People's Information Technology Program (PITP)

An Initiative by Information Science & Technology Department, Government of Sindh

DATA SCIENTIST

Course Manual

Mehran University of Engineering and Technology, Jamshoro

Data Scientist Course Outline

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Week 1 DAY 1: Introduction to Data Science

Day 1: Course Orientation and Overview

Course Overview: Certified Data Science Course

Data Science is transforming the way we understand and interact with the world, driving innovation across industries through the use of data-driven insights. This course is designed to equip students with the practical knowledge and hands-on experience required to extract, analyze, and interpret meaningful insights from large and complex datasets.

The focus of the course is on applying a range of data science techniques, tools, and frameworks to real-world problems. Throughout the course, students will gain practical experience in data cleaning, feature engineering, statistical analysis, machine learning, and data visualization. By working through case studies and projects, students will understand how data science drives decision-making and improves processes in diverse fields such as healthcare, finance, marketing, and technology.

Learning Objectives

By the end of this course, students will be able to:

1. Understand the data science pipeline, from data collection to data-driven decision making.
2. Apply statistical methods and machine learning models to solve real-world problems.
3. Use Python and industry-standard libraries such as Pandas, Scikit-learn, and Matplotlib for data analysis and visualization.
4. Work with large datasets and apply data preprocessing techniques to prepare data for analysis including Big Data on the cloud .
5. Build and evaluate predictive models using supervised and unsupervised learning techniques.
6. Interpret and communicate data-driven insights through effective visualizations and reports.
7. Implement best practices in handling data ethics and privacy.

Course Format

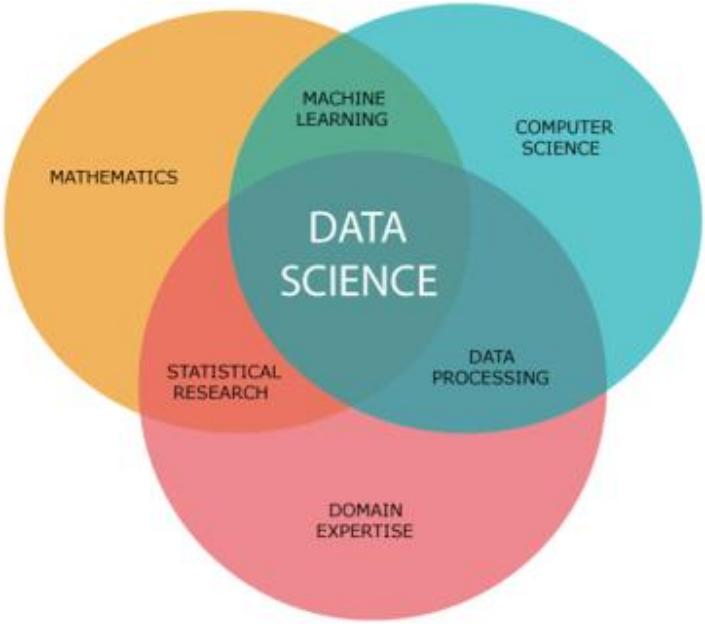
This course combines theory with extensive practical sessions, encouraging hands-on experience. Students will work on various projects and assignments designed to simulate real-world scenarios. The course also incorporates peer review and group work to foster collaboration and teamwork.

Introduction to Data Science

Data Science is an interdisciplinary field that blends statistics, computer science, and domain knowledge to extract meaningful insights and knowledge from raw data. It represents a significant shift in how we process and interpret vast amounts of information, enabling organizations and individuals to make better, data-informed decisions.

With the exponential growth of data—generated from sources such as social media, sensors, business transactions, and more—the demand for professionals skilled in data analysis has surged. Data scientists are key to unlocking the potential within these massive datasets, uncovering patterns and trends that would otherwise remain hidden.

In more simple terms, Data science is the field of study that uses mathematics, programming, and domain knowledge to extract meaningful insights from data. Data scientists would apply machine learning algorithms to data such as numbers, texts, images, videos, and more to produce artificial systems that perform tasks that require human intelligence. Using these systems, we extract insights from the data and use them to make better decisions in various situations.



We live in a world that is full of data. From traffic cameras to big corporations produces tons of data every day every minute. Just one click on the Facebook post may save lots of information about that click.

Have you ever wondered how Amazon, eBay suggests items for you to buy or How Gmail filters your emails in the spam and non-spam categories? If you want to study this field, it's time to start wondering about these kinds of stuff more.

So how do they do it?

Data science is all about using data to solve these kinds of problems. The problem could be decision making, such as identifying which email is spam and which is not. Or a product recommendation such as which movie to watch? , Or predicting the outcome such as who will be the next President of the USA?
This is how you get YouTube video recommendations as well. You watch a video, YouTube will automatically put a record in their database that you watched this video. Next time when you visit YouTube you will get the same types of videos you watched earlier. Which makes you happy since you get your favorites on the front page. So this decision YouTube made to show that particular type of video you like helps them to make user experience or lure you into YouTube more.

So, the core job of a data scientist is to understand the data, extract useful information out of it, and apply this in solving the problems.

Data Science is the future of Artificial Intelligence. Therefore, it is very important to understand what is Data Science and how can it add value to your business.

At its core, Data Science involves several key processes:

1. **Data Collection** – Gathering data from various sources such as databases, APIs, web scraping, and real-time sensors.
2. **Data Cleaning and Preprocessing** – Handling missing data, removing duplicates, managing inconsistencies, and transforming raw data into a suitable format for analysis.
3. **Exploratory Data Analysis (EDA)** – Summarizing the main characteristics of the data using visualization tools and statistical techniques to discover patterns and insights.
4. **Feature Engineering** – Creating new features or selecting the most relevant ones to improve the performance of models.
5. **Modeling and Machine Learning** – Applying statistical and machine learning algorithms to build predictive models and identify hidden relationships.
6. **Interpretation and Communication** – Presenting the results in a clear and actionable manner through reports, dashboards, or visualizations, making insights accessible to non-technical stakeholders.

The Data Science Process

The journey from raw data to actionable insights follows a structured process, often referred to as the **Data Science Pipeline**. The key steps in this pipeline are:

1. **Problem Definition** – Understanding the problem or question that needs to be answered using data.

2. **Data Acquisition** – Collecting the appropriate data to solve the problem.
3. **Data Preparation** – Cleaning and preprocessing the data to ensure it is suitable for analysis.
4. **Modeling** – Using algorithms to create models that capture the relationships between variables in the dataset.
5. **Evaluation** – Testing the model's performance using validation techniques and metrics.
6. **Deployment** – Implementing the model in a real-world environment or integrating it into applications for decision-making.
7. **Monitoring and Maintenance** – Ensuring that models continue to perform well as new data becomes available, and adjusting them as needed.

Key Tools and Techniques in Data Science

- Programming Languages: Python and R are the most widely used programming languages in data science due to their extensive libraries for data manipulation and analysis (e.g., Pandas, NumPy, Scikit-learn).
- Data Visualization: Tools like Matplotlib, Seaborn, and Tableau help data scientists create visual representations of data, making complex patterns more interpretable.
- Machine Learning: Techniques such as regression, classification, clustering, and neural networks enable data scientists to build models that predict outcomes or categorize data.
- Big Data Technologies: For handling large datasets, technologies such as Hadoop, Spark, and cloud-based platforms like AWS or Google Cloud are essential.

Importance and Applications of data science

The Role of a Data Scientist

Data Scientists must be proficient in a wide array of skills, combining deep technical expertise with the ability to interpret results in the context of the problem they are solving. In addition to technical skills, data scientists often collaborate with business stakeholders to translate complex data insights into practical solutions. This combination of technical and business acumen makes the role of a data scientist both challenging and rewarding.

Why Data Science Matters

Data Science has become a driving force in nearly every industry. In healthcare, it enables personalized medicine and predictive diagnostics. In finance, it powers fraud detection and algorithmic trading. In

marketing, it allows companies to tailor their services to individual customer preferences. By analyzing data, organizations can reduce costs, optimize operations, and create new products and services.

Applications of Data Science

Data Science is revolutionizing industries across the globe, enabling organizations to leverage vast amounts of data for insights, predictions, and innovations. Its impact is being felt across a wide range of fields, from healthcare and finance to entertainment and sports. Here are some of the most prominent applications of data science across various sectors:

1. Healthcare

Data science has transformed the healthcare industry by enabling personalized medicine, improving patient care, and optimizing operations.

- Predictive Analytics: Data science models are used to predict disease outbreaks, patient readmissions, and treatment outcomes. Predictive algorithms can forecast the likelihood of diseases based on patient data, including electronic health records (EHRs), genetics, and lifestyle.
- Medical Imaging: Advanced deep learning techniques are employed in analyzing medical images like X-rays, MRIs, and CT scans, enabling faster and more accurate diagnoses.
- Drug Discovery: Data science accelerates drug discovery by analyzing large datasets from clinical trials, biological studies, and historical drug data, identifying potential treatments faster and more cost-effectively.
- Personalized Treatment: Machine learning models help design tailored treatments based on a patient's genetic makeup, leading to personalized healthcare approaches, known as precision medicine.

2. Finance

In the financial sector, data science plays a pivotal role in risk management, fraud detection, and personalized services.

- Fraud Detection: Banks and financial institutions use machine learning algorithms to detect unusual patterns in transactions and prevent fraud. Models can analyze millions of transactions in real time and flag suspicious activity for further investigation.
- Credit Scoring: Data science models assess the creditworthiness of individuals and businesses by analyzing historical loan data, transaction histories, and social behaviors. This helps lenders make data-driven decisions on loan approvals and risk assessments.
- Algorithmic Trading: Investment firms use data science to build predictive models that forecast stock prices and market trends. These models drive automated trading systems that execute trades at high speed and high frequency based on data signals.
- Personalized Financial Advice: Data science powers robo-advisors that provide personalized investment advice by analyzing a user's financial history, goals, and risk tolerance.

3. Retail and E-commerce

Data science is a crucial enabler of personalized shopping experiences, supply chain optimization, and customer behavior analysis in retail.

- Recommendation Systems: Retailers and e-commerce platforms like Amazon and Netflix use data science algorithms to recommend products or content to users based on their past behavior, preferences, and browsing history.
- Inventory and Supply Chain Optimization: Retailers use predictive models to optimize inventory levels, reduce wastage, and ensure timely deliveries. Demand forecasting helps businesses adjust their supply chains to meet consumer demand while minimizing costs.
- Customer Segmentation: By analyzing customer data, businesses can group customers into segments based on behavior, demographics, or preferences. This allows for targeted marketing campaigns and personalized promotions, improving customer satisfaction and retention.

4. Transportation and Logistics

Data science optimizes transportation systems, reduces operational costs, and enhances customer experiences in the logistics sector.

- Route Optimization: Companies like Uber and delivery services use data science to predict the best routes for drivers, reducing fuel costs, travel time, and improving service efficiency. Algorithms take into account traffic patterns, road conditions, and real-time data.
- Predictive Maintenance: In logistics, data science models monitor vehicle health through sensors and predict when maintenance is required, minimizing downtime and improving fleet management.
- Demand Forecasting: Ride-sharing services use machine learning to forecast passenger demand in different locations, ensuring that vehicles are dispatched to the right places at the right times, improving service availability.

5. Entertainment and Media

In the entertainment industry, data science drives content recommendations, user engagement analysis, and audience segmentation.

- Streaming Services: Platforms like Netflix and Spotify use data science to recommend content based on users' past behavior, preferences, and engagement levels, making personalized experiences possible.
- Audience Analysis: Media companies analyze social media, viewing patterns, and feedback to understand audience preferences. This helps in creating content that resonates with specific demographic groups and predicts which content will be most successful.
- Sentiment Analysis: Data science techniques are used to analyze public sentiment on social media and reviews, helping entertainment companies gauge how their content is perceived by the audience and guide future decisions.

6. Sports Analytics

Data science is playing an increasingly important role in professional sports, helping teams improve performance, analyze player statistics, and engage with fans.

- Player Performance Optimization: Teams analyze players' physical performance, training data, and in-game statistics to make decisions about player rotations, tactics, and injury prevention strategies.
- Game Strategy: Coaches and analysts use data-driven insights to develop game strategies by analyzing opponents' tactics, strengths, and weaknesses. Teams like the Golden State Warriors and Liverpool FC are well-known for their data-driven approaches.
- Fan Engagement: Sports organizations use data science to enhance fan engagement through personalized content, targeted marketing, and improved in-game experiences, such as dynamic ticket pricing based on demand forecasts.

7. Government and Public Policy

Data science is increasingly being used by governments to drive decisions that improve public services, security, and policy-making.

- Smart Cities: Data from sensors and IoT devices is used in cities to monitor traffic, energy use, waste management, and public safety. Data-driven decision-making helps optimize public resources and improve the quality of urban life.
- Crime Prediction and Prevention: Law enforcement agencies use predictive analytics to identify crime hotspots and allocate resources effectively, improving public safety.
- Public Health and Policy: Governments use data science to track and respond to health outbreaks, model the spread of diseases, and assess the impact of public policies through data-driven simulations.

Conclusion

Data Science is not just about analyzing numbers; it's about solving real-world problems and making data-driven decisions. The ability to manipulate and interpret data has never been more important, and this course aims to give you the skills needed to navigate this data-driven world.

WEEK 1 Day 2: Basics of Python for Data Science

To guide students through the process of setting up Python and installing Jupyter Notebook, providing a foundation for data science programming and future lab exercises.

Python is a powerful and versatile programming language that has become the go-to tool for data science. Its extensive libraries, ease of use, and integration with various platforms have made it essential for analyzing, manipulating, and visualizing data. One of Python's key strengths is that it can

be used in multiple environments, catering to the diverse needs of data scientists. We will be covering up following:

1. Setting up Python and Jupyter Notebook:
2. How to Use Python for Data Science: Exploring Multiple Approaches

Setting up Python and Jupyter Notebook:

1: Installing Python

Python is the most commonly used language for data science. In this section, you will install Python on your system.

Steps:

1. **Download Python:**

- ✓ Go to the official Python website: https://www.python.org.
- ✓ Download the latest stable release of Python (e.g., Python 3.x).

2. **Run the Installer:**

- ✓ After downloading the installer, run the file.
- ✓ **Important**: Check the box labeled **"Add Python to PATH"** before proceeding with the installation.
- ✓ Select the **"Install Now"** option.

3. **Verify Python Installation:**

- ✓ Open a command prompt or terminal.
- ✓ Type `python --version` and press **Enter**. You should see the installed version of Python (e.g., Python 3.x.x).

4. **Install pip (Python's Package Installer):**

- ✓ If not already included, install `pip` by typing the following in the command prompt or terminal:

```
python -m ensurepip --upgrade
```

2: Installing Jupyter Notebook

Jupyter Notebook is a powerful, open-source tool used for data science, allowing for interactive code, visualizations, and narrative text all in one document.

Steps:

1. **Open Command Prompt or Terminal:**

   ✓ Once Python is installed, open the command prompt or terminal.

2. **Install Jupyter Notebook using pip:**

   ✓ In the command prompt/terminal, type the following command:

   ```
   pip install notebook
   ```

   ✓ This will install Jupyter Notebook along with all its dependencies.

3. **Verify Jupyter Installation:**

   ✓ After the installation is complete, type the following command to start Jupyter Notebook:

   ```
   jupyter notebook
   ```

   ✓ This should open a new tab in your web browser, showing the Jupyter Notebook interface.

3: Running Your First Jupyter Notebook

1. **Create a New Notebook:**

   ✓ Once Jupyter opens in your browser, click on the **New** button in the top right corner and select **Python 3** from the drop-down menu. This will create a new notebook file.

2. **Understanding the Interface:**

   ✓ Each Jupyter Notebook consists of cells that can contain code, text (written in Markdown), or other data such as images and charts.
   ✓ The first cell is empty and ready for your input.

3. **Writing Your First Python Code:**

   ✓ In the first cell, type the following Python code:

   ```
   python
   print("Hello, Data Science!")
   ```

   ✓ Press **Shift** + **Enter** to run the code. The output, `Hello, Data Science!`, will appear below the cell.

4: Installing Additional Libraries

Jupyter Notebook allows you to use a wide variety of libraries for data analysis and visualization. In this section, you will install some of the commonly used libraries in data science.

1. **Install Libraries with pip:**

   ✓ In the command prompt/terminal, type the following to install some common libraries:

   ```
   pip install numpy pandas matplotlib
   ```

   ✓ This will install:

   - **NumPy** for numerical operations.
   - **Pandas** for data manipulation and analysis.
   - **Matplotlib** for data visualization.

2. **Verify Installation in Jupyter:**

   ✓ In your Jupyter Notebook, create a new cell and enter the following:

   ```
   import numpy as np
   import pandas as pd
   import matplotlib.pyplot as plt

   print("Libraries installed successfully!")
   ```

   ✓ Run the cell by pressing **Shift + Enter**. If no error occurs, the libraries were installed successfully.

5: Customizing Jupyter Notebook

1. **Changing the Working Directory:**

   ✓ By default, Jupyter Notebook opens in your user's home directory. You can specify a custom directory to start Jupyter from.

   ✓ In the terminal or command prompt, navigate to the folder where you want to store your notebooks using `cd` (change directory), e.g.:

   ```
   bash
   cd path/to/your/folder
   ```

   ✓ Then type `jupyter notebook` to start Jupyter in the chosen directory.

2. **Changing Themes:**

   ✓ You can customize the appearance of Jupyter Notebook using third-party packages like `jupyterthemes`. Install the package:

   ```
   pip install jupyterthemes
   ```

- ✓ To change the theme, type:

```
jt -t <theme-name>
```

- ✓ For example, to apply the "monokai" theme:

```
jt -t monokai
```

6: Troubleshooting Common Issues

- **Jupyter doesn't launch in the browser:** Try opening the terminal or command prompt and running `jupyter notebook` again. If this doesn't work, type the URL provided in the terminal output directly into your browser.
- **Python is not recognized in command prompt/terminal:** Ensure that Python was added to the system's PATH during installation. If not, you can reinstall Python or manually add it to the PATH environment variable.
- **Error when importing a library:** Make sure the library is installed correctly. You can check this by running: `pip show <library-name>`

Assignment:

1. **Install Python and Jupyter Notebook** on your system.
2. Write a Python script in Jupyter Notebook that:
    a. Prints the version of Python installed on your machine.
    b. Loads a dataset using Pandas.
    c. Displays the first 5 rows of the dataset.
3. **Bonus Task**: Customize your Jupyter Notebook theme using the `jupyterthemes` package.

2 How to Use Python for Data Science: Exploring Multiple Approaches

In this section, we'll explore several ways to use Python for data science, ranging from cloud platforms to local installations, each with its advantages and ideal use cases.

Google Cloud and Google Colab:

Google Cloud is a robust platform that offers powerful computing resources and a suite of tools for machine learning and data analysis. It enables data scientists to leverage Python without worrying about the limitations of their local machines.

Google Colab, a popular notebook environment hosted by Google, is especially useful for Python-based data science tasks. It is essentially Jupyter Notebook hosted on the cloud, with the following key benefits:

- **Free and accessible**: Colab is free and only requires a Google account. There is no need to install anything on your computer, making it highly accessible.
- **Pre-installed Libraries**: Common Python libraries for data science (such as NumPy, Pandas, Scikit-learn, TensorFlow) are already installed.
- **GPU and TPU support**: Colab allows users to run Python code with access to GPUs and TPUs for accelerated computation, which is ideal for deep learning and large-scale data analysis.
- **Collaboration**: Multiple users can collaborate on the same Colab notebook in real-time, making it perfect for group projects or tutorials.

How to Get Started:

1. Go to Google Colab.
2. Create a new notebook and start writing Python code directly in the browser.
3. Access data from Google Drive or cloud storage, making it ideal for working on remote datasets.

Anaconda Distribution

Anaconda is one of the most popular frameworks for managing Python environments for data science. It simplifies package management and comes bundled with many pre-installed libraries and tools, including Jupyter Notebook, making it highly efficient for local development.

Benefits of Using Anaconda:

- **All-in-one package**: Anaconda includes Python, Jupyter Notebook, and essential libraries like Pandas, Matplotlib, Scikit-learn, and more. There is no need for individual library installations.
- **Environment management**: Anaconda makes it easy to create isolated Python environments. This allows you to work on multiple projects with different library versions without conflicts.
- **User-friendly interface**: Anaconda Navigator provides a graphical interface that allows users to manage environments, launch tools, and install packages without using the command line.

How to Get Started:

1. Download and install Anaconda from the official website.
2. Use Anaconda Navigator to launch Jupyter Notebook or Spyder for Python development.
3. Create isolated environments for specific projects using the command:

   ```
   conda create --name <environment_name> python=3.x
   ```

4. Easily install libraries using `conda install <library_name>` or `pip install`.

Anaconda is a great option for beginners who want a quick setup process with a complete set of tools, as well as for experienced users who need to manage multiple projects efficiently.

Local Installation: Python and Jupyter Notebook

If you prefer a lightweight and customizable setup, you can install Python and Jupyter Notebook directly on your machine without using any frameworks. This approach allows you to have full control over your environment and packages.

Steps to Set Up Python and Jupyter Notebook Locally:

1. **Install Python**: Download the latest version of Python from the official website. During installation, ensure you check the option to "Add Python to PATH."
2. **Install Jupyter Notebook**: Open a terminal or command prompt and install Jupyter Notebook using `pip`:

   ```
   pip install notebook
   ```

3. **Run Jupyter Notebook**: Launch the notebook by typing `jupyter notebook` in the terminal. A new tab will open in your browser, where you can start writing and executing Python code.

Why Choose This Option?

- **Flexibility**: You can manually install and manage any Python libraries you need, allowing for a fully customized environment.
- **Minimal overhead**: A local installation without Anaconda or cloud services minimizes additional software layers, giving you control over performance and resources.
- **Ideal for experimentation**: If you prefer a DIY approach or need a lightweight setup, installing Python and Jupyter Notebook directly is an excellent choice.

Integrated Development Environments (IDEs)

For data scientists who prefer more robust development environments, Python can be used in full-featured IDEs such as **PyCharm**, **VS Code**, or **Spyder**. These IDEs provide a rich set of features that make coding and debugging easier.

Key Benefits of Using IDEs:

- **Code assistance**: Advanced code autocompletion, refactoring, and syntax highlighting improve coding efficiency.
- **Built-in debuggers**: IDEs come with powerful debugging tools, which are particularly useful when working on complex data science projects.
- **Version control integration**: IDEs offer seamless integration with Git for version control, making collaboration and project management easier.
- **Visualization**: Many IDEs offer built-in support for running Jupyter Notebooks or displaying Matplotlib plots directly within the environment.

How to Get Started:

1. **PyCharm**: Download and install PyCharm from JetBrains. PyCharm provides excellent support for Python and data science workflows.
2. **VS Code**: Install Visual Studio Code and add the Python extension for a lightweight but powerful coding experience.
3. **Spyder**: If you prefer an interface similar to RStudio, try Spyder, which is specifically designed for scientific programming.

Online IDEs and Platforms

If you're working in an environment where you cannot install software or need access to Python on the go, online IDEs can be an effective alternative. Platforms such as **Replit**, **Kaggle Notebooks**, and **Deepnote** offer cloud-based development environments where you can run Python code for data science projects.

Advantages of Using Online IDEs:

- **No installation required**: These platforms run in the browser, meaning you can start coding immediately without any setup.
- **Collaboration**: Many online platforms allow for real-time collaboration, which is ideal for group projects.
- **Pre-configured environments**: Like Google Colab, these platforms often come with Python libraries and tools pre-installed, saving you time.

Popular Online Platforms:

1. **Kaggle Notebooks**: Perfect for data science competitions, Kaggle provides a Jupyter Notebook environment with popular datasets and libraries already included.
2. **Replit**: A general-purpose online IDE that supports Python and allows for easy code sharing and collaboration.
3. **Deepnote**: An advanced data science notebook platform that offers real-time collaboration, database integrations, and seamless cloud support.

Docker for Python Data Science Environments

For advanced users, **Docker** provides an isolated and reproducible environment to run Python for data science. By creating Docker containers, you can bundle your Python code, libraries, and dependencies into a self-contained environment, ensuring that your project runs the same way regardless of the host system.

Benefits of Docker for Data Science:

- **Reproducibility**: Docker ensures that your Python environment is consistent across different machines.
- **Portability**: Containers can be easily shared with team members, ensuring everyone works in the same environment.
- **Isolation**: Docker allows you to isolate your data science projects and their dependencies from your host system.

Getting Started with Docker:

1. Install Docker from the official site.
2. Create a Dockerfile that specifies your Python environment and libraries.
3. Build and run your Docker container:

```
docker build -t my_python_ds_env .
docker run -it my_python_ds_env
```

Python is an incredibly flexible tool for data science, and there are many ways to use it based on your needs, preferences, and the resources available to you. By completing this lab, you have successfully set up your Python development environment, installed Jupyter Notebook, and learned how to write and execute Python code interactively. Whether you opt for cloud-based solutions like Google Colab, frameworks like Anaconda, or a lightweight local setup with Jupyter Notebook, Python's versatility ensures that you can find the right environment for your data science projects. Moreover, more advanced options like Docker and IDEs further enhance productivity, making Python an indispensable tool for data scientists at any level.

Week 1 Day 3: Data Structures in Python

The objective of this session is to understand and practice the four fundamental data structures in Python: Lists, Tuples, Dictionaries, and Sets. By the end of this lab, students will be able to:

- Create and manipulate lists, tuples, dictionaries, and sets.
- Use the appropriate data structure for different scenarios.
- Perform operations like indexing, slicing, adding, updating, and removing elements.

Lists in Python

A **list** is an ordered, mutable collection of items. Lists allow duplicate elements and can store data of different types.

- **Mutable**: You can modify, add, or remove elements after the list is created.
- **Indexed**: Each item has an index starting from 0.
- **Allows duplicates**: You can have repeated elements.

Syntax:

```
my_list = [1, 2, 3, 4]
```

Common List Operations:

1. Creating a list:
   - ✓ `fruits = ["apple", "banana", "cherry"]`
2. Accessing elements (indexing):
   - ✓ `print(fruits[0])  # Outputs: apple`
   - ✓ `print(fruits[-1])  # Outputs: cherry (last element)`
3. Slicing a list:
   - ✓ `print(fruits[1:3])  # Outputs: ['banana', 'cherry']`

4. Adding elements:
   - ✓ Using `append()`: Adds an element to the end of the list.
     ```
     1. fruits.append("orange")
     ```
   - ✓ Using `insert()`: Adds an element at a specified position.
     ```
     1. fruits.insert(1, "kiwi")
     ```
5. Removing elements:
   - ✓ Using `remove()`: Removes the first occurrence of the specified element.
     ```
     1. fruits.remove("banana")
     ```
   - ✓ Using `pop()`: Removes an element at a specific index (default is the last element).
     ```
     1. fruits.pop(2)
     ```
6. Modifying elements:
   - ✓ `fruits[0] = "mango"  # Replaces "apple" with "mango"`

Lab Exercise 1: Working with Lists

1. Create a list of 5 favorite movies.
2. Add a movie to the list, remove one, and then modify the third movie in the list.
3. Print the modified list.
4. Slice the list to show only the first 3 movies.
5. Sort the list in alphabetical order.

Tuples in Python

A **tuple** is an ordered, immutable collection of elements. Tuples are similar to lists, but once a tuple is created, it cannot be modified.

- **Immutable**: Once defined, the elements cannot be changed.
- **Indexed**: Like lists, tuples are also indexed starting from 0.
- **Allows duplicates**: You can have repeated elements.

Syntax:

```
my_tuple = (1, 2, 3)
```

Common Tuple Operations:

1. Creating a tuple:
   - ✓ `numbers = (10, 20, 30, 40)`
2. Accessing elements (indexing):
   - ✓ `print(numbers[1])  # Outputs: 20`
3. Slicing a tuple:
   - ✓ `print(numbers[:3])  # Outputs: (10, 20, 30)`
4. Concatenating tuples:
   - ✓ `new_tuple = numbers + (50, 60)`
5. Unpacking tuples:
   - ✓ `a, b, c = (1, 2, 3)  # Unpacks the tuple into variables a, b, and c`

Lab Exercise 2: Working with Tuples

1. Create a tuple of 4 subjects you are studying this semester.
2. Access and print the second and third subjects using indexing.

3. Create a new tuple by concatenating another tuple of 2 additional subjects.
4. Use tuple unpacking to assign the elements of a tuple to separate variables.

Dictionaries in Python

A **dictionary** is an unordered, mutable collection of key-value pairs. Each element in a dictionary consists of a key and a corresponding value, and the keys must be unique.

- **Mutable**: You can add, remove, or modify elements after the dictionary is created.
- **Unordered**: Items are stored in an unordered manner (though Python 3.7+ maintains insertion order).
- **Key-value pairs**: Data is stored as pairs, where keys must be unique, but values can be duplicated.

Syntax:

```
my_dict = {'name': 'Alice', 'age': 25, 'city': 'New York'}
```

Common Dictionary Operations:

1. **Creating a dictionary:**
   - ✓ `student = {'name': 'John', 'age': 20, 'courses': ['Math', 'Science']}`
2. **Accessing values:**
   - ✓ `print(student['name'])  # Outputs: John`
   - ✓ `print(student.get('age'))  # Outputs: 20`
3. **Adding or modifying key-value pairs:**
   - ✓ `student['age'] = 21  # Modify age`
   - ✓ `student['grade'] = 'A'  # Add a new key-value pair`
4. **Removing elements:**
   - ✓ Using `del`: `del student['age']`
   - ✓ Using `pop()`: `student.pop('courses')`
5. **Iterating through a dictionary:**
   - ✓
```
for key, value in student.items():
    print(key, value)
```

Lab Exercise 3: Working with Dictionaries

1. Create a dictionary with details about yourself: name, age, and a list of hobbies.
2. Add a new key-value pair for your city and modify the age.
3. Use a loop to print all the keys and values.
4. Remove the key-value pair for your hobbies.

Sets in Python

A **set** is an unordered, mutable collection of unique elements. Sets are useful when you want to store a collection of items with no duplicates and perform set operations such as union, intersection, and difference.

- **Mutable**: You can add or remove items after the set is created.
- **Unordered**: Elements are not stored in a specific order.

- **Unique elements**: No duplicates are allowed.

Syntax:

```
my_set = {1, 2, 3}
```

Common Set Operations:

1. **Creating a set:**
   - ✓ `fruits = {'apple', 'banana', 'cherry'}`
2. **Adding elements:** `fruits.add('orange')`
3. **Removing elements:**
   - ✓ **Using `remove()`**: Raises an error if the item doesn't exist.
     `fruits.remove('banana')`
   - ✓ **Using `discard()`**: Doesn't raise an error if the item doesn't exist.
     `fruits.discard('banana')`
4. **Set operations:**
   - ✓ **Union**:
     ```
     1. set1 = {1, 2, 3}
     2. set2 = {3, 4, 5}
     3. print(set1.union(set2))  # Outputs: {1, 2, 3, 4, 5}
     ```
   - ✓ **Intersection**:
     ```
     1. print(set1.intersection(set2))  # Outputs: {3}
     ```
   - ✓ **Difference**:
     ```
     1. print(set1.difference(set2))  # Outputs: {1, 2}
     ```

Lab Exercise 4: Working with Sets

1. Create two sets of your favorite foods and a friend's favorite foods.
2. Find the union of both sets.
3. Find the intersection (common items) between the two sets.
4. Remove an item from your set, and then check if another item exists in the set.

Week 1 Day 4: Practical Session

This practical session aims to introduce students to basic Python coding. Through hands-on exercises, students will become familiar with core Python programming concepts such as variables, data types, conditionals, loops, and functions.

Exercise 1: Python Variables and Data Types

Learn to declare and initialize variables and understand different data types in Python.

- **Variables** are used to store information.
- **Data Types**: Python has several built-in data types, including:
  - `int`: Integer numbers (e.g., 10)
  - `float`: Decimal numbers (e.g., 10.5)
  - `str`: Strings (e.g., "Hello")
  - `bool`: Boolean values (`True` or `False`)

Task 1: Variable Declaration

1. Declare three variables: `name`, `age`, and `height`. Assign appropriate values to each (e.g., your name, age, and height in meters).
2. Print out the variables.

```
name = "John"
age = 22
height = 1.75

print("Name:", name)
print("Age:", age)
print("Height:", height, "meters")
```

Task 2: Identify Data Types

1. Use the `type()` function to print the data type of each variable.
2. Modify the values and observe how the data types change.

```
print(type(name))  # str
print(type(age))   # int
print(type(height))  # float
```

Exercise 2: Basic Arithmetic and Input/Output

Practice basic arithmetic operations and using input/output functions.

- Python supports arithmetic operations like addition (`+`), subtraction (`-`), multiplication (`*`), and division (`/`).

- `input()` function is used to take input from the user.

Task 1: Arithmetic Operations

1. Create two variables, `a` and `b`. Assign them values and perform basic operations like addition, subtraction, multiplication, and division.
2. Print the results of each operation.

```
a = 10
b = 5

print("Addition:", a + b)
print("Subtraction:", a - b)
print("Multiplication:", a * b)
print("Division:", a / b)
```

Task 2: Taking User Input

1. Use the `input()` function to take two numbers from the user.
2. Perform addition on the numbers and print the result.

```
num1 = float(input("Enter first number: "))
num2 = float(input("Enter second number: "))

result = num1 + num2
print("The sum is:", result)
```

Exercise 3: Conditional Statements

Understand and use conditional statements like `if`, `elif`, and `else` to control program flow.

- **Conditionals** are used to execute different code blocks based on certain conditions.
    - `if` checks a condition.
    - `elif` checks another condition if the first is false.
    - `else` executes if none of the conditions are true.

Task 1: Age Classification

1. Write a program that asks the user for their age.
2. Based on the input, classify the person as:
    - "Child" (age < 13)
    - "Teen" (13 <= age < 18)
    - "Adult" (age >= 18)

```
age = int(input("Enter your age: "))

if age < 13:
    print("You are a child.")
elif age < 18:
    print("You are a teen.")
else:
```

```
    print("You are an adult.")
```

Task 2: Even or Odd

1. Ask the user for a number.
2. Write a program that determines if the number is even or odd.

```
num = int(input("Enter a number: "))

if num % 2 == 0:
    print(f"{num} is even.")
else:
    print(f"{num} is odd.")
```

Exercise 4: Loops (For and While)

Learn how to use `for` and `while` loops to repeat tasks in a program.

- **For Loop**: Used to iterate over a sequence (list, range, etc.).
- **While Loop**: Repeats as long as a condition is `True`.

Task 1: For Loop to Print Numbers

1. Use a `for` loop to print the numbers from 1 to 10.

```
for i in range(1, 11):
    print(i)
```

Task 2: Sum of Numbers Using While Loop

1. Write a program using a `while` loop to calculate the sum of numbers from 1 to 5.

```
i = 1
total = 0

while i <= 5:
    total += i
    i += 1

print("The sum is:", total)
```

Exercise 5: Functions and Modular Code

Understand how to create functions and use them to structure code for reusability.

- A **function** is a block of reusable code that performs a specific task.
- Functions are defined using the `def` keyword.

Task 1: Create a Function

1. Write a function called `greet()` that takes a name as input and prints a greeting.

```
def greet(name):
    print("Hello, " + name + "!")

greet("Alice")
```

Task 2: Function to Add Two Numbers

1. Write a function called `add_numbers()` that takes two arguments, adds them, and returns the result.
2. Use the function to add two numbers input by the user.

```
def add_numbers(a, b):
    return a + b

num1 = float(input("Enter first number: "))
num2 = float(input("Enter second number: "))

result = add_numbers(num1, num2)
print("The sum is:", result)
```

Assignment:

1. Write a Python program that defines a function to check whether a given number is prime.
2. Test the function with numbers between 1 and 100.For a prime number, the function should return `True`, and for non-prime numbers, it should return `False`.

In this lab session, you have practiced the foundational concepts of Python programming. You now have a solid understanding of variables, data types, conditionals, loops, and functions. These building blocks are essential for more advanced data science applications that you will encounter in future sessions. Be sure to practice each concept thoroughly.Always test your code with different inputs to ensure it works as expected.

Week 1 DAY 5: Practical Session

Mini-project: Simple data manipulation with Python

In this session, students will apply Python programming skills to perform basic data manipulation tasks. They will use libraries such as `pandas` and `numpy` for data handling and manipulation, as well as practice basic operations like reading, cleaning, filtering, and analyzing data.

By the end of this session, students will:

- Be familiar with handling tabular data using **pandas**.
- Perform basic data cleaning, filtering, and summarization operations.
- Understand how to apply various data manipulation techniques for real-world data problems.

Setting Up the Environment

Make sure that Python, Jupyter Notebook (or another Python environment), and the required libraries (`pandas`, `numpy`) are properly installed and working.

Task 1: Import the Libraries

1. Open Jupyter Notebook or your preferred Python environment.
2. Import the necessary libraries to manipulate data.

```
import pandas as pd
import numpy as np
```

Loading Data with Pandas

Learn how to load CSV data into a pandas DataFrame, a powerful 2D data structure.

- Pandas DataFrame: A 2-dimensional labeled data structure with columns of potentially different types.
- Common file formats like CSV can be easily loaded into a DataFrame using `pandas`.

Task 1: Load Data from a CSV File

1. Download a sample dataset, such as the Titanic dataset, available at this URL: Titanic dataset.
2. Load this dataset into a pandas DataFrame.

```
# Load data into a pandas DataFrame
url                                                                    =
"https://raw.githubusercontent.com/datasciencedojo/datasets/master/titanic.csv"
data = pd.read_csv(url)

# Display the first 5 rows of the dataset
data.head()
```

Exercise 3: Exploring the Data

Explore the structure of the dataset to understand its size, columns, and basic statistics.

Task 1: Inspect Data

1. Print the number of rows and columns in the dataset.
2. Get a summary of the dataset's structure and types of data in each column.

```
# Get the shape of the DataFrame (number of rows and columns)
print("Shape of the dataset:", data.shape)

# Get a summary of the dataset (column names and types)
print(data.info())

# Get basic statistics of numerical columns
print(data.describe())
```

Task 2: Display Column Names

1. Display all the column names in the dataset.

```
# Display column names
print("Column names:", data.columns)
```

Exercise 4: Cleaning the Data

Perform basic data cleaning tasks, such as handling missing values and renaming columns.

Task 1: Handling Missing Data

1. Check for missing values in the dataset.
2. Drop rows or columns with missing values or fill them using a strategy (e.g., fill with mean or mode).

```
# Check for missing values
print("Missing values in each column:\n", data.isnull().sum())

# Drop rows with missing values
data_cleaned = data.dropna()

# Alternatively, fill missing values (e.g., fill 'Age' column with mean)
data['Age'].fillna(data['Age'].mean(), inplace=True)

# Verify if missing values are handled
print("Missing values after cleaning:\n", data.isnull().sum())
```

Task 2: Renaming Columns

1. Rename the `Pclass` column to `Passenger_Class` and `SibSp` to `Siblings_Spouses_Aboard`.

```
# Renaming columns
```

```
data.rename(columns={'Pclass': 'Passenger_Class', 'SibSp':
'Siblings_Spouses_Aboard'}, inplace=True)

# Display the updated column names
print(data.columns)
```

Filtering and Grouping Data

Learn how to filter and group data based on conditions.

Task 1: Filter Data

1. Filter the dataset to show only the passengers who are older than 30 years.

```
# Filter passengers older than 30 years
older_passengers = data[data['Age'] > 30]
print(older_passengers.head())
```

Task 2: Group Data

1. Group the data by `Sex` and calculate the average age of male and female passengers.

```
# Group by 'Sex' and calculate average age
avg_age_by_sex = data.groupby('Sex')['Age'].mean()
print(avg_age_by_sex)
```

Exercise 6: Analyzing Data

Perform basic data analysis using aggregation functions like `mean()`, `count()`, and `sum()`.

Task 1: Analyze Survival Rates

1. Find out how many passengers survived the Titanic disaster.

```
# Count the number of passengers who survived
survival_counts = data['Survived'].value_counts()
print("Survival counts:\n", survival_counts)
```

Task 2: Survival Rate by Passenger Class

1. Calculate the survival rate based on passenger class.

```
# Group by Passenger_Class and calculate the survival rate
survival_rate_by_class = data.groupby('Passenger_Class')['Survived'].mean() * 100
print("Survival rate by passenger class (%):\n", survival_rate_by_class)
```

Mini-Project: Simple Data Manipulation

Project Description:

Using the Titanic dataset, perform the following tasks:

1. Clean the dataset by handling missing values.
2. Analyze survival rates based on different demographic factors (age, sex, and class).
3. Visualize the results using Python libraries like `matplotlib` or `seaborn` (optional).

Assignment:

1. Write a Python program to analyze and compare the survival rates between passengers who were traveling alone and those traveling with family members (using the `Siblings_Spouses_Aboard` column).
2. Perform a more detailed analysis of survival rates across different age groups (e.g., group ages into bins: 0-10, 11-20, 21-30, etc.).

Additional Task: Visualize the distribution of passenger ages using a histogram.

In this mini-project, students practiced data loading, cleaning, filtering, and analyzing tasks. These exercises laid a solid foundation for data manipulation, which is critical for all data science tasks. As you progress, you will build on these skills to tackle more complex datasets and analyses.

WEEK 2 Day 1: Introduction to Pandas

Introduction to Pandas

Pandas is one of the most powerful and flexible libraries in Python for data manipulation and analysis. As data science and machine learning are becoming increasingly important in both academic and industrial settings, learning how to efficiently handle and process data is crucial. Pandas is a key tool for achieving this. Today, we will explore what Pandas is, why it is important, and how it can be used effectively.

What is Pandas?

Pandas is a **Python library** primarily used for **data manipulation and analysis**. It provides flexible and intuitive tools for working with **structured data**, making it easier to clean, transform, and analyze datasets. Pandas is built on top of **NumPy**, which gives it performance efficiency and speed, especially when dealing with large datasets.

Why Pandas?

Data often comes in the form of messy, incomplete, or unstructured information. Before we can analyze or visualize data, it needs to be **cleaned** and **processed**. Pandas simplifies these tasks and provides an intuitive interface to manage various types of data—like spreadsheets, SQL tables, or time series data.

Key Features of Pandas:

1. **Data Structures:**
    - **Series**: A one-dimensional array-like object. Think of it as a single column of data, similar to a list or a column in a spreadsheet.
    - **DataFrame**: A two-dimensional, tabular structure with labeled axes (rows and columns). It is the most commonly used object in Pandas and is analogous to a table in a database or an Excel spreadsheet.
2. **Data Cleaning and Transformation:**
    - Handling missing values (NaN) easily.
    - Filtering and selecting data based on conditions.
    - Combining data from different datasets (merging, joining, concatenating).
3. **Input and Output (I/O):**
    - Pandas allows reading and writing from multiple formats, including **CSV**, **Excel**, **SQL databases**, and **JSON**.
    - This flexibility makes it easy to import data from a variety of sources and export it after analysis.
4. **Efficient Data Operations:**
    - Vectorized operations: Pandas operates over entire datasets with fast, efficient operations (using NumPy at its core).
    - Grouping and aggregating data: Powerful groupby functionality for performing operations like sum, mean, or count over subsets of data.
5. **Time Series Data:**

- Pandas has strong capabilities for dealing with time-indexed data, which is common in fields like finance or scientific research.

6. **Data Visualization:**
   - Integration with **Matplotlib** and **Seaborn** libraries makes it easier to visualize data after performing analysis.

Importing the library:

```
import pandas as pd
```

Loading Data: Pandas allows you to load data into a DataFrame with just a single command:

```
df = pd.read_csv('data.csv')
```

Exploring Data: Once loaded, you can explore the data with commands like:

- df.head(): Displays the first few rows of the dataset.
- df.info(): Gives a summary of the dataset.
- df.describe(): Provides statistical insights, like mean, standard deviation, etc.

Selecting Data: Pandas allows you to select specific rows and columns:

```
# Selecting a column

df['column_name']

# Selecting multiple columns

df[['column1', 'column2']]

# Selecting rows based on condition

df[df['column_name'] > 100]
```

Handling Missing Data: Pandas simplifies dealing with missing values

```
df.dropna()  # Removes rows with missing data

df.fillna(0) # Replaces missing values with 0
```

Grouping and Aggregation: You can perform operations like summing or averaging over specific groups of data:

```
df.groupby('category_column').sum()
```

Merging DataFrames: Combining datasets is a common task, and Pandas provides easy-to-use methods:

```
merged_df = pd.merge(df1, df2, on='key_column')
```

Conclusion

In summary, Pandas is an essential tool for anyone working with data in Python. It simplifies tasks like data cleaning, transformation, and analysis, providing a rich set of functions that allow you to focus more on the analysis rather than the mechanics of handling data. Whether you're working with small datasets or large, complex ones, Pandas has tools that scale to meet your needs.

As we move forward in this course, we will dive deeper into practical applications, using Pandas to manipulate real-world datasets, perform statistical analyses, and create powerful visualizations.

Data Manipulation with Pandas

Data manipulation is at the core of data analysis, and Pandas provides powerful tools to load, transform, and filter data efficiently. Today, we will focus on the key aspects of **data manipulation**: **Loading data**, **Selecting and Filtering**, and **Handling Missing Data**. By mastering these concepts, you'll be able to streamline the data preprocessing tasks crucial in any data science pipeline.

1. Loading Data with Pandas

Before manipulating data, we first need to load it. Pandas provides intuitive functions to load data from various file formats:

- **CSV files (Comma Separated Values)** are one of the most common formats.
- **Excel spreadsheets**, **JSON files**, **SQL databases**, and others are also supported.

The command for reading a CSV file into a Pandas DataFrame is as simple as:

```
import pandas as pd
df = pd.read_csv('data.csv')
```

Why use DataFrame?
A **DataFrame** is a two-dimensional tabular data structure in Pandas with labeled axes (rows and columns), similar to a table or Excel spreadsheet. It’s highly flexible and can hold many types of data (numeric, string, etc.).

Once the data is loaded, it’s crucial to explore it:

```
df.head()  # Shows the first 5 rows of the dataset
df.tail()  # Shows the last 5 rows of the dataset
df.info()  # Summary of the dataset (data types, null values)
df.describe()  # Statistical summary (mean, std, etc.) of numeric columns
```

2. Selecting and Filtering Data

Once data is loaded into a DataFrame, the next step is selecting and filtering specific rows and columns based on your needs.

Selecting Columns

You can think of columns in a DataFrame as the features or variables in your dataset. To select them:

- Select a **single column**:

  df['column_name']

  This returns a Pandas **Series**, which is essentially a one-dimensional array-like structure.

- Select **multiple columns**:

  df[['column1', 'column2']]

  This returns a **DataFrame**.

Selecting Rows

To select specific rows based on their position, you use **iloc** (integer-location based indexing):

```
df.iloc[0]  # Selects the first row
df.iloc[10:15]  # Selects rows from index 10 to 14
```

To select rows based on **labels or conditions**, you use **loc**:

```
df.loc[df['column_name'] > 50]  # Select rows where column_name values are greater than 50
```

Filtering Data with Conditions

Filtering allows you to drill down into your dataset based on conditions. Consider filtering rows that match a specific condition, for example, selecting rows where a column has values greater than a threshold:

```
df[df['age'] > 30]
```

Multiple conditions can be combined using logical operators like **&** (AND) and **|** (OR):

```
df[(df['age'] > 30) & (df['salary'] > 50000)]
```

You can also filter based on categorical data:

```
df[df['city'] == 'New York']
```

Renaming Columns

Sometimes you might want to rename columns for clarity:

```
df.rename(columns={'old_name': 'new_name'}, inplace=True)
```

Sorting Data

Sorting is essential when analyzing data:

```
df.sort_values(by='salary', ascending=False)  # Sort by 'salary' in descending order
```

---

3. Handling Missing Data

In real-world datasets, **missing values** are common. These can arise from incomplete records, errors in data entry, or other reasons. Handling missing data is critical for maintaining the integrity of your analysis.

Identifying Missing Data

Missing values are typically represented as NaN (Not a Number). To identify missing data:

```
df.isnull()  # Returns a DataFrame of booleans where True indicates missing data
df.isnull().sum()  # Returns the count of missing values for each column
```

Dropping Missing Data

If a column or row has too many missing values and is not useful for analysis, you can drop it:

```
df.dropna()  # Drops rows with any missing values
df.dropna(axis=1)  # Drops columns with missing values
```

However, dropping missing data can sometimes lead to the loss of useful information, especially if many rows have just a few missing values.

Filling Missing Data

Instead of dropping rows or columns, you can **fill** missing values with a default value. Some common strategies include:

1. **Filling with a constant value**:

   ```
   df.fillna(0)  # Replace all NaN values with 0
   ```

2. **Filling with the mean, median, or mode**:

   df['column_name'].fillna(df['column_name'].mean(), inplace=True) # Replace NaN with column mean
   df['column_name'].fillna(df['column_name'].median(), inplace=True) # Replace NaN with column median

3. **Forward/Backward fill**: Sometimes filling missing values with the previous or next value makes sense:

   df.fillna(method='ffill') # Forward fill: fills NaN with the value in the previous row
   df.fillna(method='bfill') # Backward fill: fills NaN with the value in the next row

Replacing Specific Values

Pandas also provides functions to replace specific values. For instance, if a dataset uses some placeholder for missing values (like -1), you can replace it with NaN:

df.replace(-1, np.nan, inplace=True)

Detecting and Dropping Duplicate Rows

Sometimes datasets may contain duplicate records:

df.duplicated() # Returns a boolean Series indicating duplicate rows
df.drop_duplicates(inplace=True) # Removes duplicate rows

Practical Examples

Example: Loading, Selecting, and Filtering

Consider a dataset on employee salaries:

df = pd.read_csv('employees.csv')

# Select employees with a salary greater than $60,000 and working in the 'IT' department
high_salary_it = df[(df['salary'] > 60000) & (df['department'] == 'IT')]

# Sort by salary in descending order
high_salary_it_sorted = high_salary_it.sort_values(by='salary', ascending=False)

Example: Handling Missing Data

If the dataset contains missing ages for some employees:

df['age'].fillna(df['age'].mean(), inplace=True) # Fill missing age values with the average age

# Drop rows where both 'salary' and 'department' are missing
df.dropna(subset=['salary', 'department'], inplace=True)

Conclusion

Data manipulation with Pandas is a powerful skill that enables you to clean, filter, and analyze your datasets effectively. Whether you're dealing with missing data, selecting specific columns and rows, or applying conditions to filter your data, Pandas gives you the flexibility and efficiency you need to transform raw data into meaningful insights.

In our next sessions, we will dive deeper into advanced operations like merging datasets, applying functions across DataFrames, and more sophisticated data analysis techniques. Keep practicing!

Week 2 Day 2: Data Manipulation with Pandas

Data Aggregation and Grouping in Pandas

One of the most powerful and insightful tools in data analysis is **data aggregation** and **grouping**. These techniques allow you to summarize and explore large datasets by breaking them down into meaningful subgroups. As your intelligent lecturer today, we'll dive deep into **GroupBy** operations in Pandas and explore how you can use them for various aggregation functions.

Why Grouping and Aggregation?

In data analysis, it's often useful to **group** data based on certain criteria and then **aggregate** it using summary statistics such as sums, averages, counts, etc. For example, if you have a sales dataset, you might want to group sales by product categories and calculate the total sales for each category. Grouping and aggregation allow you to discover trends, relationships, and patterns that might otherwise go unnoticed in raw data.

1. **What is GroupBy?**

In Pandas, the **GroupBy** process can be thought of as splitting your data into distinct groups based on some criteria, then applying a function (e.g., sum, mean, count) to each group, and finally combining the results into a summary output.

The GroupBy process generally follows three steps:

- **Splitting**: Divide the data into groups based on some values.
- **Applying**: Apply a function (e.g., sum, mean) to each group.
- **Combining**: Combine the results into a new DataFrame or Series.

The groupby() function is the core of this process.

2. **Basic GroupBy Operations**

Example Dataset:

Let's assume you have a dataset of employee salaries:

```
import pandas as pd

data = {
   'Employee': ['Alice', 'Bob', 'Charlie', 'David', 'Edward', 'Frank'],
   'Department': ['HR', 'IT', 'IT', 'HR', 'IT', 'Finance'],
   'Salary': [50000, 60000, 55000, 45000, 70000, 40000],
   'Years': [5, 7, 6, 3, 9, 2]
```

}

df = pd.DataFrame(data)

The DataFrame looks like this:

Employee	Department	Salary	Years
Alice	HR	50000	5
Bob	IT	60000	7
Charlie	IT	55000	6
David	HR	45000	3
Edward	IT	70000	9
Frank	Finance	40000	2

Grouping by a Single Column

To group employees by their department:

grouped = df.groupby('Department')

This command doesn't show results immediately because it creates a **GroupBy** object. It simply shows that the data is grouped, but nothing is done with it yet. Now, let's apply some aggregation:

Sum Aggregation:

To sum the salaries within each department:

salary_sum = grouped['Salary'].sum()
print(salary_sum)

Output:

yaml

Department
Finance 40000
HR 95000
IT 185000
Name: Salary, dtype: int64

Here, the salaries have been summed within each department. This shows that the IT department has a total salary of 185,000, HR has 95,000, and Finance has 40,000.

Grouping by Multiple Columns

Sometimes you need to group by more than one column. For example, if we had additional data (like location), we might want to group by both **Department** and **Location**. For now, let's look at grouping by multiple variables like **Department** and **Years of Experience**:

```
grouped_multi = df.groupby(['Department', 'Years'])
```

Now we can aggregate over this multi-level grouping:

```
salary_mean_multi = grouped_multi['Salary'].mean()
print(salary_mean_multi)
```

Aggregating with GroupBy

Aggregation refers to applying a function to each group of data. Pandas provides a wide variety of **aggregation functions**, such as:

- sum(): Sum of values.
- mean(): Mean of values.
- count(): Count of non-NA values.
- min(), max(): Minimum and maximum values.
- std(): Standard deviation of values.

Example: Count of Employees in Each Department

```
employee_count = grouped['Employee'].count()
print(employee_count)
```

Output:

yaml

```
Department
Finance     1
HR          2
IT          3
Name: Employee, dtype: int64
```

This shows that there's 1 employee in Finance, 2 in HR, and 3 in IT.

Example: Multiple Aggregations

You can apply multiple aggregation functions at once using the agg() method:

```
salary_agg = grouped['Salary'].agg(['sum', 'mean', 'max', 'min'])
print(salary_agg)
```

Output:

```
            sum    mean    max    min
Department
Finance      40000  40000.0  40000  40000
HR           95000  47500.0  50000  45000
IT          185000  61666.7  70000  55000
```

Here, the total salary (sum), average salary (mean), maximum salary (max), and minimum salary (min) are calculated for each department. This provides a summary of salary statistics across departments.

Grouping and Applying Custom Functions

You can also apply **custom functions** to each group using apply(). This allows you to use more complex aggregation logic.

Example: Custom Function for Salary Growth

Suppose you want to compute a custom metric, like a projected salary growth based on years of experience:

```
def projected_salary_growth(group):
    return group['Salary'] + (group['Years'] * 1000)

df['Projected Salary'] = grouped.apply(projected_salary_growth)
print(df)
```

This applies the custom function to each department, calculating the projected salary based on years of experience.

Transforming Data After Grouping

The transform() function allows you to return a Series with the same shape as the original data. Unlike agg(), which reduces the data size, transform() keeps the same number of rows as the original DataFrame but applies the transformation per group.

Example: Normalizing Salaries by Department

Suppose you want to normalize the salaries within each department by subtracting the mean salary of that department:

```
df['Salary Normalized'] = grouped['Salary'].transform(lambda x: x - x.mean())
print(df)
```

Now, within each department, the normalized salary will be calculated as the difference between an employee's salary and the department's average salary.

Aggregating and Grouping on Multiple Columns

You can also perform aggregation on multiple columns at once. For instance, if you want to calculate the mean salary and mean years of experience for each department:

```
grouped_agg = grouped.agg({
   'Salary': 'mean',
   'Years': 'mean'
})
print(grouped_agg)
```

This will give you:

markdown

```
            Salary     Years
Department
Finance      40000.0  2.000000
HR           47500.0  4.000000
IT           61666.7  7.333333
```

Advanced GroupBy: Combining Aggregation with Filtering

Sometimes you want to group data and then apply **filtering** based on the result of the groupby operation.

Example: Departments with Total Salary Over 100,000

```
high_salary_departments = grouped.filter(lambda x: x['Salary'].sum() > 100000)
print(high_salary_departments)
```

This returns only the rows for departments where the total salary exceeds 100,000. This is a powerful combination of grouping, aggregation, and filtering.

GroupBy operations in Pandas are an incredibly powerful way to analyze data by breaking it into subgroups and performing computations on each group. Whether you're computing simple

aggregates like sums or means, applying custom functions, or combining multiple aggregations, the groupby() method allows you to reveal trends and insights hidden within the data.

Understanding how to manipulate and aggregate data in this way is crucial for any data analyst or data scientist. It allows you to summarize large datasets effectively, perform comparisons between groups, and uncover relationships that help drive data-driven decisions.

In the next session, we will explore more advanced topics like **pivot tables** and **multi-indexing**, which build upon the concepts of grouping and aggregation!

WEEK 2 Day 4: Practical Session

Practical Session: Hands-On Exercises with Pandas

Welcome to our practical session on data manipulation using Pandas! Today, we'll work through a series of hands-on exercises designed to solidify your understanding of data manipulation techniques. Make sure you have Pandas installed and a Jupyter Notebook or your preferred Python environment ready for practice.

Exercise 1: Loading Data

Code Template:

```
import pandas as pd

# Load your dataset
df = pd.read_csv('path_to_your_file.csv')
print(df.head())
```

Exercise 2: Exploring Data

Code Template:

```
print(df.info())
print(df.describe())
print(df.isnull().sum())
```

Exercise 3: Selecting and Filtering Data

Code Template:

```
# Select specific columns
selected_columns = df[['Column1', 'Column2']]
print(selected_columns)

# Filter rows based on a condition
filtered_data = df[df['Column3'] > value]
print(filtered_data)
```

Exercise 4: Handling Missing Data

Code Template:

```
# Fill missing values
df['Column_with_NaN'].fillna(value, inplace=True)

# Or drop rows with missing values
df.dropna(subset=['Column_with_NaN'], inplace=True)
```

Exercise 5: Grouping and Aggregation

Code Template:

```
grouped_data = df.groupby('Category')['Sales'].mean()
print(grouped_data)
```

Exercise 6: Multiple Aggregations

6. **Objective**: Apply multiple aggregation functions.

   Instructions:

   - Group by a column and calculate multiple statistics (e.g., sum, mean, count).

   Code Template:

```
aggregated_data = df.groupby('Category').agg({
   'Sales': ['sum', 'mean', 'count'],
   'Profit': ['sum', 'mean']
})
print(aggregated_data)
```

Exercise 7: Custom Functions with GroupBy

Code Template:

```
def custom_function(group):
   return group['Sales'] / group['Sales'].sum() * 100  # Percentage of total sales

percentage_sales = df.groupby('Category').apply(custom_function)
print(percentage_sales)
```

Exercise 8: Visualizing Grouped Data

8. **Objective**: Visualize the aggregated data.

   Instructions:

   - Use Matplotlib or Seaborn to create a bar plot of the aggregated results.
   - Plot the average sales per category.

   Code Template:

```
import matplotlib.pyplot as plt

aggregated_data = df.groupby('Category')['Sales'].mean().reset_index()
plt.bar(aggregated_data['Category'], aggregated_data['Sales'])
plt.title('Average Sales per Category')
```

```
plt.xlabel('Category')
plt.ylabel('Average Sales')
plt.show()
```

Wrap-Up

After completing these exercises, you should have a solid understanding of how to manipulate data using Pandas, including loading data, selecting and filtering rows and columns, handling missing values, grouping and aggregating, and visualizing the results.

Feel free to experiment with different datasets and aggregation methods. In our next session, we will explore more advanced techniques, including merging datasets and working with time series data.

Week 2 Day 5: Practical Session

Mini-project: Analyzing a dataset with Pandas

Today, you will engage in a real-world data analysis project using Pandas. This hands-on experience will not only enhance your technical skills but also help you apply analytical thinking to solve practical problems.

Project Overview

Objective: Analyze a real-world dataset to derive insights that can inform decision-making.

Dataset Example: The UCI Machine Learning Repository has a dataset titled **"Wine Quality"**, which contains various physicochemical tests and quality ratings for different wines. This dataset is perfect for exploring relationships between attributes and quality ratings, making it a suitable choice for our analysis.

Expected Outcome: A comprehensive report summarizing your findings, including visualizations and key statistics.

Steps for Your Mini-Project

Step 1: Dataset Overview

Dataset Description: The Wine Quality dataset includes attributes such as:

- fixed acidity
- volatile acidity
- citric acid
- residual sugar
- chlorides
- free sulfur dioxide
- total sulfur dioxide
- density
- pH
- sulphates
- alcohol
- quality (target variable)

Step 2: Load the Dataset

1. **Loading Data**:
    - Download the dataset from UCI Wine Quality Dataset.
    - Use pd.read_csv() to load the dataset into a Pandas DataFrame.

    Code Template:

```
import pandas as pd

df = pd.read_csv('winequality-red.csv', sep=';')  # Note the separator is semicolon
print(df.head())
```

Step 3: Explore the Data

2. **Exploratory Data Analysis (EDA)**:
    - Use df.info(), df.describe(), and df.isnull().sum() to understand the structure and identify missing values.
    - Investigate the distribution of the quality ratings.

Code Template:

```
print(df.info())
print(df.describe())
print(df.isnull().sum())
```

Step 4: Data Cleaning

3. **Data Cleaning**:
    - Check for duplicates and handle any missing values appropriately.
    - You may want to drop rows with missing values or fill them with appropriate statistics.

Code Template:

```
df.drop_duplicates(inplace=True)  # Remove duplicate rows
df.fillna(df.mean(), inplace=True)  # Fill missing values with column means
```

Step 5: Analyze and Manipulate Data

4. **Data Manipulation**:
    - Use groupby() to summarize data based on quality.
    - Calculate the average values of the physicochemical properties for each quality rating.

Code Template:

```
quality_summary = df.groupby('quality').mean()
print(quality_summary)
```

Step 6: Visualize the Data

5. **Data Visualization**:
    - Create visualizations to better understand relationships in the data.
    - Consider scatter plots to explore the relationship between alcohol content and quality.

Code Template:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Scatter plot for alcohol vs quality
plt.figure(figsize=(10, 6))
sns.scatterplot(x='alcohol', y='quality', data=df)
plt.title('Alcohol Content vs. Wine Quality')
plt.xlabel('Alcohol Content (%)')
plt.ylabel('Quality Rating')
plt.show()
```

Step 7: Summarize Findings

6. **Report Writing**:
    - Prepare a report summarizing your key findings.
    - Include visualizations and statistics that highlight important insights, such as which physicochemical properties are most correlated with wine quality.

    Report Structure:

    - **Introduction**: Describe the dataset and objectives.
    - **Data Exploration**: Summarize findings from the EDA.
    - **Data Cleaning**: Discuss any cleaning steps taken.
    - **Analysis**: Present insights from data manipulation.
    - **Visualizations**: Include relevant charts and explain their significance.
    - **Conclusion**: Summarize key takeaways.

Step 8: Present Your Findings

7. **Presentation**:
    - Prepare to present your findings to the class using Jupyter Notebook or PowerPoint.
    - Highlight key insights and explain your visualizations and their implications.

Example Analysis Questions

To guide your analysis, consider the following questions:

- What is the distribution of wine quality ratings in the dataset?
- Which physicochemical properties are most strongly correlated with wine quality?
- Are there any noticeable trends or patterns in the data based on the quality ratings?
- How does the alcohol content affect the quality of wine?

This mini-project will give you the opportunity to apply your knowledge of Pandas in a real-world context, allowing you to uncover insights from data that could be valuable in the wine industry.

Remember, the goal is to not only analyze the data but also to communicate your findings effectively. If you have any questions during the project, feel free to reach out for assistance!

Week 3: Data Visualization , Day 1: Introduction to Matplotlib

Objective: Understand the basics of Matplotlib and learn how to create and customize plots.

1. Introduction to Matplotlib (10 minutes)

- Discuss what Matplotlib is and its significance in data visualization.
- Overview of the pyplot interface.

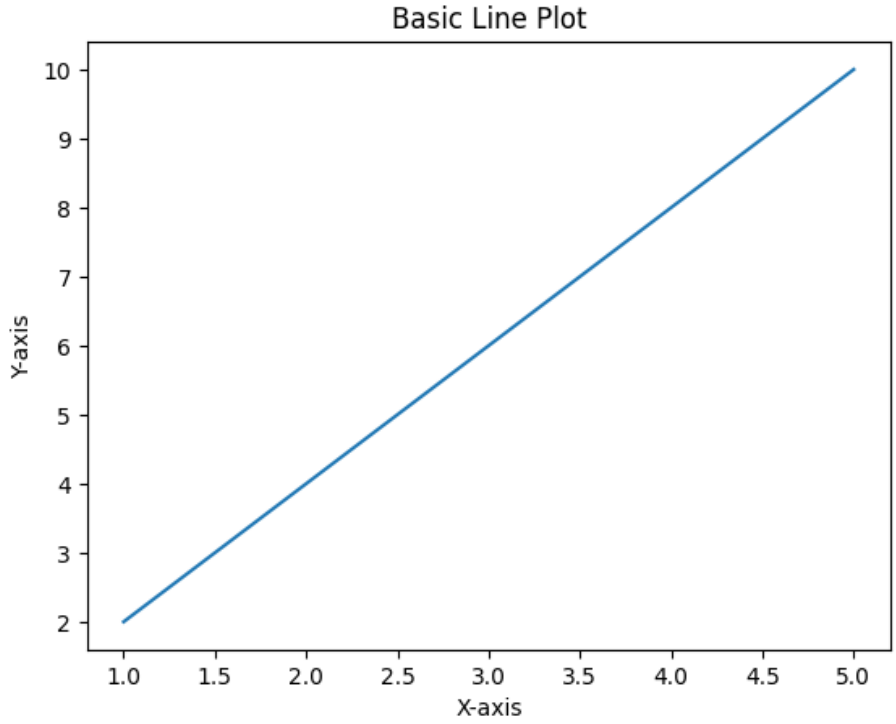
2. Basic Plotting with Matplotlib (20 minutes)

- Code Example: Creating a Basic Line Plot

```
import matplotlib.pyplot as plt

# Basic Line Plot
x = [1, 2, 3, 4, 5]
y = [2, 4, 6, 8, 10]

plt.plot(x, y)
plt.title("Basic Line Plot")
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.show()
```



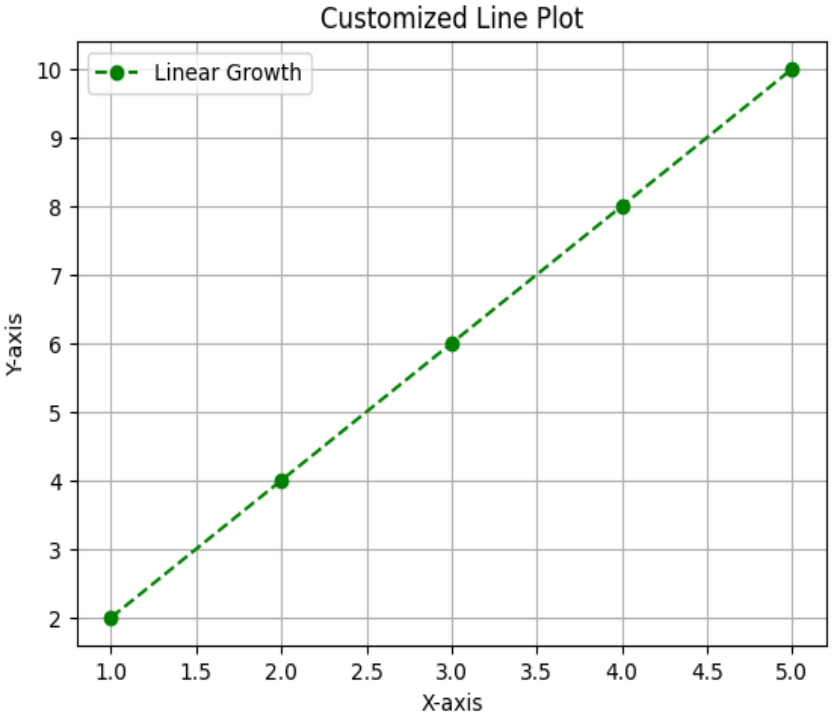
3. Customizing Plots (30 minutes)

- **Code Example: Customizing a Plot**

```
# Customized Line Plot

plt.plot(x, y, label="Linear Growth", color="green", linestyle="--", marker="o")

# Add title, labels, and legend
plt.title("Customized Line Plot")
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.legend(loc="upper left")
plt.grid(True)
plt.show()
```



- **Exercise:**
  - Task students to modify the code to plot another function (e.g., quadratic function).
  - Encourage adding gridlines, changing colors, and using different markers.

Week 3 Day 2: Advanced Visualization with Seaborn

Objective: Explore Seaborn for advanced visualizations, focusing on complex datasets.

1. Introduction to Seaborn

- Discuss the advantages of Seaborn over Matplotlib, especially for statistical data.

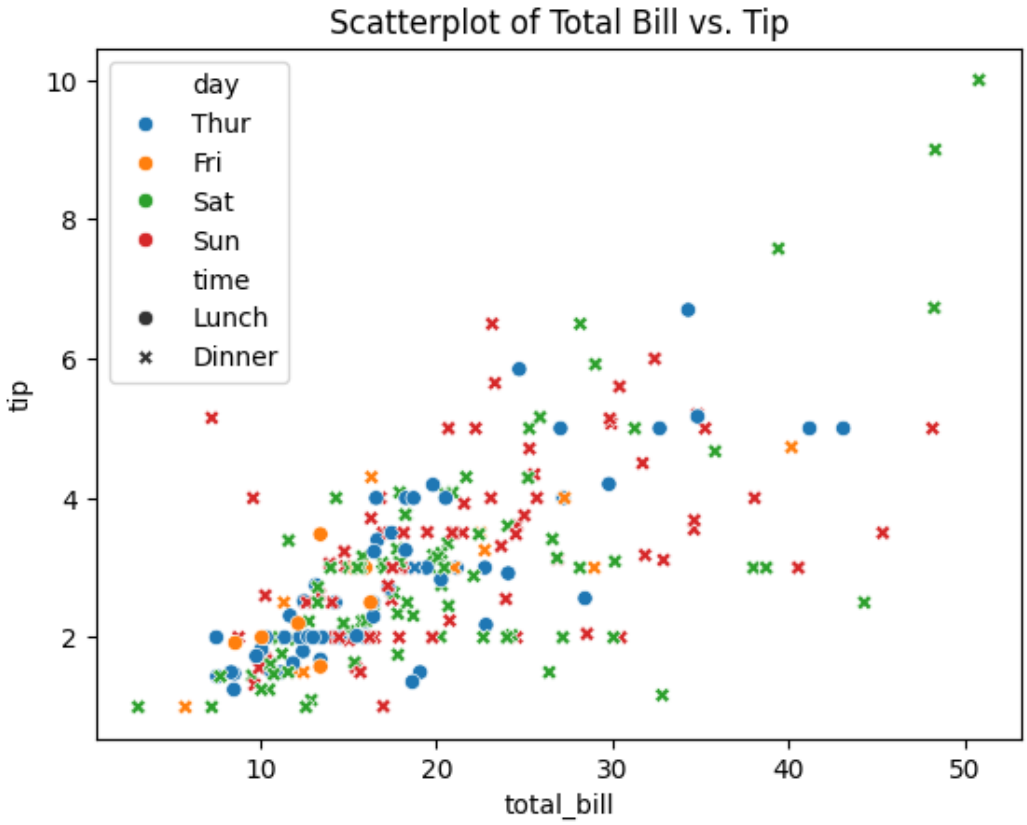
2. Creating Complex Visualizations

- Code Example: Scatterplot with Seaborn

```
import seaborn as sns
import matplotlib.pyplot as plt
from seaborn import load_dataset

# Load example dataset
tips = load_dataset("tips")

# Create a scatterplot
sns.scatterplot(data=tips, x="total_bill", y="tip", hue="day", style="time")
plt.title("Scatterplot of Total Bill vs. Tip")
plt.show()
```

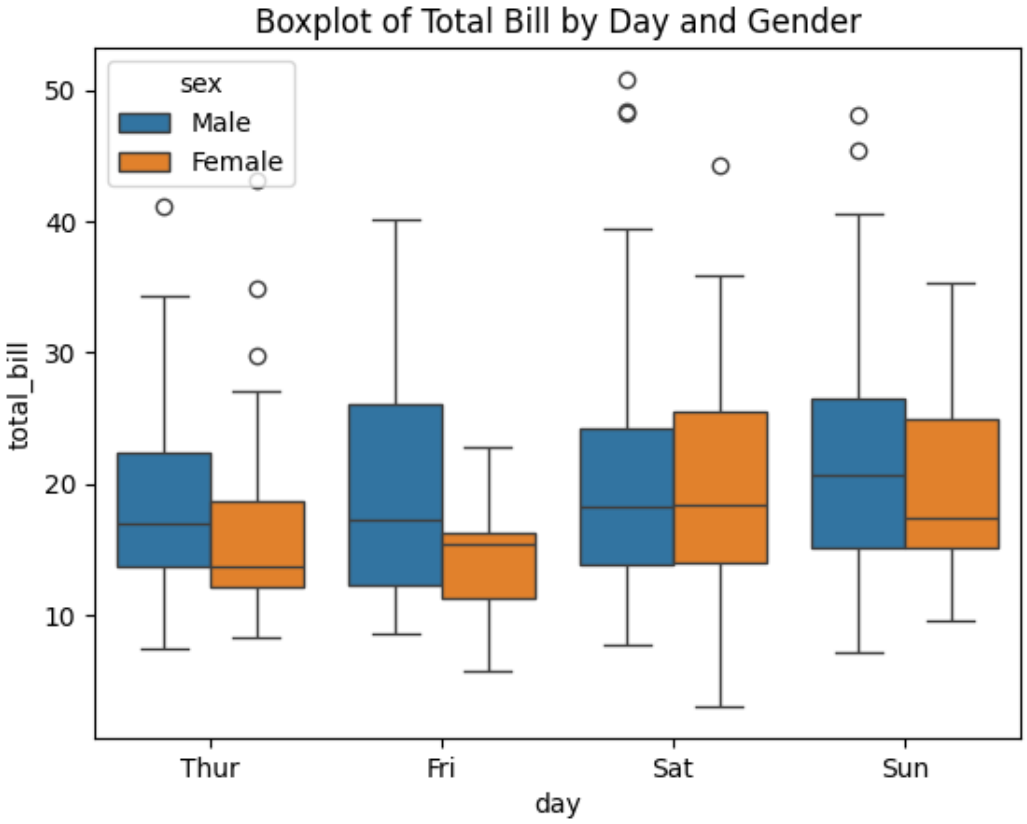


3. Plotting Categorical and Continuous Data

Code Examples: Boxplot and Violin Plot

```
# Boxplot
sns.boxplot(data=tips, x="day", y="total_bill", hue="sex")
plt.title("Boxplot of Total Bill by Day and Gender")
plt.show()

# Violin Plot
sns.violinplot(data=tips, x="day", y="total_bill", hue="sex", split=True)
plt.title("Violin Plot of Total Bill by Day and Gender")
plt.show()
```



- **Exercise:**
  - Ask students to create a bar plot or count plot using the tips dataset.

Week 3 Day 3: Practical Session

Objective: Provide students with hands-on experience in creating visualizations.

1. Hands-on Exercise

- Students will choose any dataset (Iris, Titanic, or a custom dataset) and create at least two visualizations using Matplotlib and Seaborn.

Example Code:
Loading the Dataset:

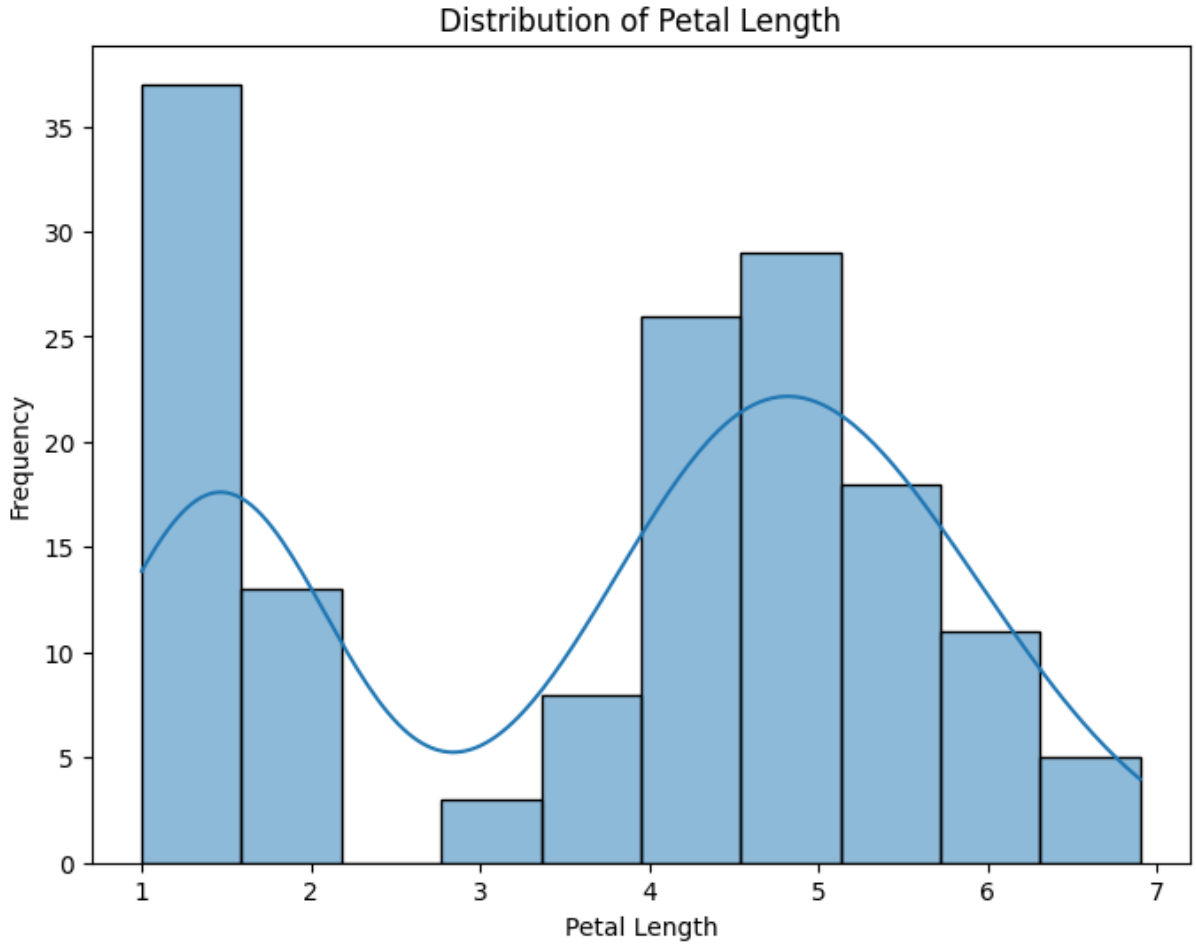
```
import seaborn as sns
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = sns.load_dataset("iris")
```

Creating Visualizations:

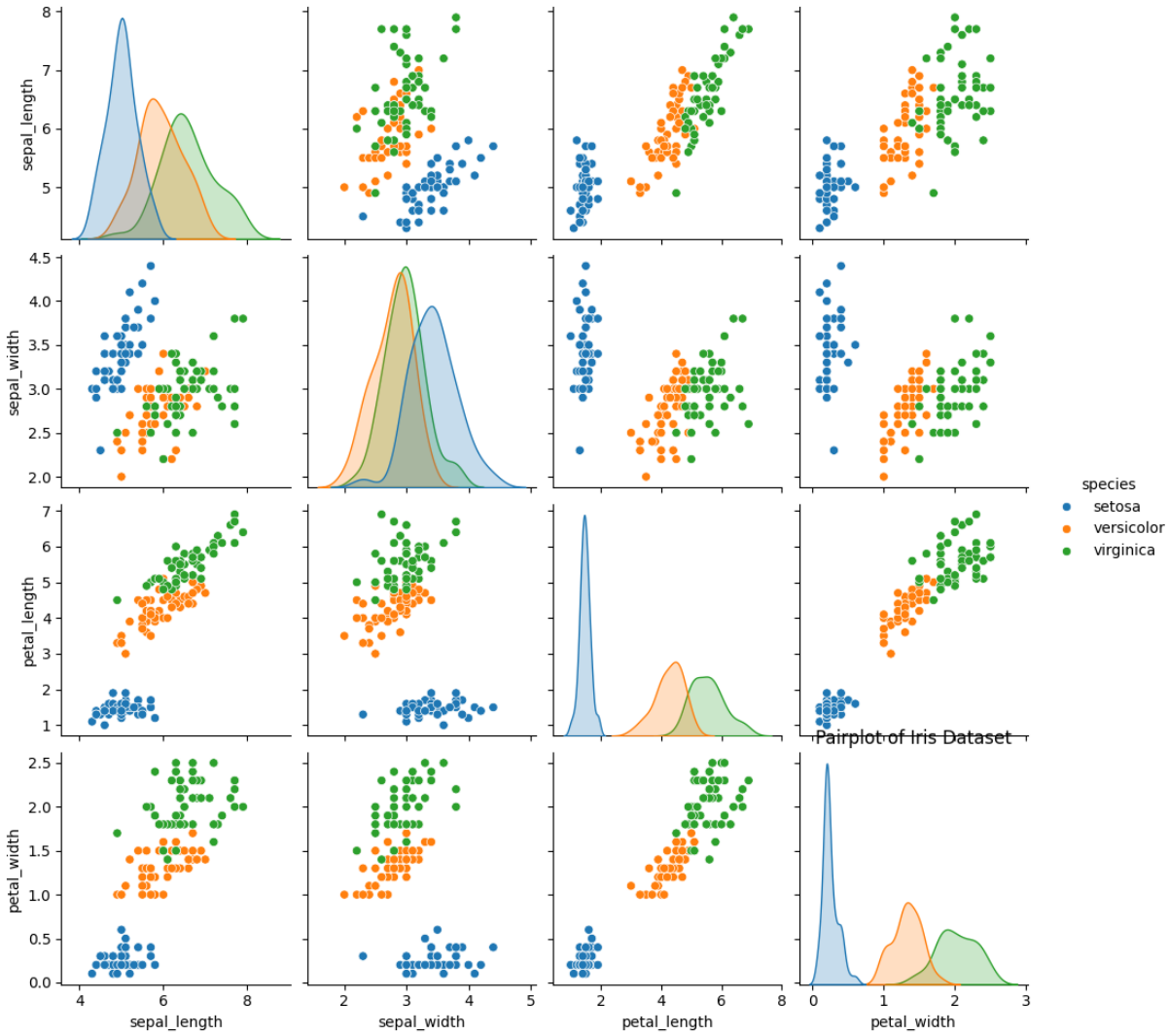
A. Histogram:

```
# Histogram for petal length
plt.figure(figsize=(8, 6))
sns.histplot(iris['petal_length'], bins=10, kde=True)
plt.title("Distribution of Petal Length")
plt.xlabel("Petal Length")
plt.ylabel("Frequency")
plt.show()
```



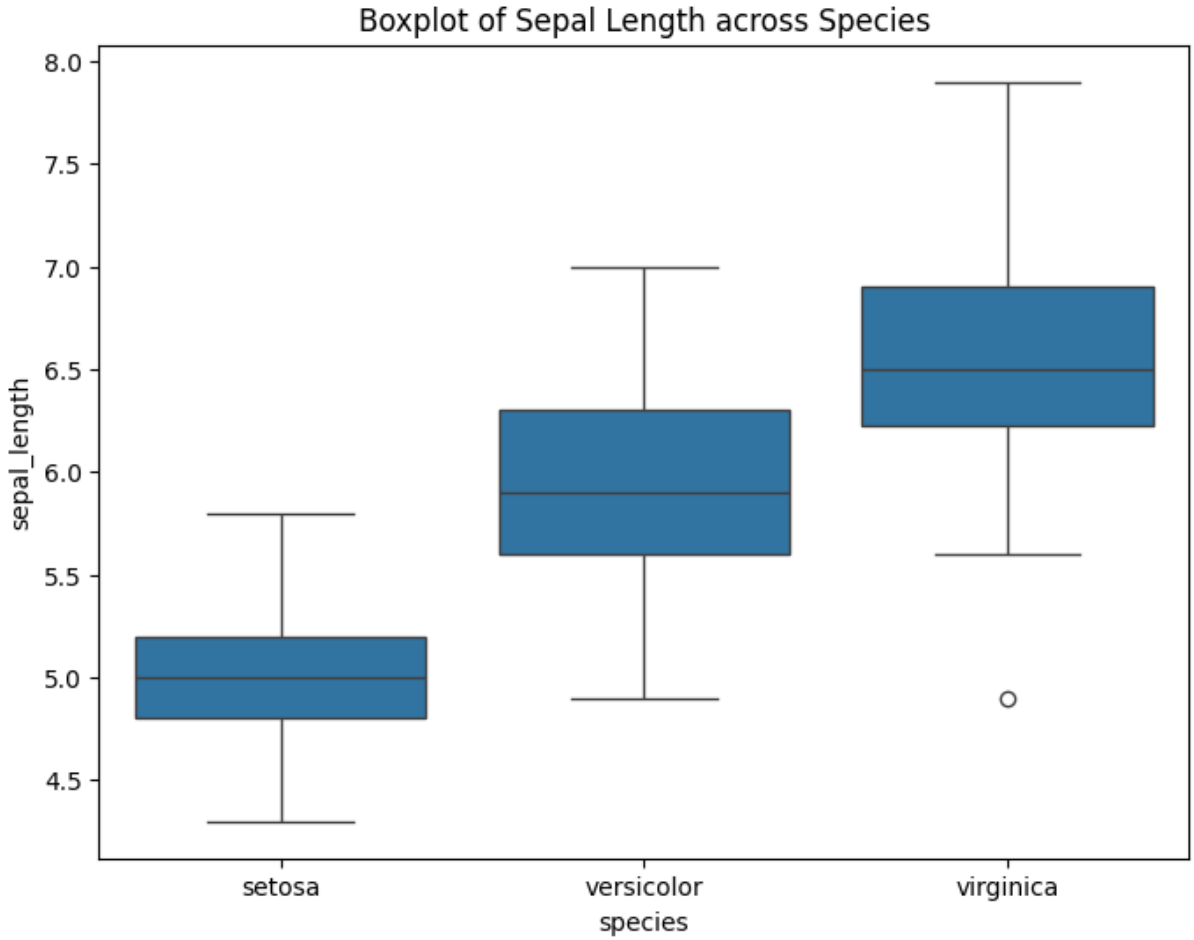
B. Pairplot:

```
# Pairplot to show relationships between features
sns.pairplot(iris, hue="species")
plt.title("Pairplot of Iris Dataset")
plt.show()
```



C. Boxplot:

```
# Boxplot to show the distribution of sepal length across species
plt.figure(figsize=(8, 6))
sns.boxplot(data=iris, x="species", y="sepal_length")
plt.title("Boxplot of Sepal Length across Species")
plt.show()
```


Boxplot of Sepal Length across Species
sepal_length
8.0
7.5
7.0
6.5
6.0
5.5
5.0
4.5
setosa
versicolor
virginica
species

Week 3 Day 4: Practical Session

Objective: Engage students in a mini-project where they apply their skills to visualize a dataset.

1. Mini-Project Instructions

- Explain the project objectives: analyze a dataset and create meaningful visualizations.

2. Project Work

- **Tasks:**
  - Load the dataset, perform exploratory data analysis (EDA), and visualize key insights.

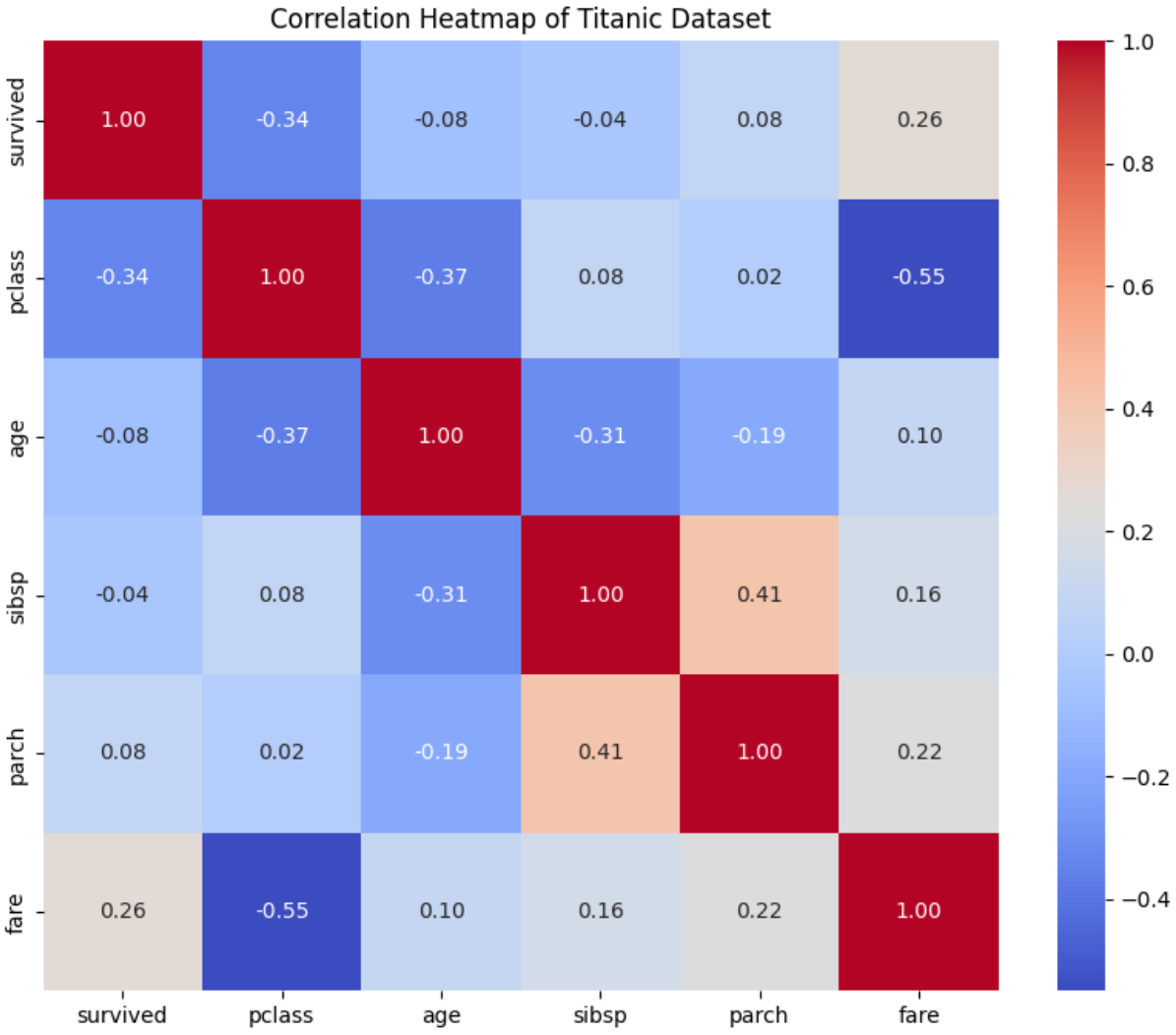
Example Code:

Loading a Dataset (e.g., Titanic):

```
# Load Titanic dataset
titanic = sns.load_dataset("titanic")
```

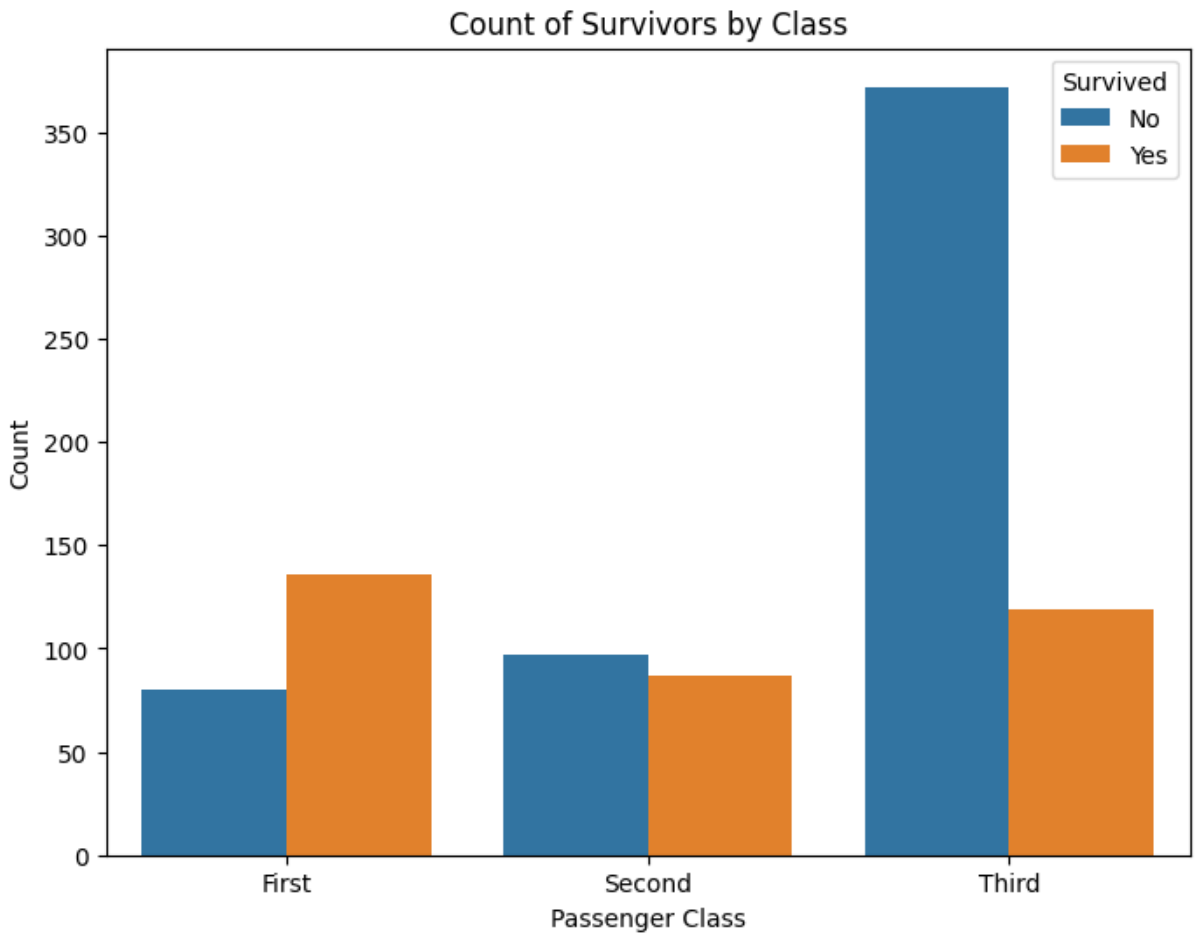
A. Heatmap of Correlations:

```
# Heatmap to show correlations between numerical features
plt.figure(figsize=(10, 8))
sns.heatmap(titanic.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Heatmap of Titanic Dataset")
plt.show()
```



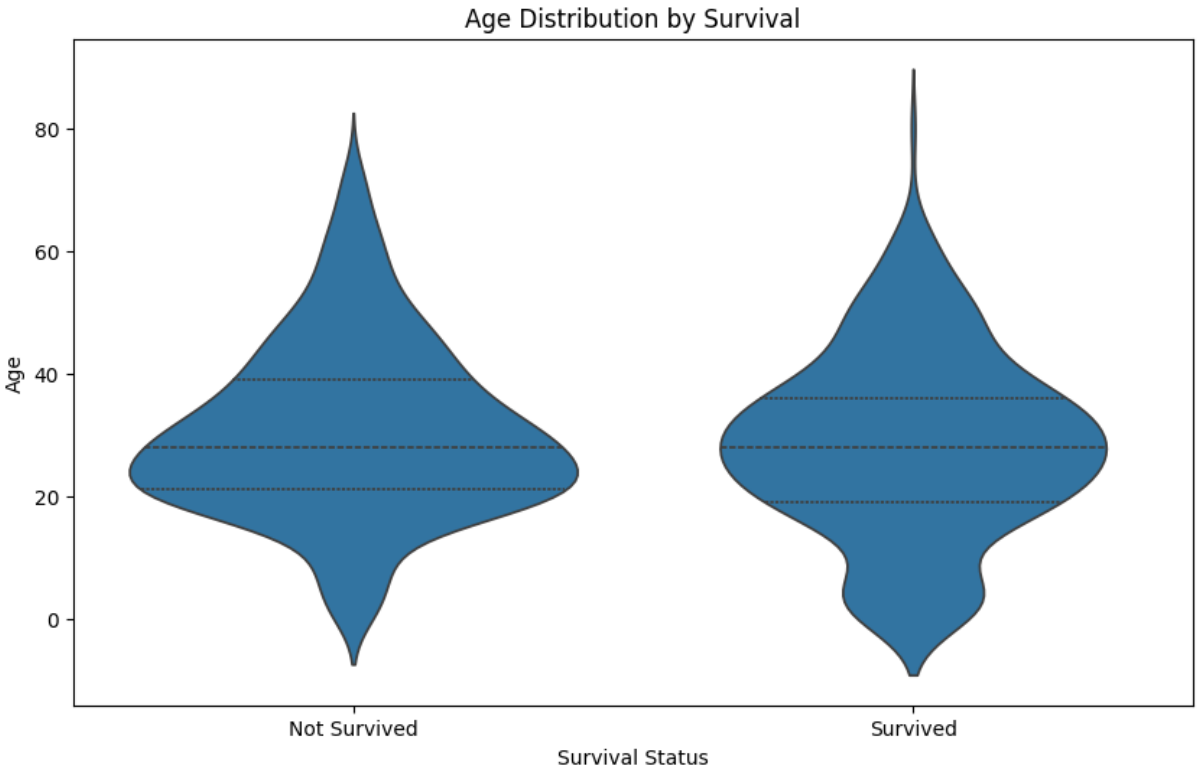
B. Bar Plot of Survival Counts by Class:

```
# Bar plot to show the count of survivors by passenger class
plt.figure(figsize=(8, 6))
sns.countplot(data=titanic, x="class", hue="survived")
plt.title("Count of Survivors by Class")
plt.xlabel("Passenger Class")
plt.ylabel("Count")
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.show()
```



C. Violin Plot of Age Distribution by Survival:

```
# Violin plot to visualize age distribution of survivors and non-survivors
plt.figure(figsize=(10, 6))
sns.violinplot(data=titanic, x="survived", y="age", inner="quartile")
plt.title("Age Distribution by Survival")
plt.xticks([0, 1], ['Not Survived', 'Survived'])
plt.xlabel("Survival Status")
plt.ylabel("Age")
plt.show()
```


Age Distribution by Survival
Age
80
60
40
20
0
Not Survived
Survived
Survival Status

Week 3 Day 5: Review and Q&A

Objective: Reinforce concepts learned during the week and address any questions.

1. Recap of Key Concepts

- Summarize the key topics covered:
- Basic and advanced plotting with Matplotlib and Seaborn.
- Data exploration and visualization techniques.

2. Open Q&A Session

- Encourage students to ask questions about their mini-projects or clarify concepts they found challenging.
- Discuss any interesting visualizations or findings from their projects.

Week 4 Day 1 : Introduction to Statistics

Introduction to Statistics

Statistics is the branch of mathematics that deals with the collection, analysis, interpretation, presentation, and organization of data. It provides tools and methods for making sense of complex data and is widely used in various fields, including data science, economics, social sciences, healthcare, and engineering. Understanding statistics is essential for making informed decisions based on data.

Statistics helps us to:

1. Describe data: Summarize and visualize data to understand its patterns and relationships.
2. Infer relationships: Draw conclusions or make predictions about a population based on sample data.
3. Make decisions: Use statistical analysis to make data-driven decisions in uncertain conditions.

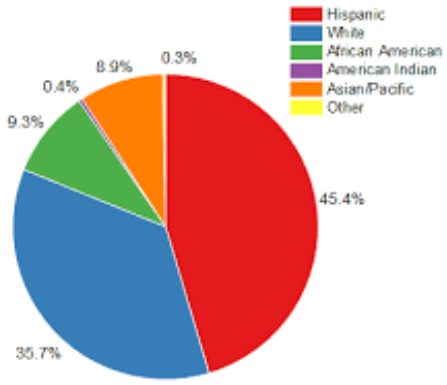
Types of Statistics

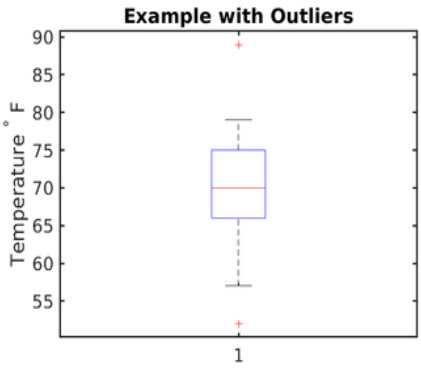
There are two primary types of statistics:

1. **Descriptive Statistics**:

   Used to summarize and describe the characteristics of a dataset.

   - Central Tendency (Mean, Median, Mode)
   - Dispersion (Range, Variance, Standard Deviation)
   - Shape (Skewness, Kurtosis)





2. **Inferential Statistics**:

Involves making predictions or inferences about a population based on a sample of data.

- Hypothesis Testing
- Confidence Intervals
- Regression Analysis

Key Concepts in Statistics

1. Population and Sample

- Population: The entire set of individuals or observations that are of interest.
- Sample: A subset of the population used to make inferences about the entire population.

2. Variables

- Qualitative (Categorical) Variables: Represent categories (e.g., gender, race, eye color).
- Quantitative (Numerical) Variables: Represent numerical values (e.g., height, weight, temperature).

3. Measures of Central Tendency

- Mean: The average of a set of numbers.
- Median: The middle value in a sorted list of numbers.
- Mode: The most frequently occurring value in a dataset.

4. Measures of Dispersion

- Range: The difference between the highest and lowest values in a dataset.
- Variance: The average of the squared differences from the mean.
- Standard Deviation: The square root of variance, showing how much data points deviate from the mean.

5. Probability

- Probability quantifies the likelihood of an event occurring. It is central to inferential statistics.
- Probability Distribution: A function that represents the probabilities of all possible values in a random variable.

6. Hypothesis Testing

- A process used to test assumptions (hypotheses) about a population parameter.
- Common tests include t-tests, ANOVA, and chi-square tests

Applications of Statistics

Statistics is used in various fields and industries, such as:

1. **Data Science**: Data analysis, predictive modeling, and machine learning rely heavily on statistical methods to extract insights from data.
2. **Healthcare**: Clinical trials and medical research use statistics to determine the effectiveness of treatments.
3. **Economics**: Economists use statistical models to forecast trends, analyze markets, and evaluate economic policies.
4. **Social Sciences**: Surveys, polls, and experiments in psychology and sociology rely on statistical methods for data interpretation.

DAY 1- Lab Overview:

This lab will provide hands-on experience with calculating and visualizing descriptive statistics using Python. You will learn how to compute common statistics like **mean**, **median**, **mode**, and **standard deviation**, as well as visualize data distributions using histograms.

By the end of the lab, you will:

- Understand how to use Python to compute descriptive statistics.
- Visualize data distributions with histograms using the `matplotlib` and `seaborn` libraries.
- Analyze the spread and central tendencies of a dataset.
- Install the following Python libraries: `pandas`, `numpy`, `matplotlib`, `seaborn`.

Install these using the command: `pip install pandas numpy matplotlib seaborn`.

Learn how to calculate fundamental descriptive statistics like mean, median, mode, and standard deviation using Python.

Task 1: Load Data

1. For this lab, we will use the **Iris** dataset. This dataset contains information about different species of iris flowers and measurements of their sepals and petals.
2. Load the Iris dataset into a pandas DataFrame.

```
# Import libraries
import pandas as pd
import numpy as np
from scipy import stats

# Load the Iris dataset
url = "https://raw.githubusercontent.com/mwaskom/seaborn-data/master/iris.csv"
data = pd.read_csv(url)

# Display the first few rows of the dataset
data.head()
```

Task 2: Calculate Mean, Median, Mode, and Standard Deviation

1. **Mean**: Calculate the average of a particular feature (e.g., sepal length).
2. **Median**: Find the middle value when the data is sorted.
3. **Mode**: Find the most frequently occurring value.
4. **Standard Deviation**: Measure the amount of variation or dispersion in the data.

```
# Mean of 'sepal_length'
mean_sepal_length = data['sepal_length'].mean()
print("Mean Sepal Length:", mean_sepal_length)

# Median of 'sepal_length'
median_sepal_length = data['sepal_length'].median()
print("Median Sepal Length:", median_sepal_length)

# Mode of 'sepal_length'
mode_sepal_length = stats.mode(data['sepal_length'])[0][0]
print("Mode Sepal Length:", mode_sepal_length)

# Standard deviation of 'sepal_length'
std_sepal_length = data['sepal_length'].std()
print("Standard Deviation of Sepal Length:", std_sepal_length)
```

Exercise 2: Visualizing Data Distributions with Histograms

Learn how to create histograms to visualize data distributions, which help understand how data points are spread across different ranges.

Task 1: Plot a Histogram of Sepal Lengths

1. Use the `matplotlib` and `seaborn` libraries to create a histogram of the **sepal_length** feature.
2. Customize the plot by adding labels, titles, and adjusting the number of bins.

```
# Import visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns

# Create a histogram of 'sepal_length'
plt.figure(figsize=(8, 6))
sns.histplot(data['sepal_length'], bins=10, kde=True, color='blue')

# Add labels and title
plt.title("Distribution of Sepal Lengths", fontsize=16)
plt.xlabel("Sepal Length (cm)", fontsize=12)
plt.ylabel("Frequency", fontsize=12)

# Display the plot
plt.show()
```

Task 2: Visualize Another Feature (e.g., Petal Length)

1. Create a histogram for the **petal_length** feature.
2. Experiment with different bin sizes to see how the visualization changes.

```
# Create a histogram of 'petal_length'
plt.figure(figsize=(8, 6))
sns.histplot(data['petal_length'], bins=15, kde=True, color='green')

# Add labels and title
plt.title("Distribution of Petal Lengths", fontsize=16)
plt.xlabel("Petal Length (cm)", fontsize=12)
plt.ylabel("Frequency", fontsize=12)

# Display the plot
plt.show()
```

Exercise 3: Exploring Data Distributions

Understand the concept of data distribution and skewness by analyzing how data is spread and whether it is normally distributed or skewed.

Task 1: Explore Data Distribution for Sepal Length

1. Check whether the **sepal_length** feature follows a normal distribution.
2. Analyze the skewness of the data.

```
# Skewness of 'sepal_length'
sepal_length_skewness = data['sepal_length'].skew()
print("Skewness of Sepal Length:", sepal_length_skewness)

# Checking if 'sepal_length' is normally distributed
sns.histplot(data['sepal_length'], kde=True)
plt.title("Normality Check of Sepal Length")
plt.show()
```

Task 2: Explore Data Distribution for Petal Width

1. Check the skewness and distribution of the **petal_width** feature.

```
# Skewness of 'petal_width'
petal_width_skewness = data['petal_width'].skew()
print("Skewness of Petal Width:", petal_width_skewness)

# Plot histogram for 'petal_width'
sns.histplot(data['petal_width'], kde=True)
plt.title("Normality Check of Petal Width")
plt.show()
```

Exercise 4: Mini-Project - Analyzing a Dataset

Apply the knowledge you've gained to a new dataset and perform a complete descriptive statistical analysis.

Task 1: Choose a New Dataset

- Choose a dataset from the UCI Machine Learning Repository or use the **Iris** dataset.

Task 2: Compute Descriptive Statistics

1. Calculate mean, median, mode, and standard deviation for the numerical features in the dataset.
2. Visualize the data distributions for at least two features using histograms.

Task 3: Analyze Data Distributions

1. Check for normality by plotting histograms and calculating the skewness.
2. Summarize your findings about the distribution patterns of the data.

Example Code (Skeleton for Project):

```
# Load a new dataset
url = "your_dataset_url_here"
new_data = pd.read_csv(url)

# Calculate mean, median, mode, and standard deviation for a numerical feature
mean_value = new_data['your_feature'].mean()
median_value = new_data['your_feature'].median()
mode_value = stats.mode(new_data['your_feature'])[0][0]
std_value = new_data['your_feature'].std()

print(f"Mean: {mean_value}, Median: {median_value}, Mode: {mode_value}, Standard
Deviation: {std_value}")

# Plot histogram
sns.histplot(new_data['your_feature'], kde=True)
plt.title("Distribution of Your Feature")
plt.show()
```

In this lab, you have practiced calculating and interpreting descriptive statistics such as the mean, median, mode, and standard deviation. You also learned how to visualize data distributions using histograms, which help reveal patterns, skewness, and spread within a dataset. These skills are fundamental for understanding any dataset and preparing it for more advanced analysis.

Additional Task: Explore other datasets and repeat the steps above for more practice. Try applying the knowledge to real-world datasets such as housing prices, stock market data, or weather patterns.

Week 4 DAY 2 Inferential Statistics

In this lab, you will explore **inferential statistics** using Python, focusing on the following key concepts:

- **Hypothesis Testing**
- **P-values**
- **Confidence Intervals**

By the end, students will be able to:

- Formulate and test hypotheses using Python.
- Calculate and interpret **p-values**.
- Construct **confidence intervals** for data analysis.
- Use popular Python libraries such as `scipy`, `statsmodels`, `pandas`, and `numpy`.

Inferential statistics allows us to make conclusions about a population based on a sample of data. It helps in decision-making and predictions in various fields such as healthcare, business, and social sciences.

Importance in Data Science: In data science, inferential statistics is crucial for validating hypotheses, making predictions, and understanding underlying data distributions. Mastering these concepts equips data scientists with the tools to draw meaningful insights from data.

Hypothesis Testing

Hypothesis testing is a statistical method that uses sample data to evaluate a hypothesis about a population parameter. Following are the steps:

1. Formulate Hypotheses
    - Null Hypothesis (H0): A statement of no effect or no difference.
    - Alternative Hypothesis (H1): A statement that contradicts the null hypothesis.
2. Choose a Significance Level (α)
    - Common choices: 0.05, 0.01.
3. Collect Data
    - Obtain a random sample from the population.
4. Calculate Test Statistic
    - Use appropriate statistical tests (e.g., t-test, z-test).
5. Determine p-value
    - Calculate the probability of observing the data given that the null hypothesis is true.
6. Make a Decision
    - Compare p-value to α.
    - Reject H0 if p-value ≤ α; otherwise, do not reject H0.

Types of Errors

- Type I Error (α): Rejecting H0 when it is true.
- Type II Error (β): Failing to reject H0 when it is false.

Understanding p-values

The p-value measures the strength of evidence against the null hypothesis. A smaller p-value indicates stronger evidence.

- **p-value ≤ α:** Reject the null hypothesis.
- **p-value > α:** Fail to reject the null hypothesis.

Common Misconceptions

- A low p-value does not prove that H0 is false; it merely suggests that the observed data would be unlikely under H0.
- The p-value does not indicate the size or importance of an effect.

Confidence Intervals

A confidence interval (CI) is a range of values used to estimate the true population parameter with a certain level of confidence (e.g., 95%).

Construction of Confidence Intervals

1. Point Estimate: Calculate the sample mean (or proportion).
2. Margin of Error: Determine the standard error and multiply by the critical value from the z or t distribution.
3. CI Formula: CI=Point Estimate ± Margin of Error

A 95% CI means that if we were to take many samples, 95% of the calculated intervals would contain the true population parameter.

Exercise 1: Hypothesis Testing

Learn how to perform hypothesis testing in Python using a dataset.

Task 1: Formulating a Hypothesis

For this task, we will use the **Iris** dataset again. We'll test whether the average **sepal length** of two species (**setosa** and **versicolor**) are significantly different.

1. **Null Hypothesis (H_0)**: The mean sepal length of **setosa** and **versicolor** are the same.
2. **Alternative Hypothesis (H_1)**: The mean sepal length of **setosa** and **versicolor** are different.

```
# Import libraries
import pandas as pd
from scipy import stats

# Load the Iris dataset
url = "https://raw.githubusercontent.com/mwaskom/seaborn-data/master/iris.csv"
data = pd.read_csv(url)

# Separate data for 'setosa' and 'versicolor'
setosa = data[data['species'] == 'setosa']['sepal_length']
versicolor = data[data['species'] == 'versicolor']['sepal_length']

# Perform independent t-test
t_stat, p_value = stats.ttest_ind(setosa, versicolor)
```

```
# Display the results
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")

# Interpret the result
alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis (H₀). The means are significantly
different.")
else:
    print("Fail to reject the null hypothesis (H₀). The means are not
significantly different.")
```

Exercise 2: Calculating P-values

Understand how to calculate and interpret p-values using Python.

Task 1: Calculate P-values for Hypothesis Testing

1. In the previous step, you already calculated the **p-value** for comparing the sepal lengths of **setosa** and **versicolor**.
2. The p-value indicates the probability that the observed data would occur if the null hypothesis were true.

Lab Code Explanation:

- The **p-value** will be small if the null hypothesis is unlikely, and large if the null hypothesis is plausible.
- Typically, a significance level (**α**) of 0.05 is used as a threshold for rejecting the null hypothesis.

Exercise 3: Constructing Confidence Intervals

Objective:

Learn how to calculate confidence intervals for a population mean.

Task 1: Compute a 95% Confidence Interval for the Sepal Length of Setosa

1. A **confidence interval** gives an estimated range of values which is likely to include the population parameter (e.g., the mean).
2. The **95% confidence interval** means that we are 95% confident that the true mean lies within this range.

```
# Mean and standard error of the mean for 'setosa'
mean_setosa = setosa.mean()
sem_setosa = stats.sem(setosa)

# Confidence interval (95% confidence level)
confidence_level = 0.95
```

```
ci = stats.t.interval(confidence_level, len(setosa)-1, loc=mean_setosa,
scale=sem_setosa)

# Display the confidence interval
print(f"95% Confidence Interval for Setosa Sepal Length: {ci}")
```

Exercise 4: Mini-Project - Applying Inferential Statistics on Real Data

Objective:

Use a real dataset to apply inferential statistics techniques such as hypothesis testing, p-value calculation, and confidence intervals.

Task 1: Choose a Dataset

You can either continue using the **Iris** dataset or choose a dataset from the UCI Machine Learning Repository or Kaggle.

Task 2: Formulate and Test a Hypothesis

1. Select two features or groups to compare. For example, compare the **mean petal width** of two different species.
2. Formulate a null and alternative hypothesis.

Task 3: Calculate P-values and Confidence Intervals

1. Perform a hypothesis test (e.g., t-test, ANOVA) to compare the groups.
2. Calculate the **p-value** to determine if the null hypothesis can be rejected.
3. Calculate the **confidence interval** for the mean of the selected feature.

Example Code:

```
python
Copy code
# Example: Comparing the petal widths of 'versicolor' and 'virginica'

# Separate data for 'versicolor' and 'virginica'
versicolor_petal_width = data[data['species'] == 'versicolor']['petal_width']
virginica_petal_width = data[data['species'] == 'virginica']['petal_width']

# Perform t-test
t_stat, p_value = stats.ttest_ind(versicolor_petal_width, virginica_petal_width)

# Calculate the 95% confidence interval for versicolor
mean_versicolor = versicolor_petal_width.mean()
sem_versicolor = stats.sem(versicolor_petal_width)
ci_versicolor = stats.t.interval(0.95, len(versicolor_petal_width)-1,
loc=mean_versicolor, scale=sem_versicolor)

# Display results
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")
print(f"95% Confidence Interval for Versicolor Petal Width: {ci_versicolor}")
```

Conclusion:

In this lab, you have:

- Performed hypothesis testing using Python.
- Calculated **p-values** to assess the significance of test results.
- Constructed **confidence intervals** to estimate population parameters.

These inferential statistics techniques are essential for making data-driven decisions and drawing meaningful conclusions from datasets. Continue practicing with different datasets and statistical tests to strengthen your skills!

Week 4 DAY -3: Overview of Correlation and Regression

Correlation and **regression** are statistical methods used to explore the relationship between variables. While correlation quantifies the degree to which two variables are related, regression enables us to model and predict outcomes based on these relationships.

Importance in Data Science Understanding correlation and regression is critical in data science as it provides insights into the relationships among variables, guiding decision-making and forecasting. These techniques are widely used in fields such as finance, marketing, healthcare, and social sciences.

- To understand the concepts of correlation and regression.
- To learn how to calculate and interpret the Pearson correlation coefficient.
- To build and evaluate simple and multiple linear regression models.
- To implement these concepts using Python.

Correlation Analysis

Correlation measures the strength and direction of a linear relationship between two continuous variables. It can be classified into:

- Positive Correlation: Both variables move in the same direction.
- Negative Correlation: One variable increases while the other decreases.
- No Correlation: No discernible relationship exists between the variables.

Pearson Correlation Coefficient

The **Pearson correlation coefficient (r)** is the most common measure of correlation, defined mathematically as:

Formula and Calculation

$$r = (n(\Sigma xy) - (\Sigma x)(\Sigma y))/sqrt[(n\Sigma x^2 - (\Sigma x)^2)(n\Sigma y^2 - (\Sigma y)^2)]$$

Where:

- n is the number of pairs of scores
- x and y are the individual sample points

Interpretation of Results

- **r = 1:** Perfect positive correlation
- **r = -1:** Perfect negative correlation
- **r = 0:** No correlation
- **0.0 to 0.3:** Weak correlation
- **0.3 to 0.7:** Moderate correlation

- **0.7 to 1.0:** Strong correlation

Practical Examples

Example 1: Analyzing Student Performance

Consider a dataset of students' study hours and exam scores. Calculate the Pearson correlation to determine the relationship.

```
python
Copy code
# Example dataset
data = {
    'Study_Hours': [1, 2, 3, 4, 5],
    'Exam_Score': [50, 55, 65, 70, 80]
}
```

Example 2: Marketing Spend vs. Sales Revenue

Investigate the correlation between marketing spend and sales revenue to optimize marketing strategies.

Exercises

1. Use a dataset (e.g., a CSV file) to calculate the Pearson correlation coefficient between two variables of your choice.
2. Create a scatter plot to visualize the correlation.

Regression Analysis

Introduction to Linear Regression

Linear regression is a statistical method for modeling the relationship between a dependent variable and one or more independent variables.

Types of Regression

- **Simple Linear Regression:** One dependent and one independent variable.
- **Multiple Linear Regression:** One dependent variable and multiple independent variables.

Simple Linear Regression Model

The simple linear regression equation is represented as:

$$Y = \beta_0 + \beta_1 X + \epsilon$$

Where:

- Y is the dependent variable
- Xis the independent variable
- β0 is the intercept
- β1 is the slope
- ϵ is the error term

Assumptions of Linear Regression

1. **Linearity:** The relationship between X and Y is linear.
2. **Independence:** Observations are independent.
3. **Homoscedasticity:** Constant variance of errors.
4. **Normality:** Errors are normally distributed.

Multiple Linear Regression

In multiple linear regression, the model is extended to include multiple independent variables:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \cdots + \beta nXn + \epsilon$$

Model Evaluation Metrics

- R-squared (R^2): Represents the proportion of variance in the dependent variable that can be explained by the independent variables.
- Adjusted R-squared: Adjusts R^2 for the number of predictors in the model.
- Mean Absolute Error (MAE): Average of the absolute differences between predicted and actual values.
- Root Mean Squared Error (RMSE): Square root of the average of squared differences.

Case Study: Predicting House Prices

1. Dataset Description: A dataset containing features such as square footage, number of bedrooms, and house price.
2. Objective: Build a regression model to predict house prices based on the features.

Exercises

1. Develop a simple linear regression model using a dataset of your choice and evaluate its performance using R^2 and RMSE.
2. Extend the regression analysis to multiple linear regression by incorporating additional features.

Python Implementation

Libraries Required

```
python
```

```
Copy code
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
```

Data Preparation

1. Load the Dataset: Load a dataset into a Pandas DataFrame.

   ```
   python
   Copy code
   data = pd.read_csv('data.csv')  # Replace with your dataset path
   ```

2. Data Cleaning: Check for missing values and outliers, and handle them appropriately.

   ```
   python
   Copy code
   print(data.isnull().sum())
   data.dropna(inplace=True)  # Example of handling missing values
   ```

Examples

Correlation Analysis

```
# Calculate Pearson correlation matrix
correlation_matrix = data.corr()
print(correlation_matrix)

# Visualize correlation matrix
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

Simple Linear Regression

```
# Prepare data for simple linear regression
X = data[['Study_Hours']]  # Independent variable
y = data['Exam_Score']      # Dependent variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Create and fit the model
simple_model = LinearRegression()
simple_model.fit(X_train, y_train)

# Predictions
y_pred = simple_model.predict(X_test)

# Model evaluation
```

```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')
print(f'Mean Absolute Error: {mae}')

# Plotting the regression line
plt.scatter(X_test, y_test, color='blue', label='Actual')
plt.plot(X_test, y_pred, color='red', label='Regression Line')
plt.title('Simple Linear Regression')
plt.xlabel('Study Hours')
plt.ylabel('Exam Score')
plt.legend()
plt.show()
```

Multiple Linear Regression

```
# Prepare data for multiple linear regression
X_multi = data[['Study_Hours', 'Previous_Score']]  # Add more features as
necessary
y_multi = data['Exam_Score']

# Split the data into training and testing sets
X_train_multi, X_test_multi, y_train_multi, y_test_multi =
train_test_split(X_multi, y_multi, test_size=0.2, random_state=42)

# Create and fit the model
multi_model = LinearRegression()
multi_model.fit(X_train_multi, y_train_multi)

# Predictions
y_multi_pred = multi_model.predict(X_test_multi)

# Model evaluation
mse_multi = mean_squared_error(y_test_multi, y_multi_pred)
r2_multi = r2_score(y_test_multi, y_multi_pred)
mae_multi = mean_absolute_error(y_test_multi, y_multi_pred)

print(f'Mean Squared Error (Multiple Regression): {mse_multi}')
print(f'R-squared (Multiple Regression): {r2_multi}')
print(f'Mean Absolute Error (Multiple Regression): {mae_multi}')
```

Visualizations

Use visualizations to enhance understanding:

- **Scatter plots** for correlation
- **Line plots** for regression predictions
- **Bar charts** for model comparison

Exercises

1. Perform a correlation analysis on a dataset of your choice and visualize the results.
2. Implement a simple linear regression model and interpret the coefficients.

3. Extend your analysis to a multiple linear regression model and evaluate its performance using different metrics.

Week 4 DAY -4 Hands-on Exercises: Statistical Analysis in Python

By the end of this session, students will be able to:

- Calculate and interpret descriptive statistics such as mean, median, mode, variance, and standard deviation.
- Conduct hypothesis tests and interpret the results using p-values and confidence intervals.
- Perform correlation and regression analysis to understand relationships between variables.
- Visualize statistical data to support decision-making.

Descriptive and Inferential Statistics

Descriptive Statistics: Descriptive statistics summarize and organize characteristics of a data set. They are used to describe basic features of the data such as central tendency (mean, median, mode), variability (standard deviation, variance), and shape (skewness, kurtosis).

Inferential Statistics: Inferential statistics help make inferences or predictions about a population based on a sample of data. This includes hypothesis testing, p-values, confidence intervals, and regression analysis.

Descriptive Statistics Exercises

Exercise 1: Summary Statistics

Task: Calculate summary statistics (mean, median, mode, variance, standard deviation) for a dataset.

```
# Sample Dataset
data = pd.DataFrame({
    'Age': [25, 30, 35, 40, 22, 27, 30, 28, 33, 40],
    'Income': [50000, 54000, 58000, 60000, 45000, 52000, 55000, 53000, 60000,
61000]
})

# Summary Statistics
summary_stats = data.describe()
print(summary_stats)
```

Exercise 2: Measures of Central Tendency

Task: Calculate the mean, median, and mode for a given dataset.

```
mean_income = data['Income'].mean()
median_income = data['Income'].median()
mode_income = data['Income'].mode()

print(f"Mean Income: {mean_income}")
print(f"Median Income: {median_income}")
print(f"Mode Income: {mode_income}")
```

Exercise 3: Measures of Dispersion

Task: Calculate the variance and standard deviation of a dataset.

```
variance_income = data['Income'].var()
std_dev_income = data['Income'].std()

print(f"Variance of Income: {variance_income}")
print(f"Standard Deviation of Income: {std_dev_income}")
```

Exercise 4: Data Visualization

Task: Visualize the distribution of data using histograms and boxplots.

```
# Histogram
plt.hist(data['Income'], bins=5, color='blue', edgecolor='black')
plt.title('Income Distribution')
plt.xlabel('Income')
plt.ylabel('Frequency')
plt.show()

# Boxplot
plt.boxplot(data['Income'])
plt.title('Boxplot of Income')
plt.ylabel('Income')
plt.show()
```

Inferential Statistics Exercises

Exercise 5: Hypothesis Testing

Scenario: A company claims that the average income of its employees is $55,000. Use hypothesis testing to verify this claim.

Task: Perform a one-sample t-test.

```
# One-sample t-test
t_stat, p_value = stats.ttest_1samp(data['Income'], 55000)

print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")

if p_value < 0.05:
    print("Reject the null hypothesis: The average income is not $55,000.")
else:
    print("Fail to reject the null hypothesis: The average income is $55,000.")
```

Exercise 6: Confidence Intervals

Task: Calculate the 95% confidence interval for the mean income.

```
confidence_interval = stats.t.interval(alpha=0.95, df=len(data['Income'])-1,
loc=np.mean(data['Income']), scale=stats.sem(data['Income']))

print(f"95% Confidence Interval for Income: {confidence_interval}")
```

Exercise 7: P-Values Interpretation

Task: Interpret the p-value from the t-test performed in Exercise 5.

```
# Interpretation of p-value
if p_value < 0.05:
    print("The p-value is less than 0.05, suggesting strong evidence against the
null hypothesis.")
else:
    print("The p-value is greater than 0.05, suggesting weak evidence against the
null hypothesis.")
```

Exercise 8: Correlation Analysis

Task: Calculate the Pearson correlation coefficient between Age and Income.

```
correlation, _ = stats.pearsonr(data['Age'], data['Income'])
print(f"Pearson Correlation between Age and Income: {correlation}")
```

Exercise 9: Linear Regression

Task: Perform simple linear regression to predict income based on age.

```
# Prepare data for regression
X = data['Age']
y = data['Income']

# Add constant term
X = sm.add_constant(X)

# Perform regression
model = sm.OLS(y, X).fit()
predictions = model.predict(X)

# Print the regression summary
print(model.summary())

# Plot the regression line
plt.scatter(data['Age'], data['Income'], label="Data Points")
plt.plot(data['Age'], predictions, color='red', label="Regression Line")
plt.title('Income vs. Age: Linear Regression')
plt.xlabel('Age')
plt.ylabel('Income')
plt.legend()
plt.show()
```

In this practical session, you have performed hands-on exercises related to both descriptive and inferential statistics using Python. You learned to calculate summary statistics, perform hypothesis testing, compute confidence intervals, and build regression models. These skills are fundamental for conducting statistical analysis in real-world data science projects.

Week 4 Day- 5 Mini-Project Task: Performing a Statistical Analysis on a Dataset

Project Title: Statistical Analysis of any Dataset : Exploring Trends, Patterns, and Insights

The aim of this mini-project is to apply fundamental statistical techniques to perform an in-depth analysis of a chosen dataset. Students will explore, visualize, and summarize the data, using statistical methods to uncover patterns, relationships, and trends, and present their findings in a clear and interpretable manner.

Project Description:

You are required to select any dataset of your choice (it could be a dataset from a public repository such as Kaggle, UCI Machine Learning Repository, or any other source). Using this dataset, you will perform a comprehensive statistical analysis that should include the following:

Task Breakdown:

Part 1: Dataset Selection & Preprocessing

1. **Dataset Selection**: Choose a dataset with at least 500 rows and 5 features (columns).
2. **Data Cleaning**:

   Check for missing data and handle appropriately (e.g., imputation, removal).
   Identify outliers and anomalies using basic statistical methods (e.g., Z-scores, IQR).
   Convert categorical variables into numerical formats (if applicable).
   Normalize or standardize numerical variables as necessary.

Deliverables:

- A description of the dataset, including the data source, context, and features.
- Preprocessing steps including handling of missing values and outliers.

Part 2: Descriptive Statistical Analysis

1. **Summary Statistics**:

   - ✓ Calculate and interpret basic descriptive statistics for all numerical variables (mean, median, mode, variance, standard deviation, range).
   - ✓ Identify the distribution of variables (normality, skewness, kurtosis).

2. **Correlation Analysis**:

   - ✓ Compute correlation coefficients (Pearson, Spearman, or Kendall depending on the data type) between pairs of features.
   - ✓ Interpret the strength and direction of relationships.
   - ✓ Visualize these correlations using a heatmap or pair plot.

Deliverables:

- Summary table of descriptive statistics.
- Correlation analysis and visual representation (e.g., heatmap).

Part 3: Hypothesis Testing

1. **Formulate Hypotheses**:

    - ✓ Define two hypotheses based on the dataset features (e.g., relationship between two variables or a comparison of two groups).
    - ✓ Perform appropriate statistical tests such as:

        - **T-tests** (for comparing means between two groups).
        - **Chi-square tests** (for categorical data).
        - **ANOVA** (for comparing means between more than two groups).
        - **Mann-Whitney U test** (if data is non-parametric).
2. **Interpretation**:

    - ✓ Clearly define the null and alternative hypotheses.
    - ✓ Report p-values and interpret whether to reject or fail to reject the null hypothesis.

Deliverables:

- Stated hypotheses with explanation.
- Detailed report on hypothesis testing (test applied, results, and conclusion).

Part 4: Data Visualization

1. **Exploratory Data Analysis (EDA)**:

    - ✓ Use visual tools to explore the data and communicate insights. This should include:

        - Histograms, box plots, and density plots for continuous variables.
        - Bar charts, pie charts, and stacked bar plots for categorical data.
        - Scatter plots and line charts to show relationships between variables.
2. **Advanced Visualization**:

    - ✓ Create an interactive dashboard or plot using libraries like `Plotly`, `Seaborn`, or `Matplotlib`.

Deliverables:

- At least five different visualizations with clear explanations.
- Interactive plot or dashboard (optional but encouraged).

Part 5: Conclusions & Recommendations

1. **Insights**:

- ✓ Summarize the key findings of your statistical analysis.
- ✓ Highlight any patterns, trends, or anomalies found.
- ✓ Discuss limitations of the analysis.

2. **Recommendations**:
    - Based on the analysis, suggest actionable insights or potential areas for further investigation.

Deliverables:

- A written conclusion summarizing key insights.
- A set of actionable recommendations or future research directions.

Tools & Technologies:

- **Programming Language**: Python
- **Libraries**:
    - `Pandas` for data manipulation.
    - `NumPy` for numerical operations.
    - `Matplotlib`/`Seaborn` for visualizations.
    - `SciPy`/`statsmodels` for statistical tests.
    - `Plotly` for interactive visualizations (optional).

Report Submission:

- Submit a Jupyter Notebook that includes:
- All code for data preprocessing, analysis, visualization, and interpretation.
- Comments explaining the logic and methodology used.
- A final report (maximum 10 pages) in PDF format detailing each of the steps and findings.

WEEK 5 : Introduction to Machine Learning
Day 1 : Basics of Machine Learning

Machine learning is a subset of artificial intelligence (AI) that involves the development of algorithms and statistical models enabling computers to perform specific tasks effectively without explicit programming. This is achieved by allowing systems to learn from and make decisions or predictions based on data. Machine learning is revolutionizing various fields by automating tasks and uncovering insights from complex data patterns that are beyond human capability to detect.

Why use Machine Learning?
Machine learning (ML) is essential across industries for several compelling reasons:

1. **Automation and Efficiency:**
   - ML automates tasks, freeing up human resources and improving operational efficiency.
2. **Enhanced Data Insights:**
   - Recognizes patterns and correlations in large datasets, enabling predictive analytics and informed decision-making.
3. **Improved Accuracy:**
   - ML algorithms deliver precise predictions and classifications, continuously learning and improving over time.
4. **Personalization:**
   - Creates tailored user experiences and targeted marketing strategies based on individual preferences and behaviors.
5. **Cost Reduction:**
   - Reduces operational costs through automation and fraud detection, saving resources and mitigating losses.
6. **Innovation and Competitive Advantage:**
   - Drives innovation by enabling new products and services, providing a competitive edge through data-driven strategies.
7. **Real-World Applications:**
   - Applies across healthcare, finance, retail, manufacturing, transportation, enhancing processes from diagnosis to supply chain management.
8. **Handling Complex Data:**
   - Processes high-dimensional data efficiently, extracting insights crucial for strategic decision-making.
9. **Real-Time Decision Making:**
   - Supports real-time analytics and adaptive systems, ensuring decisions are based on current, actionable data.
10. **Interdisciplinary Impact:**
    - Versatile applications span multiple disciplines, fostering collaboration and solving diverse, complex challenges.

Real-Life Examples of Machine Learning

Machine learning (ML) applications are ubiquitous in various industries, transforming how businesses operate and enhancing everyday experiences. Here are some compelling real-life examples:

1. **Healthcare:**
   - **Medical Diagnosis:** ML algorithms analyze patient data (such as symptoms and medical history) to assist doctors in diagnosing diseases accurately and early detection of illnesses.
   - **Personalized Treatment:** ML models predict optimal treatment plans based on genetic data, medical records, and patient demographics, improving patient outcomes.
2. **Finance:**
   - **Credit Scoring:** Banks use ML to assess creditworthiness by analyzing past behavior and financial data, predicting the likelihood of loan repayment.
   - **Fraud Detection:** ML algorithms detect unusual patterns in transactions, identifying and preventing fraudulent activities in real time.
3. **Retail:**
   - **Recommendation Systems:** E-commerce platforms employ ML to suggest products based on customer browsing history, purchase patterns, and preferences, enhancing user experience and increasing sales.
   - **Inventory Management:** ML predicts demand trends and optimizes inventory levels, reducing stockouts and overstock situations.
4. **Manufacturing:**
   - **Predictive Maintenance:** ML models analyze sensor data from machinery to predict equipment failure before it occurs, enabling proactive maintenance and minimizing downtime.
   - **Quality Control:** ML algorithms inspect products on production lines, identifying defects with greater accuracy and consistency than human inspection.
5. **Transportation:**
   - **Autonomous Vehicles:** ML powers self-driving cars by interpreting real-time data from sensors (like cameras and radar) to navigate roads, detect obstacles, and make driving decisions.
   - **Route Optimization:** Logistics companies use ML to optimize delivery routes based on traffic conditions, weather forecasts, and historical data, reducing delivery times and costs.
6. **Marketing:**
   - **Customer Segmentation:** ML clusters customers into segments based on behavior and demographics, enabling targeted marketing campaigns and personalized promotions.
   - **Sentiment Analysis:** ML algorithms analyze social media and customer feedback to gauge public sentiment about products and brands, informing marketing strategies.
7. **Natural Language Processing (NLP):**
   - **Chatbots and Virtual Assistants:** NLP models power conversational interfaces that understand and respond to natural language queries, enhancing customer support and service interactions.
   - **Language Translation:** ML-driven translation tools translate text and speech between languages, facilitating global communication and collaboration.
8. **Entertainment:**
   - **Content Recommendation:** Streaming platforms use ML to recommend movies, TV shows, and music based on user preferences, viewing history, and ratings, improving content discovery.

9. **Energy:**
    - **Smart Grids:** ML optimizes energy distribution and consumption by predicting demand patterns, managing renewable energy sources, and improving grid stability and efficiency.
10. **Education:**
    - **Adaptive Learning:** ML algorithms personalize educational content and pathways based on student performance and learning styles, enhancing learning outcomes and engagement.

Roadmap to Learn Machine Learning

Phase 1: Fundamentals

In Phase 1, mastering the fundamentals of mathematics, statistics, and programming lays the groundwork for a solid understanding of machine learning. From linear algebra and calculus to probability and Python programming, these foundational skills provide the essential toolkit for manipulating data, understanding algorithms, and optimizing models. By delving into these areas, aspiring data scientists and machine learning enthusiasts build the necessary expertise to tackle complex problems and drive innovation in the field.

1. **Mathematics and Statistics:**
    - **Linear Algebra:**
        Learn vectors, matrices, and operations (addition, multiplication, inversion).
        Study Eigenvalues and Eigenvectors.
    - **Calculus:**
        Understand differentiation and integration.
        Study partial derivatives and gradient descent.
    - **Probability and Statistics:**
        Learn probability distributions (normal, binomial, Poisson).
        Study Bayes' theorem, expectation, variance, and hypothesis testing.
2. **Programming Skills:**
    - **Python Programming:**
        Basics: syntax, data structures (lists, dictionaries, sets), control flow (loops, conditionals).
        Intermediate: functions, modules, object-oriented programming.
    - **Python Libraries for Data Science:**
        NumPy for numerical computations.
        Pandas for data manipulation and analysis.
        Matplotlib and Seaborn for data visualization.
        Scikit-Learn for machine learning algorithms.

Phase 2: Data Handling and Visualization

Phase 2 focuses on mastering essential techniques for data acquisition, preparation, and exploration, crucial for effective machine learning. From collecting diverse data formats such as CSV, JSON, and XML, to utilizing SQL for database access and leveraging web scraping and APIs for data extraction, this phase equips learners with the tools to gather comprehensive datasets. Furthermore, it emphasizes the critical steps of cleaning and preprocessing data, including handling missing values, encoding categorical variables, and standardizing data for consistency. Exploratory Data Analysis (EDA) techniques, such as visualization through histograms, scatter plots, and box plots, alongside summary statistics, uncover valuable insights and patterns within the data, laying the foundation for informed decision-making and robust machine learning models.

1. **Data Collection:**
    - Understand data formats (CSV, JSON, XML).

- Learn to access data from databases using SQL.
- Basics of web scraping and APIs.

2. **Data Cleaning and Preprocessing:**
   - Handle missing values, encode categorical variables, and normalize data.
   - Perform data transformation (standardization, scaling).
3. **Exploratory Data Analysis (EDA):**
   - Use visualization techniques (histograms, scatter plots, box plots) to identify patterns and outliers.
   - Perform summary statistics to understand data distributions.

Phase 3: Core Machine Learning Concepts

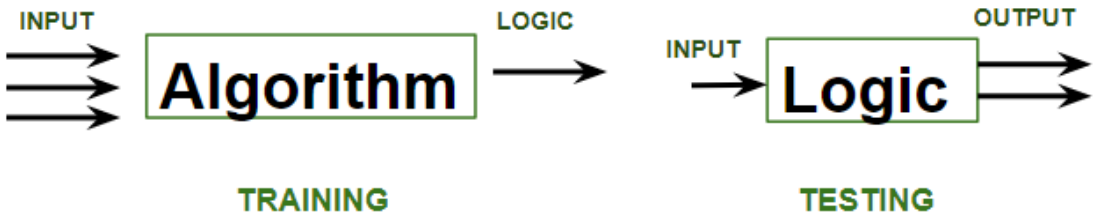
In Phase 3, delving into core machine learning concepts opens doors to understanding and implementing various learning paradigms and algorithms. Supervised learning focuses on predicting outcomes with labeled data, while unsupervised learning uncovers hidden patterns in unlabeled data. Reinforcement learning, inspired by behavioral psychology, teaches algorithms through trial-and-error interactions. Common algorithms like linear regression and decision trees empower predictive modeling, while evaluation metrics like accuracy and F1-score gauge model performance. Together with cross-validation techniques, these components form the bedrock for developing robust machine learning solutions.

Understanding Different Types of ML:

- Supervised Learning: Regression and classification tasks.
- Unsupervised Learning: Clustering and dimensionality reduction.
- Reinforcement Learning: Learning through rewards and penalties.

Supervised Machine Learning

Supervised learning is a machine learning technique that is widely used in various fields such as finance, healthcare, marketing, and more. It is a form of machine learning in which the algorithm is trained on labeled data to make predictions or decisions based on the data inputs.In supervised learning, the algorithm learns a mapping between the input and output data. This mapping is learned from a labeled dataset, which consists of pairs of input and output data. The algorithm tries to learn the relationship between the input and output data so that it can make accurate predictions on new, unseen data.



Supervised learning is where the model is trained on a labelled dataset. A **labelled** dataset is one that has both input and output parameters. In this type of learning both training and validation, datasets are labelled as shown in the figures below.

The labeled dataset used in supervised learning consists of input features and corresponding output labels. The input features are the attributes or characteristics of the data that are used to make

predictions, while the output labels are the desired outcomes or targets that the algorithm tries to predict.

User ID	Gender	Age	Salary	Purchased
15624510	Male	19	19000	0
15810944	Male	35	20000	1
15668575	Female	26	43000	0
15603246	Female	27	57000	0
15804002	Male	19	76000	1
15728773	Male	27	58000	1
15598044	Female	27	84000	0
15694829	Female	32	150000	1
15600575	Male	25	33000	1
15727311	Female	35	65000	0
15570769	Female	26	80000	1
15606274	Female	26	52000	0
15746139	Male	20	86000	1
15704987	Male	32	18000	0
15628972	Male	18	82000	0
15697686	Male	29	80000	0
15733883	Male	47	25000	1

Figure A: CLASSIFICATION

Temperature	Pressure	Relative Humidity	Wind Direction	Wind Speed
10.69261758	986.882019	54.19337313	195.7150879	3.278597116
13.59184184	987.8729248	48.0648859	189.2951202	2.909167767
17.70494885	988.1119385	39.11965597	192.9273834	2.973036289
20.95430404	987.8500366	30.66273218	202.0752869	2.965289593
22.9278274	987.2833862	26.06723423	210.6589203	2.798230886
24.04233986	986.2907104	23.46918024	221.1188507	2.627005816
24.41475295	985.2338867	22.25082295	233.7911987	2.448749781
23.93361956	984.8914795	22.35178837	244.3504333	2.454271793
22.68800023	984.8461304	23.7538641	253.0864716	2.418341875
20.56425726	984.8380737	27.07867944	264.5071106	2.318677425
17.76400389	985.4262085	33.54900114	280.7827454	2.343950987
11.25680746	988.9386597	53.74139903	68.15406036	1.650191426
14.37810685	989.6819458	40.70884681	72.62069702	1.553469896
18.45114201	990.2960205	30.85038484	71.70604706	1.005017161
22.54895853	989.9562988	22.81738811	44.66042709	0.264133632
24.23155922	988.796875	19.74790765	318.3214111	0.329656571

Figure B: REGRESSION

Both the above figures have labelled data set as follows:

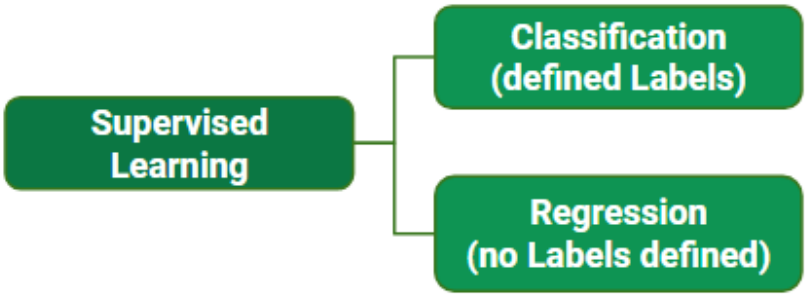
- **Figure A:** It is a dataset of a shopping store that is useful in predicting whether a customer will purchase a particular product under consideration or not based on his/ her gender, age, and salary.
  Input: Gender, Age, Salary
  Output: Purchased i.e. 0 or 1; 1 means yes the customer will purchase and 0 means that the customer won't purchase it.
- **Figure B:** It is a Meteorological dataset that serves the purpose of predicting wind speed based on different parameters.
- **Input:** Dew Point, Temperature, Pressure, Relative Humidity, Wind Direction
  Output: Wind Speed

Training the system: While training the model, data is usually split in the ratio of 80:20 i.e. 80% as training data and the rest as testing data. In training data, we feed input as well as output for 80% of data. The model learns from training data only. We use different machine learning algorithms(which we will discuss in detail in the next articles) to build our model. Learning means that the model will build some logic of its own.

Once the model is ready then it is good to be tested. At the time of testing, the input is fed from the remaining 20% of data that the model has never seen before, the model will predict some value and we will compare it with the actual output and calculate the accuracy.

Types of Supervised Learning Algorithm
Supervised learning is typically divided into two main categories: regression and classification. In regression, the algorithm learns to predict a continuous output value, such as the price of a house or

the temperature of a city. In classification, the algorithm learns to predict a categorical output variable or class label, such as whether a customer is likely to purchase a product or not.
One of the primary advantages of supervised learning is that it allows for the creation of complex models that can make accurate predictions on new data. However, supervised learning requires large amounts of labeled training data to be effective. Additionally, the quality and representativeness of the training data can have a significant impact on the accuracy of the model. Supervised learning can be further classified into two categories:



Regression
Regression is a supervised learning technique used to predict continuous numerical values based on input features. It aims to establish a functional relationship between independent variables and a dependent variable, such as predicting house prices based on features like size, bedrooms, and location.
The goal is to minimize the difference between predicted and actual values using algorithms like Linear Regression, Decision Trees, or Neural Networks, ensuring the model captures underlying patterns in the data.

Classification
Classification is a type of supervised learning that categorizes input data into predefined labels. It involves training a model on labeled examples to learn patterns between input features and output classes. In classification, the target variable is a categorical value. For example, classifying emails as spam or not.

The model's goal is to generalize this learning to make accurate predictions on new, unseen data. Algorithms like Decision Trees, Support Vector Machines, and Neural Networks are commonly used for classification tasks.
NOTE: There are common Supervised Machine Learning Algorithm that can be used for both regression and classification task.
Supervised Machine Learning Algorithm
Supervised learning can be further divided into several different types, each with its own unique characteristics and applications. Here are some of the most common types of supervised learning algorithms:

- **Linear Regression** : Linear regression is a type of regression algorithm that is used to predict a continuous output value. It is one of the simplest and most widely used algorithms in supervised learning. In linear regression, the algorithm tries to find a linear relationship between the input features and the output value. The output value is predicted based on the weighted sum of the input features.

- **Logistic Regression** : Logistic regression is a type of classification algorithm that is used to predict a binary output variable. It is commonly used in machine learning applications where the output variable is either true or false, such as in fraud detection or spam filtering. In logistic regression, the algorithm tries to find a linear relationship between the input features and the output variable. The output variable is then transformed using a logistic function to produce a probability value between 0 and 1.
- **Decision Trees** : Decision tree is a tree-like structure that is used to model decisions and their possible consequences. Each internal node in the tree represents a decision, while each leaf node represents a possible outcome. Decision trees can be used to model complex relationships between input features and output variables.
  A decision tree is a type of algorithm that is used for both classification and regression tasks.
    - Decision Trees Regression: Decision Trees can be utilized for regression tasks by predicting the value linked with a leaf node.
    - Decision Trees Classification: Random Forest is a machine learning algorithm that uses multiple decision trees to improve classification and prevent overfitting.
- **Random Forests** : Random forests are made up of multiple decision trees that work together to make predictions. Each tree in the forest is trained on a different subset of the input features and data. The final prediction is made by aggregating the predictions of all the trees in the forest. Random forests are an ensemble learning technique that is used for both classification and regression tasks.
    - Random Forest Regression : It combines multiple decision trees to reduce overfitting and improve prediction accuracy.
    - Random Forest Classifier: Combines several decision trees to improve the accuracy of classification while minimizing overfitting.
    -
- **Support Vector Machine(SVM)** : The SVM algorithm creates a hyperplane to segregate n-dimensional space into classes and identify the correct category of new data points. The extreme cases that help create the hyperplane are called support vectors, hence the name Support Vector Machine.
  A Support Vector Machine is a type of algorithm that is used for both classification and regression tasks
    - Support Vector Regression: It is a extension of Support Vector Machines (SVM) used for predicting continuous values.
    - Support Vector Classifier: It aims to find the best hyperplane that maximizes the margin between data points of different classes.
- **K-Nearest Neighbors (KNN)** : KNN works by finding k training examples closest to a given input and then predicts the class or value based on the majority class or average value of these neighbors. The performance of KNN can be influenced by the choice of k and the distance metric used to measure proximity. However, it is intuitive but can be sensitive to noisy data and requires careful selection of k for optimal results.

- A K-Nearest Neighbors (KNN) is a type of algorithm that is used for both classification and regression tasks.

    - K-Nearest Neighbors Regressio n: It predicts continuous values by averaging the outputs of the k closest neighbors.
    - K-Nearest Neighbors Classification: Data points are classified based on the majority class of their k closest neighbors.

- **Gradient Boosting** : Gradient Boosting combines weak learners, like decision trees, to create a strong model. It iteratively builds new models that correct errors made by previous ones. Each new model is trained to minimize residual errors, resulting in a powerful predictor capable of handling complex data relationships.
  A Gradient Boosting is a type of algorithm that is used for both classification and regression tasks.
    - Gradient Boosting Regression: It builds an ensemble of weak learners to improve prediction accuracy through iterative training.
    - Gradient Boosting Classification: Creates a group of classifiers to continually enhance the accuracy of predictions through iterations

Dimensions of Supervised Machine Learning Algorithm

When discussing the dimensions of supervised machine learning algorithms, we refer to various aspects that characterize and influence the performance, complexity, and applicability of these algorithms. These dimensions provide a framework for understanding how an algorithm operates, its strengths and weaknesses, and how it can be optimized for specific tasks. Here's an explanation of key dimensions:

1. Complexity

- **Model Complexity:** This refers to the intricacy of the algorithm's structure. Simple models like linear regression are easy to understand and interpret, but they may not capture complex relationships in data. On the other hand, more complex models like deep neural networks can capture intricate patterns but are harder to interpret and require more computational resources.
- **Overfitting and Underfitting:** Complexity is closely tied to overfitting (where the model learns the noise in the training data) and underfitting (where the model is too simple to capture the underlying pattern). Balancing complexity is crucial for creating a model that generalizes well to unseen data.

2. Interpretability

- **Transparency:** Some algorithms, like decision trees, are highly interpretable, meaning their decision-making process can be easily understood by humans. Other algorithms, like neural networks, operate as "black boxes," where the reasoning behind a prediction is not easily discernible.
- **Feature Importance:** In interpretability, understanding which features (input variables) are most influential in making predictions is important. This can be straightforward in algorithms like linear regression, where coefficients directly indicate feature importance, but more challenging in complex models like ensemble methods or neural networks.

3. Scalability

- **Data Size:** Scalability refers to the algorithm's ability to handle large datasets. Some algorithms, like K-Nearest Neighbors (KNN) , may become computationally expensive as the dataset grows, while others, like linear models or decision trees, can scale more efficiently with large datasets.
- **Dimensionality:** Scalability also considers how well an algorithm performs as the number of features (dimensions) increases. High-dimensional data can lead to challenges like the "curse of dimensionality," where the data becomes sparse, and distance measures (used in algorithms like KNN) become less meaningful.

4. **Flexibility**

- **Adaptability to Different Data Types:** Flexibility indicates how well an algorithm can be adapted to different types of data (e.g., categorical, continuous, or mixed data types). Some algorithms are inherently more flexible, like decision trees , which can handle both categorical and continuous data.
- **Handling Missing Data:** Flexibility also involves how well an algorithm can handle incomplete data. Some algorithms can naturally handle missing values, while others may require data imputation or other preprocessing steps.

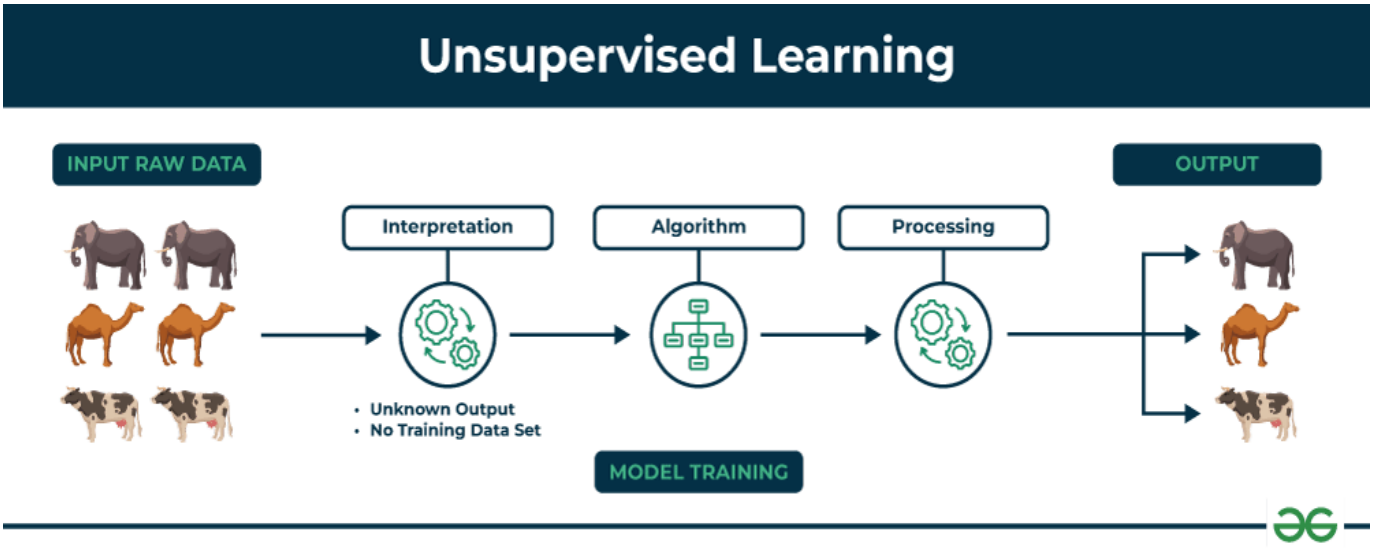
5. **Training Time and Computational Efficiency**

- **Algorithm Efficiency:** This dimension measures the time and computational resources required to train the model. Algorithms like linear regression or Naive Bayes are generally fast to train, while more complex models like support vector machines (SVM) or neural networks might require significant computational power and time, especially on large datasets.
- **Resource Requirements:** The efficiency of an algorithm also depends on the hardware and software environment. Some algorithms can be parallelized to speed up training, while others may be limited by memory or processing power.

Unsupervised Machine Learning

Unsupervised learning is a branch of machine learning that deals with unlabeled data. Unlike supervised learning, where the data is labeled with a specific category or outcome, unsupervised learning algorithms are tasked with finding patterns and relationships within the data without any prior knowledge of the data's meaning. This makes unsupervised learning a powerful tool for exploratory data analysis, where the goal is to understand the underlying structure of the data.

In artificial intelligence, machine learning that takes place in the absence of human supervision is known as unsupervised machine learning. Unsupervised machine learning models, in contrast to supervised learning, are given unlabeled data and allow discover patterns and insights on their own—without explicit direction or instruction.
Unsupervised machine learning analyzes and clusters unlabeled datasets using machine learning algorithms. These algorithms find hidden patterns and data without any human intervention, i.e., we don't give output to our model. The training model has only input parameter values and discovers the groups or patterns on its own.



How does unsupervised learning work?

Unsupervised learning works by analyzing unlabeled data to identify patterns and relationships. The data is not labeled with any predefined categories or outcomes, so the algorithm must find these patterns and relationships on its own. This can be a challenging task, but it can also be very rewarding, as it can reveal insights into the data that would not be apparent from a labeled dataset. Data-set in Figure A is Mall data that contains information about its clients that subscribe to them. Once subscribed they are provided a membership card and the mall has complete information about the customer and his/her every purchase. Now using this data and unsupervised learning techniques, the mall can easily group clients based on the parameters we are feeding in.

CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
1	Male	19	15	39
2	Male	21	15	81
3	Female	20	16	6
4	Female	23	16	77
5	Female	31	17	40
6	Female	22	17	76
7	Female	35	18	6
8	Female	23	18	94
9	Male	64	19	3
10	Female	30	19	72
11	Male	67	19	14
12	Female	35	19	99
13	Female	58	20	15
14	Female	24	20	77
15	Male	37	20	13
16	Male	22	20	79
17	Female	35	21	35

Figure A

The input to the unsupervised learning models is as follows:

- **Unstructured data**: May contain noisy(meaningless) data, missing values, or unknown data

- **Unlabeled data**: Data only contains a value for input parameters, there is no targeted value(output). It is easy to collect as compared to the labeled one in the Supervised approach.

Unsupervised Learning Algorithms

There are mainly 3 types of Algorithms which are used for Unsupervised dataset.

- Clustering
- Association Rule Learning
- Dimensionality Reduction

Clustering

Clustering in unsupervised machine learning is the process of grouping unlabeled data into clusters based on their similarities. The goal of clustering is to identify patterns and relationships in the data without any prior knowledge of the data's meaning.

Broadly this technique is applied to group data based on different patterns, such as similarities or differences, our machine model finds. These algorithms are used to process raw, unclassified data objects into groups. For example, in the above figure, we have not given output parameter values, so this technique will be used to group clients based on the input parameters provided by our data.

Some common clustering algorithms

- K-means Clustering: Partitioning Data into K Clusters
- Hierarchical Clustering: Building a Hierarchical Structure of Clusters
- Density-Based Clustering (DBSCAN): Identifying Clusters Based on Density
- Mean-Shift Clustering: Finding Clusters Based on Mode Seeking
- Spectral Clustering: Utilizing Spectral Graph Theory for Clustering

Association Rule Learning

Association rule learning is also known as association rule mining is a common technique used to discover associations in unsupervised machine learning. This technique is a rule-based ML technique that finds out some very useful relations between parameters of a large data set. This technique is basically used for market basket analysis that helps to better understand the relationship between different products. For e.g. shopping stores use algorithms based on this technique to find out the relationship between the sale of one product w.r.t to another's sales based on customer behavior. Like if a customer buys milk, then he may also buy bread, eggs, or butter. Once trained well, such models can be used to increase their sales by planning different offers.

- Apriori Algorithm: A Classic Method for Rule Induction
- FP-Growth Algorithm: An Efficient Alternative to Apriori
- Eclat Algorithm: Exploiting Closed Itemsets for Efficient Rule Mining
- Efficient Tree-based Algorithms: Handling Large Datasets with Scalability

Dimensionality Reduction

Dimensionality reduction is the process of reducing the number of features in a dataset while preserving as much information as possible. This technique is useful for improving the performance of machine learning algorithms and for data visualization. Examples of dimensionality reduction algorithms includeDimensionality reduction is the process of reducing the number of features in a dataset while preserving as much information as possible.

- Principal Component Analysis (PCA): Linear Transformation for Reduced Dimensions
- Linear Discriminant Analysis (LDA): Dimensionality Reduction for Discrimination
- Non-negative Matrix Factorization (NMF): Decomposing Data into Non-negative Components
- Locally Linear Embedding (LLE): Preserving Local Geometry in Reduced Dimensions
- Isomap: Capturing Global Relationships in Reduced Dimensions

Challenges of Unsupervised Learning

Here are the key challenges of unsupervised learning

- **Evaluation:** Assessing the performance of unsupervised learning algorithms is difficult without predefined labels or categories.
- **Interpretability:** Understanding the decision-making process of unsupervised learning models is often challenging.
- **Overfitting:** Unsupervised learning algorithms can overfit to the specific dataset used for training, limiting their ability to generalize to new data.
- **Data quality:** Unsupervised learning algorithms are sensitive to the quality of the input data. Noisy or incomplete data can lead to misleading or inaccurate results.
- **Computational complexity:** Some unsupervised learning algorithms, particularly those dealing with high-dimensional data or large datasets, can be computationally expensive.

Advantages of Unsupervised learning

- **No labeled data required:** Unlike supervised learning, unsupervised learning does not require labeled data, which can be expensive and time-consuming to collect.
- **Can uncover hidden patterns:** Unsupervised learning algorithms can identify patterns and relationships in data that may not be obvious to humans.
- **Can be used for a variety of tasks:** Unsupervised learning can be used for a variety of tasks, such as clustering, dimensionality reduction, and anomaly detection.
- **Can be used to explore new data:** Unsupervised learning can be used to explore new data and gain insights that may not be possible with other methods.

Disadvantages of Unsupervised learning

- **Difficult to evaluate:** It can be difficult to evaluate the performance of unsupervised learning algorithms, as there are no predefined labels or categories against which to compare results.
- **Can be difficult to interpret:** It can be difficult to understand the decision-making process of unsupervised learning models.
- **Can be sensitive to the quality of the data:** Unsupervised learning algorithms can be sensitive to the quality of the input data. Noisy or incomplete data can lead to misleading or inaccurate results.
- **Can be computationally expensive:** Some unsupervised learning algorithms, particularly those dealing with high-dimensional data or large datasets, can be computationally expensive

Applications of Unsupervised learning

- **Customer segmentation:** Unsupervised learning can be used to segment customers into groups based on their demographics, behavior, or preferences. This can help businesses to better understand their customers and target them with more relevant marketing campaigns.
- **Fraud detection:** Unsupervised learning can be used to detect fraud in financial data by identifying transactions that deviate from the expected patterns. This can help to prevent fraud by flagging these transactions for further investigation.
- **Recommendation systems:** Unsupervised learning can be used to recommend items to users based on their past behavior or preferences. For example, a recommendation system might use unsupervised learning to identify users who have similar taste in movies, and then recommend movies that those users have enjoyed.
- **Natural language processing (NLP):** Unsupervised learning is used in a variety of NLP tasks, including topic modeling, document clustering, and part-of-speech tagging.

- **Image analysis:** Unsupervised learning is used in a variety of image analysis tasks, including image segmentation, object detection, and image pattern recognition.

Week 5 Day 2: Data Preprocessing

In this lab, you will focus on **data preprocessing** techniques, which are essential for preparing raw data for machine learning models. The key tasks covered in this lab include:

- **Cleaning and preparing data** for modeling.
- **Feature scaling** and **encoding** categorical variables.

By the end of the lab, you will:

- Clean and handle missing data.
- Scale numerical features.
- Encode categorical variables using methods like one-hot encoding and label encoding.

Data is a crucial component in the field of Machine Learning. It refers to the set of observations or measurements that can be used to train a machine-learning model. The quality and quantity of data available for training and testing play a significant role in determining the performance of a machine-learning model. Data can be in various forms such as numerical, categorical, or time-series data, and can come from various sources such as databases, spreadsheets, or APIs. Machine learning algorithms use data to learn patterns and relationships between input variables and target outputs, which can then be used for prediction or classification tasks.
Data is typically divided into two types:

1. Labeled data
2. Unlabeled data

Labeled data includes a label or target variable that the model is trying to predict, whereas unlabeled data does not include a label or target variable. The data used in machine learning is typically numerical or categorical. Numerical data includes values that can be ordered and measured, such as age or income. Categorical data includes values that represent categories, such as gender or type of fruit.

Data can be divided into training and testing sets. The training set is used to train the model, and the testing set is used to evaluate the performance of the model. It is important to ensure that the data is split in a random and representative way.

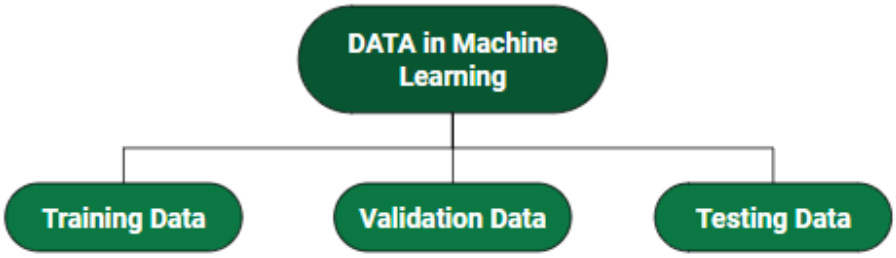
Data preprocessing is an important step in the machine learning pipeline. This step can include cleaning and normalizing the data, handling missing values, and feature selection or engineering.

DATA: It can be any unprocessed fact, value, text, sound, or picture that is not being interpreted and analyzed. Data is the most important part of all Data Analytics, Machine Learning, and Artificial Intelligence. Without data, we can't train any model and all modern research and automation will go in vain. Big Enterprises are spending lots of money just to gather as much certain data as possible.
Example: Why did Facebook acquire WhatsApp by paying a huge price of $19 billion?
The answer is very simple and logical – it is to have access to the users' information that Facebook may not have but WhatsApp will have. This information about their users is of paramount importance to Facebook as it will facilitate the task of improvement in their services.

INFORMATION: Data that has been interpreted and manipulated and has now some meaningful inference for the users.
KNOWLEDGE: Combination of inferred information, experiences, learning, and insights. Results in awareness or concept building for an individual or organization.

How do we split data in Machine Learning?

- **Training Data:** The part of data we use to train our model. This is the data that your model actually sees(both input and output) and learns from.
- **Validation Data:** The part of data that is used to do a frequent evaluation of the model, fit on the training dataset along with improving involved hyperparameters (initially set parameters before the model begins learning). This data plays its part when the model is actually training.
- **Testing Data:** Once our model is completely trained, testing data provides an unbiased evaluation. When we feed in the inputs of Testing data, our model will predict some values(without seeing actual output). After prediction, we evaluate our model by comparing it with the actual output present in the testing data. This is how we evaluate and see how much our model has learned from the experiences feed in as training data, set at the time of training.



Consider an example:

There's a Shopping Mart Owner who conducted a survey for which he has a long list of questions and answers that he had asked from the customers, this list of questions and answers is **DATA**. Now every time when he wants to infer anything and can't just go through each and every question of thousands of customers to find something relevant as it would be time-consuming and not helpful. In order to reduce this overhead and time wastage and to make work easier, data is manipulated through software, calculations, graphs, etc. as per your own convenience, this inference from manipulated data is **Information**. So, Data is a must for Information. Now **Knowledge** has its role in differentiating between two individuals having the same information. Knowledge is actually not technical content but is linked to the human thought process.

Different Forms of Data

- **Numeric Data** : If a feature represents a characteristic measured in numbers , it is called a numeric feature.
- **Categorical Data :** A categorical feature is an attribute that can take on one of the limited , and usually fixed number of possible values on the basis of some qualitative property . A categorical feature is also called a nominal feature.
- **Ordinal Data** : This denotes a nominal variable with categories falling in an ordered list . Examples include clothing sizes such as small, medium , and large , or a measurement of customer satisfaction on a scale from "not at all happy" to "very happy".

Properties of Data –

1. **Volume:** Scale of Data. With the growing world population and technology at exposure, huge data is being generated each and every millisecond.
2. **Variety:** Different forms of data – healthcare, images, videos, audio clippings.
3. **Velocity:** Rate of data streaming and generation.
4. **Value:** Meaningfulness of data in terms of information that researchers can infer from it.
5. **Veracity:** Certainty and correctness in data we are working on.
6. **Viability**: The ability of data to be used and integrated into different systems and processes.
7. **Security**: The measures taken to protect data from unauthorized access or manipulation.
8. **Accessibility**: The ease of obtaining and utilizing data for decision-making purposes.
9. **Integrity**: The accuracy and completeness of data over its entire lifecycle.
10. **Usability**: The ease of use and interpretability of data for end-users.

Some facts about Data:

- As compared to 2005, 300 times i.e. 40 Zettabytes (1ZB=10^21 bytes) of data will be generated by 2020.
- By 2011, the healthcare sector has a data of 161 Billion Gigabytes
- 400 Million tweets are sent by about 200 million active users per day
- Each month, more than 4 billion hours of video streaming is done by the users.
- 30 Billion different types of content are shared every month by the user.
- It is reported that about 27% of data is inaccurate and so 1 in 3 business idealists or leaders don't trust the information on which they are making decisions.

The above-mentioned facts are just a glimpse of the actually existing huge data statistics. When we talk in terms of real-world scenarios, the size of data currently presents and is getting generated each and every moment is beyond our mental horizons to imagine.

Example:

Imagine you're working for a car manufacturing company and you want to build a model that can predict the fuel efficiency of a car based on the weight and the engine size. In this case, the target variable (or label) is the fuel efficiency, and the features (or input variables) are the weight and engine size. You will collect data from different car models, with corresponding weight and engine size, and their fuel efficiency. This data is labeled and it's in the form of (weight,engine size,fuel efficiency) for each car. After having your data ready, you will then split it into two sets: training set and testing set, the training set will be used to train the model and the testing set will be used to evaluate the performance of the model. Preprocessing could be needed for example, to fill missing values or handle outliers that might affect your model accuracy.

Exercise 1: Data Cleaning

Learn how to clean a dataset by handling missing or erroneous data and renaming columns.

Task 1: Load and Clean a Dataset

For this lab, we'll use a sample dataset called the **Titanic dataset**, which contains information on passengers, including whether they survived or not.

```
# Import required libraries
import pandas as pd

# Load the Titanic dataset from a URL
url =
"https://raw.githubusercontent.com/datasciencedojo/datasets/master/titanic.csv"
data = pd.read_csv(url)

# View the first few rows of the dataset
print(data.head())

# Cleaning: Dropping irrelevant columns
data_cleaned = data.drop(['Name', 'Ticket', 'Cabin'], axis=1)

# Renaming columns for readability
data_cleaned.rename(columns={'Pclass': 'Passenger_Class', 'SibSp':
'Siblings_Spouse_Aboard', 'Parch': 'Parents_Children_Aboard'}, inplace=True)

# Display the cleaned dataset
print(data_cleaned.head())
```

Exercise 2: Handling Missing Data

Learn how to handle missing data, which is a crucial part of data preprocessing.

Task 1: Identify and Handle Missing Values

1. Use the `.isnull()` method to detect missing values.
2. Use techniques like **imputation** or **dropping** rows/columns with missing data.

```
Copy code
# Checking for missing values
missing_data = data_cleaned.isnull().sum()
print("Missing values in each column:\n", missing_data)

# Imputation: Fill missing values in 'Age' with the median
data_cleaned['Age'].fillna(data_cleaned['Age'].median(), inplace=True)

# Dropping rows where 'Embarked' has missing values
data_cleaned.dropna(subset=['Embarked'], inplace=True)

# Checking again for missing data
print("Missing values after cleaning:\n", data_cleaned.isnull().sum())
```

Exercise 3: Feature Scaling

Learn how to scale numerical features, a key step to ensure the model treats all features equally.

Task 1: Apply Feature Scaling

1. Use **Standardization** (scaling data to a mean of 0 and a standard deviation of 1) or **Min-Max Scaling** (scaling data to a range between 0 and 1).

```
# Import MinMaxScaler for feature scaling
from sklearn.preprocessing import MinMaxScaler

# Initialize the scaler
scaler = MinMaxScaler()

# Select numerical columns for scaling
numerical_cols = ['Age', 'Fare']

# Apply scaling to the numerical columns
data_cleaned[numerical_cols] = scaler.fit_transform(data_cleaned[numerical_cols])

# Display the scaled dataset
print("Scaled data:\n", data_cleaned[numerical_cols].head())
```

Exercise 4: Encoding Categorical Data

Convert categorical variables into numerical format for machine learning algorithms.

Task 1: One-Hot Encoding

One-hot encoding transforms categorical columns into binary columns.

```
# One-Hot Encoding for 'Embarked' and 'Sex'
data_encoded = pd.get_dummies(data_cleaned, columns=['Embarked', 'Sex'],
drop_first=True)

# Display the encoded dataset
print("Encoded data:\n", data_encoded.head())
```

In this lab, you learned:

- How to clean and prepare data by removing irrelevant features and handling missing data.
- Feature scaling techniques such as Min-Max Scaling.
- Encoding categorical data using one-hot encoding.

These preprocessing steps are essential to ensure that machine learning models can interpret and learn from the data effectively. Continue to practice with different datasets to gain more experience!

Week 5 Day 3: Building a Simple Model

Objective:

Get familiar with **scikit-learn**, its key features, and how it helps in building machine learning models.

What is scikit-learn?

scikit-learn is a free machine learning library that offers a wide variety of efficient tools for data mining and data analysis. It provides various algorithms for classification, regression, clustering, and dimensionality reduction. It is built on top of libraries such as **NumPy**, **SciPy**, and **matplotlib**.

---

2. Data Preprocessing

Data preprocessing is a critical step before building machine learning models. It involves:

- Handling missing data.
- Encoding categorical variables into numerical format.
- Scaling numerical features.

Step 1: Import Required Libraries

```
python
Copy code
# Import essential libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
```

Step 2: Load and Explore the Dataset

For this lab, we'll use the **Iris dataset**, a classic dataset for classification problems.

```
python
Copy code
# Load the Iris dataset from a URL
url = "https://raw.githubusercontent.com/mwaskom/seaborn-data/master/iris.csv"
data = pd.read_csv(url)

# Display the first few rows
print(data.head())
```

Handling Missing Data

In some cases, datasets may have missing values. It's important to either remove or impute them.

```
python
Copy code
# Check for missing values
print("Missing values:\n", data.isnull().sum())

# Since the Iris dataset doesn't have missing values, we'll skip this step.
# But you can handle missing data like this:
# data.fillna(data.mean(), inplace=True)  # Fill missing values with mean
```

Encoding Categorical Variables

The target variable **species** in the Iris dataset is categorical and needs to be converted to numerical format using **Label Encoding**.

```
python
Copy code
# Encode the categorical target variable
label_encoder = LabelEncoder()
data['species'] = label_encoder.fit_transform(data['species'])

# Display the first few rows after encoding
print(data.head())
```

Feature Scaling

Feature scaling ensures that all numerical values are on a similar scale, improving model performance.

```
python
Copy code
# Define features (X) and target (y)
X = data.drop(columns=['species'])  # Features
y = data['species']  # Target

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Initialize the scaler and scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Display the scaled features
print("Scaled training features:\n", X_train_scaled[:5])
```

---

3. Building a Simple Classification Model

In this step, we'll build a simple classification model using the **Logistic Regression** algorithm from **scikit-learn**.

Step 1: Import and Train the Model

```
python
Copy code
# Import the Logistic Regression model
from sklearn.linear_model import LogisticRegression

# Initialize the model
model = LogisticRegression()

# Train the model
model.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test_scaled)
```

Step 2: Display Predictions

```
python
Copy code
# Display the first few predictions alongside the actual values
print("Predicted species:\n", y_pred[:10])
print("Actual species:\n", y_test[:10].values)
```

---

4. Model Evaluation

After building the model, it is crucial to evaluate its performance using appropriate metrics.

Step 1: Calculate Accuracy

```
python
Copy code
# Import accuracy score
from sklearn.metrics import accuracy_score

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Model Accuracy: {accuracy * 100:.2f}%")
```

Step 2: Confusion Matrix

A **confusion matrix** provides insights into how well the model is performing in terms of true positives, false positives, true negatives, and false negatives.

```
python
Copy code
# Import confusion matrix
from sklearn.metrics import confusion_matrix

# Generate the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
```

```
print("Confusion Matrix:\n", conf_matrix)
```

Step 3: Classification Report

A **classification report** provides a detailed analysis, including **precision**, **recall**, **F1-score**, and **support** for each class.

```
python
Copy code
# Import classification report
from sklearn.metrics import classification_report

# Generate the classification report
class_report = classification_report(y_test, y_pred)
print("Classification Report:\n", class_report)
```

Week 5 Day 3: Practical Session: Hands-on Exercises

Exercise 1: Data Preprocessing with scikit-learn

In this exercise, you will:

1. Load a dataset of your choice.
2. Perform data cleaning by handling missing values.
3. Encode categorical features.
4. Scale the numerical features.

Exercise 2: Building and Evaluating Classification Models

In this exercise, you will:

1. Split the preprocessed data into training and testing sets.
2. Build a classification model using a different algorithm such as **K-Nearest Neighbors (KNN)** or **Random Forest**.
3. Evaluate the model's performance using accuracy, confusion matrix, and classification report.

Code Example for K-Nearest Neighbors (KNN):

```
python
Copy code
# Import KNN classifier
from sklearn.neighbors import KNeighborsClassifier

# Initialize KNN model
knn_model = KNeighborsClassifier(n_neighbors=5)

# Train the model
knn_model.fit(X_train_scaled, y_train)

# Make predictions
y_pred_knn = knn_model.predict(X_test_scaled)

# Evaluate the KNN model
accuracy_knn = accuracy_score(y_test, y_pred_knn)
print(f"KNN Model Accuracy: {accuracy_knn * 100:.2f}%")

# Confusion Matrix for KNN
conf_matrix_knn = confusion_matrix(y_test, y_pred_knn)
print("KNN Confusion Matrix:\n", conf_matrix_knn)

# Classification Report for KNN
class_report_knn = classification_report(y_test, y_pred_knn)
print("KNN Classification Report:\n", class_report_knn)
```

Mini-Project:

- Choose a new dataset, preprocess it, and apply a **classification algorithm** such as **Decision Trees**, **Random Forest**, or **SVM**.
- Evaluate the model's performance and compare it with the results of other algorithms.

Conclusion:

In this lab, you:

- Gained an introduction to **scikit-learn** and its machine learning capabilities.
- Performed **data preprocessing** by handling missing values, encoding categorical variables, and scaling features.
- Built and evaluated a simple classification model.
- Practiced using different classification algorithms and evaluation metrics.

Week 5 Day 5 : Practical Session : Mini-project: Building and evaluating a simple model

In this lab manual, we will explore basic machine learning concepts and differentiate between supervised and unsupervised learning by implementing hands-on exercises in Python.

By the end of this session, students will be able to:

- Understand the key differences between supervised and unsupervised learning.
- Implement a classification algorithm (supervised learning).
- Implement a clustering algorithm (unsupervised learning).
- Visualize the results of machine learning models.

3. Machine Learning Setup

Required Libraries:

Ensure the following Python libraries are installed:

```
pip install numpy pandas matplotlib seaborn scikit-learn
```

Import Libraries:

```
python
Copy code
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.cluster import KMeans
from sklearn.datasets import load_iris
from sklearn.tree import DecisionTreeClassifier
```

Review of Supervised and Unsupervised Learning

Supervised Learning:

Supervised learning is a type of machine learning where the algorithm learns from labeled data. The input data contains both the features and the correct output (target) labels. The goal is to map the input to the output by learning from the data, and then make predictions on new, unseen data.

Example algorithms:

- **Classification**: Decision Trees, Support Vector Machines, Neural Networks
- **Regression**: Linear Regression, Ridge Regression

Unsupervised Learning:

Unsupervised learning is a type of machine learning where the algorithm learns patterns from data that has no labels. The goal is to uncover hidden structures within the data by grouping similar data points together.

Example algorithms:

- **Clustering**: K-Means, Hierarchical Clustering
- **Dimensionality Reduction**: PCA (Principal Component Analysis)

Hands-on Exercise 1: Supervised Learning (Classification)

In this exercise, we will implement a simple classification algorithm (Decision Tree) using the **Iris dataset**.

Dataset: Iris Flower Dataset

This dataset consists of 150 samples from each of three species of Iris flowers (Iris setosa, Iris virginica, Iris versicolor). Four features are measured from each sample: the lengths and the widths of the sepals and petals.

Objective:

Build a decision tree classifier to predict the species of an Iris flower based on its features.

Steps:

1. **Load the Dataset**:

```
# Load Iris dataset
iris = load_iris()
data = pd.DataFrame(iris.data, columns=iris.feature_names)
data['species'] = iris.target
```

2. **Split the Data into Training and Testing Sets**:

```
# Split data into features (X) and target (y)
```

```
X = data.drop('species', axis=1)
y = data['species']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)
```

3. **Train the Decision Tree Classifier**:

```
python
Copy code
# Initialize the Decision Tree classifier
clf = DecisionTreeClassifier()

# Train the model
clf.fit(X_train, y_train)
```

4. **Make Predictions**:

```
# Predict on the test set
y_pred = clf.predict(X_test)
```

5. **Evaluate the Model**:

```
# Evaluate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print(f"Confusion Matrix:\n {conf_matrix}")
```

6. **Visualize the Results**:

```
# Visualize the confusion matrix
sns.heatmap(conf_matrix, annot=True, cmap="Blues", fmt='g')
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

Expected Outcome:

A trained decision tree model with an accuracy score and a visualized confusion matrix that shows how well the model performs on unseen data.

Hands-on Exercise 2: Unsupervised Learning (Clustering)

In this exercise, we will implement the **K-Means clustering algorithm** using the same Iris dataset. Since the data is unlabeled for clustering, we will ignore the species labels for this exercise.

Objective:

Perform clustering on the Iris dataset to group similar data points together.

Steps:

1. **Prepare the Data**:

```
# Load data (without species labels)
X = iris.data
```

2. **Apply K-Means Clustering**:

```
# Initialize K-Means with 3 clusters
kmeans = KMeans(n_clusters=3, random_state=42)

# Fit the model
kmeans.fit(X)

# Get cluster labels
clusters = kmeans.labels_
```

3. **Visualize the Clusters**:

```
# Visualize the clusters in a scatter plot
plt.scatter(X[:, 0], X[:, 1], c=clusters, cmap='viridis', marker='o')
plt.title('K-Means Clustering on Iris Dataset')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.show()
```

4. **Interpret the Results**:

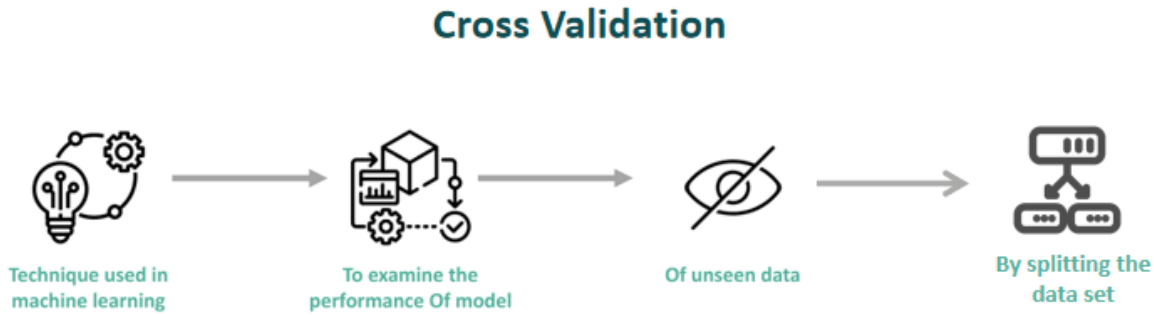
```
# Compare clusters with actual species (just for observation)
comparison_table = pd.DataFrame({'Cluster': clusters, 'Actual Species':
iris.target})
print(comparison_table.head())
```

You will observe distinct clusters representing the different species of Iris flowers, as identified by the K-Means algorithm.

In this practical session, you have explored the fundamental concepts of machine learning through hands-on exercises in Python. You learned the difference between supervised and unsupervised learning by implementing a decision tree classifier and K-Means clustering algorithm. These basic concepts are key to building more complex machine learning models for various applications.

WEEK 6 Day 1: Model Evaluation and Improvement

- **Cross-validation, hyperparameter tuning**
  - ✓ **Cross-validation**: Cross validation is a technique used to evaluate the performance of a machine learning model**.**
  - ✓ The basic idea of cross validation is to split the data into training and validation sets.



- **Types of Cross-validation**
  - ✓ K-Fold Cross-Validation
  - ✓ Stratified K-Fold Cross-Validation
  - ✓ Leave-one-out Cross-Validation

- **Hyperparameter tuning**

✓ Hyperparameters are configuration variables that are set before the training process of a model begin.

- **Methods of Hyperparameter Tuning:**

✓ Grid Search
✓ Random Search
✓ Bayesian Optimization
✓ **Task**
How Cross-Validation is used in Hyperparameter Tuning?

Week 6 Day 2: Working with Real-World Data

- **Handling large datasets**
  - ✓ Sampling the Dataset

```
import pandas as pd

# Load a fraction of the dataset (e.g., 10%)
data = pd.read_csv('large_dataset.csv', skiprows=lambda i: i > 0 and i % 10 != 0)
```

  - ✓ Batch Processing / Chunking

```
chunk_size = 10**6  # 1 million rows at a time
for chunk in pd.read_csv('large_dataset.csv', chunksize=chunk_size):
    # Process each chunk here
    process(chunk)
```

  - ✓ Using Dask for Out-of-Core Computation

```
import dask.dataframe as dd

# Load the large dataset with Dask
df = dd.read_csv('large_dataset.csv')

# Perform computations
mean_value = df['column_name'].mean().compute()
print("Mean value:", mean_value)
```

  - ✓ Saving and Loading Data with Parquet

```
# Save dataframe to Parquet
df.to_parquet('data.parquet')

# Load Parquet file
df = pd.read_parquet('data.parquet')
```

- **Data pipelines**
  - ✓ Data Ingestion: You can pull data from an API, a database, or local files. Here's an example of reading from a CSV file.
  - ✓ Data Validation & Cleansing: Data cleaning can involve removing missing values, handling duplicates, correcting formats, etc.

- ✓ Data Transformation: Transformation might include feature engineering, normalization, aggregation, etc
- ✓ Data Storage:After processing, you can store the cleaned data in a database or file format like Parquet, CSV, or JSON.
- ✓ Data Visualization:You can create visualizations to report the results.

- **Task**

  Write the Python code for above mentioned Data pipeline steps.

Week 6 Day 3: Unsupervised Learning

Clustering techniques (k-means, hierarchical)

- ✓ **K-Means Clustering:**
- Partitions data into kkk clusters by minimizing the variance within each cluster.
- Simple and efficient, but requires the number of clusters kkk to be specified in advance.
- ✓ **Hierarchical Clustering**:
- Builds a tree of clusters (dendrogram) either through agglomerative (bottom-up) or divisive (top-down) approaches.
- No need to specify the number of clusters upfront.
- ✓ **DBSCAN (Density-Based Spatial Clustering of Applications with Noise)**:
- Groups together points that are close to each other based on a distance metric and a minimum number of points.
- Can identify noise and works well with clusters of varying shapes and sizes.
- ✓ **Gaussian Mixture Models (GMM)**:
- Assumes that the data is generated from a mixture of several Gaussian distributions.
- Uses Expectation-Maximization (EM) to find the best-fit parameters.

Week 6 Day 4: Practical Session Hands-on exercises: Advanced modeling techniques

Convolutional Neural Networks (CNNs) are powerful for image classification, object detection, and other tasks involving spatial data. Here we using CIFAR-10 Dataset.

Install Dependencies

```
pip install tensorflow keras numpy matplotlib
```

Import Libraries

```
import tensorflow as tf
from tensorflow.keras import layers, models
import numpy as np
import matplotlib.pyplot as plt
```

Load and Preprocess Data

```
# Load the CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()

# Normalize pixel values to be between 0 and 1
x_train, x_test = x_train / 255.0, x_test / 255.0

# Check the shape of the data
print("Training data shape:", x_train.shape)
print("Testing data shape:", x_test.shape)
```

Build the CNN Model

```
model = models.Sequential()

# 1st Convolutional Layer
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)))
model.add(layers.MaxPooling2D((2, 2)))

# 2nd Convolutional Layer
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

# 3rd Convolutional Layer
model.add(layers.Conv2D(64, (3, 3), activation='relu'))

# Flatten the output
model.add(layers.Flatten())

# Fully connected layer
model.add(layers.Dense(64, activation='relu'))

# Output layer with 10 classes (for CIFAR-10)
model.add(layers.Dense(10))
```

Compile the Model

```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])

# Print model summary
model.summary()
```

Train the Model

```
# Train the model
history = model.fit(x_train, y_train, epochs=10,
                    validation_data=(x_test, y_test))
```

Evaluate the Model

```
# Evaluate the model
test_loss, test_acc = model.evaluate(x_test, y_test, verbose=2)
print(f"Test Accuracy: {test_acc:.4f}")
```

Visualize Training Results

```
# Plot accuracy and loss over epochs
plt.figure(figsize=(12, 4))

# Accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.show()
```

WEEK 6 Day 5: Practical Session Mini-project: Implementing an advanced model

Mini-Project Task: Implementing an Advanced Machine Learning Model

Project Title: Implementation and Evaluation of an Advanced Machine Learning Model on [any specified Dataset]

Objective:

The goal of this mini-project is to implement an advanced machine learning model on a selected dataset and evaluate its performance using various metrics. Students will experiment with a cutting-edge model (e.g., a deep learning model, ensemble methods, or a sequence model) and compare its performance against a baseline. The focus will be on model implementation, hyperparameter tuning, evaluation, and interpretation of results.

Task Breakdown:

Part 1: Dataset Selection & Preprocessing

1. **Dataset Selection**:
    - Select a complex, real-world dataset suitable for an advanced machine learning model (at least 1000 instances and 10 features). You can use datasets from sources like Kaggle, UCI Machine Learning Repository, or custom sources.
    - Datasets can include tabular, image, text, or time-series data based on the chosen model.
2. **Data Preprocessing**:
    - Perform necessary preprocessing steps including:
        - Handling missing values and outliers.
        - Feature scaling (normalization/standardization).
        - Encoding categorical variables (if necessary).
        - Splitting the dataset into training and testing sets (e.g., 80/20 split).
        - For text or sequence data, apply techniques like tokenization and embedding.

Deliverables:

- Description of the dataset, its source, and the relevance of features to the problem.
- Details of data preprocessing and transformations.

Part 2: Baseline Model Implementation

1. **Select a Baseline Model**:
    - Implement a basic machine learning model such as **Logistic Regression**, **Decision Tree**, or **Random Forest**. This model will serve as a comparison for your advanced model.
2. **Train and Evaluate the Baseline Model**:

- Use appropriate evaluation metrics (accuracy, precision, recall, F1-score for classification; RMSE, MAE for regression) to assess the baseline model.
- If applicable, visualize learning curves or feature importance.

Deliverables:

- Implementation of the baseline model.
- Performance metrics and any visualizations for the baseline model.

Part 3: Advanced Machine Learning Model Implementation

1. **Model Selection**:
   - Choose an advanced machine learning model based on the dataset and problem type. Possible models include:
     - **Deep Neural Networks (DNNs)** for tabular data or regression/classification tasks.
     - **Convolutional Neural Networks (CNNs)** for image data.
     - **Recurrent Neural Networks (RNNs)**, **Long Short-Term Memory (LSTM)**, or **Transformer-based models** for time-series or sequential data.
     - **XGBoost**, **LightGBM**, or **CatBoost** for high-dimensional tabular data.
     - **Generative Adversarial Networks (GANs)** for generating new data or **Autoencoders** for anomaly detection or data compression.
2. **Model Architecture**:
   - For deep learning models, design the architecture (layers, neurons, activation functions).
   - For ensemble models, explain the core concepts (boosting, bagging, etc.).
   - Experiment with various architectures and hyperparameters (number of layers, dropout rates, learning rates, optimizers, etc.).
3. **Training the Model**:
   - Train the advanced model using the training dataset.
   - Apply **early stopping**, **cross-validation**, or other techniques to prevent overfitting.
   - Log the training process, showing loss curves and validation accuracy/performance.
4. **Hyperparameter Tuning**:
   - Use techniques like **Grid Search** or **Random Search** for hyperparameter tuning.
   - Explore and experiment with multiple hyperparameters (learning rate, batch size, etc.).

Deliverables:

- Full implementation of the advanced machine learning model.
- Hyperparameter tuning results and training logs (loss curves, validation accuracy).

Part 4: Model Evaluation & Comparison

1. **Evaluate the Advanced Model**:
   - Apply evaluation metrics to the test dataset (accuracy, precision, recall, F1-score for classification; RMSE, MAE for regression).
   - For time-series or sequential models, use metrics like **mean absolute scaled error (MASE)** or **symmetric mean absolute percentage error (SMAPE)**.

    - Plot confusion matrix, ROC curves, precision-recall curves, or regression error plots as applicable.
    - Visualize attention maps (for transformers) or feature importance (for tree-based models).
2. **Comparison with Baseline**:
    - Compare the performance of the advanced model with the baseline model in terms of evaluation metrics.
    - Discuss where the advanced model outperforms the baseline and where it may fall short.

Deliverables:

- Evaluation metrics and visualizations for the advanced model.
- Comparative analysis between baseline and advanced models, highlighting improvements and challenges.

Part 5: Model Interpretation & Insights

1. **Interpretation of Results**:
    - Interpret the model's predictions and performance.
    - For deep learning models, try model interpretation techniques like **Grad-CAM** (for CNNs) or **LIME**/**SHAP** (for tabular data).
    - For tree-based models, visualize feature importance and discuss the contribution of different features.
2. **Discussion**:
    - Provide insights into why the model performed well or poorly in specific areas.
    - Discuss the potential limitations of the model and suggestions for further improvements.
    - Highlight any real-world implications or applications of your findings.

Deliverables:

- Interpretation of model performance and feature importance.
- Insights and discussion of the model's strengths and weaknesses.

Tools & Technologies:

- **Programming Language**: Python
- **Libraries**:
    - `Scikit-learn` for baseline models.
    - `TensorFlow`/`Keras` or `PyTorch` for advanced models.
    - `XGBoost`, `LightGBM`, or `CatBoost` for ensemble methods.
    - `Matplotlib`, `Seaborn`, `Plotly` for visualizations.
    - `LIME`, `SHAP`, or `Grad-CAM` for model interpretability.

Tasks (Optional):

1. **Model Deployment**:
    - Create a REST API using `Flask` or `FastAPI` to deploy your trained model.
2. **Advanced Tuning**:
    - Experiment with advanced techniques like **Transfer Learning**, **Data Augmentation** (for images), or **Sequence Padding** (for text/time-series).
3. **Ensemble of Models**:
    - Combine multiple models using **Stacking** or **Blending** to further improve performance.

Report Submission:

- Submit a Jupyter Notebook containing:
    - All code, explanations, and results of your experiments.
    - Detailed comments explaining your methodology, model choices, and interpretation of results.
- Final report (max 15 pages) summarizing:
    - Dataset, preprocessing, model implementation, results, and insights.

WEEK 7 Day 1: Working with Big Data on the Cloud

Learning Outcomes:

- ✓ Gain a foundational understanding of Big Data and its significance in the digital age.
- ✓ Articulate the defining characteristics of Big Data and the challenges it presents.
- ✓ Differentiate between structured, semi-structured, and unstructured data with precision.
- ✓ Develop a conceptual understanding of distributed storage and computational paradigms, particularly Hadoop and MapReduce.
- ✓ Engage with foundational tools and frameworks in the Big Data ecosystem, applying them to practical problems.
- ✓ Perform preliminary analysis on datasets leveraging Big Data techniques and platforms.

Introduction to Big Data

Definition and Scope: Big Data refers to datasets whose size or complexity exceeds the capabilities of traditional data processing systems. Its rise is fueled by the digital transformation of industries, where data is continuously generated from sensors, transactions, and digital interactions.

Key Characteristics (The Four Vs):

1. **Volume**: The exponential growth in the amount of data generated across various domains.
2. **Velocity**: The rapid rate at which data is produced and the increasing need for real-time processing.
3. **Variety**: The diverse forms of data, including text, images, audio, and video, which pose integration challenges.
4. **Veracity**: The uncertainty inherent in data due to inconsistencies, noise, and reliability issues.

Data Classification: Structured, Semi-Structured, and Unstructured

Data classification in Big Data refers to the organization of data into different categories based on its format, organization, and how easily it can be processed. Understanding these distinctions is crucial for selecting the appropriate tools, storage, and processing methods.

- **Structured Data**: This data is highly organized, typically residing in databases where it is stored in predefined rows and columns (e.g., SQL databases). It follows a strict schema and is easily searchable using conventional data query languages like SQL.
- **Semi-Structured Data**: Semi-structured data doesn't conform strictly to a formal data model or schema but contains tags or markers that separate elements (e.g., JSON, XML). This type of data is more flexible than structured data but still has some organizational properties that allow for easier processing than unstructured data.
- **Unstructured Data**: Unstructured data lacks a predefined structure or format. This includes data like videos, images, text documents, and social media posts. Because it doesn't fit neatly into relational databases, processing and analyzing unstructured data often requires specialized tools and techniques.

Distributed Storage and Computational Paradigms

Distributed storage and computational paradigms are foundational concepts in Big Data, designed to address the challenges posed by the massive scale, complexity, and real-time requirements of modern data. Traditional data processing methods become inefficient or impractical when working with data on the scale of terabytes, petabytes, or even exabytes. Hence, distributed systems offer a solution by dividing data and computational tasks across multiple machines, or nodes, working in parallel.

Key Concepts:

1. **Distributed Storage**:

    - In distributed storage, data is split into smaller chunks or "blocks" and stored across multiple nodes in a network. This allows for fault tolerance, improved performance, and scalability, as each node stores and retrieves only part of the overall dataset.
    - **Example: Hadoop Distributed File System (HDFS)**: HDFS is one of the most popular distributed storage systems. It divides large files into smaller blocks and distributes them across a cluster of machines. Redundancy is built in to ensure that if one node fails, the data can still be retrieved from another node that holds a copy of the block.

2. **Distributed Computation**:

    - Distributed computation involves breaking down large, complex tasks into smaller subtasks, which can be processed simultaneously on different nodes in the cluster. This parallelism allows for much faster processing times and makes it possible to analyze vast datasets.
    - **Example: MapReduce**: MapReduce is a programming model that works in two phases: the **Map** phase processes and organizes the data into key-value pairs, and the **Reduce** phase aggregates the results of the Map phase to generate the final output. This model is highly scalable and well-suited for analyzing large-scale datasets in a distributed manner.

Benefits of Distributed Systems:

- **Scalability**: Distributed systems can easily scale by adding more nodes, allowing for seamless expansion as data grows.
- **Fault Tolerance**: With data replicated across multiple nodes, system failures are mitigated by redistributing tasks and data to healthy nodes.
- **Speed**: Parallel processing reduces the time required to analyze and process large datasets, ensuring faster insights.

Popular Distributed Storage and Computational Paradigms:

- **Hadoop**: An open-source framework that enables distributed storage (via HDFS) and distributed processing (via MapReduce).
- **Apache Spark**: Extends distributed computation with in-memory processing, making it significantly faster for iterative algorithms and tasks like machine learning.

Introduction to Key Big Data Tools

In the landscape of Big Data, Apache Hadoop and Apache Spark are two foundational tools that have transformed how organizations store, process, and analyze vast amounts of data. Each tool serves distinct purposes but often works in tandem to enable comprehensive data solutions.

1. Apache Hadoop

- **Overview**: An open-source framework designed for the distributed processing of large datasets across clusters of computers using simple programming models. Hadoop is particularly effective for handling large volumes of data that traditional systems struggle with.
- **Key Components**:

  - ✓ **Hadoop Distributed File System (HDFS)**: A highly scalable storage system that splits large files into smaller blocks and distributes them across multiple nodes in a cluster. This architecture ensures high availability and fault tolerance by replicating data across nodes.
  - ✓ **MapReduce**: A programming model for processing large datasets in parallel. The Map phase processes input data and produces intermediate key-value pairs, while the Reduce phase aggregates these pairs to produce the final output.

- **Use Cases**:

✓ Data warehousing, log processing, and large-scale analytics in sectors like finance, healthcare, and retail.

- **Advantages**:

  - ✓ Scalability: Easily accommodates increasing data volumes by adding more nodes.
  - ✓ Fault Tolerance: Data replication ensures that data remains accessible even in case of node failures.

2. Apache Spark

- **Overview**: A powerful open-source data processing engine that supports both batch and real-time data processing. Spark is known for its speed and ease of use, making it suitable for a variety of data processing tasks.

- **Key Features**:

  - ✓ **In-Memory Processing**: Spark processes data in memory, which allows for much faster computations compared to Hadoop's MapReduce, particularly for iterative tasks commonly found in machine learning and data analysis.
  - ✓ **Unified Framework**: Supports multiple processing paradigms, including batch processing, streaming, machine learning, and graph processing, all within a single framework.

- **Use Cases**:
    - ✓ Real-time data analytics, machine learning, and interactive data analysis.
- **Advantages**:
    - ✓ Performance: In-memory processing reduces the need for disk I/O, resulting in significantly faster data processing times.
    - ✓ Flexibility: The ability to handle various data processing tasks makes Spark suitable for diverse applications.

Data Processing and Analysis

Data processing and analysis are fundamental components of the Big Data lifecycle, enabling organizations to extract meaningful insights from vast amounts of information. Two critical processes in this context are the ETL (Extract, Transform, Load) process and distributed analytics.

1. ETL Process

Overview: The ETL process is a systematic method for preparing large datasets for analysis. It involves three key stages:

- **Extract**: This stage involves retrieving data from various sources, which may include databases, data lakes, APIs, and flat files. The goal is to gather all relevant data needed for analysis, regardless of its source or format.
- **Transform**: Once the data is extracted, it undergoes transformation to clean, enrich, and convert it into a suitable format for analysis. This can include:
    - ✓ Data cleansing (removing duplicates, correcting errors)
    - ✓ Data normalization (ensuring consistent formats)
    - ✓ Aggregation (summarizing data)
    - ✓ Enrichment (adding relevant information from other sources)
- **Load**: The final step involves loading the transformed data into a target system, such as a data warehouse or data lake, where it can be easily accessed and analyzed.

Adapting ETL for Big Data:

- The traditional ETL process can be challenging with large datasets due to the volume, variety, and velocity of data in Big Data environments. To address these challenges, modern ETL tools leverage distributed computing frameworks (such as Apache Spark or Hadoop) to perform transformations across multiple nodes.
- **Distributed Transformation**: By distributing the transformation tasks, ETL processes can handle larger datasets more efficiently. Each node processes a portion of the data in parallel, reducing the time required for transformation and enabling scalability as data volumes grow.

2. Basic Big Data Analytics

Overview: Big Data analytics refers to the process of examining large datasets to uncover trends, patterns, and insights that can inform decision-making. The scale and complexity of Big Data require specialized frameworks that can process and analyze data effectively.

Distributed Analytics:

- Distributed analytics involves analyzing large-scale datasets across a distributed computing environment. This approach utilizes the processing power of multiple nodes to perform computations in parallel, significantly speeding up the analysis.
- **Scalable Frameworks**: Technologies like Apache Spark and Apache Flink enable distributed analytics by allowing organizations to run complex queries and algorithms on large datasets efficiently. These frameworks support various analytics tasks, including:

    - ✓ **Descriptive Analytics**: Understanding historical data to summarize trends.
    - ✓ **Predictive Analytics**: Using statistical models and machine learning to forecast future events.
    - ✓ **Prescriptive Analytics**: Providing recommendations based on data-driven insights.

Benefits of Distributed Analytics:

- **Speed**: The ability to process large datasets in parallel leads to faster insights.
- **Scalability**: As data volumes increase, distributed frameworks can scale by adding more nodes to the cluster.
- **Real-time Processing**: Distributed analytics supports real-time data processing, enabling organizations to react quickly to changing conditions.

Task

1. Identify real-world examples that demonstrate each of the 4 Vs in industries like healthcare, finance, and social media.
2. Review the datasets provided above.
    - For each dataset, classify it as Structured, Semi-Structured, or Unstructured based on its description.
    - Provide a brief justification for your classification.

Sr#	Description	Type	Reason
1	This dataset contains customer transaction records stored in a relational database. It includes fields such as Transaction_ID, Customer_ID, Date, Amount, and Product_ID.		
2	Log files generated by a web server contain entries with fields such as Timestamp, IP Address, Request Method, Status Code, and User Agent.		
3	A dataset capturing real-time data from IoT sensors, stored in JSON format. It includes fields such as sensor_id, timestamp, temperature, and humidity.		
4	User-generated reviews for products, consisting of free-text descriptions of the customers' opinions, with varying lengths and writing styles.		

5	User-generated reviews for products, consisting of free-text descriptions of the customers' opinions, with varying lengths and writing styles.		
6	Employee details stored in XML format, containing fields like Employee_ID, Name, Position, Salary, and Department.		
7	Employee details stored in XML format, containing fields like Employee_ID, Name, Position, Salary, and Department.		
8	A collection of social media posts including text, images, and videos. The data is highly varied and lacks a consistent format.		

3. What is the primary advantage of using a distributed storage system like HDFS for handling large datasets, and how does it improve fault tolerance?
4. Describe one key advantage of Apache Spark over Apache Hadoop in terms of data processing speed. Provide a specific scenario where this advantage would be beneficial.
5. Explain the ETL process (Extract, Transform, Load) and discuss how it adapts to the challenges of Big Data through distributed processing. Additionally, describe the benefits of using distributed analytics frameworks for analyzing large-scale datasets.

WEEK 7 Day 3: Working with Big Data on the Cloud

1. Introduction to Big Data and Cloud Computing

Big Data

Big data refers to data that is too large, complex, or fast for traditional data-processing tools. It is characterized by **Volume**, **Velocity**, **Variety**, and **Veracity**.

Cloud Computing

Cloud computing provides scalable, on-demand computing resources, enabling users to handle big data more efficiently. Key advantages of using the cloud for big data include:

- **Scalability**: Dynamic resource allocation based on demand.
- **Cost-effectiveness**: Pay only for what you use.
- **Speed**: Easy to deploy and run powerful processing frameworks like Hadoop and Spark.

2. Lab Setup: Cloud Environment and Access

For this lab, you will need access to one of the following cloud platforms: **Amazon Web Services (AWS)**, **Google Cloud Platform (GCP)**, or **Microsoft Azure**. Follow the steps below to set up your environment.

Amazon Web Services (AWS) Setup:

1. **Sign up for AWS**: If you do not have an AWS account, create one at aws.amazon.com.
2. **Create an S3 Bucket**:
    - Go to the **Amazon S3** console.
    - Click **Create bucket** and follow the steps to create a bucket.
    - Note down your bucket name for use in later steps.
3. **Launch an EMR Cluster**:
    - In the AWS Management Console, go to **EMR** (Elastic MapReduce).
    - Click on **Create cluster** and configure it for **Apache Spark**.
    - Wait for the cluster to launch.

Google Cloud Platform (GCP) Setup:

1. **Sign up for Google Cloud**: Create a GCP account at cloud.google.com if you don't have one.
2. **Create a Google Cloud Storage (GCS) Bucket**:
    - Go to **Cloud Storage** in the GCP console.
    - Click **Create Bucket** and follow the prompts.

3. **Enable BigQuery**:
    - In the GCP console, go to **BigQuery**.
    - Enable it to start working with structured datasets.

Microsoft Azure Setup:

1. **Sign up for Microsoft Azure**: If you don't have an Azure account, create one at azure.microsoft.com.
2. **Create an Azure Blob Storage Account**:
    - Go to the **Storage Accounts** section in the Azure portal.
    - Click **Create**, and choose **Blob Storage**.
3. **Launch Azure Databricks**:
    - Go to the **Databricks** service.
    - Create a new workspace and cluster for big data processing using Apache Spark.

3. Data Storage in the Cloud

A. Amazon S3 (AWS)

Amazon Simple Storage Service (S3) is used to store and retrieve large amounts of data. S3 buckets can handle massive datasets, making it ideal for big data.

Steps to Upload Data to S3:

1. Go to the **S3 console**.
2. Select your **bucket**, then click **Upload**.
3. Choose the files you want to upload, and click **Start Upload**.

Access Data Programmatically:

- Use the `boto3` library in Python to interact with S3:

```
python
Copy code
import boto3

# Create S3 client
s3 = boto3.client('s3')

# Upload file to S3
s3.upload_file('data.csv', 'your_bucket_name', 'data.csv')
```

B. Google Cloud Storage (GCP)

Google Cloud Storage is a unified object storage service that allows for massive scalability. It can store any amount of data and serve it anywhere.

Steps to Upload Data to GCS:

1. Go to the **Cloud Storage** console.
2. Select your **bucket**, then click **Upload Files**.

Access Data Programmatically:

- Use the `google-cloud-storage` library to interact with GCS:

```
python
Copy code
from google.cloud import storage

# Initialize client
client = storage.Client()

# Get bucket and upload file
bucket = client.get_bucket('your_bucket_name')
blob = bucket.blob('data.csv')
blob.upload_from_filename('data.csv')
```

C. Azure Blob Storage (Azure)

Azure Blob Storage is optimized for storing massive amounts of unstructured data. It supports big data analytics with scalability and flexibility.

Steps to Upload Data to Blob Storage:

1. Go to the **Azure Portal**.
2. Navigate to your **Storage Account**, then select **Containers**.
3. Upload your data file to the container.

Access Data Programmatically:

- Use the `azure-storage-blob` package in Python to interact with Blob Storage:

```
from azure.storage.blob import BlobServiceClient

# Create a BlobServiceClient
blob_service_client =
BlobServiceClient.from_connection_string('your_connection_string')

# Upload a file to Blob Storage
blob_client = blob_service_client.get_blob_client(container="your_container",
blob="data.csv")
with open("data.csv", "rb") as data:
    blob_client.upload_blob(data)
```

4. Data Processing in the Cloud

A. Processing Data with Apache Spark on AWS EMR

Apache Spark is an open-source distributed computing system used for big data processing. AWS Elastic MapReduce (EMR) enables scalable Spark processing.

1. **Log into the EMR Cluster**:
   Use SSH to connect to the EMR cluster once it's launched:

```
ssh -i your-key.pem hadoop@<master-node-public-DNS>
```

2. **Run Spark Jobs**:
    - Upload your dataset to S3, then run Spark jobs to process the data.

```
from pyspark.sql import SparkSession

# Initialize Spark session
spark = SparkSession.builder.appName('BigDataProcessing').getOrCreate()

# Read data from S3
df = spark.read.csv('s3://your_bucket_name/data.csv', header=True)
df.show()
```

B. Google BigQuery for Data Processing

Google BigQuery is a serverless, highly scalable data warehouse designed for big data analytics.

1. **Upload Data to BigQuery**:
    - Upload your dataset via the BigQuery console or GCS.
2. **Run Queries on Big Data**:

```
SELECT *
FROM `project_id.dataset_id.table_name`
LIMIT 1000;
from google.cloud import bigquery

# Create a BigQuery client
client = bigquery.Client()

# Query the data
query = "SELECT * FROM `project_id.dataset_id.table_name` LIMIT 1000"
query_job = client.query(query)

# Process query results
for row in query_job:
    print(row)
```

C. Azure Databricks for Big Data Processing

Azure Databricks provides a cloud-based environment for big data analytics using Apache Spark.

1. **Create a Cluster**:
    - Go to **Azure Databricks** and create a cluster.
2. **Load Data**:
    - Load data into your Databricks workspace using Azure Blob Storage or directly from your local machine.
3. **Run Spark Jobs**:

```
python
Copy code
# In Databricks, use the following to read data from blob storage
df = spark.read.csv('/mnt/your_blob_container/data.csv', header=True)
df.show()
```

5. Hands-on Tasks

Task 1: Store and Retrieve Data in Cloud Storage

- Choose one cloud platform (AWS, GCP, or Azure) and upload a dataset to the respective storage service (S3, GCS, or Blob Storage). Write a Python script to upload, retrieve, and display the data.

Task 2: Process Big Data with Apache Spark

- Using AWS EMR, Google Dataproc, or Azure Databricks, process a large dataset using Apache Spark. Perform a basic transformation and aggregation.

Task 3: Analyze Big Data with SQL Queries

- If using Google Cloud, run SQL queries on your dataset in BigQuery. Otherwise, run Spark SQL on AWS or Azure.

In this lab, you learned how to handle big data in the cloud using services like **Amazon S3**, **Google Cloud Storage**, and **Azure Blob Storage**. You also explored how to process large datasets using **Apache Spark** and **Google BigQuery**. These skills are fundamental for modern big data analytics and cloud-based data engineering.

Week 7 Day 4: Practical Session on Big Data Processing

Lab Topic: Hands-on Exercises in Big Data Processing

Lab Objectives:

1. Understand the basics of Big Data processing and tools used in the ecosystem.
2. Gain hands-on experience in handling large-scale datasets using big data frameworks like Hadoop and Apache Spark.
3. Learn how to process and analyze big data using distributed computing.

Prerequisites:

- Basic understanding of distributed computing.
- Familiarity with Python and basic SQL.
- Installed software: Hadoop, Apache Spark, Jupyter Notebook, and related packages (`pyspark`).

Lab Setup:

1. **Hadoop Installation** (Optional):
   - If Hadoop is not set up, follow these instructions to install:
     - Set up Hadoop in **Pseudo-distributed Mode**.
     - Install Java Development Kit (JDK 8+).
     - Download Hadoop and configure environment variables.
     - Format the HDFS (Hadoop Distributed File System).
     - Start the Hadoop services (NameNode, DataNode, etc.).
2. **Apache Spark Installation**:
   - Install Spark on the local system or set up on a cloud service (AWS EMR, Databricks).
   - Ensure the installation of `pyspark` for Python integration:

     ```
     bash
     Copy code
     pip install pyspark
     ```

3. **Dataset**:
   - Download the publicly available large dataset (1GB or larger) for the lab session. Example datasets:
     - **NYC Taxi Trips Dataset**: Contains millions of records of taxi rides in NYC.
     - **Amazon Product Reviews**: Large-scale product reviews data for sentiment analysis.
     - **COVID-19 Open Research Dataset (CORD-19)**: A large dataset of academic papers for text processing.
4. **Lab Environment**:

- Jupyter Notebook or any preferred IDE for coding (PyCharm, VS Code).

Lab Structure

Part 1: Introduction to Big Data Processing and Distributed Systems

Step 1: Introduction to Big Data Ecosystem

- Discuss the difference between traditional RDBMS and Big Data processing systems.
- Explore common big data frameworks:
  - **Hadoop**: Distributed storage and processing via HDFS and MapReduce.
  - **Apache Spark**: In-memory distributed processing for faster performance.
  - **Hive**: SQL-based querying on Hadoop datasets.
  - **HBase**: Distributed, scalable NoSQL database.

Step 2: HDFS Basics

- Explore Hadoop Distributed File System (HDFS) through terminal commands:
  - **Creating Directories in HDFS**:

    ```
    bash
    Copy code
    hadoop fs -mkdir /user/student/input
    ```

  - **Copying Files to HDFS**:

    ```
    bash
    Copy code
    hadoop fs -put local_file.csv /user/student/input
    ```

  - **Listing Files in HDFS**:

    ```
    bash
    Copy code
    hadoop fs -ls /user/student/input
    ```

Step 3: Understanding MapReduce

- Brief overview of the **MapReduce** programming model.
  - **Map phase**: Break data into smaller chunks.
  - **Reduce phase**: Aggregate intermediate data.

Exercise:

- Run a simple WordCount example using Hadoop MapReduce.

Part 2: Big Data Processing with Apache Spark

Step 1: Introduction to Apache Spark

- Discuss the advantages of Spark over Hadoop MapReduce.
  - **In-memory computation**.
  - **Ease of use with APIs in Python (PySpark), Scala, and Java**.
  - **Resilient Distributed Datasets (RDDs)**: Immutable, distributed data collections.

Step 2: SparkSession Setup

- Create a SparkSession to work with PySpark:

```
python
Copy code
from pyspark.sql import SparkSession

spark = SparkSession.builder \
    .appName("Big Data Lab") \
    .getOrCreate()
```

Step 3: Loading Data into Spark

- Load the large dataset into Spark:

```
python
Copy code
df = spark.read.csv('hdfs://user/student/input/large_dataset.csv',
header=True, inferSchema=True)
df.show(5)
```

Part 3: Data Processing and Transformation Using Spark

Step 1: Basic Data Exploration with PySpark

- Explore the schema and the first few rows of the dataset:

```
python
Copy code
df.printSchema()
df.show(10)
```

- Perform basic statistics:

```
python
Copy code
df.describe().show()
```

Step 2: Data Cleaning and Filtering

- **Handling Missing Values**:

```
python
Copy code
df_cleaned = df.na.drop()
```

- **Filtering Data**:

```
python
Copy code
df_filtered = df.filter(df['column_name'] > 100)
```

Step 3: Data Transformation and Aggregation

- **Group By and Aggregate**:

```
python
Copy code
df.groupBy("column").count().show()
```

- **Column Transformation**:

```
python
Copy code
df_transformed = df.withColumn("new_column", df['existing_column'] * 2)
df_transformed.show(5)
```

Part 4: Machine Learning with Spark MLlib

Step 1: Introduction to MLlib

- Overview of Spark's machine learning library, **MLlib**.
- Discuss its use for large-scale data and distributed learning algorithms.

Step 2: Feature Engineering

- **VectorAssembler**: Combine multiple columns into a feature vector:

```
python
Copy code
from pyspark.ml.feature import VectorAssembler

assembler = VectorAssembler(inputCols=["col1", "col2", "col3"],
outputCol="features")
df_features = assembler.transform(df_cleaned)
df_features.select("features").show(5)
```

Step 3: Implementing a Machine Learning Model

- Train a **Linear Regression** model on the dataset:

```
python
```

```
Copy code
from pyspark.ml.regression import LinearRegression

lr = LinearRegression(featuresCol='features', labelCol='label')
lr_model = lr.fit(df_features)

# Model summary
print(f"Coefficients: {lr_model.coefficients}")
print(f"Intercept: {lr_model.intercept}")
```

- **Evaluating the Model**:

```
python
Copy code
training_summary = lr_model.summary
print(f"RMSE: {training_summary.rootMeanSquaredError}")
print(f"R2: {training_summary.r2}")
```

Part 5: Distributed Processing in Spark

Step 1: Partitioning and Parallel Processing

- Understand how Spark partitions data across nodes in a cluster.
- Experiment with partitioning:

```
python
Copy code
df_repartitioned = df.repartition(4)
print(f"Number of partitions: {df_repartitioned.rdd.getNumPartitions()}")
```

Step 2: Caching and Persistence

- Use caching to store intermediate results in memory:

```
python
Copy code
df.cache()
df.count()  # Forces caching
```

Part 6: Advanced Spark: Streaming and Real-time Data Processing

Step 1: Introduction to Spark Streaming

- Overview of Spark's real-time processing capability using **DStreams** and **Structured Streaming**.

Step 2: Structured Streaming Example

- Create a streaming DataFrame and process real-time data:

```
python
```

```
Copy code
streaming_df = spark.readStream.format("csv").option("header",
"true").load("/path/to/streaming/data")
```

- Apply transformations on streaming data:

```
python
Copy code
query =
streaming_df.groupBy("category").count().writeStream.outputMode("complete")
.format("console").start()
query.awaitTermination()
```

Part 7: Conclusion and Discussion

- Discuss the challenges and solutions in big data processing.
- Explore opportunities to use Spark for real-world big data problems, such as:
  - Log analysis.
  - Real-time monitoring.
  - Large-scale data analytics (e.g., customer behavior analysis).

Assignments & Follow-up Tasks

1. **Assignment**: Use a different dataset (e.g., movie reviews, stock market data) to apply Spark for preprocessing, transformation, and modeling.
2. **Advanced Task**: Implement a classification algorithm like Decision Tree or Random Forest on a big dataset using Spark MLlib.
3. **Optional Task**: Set up a real-time streaming pipeline using Kafka and Spark Streaming.

Reference Resources:

- Hadoop Official Documentation
- Apache Spark Documentation
- PySpark API Reference
- Kaggle Datasets

This lab manual provides a thorough guide for handling big data using distributed processing frameworks like Hadoop and Apache Spark, giving students hands-on experience with modern big data tools and techniques.

WEEK 7 Day 5: Practical Session

Lab Task: Mini-Project on Analyzing Big Data on the Cloud

Lab Topic: Analyzing Big Data on the Cloud

Objective:

The objective of this mini-project is to utilize cloud computing resources to analyze a large dataset, demonstrating the practical application of big data analytics in a cloud environment. Students will learn how to set up a cloud environment, process big data using cloud services, and analyze the results.

Prerequisites:

- Basic understanding of cloud computing concepts.
- Familiarity with Python and SQL.
- Set up an account on a cloud platform (e.g., AWS, Google Cloud Platform, or Microsoft Azure).

Lab Setup:

1. **Cloud Platform Selection**:
    - Choose a cloud platform (AWS, GCP, or Azure) and set up an account. Use free-tier resources if available.
2. **Dataset Selection**:
    - Select a large dataset for analysis. Possible sources include:
        - **Kaggle**: Public datasets in various domains (e.g., healthcare, finance, e-commerce).

        - **AWS Public Datasets**: Large datasets hosted on AWS for various analyses.
        - **Google Cloud Public Datasets**: Datasets accessible in Google Cloud.
3. **Cloud Service Setup**:
    - **AWS**:
        - Launch an EC2 instance (t2.micro for free tier) with an appropriate AMI (Amazon Machine Image).
        - Install necessary packages (e.g., `pandas`, `numpy`, `pyspark`, `sqlalchemy`).
    - **GCP**:
        - Use Google Cloud Platform's BigQuery and Cloud Storage.
    - **Azure**:
        - Set up Azure Data Lake Storage and Azure Databricks for analysis.

Mini-Project Structure

Part 1: Setting Up the Environment

1. **Launch Cloud Resources**:
    - Create an EC2 instance (AWS) or equivalent on your chosen cloud platform.
    - Configure security settings to allow SSH access.
2. **Install Required Libraries**:
    - Connect to the instance via SSH and install required libraries.

```
bash
Copy code
pip install pandas numpy pyspark sqlalchemy
```

3. **Upload Dataset**:
    - Upload the selected dataset to the cloud instance or directly to cloud storage (S3 for AWS, GCS for GCP, or Azure Blob Storage).

Part 2: Data Ingestion and Exploration

1. **Load Data**:
    - Use Python and `pandas` or `PySpark` to read the dataset from cloud storage.

```
python
Copy code
import pandas as pd
df = pd.read_csv('s3://your-bucket-name/dataset.csv')  # AWS S3 example
```

2. **Data Exploration**:
    - Display basic information about the dataset.

```
python
```

```
Copy code
print(df.info())
print(df.describe())
```

3. **Visualize Initial Findings**:
   - Create basic visualizations using `matplotlib` or `seaborn` to understand data distribution.

```
python
Copy code
import matplotlib.pyplot as plt
df['column_name'].hist()
plt.show()
```

Part 3: Data Cleaning and Transformation

1. **Data Cleaning**:
   - Handle missing values (imputation or removal).
   - Remove duplicates if necessary.

```
python
Copy code
df = df.dropna()
df = df.drop_duplicates()
```

2. **Data Transformation**:
   - Apply necessary transformations (e.g., scaling, encoding categorical variables).

```
python
Copy code
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['encoded_column'] = le.fit_transform(df['categorical_column'])
```

Part 4: Big Data Processing Using Spark

1. **Initialize Spark Session**:

```
python
Copy code
from pyspark.sql import SparkSession
spark = SparkSession.builder.appName("Big Data Analysis").getOrCreate()
```

2. **Load Data into Spark**:
   - Convert the `pandas` DataFrame to a Spark DataFrame.

```
python
Copy code
spark_df = spark.createDataFrame(df)
```

3. **Perform Data Analysis**:

- Use Spark to conduct group-by operations, aggregations, and other analyses.

```
python
Copy code
result = spark_df.groupBy('column_name').count()
result.show()
```

Part 5: Advanced Analysis and Machine Learning

1. **Feature Engineering**:
   - Create new features based on existing data.

```
python
Copy code
from pyspark.sql.functions import col
spark_df = spark_df.withColumn('new_feature', col('existing_feature') * 2)
```

2. **Machine Learning Model Implementation**:
   - Use Spark MLlib to train a simple model (e.g., Linear Regression or Decision Tree).

```
python
Copy code
from pyspark.ml.regression import LinearRegression
lr = LinearRegression(featuresCol='features', labelCol='label')
lr_model = lr.fit(spark_df)
```

3. **Model Evaluation**:
   - Evaluate model performance using appropriate metrics (e.g., RMSE).

```
python
Copy code
training_summary = lr_model.summary
print(f"RMSE: {training_summary.rootMeanSquaredError}")
```

Part 6: Results Presentation and Discussion

1. **Results Visualization**:
   - Create visualizations of model predictions versus actual values.

```
python
Copy code
predictions = lr_model.transform(spark_df)
predictions.select("prediction", "label").show(10)
```

2. **Discussion**:
   - Discuss insights gained from the analysis.
   - Address challenges faced during the project and how they were overcome.
3. **Documentation**:
   - Document the entire process, including code snippets, visualizations, and findings, in a Jupyter Notebook or a report.

Follow-up Tasks:

1. **Assignment**: Explore a different dataset and apply similar techniques, focusing on a specific analysis (e.g., sentiment analysis on reviews).
2. **Advanced Task**: Implement an advanced machine learning model (e.g., Random Forest, XGBoost) and compare results with the basic model used in this project.
3. **Cloud Deployment**: Explore options for deploying the analysis as a web application (using Flask or Streamlit) on the cloud.

Reference Resources:

- AWS Documentation
- Google Cloud Platform Documentation
- Microsoft Azure Documentation
- Apache Spark Documentation

This mini-project provides a comprehensive hands-on experience in analyzing big data on the cloud, allowing students to apply theoretical knowledge in a practical environment while familiarizing themselves with essential cloud services and big data tools.

Week 8: Final Project and Review

Overview

In the final week of the course, students will synthesize their learning through a comprehensive project that involves planning, implementing, refining, and presenting a data-driven analysis. This week aims to enhance practical skills, teamwork, and the ability to communicate findings effectively.

Week 8 Day 1: Project Planning

Objectives:

- Define project requirements and scope.
- Establish clear project objectives and deliverables.
- Outline project timelines and individual roles.

Activities:

1. **Group Formation**:
    - Students will form groups of 3-4 members, ensuring a mix of skills and knowledge.
2. **Brainstorming Session**:
    - Each group conducts a brainstorming session to generate project ideas. Consider the following prompts:
        - What real-world problems can data science solve?
        - Which datasets are available that align with group interests?
        - What analytical techniques have we learned that we can apply?
3. **Selecting a Project Topic**:
    - Based on the brainstorming session, each group will select a project topic. They should consider:
        - Relevance to current industry trends.
        - Availability and quality of data.
        - Feasibility within the given timeline.
4. **Defining Project Requirements**:
    - Create a detailed requirements document that includes:
        - **Project Title**: A concise and descriptive title.
        - **Objectives**: Specific aims of the project.
        - **Scope**: What will be included/excluded in the analysis.
        - **Stakeholders**: Who will benefit from the analysis or who will be involved in decision-making.
5. **Data Sources Identification**:
    - Research and identify potential datasets:
        - Public repositories (e.g., Kaggle, UCI Machine Learning Repository).
        - APIs for real-time data (e.g., Twitter, OpenWeather).
        - Government databases or proprietary data sources.

6. **Project Timeline Development**:
    - Develop a Gantt chart outlining milestones and deadlines for key deliverables:
        - Data acquisition and cleaning.
        - Exploratory Data Analysis (EDA).
        - Model development and evaluation.
        - Final report and presentation preparation.
7. **Role Assignments**:
    - Assign roles based on individual strengths and interests, such as:
        - Data Engineer: Responsible for data acquisition and preprocessing.
        - Data Analyst: Conducts EDA and visualizations.
        - Data Scientist: Develops models and analyses results.
        - Project Manager: Coordinates the group and ensures timelines are met.

Deliverables:

- A comprehensive project proposal document that includes the project title, objectives, scope, data sources, project timeline, and team roles.

Week 8 Day 2: Project Implementation

Objectives:

- Begin developing the project based on the defined requirements.
- Implement data preprocessing and initial analysis.

Activities:

1. **Data Acquisition**:
    - Groups will access and download their chosen datasets.
    - Ensure data integrity by checking for missing values and anomalies upon loading.
2. **Data Cleaning and Preparation**:
    - Each group will utilize appropriate libraries (e.g., Pandas, PySpark) to clean the data. Key steps include:
        - **Handling Missing Values**: Use strategies such as imputation, removal, or filling with mean/median/mode.
        - **Data Type Conversion**: Ensure each column has the correct data type for analysis.
        - **Removing Duplicates**: Check for and remove any duplicate rows.

    Example Code (Pandas):

```
python
Copy code
import pandas as pd

df = pd.read_csv('data.csv')
df = df.dropna()  # Remove missing values
df = df.drop_duplicates()  # Remove duplicates
```

3. **Exploratory Data Analysis (EDA)**:
    - Conduct EDA to summarize the main characteristics of the dataset. Techniques include:
        - Descriptive statistics (mean, median, mode, standard deviation).
        - Visualizations using Matplotlib and Seaborn (histograms, box plots, scatter plots).

    Example Visualization:

```
python
Copy code
import seaborn as sns
import matplotlib.pyplot as plt

sns.histplot(df['column_name'], bins=30)
plt.title('Distribution of Column Name')
plt.show()
```

4. **Initial Modeling**:
    - Groups will develop initial models based on their project objectives. This could include:
        - Regression analysis for continuous outcomes.
        - Classification for categorical outcomes.
    - Use Scikit-learn or Spark MLlib for implementation.
5. **Documentation**:
    - Maintain a detailed log of all steps taken, including code snippets, observations, and insights derived from EDA.

Deliverables:

- A Jupyter Notebook or report documenting the data cleaning steps, EDA findings, and initial model implementations.

Week 8 Day 3: Project Implementation

Objectives:

- Continue developing the project.
- Debug and refine models.

Activities:

1. **Refining Models**:
    - Evaluate the performance of initial models using appropriate metrics (e.g., RMSE for regression, accuracy for classification).
    - Perform model selection using techniques such as cross-validation.

    Example Code for Cross-Validation:

    ```
    python
    Copy code
    from sklearn.model_selection import cross_val_score

    scores = cross_val_score(model, X, y, cv=5)
    print("Mean CV Score:", scores.mean())
    ```

2. **Hyperparameter Tuning**:
    - Use GridSearchCV or RandomizedSearchCV to optimize model parameters.
    - Document the impact of different parameters on model performance.
3. **Debugging**:
    - Address any issues encountered during the modeling process. Common debugging techniques include:
        - Reviewing error messages carefully.
        - Using print statements or logging to track variable states.
        - Simplifying complex functions to isolate issues.
4. **Feature Engineering**:
    - Identify new features that could improve model performance. Techniques may include:
        - Creating interaction terms.
        - Applying transformations (e.g., logarithmic, polynomial).
        - Encoding categorical variables using one-hot encoding or label encoding.

    Example Code for Feature Engineering:

    ```
    python
    Copy code
    from sklearn.preprocessing import OneHotEncoder

    encoder = OneHotEncoder()
    encoded_features = encoder.fit_transform(df[['categorical_column']])
    ```

5. **Continued Documentation**:
    - Update the project log with model refinements, debugging processes, and new feature additions.

Deliverables:

- An updated Jupyter Notebook or report detailing refined models, hyperparameter tuning results, and feature engineering efforts.

Week 8 Day 4: Finalizing the Project

Objectives:

- Complete and document the project.
- Prepare for the final presentation.

Activities:

1. **Final Model Selection**:
    - Review all models developed and select the best-performing one based on evaluation metrics.
    - Provide justification for the chosen model based on performance and business relevance.
2. **Comprehensive Documentation**:
    - Compile all project components into a final report, including:
        - **Title Page**: Title, group members, date.
        - **Abstract**: Brief summary of the project.
        - **Introduction**: Background information and project motivation.
        - **Data Sources and Preprocessing**: Detailed explanation of datasets and cleaning methods.
        - **Exploratory Data Analysis**: Key findings and visualizations.
        - **Modeling Process**: Description of modeling approaches, performance metrics, and final model selection.
        - **Conclusions**: Summarize findings, implications, and potential future work.
3. **Preparing the Presentation**:
    - Create a professional slide deck summarizing the project. Key slides to include:
        - Introduction to the project and team members.
        - Overview of the dataset and key findings from EDA.
        - Modeling approach, results, and final model evaluation.
        - Conclusions and recommendations.

    Example Slide Structure:

    - Slide 1: Title Slide
    - Slide 2: Project Overview
    - Slide 3: Data Overview
    - Slide 4: EDA Highlights
    - Slide 5: Modeling Approach
    - Slide 6: Results
    - Slide 7: Conclusions and Future Work

Deliverables: A complete project report and presentation slides prepared for the final review.

Week 8 Day 5: Presentation and Evaluation

Objectives:

- Present the project to peers and instructors.
- Receive feedback and celebrate course completion.

Activities:

1. **Project Presentations**:
    - Each group presents their project, allowing 10-15 minutes for the presentation followed by a Q&A session.
    - Encourage each member to participate in the presentation to demonstrate collaborative effort.
2. **Feedback Session**:
    - Peers and instructors provide constructive feedback on the presentations. Focus areas may include:
        - Clarity of the presentation.
        - Depth of analysis and insights.
        - Engagement with the audience.
3. **Final Reflections**:
    - After presentations, conduct a reflection session where students can share their experiences, challenges faced, and lessons learned throughout the project.
4. **Course Completion Certificates**:
    - Distribute certificates of completion to all participants.
    - Encourage students to share their certificates on LinkedIn or other professional networks.

Deliverables:

- Completed presentations and feedback forms.