: Another way of handling wrong data is to remove the rows that contains wrong data. This way you do not have to find out what to replace them with, and there is a good chance you do not need them to do your analyses.

Duplicating Rows: Duplicate rows are rows that have been registered more than one time. To discover duplicates, we can use the duplicated () method. This method returns a Boolean value for each row. Duplicate rows are rows that have been registered more than one time.

Example: Returns True for every row that is a duplicate, otherwise False.

```
print(df.duplicated())
```

How to deal?

1) Removing duplicates: To remove duplicates, use the drop_duplicates() method. Example: Remove all duplicates:

df.drop_duplicates(inplace = True)

14.29 Data Transformation Operations

1. Rescaling data
2. Normalizing data
3. Binarizing data
4. Standardizing data
5. Label encoding
6. One hot encoding

Summary

- Indentation refers to the spaces at the beginning of a code line.Where in other programming languages the indentation in code is for readability only, the indentation in Python is very important.Python uses indentation to indicate a block of code.

- Comments can be used to explain Python code.Comments can be used to make the code more readable.Comments can be used to prevent execution when testing code. Comments can be created using a specific way in Python. Comments start with # and Python will ignore them.
- Strings are used to record textual information as well as arbitrary collections of bytes.A sequence in Python—that is, a positionally ordered collection of other objects. Sequences maintain a left-to-right order among the items they contain: their items are stored and fetched by their relative position.
- Python also comes with Booleans (with predefined True and False objects that are essentially just the integers 1 and 0 with custom display logic), and it has long supported a special placeholder object called None commonly used to initialize names and objects:
- The core functionality of NumPy is its "ndarray", for n-dimensional array, data structure. In contrast to Python's built-in list data structure, these arrays are homogeneously typed: all elements of a single array must be of the same type.

Keywords

- **Interpreted:**An interpreted language is a programming language which are generally interpreted, without compiling a program into machine instructions. It is one where the instructions are not directly executed by the target machine, but instead read and executed by some other program.
- **Object-oriented:**Object-oriented language is a high-level computer programming language that implements objects and their associated procedures within the programming context to create software programs.Object-oriented language uses an object-oriented programming technique that binds related data and functions into an object and encourages reuse of these objects within the same and other programs.
- **High-level:**Python is a high-level language which just means that it's simpler for a human to use. Low-level languages such as C/C++ require a much more detailed understanding of how a computer works.With a high-level language, many of these details are abstracted away to make your life easier. Python uses dynamic semantics, meaning that its variables are dynamic objects.
- **Python variables:**Variables are containers for storing data values.Python has no command for declaring a variable.A variable is created the moment you first assign a value to it.
- **Sets**: These are neither mappings nor sequences; rather, they are unordered collections of unique and immutable objects. Sets are created by calling the built-in set function or using new set literals and expressions in 3.0, and they support the usual mathematical set operations (the choice of new {...} syntax for set literals in 3.0 makes sense, since sets are much like the keys of a valueless dictionary).

SelfAssessment

1. Python is

A. High level language
B. Interpreted
C. Object oriented
D. All of the above

2. Which of the following are the features of python programming language?

A. Open source
B. Powerful
C. Simple
D. All of the above

3. On which platform, Python language can work?
A. Windows
B. Linux
C. Mac
D. All of the above

4. Which symbol is used to specify a comment in Python?
A. #
B. $
C. %
D. ^

5. The variable name my_variable_name represents which case?
A. Pascal case
B. Snake case
C. Camel case
D. None of the above

6. Which of the following are data transformation operations?
A. Normalizing data
B. Binarizing data
C. Standardizing data
D. All of the above

7. Which of the following are immutable in nature?
A. Strings
B. Tuples
C. Both Strings and tuples
D. None of the above

8. Python language is used in
A. Web applications
B. Desktop applications
C. Cybersecurity
D. All of the above

9. Which of the following are the data structures of Pandas?
A. Series
B. Dataframes
C. Both of the above
D. None of the above

10. Which of the following is a multi-dimensional table?
A. Series
B. Dataframes
C. Both of the above
D. None of the above

11. The hstack() function is for
A. Stacking along rows
B. Stacking along columns
C. Stacking along height
D. None of the above

12. The strings data types of python supports
A. Indexing
B. Slicing
C. Concatenation
D. All of the above

13. Which of the following is the mutable data type in Python?
A. List
B. Tuple
C. String
D. None of the above

14. The lists are
A. Positionally ordered
B. No fixed size
C. Mutable
D. All of the above

15. Which of the following does not own the data in numPy?
A. Copy
B. View
C. Both of the above
D. None of the above

Answers for Self Assessment

1.	D	2.	D	3.	D	4.	A	5.	B
6.	D	7.	C	8.	D	9.	C	10.	B
11.	A	12.	D	13.	A	14.	D	15.	B

Review Questions

1. What is Python? Write about its features in detail.

2. How can we compare Python with other programming languages? Write the differences.
3. What is numPy? What kind of operations can be performed on it?
4. What is Pandas? What are the different data structures it has?
5. What is data cleaning? Which different strategies are used for cleaning the data?

Further Readings

https://www.ibm.com/in-en/cloud/learn/machine-learning

Web Links

https://www.techtarget.com/searchenterpriseai/definition/machine-learning-ML

Unit 15: Machine Learning Packages in Python

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Summary

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Objectives

After studying this unit, you will be able to

- Understand the machine learning with Python
- Understand about matplotlib and seaborn
- Understand simple plot and scatter plot
- Understand categorical data plotting using seaborn()
- Understand how to visualize distribution of data using seaborn
- Understand heatmaps
- Understand the basics of sci-kit learn package
- Understand how to preprocess the data using sci-kit learn package
- Understand SVM and its use

Introduction

Machine learning is a branch of artificial intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy.ML is a subset of AI.It has various applications.

Libraries for Machine learning in Python

1. NumPy

2. Pandas
3. Matplotlib
4. Scikit-learn

Many more

Environment

- Jupyter.
- It is ideal for ML.
- Download it from Anaconda.com/Downloads.

Extension

- Extension of Jupyter notebook - .ipynb

Loading a dataset in Jupyter

- Put the dataset in place where we have Jupyter.

Import pandas as pd

df = pd.read_csv('vgsales.csv')

Basic functions

1) df.shape
2) df.describe()
3) df.values()

Jupyter modes

1) Edit mode: Green bar on left. Press ESC after it.
2) Command mode: Blue bar on left.

Real-world problem

Suppose we have an online music store and when the user signup it asks for age and gender. Based upon the profile, it recommends various music albums they are likely to buy. So, here in this problem we are going to use machine learning to increase the sales.

15.1 Steps in a Machine Learning Project

1. Import the data
2. Clean the data
3. Split the data
4. Create a model
5. Train the model
6. Makes a prediction
7. Evaluate and improve

Step 1: Import the data

```
Import pandas as pd
music_data = pd.read_csv('music.csv')
music_data
```

Step 2: Cleaning the data

It involves removing the duplicates and null values. This dataset does not contain the noisy data.

Step 3: Split the dataset

```
import pandas as pd
music_data = pd.read_csv('music.csv')
X = music_data.drop(Columns = ['genre'])
y = music_data(['genre'])
```

Step 4: Create a model

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
music_data = pd.read_csv('music.csv')
X = music_data.drop(Columns = ['genre'])
y = music_data(['genre'])
model = DecisonTreeClassifier
```

Step 5: Make predictions

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
music_data = pd.read_csv('music.csv')
X = music_data.drop(Columns = ['genre'])
y = music_data(['genre'])
model = DecisonTreeClassifier
Model.fit(X,y)
predictions = model.predict([ [21,1],[22,0] ])
predictions
```

Till now, we were passing the entire dataset for training and just taken 2 values for testing. But now we will divide the dataset in 2 parts

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
music_data = pd.read_csv('music.csv')
X = music_data.drop(Columns = ['genre'])
y = music_data(['genre'])
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3)
model = DecisonTreeClassifier
Model.fit(X_train,y_train)
predictions = model.predict(X_test)
score = accuracy_score(y_test, predictions)
score
```

15.2 What is Matplotlib?

Matplotlib is a plotting library for creating static, animated, and interactive visualizations in Python. Matplotlib can be used in Python scripts, the Python and IPython shell, web application servers, and various graphical user interface toolkits like Tkinter, awxPython, etc.

Installing matplotlib

- File → Settings → + → Search matplotlib → Install.

What is pyplot?

Pyplot is a Matplotlib module which provides a MATLAB-like interface. Matplotlib is designed to be as usable as MATLAB, with the ability to use Python and the advantage of being free and open-source. Each pyplot function makes some change to a figure: e.g., creates a figure, creates a plotting area in a figure, plots some lines in a plotting area, decorates the plot with labels, etc. The various plots we can utilize using Pyplot are **Line Plot**, **Histogram**, **Scatter**, **3D Plot**, **Image**, **Contour**, and **Polar**.

For plotting, first we need to import pyplot API from the library.

```
import matplotlib.pyplot as plt
```

Example: The number of views a Youtube channel got in last 7 days

```
import matplotlib.pyplot as plt
views = [534,689,258,401,724,689,350]
plt.plot(views)
plt.show()
```

When you pass a single parameter, the data is assumed to be of y-axis.

```
import matplotlib.pyplot as plt
views = [534,689,258,401,724,689,350]
days = range(1,8)
plt.plot(days,views)
plt.show()

// Labels and Legends
plt.xlabel('Day No.')
plt.ylabel('Views')
plt.plot(days,views,label='Youtube Views')
plt.legend()
```

// Changing the position of legend

plt.legend(loc='upper right')

// Adding a title

plt.title('Youtube views on a daily basis')

// Colors

plt.plot(days, views, label = 'Youtube Views', color='red')

// Markers

plt.plot(days, views, label = 'Youtube Views', color='red', marker = 'o')

// Marker color

plt.plot(days, views, label = 'Youtube Views', color='red', marker = 'o', marker facecolor = 'g')

// Line style

plt.plot(days, views, label = 'Youtube Views', color='red', marker = 'o', marker facecolor = 'g', linestyle = 'dashed')

// Line width

plt.plot(days, views, label = 'Youtube Views', color='red', marker = 'o', marker facecolor = 'g', linestyle = 'dashed', linewidth = 5)

// Adding multiple plots

This includes plotting multiple datasets into one plot.Three datasets are

y_views = [534,689,258,401,724,689,350]

f_views = [123,342,700,304,405,650,325]

t_views = [202,209,176,415,824,389,550]

// Plotting

import matplotlib.pyplot as plt

y_views = [534,689,258,401,724,689,350]

f_views = [123,342,700,304,405,650,325]

t_views = [202,209,176,415,824,389,550]

days = range(1,8)

plt.plot(days, y_views, label = 'Youtube views', marker = 'o', markerfacecolor = 'blue')

plt.plot(days, f_views, label = 'Facebook views', marker = 'o', markerfacecolor = 'orange')

plt.plot(days, t_views, label = 'Twitter views', marker = 'o', markerfacecolor = 'green')

plt.xlabel('Day No.')

plt.ylabel('Views')

```
plt.title('Youtube views on a daily basis')
plt.legend(loc='upper right')
plt.show()
```

// Setting X and Y axes limit

Matplotlib automatically choses x and y limits to spread data.To avoid outliers in plot, we need to use the methods x_limit and y_limit.

```
plt.xlim(1,5)
plt.ylim(100,500)
```

// Setting up grids in your plots

```
plt.grid(True)
```

// Adding different kinds of styling to grid

```
plt.grid(True,linewidth=2,color='r',linestyle='-.')
```

// Saving plots

```
plt.savefig('img1.png')
```

Scatter plots

Scatter plots are used to compare trends in different categories of data types through graphs.A scatter plot is **a set of points plotted on a horizontal and vertical axis**.Scatter plots are important in statistics because they can show the extent of correlation between two or more kinds of variables.

```
import matplotlib.pyplot as plt
y_views=[534, 689,258,401,724,689,435,534,545,435,423,789,905,561]
days = range(1,15)
plt.scatter(days,y_views)
plt.show()
```

// Adding legend

```
plt.scatter(days,y_views,'Youtube Views')
plt.legend()
```

// Changing the position of a legend

```
plt.scatter(days,y_views,'Youtube Views')
plt.legend(loc='upper right')
```

// Adding labels to scatter plot

```
plt.xlabel('Days No.')
plt.ylabel('Views')
```

// Adding title to scatter plot

plt.title('Daily views for marketing channels)

// Adding grids

plt.grid(True)

// Changing styles

plt.grid(True,linestyle='-.')

// Changing styles

plt.grid(True,linestyle='-.',linewidth=2)

15.3 What is Seaborn?

Seaborn is an open-source Python library built on top of matplotlib. It is used for data visualization and exploratory data analysis. Seaborn works easily with dataframes and the Pandas library. The graphs created can also be customized easily.

Benefits

- Graphs can help us find data trends that are useful in any machine learning or forecasting project.
- Graphs make it easier to explain your data to non-technical people.
- Visually attractive graphs can make presentations and reports much more appealing to the reader.

Installing Seaborn

- File → Settings → Python Interpreter → + → Seaborn → Install Package.

  OR

  pip install seaborn

then import the seaborn using import seaborn

Numerical Data Plotting

For numerical data plotting, the available functions are:

- relplot()
- scatterplot()
- lineplot()

Categorical Data Plotting

For categorical data plotting, the available functions are:

- catplot()
- boxplot()

- stripplot()
- swarmplot()

Visualizing Distribution of Data

For visualizing distribution of data, the functions available are:

- distplot()
- kdeplot()
- jointplot()
- rugplot()

Linear Regression and Relationships

For linear regression and relationships, the available functions are:

- regplot()
- implot()

Controlling Plotted Figure Aesthetics

For controlling plotted figure aesthetics, the available functions are

- Figure Styling
- Axes Styling
- Color Palattes

15.4 Numerical Data Plotting

```
import seaborn as sns

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

%matplotlib inline

// %matplotlib inline: This line ensures that all the plotted figures should appear after the cell execution

//Load data

tips = sns.load_dataset('tips')

//Here, you can check the dataset using the head and tail functions.

sns.relplot(x='total_bill',y='tip', data=tips)

// Facetgrid – It can plot so many axes on a single figure

//Segerate the tips based on smoking.

sns.relplot(x='total_bill',y='tip', data=tips, hue='smoker')

sns.relplot(x='total_bill',y='tip', data=tips, hue='smoker', style='time')
```

```
sns.relplot(x='total_bill',y='tip', data=tips, hue='size')

sns.relplot(x='total_bill',y='tip', data=tips, hue='size', palette = 'ch:r=-0.5, l=0.95')

sns.relplot(x='total_bill', y='tips', data=tips, size='size')

sns.relplot(x='total_bill',y='tip', data=tips, size='size', sizes=(50,500))

from numpy.random import randn

df = pd.DataFrame(dict(time = np.arange(500),value = randn(500).cumsum()))

df.head()

sns.relplot(x='time',y='value',kind='line',data = df)
```

15.5 Categorical Data Plotting

For categorical data plotting, the available functions are:

- catplot()
- boxplot()
- stripplot()
- swarmplot()

There are a number of axes level functions for plotting categorical data in different ways and a figure-level interface, catplot(), that gives unified higher level access to them.

Three Different Families

- Categorical scatter plot

1) stripplot() (with kind="strip()"; the default)
2) swarmplot() (with kind="swarm")

- Categorical distribution plot

1) boxplot() (with kind="box")
2) violonplot() (with kind= "violin")
3) boxenplot() (with kind="boxen")

- Categorical estimate plots:

1) pointplot() (with kind = "point")
2) barplot() (with kind="bar")
3) countplot() (with kind="count")

Categorical Scatterplots

```
import seaborn as sns

import numpy as np

import pandas as pd
```

```
import matplotlib.pyplot as plt

//Loading of dataset

tips=sns.load_dataset("tips")

tips.head()

catplot()

sns.catplot(x="day",y="total_bill",data=tips)

//The jitter parameter controls the magnitude of jitter or disables it altogether.

sns.catplot(x="day",y="total_bill",jitter=False,data=tips)
```

The second approach adjusts the points along the categorical axis using an algorithm that prevents them from overlapping. It can give a better representation of the distribution of observations, although it only works well for relatively small datasets. This kind of plot is sometimes called a "beeswarm" and is drawn in seaborn by swarmplot(), which is activated by setting kind="swarm" in catplot().

Swarm plot

```
sns.catplot(x="day",y="total_bill",kind="swarm",data=tips)
```

Likerelational plots, it's possible to add another dimension to a categorical plot by using a hue semantic.

```
sns.catplot(x="day",y="total_bill",kind="swarm",data=tips,hue="sex")
```

In these examples, that's always corresponded to the horizontal axis. But it's often helpful to put the categorical variable on the vertical axis (particularly when the category names are relatively long or there are many categories). To do this, swap the assignment of variables to axes.

```
sns.catplot(x="total_bill",y="day",kind="swarm",data=tips,hue="sex")
```

As the size of the dataset grows, categorical scatter plots become limited in the information they can provide about the distribution of values within each category.

Boxplot

This kind of plot shows the three quartile values of the distribution along with extreme values. The "whiskers" extend to points that lie within 1.5 IQRs of the lower and upper quartile, and then observations that fall outside this range are displayed independently. This means that each value in the boxplot corresponds to an actual observation in the data.

```
sns.catplot(x="day",y="total_bill",kind="box",data=tips)
```

When adding a hue semantic, the box for each level of the semantic variable is moved along the categorical axis so they don't overlap.

```
sns.catplot(x="day",y="total_bill",kind="box",data=tips,hue="smoker")
```

A related function, boxenplot() draws a plot that is similar to a box plot but optimized for showing more information about the shape of the distribution. It is best suited for larger datasets.

```
//Load the dataset

diamonds=sns.load_dataset("diamonds")

diamonds.head()
```

Boxenplot

sns.catplot(x="color", y="price", kind="boxen", data=diamonds.sort_values("color"))

Violinplot

sns.catplot(x="total_bill", y="day", hue="sex", kind="violin", data=tips)

For other applications, rather than showing the distribution within each category, you might want to show an estimate of the central tendency of the values. Seaborn has two main ways to show this information-

1) Bar plot
2) Point plot

Bar plot

In seaborn, the barplot() function operates on a full dataset and applies a function to obtain the estimate (taking the mean by default). When there are multiple observations in each category, it also uses bootstrapping to compute a confidence interval around the estimate, which is plotted using error bars.

// Loading of dataset

titanic=sns.load_dataset("titanic")

titanic.head()

sns.catplot(x="sex", y="survived", hue="class", kind="bar", data=titanic)

Countplot

A special case for the bar plot is when you want to show the number of observations in each category rather than computing a statistic for a second variable. This is similar to a histogram over a categorical, rather than quantitative, variable. In seaborn, it's easy to do so with the countplot() function.

sns.catplot(x="deck", kind="count", palette="ch:.25", data=titanic)

Point plot

An alternative style for visualizing the same information is offered by the pointplot() function. This function also encodes the value of the estimate with height on the other axis, but rather than showing a full bar, it plots the point estimate and confidence interval.

sns.catplot(x="sex", y="survived", hue="class", kind="point", data=titanic)

15.6 Visualizing distributions of data

An early step in any effort to analyze or model data should be to understand how the variables are distributed. The techniques for distribution visualization can provide quick answers to many important questions.

1. What range do the observations cover?

2. What is their central tendency?
3. Are they heavily skewed in one direction?
4. Is there evidence for bimodality?
5. Are there significant outliers?
6. Do the answers to these questions vary across subsets defined by other variables?

Functions

The axes and figure level functions are:

- The axes level functions are:

1) histplot()
2) kdeplot()
3) ecdfplot()
4) rugplot()

- Figure level functions

1) distplot()
2) jointplot()
3) pairplot()

Plotting univariate histograms

The most common approach to visualizing a distribution is the histogram.A histogram is a bar plot where the axis representing the data variable is divided into a set of discrete bins and the count of observations falling within each bin is shown using the height of the corresponding bar.

```
import seaborn as sns

import matplotlib.pyplot as plt

import pandas as pd

import numpy as np

// Loading of dataset

penguins = sns.load_dataset("penguins")

// Plotting univariate histograms

sns.displot(penguins, x="flipper_length_mm")
```

Choosing the bin size

The size of the bins is an important parameter and using the wrong bin size can mislead by obscuring important features of the data or by creating apparent features out of random variability.By default, displot() and histplot() choose a default bin size based on the variance of the data and the number of observations. But you should not be over-reliant on such automatic approaches, because they depend on assumptions about the structure of your data.To choose the size directly, set the binwidth parameter.

```
sns.displot(penguins,x="flipper_length_mm",binwidth=3)
```

Choosing the number of bins

It may make more sense to specify the *number* of bins, rather than their size:

sns.displot(penguins, x="flipper_length_mm",bins=20)

Conditioning on other variables

The displot() and histplot() provide support for conditional subsetting via the hue semantics. Assigning a variable to hue will draw a separate histogram for each of its unique values and distinguish them by color.

sns.displot(penguins,x="flipper_length_mm",hue="species")

By default, the different histograms are "layered" on top of each other, and, in some cases, they may be difficult to distinguish. One option is to change the visual representation of the histogram from a bar plot to a "step" plot.

sns.displot(penguins, x="flipper_length_mm", hue="species", element="step")

Because displot() is a figure-level function and is drawn onto a Facetgrid, it is also possible to draw each individual distribution in a separate subplot by assigning the second variable to column or row rather than hue.

sns.displot(penguins, x="flipper_length_mm", col="sex")

This represents the distribution of each subset well, but it makes it more difficult to draw direct comparisons.

Normalized Histogram Statistics

Before we do, another point to note is that, when the subsets have unequal numbers of observations, comparing their distributions in terms of counts may not be ideal. One solution is to *normalize* the counts using the stat parameter.

sns.displot(penguins, x="flipper_length_mm", hue="species", stat="density")

By default, however, the normalization is applied to the entire distribution, so this simply rescales the height of the bars. By setting common_norm=False, each subset will be normalized independently.

sns.displot(penguins, x="flipper_length_mm", hue="species", stat="density",common_norm=False)

Density normalization scales the bars so that their *areas* sum to 1. As a result, the density axis is not directly interpretable. Another option is to normalize the bars to that their *heights* sum to 1. This makes most sense when the variable is discrete, but it is an option for all histograms:

sns.displot(penguins, x="flipper_length_mm", hue="species", stat="probability")

Kernel Density Estimation

A histogram aims to approximate the underlying probability density function that generated the data by binning and counting observations. Kernel density estimation (KDE) presents a different solution to the same problem. Rather than using discrete bins, a KDE plot smooths the observations with a Gaussian kernel, producing a continuous density estimate.

sns.displot(penguins, x="flipper_length_mm", kind="kde")

Choosing the smoothing bandwidth

Much like with the bin size in the histogram, the ability of the KDE to accurately represent the data depends on the choice of smoothing bandwidth. An over-smoothed estimate might erase meaningful features, but an under-smoothed estimate can obscure the true shape with random noise.The easiest way to check the robustness of the estimate is to adjust the default bandwidth:

sns.displot(penguins, x="flipper_length_mm", kind="kde",bw_adjust=.25)

Note how the narrow bandwidth makes the bimodality much more apparent, but the curve is much less smooth. In contrast, a larger bandwidth obscures the bimodality almost completely:

sns.displot(penguins, x="flipper_length_mm", kind="kde",bw_adjust=2)

Empirical Cumulative Distribution

This plot draws a monotonically increasing curve through each datapoint such that the height of the curve reflects the proportion of observations with a smaller value.

sns.displot(penguins,x="flipper_length_mm",kind="ecdf")

Advantages of ECDF

The ECDF plot has two key advantages.

- Unlike histogram or KDE, it directly represents each datapoint. That means there is no bin size or smoothing parameter to consider.
- Additionally, because the curve is monotonically increasing, it is well-suited for comparing multiple distributions.
- sns.displot(penguins, x="flipper_length_mm", hue="species",kind="ecdf")

Visualizing bivariate distribution

Till now, we have discussed only univariate distribution, means distribution on only a single variable. Assigning a second variable to y, will plot a bivariate distribution.

sns.displot(penguins, x="flipper_length_mm", y="bill_depth_mm")

A bivariate histogram bins the data within rectangles that tile the plot and then shows the count of observations within each rectangle with the fill color.Similarly, a bivariate KDE plot smoothes the (x, y) observations with a 2D Gaussian. The default representation then shows the *contours* of the 2D density.

sns.displot(penguins, x="flipper_length_mm", y="bill_depth_mm",kind="kde")

Several other figure-level plotting functions in seaborn make use of the histplot() and kdeplot() functions.

Plotting Joint and Marginal Distributions

The first is jointplot() which augments a bivariate relatonal or distribution plot with the marginal distributions of the two variables. By default, jointplot() represents the bivariate distribution using scatterplot() and the marginal distributions using histplot().

sns.jointplot(data=penguins, x="bill_length_mm", y="bill_depth_mm")

Similar to displot(), setting a different kind="kde" in jointplot() will change both the joint and marginal plots the use kdeplot().

sns.jointplot(data=penguins, x="bill_length_mm", y="bill_depth_mm", hue="species", kind="kde")

Plotting Many Distributions

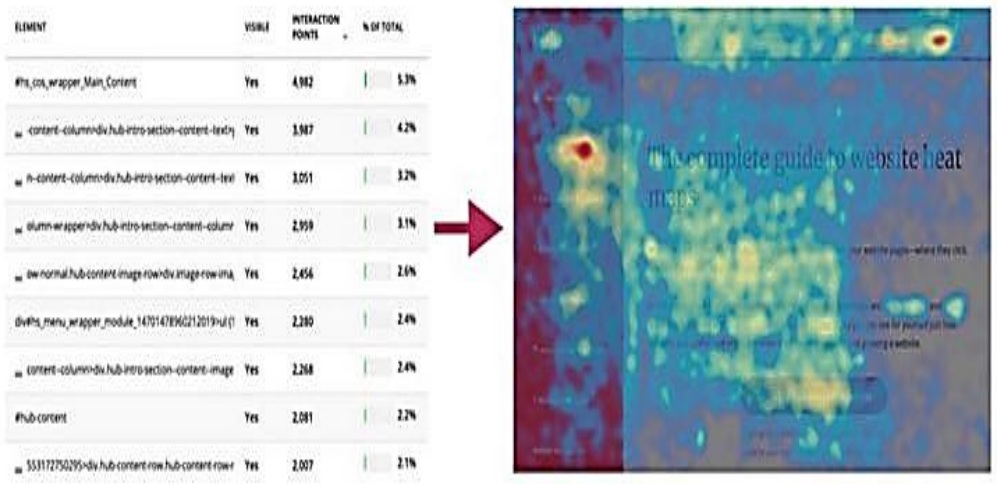
The pairplot() function offers a similar blend of joint and marginal distributions. Rather than focusing on a single relationship, however, pairplot() uses a "small-multiple" approach to visualize the univariate distribution of all variables in a dataset along with all of their pairwise relationships.

sns.pairplot(penguins)

Heatmaps

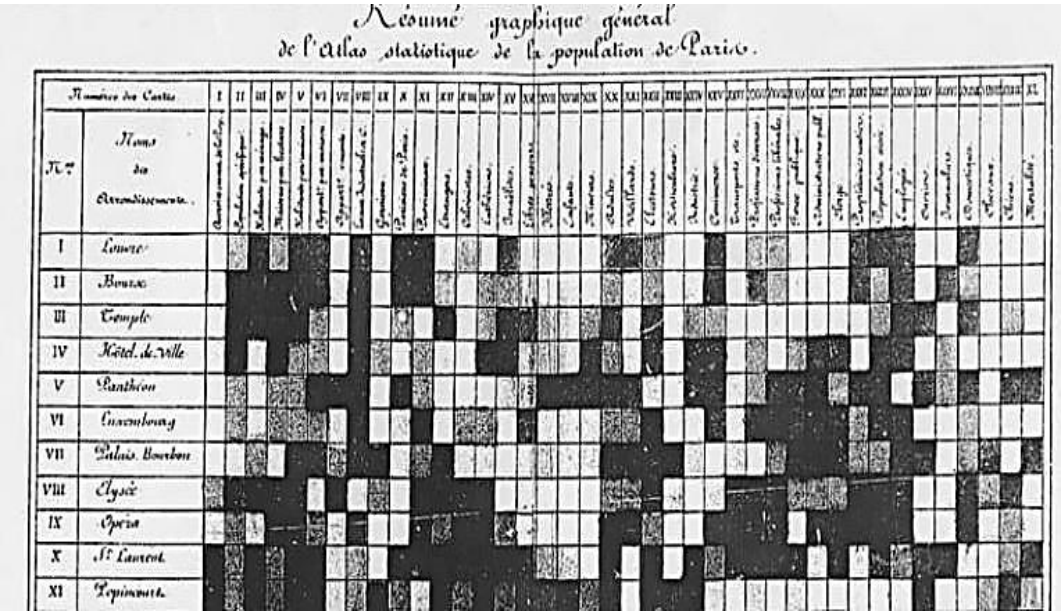
Heatmaps are a powerful way to understand what users do on your website pages—where they click, how far they scroll, what they look at or ignore.A heatmap (or heat map) is a graphical representation of data where values are depicted by color.They are essential in **detecting what does or doesn't work on a website or product page**. By experimenting with how certain buttons and elements are positioned on your website, heatmaps allow you to **evaluate your product's performance and increase user engagement and retention** as you prioritize the jobs to be done that boost customer value.Heatmaps make it easy to visualize complex data and understand it briefly.

Visualization

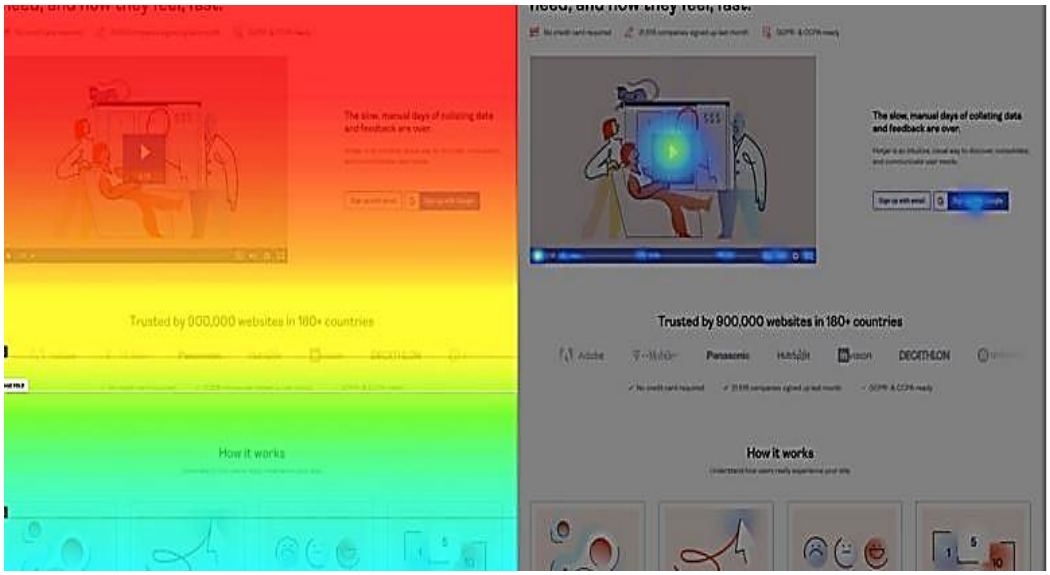


Use

In the 19th century, manual gray-scale shading was used to depict data patterns in matrices and tables.



The term heatmap was first trademarked in the early 1990s, when software designer Cormac Kinney created a tool to graphically display real-time financial market information. Website and product heatmaps visualize **the most popular (hot) and unpopular (cold) elements of your site's webpage** content using colors on a scale from red to blue.Heatmaps give product teams, marketers, digital and data analysts, UX designers, social media specialists—and anyone who sells anything online—deep insights into people's behavior on their site, helping them discover why users aren't adopting their product, using call-to-action (CTA) buttons, or converting.By aggregating user behavior, heatmaps facilitate data analysis—combining quantitative and qualitative data—and give **a snapshot understanding of how your target audience interacts with an individual website or product page**—what they click on, scroll through, or ignore—which helps you identify trends and optimize your product and site to increase user engagement and sales.



It is plotted using seaborn library.

seaborn.heatmap(data, *, vmin=None, vmax=None, cmap=None, center=None, robust=False, annot=None, fmt='.2g', annot_kws=None, linewidths=0, linecolor='white', cbar=True,

cbar_kws=None, cbar_ax=None, square=False, xticklabels='auto', yticklabels='auto', mask=None, ax=None, **kwargs)

//Parameters

data: rectangular dataset: 2D dataset that can be coerced into andarray. If a Pandas DataFrame is provided, index/column information will be used to label the columns and rows.

vmin, vmax: floats, optional: Values to anchor the colormap, otherwise they are inferred from the data and other keyword arguments.

cmap: matplotlib colormap name or object, or list of colors, optional: The mapping from data values to color space. If not provided, the default will depend on whether the center is set.

center: float, optional: The value at which to center the colormap when plotting divergent data. Using this parameter will change the default cmap if none is specified.

//Plot a heatmap for a numpy array:

```
import numpy as np; np.random.seed(0)

import seaborn as sns; sns.set_theme()

uniform_data=np.random.rand(10,12)

ax=sns.heatmap(uniform_data)
```

15.7 Sci-kit Learn Package

Scikit-learn (Sklearn) is the most useful and robust library for machine learning in Python. It provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, clustering, and dimensionality reduction via a consistency interface in Python. This library, which is largely written in Python, is built upon NumPy, SciPy and Matplotlib.

Prerequisites

There are a few prerequisites for learning sci-kit learn package. These includes:

- Basic knowledge of machine learning
- Python
- NumPy
- Scipy
- Matplotlib.

Installation

It will be installed as:

pip install –U scikit-learn

Features

Rather than focusing on loading, manipulating, and summarizing data, Scikit-learn library is focused on modeling the data. Some of the most popular groups of models provided by Sklearn are as follows −

- **Supervised Learning algorithms** − Almost all the popular supervised learning algorithms, like Linear Regression, Support Vector Machine (SVM), Decision Tree etc., are part of scikit-learn.
- **Unsupervised Learning algorithms** − On the other hand, it also has all the popular unsupervised learning algorithms from clustering, factor analysis, PCA (Principal Component Analysis) to unsupervised neural networks.
- **Clustering** − This model is used for grouping unlabeled data.
- **Cross Validation** − It is used to check the accuracy of supervised models on unseen data.
- **Dimensionality Reduction** − It is used for reducing the number of attributes in data which can be further used for summarization, visualization, and feature selection.
- **Ensemble methods** − As name suggest, it is used for combining the predictions of multiple supervised models.
- **Feature extraction** − It is used to extract the features from data to define the attributes in image and text data.
- **Feature selection** − It is used to identify useful attributes to create supervised models.
- **Open Source** − It is an open-source library and commercially usable under BSD license.

A collection of data is called a dataset. It is having the following two components −

1) Features

2) Response

1) Features − The variables of data are called its features. They are also known as predictors, inputs, or attributes.

- **Feature matrix** − It is the collection of features in case there are more than one.
- **Feature Names** − It is the list of all the names of the features.

2) Response − It is the output variable that basically depends upon the feature variables. They are also known as target, label, or output.

- **Response Vector** − It is used to represent response column. Generally, we have just one response column.
- **Target Names** − It represents the possible values taken by a response vector.

```
import matplotlib.pyplot as plt

import numpy as np

import pandas as pd

from sklearn.datasets import load_iris

iris = load_iris()
```

```
X= iris.data

Y= iris.target

feature_names = iris.feature_names

target_names = iris.target_names

print("Feature names:", feature_names)

print("Target names:", target_names)

print("\nFirst 10 rows of X:\n", X[:10])
```

//Splitting the Dataset

To check the accuracy of our model, we can split the dataset into two pieces-**a training set** and **a testing set**. Use the training set to train the model and testing set to test the model. After that, we can evaluate how well our model did.We will split the data into 70:30 ratio, i.e., 70% data will be used as training data and 30% will be used as testing data.

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 1)
```

It uses **train_test_split()** function of scikit-learn to split the dataset. This function has the following arguments −

1) X, y − Here, **X** is the **feature matrix** and y is the **response vector**, which needs to be split.

2) **test_size** − This represents the ratio of test data to the total given data. As in the above example, we are setting **test_data = 0.3** for 150 rows of X. It will produce test data of 150*0.3 = 45 rows.

3) random_size − It is used to guarantee that the split will always be the same. This is useful in situations where you want reproducible results.

//Train the model

Next, we can use our dataset to train some prediction-model.

```
from sklearn.neighbors import KNeighborsClassifier

from sklearn import metrics

classifier_knn = KNeighborsClassifier(n_neighbors = 3)

classifier_knn.fit(X_train, y_train)

y_pred = classifier_knn.predict(X_test)

print("Accuracy:", metrics.accuracy_score(y_test, y_pred))

sample = [[5, 5, 3, 2], [2, 4, 3, 5]]

preds = classifier_knn.predict(sample)

pred_species = [iris.target_names[p] for p in preds]

print("Predictions:", pred_species)
```

//Model Persistence

Once you train the model, it is desirable that the model should be persist for future use so that we do not need to retrain it again and again. It can be done with the help of **dump** and **load** features of ***joblib*** package.

15.8 Pre-processing the Data

The **preprocessing** package has the following techniques −

1) Binarization
2) Mean Removal
3) Scaling
4) Normalization

Binarization

This preprocessing technique is used when we need to convert our numerical values into Boolean values.

```
import numpy as np

from sklearn import preprocessing

input_data=np.array([[2.1, -1.9, 5.5],[-1.5, 2.4, 3.5],[0.5, -7.9, 5.6], [5.9, 2.3, -5.8]])

data_binarized=preprocessing.Binarizer(threshold=0.5).transform(Input_data)

print("\nBinarized data:\n", data_binarized)
```

We used **threshold value** = 0.5 and that is why, all the values above 0.5 would be converted to 1, and all the values below 0.5 would be converted to 0.

Mean Removal

This technique is used to eliminate the mean from feature vector so that every feature centered on zero.

```
print("Mean =", Input_data.mean(axis=0))

print("Stddeviation = ", Input_data.std(axis=0))

data_scaled = preprocessing.scale(Input_data)

print("Mean_removed =", data_scaled.mean(axis=0))

print("Stddeviation_removed =", data_scaled.std(axis=0))
```

Scaling

We use this preprocessing technique for scaling the feature vectors. Scaling of feature vectors is important, because the features should not be synthetically large or small.

```
data_scaler_minmax = preprocessing.MinMaxScaler(feature_range=(0,1))

data_scaled_minmax = data_scaler_minmax.fit_transform(Input_data)

print ("\nMin max scaled data:\n", data_scaled_minmax)
```

Normalization

We use this preprocessing technique for modifying the feature vectors. Normalization of feature vectors is necessary so that the feature vectors can be measured at a common scale. There are two types of normalization as follows −

1) L1 normalization
2) L2 normalization

- L1 Normalization

```
data_normalized_l1 = preprocessing.normalize(Input_data, norm='l1')

print("\nL1 normalized data:\n", data_normalized_l1)
```

- L2 Normalization

```
data_normalized_l2 = preprocessing.normalize(Input_data, norm='l2')

print("\nL1 normalized data:\n", data_normalized_l2)
```

Data Representation

The data can be represented as:

- A table
- A feature matrix

A table:

The best way to represent data in Scikit-learn is in the form of tables. A table represents a 2-D grid of data where rows represent the individual elements of the dataset and the columns represents the quantities related to those individual elements.**The iris dataset** in the form of a Pandas DataFrame with the help of python **seaborn** library.

```
import seaborn as sns

iris = sns.load_dataset('iris')

iris.head()
```

Each row of the data represents a single observed flower, and the number of rows represents the total number of flowers in the dataset. Generally, we refer to the rows of the matrix as samples.On the other hand, each column of the data represents quantitative information describing each sample. Generally, we refer to the columns of the matrix as features.

A feature matrix:

Features matrix may be defined as the table layout where information can be thought of as a 2-D matrix. It is stored in a variable named **X** and assumed to be two dimensional with shape [n_samples, n_features]. Mostly, it is contained in a NumPy array or a Pandas DataFrameAlong with Features matrix, denoted by X, we also have target array. It is also called label. It is denoted by y. The label or target array is usually one-dimensional having length n_samples. It is generally

contained in NumPy ***array*** or Pandas ***Series***. Target array may have both the values, continuous numerical values, and discrete values.

15.9 Support Vector Machines

Support vector machines (SVMs) are powerful, yet flexible supervised machine learning methods used for classification, regression, and outliers' detection. SVMs are very efficient in high dimensional spaces and generally are used in classification problems.SVMs are popular and memory efficient because they use a subset of training points in the decision function.

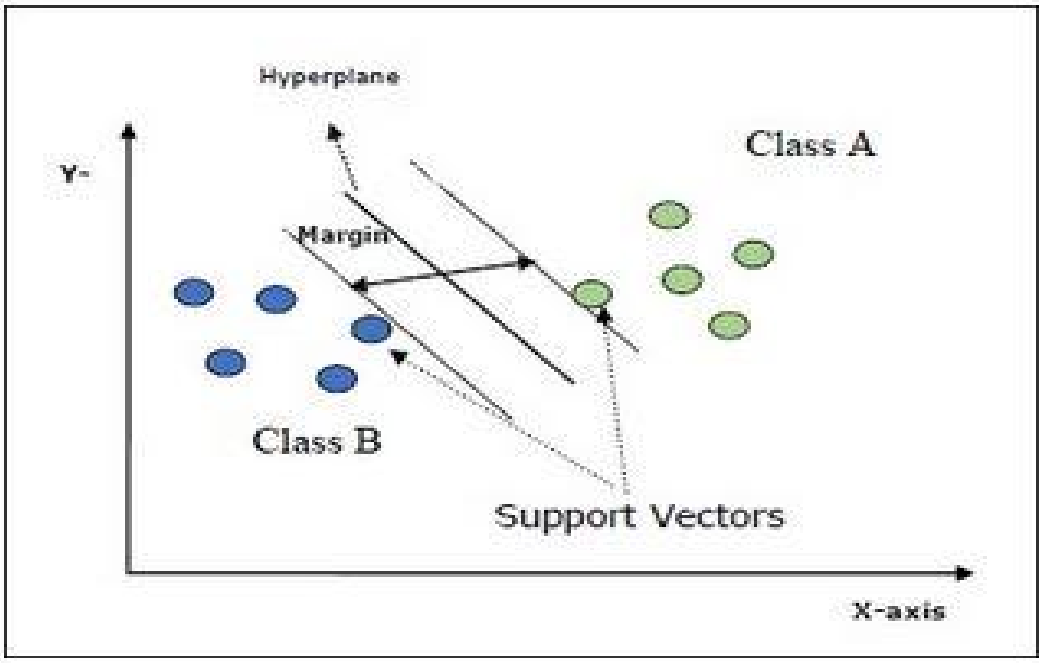
Goal of SVM

The main goal of SVMs is to divide the datasets into number of classes to find a **maximum marginal hyperplane (MMH)** which can be done in the following two steps −

- Support Vector Machines will first generate hyperplanes iteratively that separate the classes in the best way.
- After that it will choose the hyperplane that segregates the classes correctly.

Important Concepts

- **Support Vectors** − They may be defined as the datapoints which are closest to the hyperplane. Support vectors help in deciding the separating line.
- **Hyperplane** − The decision plane or space that divides set of objects having different classes.
- **Margin** − The gap between two lines on the closet data points of different classes is called margin.



Classification of SVM

Scikit-learn provides three classes namely **SVC, NuSVC** and **LinearSVC** which can perform multiclass-class classification.

SVC

It is C-support vector classification whose implementation is based on **libsvm**. The module used by scikit-learn is **sklearn.svm.SVC**. This class handles multiclass support according to one-vs-one scheme. The parameters used by **sklearn.svm.SVC** class

1) **C** − float, optional, default = 1.0

It is the penalty parameter of the error term.

2) **kernel** − string, optional, default = 'rbf'

This parameter specifies the type of kernel to be used in the algorithm. we can choose any one among, **'linear', 'poly', 'rbf', 'sigmoid', 'precomputed'**. The default value of kernel would be **'rbf'**.

3) ***degree*** − *int, optional, default = 3*

It represents the degree of the 'poly' kernel function and will be ignored by all other kernels.

4) ***gamma*** − *{'scale', 'auto'} or float,*

It is the kernel coefficient for kernels 'rbf', 'poly' and 'sigmoid'.

5) ***optinal default*** − = *'scale'*

If you choose default i.e. gamma = 'scale' then the value of gamma to be used by SVC is $1/(n_features*X.var())$.

On the other hand, if gamma= 'auto', it uses $1/n_features$.

6) ***coef0*** − *float, optional, Default=0.0*

An independent term in kernel function which is only significant in 'poly' and 'sigmoid'.

7) ***tol*** − *float, optional, default = 1.e-3*

This parameter represents the stopping criterion for iterations.

8) ***shrinking*** − *Boolean, optional, default = True*

This parameter represents whether we want to use shrinking heuristic or not.

9) v***erbose*** − *Boolean, default: false*

It enables or disables verbose output. Its default value is false.

10) ***probability*** − *boolean, optional, default = true*

This parameter enables or disables probability estimates. The default value is false, but it must be enabled before we call fit.

11) max_iter − *int, optional, default = -1*

As the name suggest, it represents the maximum number of iterations within the solver. Value -1 means there is no limit on the number of iterations.

12) ***cache_size*** − *float, optional*

This parameter will specify the size of the kernel cache. The value will be in MB(MegaBytes).

13) ***class_weight*** − *{dict, 'balanced'}, optional*

This parameter will set the parameter C of class j to $class_weight[j]*C$ for SVC. If we use the default option, it means all the classes are supposed to have weight one. On the other hand, if you choose ***class_weight:balanced***, it will use the values of y to automatically adjust weights.

14) ***random_state*** − *int, RandomState instance or None, optional, default = none*

This parameter represents the seed of the pseudo random number generated which is used while shuffling the data. Followings are the options −

int − In this case, *random_state* is the seed used by random number generator.

RandomState instance − In this case, random_state is the random number generator.

None − In this case, the random number generator is the RandonState instance used by np.random.

15) ***decision_function_shape*** − *ovo', 'ovr', default = 'ovr'*

This parameter will decide whether the algorithm will return **'ovr'** (one-vs-rest) decision function of shape as all other classifiers, or the original **ovo**(one-vs-one) decision function of libsvm.

16) ***break_ties*** − *boolean, optional, default = false*

True − The predict will break ties according to the confidence values of decision_function

False − The prediction will return the first class among the tied classes.

The attributes used by **sklearn.svm.SVC** class

1) ***support_*** − *array-like, shape = [n_SV]*

It returns the indices of support vectors.

2) ***support_vectors_*** − *array-like, shape = [n_SV, n_features]*

It returns the support vectors.

3) ***n_support_*** − *array-like, dtype=int32, shape = [n_class]*

It represents the number of support vectors for each class.

4) ***dual_coef_*** − *array, shape = [n_class-1,n_SV]*

These are the coefficient of the support vectors in the decision function.

5) ***coef_*** − *array, shape = [n_class * (n_class-1)/2, n_features]*

This attribute, only available in case of linear kernel, provides the weight assigned to the features.

6) intercept_ − *array, shape = [n_class * (n_class-1)/2]*

It represents the independent term (constant) in decision function.

7) ***fit_status_*** − *int*

The output would be 0 if it is correctly fitted. The output would be 1 if it is incorrectly fitted.

8) ***classes_*** − *array of shape = [n_classes]*

It gives the labels of the classes.

Implementation

Like other classifiers, SVC also has to be fitted with following two arrays −An array **X** holding the training samples. It is of size [n_samples, n_features].An array **Y** holding the target values i.e., class labels for the training samples. It is of size [n_samples].

```
import numpy as np

X=np.array([[-1,1], [-2,-1],[1,1],[2,1]])

y=np.array([1,1,2,2])

from sklearn.svm import SVC

SVCClf = SVC (kernel='linear', gamma='scale', shrinking=False)

SVCClf.fit(X,y)
```

Example

Now, once fitted, we can get the weight vector with the help of following python script −

```
SVCClf.coef_

O/P: array([[0.5,0.5]])
```

We can get the value of other attributes as follows −

```
SVCClf.predict([[-0.5,0.8]])

O/P: array([1])
```

Summary

- ML is a subset of AI.It has various applications.
- The basic functions available are: df.shape(), df.describe() and df.values()
- Matplotlib can be used in Python scripts, the Python and IPython shell, web application servers, and various graphical user interface toolkits like Tkinter, awxPython, etc.
- Each pyplot function makes some change to a figure: e.g., creates a figure, creates a plotting area in a figure, plots some lines in a plotting area, decorates the plot with labels, etc.
- Scatter plots are important in statistics because they can show the extent of correlation between two or more kinds of variables.
- Seaborn works easily with dataframes and the Pandas library.
- Graphs can help us find data trends that are useful in any machine learning or forecasting project.
- Graphs make it easier to explain your data to non-technical people.
- There are a number of axes level functions for plotting categorical data in different ways and a figure-level interface, catplot(), that gives unified higher level access to them.
- Countplotis like a histogram over a categorical, rather than quantitative, variable. In seaborn, it's easy to do so with the countplot() function.

Keywords

- **Matplotlib:** It is a plotting library for creating static, animated, and interactive visualizations in Python.
- **Pyplot:** It is a Matplotlib module which provides a MATLAB-like interface. The various plots we can utilize using Pyplot are **Line Plot**, **Histogram**, **Scatter**, **3D Plot**, **Image**, **Contour**, and **Polar**.
- **Scatter plots:** Scatter plots are used to compare trends in different categories of data types through graphs.
- **Seaborn**: It is an open-source Python library built on top of matplotlib. It is used for data visualization and exploratory data analysis.
- **Barplot()**: In seaborn, the barplot() function operates on a full dataset and applies a function to obtain the estimate (taking the mean by default).
- **Histogram:** A histogram aims to approximate the underlying probability density function that generated the data by binning and counting observations.
- **Kernel density estimation**: KDE presents a different solution to the same problem. Rather than using discrete bins, a KDE plot smooths the observations with a Gaussian kernel, producing a continuous density estimate.
- **Scikit-learn (Sklearn)**: It is the most useful and robust library for machine learning in Python. This library, which is largely written in Python, is built upon NumPy, SciPy and Matplotlib.

Self-Assessment

1. Which libraries are available for machine learning in Python?

A. NumPy
B. Pandas
C. Matplotlib
D. All of the above

2. Using Pyplot, we can

A. Create a figure
B. Create a plotting area in figure
C. Adding labels
D. All of the above

3. When you pass a single parameter, the data is assumed to be of

A. X-axis
B. Y-axis
C. Z-axis
D. XYZ-axis

4. For numerical plotting, we use

A. relplot()
B. scatterplot()
C. lineplot()
D. All of the above

5. Which of the following is used for categorical data plotting?

A. lineplot()
B. boxplot()
C. distplot()

D. None of the above

6. For visualization of distribution of data, we use
A. lineplot()
B. boxplot()
C. distplot()
D. None of the above

7. For linear regression and relationships, we use
A. regpolt()
B. implot()
C. Both of the above
D. None of the above

8. The categorical scatter plot are
A. stripplot()
B. swarmplot()
C. Both of the above
D. None of the above

9. Which of the following is optimized for showing more information about the shape of the distribution?
A. Boxplot()
B. Boxenplot()
C. Voilinplot()
D. None of the above

10. To show an estimate of the central tendency of the values, Seaborn has
A. Bar plot
B. Point plot
C. Both of the above

11. What is a special case for the bar plot is when you want to show the number of observations in each category rather than computing a statistic for a second variable?
A. Countplot
B. Scatterplot
C. Pointplot
D. None of the above

12. The axes level functions are:
A. histplot()
B. kdeplot()
C. ecdfplot()
D. All of the above

13. Density normalization scales the bars so that their *areas* sum to
A. -1
B. 0
C. 1
D. Not defined

14. What is a powerful way to understand what users do on your website pages—where they click, how far they scroll, what they look at or ignore?
A. Barplot
B. Heatmaps
C. Pointplot
D. Histogram

15. Which preprocessing technique is used when we need to convert our numerical values into Boolean values?
A. Binarization
B. Scaling
C. Normalization
D. None of the above

Answers for Self Assessment

1.	D	2.	D	3.	B	4.	D	5.	B
6.	C	7.	C	8.	C	9.	B	10.	C
11.	A	12.	D	13.	C	14.	B	15.	A

Review Questions

1. Explain the libraries which are used for machine learning in Python?
2. Explain the steps for solving a problem using machine learning.
3. What is matplotlib? Also explain its installation steps and Pyplot.
4. What is scatter plot? Also tell how to add different functions to it.
5. What is pre-processing of data? Which techniques are available under it?
6. What is support vector machine? Also write about its goal and important features.

Further Readings

https://www.r-project.org/about.html

https://www.geeksforgeeks.org/r-programming-language-introduction/

Unit 16: RapidMiner

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Summary

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Objectives

After this unit, you will be able to:

- Understand the basics of RapidMiner
- Understand how to import data
- Understand how to export data
- Understand how to implement algorithms

Introduction

Data mining or data analysis in general has become more and more important, since large amounts of data are available and open new opportunities for enhanced empirical sciences, planning and control, and targeted marketing and information services. RapidMiner is a system which supports the design and documentation of an overall data mining process. It offers not only an almost comprehensive set of operators, but also structures that express the control ow of the process. Rapid Miner is a platform for data scientists and big data analysts to quickly analyze their data. RapidMiner is a comprehensive platform with visual workflow design and full automation. Rapid Miner has taken a huge leap in the AI community since it is most popularly used by non-programmers and researchers.

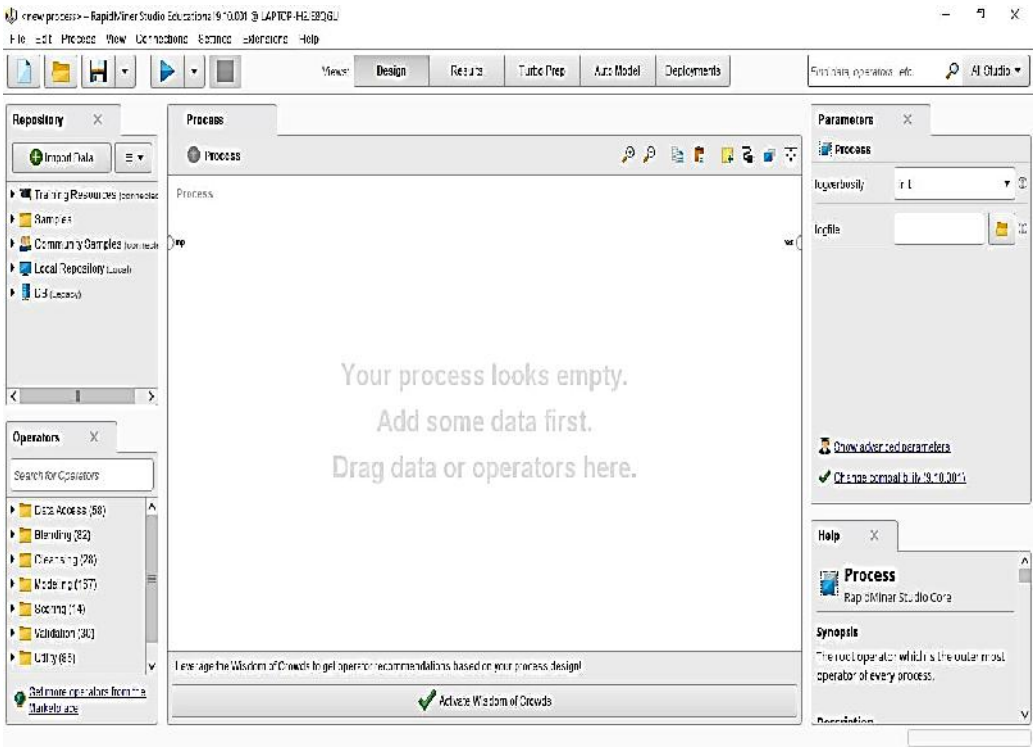
Why RapidMiner

- The platform provides a vast number of options in terms of plugins and data analysis techniques. It provides various product extensions as well, which makes the difficult tasks easier.
- Apart from this,it is also compatible with iOS, Android, and web application tools like Node JS and flask.
- It is best for non-programmers.

16.1 Architecture of RapidMiner

The idea behind Rapid Mining tool is to create one place for everything. Starting from providing multiple datasets to model deployment through the platform you can do it all here. Some of the facilities of this platform are:

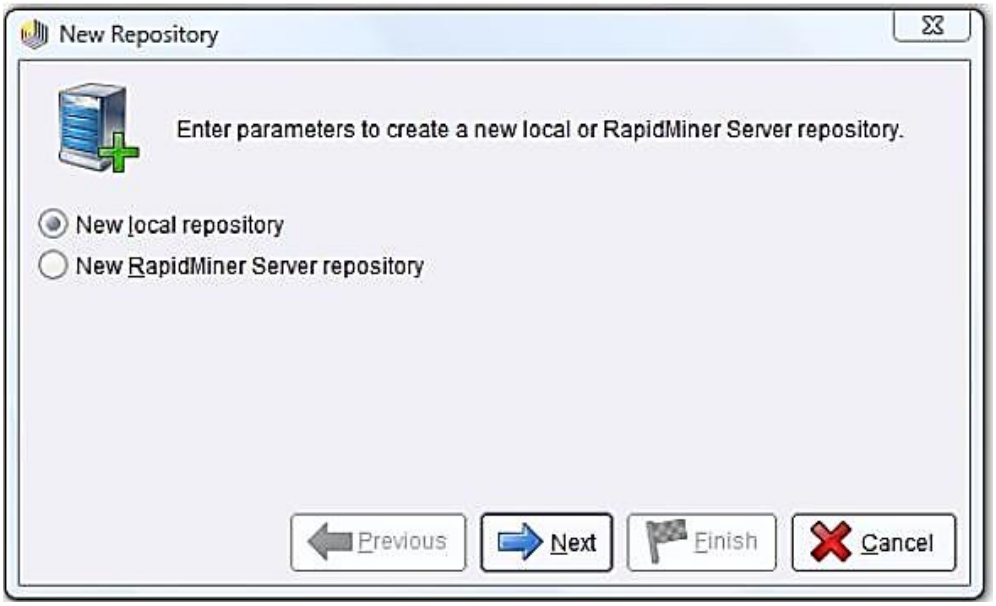
1. Rapid Miner provides its own collection of datasets, but it also provides options to set up a database in the cloud for storing large amounts of data. You can store and load the data from Hadoop, Cloud, RDBMS, NoSQL etc. Apart from this, you can load your CSV data very easily and start using it as well.
2. The standard implementation of procedures like data cleaning, visualization, pre-processing can be done with drag and drop options without having to write even a single line of code.
3. Rapid Miner provides a wide range of machine learning algorithms in classification, clustering, and regression as well. You can also train optimal deep learning algorithms like Gradient Boost, XGBoost etc. Not only this, but the tool also provides the ability to perform pruning and tuning.
4. Finally, to bind everything together, you can easily deploy your machine learning models to the web or to mobiles through this platform. You just need to create user interfaces to collect real-time data and run it on the trained model to serve a task.



16.2 Installation of RapidMiner

- Open http://www.rapidminer.com website.
- Choose your operating system to start downloading the appropriate installation packages.
- When the downloading of exe file is done. We need to install it by double click on .exe file.
- Click on next.
- We need to agree on license so that the further processing can be done.
- Choose the destination folder where we want to install it by clicking on Browse.
- Click on install.
- Click on Finish and Launch the RapidMiner.
- Create an account and login.

If you are starting RapidMiner Studio for the first time, you will be asked to create a new repository. For a local repository you just need to specify a name (alias) and define anydirectory on your hard drive. You can select the directory directly by clicking on the folder icon on the right. It is advisable to create a new directory in a convenient place within the file dialog that then appears and then use this new directory as a basis for your local repository. This repository serves as a central storage location for your data and analysis processes and will accompany you soon.



Perspective and Views:

After choosing the repository you will be welcomed into the Home Perspective. The right section shows current news about RapidMiner if you are connected to the Internet. The list in the centre shows the typical actions, which you will perform frequently after starting RapidMiner Studio.

1. New Process:Opens the design perspective and creates a new analysis process.
2. Open: Opens a repository browser if you click on the button. You can choose and open an existing process in the design perspective. If you click on the arrow button on the right side, a list of recently opened processes appears. You can select one and it will be opened in the design perspective.
3. Application Wizard: You can use the Application Wizard to solve typical data mining problems with your data in three steps. The Direct Marketing Wizard allows you to find marketing actions with the highest conversion rates. The Predictive Maintenance Wizard predicts necessary maintenance activities. The Churn Analysis Wizard allows you to identify which customers are most likely to churn and why. The Sentiment Analysis Wizard analyses a social media stream and gives you an insight into customers' thinking.

4. Tutorials:Starts a tutorial window which shows several available tutorials from creating the first analysis process to data transformation. Each tutorial can be used directly within RapidMiner Studio and introduces some data mining concepts using a selection of analysis processes.

16.3 Views in Rapid Miner

Operators' View

All work steps (operators) available in RapidMiner Studio are presented in groups here and can therefore be included in the current process. You can navigate within the groups in a simple manner and browse in the operators provided to your heart's desire. If RapidMiner Studio has been extended with one of the available extensions, then the additional operators can also be found here. Without extensions you will find at least the following groups of operators in the tree structure.

1. Process Control: Operators such as loops or conditional branches which can control the process.
2. Utility: Auxiliary operators which, alongside the operator \Subprocess" for grouping subprocesses, also contain the important macro-operators as well as the operators for logging.
3. Repository Access:Contains operators for read and write access in repositories.
4. Import: Contains many operators to read data and objects from external formats such as files, databases etc.
5. Export:Contains many operators for writing data and objects into external formats such as files, databases etc.
6. Data Transformation: Probably the most important group in the analysis in terms of size and relevance. All operators are located here for transforming both data and meta data.
7. Modeling:Contains the actual data mining process such as classification methods, regression methods, clustering, weightings, methods for association rules, correlation and similarity analyses as well as operators, in order to apply the generated models to new data sets.
8. Evaluation:Operators which can compute the quality of a model and thus for new data, e.g.,cross-validations, bootstrapping etc.

Repositories View

The repository is a central component of RapidMiner Studio which was introduced in Version 5. It is used for the management and structuring of your analysis processes into projects and at the same time as both a source of data as well as of the associated meta data.

Process View

The Process View shows the individual steps within the analysis process as well as their interconnections. New steps can be added to the current process in several ways. Connections between these steps can be defined and detached again. Finally, it is even possible to define the order of the steps in this perspective.

16.4 Operators

Working with RapidMiner Studio fundamentally consists in defining analysis processes by indicating a succession of individual work steps. In RapidMiner Studio, these process components are called operators. An operator is defined by several things:

- The description of the expected inputs.
- The description of the supplied outputs.
- The action performed by the operator on the inputs, which ultimately leadsto the supply of the outputs.

- Several parameters which can control the action performed.

The inputs and outputs of operators are generated or consumed via ports. A port expects a specific type of input. input ports are placed on the left side and output ports are placed on the right side.

Such an operator can for example import data from the repository, a database or from files. In this case it would have no input ports, although it would have a parameter at least specifying the location of the data. Other operators transform their inputs and return an object of the same type. Operators that transform data belong in this group. And other operators still consume their input and transform it into a completely new object: many data mining methods come under this category and supply a model for the given input data for example.The color of the ports indicates the input type a port must be supplied with. For example, a bluish color indicates that an example set is required. If the upper half of the port and the name of the port are red, then this indicates a problem. Output ports are white if the result is unclear or cannot (yet) be supplied in the current configuration. As soon as all necessary configurations are complete, i.e., all necessary parameters are defined and all necessary input ports connected,then the output ports are colored according to their type. But not only the ports can visualize their status by means of different status indicators, but also the complete operator.

Status light:Indicates whether there is a problem like parameters that have not yet been set or unconnected input ports (red), whether the configuration is basically complete, but the operator has not yet been implemented since then (yellow) or whether everything is OK, and the operator has also already been implemented successfully (green).

Warning triangle: Indicates when there are status messages for this operator.

Breakpoint:Indicates whether process execution is to be stopped before or after this operator to give the analyst the opportunity to examine intermediate results.

Comment:If a comment has been entered for this operator, then this is indicated by this icon.

Subprocess:This is a very important indication, since some operators have one or more subprocesses. It is shown by this indication whether there is such a subprocess. You can double click on the operator concerned to go down into the subprocesses.

Inserting Operators

You can insert new operators into the process in different ways. Here are thedetails of the different ways:

- Via drag & drop from the Operators View as described above,
- Via double click on an operator in the Operators View,
- Via dialog which is opened by the menu entry \Edit" { \ New Operator. . . " (Ctrl-I),
- Via context menu in a free area of the white process area and there via the submenu\New Operator" and the selection of an operator.

Connecting Operators

After you have inserted new operators, you can interconnect the operators inserted. There are basically three ways available to you,

Connections 1: Automatically when inserting

Connections 2: Manually

Connections 3: Fully automatically

Selecting Operators

On order to edit parameters you must select an individual operator. You willrecognise the operator currently selected by its orange frame as well as its shadow. If you wish to perform an action for several operators at the same time, for example moving or deleting, please select the relevant operators by dragging a frame around these. To add individual operators to the current selection or exclude individual operators from the current selection, please hold the CTRL key down while you click on the relevant operators or add further operators by dragging a frame.

Moving Operators

Select one or more operators as described above. Now move the cursor onto one of the selected operators and drag the mouse while holding down the button. All selected operators will now be moved to a new place depending on where you move the mouse. If, during this movement, you reach the edge of the white area, then this will be automatically enlarged accordingly. If you should reach the edge of the visible area, then this will also be moved along automatically.

Copying Operators

Select one or more operators as described above. Now press Ctrl+C to copy the selected operators and press Ctrl+V to paste them. All selected operators willnow be placed to a new place next to the original operators, where you can movethem further.

Deleting Operators

Select one or more operators as described above. You can now delete the selectedoperators by

- Pressing the DELETE key,
- Selecting the action \Delete" in the context menu of one of the selectedoperators,
- By means of the menu entry “Edit” – “Delete".

16.5 Pre-Processing

Only a small (though decisive) part of an overall data mining process is about model building. Evaluating and visualizing the results is the concluding part. The largest part is the pre-processing.

- It starts with reading in the data and declaring the meta data. RapidMiner supports many data formats and offers operators for assigning not only value domains of attributes (attribute type), but also their role in the learning process.
- The inspection of the data through diverse plots is an important step in developing the case at hand. In many case studies, this step is not recorded, since after the exploration it is no longer necessary. The understanding of the analysis task and the data leads to the successful process.
- Operators that change the given representation are important to bridge the gap betweenthe given data and the input format that a learner needs. Most analysts have a favourite learning method and tweak the given data until they suit this algorithm well. If frequent set mining is the favourite, the analyst will transform m nominal values of one attribute into m binomial attributes so that frequent set mining can be applied. If the attribute type requirements of a learner are not yet fulfilled, RapidMiner proposes fixes.
- The discretization of real-valued attributes into nominal- or binomial-valued attributes is more complex and, hence, RapidMiner offers a variety of operators for this task.
- Beyond type requirements, features extraction and construction allow learners to find interesting information in data which otherwise would be hidden. A very large collection of operators offers the transformation of representations. The text processing plug-in, the value

series plug-in, and the image processing plug-in are specifically made for the pre-processing of texts, time series or value series in general, and images.

- The feature selection plug-in automatically applies user-specified criteria to design the best feature set for a learning task. Moreover, it evaluates the selected features with respect to stability. For real-world applications, it is important that good performance is achieved at any sample of data. It is not sufficient that the selected features allow a good performance on average in the cross-validation runs, but it must be guaranteedthat the features allow a sufficiently good performance on every data sample.

16.6 Building a First Process

One of the first steps in a process for data analysis is usually to load some data into thesystem. RapidMiner supports multiple methods for accessing datasets. It supports morethan 40 different file types and of course all major database systems. If the data is notoriginally stored in a relational database system, the best approach is to import the datafirst into the RapidMiner repository.

Loading Data:The very first operation in our process should be to load the data from the repository again to make it available for the next analysis steps. Import: Contains many operators to read data and objects from external formats such as files, databases, etc. For export, it contains many operators for writing data and objects into external formats such as files, databases, etc.

1. Go to the Repositories view and open the repository Samples delivered with rapidMiner. Click on the small plus sign in front of this repository. You should now see two folders named data and processes. Open the data folder and you will and a collection of datasets coming together with RapidMiner. Click on the dataset and drag it onto the large white view named Process in the centre of your frame. After releasing the dataset somewhere on the white area, it should be transformed into an operator named Retrieve with a bluish output port on the right side. RapidMiner automatically has transformed the dataset into an operator loading the dataset. If you click on the operator; you can see a parameter in the Parameters view pointing to the data location. The Retrieve operator in general, well, retrieves objects from a repository and makes them available in your process.
2. Click on the output port of the Retrieve operator and then click on the first res port on the right side. Alternatively, you can also drag a connection line between the two ports.

16.7 Important Things

Product Extensions

There are several extensions available for the product. As per the requirements, we can install the extensions. This can be done as:

- Extensions → marketplace (updates and extensions)

Visualizing Data

Once the data is loaded. Then we can visualize it. This will ensure about the missing values (if any), total number of values, middle value etc.

Turbo Prep

Turbo prep substantially reduces the time spent on data extraction, loading and transformation. The features Turbo Prep includes are:

- Transform: For transforming the features into a new one.
- Cleanse:The data does not come in perfect shape. The cleansing of data is if it includes any missing data or null values. The data may need to be joined from multiple tables which

contains missing values, inconsistencies, duplicates or typing mistakes. This can be done for both categorical as well as for numerical data.

- Generate: The features are generated using Generate. It includes adding of columns, and adding function and constants.
- Pivot: The pivot table can be generated using the feature of pivot.Pivot table is used to rearrange and aggregate the data.First filter out the data by applying filter on missing values by transforming it – is not missing filter.
- Merge: If two data need to be merged then the Merge can be used in Turbo Prep. This merging requires one of the columns should work as primary key in first table whereas in another table, the same column name should also be there. It includes appending of data, right join, left join, inner join etc. While appending the data, columns should be same in both tables.

16.8 Creating a Model

Creating a Decision Tree Model

- Load the data customer churn data for experimentation.
- If you look at data, few of the values in label column are missing, so we need to filter out the missing values using the filter example operator of RapidMiner.
- Click on Statistics to see if there are any other missing values.

Applying the model

- Create a copy of the process which we have just created and give it a valid name.
- Now we will apply the model which we have just built on the data which contains? In the dataset.
- In RapidMiner, the output port relates to only one other port. But if we want multiple connections, then we need to implement multiply operator.
- In one set, take those data examples which have their label.
- In another set, take those examples which do not have their label.
- Connect the labelled example filter to decision tree and connect the unlabelled example filter to directly result.
- Apply the model which is built.

Training a Model

- We first train a model and then test a model, so that we can see how the predictions can be made.
- Take the customer churn data for experimentation.
- Filter out the data for training which contains labelled data.
- Apply decision tree operator.
- Implement apply model operator.
- Use multiply operator.
- Use performance operator.
- Check the accuracy of the model. It just shows the training accuracy. If we need to find out the predictive accuracy, then we need to validate the model.

Validating a Model

- Retrieve customer churn data.
- Add filter examples

- Add cross validation.
- Double click on cross validation.
- In training, connect the decision tree.
- In testing, apply the model, and check the performance.

Summary

- RapidMiner is a system which supports the design and documentation of an overall data mining process. It offers not only an almost comprehensive set of operators, but also structures that express the control ow of the process.
- Rapid Miner provides a wide range of machine learning algorithms in classification, clustering, and regression as well. You can also train optimal deep learning algorithms like Gradient Boost, XGBoost etc. Not only this, but the tool also provides the ability to perform pruning and tuning.
- In operator'sview, all work steps (operators) available in RapidMiner Studio are presented in groups here and can therefore be included in the current process.
- The sources of displaying results are automatic opening, results from repositories, results from ports.
- You can easily deploy your machine learning models to the web or to mobiles through this platform. You just need to create user interfaces to collect real-time data and run it on the trained model to serve a task.

Keywords

- **Rapidminer**: It is a platform for data scientists and big data analysts to quickly analyze their data. It is a comprehensive platform with visual workflow design and full automation. It has taken a huge leap in the AI community since it is most popularly used by non-programmers and researchers.
- **Repository view**: The repository is a central component of RapidMiner Studio which was introduced in Version 5. It is used for the management and structuring of your analysis processes into projects and at the same time as both a source of data as well as of the associated meta data.
- **Process view:**The Process View shows the individual steps within the analysis process as well as their interconnections. New steps can be added to the current process in several ways. Connections between these steps can be defined and detached again. Finally, it is even possible to define the order of the steps in this perspective.

SelfAssessment

1. Data analysis is a process of

A. Inspecting data
B. Cleaning data
C. Transforming data
D. All of the above

2. Data analysis uses _____ to get insights from data.

A. Statistical figures
B. Numerical aspects

C. Statistical methods
D. None of the above

3. RapidMiner is a system which
A. supports the design of data mining process.
B. Supports the documentation of data mining process.
C. Offers a set of operators
D. All of the above

4. Rapidminer provides the implementation of
A. Data cleaning procedures
B. Data visualization procedures
C. Data pre-processing procedures
D. All of the above-mentioned procedures

5. Rapiminer
A. Provides a vast number of plugins
B. Is compatible with many OSs
C. Pre-processes the data
D. All of the above

6. The operators view of rapidminer has
A. Process control
B. Utility
C. Import option
D. All of the above

7. In rapidminer, we can store and load the data from
A. Hadoop
B. Cloud
C. RDBMS
D. Either of the above

8. The operators view contains the operators for
A. Data transformation
B. Modelling
C. Evaluation
D. All of the above

9. Rapid Miner is best for non-programmers
A. True
B. False

10. Which web application is compatible with RapidMiner?
A. Node JS
B. Flask

C. Both of the above
D. None of the above

11. What is used for the management and structuring of your analysis processes into projects and at the same time as both a source of data as well as of the associated meta data?
A. Repositories views
B. Process views
C. Operators views
D. None of the above

12. Which of the following views shows the individual steps within the analysis process as well as their interconnections?
A. Repositories views
B. Process views
C. Operators views
D. None of the above

13. The deletion operator works by
A. Pressing the DELETE key,
B. Selecting the action \Delete" in the context menu of one of the selected operators,
C. By means of the menu entry “Edit” – “Delete".
D. Either of the above

14. Using Turbo Prep, we can reduce the time substantially spent on
A. Transformation
B. Cleansing
C. Merging
D. All of the above

15. While merging of data, we can perform
A. Inner join
B. Outer join
C. Appending
D. All of the above mentioned

Answers for Self Assessment

1.	D	2.	C	3.	D	4.	D	5.	D
6.	D	7.	D	8.	D	9.	A	10.	C
11.	A	12.	B	13.	D	14.	D	15.	D

Review Questions

1. What is rapidminer used for? How do I add extensions in rapiminer?
2. How to start rapidminer? What is apply model in rapidminer?

3. What are operators in rapidminer? How do we get the confusion matrix in rapidminer?
4. What is classification, clustering, and cross-validation in rapidminer? Explain with examples.
5. What is data analysis? How rapidminer is used for this?

Further Readings

https://www.ibm.com/in-en/cloud/learn/machine-learning

Web Links

https://www.techtarget.com/searchenterpriseai/definition/machine-learning-ML

Unit 17: Tableau

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Objectives

After studying this unit, you will be able to:

- Understand the basics of Tableau
- Know about the products of Tableau
- Know about the supported databases
- Understand how to prepare the data in Tableau
- Understanding data visualization

Introduction

Tableau Software is an American interactive data visualizationsoftware company focused on business intelligence. It was founded in 2003 in Mountain View, California, and is currently headquartered in Seattle, Washington. In 2019 the company was acquired by Salesforce for $15.7

billion. At the time, this was the largest acquisition by Salesforce since its foundation. It was later surpassed by Salesforce's acquisition of Slack.

The company's founders, Christian Chabot, Pat Hanrahan and Chris Stolte, were researchers at the Department of Computer Science at Stanford University. They specialized in visualization techniques for exploring and examining relational databases and data cubes, and started the company as a commercial outlet for research at Stanford from 1999 to 2002. Tableau products query relational databases, online analytical processing cubes, cloud databases, and spreadsheets to generate graph-type data visualizations. The software can also extract, store, and retrieve data from an in-memory data engine.

Tableau is a business intelligence tool which helps us in analyzing data in a visualmanner,maybe a graph, report etc.Suppose we have a database in MSEXCEL, if we want to analyse data in the forms of graphs or reports, we can use Tableau. It is a great tool for visually analyzing the data. Users can create and distribute an interactive and shareable dashboard, which depicts the trends, variations, and density of the data in the form of graphs and charts. Tableau can connect to files, relational and Big Data sources to acquire and process data. The software allows data blending and real-time collaboration, which makes it unique. It is used by businesses, academic researchers, and many government organizations for visual data analysis. It is also positioned as a leader Business Intelligence and Analytics Platform in Gartner Magic Quadrant.

17.1 Features of Tableau

As a leading data visualization tool, Tableau has many desirable and unique features. Its powerful data discovery and exploration application allows you to answer important questions in seconds. You can use Tableau's drag and drop interface to visualize any data, explore different views, and even combine multiple databases easily. It does not require any complex scripting. Anyone who understands the business problems can address it with a visualization of the relevant data. After analysis, sharing with others is as easy as publishing to Tableau Server. Tableau provides solutions for all kinds of industries, departments, and data environments. Following are some unique features which enable Tableau to handle diverse scenarios.

- Speed of Analysis − As it does not require high level of programming expertise, any user with access to data can start using it to derive value from the data.
- Self-Reliant − Tableau does not need a complex software setup. The desktop version which is used by most users is easily installed and contains all the features needed to start and complete data analysis.
- Visual Discovery − The user explores and analyses the data by using visual tools like colours, trend lines, charts, and graphs. There is very little script to be written as nearly everything is done by drag and drop.
- Blend Diverse Data Sets − Tableau allows you to blend different relational, semi-structured and raw data sources in real time, without expensive up-front integration costs. The users don’t need to know the details of how data is stored.
- Architecture Agnostic − Tableau works in all kinds of devices where data flows. Hence, the user need not worry about specific hardware or software requirements to use Tableau.
- Real-Time Collaboration − Tableau can filter, sort, and discuss data on the fly and embed a live dashboard in portals like SharePoint site or Salesforce. You can save your view of data and allow colleagues to subscribe to your interactive dashboards, so they see the very latest data just by refreshing their web browser.
- Centralized Data − Tableau server provides a centralized location to manage all the organization’s published data sources. You can delete, change permissions, add tags, and manage schedules in one convenient location. It’s easy to schedule extract refreshes and manage them in the data server. Administrators can centrally define a schedule for extracts on the server for both incremental and full refreshes.

17.2 Download and Install Tableau Desktop

Download

- Go to website www.tableau.com.
- Go to try now (Only for 14 days).
- Enter your details.
- And download free trial.
- We can try other versions also like Tableau Cloud and Tableau Server.
- Before installation, we need to check for system requirements.

System Requirements

The system requirements are different for operating systems.

Windows

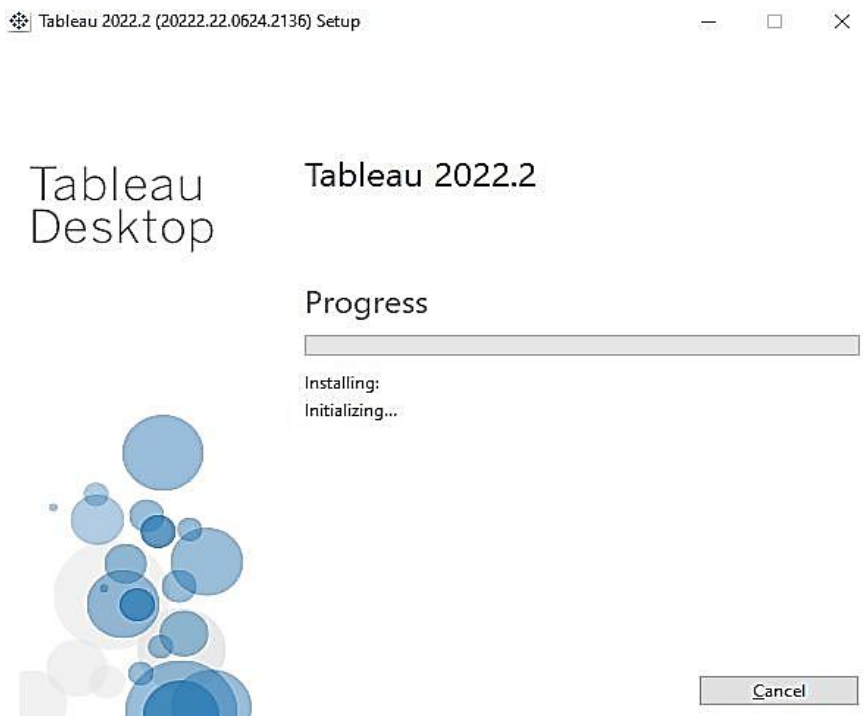
- Microsoft Windows 8/8.1, Windows 10 (x64)
- 2 GB memory
- 1.5 GB minimum free disk space
- CPUs must support SSE4.2 and POPCNT instruction sets

Mac

- macOS Mojave 10.14, macOS Catalina 10.15, and Big Sur 11.4+
- Intel processors
- M1 processors under Rosetta 2 emulation mode
- 1.5 GB minimum free disk space
- CPUs must support SSE4.2 and POPCNT instruction sets

Installation

- Double click on .exe file
- Accept the agreement. Click on Install.



17.3 Basic Operations in Tableau

There are some basic operations in Tableau to get acquainted with its interface. There are three basic steps involved in creating any Tableau data analysis report. These three steps are −

Connect to a data source − It involves locating the data and using an appropriate type of connection to read the data. On opening Tableau, you will get the start page showing various data sources. Under the header "Connect", you have options to choose a file or server or saved data source. Under Files, choose excel. Then navigate to the file "Sample – Superstore.xls" as mentioned above. The excel file has three sheets named Orders, People and Returns. Choose Orders.

Choose dimensions and measures − This involves selecting the required columns from the source data for analysis. Next, choose the data to be analyzed by deciding on the dimensions and measures. Dimensions are the descriptive data while measures are numeric data. When put together, they help visualize the performance of the dimensional data with respect to the data which are measures. Choose Category and Region as the dimensions and Sales as the measure. Drag and drop them as shown in the following screenshot. The result shows the total sales in each category for each region.

Apply visualization technique − This involves applying required visualization methods, such as a specific chart or graph type to the data being analyzed. In the previous step, you can see that the data is available only as numbers. You must read and calculate each of the values to judge the performance. However, you can see them as graphs or charts with different colors to make a quicker judgment. We drag and drop the sum (sales) column from the Marks tab to the Columns shelf. The table showing the numeric values of sales now turns into a bar chart automatically.

17.4 Data types supported by Tableau

As a data analysis tool, Tableau classifies every piece of data into one of the four categories namely - String, Number, Boolean and date time. Once data is loaded from the source, Tableau automatically assigns the data types. Contrarily, you can also change some of the data types if it satisfies the data conversion rule. The user must specify the data type for calculated fields.

DATA TYPE	DESCRIPTION
STRING	Any sequence of zero or more characters. They are enclosed within single quotes. The quote itself can be included in a string

	by writing it twice.
NUMBER	These are either integers or floating points. It is advised to round the floating-point numbers while using them in calculations.
BOOLEAN	They are logical values.
DATE & DATETIME	Tableau recognizes dates in almost all formats. But in case we need to force Tableau to recognize a string as date, then we put a # sign before the data.

17.5 Tableau Data Terminology

As a powerful data visualization tool, Tableau has many unique terms and definitions. You need to get acquainted with their meaning before you start using the features in Tableau. The following list of terms is comprehensive and explains the terms most frequently used.

1. Alias:An alternative name that you can assign to a field or to a dimension member.
2. Bin: A user-defined grouping of measures in the data source.
3. Bookmark:A. tbm file in the Bookmarks folder in the Tableau repository that contains a single worksheet. Much like web browser bookmarks, tbm files are a convenient way to quickly display different analyses.
4. Calculated Field: A new field that you create by using a formula to modify the existing fields in your data source.
5. Crosstab:A text table view. Use text tables to display the numbers associated with dimension members.
6. Dashboard:A combination of several views arranged on a single page. Use dashboards to compare and monitor a variety of data simultaneously.
7. Data Pane: A pane on the left side of the workbook that displays the fields of the data sources to which Tableau is connected. The fields are divided into dimensions and measures. The data pane also displays custom fields such as calculations, binned fields, and groups. You build views of your data by dragging fields from the data pane onto the various shelves that are a part of every worksheet.
8. Data Source Page: A page where you can set up your data source. The data source page generally consists of four main areas − left pane, join area, preview area, and metadata area.
9. Dimension:A field of categorical data. Dimensions typically hold discrete data such as hierarchies and members that cannot be aggregated. Examples of dimensions include dates, customer names, and customer segments.
10. Extract:A saved subset of a data source that you can use to improve performance and analyze offline. You can create an extract by defining filters and limits that include the data you want in the extract.
11. Filters Shelf: A shelf on the left of the workbook that you can use to exclude data from a view by filtering it using measures and dimensions.
12. Format Pane: A pane that contains formatting settings that control the entire worksheet, as well as individual fields in the view. When open, the Format pane appears on the left side of the workbook.
13. Level of Detail (LOD) Expression: A syntax that supports aggregation at dimensionalities other than the view level. With the level of detail expressions, you can attach one or more dimensions to any aggregate expression.

14. Marks: Apart of the view that visually represents one or more rows in a data source. A mark can be, for example, a bar, line, or square. You can control the type, color, and size of marks.
15. Marks Card: A card to the left of the view, where you can drag fields to control mark properties such as type, color, size, shape, label, tooltip, and detail.
16. Pages Shelf: A shelf to the left of the view that you can use to split a view into a sequence of pages based on the members and values in a discrete or continuous field. Adding a field to the Pages shelf is like adding a field to the Rows shelf, except that a new page is created for each new row.
17. Rows Shelf: A shelf at the top of the workbook that you can use to create the rows of a data table. The shelf accepts any number of dimensions and measures. When you place a dimension on the Rows shelf, Tableau creates headers for the members of that dimension. When you place a measure on the Rows shelf, Tableau creates quantitative axes for that measure.
18. Shelves:Named areas to the left and top of the view. You build views by placing fields onto the shelves. Some shelves are available only when you select certain mark types. For example, the Shape shelf is available only when you select the Shape mark type.
19. Workbook: A file with a .twb extension that contains one or more worksheets (and possibly also dashboards and stories).
20. Worksheet:A sheet where you build views of your data by dragging fields onto shelves.

17.6 Tableau Products

There are various products available from Tableau. These are:

- Tableau Desktop
- Tableau Online
- Tableau Server
- Tableau Reader
- Tableau Public

The first two, i.e., Tableau Desktop and Tableau Online are used to create different types of reports. The last three, i.e., Tableau Server, Tableau Reader and Tableau Public are used for publishing the reports.

17.7 Supported Databases

Several databases are supported by Tableau. These are:

- Spreadsheet
- Database
- Big Data
- Access Data warehouse
- Cloud Applications
- Cloud Databases
- 50+ Different Databases

17.8 Places to Publish the Results

When the task is completed. There are several places where we can publish the results. These are:

- Desktop

- Tablet
- Phone

Suppose the data is placed in MS EXCEL, if we want to create a report or chart, then first create a pivot table. Tableau recognizes the data by dividing into two parts,i.e., dimensions and measures.The texts, dates and the geographical locations are taken as dimensions whereas the numbers, figures and the float values that are considered as measures.

17.9 Why use Tableau?

Now a day, Tableau is the most used software for data visualization tasks. There are several reasons to use Tableau for this. Some of the reasons are:

1. Great speed
2. User-friendly
3. Beautiful and interactive dashboard
4. Direct connection
5. Easy publishing and sharing
6. Growing market

17.10 Tableau Data Sources

Tableau can connect to all the popular data sources which are widely used. Tableau's native connectors can connect to the following types of data sources.

- File Systems such as CSV, Excel, etc.
- Relational Systems such as Oracle, SQL Server, DB2, etc.
- Cloud Systems such as Windows Azure, Google Big Query, etc.
- Other Sources using ODBC

The following pictures show most of the data sources available through Tableau's native data connectors.

Connecting to a file

Connecting to a server

17.11 Data Extraction

Data extraction in Tableau creates a subset of data from the data source. This is useful in increasing the performance by applying filters. It also helps in applying some features of Tableau to data which may not be available in the data source like finding the distinct values in the data. However, the data extract feature is most frequently used for creating an extract to be stored in the local drive for offline access by Tableau.

Creating an extract

Extraction of data is done by following the menu - Data → Extract Data. It creates many options such as applying limits to how many rows to be extracted and whether to aggregate data for dimensions.

Applying extract filters

To extract a subset of data from the data source, you can create filters which will return only the relevant rows. Let's consider the Sample Superstore data set and create an extract. In the filter option, choose Select from list and tick mark the checkbox value for which you need to pull the data from the source.

Adding new data to extract

To add more data for an already created extract, you can choose the option Data → Extract → Append Data from File. In this case, browse the file containing the data and click OK to finish. Of course, the number and datatype of columns in the file should be in sync with the existing data.

Extract History

You can verify the history of data extracts to be sure about how many times the extract has happened and at what times. For this, you can use the menu - Data → Extract History.

17.12 Live vs Extract

- Live: It will be connected to your live current data.
- Extract: The screenshot taken of your previous data at a particular point of time.

Example

- After connecting to the data, there are two options: live and extract.
- In live, the data after changes done can be updated using REFRESH button.
- In extract, the data after changes done can be updated using by Data → Refresh data source

17.13 View Data

In the left side, we have all the sheets which are available under the dataset. There are various ways by which we can view them.

1. Drag and drop method.
2. Click on sheet and a dialog box will open. If we want to see a smaller number of records. Then that can also be done by writing the number in the box and click on Go button.

If we want to hide any column, then that can be hidden by clicking and selecting hide. The same can be unhidden as well.

17.14 Column Formatting

- Rename a column – Double click on Column name and rename.
- Copy a column – For copying a column, go to copy values and paste it.

If we want to copy only few records, just select those records, and paste it.If we want to copy the entire record, then CTRL-A and CTRL-C and paste it. We can also perform splitting. Like split a column into two columns, select split and split the columns, custom split can also be used.

Sorting of Columns

If we want to sort the column name, then that can be done by selecting A-Z ascending/ Z-A ascending from settings.If we have multiple tables, then A-Z ascending per table/ Z-A ascending per table can be used.The default sorting is data source order.If we want to sort a particular column, then that can be done by clicking next to the column name.

Drill Down and Hierarchies

Hierarchies →City, state and country, and Day, month, quarter, and year. There are some categories which are auto defined.For example, between order date and sales. So, this is known as discrete data.We can also view continuous data as well.

Tableau-Groupings

When we create a group, then that group will be stored as a dimension here.

Measure names and values

These are auto-generated fields. They follow italic format.For example: Take orders (count) from the left side and drop it in Text marks. It will show you the total number of records.It can also be verified as: take category in rows and get grand total from analysis tab.We can also get the summary of all the measure values, take the measure names in rows and measure values in label.

17.15 Introduction to Charts

It is a very powerful tool for creating different types of charts.Tableau uses a visualization query language for creating a chart.Shown using show me button.Using these dimensions and measures, we can create charts in Tableau. We can create a total 24 types of charts. Some of these are:

- Bar chart
- Stacked bar chart
- Line chart
- Pie chart
- Scatter chart
- Packed bubble chart
- Word map
- Tree maps
- Waterfall Chart

- India map
- US map
- Basic funnel chart

Summary

- Tableau is a business intelligence tool which helps us in analyzing data in a visual manner, maybe a graph, report etc.
- Suppose we have a database in MSEXCEL, if we want to analyse data in the forms of graphs or reports, we can use Tableau.
- It is a great tool for visually analyzing the data. Users can create and distribute an interactive and shareable dashboard, which depicts the trends, variations, and density of the data in the form of graphs and charts.
- Tableau can connect to files, relational and Big Data sources to acquire and process data.
- The software allows data blending and real-time collaboration, which makes it unique. It is used by businesses, academic researchers, and many government organizations for visual data analysis.

Keywords

- Alias:An alternative name that you can assign to a field or to a dimension member.
- Bin**:**A user-defined grouping of measures in the data source.
- Bookmark: A. tbm file in the Bookmarks folder in the Tableau repository that contains a single worksheet. Much like web browser bookmarks, .tbm files are a convenient way to quickly display different analyses.
- Calculated Field: A new field that you create by using a formula to modify the existing fields in your data source.
- Crosstab**:**A text table view. Use text tables to display the numbers associated with dimension members.

SelfAssessment

1. Which of the following are features of Tableau?

A. Speed of analysis
B. Self-Reliant
C. Visual Discovery
D. All the above mentioned

2. Which of the following are basic operations in Tableau?

A. Connect to a data source
B. Choose dimensions and measures
C. Apply visualization technique
D. All the above mentioned

3. Which of the following charts can be created in Tableau?

A. Bar chart
B. Line chart

C. Both above
D. None of the above

4. Where can we publish the results in Tableau?
A. Phone
B. Desktop
C. Tablet
D. All of the above

5. Which of the following databases are supported by Tableau?
A. Big Data
B. Cloud databases
C. Spreadsheet
D. All of the above

6. Which of the following are the features of Tableau?
A. Real time collaboration
B. Centralized data
C. Both of the above
D. None of the above

7. Which of the following data source can be used to connect in Tableau?
A. JSON File
B. PDF File
C. Spatial File
D. All of the above mentioned

8. Which of the following are the products of Tableau?
A. Tableau Desktop
B. Tableau Server
C. Tableau Reader
D. All of the above

9. Which of the following datatypes are supported in Tableau?
A. Date
B. String
C. Number
D. All of the above

10. After connecting to the data, which options are available in Tableau?
A. Live
B. Extract
C. Both live and extract
D. None of the above

11. Which of the following data types represents the logical values only?
A. String

B. Boolean
C. Number
D. Date

12. Tableau recognizes the data by dividing into two parts, i.e., dimensions and measures. The texts and dates are considered as
A. A dimension
B. A measure
C. Either of the above
D. None of the above

13. Tableau recognizes the data by dividing into two parts, i.e., dimensions and measures. figures and the float values that are considered as
A. A dimension
B. A measure
C. Either of the above
D. None of the above

14. What is used to create different types of reports?
A. Tableau Desktop
B. Tableau Online
C. Both of the above
D. None of the above

15. What are the reasons for using Tableau?
A. Direct connection
B. Easy publishing and sharing
C. Growing market
D. All of the above

Answers for Self Assessment

1.	D	2.	D	3.	C	4.	D	5.	D
6.	C	7.	D	8.	D	9.	D	10.	C
11.	B	12.	A	13.	B	14.	C	15.	D

Review Questions

1. What is Tableau? Give any five important features of Tableau software.
2. What are the features of tableau? Why is this considered as a good data visualization tool?
3. What are charts? How can we create the charts using Tableau?
4. What are Tableau products? Also tell about the supported databases with Tableau.
5. What are the basic operations in Tableau? Also tell about the supported data types of Tableau.

Further Readings

https://www.ibm.com/in-en/cloud/learn/machine-learning

Web Links

https://www.techtarget.com/searchenterpriseai/definition/machine-learning-ML

Unit 18: KNIME

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Objectives

Introduction

18.1 KNIME Analytics Platform

18.2 Executing Workflow

18.3 Implementing Algorithms

18.4 Data Importing

18.5 Solving a Machine Learning Problem

Summary

Keywords

Self Assessment

Answers for Self Assessment

Review Questions

Objectives

After studying this unit, you will be able to

- Understand what KNIME is
- Understand the use of KNIME
- Understand the capabilities of KNIME
- Understand the data preparation in KNIME
- Understand the implementation of algorithms in KNIME

Introduction

KNIME is Konstanz Information Miner.It is free and open-source data analytics, reporting and integration platform for creating data science.It helps you discover the potential hidden in your data, mine for fresh insights or predict new features.KNIME integrates various components for machine learning and data mining through its modular data pipelining "Building Blocks of Analytics" concept.It is a platform, not a programming language. It is a code free environment. It is used to accomplish the same task as R, Python.It is also termed as code free analytics computation. The machine learning, deep learning, NLP, ETL and API integration is also done using KNIME.

The challenge?

- Developing Machine Learning models is always considered very challenging due to its cryptic nature.
- Generally, to develop machine learning applications, you must be a good developer with an expertise in command-driven development.

Why use KNIME?

- KNIME provides a graphical interface (a user-friendly GUI) for the entire development.

- In KNIME, you simply must define the workflow between the various predefined nodes provided in its repository.
- KNIME provides several predefined components called nodes for various tasks such as reading data, applying various ML algorithms, and visualizing data in various formats.
- Thus, for working with KNIME, no programming knowledge is required.

A graphical user interface and use of Java Database Connectivity allows assembly of nodes blending different data sources, including preprocessing (ETL: Extraction, Transformation, Loading), for modeling, data analysis and visualization without, or with only minimal, programming.

Use of KNIME

Since 2006, KNIME has been used in pharmaceutical research, it is also used in other areas such as CRM customer data analysis, business intelligence, text mining and financial data analysis. Recently attempts were made to use KNIME as robotic process automation (RPA) tool.

Capabilities of KNIME

- KNIME allows users to visually create data flows (or pipelines), selectively execute some or all analysis steps, and later inspect the results, models, using interactive widgets and views.
- KNIME is written in Java and based on Eclipse.
- It makes use of extension mechanisms to add plugins providing additional functionality.
- The core version already includes hundreds of modules for data integration (file I/O, database nodes supporting all common database management systems through JDBC or native connectors: SQLite, MS-Access, SQL Server, MySQL, Oracle, PostgreSQL, Vertica and H2), data transformation (filter, converter, splitter, combiner, joiner) as well as the commonly used methods of statistics, data mining, analysis, and text analytics.
- Visualization is supported with the free Report Designer extension.
- KNIME workflows can be used as data sets to create report templates that can be exported to document formats such as doc, ppt, xls, pdf and others.
- KNIMEs core-architecture allows processing of large data volumes that are only limited by the available hard disk space (not limited to the available RAM). E.g., KNIME allows analysis of 300 million customer addresses, 20 million cell images and 10 million molecular structures.
- Additional plugins allow the integration of methods for text mining, Image mining, as well as time series analysis and network.
- KNIME integrates various other open-source projects, e.g., machine learning algorithms from Weka, H2O.ai, Keras, Spark, the R project and LIBSVM; as well as plotly, JFreeChart, ImageJ, and the Chemistry Development Kit.
- KNIME is implemented in Java nevertheless it allows for wrappers calling other code in addition to providing nodes that allow to run Java, Python, R, Ruby, and other code fragments.

Tools of KNIME

KNIME is a low-code data science and data preparation platform that makes understanding data and designing analytic workflows accessible to everyone. The KNIME suite includes two tools:

KNIME Analytics Platform is a desktop-based tool where analysts and developers construct workflows.

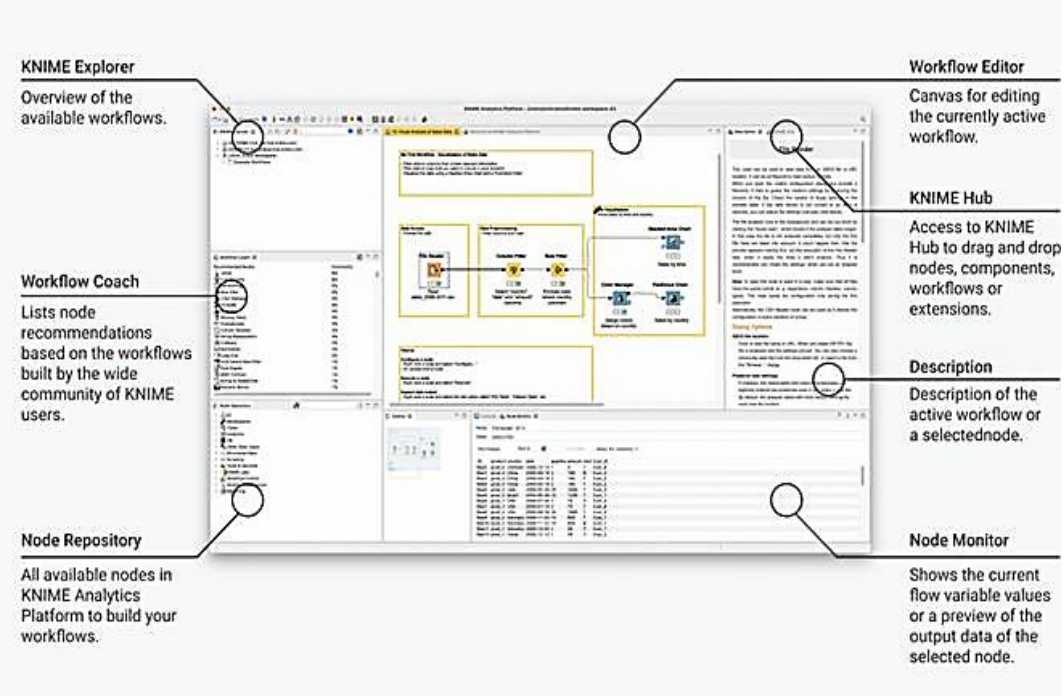
KNIME Server is enterprise software designed for team-based collaboration, automation, management, and deployment of workflows.

As a company, KNIME is dedicated to creating an accessible and open-source tool, and to that end KNIME Analytics Platform is **free** for anybody to download and use. However, do not let the cost fool you; KNIME is a full-featured and incredibly powerful tool for building data prep workflows of any level of complexity.Whether you need to connect to Excel files, a Snowflake database, process audio files, analyze images, or build an interactive dashboard, KNIME can do it. Using KNIME is incredibly easy.Its drag-and-drop interface allows developers to connect to data, perform manipulations and calculations, create interactive visualizations, and much more — without any need for coding.You can, however, code in Python, R, Java, JavaScript, or CSS within KNIME if you want.

General Concepts

KNIME Analytics Platform is a free, open-source software for the entire data science life cycle. KNIME's visual programming environment provides the tools to not only access, transform, and clean data but also train algorithms, perform deep learning, create interactive visualizations, and more.The KNIME Analytics Platform user interface is also referred to as workbench.

18.1 KNIME Analytics Platform



Views in KNIME Analytics Platform

The workbench consists of several views.

1) KNIME Explorer: This gives the overview of available workflows. The first two categories list the workspaces defined on the KNIME server. The third option, LOCAL, is used for storing all the workspaces that you create on your local machine.
2) Workflow Coach: It lists node recommendations based on the workflows built by the wide community of KNIME users.

3) Node Repository: All available nodes in KNIME analytics platform to build your workflows. The entire repository is nicely categorized based on the node functions. You will find categories such as –

- IO
- Views
- Analytics

Under each category you would find several options. Just expand each category view to see what you have there.

4) Workflow Editor/Workspace: Canvas for editing the currently active workflows. Each workspace contains one or more nodes.

5) KNIME Hub: Access to KNIME hub to drag and drop nodes, components, workflows, or extensions.

6) Description: Description of the active workflow or a selected node. Clicking on any other node shows the description of the selected node. Thus, this view becomes very useful in the initial stages of learning when you do not precisely know the purpose of the various nodes in the workspace and/or the nodes repository.

7) Node Monitor: Shows the current flow variable values of a preview of the output data of the selected node.

8) Outline: The workspace view may not be able to show you the entire workflow at a time. That is the reason the outline view is provided.The outline view shows a miniature view of the entire workspace. There is a zoom window inside this view that you can slide to see the different portions of the workflow in the **Workspace** view.

9) Console: As the name indicates, the **Console** view provides a view of the various console messages while executing your workflow. The **Console** view is useful in diagnosing the workflow and examining the analytics results.

Enabling/Disabling views: The various views that you have seen so far can be turned on/off easily. Clicking the Close icon in the view will **close** the view. To reinstate the view, go to the **View** menu option and select the desired view. The selected view will be added to the workbench.

Nodes and workflows

When you are assembling a visual workflow, you will be using "nodes". A node is displayed as a colored box and performs an individual task. A collection of interconnected nodes is your assembled workflow and represents some part – or all – of your data analysis project.Each **node** can perform all kinds of tasks, e.g., reading and writing files, transforming data, training models, or creating visualizations. All the different types of nodes are found in the Node Repository (in the lower-left corner). The data are routed through the node via input and output ports. A node can have data as input or output as well as other objects, such as connections or machine learning models, SQL queries, or data properties. Each object inputs or outputs the node via a dedicated port.Only ports of the same type can be connected. Nodes are color-coded, according to their category, e.g., all yellow nodes are for data wrangling. Depending on their task, nodes also have specific settings, which can be adjusted in their configuration dialog.

A **workflow** in KNIME Analytics Platform consists of several, combined nodes. The data flows through the workflow from left to right through the node connections.You can use a so-called **annotation** – a colored frame that can be placed freely inside a workflow – to document the steps in your workflow.

Components are like metanodes but instead of just grouping some nodes for the sake of transparency, they encapsulate and abstract the functionalities of the logical block. Components serve a similar purpose as nodes, whereas a metanode is more of a visual appearance improvement.

Installation

1) Open the website https://www.knime.com.
2) Click on Download option.
3) Fill in the required details: Email, first name, last name, country, department, organization, role and click on download.
4) Choose the appropriate operating system and click on download.
5) Double click on the downloaded .exe file and install it.

Running Your First Workflow

- Loading decision tree classifier
- LOCAL / Example Workflows / Basic Examples / Building a Simple Classifier.

Double click on the selected item to open the workflow. Observe the Workspace view. You will see the workflow containing several nodes. The purpose of this workflow is to predict the income group from the democratic attributes of the adult data set taken from UCI Machine Learning Repository. The presence of several nodes picked up from the **Nodes** repository and connected in a workflow by arrows. The connection indicates that the output of one node is fed to the input of the next node.

Executing

Before we investigate the execution of the workflow, it is important to understand the status report of each node. Examine any node in the workflow. At the bottom of each node, you would find a status indicator containing three circles.

Different states of a node

A simple traffic light system underneath each node shows you whether the node is already configured, executed, or whether an error has occurred.

1) Not Configured: The node is waiting for configuration or incoming data.
2) Configured: The node has been configured correctly and can be executed successfully.
3) Executed: The node was successfully executed. Results may be viewed and used in downstream nodes.
4) Error: The node has encountered an error during execution.

18.2 Executing Workflow

The status indicator is red indicating that this node has not been executed so far. During the execution, the center circle which is yellow in color would light up. On successful execution, the last circle turns green. There are more indicators to give you the status information in case of errors. It contains various nodes which are listed as:

- File Reader,
- Color Manager
- Partitioning
- Decision Tree Learner
- Decision Tree Predictor
- Score

- Interactive Table
- Scatter Plot
- Statistics

File Reader

There is some description at the top of the window that is provided by the creator of the workflow.It says that this node reads the adult data set. The name of the file is **adult.csv** as seen from the description underneath the node symbol. The **File Reader** has two outputs - one goes to **Color Manager** node and the other one goes to **Statistics** node.If you right click the **File Manager**, a popup menu would show up as follows −The **Configure** menu option allows for the node configuration.The **Execute** menu runs the node. Note that if the node has already been run and if it is in a green state, this menu is disabled. Also, note the presence of **the Edit Note Description** menu option. This allows you to write the description for your node.

Color Manager

Select the **Color Manager** node and go into its configuration by right clicking on it. A colors settings dialog would appear. Select the **income** column from the dropdown list.

Partitioning

In machine learning, we usually split the entire available data in two parts. The larger part is used in training the model, while the smaller portion is used for testing. There are different strategies used for partitioning the data.To define the desired partitioning, right click on the **Partitioning** node and select the **Configure** option.

Decision Tree Learner

The **Decision Tree Learner** node as the name suggests uses the training data and builds a model.As you see the **Class** is **income**. Thus, the tree would be built based on the income column and that is what we are trying to achieve in this model.After this node runs successfully, your model would be ready for testing.

Decision Tree Predictor

The Decision Tree Predictor node applies the developed model to the test data set and appends the model predictions.The output of the predictor is fed to two different nodes - **Scorer** and **Scatter Plot**.

Scorer

This node generates the **confusion matrix**. To view it, right click on the node.

18.3 Implementing Algorithms

Data can be from any source

Open and combine simple text formats (CSV, PDF< XLS, JSON, etc.), unstructured data types (images, documents, networks, modules, etc.) or time series data.Connect to a host of databases and data warehouses to integrate data from Oracle, Microsoft SQL, Apache Hive, Snowflake and more.Access and retrieve data from sources such as Salesforce, SharePoint, SAP Reader, Twitter, AWS S3, Google Sheets, Azure and many more.

Shape your data

Derive statistics or apply statistical tests to validate a hypothesis. Integrate dimension reduction, correlation analysis and more into your workflows.Aggregate, sort, filter and join data either on your local machine, in-database or in distributed big data environments.Clean data through normalization, data type conversion and missing value handling. Detect out of range values with outlier and anomaly detection algorithms.Extract and select features to prepare your dataset for machine learning.

Leverage Machine Learning and AI

Build machine learning algorithms for using a range of algorithms.Optimize model performance with hyperparameter optimization, boosting, bagging, stacking, or building complex ensembles.Validate models by applying performance metrics. Perform CV to guarantee model stability.

Discover and share data insights

Visualize data with classic and advanced charts and customize the data as per the needs.Display summary statistics about columns in a KNIME table and filter out anything that is irrelevant.Reports could be exported in various formats such as PDF, PowerPoint or other formats for presenting results to stakeholders.Store processed data or analytics results in many common file formats or databases.

18.4 Data Importing

Go to node repository for importing of data.Search for file reader.Drag and drop file reader in the workspace.Configure-Browse the file.Execute the node.Check the file table.Once the data has been imported, we can

1) Remove the column
2) Limit the data
3) Grouping the functionality
4) Data Genre (Categories)
5) Writing the respective data in a csv or excel file.
6) Plots

Remove the column

- Take column filter from node repository and exclude the columns.
- Check using filtered table.

Limit data

- Apply row filter.
- Find a column to test: variety.
- Use a matching criterion.
- Execute it.
- Click on apply and OK.

Writer

- The data can also be written to a file using writer.

18.5 Solving a Machine Learning Problem

1. The first thing is to read the dataset using a file reader.

2. If you want to see the statistics of data, then you can take the statistics node from repository and then make a connection and you can have the statistics of data.

3. The next step is to split the dataset into training and testing datasets. Use the partitioning node for this.

4. Use a classification algorithm to classify the data.

5. We used the decision tree learner for training dataset and the decision tree predictor for testing dataset.

6. Use the scorer node to check the confusion matrix.

Summary

- KNIME is Konstanz Information Miner.It is free and open-source data analytics, reporting and integration platform for creating data science.
- KNIME workflows can be used as data sets to create report templates that can be exported to document formats such as doc, ppt, xls, pdf and others.
- KNIMEs core-architecture allows processing of large data volumes that are only limited by the available hard disk space (not limited to the available RAM).
- KNIME is implemented in Java nevertheless it allows for wrappers calling other code in addition to providing nodes that allow to run Java, Python, R, Ruby, and other code fragments.
- Workflow Editor/Workspace is acanvas for editing the currently active workflows. Each workspace contains one or more nodes.

Keywords

- **KNIME**: KNIME provides a graphical interface (a user-friendly GUI) for the entire development. In KNIME, you simply must define the workflow between the various predefined nodes provided in its repository.
- **Nodes**:KNIME provides several predefined components called nodes for various tasks such as reading data, applying various ML algorithms, and visualizing data in various formats.
- **KNIME Analytics Platform:** Itis a desktop-based tool where analysts and developers construct workflows.
- **KNIME Server:** It is enterprise software designed for team-based collaboration, automation, management, and deployment of workflows.
- **KNIME Explorer**: This gives the overview of available workflows. The first two categories list the workspaces defined on the KNIME server. The third option, LOCAL, is used for storing all the workspaces that you create on your local machine.
- **KNIME Hub**: Access to KNIME hub to drag and drop nodes, components, workflows, or extensions.

SelfAssessment

1. What is KNIME?

A. Knowledge Information Miner
B. Konstanz Information Miner
C. Knot Information Miner
D. None of the above

2. The nodes in KNIME are used for
A. Reading data
B. Applying algorithms
C. Visualizing data
D. All of the above

3. Which of the following is the capabilities of KNIME?
A. Visually create dataflows
B. Allows processing of large data volumes
C. Designing of various workflows
D. All of the above

4. Which of the following is a enterprise software edition?
A. KNIME Analytics Platform
B. KNIME Server
C. Either of the above
D. None of the above

5. Which of the following is a desktop-based tool?
A. KNIME Analytics Platform
B. KNIME Server
C. Either of the above
D. None of the above

6. KNIME server is for
A. Team based collaboration
B. Automation and management
C. Deployment of workflows
D. All of the above

7. KNIME's visual programming environment provides the tools for
A. Accessing data
B. Transforming data
C. Cleaning data
D. All of the above

8. Which of the views gives the overview of available workflows?
A. KNIME Explorer
B. Workflow Coach
C. Node repository
D. KNIME Hub

9. Which of the following is used to drag and drop nodes, components, workflows or extensions?
A. KNIME Explorer
B. Workflow Coach
C. Node repository
D. KNIME Hub

10. What is a canvas for editing the currently active workflows?
A. KNIME Explorer
B. Workflow Editor

C. Node repository
D. KNIME Hub

11. What lists node recommendations based on the workflows built by the wide community of KNIME users?
A. Workflow Coach
B. Workflow Editor
C. Node repository
D. KNIME Hub

12. What shows the current flow variable values of a preview of the output data of the selected node?
A. Node monitor
B. Outline
C. Node repository
D. None of the above

13. Which view is useful in diagnosing the workflow and examining the analytics results?
A. Outline
B. Console
C. Node repository
D. None of the above

14. In KNIME, on successful execution, the last circle turns …….
A. Yellow
B. Green
C. Red
D. Blue

15. The status indicator is ……. indicating that this node has not been executed so far.
A. Yellow
B. Green
C. Red
D. Blue

Answers for Self Assessment

l.	B	2.	D	3.	D	4.	B	5.	A
6.	D	7.	D	8.	A	9.	D	10.	B
11.	A	12.	A	13.	B	14.	B	15.	C

Review Questions

1. What is KNIME? Why to use KNIME?
2. Explain the capabilities of KNIME?
3. What is KNIME analytics platform? Explain its views in detail.
4. What is a node in KNIME analytics platform? Explain its different states.
5. Explain the steps involved in solving a simple machine learning problem using KNIME.

Unit 19: Big Data

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Objectives

After studying this unit, you will be able to:

- Understand big data
- Understand the foundations for Big Data
- Understand the applications of Big Data
- Understand the programming for big data scientific analysis

Introduction

Computer data is information processed or stored by a computer. This information may be in the form of text documents, images, audio clips, software programs, or other types of data. The quantities, characters, or symbols on which operations are performed by a computer, which may be stored and transmitted in the form of electrical signals and recorded on magnetic, optical, or mechanical recording media. Computer data may be processed by the computer's CPU and is stored in files and folders on the computer's hard disk. At its most rudimentary level, computer data is a bunch of ones and zeros, known as binary data. Because all computer data is in binary format, it can be created, processed, saved, and stored digitally. This allows data to be transferred from one computer to another using a network connection or various media devices. It also does not deteriorate over time or lose quality after being used multiple times.

19.1 What is considered as a Big Data?

Big data is also data but with huge size.Big Data is a collection of data that is huge in volume yet growing exponentially with time. It is a data with so large size and complexity that none of traditional data management tools can store it or process it efficiently.

Big data refers to data sets that are too large or complex to be dealt with by traditional data-processingapplication software. Data with many fields (rows) offer greater statistical power, while data with higher complexity (more attributes or columns) may lead to a higher false discovery rate. Big data analysis challenges include capturing data, data storage, data analysis, search, sharing, transfer, visualization, querying, updating, information privacy, and data source. Big data was originally associated with three key concepts: volume, variety, and velocity. The analysis of big data presents challenges in sampling, and thus previously allowing for only observations and sampling. Thus, a fourth concept, veracity, refers to the quality or insightfulness of the data. Without sufficient investment in expertise for big data veracity, then the volume and variety of data canproduce costs and risks that exceed an organization's capacity to create and capture value from big data.

Current usage of the term big data tends to refer to the use of predictive analytics, user behavior analytics, or certain other advanced data analytics methods that extract value from big data, and seldom to a particular size of data set. "There is little doubt that the quantities of data now available are indeed large, but that's not the most relevant characteristic of this new data ecosystem."Analysis of data sets can find new correlations to "spot business trends, prevent diseases, combat crime and so on". Scientists, business executives, medical practitioners, advertising and governments alike regularly meet difficulties with large data-sets in areas including Internet searches, fintech, healthcare analytics, geographic information systems, urban informatics, and business informatics. Scientists encounter limitations in e-Science work, including meteorology, genomics, connect omics, complex physics simulations, biology, and environmental research.

19.2 Examples of Big Data

- The **New York Stock Exchange** is an example of Big Data that generates about **one terabyte** of new trade data per day.
- The statistic shows that **500+terabytes** of new data get ingested into the databases of social media site **Facebook**, every day. This data is mainly generated in terms of photo and video uploads, message exchanges, putting comments etc.
- A single **Jet engine** can generate **10+terabytes** of data in **30 minutes** of flight time. With many thousand flights per day, generation of data reaches up to many **Petabytes.**
- Transaction processing systems.
- Customer databases, documents, emails, medical records, internet clickstream logs, mobile apps.

19.3 The varies v in Big Data

There are five varies v's in big data. The data is considered as big data because of these features. These are:

1) Volume
2) Velocity
3) Variety
4) Veracity
5) Value

1. **Volume:** The name 'Big Data' itself is related to a size which is enormous.Volume is a huge amount of data.To determine the value of data, size of data plays a very crucial role. If the volume of data is very large, then it is considered as a 'Big Data'. This means whether a particular data can be considered as a Big Data or not, is dependent upon the volume of data.Hence while dealing with Big Data, it is necessary to consider a characteristic 'Volume'.Example: In the year 2016, the estimated global mobile traffic was 6.2 Exabytes(6.2 billion GB) per month. Also, by the year 2022 we will have almost 45000 ExaBytes of data.

2. **Velocity:** Velocity refers to the high speed of accumulation of data.In Big Data velocity data flows in from sources like machines, networks, social media, mobile phones etc. There is a massive and continuous flow of data. This determines the potential of data that how fast the data is generated and processed to meet the demands.Example: There are more than 3.5 billion searches per day are made on Google. Also, Facebook users are increasing by 22%(Approx.) year by year.

3. **Variety:** It refers to nature of data that is structured, semi-structured and unstructured data.It also refers to heterogeneous sources.Variety is basically the arrival of data from new sources that are both inside and outside of an enterprise. It can be structured, semi-structured and unstructured**.**

- **Structured data**: This data is basically an organized data. It generally refers to data that has defined the length and format of data.
- **Semi- Structured data**: This data is basically semi-organized data. It is generally a form of data that do not conform to the formal structure of data. Log files are the examples of this type of data.
- **Unstructured data**: This data basically refers to unorganized data. It generally refers to data that doesn't fit neatly into the traditional row and column structure of the relational database. Texts, pictures, videos etc. are the examples of unstructured data which can't be stored in the form of rows and columns.

4. **Veracity:**It refers to inconsistencies and uncertainty in data, that is data which is available can sometimes get messy and quality and accuracy are difficult to control.Big Data is also variable because of the multitude of data dimensions resulting from multiple disparate data types and sources.Example: Data in bulk could create confusion whereas a smaller amount of data could convey half or Incomplete Information.

5. **Value:** After having the 4 Vs into account there comes one more V which stands for Value. The bulk of Data having no Value is of no good to the company, unless you turn it into something useful.Data in itself is of no use or importance, but it needs to be converted into something valuable to extract Information. Hence, you can state that Value! is the most important V of all the 5V's.

19.4 Role of Big Data in Data Science

At a high level, *data science* is a set of fundamental principles that support and guide the principled extraction of information and knowledge from data. The most closely related concept to data science is *data mining*—the actual extraction of knowledge from data via technologies that incorporate these principles. Data science is a very popular and prominent term used to describe many different data-related processes and techniques. Big data on the other hand is relatively new in the sense that the amount of data collected, and the associated challenges continues to require new and innovative hardware and techniques for handling it.Data is everywhere and is found in huge and exponentially increasing quantities. Data science reflects the ways in which data is discovered, conditioned, extracted, compiled, processed, analyzed, interpreted, modeled,

visualized, reported on, and presented regardless of the size of the data being processed.Big Data is essentially a special application of data science, in which the data sets are enormous and require overcoming logistical challenges to deal with them. The primary concern is efficiently capturing, storing, extracting, processing, and analyzing information from these enormous data sets.

Dimensions of Scalability

Data Scaling: To manage, store and process this overflow of data, a technique called "data scaling" has become necessary for many organizations dealing with exploding datasets.A scalable data platform accommodates rapid changes in the growth of data, either in traffic or volume. These platforms utilize added hardware or software to increase output and storage of data.

19.5 Common Performance Bottlenecks

Companies should implement scalability into their organization precisely when performance issues arise. These issues can negatively impact the workflow, efficiency, and customer retention. There are three common, key performance bottlenecks, that often point the way toward a proper resolution with data scaling:

1. H**igh CPU Usage:** It is the most common bottleneck, and the most visible. Slowing and erratic performance is a key indicator of high CPU usage and can often be a harbinger of other issues.

2. L**ow Memory:** It is the next most common bottleneck. Servers without enough memory to handle an application load can slow the application completely. Low memory can require a RAM upgrade, but this can also be an indicator of a memory leak, which requires finding and repairing the leak within the application's code.

3. **High Disk Usage:** It is another common bottleneck. This is often caused by maxed out disks and is a huge indicator of the need for a data scale.

19.6 Scaling Up vs Scaling Out

Once a decision has been made for data scaling, the specific scaling approach must be chosen. There are two commonly used types of data scaling, up and out.

- **Scaling up**, or vertical scaling, involves obtaining a faster server with more powerful processors and more memory. This solution uses less network hardware, and consumes less power; but ultimately, for many platforms may only provide a short-term fix, especially if continued growth is expected.
- **Scaling out**, or horizontal scaling, involves adding servers for parallel computing. The scale out technique is a long-term solution, as more and more servers may be added when needed.

19.7 Foundations for Big Data Systems

With information streaming in from more sources than ever before, organizations face the daunting challenge of gaining insights from new data sources and types, including structured and unstructured sources. In addition to the growing volume and variety of data, there's also the issue of velocity, which refers to the speed at which data is coming in and how fast you need to be able to take advantage of it. Building applications for handling big data requires laser-like focus on solutions that allow you to deliver scalable, reliable, and flexible infrastructure for fast-growing analytics environments. The "right" infrastructure—one that is optimized for performance, flexibility and long-term value—can contribute to successful business results by:

- Accelerating analytics and speeding up time to business insights
- Sharing compute resources for optimum utilization and reduced capital costs
- Enabling advanced storage virtualization, along with policy-based tiering, to balance storage cost and performance

- Reducing complexity, simplifying management, and enabling workers to focus on strategic priorities

If big data already plays a dominant role within your business, your organizational changes and successes have likely been dramatic.On the other hand, if data is still playing a limited, traditional role at the edges of individual departments, depending on your business needs and goals, you may want to consider moving big data analytics to the center of your business.Once you've decided to give big data a more central role, you need a clearly defined infrastructure strategy to help ensure your analytical initiatives are built on a solid foundation.

There are a total of six best practices that your implementation teams can follow to maximize your return on investment and increase your chances of success.

1. Identify the business opportunity
2. Think big, but start small
3. Experiment with different approaches
4. Optimize your computing resources
5. Focus on data management
6. Build on your initial successes

19.8 Programming for Scientific Big Data Analytics

The term 'big data' is flourishing in all different sectors across the world in these recent years. Organizations have recognized the power of big data to attract consumers as well as revenue through in-depth insights.

Programming Languages for Big Data

There are various programming languages that we can use for big data problems. These are:

1. Python
2. R
3. Julia
4. C/C++
5. JAVA
6. SCALA
7. JAVASCRIPT
8. SQL
9. SWIFT
10. MATLAB
11. SAS

19.9 Applications of Big Data

There are various applications of big data. These are:

1. Banking and securities
2. Communications, media and entertainment
3. Healthcare providers
4. Education

5. Manufacturing and natural resources
6. Government
7. Insurance
8. Retail and wholesale trade
9. Transportation
10. Energy and utilities

Summary

- Big data is also data but with huge size.
- Big data refers to data sets that are too large or complex to be dealt with by traditional data-processingapplication software.
- Data with many fields (rows) offer greater statistical power, while data with higher complexity (more attributes or columns) may lead to a higher false discovery rate.
- Big data analysis challenges include capturing data, data storage, data analysis, search, sharing, transfer, visualization, querying, updating, information privacy, and data source.
- To manage, store and process this overflow of data, a technique called "data scaling" has become necessary for many organizations dealing with exploding datasets.A scalable data platform accommodates rapid changes in the growth of data, either in traffic or volume. These platforms utilize added hardware or software to increase output and storage of data.

Keywords

- **Big Data:** It is a collection of data that is huge in volume yet growing exponentially with time. It is data with so large size and complexity that none of traditional data management tools can store it or process it efficiently.
- **Varies V's:** The varies Vs of big data are:Volume, velocity, variety, veracity and value.
- **Variety**: It refers to nature of data that is structured, semi-structured and unstructured data.It also refers to heterogeneous sources.Variety is basically the arrival of data from new sources that are both inside and outside of an enterprise. It can be structured, semi-structured and unstructured.
- **Scaling up**: It is also known as vertical scaling, involves obtaining a faster server with more powerful processors and more memory. This solution uses less network hardware, and consumes less power; but ultimately, for many platforms may only provide a short-term fix, especially if continued growth is expected.
- **Scaling out**: It is also known as horizontal scaling, involves adding servers for parallel computing. The scale out technique is a long-term solution, as more and more servers may be added when needed.

SelfAssessment

1. Computer data is information processed or stored by a computer. This information may be in the form of

A. Text data
B. Images
C. Audio clips
D. Any of the above

2. Big data analysis challenges include

A. capturing data

B. Data analysis

C. Search, sharing

D. All of the above

3. The challenges occur in big data analysis are

A. Data transfer

B. Data visualization

C. Data querying, and updating

D. All of the above

4. Which of the following are varies V's of big data?

A. Velocity

B. Variety

C. Value

D. All of the above mentioned

5. What refers to the high speed of accumulation of data?

A. Velocity

B. Variety

C. Value

D. None of the above

6. What refers to nature of data that is structured, semi-structured and unstructured data?

A. Velocity

B. Variety

C. Value

D. None of the above

7. What refers to inconsistencies and uncertainty in data, that is, the data which is available can sometimes get messy; and quality and accuracy are difficult to control?

A. Velocity

B. Variety

C. Value

D. Veracity

8. Which of the following is known as vertical scaling?

A. Scaling up

B. Scaling out

9. Which of the following is known as horizontal scaling?

A. Scaling up

B. Scaling out

10. Which of the following are the applications of big data?

A. Banking and securities

B. Communications, media and entertainment

C. Healthcare providers

D. All of the above mentioned

11. _____ is a collection of data that is used in volume, yet growing exponentially with time

A. Big database

B. Big DBMS

C. Big Data

D. Big Datafile

12. Which of the following are the benefits of big data processing?

A. Business can utilize intelligence while taking decisions

B. Better operational efficiency

C. Improve customer service

D. All of the above

13. Which of the following are considered as bottlenecks for big data problems?

A. Low memory

B. High disk usage

C. Both a and b

D. None of the above

14. Which of the following uses less network hardware?

A. Scaling up

B. Scaling out

C. Scaling in

D. None of the above

15. Which programming language is used for big data?

A. Python

B. R

C. Julia

D. All of the above

Answers for Self Assessment

l.	D	2.	D	3.	D	4.	D	5.	A
6.	B	7.	D	8.	A	9.	B	10.	D
11.	C	12.	D	13.	C	14.	A	15.	D

Review Questions

1. What is big data? Also tell its characteristics in detail.
2. Why is data considered as big data today? Explain.
3. What are common performance bottlenecks in big data? What is done to improve it?
4. What is scaling of data? Which strategies are used for scaling of big data?
5. What is role of big data in data science? Give the examples of big data.

Further Readings

https://www.geeksforgeeks.org/life-cycle-phases-of-data-analytics/

Web Links

https://www.simplilearn.com/tutorials/data-science-tutorial/what-is-data-science

Unit 20: Big Data

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Objectives

After studying this unit, you will be able to:

- Understand big data
- Understand the foundations for Big Data
- Understand the applications of Big Data
- Understand the programming for big data scientific analysis

Introduction

Computer data is information processed or stored by a computer. This information may be in the form of text documents, images, audio clips, software programs, or other types of data. The quantities, characters, or symbols on which operations are performed by a computer, which may be stored and transmitted in the form of electrical signals and recorded on magnetic, optical, or mechanical recording media. Computer data may be processed by the computer's CPU and is stored in files and folders on the computer's hard disk. At its most rudimentary level, computer data is a bunch of ones and zeros, known as binary data. Because all computer data is in binary format, it can be created, processed, saved, and stored digitally. This allows data to be transferred from one computer to another using a network connection or various media devices. It also does not deteriorate over time or lose quality after being used multiple times.

20.1 What is considered as a Big Data?

Big data is also data but with huge size.Big Data is a collection of data that is huge in volume yet growing exponentially with time. It is a data with so large size and complexity that none of traditional data management tools can store it or process it efficiently.

Big data refers to data sets that are too large or complex to be dealt with by traditional data-processingapplication software. Data with many fields (rows) offer greater statistical power, while data with higher complexity (more attributes or columns) may lead to a higher false discovery rate. Big data analysis challenges include capturing data, data storage, data analysis, search, sharing, transfer, visualization, querying, updating, information privacy, and data source. Big data was originally associated with three key concepts: volume, variety, and velocity. The analysis of big data presents challenges in sampling, and thus previously allowing for only observations and sampling. Thus, a fourth concept, veracity, refers to the quality or insightfulness of the data. Without sufficient investment in expertise for big data veracity, then the volume and variety of data canproduce costs and risks that exceed an organization's capacity to create and capture value from big data.

Current usage of the term big data tends to refer to the use of predictive analytics, user behavior analytics, or certain other advanced data analytics methods that extract value from big data, and seldom to a particular size of data set. "There is little doubt that the quantities of data now available are indeed large, but that's not the most relevant characteristic of this new data ecosystem."Analysis of data sets can find new correlations to "spot business trends, prevent diseases, combat crime and so on". Scientists, business executives, medical practitioners, advertising and governments alike regularly meet difficulties with large data-sets in areas including Internet searches, fintech, healthcare analytics, geographic information systems, urban informatics, and business informatics. Scientists encounter limitations in e-Science work, including meteorology, genomics, connect omics, complex physics simulations, biology, and environmental research.

20.2 Examples of Big Data

- The **New York Stock Exchange** is an example of Big Data that generates about **one terabyte** of new trade data per day.
- The statistic shows that **500+terabytes** of new data get ingested into the databases of social media site **Facebook**, every day. This data is mainly generated in terms of photo and video uploads, message exchanges, putting comments etc.
- A single **Jet engine** can generate **10+terabytes** of data in **30 minutes** of flight time. With many thousand flights per day, generation of data reaches up to many **Petabytes.**
- Transaction processing systems.
- Customer databases, documents, emails, medical records, internet clickstream logs, mobile apps.

20.3 The varies v in Big Data

There are five varies v's in big data. The data is considered as big data because of these features. These are:

1) Volume
2) Velocity
3) Variety
4) Veracity
5) Value

1. **Volume:** The name 'Big Data' itself is related to a size which is enormous.Volume is a huge amount of data.To determine the value of data, size of data plays a very crucial role. If the volume of data is very large, then it is considered as a 'Big Data'. This means whether a particular data can be considered as a Big Data or not, is dependent upon the volume of data.Hence while dealing with Big Data, it is necessary to consider a characteristic 'Volume'.Example: In the year 2016, the estimated global mobile traffic was 6.2 Exabytes(6.2 billion GB) per month. Also, by the year 2022 we will have almost 45000 ExaBytes of data.

2. **Velocity:** Velocity refers to the high speed of accumulation of data.In Big Data velocity data flows in from sources like machines, networks, social media, mobile phones etc. There is a massive and continuous flow of data. This determines the potential of data that how fast the data is generated and processed to meet the demands.Example: There are more than 3.5 billion searches per day are made on Google. Also, Facebook users are increasing by 22%(Approx.) year by year.

3. **Variety:** It refers to nature of data that is structured, semi-structured and unstructured data.It also refers to heterogeneous sources.Variety is basically the arrival of data from new sources that are both inside and outside of an enterprise. It can be structured, semi-structured and unstructured**.**

- **Structured data**: This data is basically an organized data. It generally refers to data that has defined the length and format of data.
- **Semi- Structured data**: This data is basically semi-organized data. It is generally a form of data that do not conform to the formal structure of data. Log files are the examples of this type of data.
- **Unstructured data**: This data basically refers to unorganized data. It generally refers to data that doesn't fit neatly into the traditional row and column structure of the relational database. Texts, pictures, videos etc. are the examples of unstructured data which can't be stored in the form of rows and columns.

4. **Veracity:**It refers to inconsistencies and uncertainty in data, that is data which is available can sometimes get messy and quality and accuracy are difficult to control.Big Data is also variable because of the multitude of data dimensions resulting from multiple disparate data types and sources.Example: Data in bulk could create confusion whereas a smaller amount of data could convey half or Incomplete Information.

5. **Value:** After having the 4 Vs into account there comes one more V which stands for Value. The bulk of Data having no Value is of no good to the company, unless you turn it into something useful.Data in itself is of no use or importance, but it needs to be converted into something valuable to extract Information. Hence, you can state that Value! is the most important V of all the 5V's.

20.4 Role of Big Data in Data Science

At a high level, *data science* is a set of fundamental principles that support and guide the principled extraction of information and knowledge from data. The most closely related concept to data science is *data mining*—the actual extraction of knowledge from data via technologies that incorporate these principles. Data science is a very popular and prominent term used to describe many different data-related processes and techniques. Big data on the other hand is relatively new in the sense that the amount of data collected, and the associated challenges continues to require new and innovative hardware and techniques for handling it.Data is everywhere and is found in huge and exponentially increasing quantities. Data science reflects the ways in which data is discovered, conditioned, extracted, compiled, processed, analyzed, interpreted, modeled,

visualized, reported on, and presented regardless of the size of the data being processed.Big Data is essentially a special application of data science, in which the data sets are enormous and require overcoming logistical challenges to deal with them. The primary concern is efficiently capturing, storing, extracting, processing, and analyzing information from these enormous data sets.

Dimensions of Scalability

Data Scaling: To manage, store and process this overflow of data, a technique called "data scaling" has become necessary for many organizations dealing with exploding datasets.A scalable data platform accommodates rapid changes in the growth of data, either in traffic or volume. These platforms utilize added hardware or software to increase output and storage of data.

20.5 Common Performance Bottlenecks

Companies should implement scalability into their organization precisely when performance issues arise. These issues can negatively impact the workflow, efficiency, and customer retention. There are three common, key performance bottlenecks, that often point the way toward a proper resolution with data scaling:

1. H**igh CPU Usage:** It is the most common bottleneck, and the most visible. Slowing and erratic performance is a key indicator of high CPU usage and can often be a harbinger of other issues.

2. L**ow Memory:** It is the next most common bottleneck. Servers without enough memory to handle an application load can slow the application completely. Low memory can require a RAM upgrade, but this can also be an indicator of a memory leak, which requires finding and repairing the leak within the application's code.

3. **High Disk Usage:** It is another common bottleneck. This is often caused by maxed out disks and is a huge indicator of the need for a data scale.

20.6 Scaling Up vs Scaling Out

Once a decision has been made for data scaling, the specific scaling approach must be chosen. There are two commonly used types of data scaling, up and out.

- **Scaling up**, or vertical scaling, involves obtaining a faster server with more powerful processors and more memory. This solution uses less network hardware, and consumes less power; but ultimately, for many platforms may only provide a short-term fix, especially if continued growth is expected.
- **Scaling out**, or horizontal scaling, involves adding servers for parallel computing. The scale out technique is a long-term solution, as more and more servers may be added when needed.

20.7 Foundations for Big Data Systems

With information streaming in from more sources than ever before, organizations face the daunting challenge of gaining insights from new data sources and types, including structured and unstructured sources. In addition to the growing volume and variety of data, there's also the issue of velocity, which refers to the speed at which data is coming in and how fast you need to be able to take advantage of it. Building applications for handling big data requires laser-like focus on solutions that allow you to deliver scalable, reliable, and flexible infrastructure for fast-growing analytics environments. The "right" infrastructure—one that is optimized for performance, flexibility and long-term value—can contribute to successful business results by:

- Accelerating analytics and speeding up time to business insights
- Sharing compute resources for optimum utilization and reduced capital costs
- Enabling advanced storage virtualization, along with policy-based tiering, to balance storage cost and performance

- Reducing complexity, simplifying management, and enabling workers to focus on strategic priorities

If big data already plays a dominant role within your business, your organizational changes and successes have likely been dramatic.On the other hand, if data is still playing a limited, traditional role at the edges of individual departments, depending on your business needs and goals, you may want to consider moving big data analytics to the center of your business.Once you've decided to give big data a more central role, you need a clearly defined infrastructure strategy to help ensure your analytical initiatives are built on a solid foundation.

There are a total of six best practices that your implementation teams can follow to maximize your return on investment and increase your chances of success.

1. Identify the business opportunity
2. Think big, but start small
3. Experiment with different approaches
4. Optimize your computing resources
5. Focus on data management
6. Build on your initial successes

20.8 Programming for Scientific Big Data Analytics

The term 'big data' is flourishing in all different sectors across the world in these recent years. Organizations have recognized the power of big data to attract consumers as well as revenue through in-depth insights.

Programming Languages for Big Data

There are various programming languages that we can use for big data problems. These are:

1. Python
2. R
3. Julia
4. C/C++
5. JAVA
6. SCALA
7. JAVASCRIPT
8. SQL
9. SWIFT
10. MATLAB
11. SAS

20.9 Applications of Big Data

There are various applications of big data. These are:

1. Banking and securities
2. Communications, media and entertainment
3. Healthcare providers
4. Education

5. Manufacturing and natural resources
6. Government
7. Insurance
8. Retail and wholesale trade
9. Transportation
10. Energy and utilities

Summary

- Big data is also data but with huge size.
- Big data refers to data sets that are too large or complex to be dealt with by traditional data-processingapplication software.
- Data with many fields (rows) offer greater statistical power, while data with higher complexity (more attributes or columns) may lead to a higher false discovery rate.
- Big data analysis challenges include capturing data, data storage, data analysis, search, sharing, transfer, visualization, querying, updating, information privacy, and data source.
- To manage, store and process this overflow of data, a technique called "data scaling" has become necessary for many organizations dealing with exploding datasets.A scalable data platform accommodates rapid changes in the growth of data, either in traffic or volume. These platforms utilize added hardware or software to increase output and storage of data.

Keywords

- **Big Data:** It is a collection of data that is huge in volume yet growing exponentially with time. It is data with so large size and complexity that none of traditional data management tools can store it or process it efficiently.
- **Varies V's:** The varies Vs of big data are:Volume, velocity, variety, veracity and value.
- **Variety**: It refers to nature of data that is structured, semi-structured and unstructured data.It also refers to heterogeneous sources.Variety is basically the arrival of data from new sources that are both inside and outside of an enterprise. It can be structured, semi-structured and unstructured.
- **Scaling up**: It is also known as vertical scaling, involves obtaining a faster server with more powerful processors and more memory. This solution uses less network hardware, and consumes less power; but ultimately, for many platforms may only provide a short-term fix, especially if continued growth is expected.
- **Scaling out**: It is also known as horizontal scaling, involves adding servers for parallel computing. The scale out technique is a long-term solution, as more and more servers may be added when needed.

SelfAssessment

1. Computer data is information processed or stored by a computer. This information may be in the form of

A. Text data
B. Images
C. Audio clips
D. Any of the above

2. Big data analysis challenges include

A. capturing data

B. Data analysis

C. Search, sharing

D. All of the above

3. The challenges occur in big data analysis are

A. Data transfer

B. Data visualization

C. Data querying, and updating

D. All of the above

4. Which of the following are varies V's of big data?

A. Velocity

B. Variety

C. Value

D. All of the above mentioned

5. What refers to the high speed of accumulation of data?

A. Velocity

B. Variety

C. Value

D. None of the above

6. What refers to nature of data that is structured, semi-structured and unstructured data?

A. Velocity

B. Variety

C. Value

D. None of the above

7. What refers to inconsistencies and uncertainty in data, that is, the data which is available can sometimes get messy; and quality and accuracy are difficult to control?

A. Velocity

B. Variety

C. Value

D. Veracity

8. Which of the following is known as vertical scaling?

A. Scaling up

B. Scaling out

9. Which of the following is known as horizontal scaling?

A. Scaling up

B. Scaling out

10. Which of the following are the applications of big data?

A. Banking and securities

B. Communications, media and entertainment

C. Healthcare providers

D. All of the above mentioned

11. _____ is a collection of data that is used in volume, yet growing exponentially with time

A. Big database

B. Big DBMS

C. Big Data

D. Big Datafile

12. Which of the following are the benefits of big data processing?

A. Business can utilize intelligence while taking decisions

B. Better operational efficiency

C. Improve customer service

D. All of the above

13. Which of the following are considered as bottlenecks for big data problems?

A. Low memory

B. High disk usage

C. Both a and b

D. None of the above

14. Which of the following uses less network hardware?

A. Scaling up

B. Scaling out

C. Scaling in

D. None of the above

15. Which programming language is used for big data?

A. Python

B. R

C. Julia

D. All of the above

Answers for Self Assessment

l.	D	2.	D	3.	D	4.	D	5.	A
6.	B	7.	D	8.	A	9.	B	10.	D
11.	C	12.	D	13.	C	14.	A	15.	D

Review Questions

1. What is big data? Also tell its characteristics in detail.
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Further Readings

https://www.geeksforgeeks.org/life-cycle-phases-of-data-analytics/

Web Links

https://www.simplilearn.com/tutorials/data-science-tutorial/what-is-data-science

LOVELY PROFESSIONAL UNIVERSITY
Jalandhar-Delhi G.T. Road (NH-1)
Phagwara, Punjab (India)-144411
For Enquiry: +91-1824-521360
Fax.: +91-1824-506111
Email: odl@lpu.co.in