Experiment – 1

Aim: Describing data, viewing, and manipulating data

Theory: Data viewing and manipulation are critical processes in data science, enabling analysts and data scientists to explore, clean, and transform datasets for further analysis.

Data Viewing

The process of data viewing involves examining raw data to understand its structure, content, and potential issues. Tools like pandas in Python or data frames in R allow users to load and view datasets, enabling quick inspections of rows, columns, and data types. Typical methods include:

Head and Tail Views: Displaying the first or last few rows of a dataset to get a sense of the data without loading it entirely.

Summarization: Functions like describe() or info() provide summary statistics (mean, median, standard deviation) and metadata (data types, missing values) that give an overview of the dataset's characteristics.

These methods help in detecting anomalies such as missing data, outliers, and inconsistencies, guiding the need for further manipulation.

Data Manipulation

Data manipulation refers to the process of cleaning, reshaping, and transforming data to make it suitable for analysis. The main steps include:

Handling Missing Data: Missing values can be dealt with by filling them using techniques like mean or median imputation or removing them if they don't add significant value.

Filtering and Subsetting: Data filtering involves selecting rows and columns based on conditions, such as removing irrelevant data or focusing on specific variables.

Data Transformation: Transformations involve converting data types, scaling numerical values, or encoding categorical variables. Operations such as merging datasets, pivoting tables, or adding new calculated columns are also common.

Efficient data manipulation not only cleans the data but also reshapes it to align with the requirements of the analytical model or algorithm being applied. This process ensures that the dataset is in a structured form suitable for further statistical or machine learning analysis.

Source Code:

```
import pandas as pd

# Load a dataset
data = pd.read_csv('Customer.csv')

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

# Get the summary statistics
print(data.describe())

# Manipulating data: Adding a new column
data['new_column'] = data['purchase_amount'] * 2

# View modified dataset
print(data.head())
```

Output:

```
   user_id  age  annual_income  purchase_amount  loyalty_score region  \
0        1   25          45000              200            4.5  North
1        2   34          55000              350            7.0  South
2        3   45          65000              500            8.0   West
3        4   22          30000              150            3.0   East
4        5   29          47000              220            4.8  North

   purchase_frequency
0                  12
1                  18
2                  22
3                  10
4                  13
          user_id         age  annual_income  purchase_amount  loyalty_score  \
count  238.000000  238.000000     238.000000       238.000000     238.000000
mean   119.500000   38.676471   57407.563025       425.630252       6.794118
std     68.848868    9.351118   11403.875717       140.052062       1.899047
min      1.000000   22.000000   30000.000000       150.000000       3.000000
25%     60.250000   31.000000   50000.000000       320.000000       5.500000
50%    119.500000   39.000000   59000.000000       440.000000       7.000000
75%    178.750000   46.750000   66750.000000       527.500000       8.275000
max    238.000000   55.000000   75000.000000       640.000000       9.500000

       purchase_frequency
count          238.000000
mean            19.798319
std              4.562884
min             10.000000
25%             17.000000
50%             20.000000
75%             23.000000
max             28.000000

   user_id  age  annual_income  purchase_amount  loyalty_score region  \
0        1   25          45000              200            4.5  North
1        2   34          55000              350            7.0  South
2        3   45          65000              500            8.0   West
3        4   22          30000              150            3.0   East
4        5   29          47000              220            4.8  North

   purchase_frequency  new_column
0                  12         400
1                  18         700
2                  22        1000
3                  10         300
4                  13         440
```

Viva-Voce:

Q1) What is the purpose of data viewing in data analysis, and what tools are commonly used?

A1) Data viewing involves inspecting the raw data to understand its structure, quality, and content. Common tools include data frames in libraries like pandas (Python) and tibbles (R), which allow users to preview rows, columns, and summary statistics to identify potential issues and guide further analysis.

Q2) How can you view the first and last few rows of a dataset using pandas in Python?

A2) In pandas, you can use the head() method to view the first few rows and the tail() method to view the last few rows of a DataFrame. For example, df.head() displays the first five rows, and df.tail() shows the last five rows by default.

Q3) What are some common data manipulation tasks, and how are they performed in Python?

A3) Common data manipulation tasks include filtering, sorting, merging, and aggregating data. In Python, pandas provides functions such as filter(), sort_values(), merge(), and groupby() to perform these operations. For example, df.sort_values(by='column_name') sorts data by a specific column.

Q4) How can you handle missing values in a dataset using pandas?

A4) Missing values can be handled using methods like fillna() to replace them with a specific value or method (e.g., mean, median), or dropna() to remove rows or columns containing missing values. For example, df.fillna(value=0) replaces all missing values with 0.

Q5) What is data normalization, and why is it important in data manipulation?

A5) Data normalization is the process of scaling data to a standard range or distribution, often to ensure that features contribute equally to analysis or modeling. It is important because it can improve the performance and convergence of machine learning algorithms and make comparisons between features more meaningful. Common normalization techniques include min-max scaling and z-score standardization.

Experiment – 2

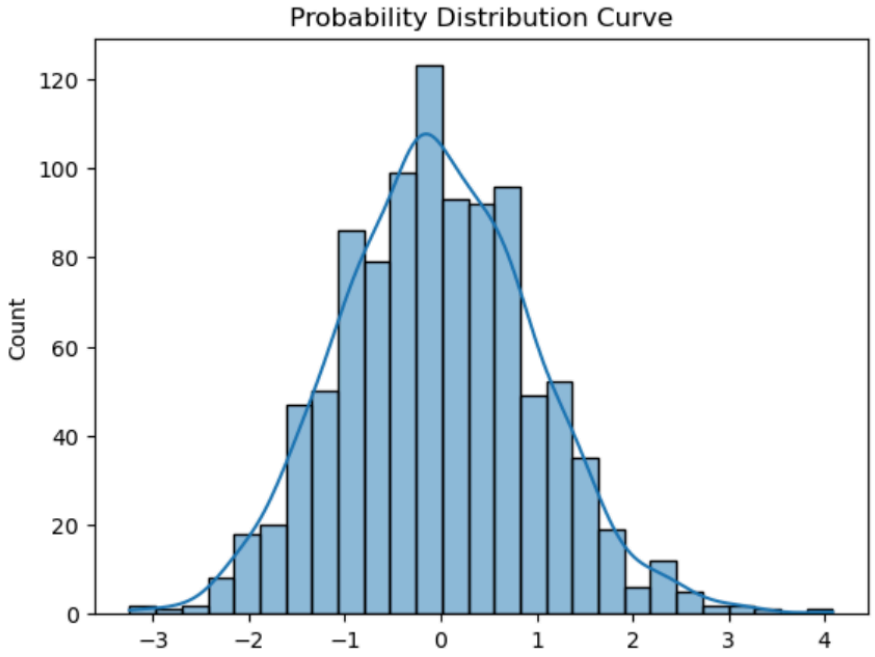
Aim: To plot the probability distribution curve.

Theory: Probability curves in data science represent the distribution of possible outcomes for a random variable, providing insights into data behaviour and uncertainty. Common curves include the normal distribution (bell curve), which is symmetric around the mean, and skewed distributions where one tail is longer than the other. These curves help in modelling real-world phenomena, identifying patterns, and making predictions. For example, the normal curve is widely used due to the central limit theorem, which states that the sum of independent variables tends toward a normal distribution. Understanding probability curves is crucial for tasks like statistical inference and machine learning.

Source Code:

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

# Generate random data
data = np.random.normal(0, 1, 1000)

# Plot the probability distribution curve
sns.histplot(data, kde=True)
plt.title('Probability Distribution Curve')
plt.show()
```

Output:



Viva-Voce:

Q1) What is a probability curve, and why is it important in data science?

A1) A probability curve represents the likelihood of different outcomes for a random variable. It's important in data science because it helps in modeling uncertainty, understanding distributions, and making predictions based on the data.

Q2) Can you explain the normal distribution and its significance?

A2) The normal distribution, also known as the bell curve, is symmetric and centered around the mean. It's significant because many real-world phenomena follow a normal distribution, and it forms the basis of statistical inference due to the central limit theorem.

Q3) What are skewed distributions, and how do they differ from normal distributions?

A3) Skewed distributions have one tail longer than the other, indicating that data is not symmetrically distributed. Unlike normal distributions, where the mean, median, and mode coincide, in skewed distributions, these measures of central tendency differ.

Q4) How does the shape of a probability curve impact data analysis?

A4) The shape of a probability curve affects the choice of statistical methods and models. For example, normally distributed data allows for parametric tests, while skewed or non-normal distributions may require non-parametric tests or data transformation.

Q5) What is the role of the central limit theorem in probability curves?

A5) The central limit theorem states that the sum or average of a large number of independent random variables tends to follow a normal distribution, regardless of the original distribution. This theorem underpins many statistical techniques and allows the use of normal distribution-based models in diverse situations.

Experiment – 3

Aim: To perform Chi-square test on various datasets.

Theory: Chi-square tests in data science are used to determine the relationship between categorical variables and assess the goodness of fit or independence within a dataset. By comparing observed data with expected outcomes, the test evaluates whether deviations are due to chance or a significant association. In a goodness-of-fit test, chi-square determines how well an observed distribution matches a theoretical one, while in independence tests, it checks if two categorical variables are related. The chi-square statistic is calculated by summing the squared differences between observed and expected values, divided by the expected values, providing insight into data dependencies and patterns.

Source Code:

```
import pandas as pd
from scipy.stats import chi2_contingency

# Create a contingency table
data = {'Observed': [50, 30, 20], 'Expected': [40, 40, 20]}
df = pd.DataFrame(data)

# Perform chi-square test
chi2, p, dof, expected = chi2_contingency([df['Observed'], df['Expected']])
print(f"Chi2 Statistic: {chi2}, p-value: {p}")
```

Output:

```
Chi2 Statistic: 2.5396825396825395, p-value: 0.28087620176428163
```

Viva-Voce:

Q1) What is a chi-square test, and when is it used in data science?

A1) A chi-square test assesses the association between categorical variables or the goodness of fit between observed and expected frequencies. It's used to determine if there is a significant difference between expected and observed data, helping in hypothesis testing and evaluating model performance.

Q2) Explain the difference between the chi-square test of independence and the chi-square goodness-of-fit test.

A2) The chi-square test of independence examines whether two categorical variables are related or independent, using a contingency table. The chi-square goodness-of-fit test compares observed data against a theoretical distribution to see if the data follows the expected distribution.

Q3) How is the chi-square statistic calculated?

A3) The chi-square statistic is calculated by summing the squared differences between observed and expected frequencies, divided by the expected frequencies:

$$x_c^2 = \frac{\Sigma\,(O_i - E_i)^2}{E_i}$$

Where,

c = Degrees of freedom

O = Observed Value

E = Expected Value

Q4) What are the assumptions of the chi-square test?

A4) The main assumptions are that the data should be categorical, the observations should be independent, and the expected frequency in each cell of the contingency table should be at least 5 for the test to be valid.

Q5) How do you interpret the results of a chi-square test?

A5) The results are interpreted by comparing the chi-square statistic to a critical value from the chi-square distribution table or by looking at the p-value. A significant p-value (typically <0.05) indicates that there is a significant difference between observed and expected frequencies, suggesting a relationship or discrepancy in the data.

Experiment – 4

Aim: To use Python as a programming tool for the analysis of data structures.

Theory: Python is a powerful programming tool for analyzing data structures due to its simplicity, flexibility, and vast ecosystem of libraries. It supports a variety of built-in data structures like lists, dictionaries, tuples, and sets, allowing for efficient data manipulation. Libraries such as NumPy and pandas enhance Python's capabilities by providing specialized data structures like arrays and DataFrames for handling large datasets. Python's rich collection of algorithms and functions helps in sorting, searching, and transforming data, making it a preferred choice for tasks like data analysis, machine learning, and algorithm design, all while ensuring readable and maintainable code.

Source Code:

```
import numpy as np

# Example of array manipulation using NumPy
array = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])

# View array
print("Array:\n", array)

# Sum of all elements
print("Sum of elements:", np.sum(array))

# Transpose of the array
print("Transpose:\n", np.transpose(array))
```

Output:

```
Array:
 [[1 2 3]
 [4 5 6]
 [7 8 9]]
Sum of elements: 45
Transpose:
 [[1 4 7]
 [2 5 8]
 [3 6 9]]
```

Viva-Voce:

Q1) Why is Python a popular choice for data structure analysis in data science?

A1) Python is popular due to its readability, extensive libraries (such as NumPy, pandas, and SciPy), and ease of integration with other tools. Its versatile data structures (lists, dictionaries, sets, tuples) and powerful data manipulation capabilities make it well-suited for analyzing and managing complex datasets.

Q2) What role do libraries like NumPy and pandas play in data structure analysis?

A2) NumPy provides support for numerical operations with its array object, enabling efficient handling of large datasets and mathematical computations. Pandas offers data structures like DataFrames and Series, which simplify data manipulation, analysis, and cleaning, making it easier to work with tabular data.

Q3) How do Python's built-in data structures compare to those provided by libraries like pandas?

A3) Python's built-in data structures (lists, dictionaries, tuples, sets) are versatile but may lack efficiency for large-scale data operations. Pandas provides specialized data structures like DataFrames and Series designed for handling large datasets with functionalities for data alignment, indexing, and complex operations that are more efficient and user-friendly for data analysis.

Q4) What are the advantages of using Python for handling and analyzing large datasets?

A4) Python offers advantages such as its powerful libraries (e.g., NumPy for numerical operations, pandas for data manipulation), scalability through integration with big data tools, and a wide range of visualization libraries (e.g., Matplotlib, Seaborn). These tools facilitate efficient data handling, analysis, and visualization, making Python a robust choice for large datasets.

Q5) Can you describe a common workflow for data analysis using Python?

A5) A common workflow includes:

- Data Collection: Importing data from various sources (CSV, databases, APIs) using libraries like pandas.
- Data Cleaning: Handling missing values, outliers, and inconsistencies using pandas.
- Data Transformation: Reshaping data, merging datasets, and feature engineering.
- Analysis: Performing statistical analysis and model building using libraries like NumPy, pandas, and SciPy.
- Visualization: Creating plots and charts with Matplotlib or Seaborn to interpret and present the findings.

Experiment – 5

Aim: To perform various operations such as data storage, analysis, and visualization

Theory: Data storage, analysis, and visualization are fundamental aspects of data science, each playing a crucial role in deriving insights from data.

Data Storage: Efficient data storage solutions, such as databases (SQL, NoSQL), data lakes, and cloud storage systems, ensure data is well-organized, accessible, and scalable for future analysis. Tools like MySQL, MongoDB, and AWS S3 are commonly used.

Data Analysis: Python, R, and SQL offer powerful methods to explore, clean, and manipulate data. Libraries like pandas, NumPy, and SciPy allow for complex analysis, statistical modeling, and handling large datasets.

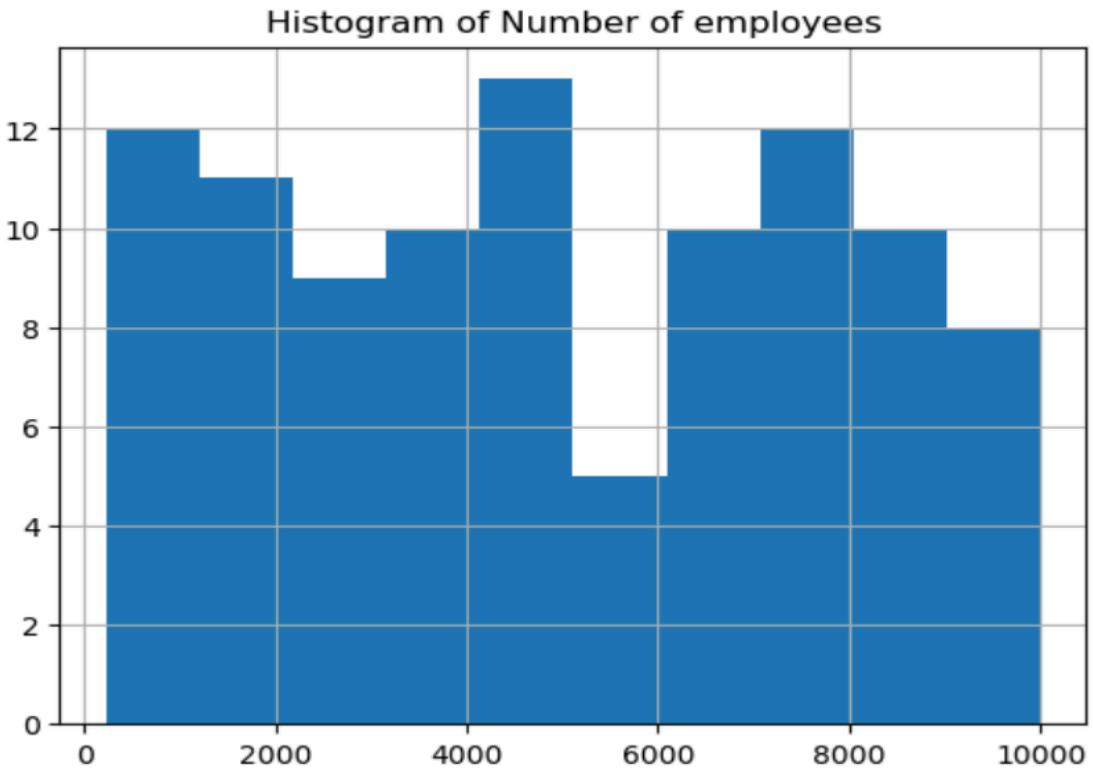
Data Visualization: Visualization tools like Matplotlib, Seaborn, and Tableau are essential for presenting data trends, distributions, and insights in graphical formats. Visualizations simplify complex data, enabling better decision-making.

Source Code:

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

# Load dataset
data = pd.read_csv('organizations.csv')

# Data storage: Save the dataset to a new file
data.to_csv('new_dataset.csv', index=False)

# Data analysis: Describe the dataset
print(data.describe())

# Data visualization: Plot a histogram
data['Number of employees'].hist()
plt.title('Histogram of Number of employees')
plt.show()
```

Output:

```
              Index      Founded  Number of employees
count   100.000000   100.000000           100.000000
mean     50.500000  1995.410000          4964.860000
std      29.011492    15.744228          2850.859799
min       1.000000  1970.000000           236.000000
25%      25.750000  1983.500000          2741.250000
50%      50.500000  1995.000000          4941.500000
75%      75.250000  2010.250000          7558.000000
max     100.000000  2021.000000          9995.000000
```



Viva-Voce:

Q1) What are the common methods for data storage in data science?

A1) Data can be stored in various formats, such as relational databases (SQL), NoSQL databases (e.g., MongoDB), flat files (CSV, JSON), or cloud storage (AWS S3, Google Cloud). These methods depend on factors like the type of data, the need for scalability, and query performance requirements.

Q2) How is data analysis performed in data science, and which tools are commonly used?

A2) Data analysis involves exploring, cleaning, and modeling data to extract insights. Common tools include Python libraries like pandas and NumPy for handling data, R for statistical analysis, and SQL for querying structured data. These tools allow for operations like filtering, aggregating, and visualizing data.

Q3) What is the role of cloud storage in data science, and how does it benefit data analysis?

A3) Cloud storage (e.g., AWS S3, Google Cloud Storage) enables scalable, accessible, and cost-effective data management. It allows data scientists to store vast amounts of data without worrying about physical infrastructure, facilitating collaboration and integration with cloud-based analysis tools for large-scale processing.

Q4) What are the key differences between descriptive and inferential data analysis?

A4) Descriptive analysis summarizes data with measures like mean, median, and standard deviation, providing an overview of the dataset. Inferential analysis goes beyond the data at hand to make predictions or inferences about a larger population based on a sample, often using hypothesis testing or predictive modeling.

Q5) How do tools like Matplotlib and Seaborn assist in data visualization?A5) Matplotlib and Seaborn are Python libraries used to create static, animated, or interactive plots. Matplotlib provides detailed control over plot elements, while Seaborn simplifies the creation of complex visualizations .

Experiment – 6

Aim: To perform descriptive statistics analysis and data visualization.

Theory: Descriptive statistical analysis and data visualization are key techniques in summarizing and interpreting data in data science.

Descriptive Statistical Analysis: This method involves summarizing data using measures like mean, median, mode, standard deviation, and variance. It helps in understanding the central tendency, spread, and overall distribution of data, offering insights without making predictions. It's the foundation for understanding the dataset's basic characteristics.

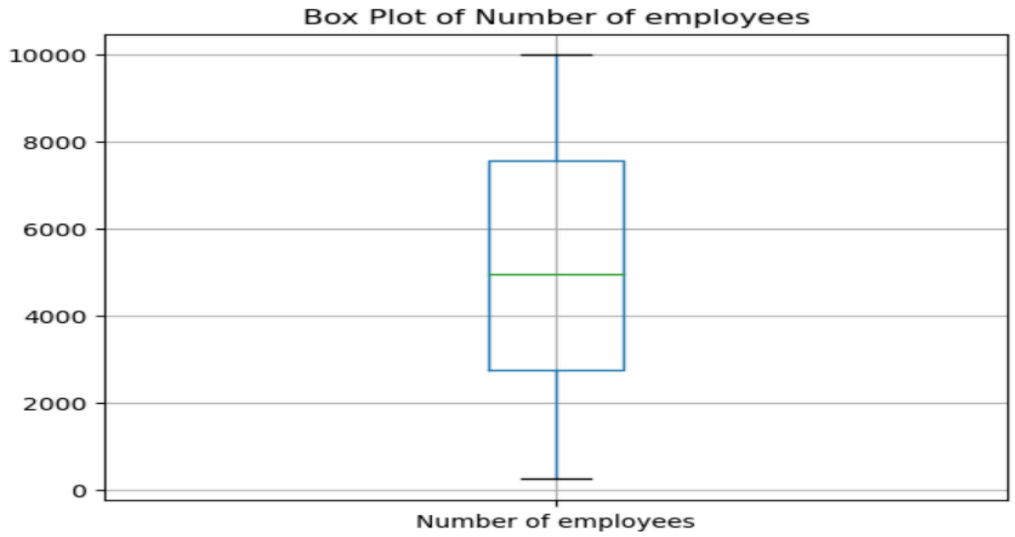
Data Visualization: Complementing descriptive statistics, data visualization tools like Matplotlib, Seaborn, and Power BI create graphical representations (histograms, box plots, bar charts) of these summaries, making patterns, trends, and outliers easily understandable, aiding in effective communication of data insights.

Source Code:

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

# Load dataset
data = pd.read_csv('organizations.csv')

# Descriptive statistics
print(data.describe())

# Data visualization: Box plot of a column
data.boxplot(column='Number of employees')
plt.title('Box Plot of Number of employees')
plt.show()
```

Output:

```
              Index      Founded  Number of employees
count    100.000000   100.000000           100.000000
mean      50.500000  1995.410000          4964.860000
std       29.011492    15.744228          2850.859799
min        1.000000  1970.000000           236.000000
25%       25.750000  1983.500000          2741.250000
50%       50.500000  1995.000000          4941.500000
75%       75.250000  2010.250000          7558.000000
max      100.000000  2021.000000          9995.000000
```



Viva-Voce:

Q1) What is descriptive statistical analysis, and what are its main components?

A1) Descriptive statistical analysis involves summarizing and describing the main features of a dataset using measures such as mean, median, mode, standard deviation, and range. It provides insights into the central tendency, dispersion, and overall distribution of data without making predictions or generalizations.

Q2) How do measures of central tendency differ from measures of dispersion in descriptive statistics?

A2) Measures of central tendency (mean, median, mode) describe the center or typical value of a dataset. Measures of dispersion (standard deviation, variance, range) describe the spread or variability around the central value. Together, they provide a comprehensive summary of the dataset's characteristics.

Q3) Why is data visualization important in the context of descriptive statistics?

A3) Data visualization is crucial as it helps to communicate the insights gained from descriptive statistics in a clear and intuitive manner. Visual tools like histograms, box plots, and scatter plots make it easier to identify patterns, trends, and anomalies in the data, facilitating better understanding and decision-making.

Q4) Can you explain the role of histograms and box plots in visualizing descriptive statistics?

A4) Histograms display the distribution of numerical data by showing the frequency of data points within specified ranges or bins, revealing the shape and spread of the data. Box plots, on the other hand, provide a visual summary of data distribution through quartiles, highlighting the median, spread, and potential outliers.

Q5) How can descriptive statistical measures be used to identify data quality issues?

A5) Descriptive statistical measures can reveal data quality issues by highlighting inconsistencies, such as unusual values or outliers. For example, an unusually high standard deviation might indicate data entry errors, while skewed distributions can signal data problems or imbalances that need addressing before further analysis.

Experiment – 7

Aim: To perform Principal Component Analysis on datasets.

Theory: Component analysis in datasets refers to techniques that reduce the dimensionality of data while retaining essential patterns and variance.

Principal Component Analysis (PCA): PCA is a widely used method in component analysis, transforming a dataset into a set of linearly uncorrelated components. It reduces the number of variables by identifying the directions (principal components) that capture the most variance in the data, making it easier to analyze and visualize complex, high-dimensional datasets.

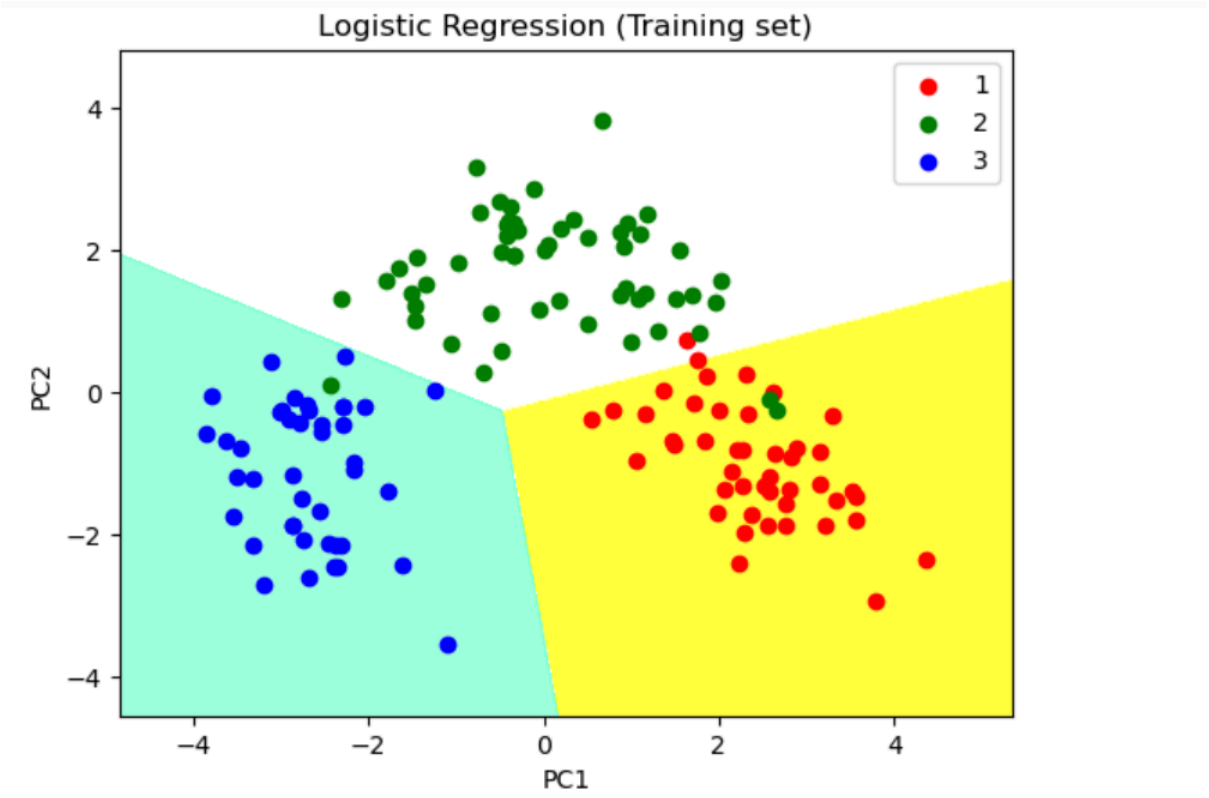
Visualization: PCA and other component analysis techniques can be visualized through 2D or 3D plots, helping data scientists interpret data structure, identify patterns, and detect relationships between variables efficiently.

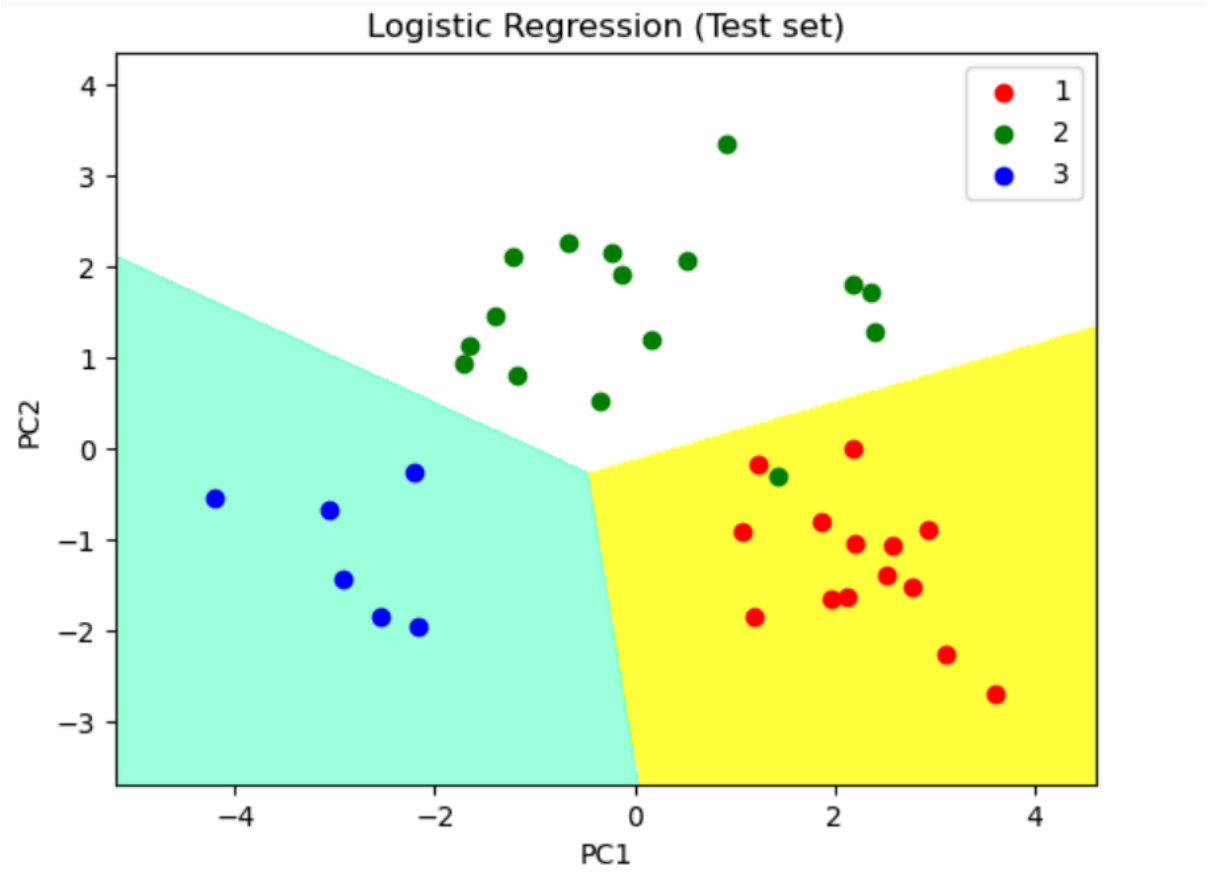
Source Code:

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

# importing or loading the dataset
dataset = pd.read_csv('wine.csv')

# distributing the dataset into two components X and Y
X = dataset.iloc[:, 0:13].values
y = dataset.iloc[:, 13].values

# Splitting the X and Y into the  Training set and Testing set
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)

# performing preprocessing part
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)


# Applying PCA function on training and testing set of X component
from sklearn.decomposition import PCA

pca = PCA(n_components=2)

X_train = pca.fit_transform(X_train)
X_test = pca.transform(X_test)

explained_variance = pca.explained_variance_ratio_

# Fitting Logistic Regression To the training set
from sklearn.linear_model import LogisticRegression

classifier = LogisticRegression(random_state=0)
classifier.fit(X_train, y_train)

# Predicting the test set result using predict function under LogisticRegression
y_pred = classifier.predict(X_test)

# making confusion matrix between test set of Y and predicted value.
from sklearn.metrics import confusion_matrix
```

```
cm = confusion_matrix(y_test, y_pred)

# Predicting the training set result through scatter plot
from matplotlib.colors import ListedColormap

X_set, y_set = X_train, y_train
X1, X2 = np.meshgrid(np.arange(start=X_set[:, 0].min() - 1,
                               stop=X_set[:, 0].max() + 1, step=0.01),
                     np.arange(start=X_set[:, 1].min() - 1,
                               stop=X_set[:, 1].max() + 1, step=0.01))

plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(),X2.ravel()]).T).reshape(X1.shape), alpha=0.75,
cmap=ListedColormap(('yellow', 'white', 'aquamarine')))

plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())

for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                color=ListedColormap(('red', 'green', 'blue'))(i), label=j)

plt.title('Logistic Regression (Training set)')
plt.xlabel('PC1')  # for Xlabel
plt.ylabel('PC2')  # for Ylabel
plt.legend()  # to show legend

# show scatter plot
plt.show()

# Visualising the Test set results through scatter plot
X_set, y_set = X_test, y_test

X1, X2 = np.meshgrid(np.arange(start=X_set[:, 0].min() - 1, stop=X_set[:, 0].max() + 1, step=0.01),
                     np.arange(start=X_set[:, 1].min() - 1, stop=X_set[:, 1].max() + 1, step=0.01))

plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(), X2.ravel()]).T).reshape(X1.shape), alpha=0.75,
             cmap=ListedColormap(('yellow', 'white', 'aquamarine')))

plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())

for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1],
                color=ListedColormap(('red', 'green', 'blue'))(i), label=j)

# title for scatter plot
plt.title('Logistic Regression (Test set)')
plt.xlabel('PC1')  # for Xlabel
plt.ylabel('PC2')  # for Ylabel
plt.legend()

# show scatter plot
plt.show()
```

Output:


Logistic Regression (Training set)
1
2
3
PC2
PC1
4
2
0
−2
−4
−4
−2
0
2
4


Logistic Regression (Test set)
1
2
3
PC2
PC1
4
3
2
1
0
−1
−2
−3
−4
−2
0
2
4

Viva-Voce:

Q1) What is component analysis, and what are its main objectives?

A1) Component analysis refers to techniques used to reduce the dimensionality of datasets while retaining important information. Its main objectives are to simplify data, identify underlying patterns, and make complex datasets easier to visualize and analyze. Common techniques include Principal Component Analysis (PCA) and Factor Analysis.

Q2) How does Principal Component Analysis (PCA) work, and what is its purpose?

A2) PCA works by transforming the original dataset into a new set of orthogonal (uncorrelated) components called principal components. These components are ordered by the amount of variance they explain in the data. The purpose of PCA is to reduce the dimensionality of the data while preserving as much variance as possible, making it easier to analyze and visualize.

Q3) What is the significance of the explained variance in PCA?

A3) Explained variance indicates the proportion of the total variance in the dataset that is captured by each principal component. It helps in understanding how much information each component retains and guides the selection of a subset of components that can effectively represent the original data.

Q4) How can you interpret the results of a PCA analysis?

A4) The results of PCA can be interpreted by examining the principal components' loadings, which show the contribution of each original variable to the components. The explained variance plot (scree plot) helps determine the number of components to retain. Visualizing the data projected onto the principal components can reveal patterns and relationships.

Q5) What are some potential limitations of PCA?

A5) PCA assumes linear relationships between variables and may not capture complex, non-linear patterns. It also requires careful interpretation, as principal components are combinations of original variables, which may not always have a straightforward or meaningful interpretation. Additionally, PCA is sensitive to scaling, so data normalization is often necessary.

Experiment – 8

Aim: To perform linear regression on datasets.

Theory: Linear regression is a fundamental technique in data science for modeling the relationship between a dependent variable and one or more independent variables.

Linear Regression: This method fits a straight line (regression line) through the dataset that best represents the relationship between variables. The equation of the line,

$$y = mx + b$$

y=mx+b, shows how changes in the independent variable(s) predict changes in the dependent variable. It's used for prediction, trend analysis, and forecasting.

Visualization: The regression line is often visualized on a scatter plot, with data points and the fitted line providing a clear representation of the correlation, making it easier to assess the model's accuracy and goodness of fit.

Source Code:

```
import numpy as np
from sklearn.linear_model import LinearRegression

x = [[0, 1], [5, 1], [15, 2], [25, 5], [35, 11], [45, 15], [55, 34], [60, 35]]
y = [4, 5, 20, 14, 32, 22, 38, 43]
x, y = np.array(x), np.array(y)

model = LinearRegression().fit(x, y)

r_sq = model.score(x, y)
print(f"coefficient of determination: {r_sq}")
print(f"intercept: {model.intercept_}")
print(f"coefficients: {model.coef_}")

y_pred = model.predict(x)
print(f"predicted response:\n{y_pred}")
```

Output:

```
coefficient of determination: 0.8615939258756776
intercept: 5.52257927519819
coefficients: [0.44706965 0.25502548]
predicted response:
[ 5.77760476  8.012953   12.73867497 17.9744479  23.97529728 29.4660957
 38.78227633 41.27265006]
```

Viva-Voce:

Q1) What is linear regression, and how is it used in data analysis?

A1) Linear regression is a statistical technique used to model the relationship between a dependent variable and one or more independent variables by fitting a linear equation to observed data. It is used to predict the value of the dependent variable based on the values of the independent variables and to identify trends and relationships in the data.

Q2) How do you interpret the coefficients of a linear regression model?

A2) In linear regression, the coefficients represent the change in the dependent variable for a one-unit change in the independent variable, holding all other variables constant. A positive coefficient indicates a direct relationship, while a negative coefficient suggests an inverse relationship.

Q3) What is the purpose of the R-squared value in linear regression?

A3) The R-squared value measures the proportion of the variance in the dependent variable that is explained by the independent variables in the model. It provides an indication of how well the model fits the data, with higher values indicating a better fit.

Q4) What are some common assumptions of linear regression that should be checked?

A4) Common assumptions include linearity (the relationship between variables is linear), independence (residuals are independent), homoscedasticity (constant variance of residuals), and normality (residuals are normally distributed). Checking these assumptions ensures the validity of the regression model and its predictions.

Q5) How can you assess the quality of a linear regression model beyond R-squared?

A5) Besides R-squared, model quality can be assessed using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) to evaluate prediction accuracy. Residual plots and diagnostic tests can also be used to check for violations of model assumptions and to identify any patterns that might suggest model improvements.

Experiment – 9

Aim: To perform Data Aggregation and GroupWise Operations.

Theory: Data aggregation and groupwise operations are essential techniques in data science for summarizing and analyzing data based on specific groups or categories.

Data Aggregation: This process involves combining data from multiple records to calculate summary statistics like sums, averages, counts, or maximum/minimum values. It helps in simplifying large datasets to gain meaningful insights, often using functions such as groupby() in pandas for Python.

Groupwise Operations: These operations allow for applying functions or transformations to subsets of data that share common attributes. For example, grouping by a categorical variable (like region or product) and performing operations on each group helps uncover trends, patterns, and relationships that may vary across different groups.

Visualization: Groupwise data can be effectively visualized using bar charts, pie charts, or box plots to compare groups and highlight variations or similarities, making it easier to communicate insights from the data.

Source Code:

```
# import module
import pandas as pd

# Creating our dataset
df = pd.DataFrame([[9, 4, 8, 9],[8, 10, 7, 6], [7, 6, 8, 5]], columns=['Maths', 'English','Science', 'History'])

# display dataset
print(df)
print(df.sum())
print(df.describe())
print(df.agg(['sum', 'min', 'max']))

a = df.groupby('Maths')
a.first()
b = df.groupby(['Maths', 'Science'])
b.first()
```

Output:

```
   Maths  English  Science  History
0      9        4        8        9
1      8       10        7        6
2      7        6        8        5
Maths      24
English    20
Science    23
History    20
```

```
dtype: int64
       Maths    English   Science   History
count    3.0   3.000000  3.000000  3.000000
mean     8.0   6.666667  7.666667  6.666667
std      1.0   3.055050  0.577350  2.081666
min      7.0   4.000000  7.000000  5.000000
25%      7.5   5.000000  7.500000  5.500000
50%      8.0   6.000000  8.000000  6.000000
75%      8.5   8.000000  8.000000  7.500000
max      9.0  10.000000  8.000000  9.000000
     Maths  English  Science  History
sum     24       20       23       20
min      7        4        7        5
max      9       10        8        9
```

|:

		English	History
Maths	**Science**		
7	**8**	6	5
8	**7**	10	6
9	**8**	4	9

Viva-Voce:

Q1) What is data aggregation, and why is it important in data analysis?

A1) Data aggregation involves summarizing and combining data from multiple records or sources to compute aggregate values such as sums, averages, or counts. It is important because it helps in simplifying large datasets, providing meaningful summaries and insights, and facilitating comparative analysis.

Q2) How do you perform groupwise operations in Python using pandas?

A2) In Python, pandas provides the groupby() function to perform groupwise operations. By grouping data based on one or more columns, you can apply aggregate functions (like sum, mean, count) or transformations to each group. For example, df.groupby('column').mean() calculates the mean of each group in the specified column.

Q3) What are some common aggregation functions used in data analysis?

A3) Common aggregation functions include sum (total value), mean (average value), median (middle value), count (number of entries), min (minimum value), and max (maximum value). These functions help in summarizing the data and extracting key metrics.

Q4) How can you handle missing values during aggregation?

A4) During aggregation, missing values can be handled by using functions like fillna() to impute missing values or by choosing to ignore them with options like dropna(). Aggregation functions often have parameters to handle missing values, such as skipna=True in pandas, which excludes NaNs from calculations.

Q5) What is the difference between aggregation and transformation in groupwise operations?

A5) Aggregation involves computing summary statistics for each group, such as totals or averages, and returning a reduced dataset. Transformation, on the other hand, involves applying functions to each group.

1. Time Series Analysis

A.

Aim

To analyze and forecast time series data using statistical and machine learning techniques.

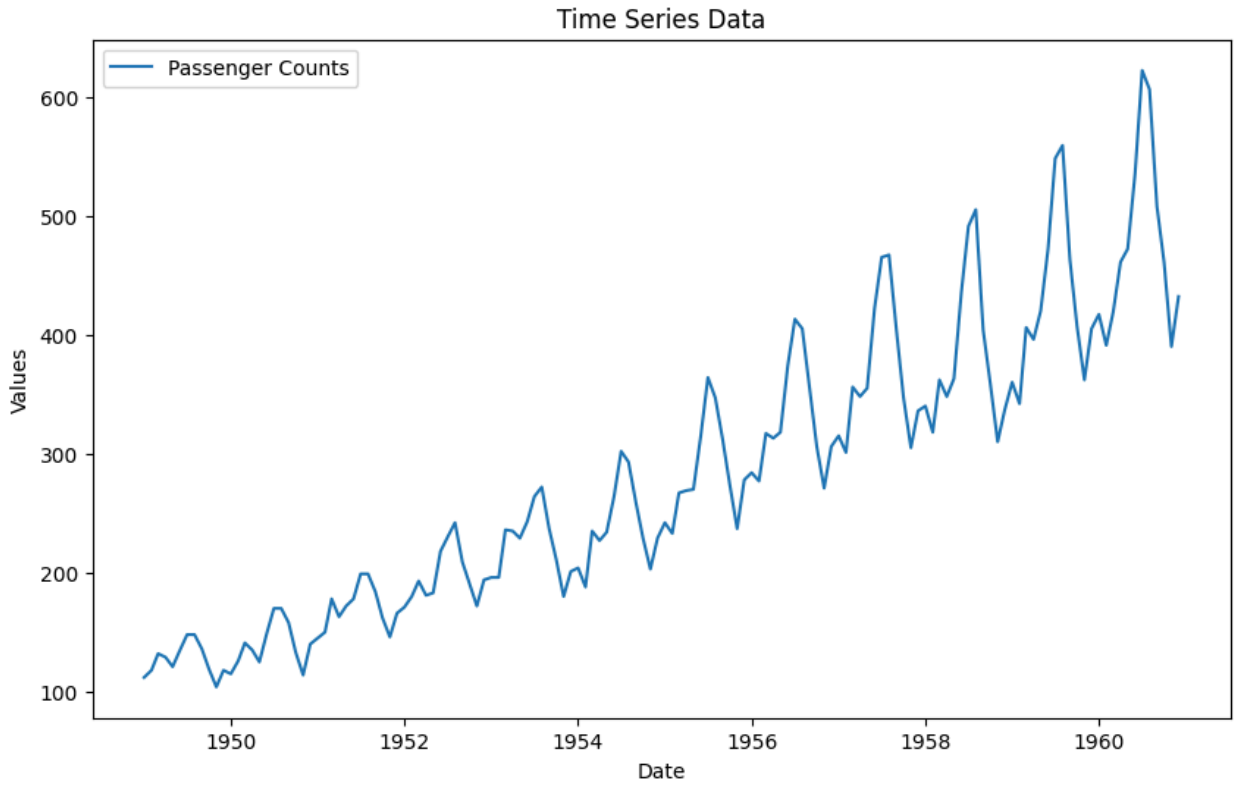
Theory

Time series analysis involves techniques to explore, model, and forecast values over time. Key steps include seasonal decomposition, moving averages, ARIMA for forecasting, and using evaluation metrics like MAE and RMSE to measure accuracy.

Source Code:

```
# Import libraries
import pandas as pd
import matplotlib.pyplot as plt

# Load dataset (e.g., stock prices or weather data)
data =
pd.read_csv('https://raw.githubusercontent.com/jbrownlee/Datasets/master/a
irline-passengers.csv')
data['Month'] = pd.to_datetime(data['Month'])
data.set_index('Month', inplace=True)

# Visualize the data
plt.figure(figsize=(10, 6))
plt.plot(data, label='Passenger Counts')
plt.title('Time Series Data')
plt.xlabel('Date')
plt.ylabel('Values')
plt.legend()
plt.show()
```

Output:


Time Series Data
Passenger Counts
600
500
400
300
200
100
Values
1950
1952
1954
1956
1958
1960
Date

1.2 Seasonal Decomposition

Aim

To decompose a time series into its trend, seasonal, and residual components.

Theory

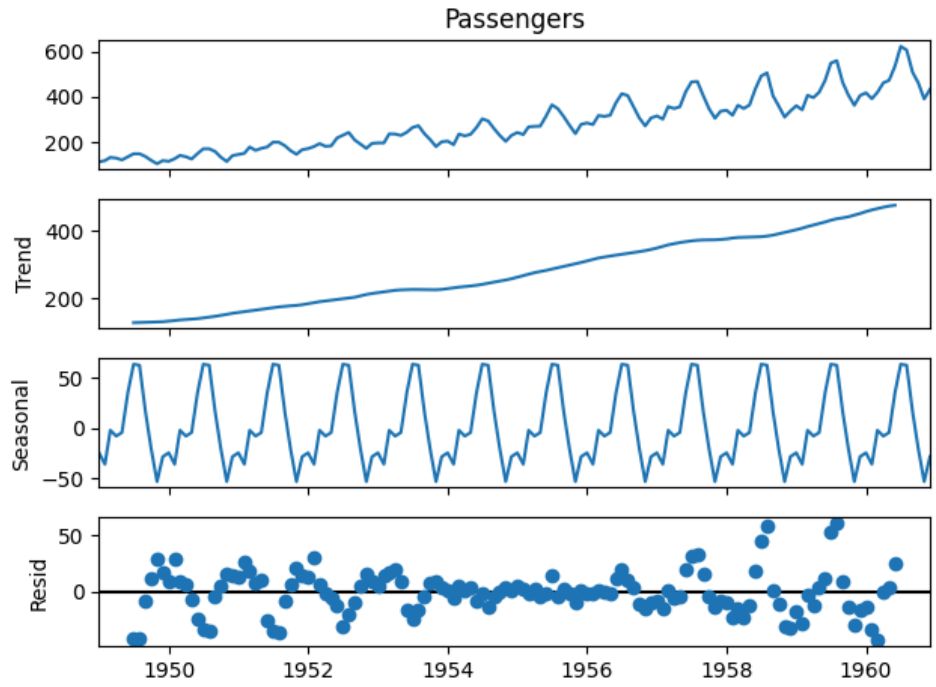
Seasonal decomposition splits time series data into:

1. **Trend:** Long-term progression of the series.
2. **Seasonal:** Short-term repeating patterns.
3. **Residual:** Noise or random fluctuations. This helps understand the underlying structure of the data and guides forecasting.

Source Code:

```
from statsmodels.tsa.seasonal import seasonal_decompose

# Perform seasonal decomposition
result = seasonal_decompose(data['Passengers'], model='additive')
result.plot()
plt.show()
```

Output:



1.3 Moving Average Forecasting

Aim

To smooth time series data using a moving average model and make short-term forecasts.

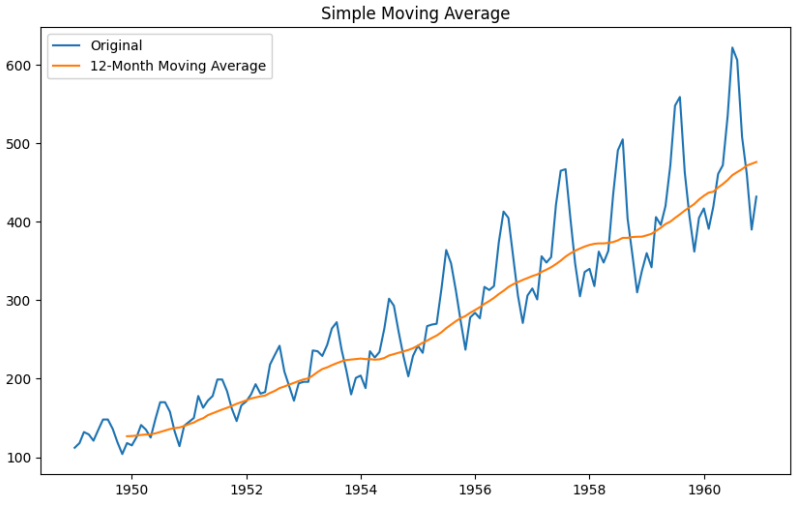
Theory

The moving average model calculates the average of data points over a specified window size, reducing noise and highlighting trends. It is useful for detecting overall patterns but lacks predictive ability for non-stationary data.

Source Code:

```
# Moving average
data['SMA_12'] = data['Passengers'].rolling(window=12).mean()

# Plot
plt.figure(figsize=(10, 6))
plt.plot(data['Passengers'], label='Original')
plt.plot(data['SMA_12'], label='12-Month Moving Average')
plt.title('Simple Moving Average')
plt.legend()
plt.show()
```

Output:



1.4 ARIMA Model

Aim

To apply the ARIMA model for time series forecasting.

Theory

ARIMA (AutoRegressive Integrated Moving Average) is a popular statistical model for forecasting time series. It consists of:

- **AR (AutoRegression):** Relationship between past and present values.
- **I (Integrated):** Differencing to make data stationary.
- **MA (Moving Average):** Relationship between past forecast errors.

The model's parameters (p, d, q) are chosen based on data characteristics.

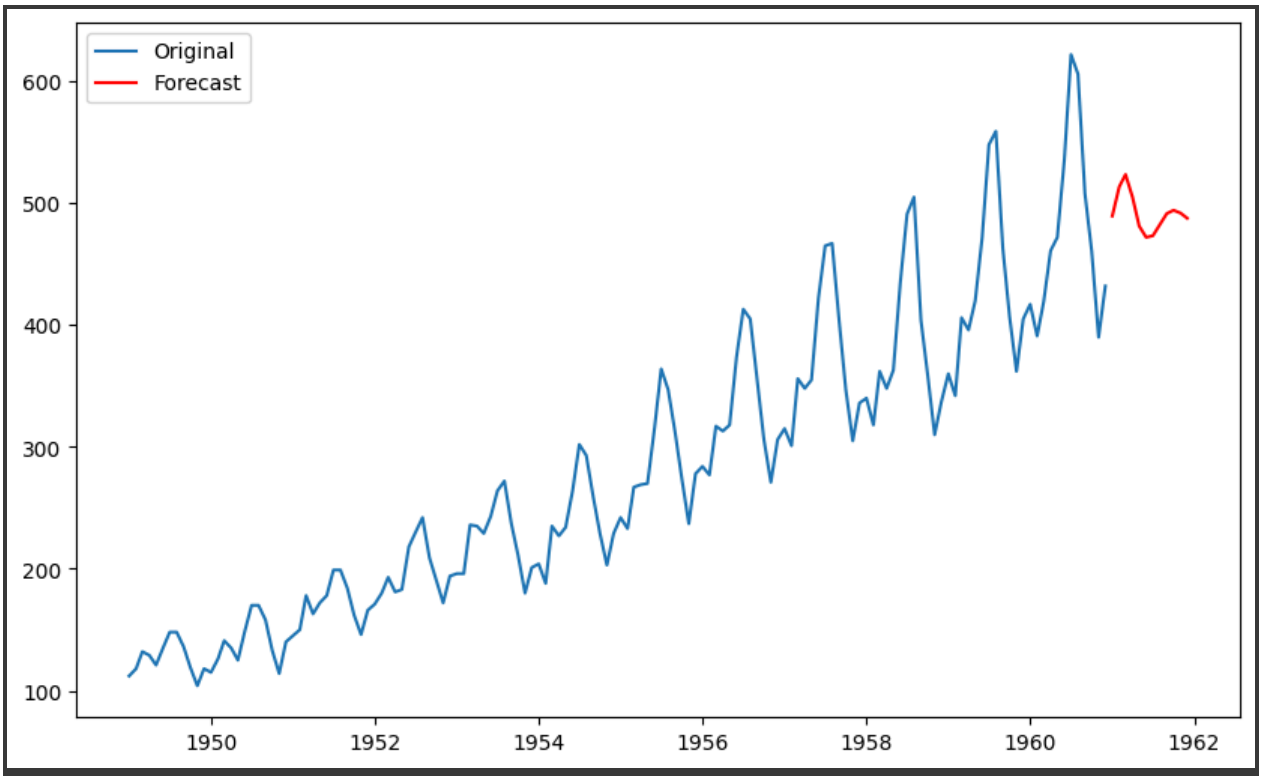
Source Code:

```
from statsmodels.tsa.arima.model import ARIMA

# Fit ARIMA model
model = ARIMA(data['Passengers'], order=(5, 1, 0))
model_fit = model.fit()

# Forecast
forecast = model_fit.forecast(steps=12)
print("Forecast:\n", forecast)

# Plot
plt.figure(figsize=(10, 6))
plt.plot(data['Passengers'], label='Original')
plt.plot(forecast, label='Forecast', color='red')
plt.legend()
plt.show()
```

Output:

```
Forecast:
 1961-01-01    489.459724
1961-02-01    513.421772
1961-03-01    523.538285
1961-04-01    505.021114
1961-05-01    481.184564
```

```
1961-06-01    471.972590
1961-07-01    473.299157
1961-08-01    482.408891
1961-09-01    491.484805
1961-10-01    494.185149
1961-11-01    491.917080
1961-12-01    487.640958
Freq: MS, Name: predicted_mean, dtype: float64
```



1.5 Evaluate Forecasting

Aim

To evaluate the performance of time series forecasting using metrics like MAE and RMSE.

Theory

Forecast accuracy is measured using:

- Mean Absolute Error (MAE): Average absolute difference between actual and predicted values.
- Root Mean Squared Error (RMSE): Square root of the average squared differences. Lower values of MAE and RMSE indicate better forecasting performance.

Source Code:

```
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

# Metrics
actual = data['Passengers'][-12:]
predicted = forecast[:12]
mae = mean_absolute_error(actual, predicted)
rmse = np.sqrt(mean_squared_error(actual, predicted))

print(f"MAE: {mae}, RMSE: {rmse}")
```

Output:

```
MAE: 74.60026688791862, RMSE: 86.3153811004276
```

1.6 ACF and PACF

Aim

To evaluate the performance of time series forecasting using metrics like MAE and RMSE.

Theory

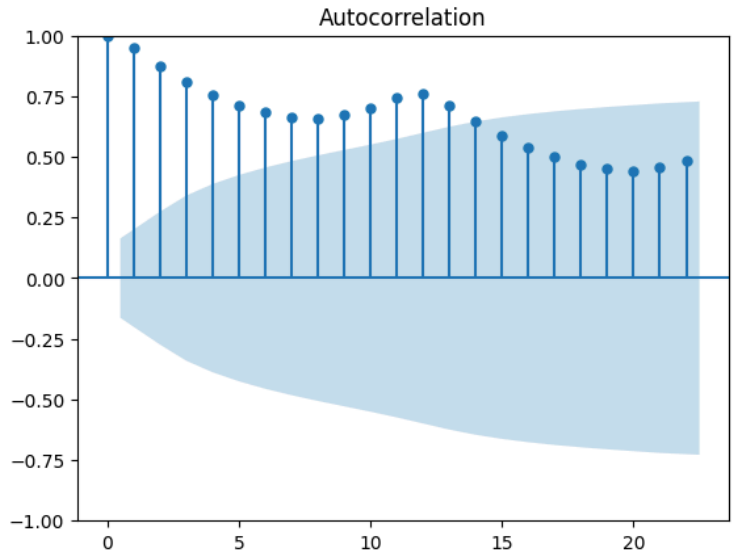
Forecast accuracy is measured using:

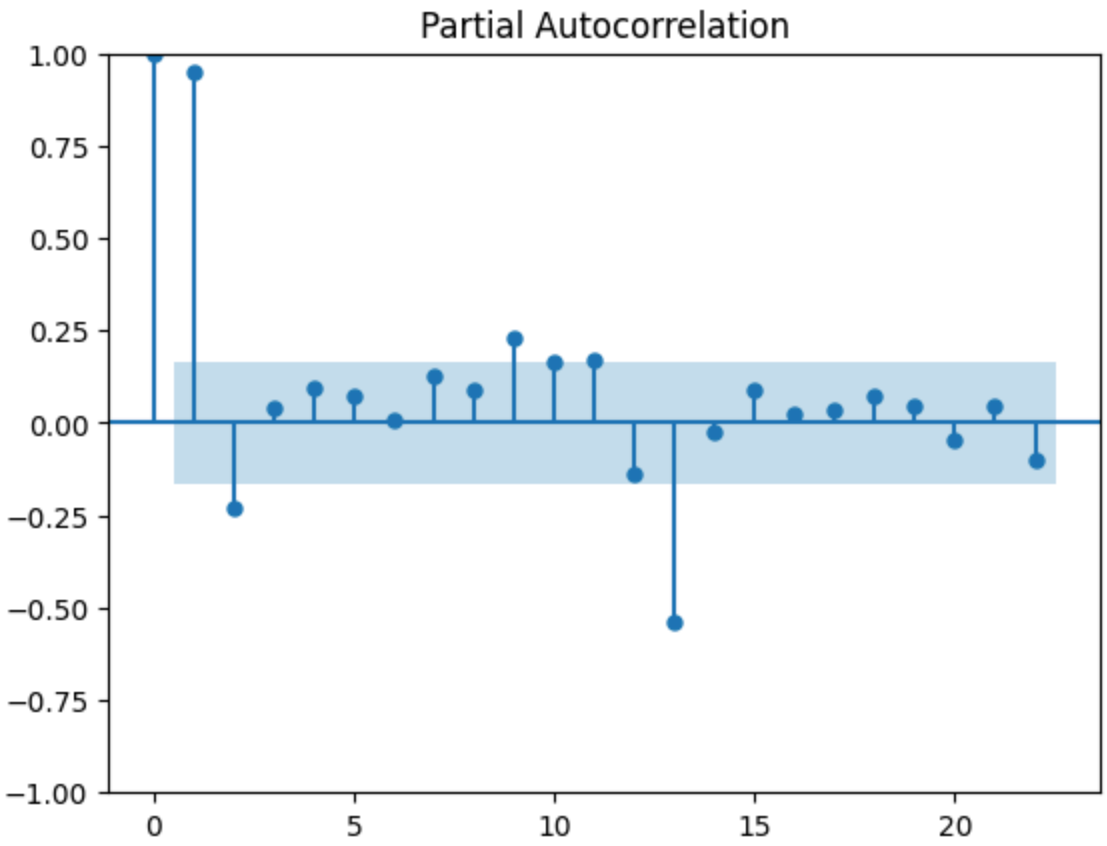
- Mean Absolute Error (MAE): Average absolute difference between actual and predicted values.
- Root Mean Squared Error (RMSE): Square root of the average squared differences. Lower values of MAE and RMSE indicate better forecasting performance.

Source Code:

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

plot_acf(data['Passengers'])
plt.show()

plot_pacf(data['Passengers'])
plt.show()
```

Output:




Partial Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20

1.7 Time Series Cross-Validation

Source Code:

```
from sklearn.model_selection import TimeSeriesSplit

# Time Series Cross-Validation
tscv = TimeSeriesSplit(n_splits=5)
for train_index, test_index in tscv.split(data):
    print("Train:", train_index, "Test:", test_index)
```

Output:

```
Train: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23] Test: [24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47]
Train: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47] Test: [48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71]
Train: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71] Test: [72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95]
Train: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71
 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95] Test: [ 96  97  98  99 100 101 102 103 104 105 106 107 108 109 110 111 112 113
 114 115 116 117 118 119]
Train: [  0   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17
  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34  35
  36  37  38  39  40  41  42  43  44  45  46  47  48  49  50  51  52  53
  54  55  56  57  58  59  60  61  62  63  64  65  66  67  68  69  70  71
  72  73  74  75  76  77  78  79  80  81  82  83  84  85  86  87  88  89
  90  91  92  93  94  95  96  97  98  99 100 101 102 103 104 105 106 107
 108 109 110 111 112 113 114 115 116 117 118 119] Test: [120 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137
 138 139 140 141 142 143]
```

2. Clustering Techniques

Aim

To apply and evaluate clustering techniques for grouping similar data points.

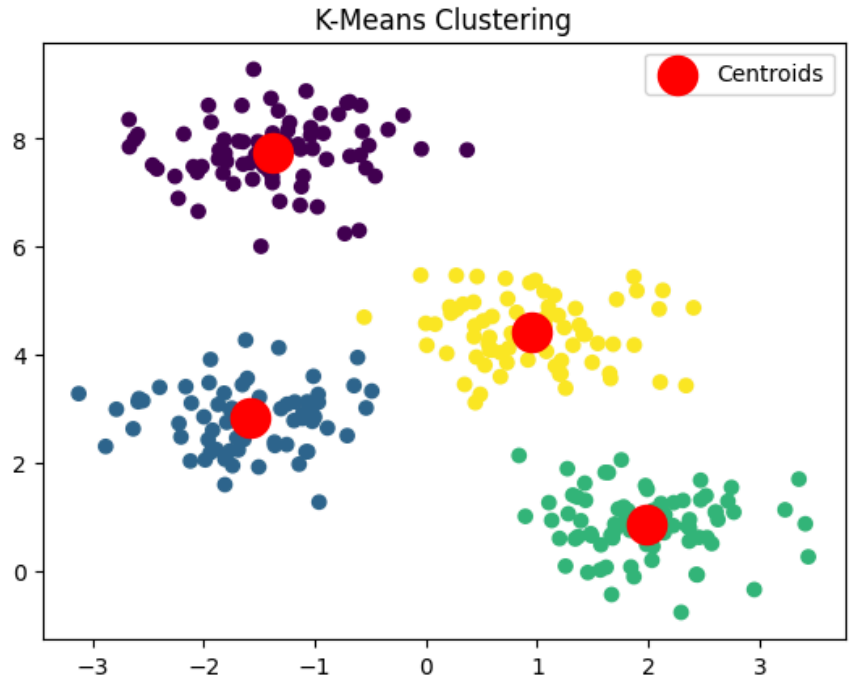
Theory

Clustering involves partitioning datasets into groups. Methods like K-Means, Hierarchical Clustering, and DBSCAN identify patterns, while dimensionality reduction techniques like PCA and t-SNE enhance visualization.

Source Code:

```
from sklearn.cluster import KMeans
from sklearn.datasets import make_blobs

# Generate data
X, _ = make_blobs(n_samples=300, centers=4, cluster_std=0.6,
random_state=0)

# Apply K-Means
kmeans = KMeans(n_clusters=4)
y_kmeans = kmeans.fit_predict(X)

# Plot
plt.scatter(X[:, 0], X[:, 1], c=y_kmeans, cmap='viridis')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1],
s=300, c='red', label='Centroids')
plt.title('K-Means Clustering')
plt.legend()
plt.show()
```

Output:



2.2 Hierarchical Clustering

Aim

To group similar data points using hierarchical clustering and visualize the results with a dendrogram.

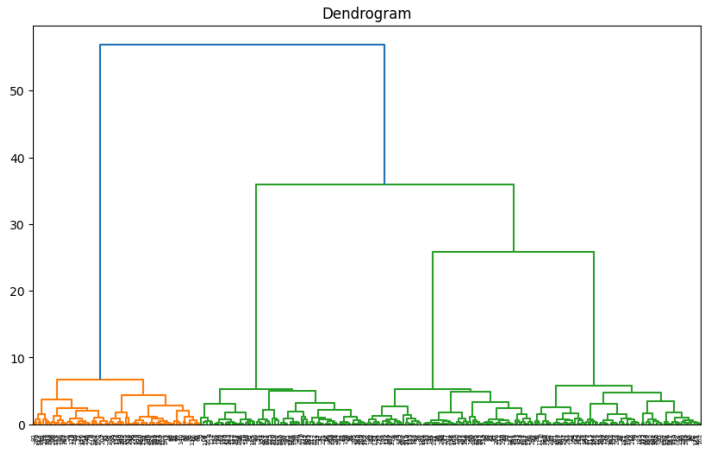
Theory

Hierarchical clustering is a method of clustering that builds a hierarchy of clusters by either merging smaller clusters (agglomerative) or splitting larger ones (divisive). A dendrogram represents this hierarchy, illustrating the arrangement of clusters and the order of their merges, providing insights into the relationships between data points.

Source Code:

```
from scipy.cluster.hierarchy import dendrogram, linkage

# Hierarchical Clustering
linked = linkage(X, 'ward')

# Dendrogram
plt.figure(figsize=(10, 6))
dendrogram(linked)
plt.title('Dendrogram')
plt.show()
```

Output:



2.3 DBSCAN Clustering

Aim

To perform clustering using the DBSCAN algorithm and identify core points, border points, and noise.

Theory

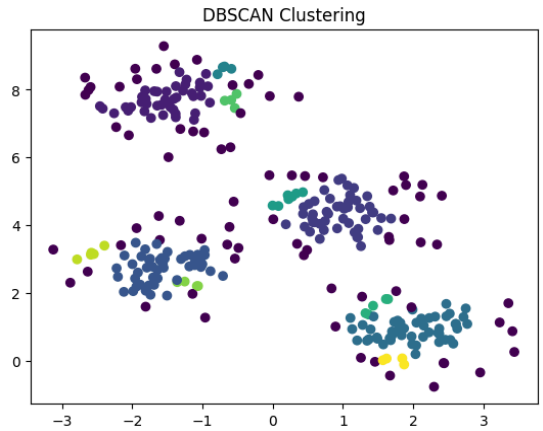
DBSCAN (Density-Based Spatial Clustering of Applications with Noise) groups data points based on density:

- **Core Points:** Points with sufficient neighbors within a radius (ε).
- **Border Points:** Points within the radius of a core point but lacking neighbors.
- **Noise:** Points that do not belong to any cluster. This method is robust to noise and does not require the number of clusters to be predefined.

Source Code:

```
from sklearn.cluster import DBSCAN

# Apply DBSCAN
dbscan = DBSCAN(eps=0.3, min_samples=5).fit(X)
labels = dbscan.labels_

# Plot
plt.scatter(X[:, 0], X[:, 1], c=labels, cmap='viridis')
plt.title('DBSCAN Clustering')
plt.show()
```

Output:



2.4 Gaussian Mixture Model

Aim

To apply the Gaussian Mixture Model for clustering and visualize the resulting clusters.

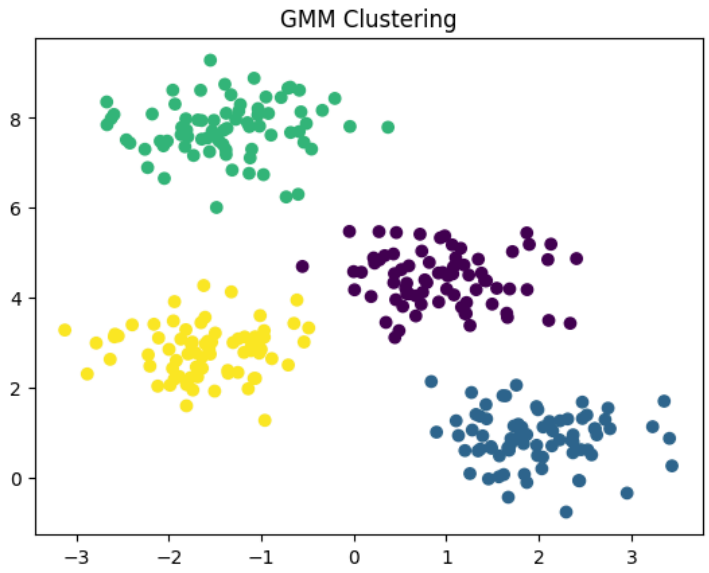
Theory

The Gaussian Mixture Model assumes data points are generated from a mixture of Gaussian distributions. It uses probabilistic approaches to assign data points to clusters, allowing for overlapping clusters. GMM is more flexible than K-Means because it captures variances and covariances of clusters, accommodating non-spherical cluster shapes.

Source Code:

```
from sklearn.mixture import GaussianMixture

# Apply GMM
gmm = GaussianMixture(n_components=4)
gmm_labels = gmm.fit_predict(X)

# Plot
plt.scatter(X[:, 0], X[:, 1], c=gmm_labels, cmap='viridis')
plt.title('GMM Clustering')
plt.show()
```

Output:



2.5 Evaluate Clustering

Aim

To evaluate the performance of clustering algorithms using metrics like the Silhouette Score.

Theory

The Silhouette Score measures the quality of clustering by comparing the average intra-cluster distance (compactness) to the nearest inter-cluster distance (separation). Values range from -1 to 1:

- 1: Perfect clustering.
- 0: Overlapping clusters.
- Negative values: Incorrect clustering.
  This metric helps determine the effectiveness of clustering algorithms.

Source Code:

```
from sklearn.metrics import silhouette_score

# Silhouette Score
score = silhouette_score(X, y_kmeans)
print("Silhouette Score for K-Means:", score)
```

Output:

```
Silhouette Score for K-Means: 0.6819938690643478
```

2.6 Image Data Clustering

Aim

To apply clustering techniques to image data and visualize the resulting clusters.

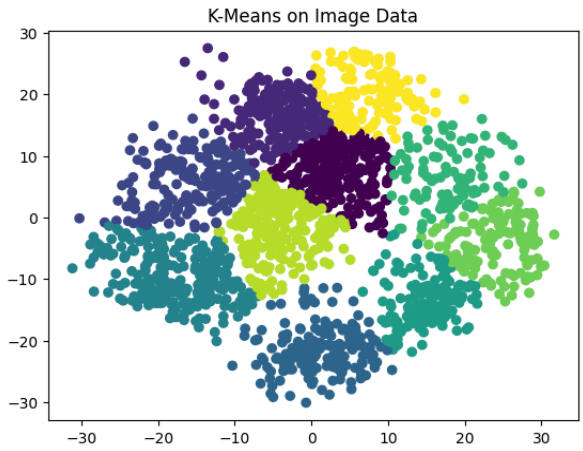
Theory

Image data clustering involves grouping pixel values or feature vectors derived from images. Techniques like K-Means or DBSCAN identify patterns or segments within the image. Dimensionality reduction, such as PCA, is often applied beforehand to simplify the high-dimensional image data for better clustering results.

Source Code:

```
from sklearn.datasets import load_digits
from sklearn.decomposition import PCA

# Load image data
digits = load_digits()
data = PCA(2).fit_transform(digits.data)

# K-Means
kmeans = KMeans(n_clusters=10)
labels = kmeans.fit_predict(data)

# Plot
plt.scatter(data[:, 0], data[:, 1], c=labels, cmap='viridis')
plt.title('K-Means on Image Data')
plt.show()
```

Output:



2.7 Compare K-Means and DBSCAN

Aim

To compare the performance of K-Means and DBSCAN clustering on a dataset.

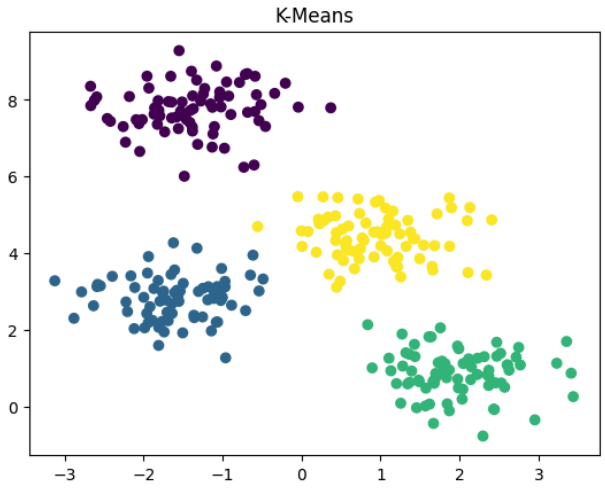
Theory

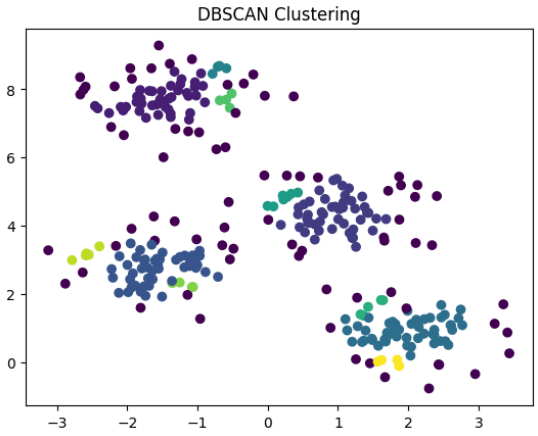
- K-Means: Groups data based on minimizing the variance within clusters. It works well for spherical clusters but is sensitive to noise and requires the number of clusters to be specified.
- DBSCAN: Groups based on density, is robust to noise, and does not need the number of clusters predefined. It works better for datasets with varying densities and non-spherical clusters. Comparing their outputs helps understand their strengths and limitations.

Source Code:

```
# K-Means and DBSCAN comparison
plt.scatter(X[:, 0], X[:, 1], c=y_kmeans, cmap='viridis', label='K-Means')
plt.title('K-Means')
plt.show()

plt.scatter(X[:, 0], X[:, 1], c=labels, cmap='viridis', label='DBSCAN')
plt.title('DBSCAN')
plt.show()
```

Output:




DBSCAN Clustering
8
6
4
2
0
−3
−2
−1
0
1
2
3

2.8 Dimensionality Reduction Using PCA

Aim

To reduce the dimensionality of data using PCA and cluster the reduced data.

Theory

Principal Component Analysis (PCA) reduces high-dimensional data into a smaller number of components by maximizing variance while retaining the essential structure. Dimensionality reduction with PCA simplifies clustering by:

1. Improving computational efficiency.
2. Eliminating noise or irrelevant features.
3. Enhancing visualization, especially when reducing to 2D or 3D.
   PCA is often a preprocessing step before applying clustering algorithms.

Source Code:

```
from sklearn.decomposition import PCA

# PCA
pca = PCA(n_components=2)
X_reduced = pca.fit_transform(X)

# K-Means on reduced data
kmeans = KMeans(n_clusters=4)
labels = kmeans.fit_predict(X_reduced)

# Plot
plt.scatter(X_reduced[:, 0], X_reduced[:, 1], c=labels, cmap='viridis')
plt.title('PCA + K-Means')
plt.show()
```

Output: