MACHINE LEARNING

LAB MANUAL

ACADEMIC YEAR : 2024-25

COURSE CODE : BCSL606

CLASS : 6th SEM

Name of the Student: ______________________________

USN: ____

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SHRIDEVI INSTITUTE OF ENGINEERING AND TECHNOLOGY

Sira Road, NH-4, Maralenahalli, Karnataka 572106

Machine Learning lab		Semester	6
Course Code	BCSL606	CIE Marks	50
Teaching Hours/Week (L:T:P: S)	0:0:2:0	SEE Marks	50
Credits	01	Exam Hours	100
Examination type (SEE)	Practical		

Course objectives:

- To become familiar with data and visualize univariate, bivariate, and multivariate data using statistical techniques and dimensionality reduction.
- To understand various machine learning algorithms such as similarity-based learning, regression, decision trees, and clustering.
- To familiarize with learning theories, probability-based models and developing the skills required for decision-making in dynamic environments.

Sl.NO	Experiments
1	Develop a program to create histograms for all numerical features and analyze the distribution of each feature. Generate box plots for all numerical features and identify any outliers. Use California Housing dataset. **Book 1: Chapter 2**
2	Develop a program to Compute the correlation matrix to understand the relationships between pairs of features. Visualize the correlation matrix using a heatmap to know which variables have strong positive/negative correlations. Create a pair plot to visualize pairwise relationships between features. Use California Housing dataset. **Book 1: Chapter 2**
3	Develop a program to implement Principal Component Analysis (PCA) for reducing the dimensionality of the Iris dataset from 4 features to 2. **Book 1: Chapter 2**
4	For a given set of training data examples stored in a .CSV file, implement and demonstrate the Find-S algorithm to output a description of the set of all hypotheses consistent with the training examples. **Book 1: Chapter 3**
5	Develop a program to implement k-Nearest Neighbour algorithm to classify the randomly generated 100 values of x in the range of [0,1]. Perform the following based on dataset generated. a. Label the first 50 points $\{x_1,\ldots\ldots,x_{50}\}$ as follows: if (xi ≤ 0.5), then $x_i \in \text{Class}_1$, else $x_i \in \text{Class}_1$ b. Classify the remaining points, $x_{51},\ldots\ldots,x_{100}$ using KNN. Perform this for $k=1,2,3,4,5,20,30$ **Book 2: Chapter – 2**
6	Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs **Book 1: Chapter – 4**
7	Develop a program to demonstrate the working of Linear Regression and Polynomial Regression. Use Boston Housing Dataset for Linear Regression and Auto MPG Dataset (for vehicle fuel efficiency prediction) for Polynomial Regression. **Book 1: Chapter – 5**
8	Develop a program to demonstrate the working of the decision tree algorithm. Use Breast Cancer Data set for building the decision tree and apply this knowledge to classify a new sample. **Book 2: Chapter – 3**

9	Develop a program to implement the Naive Bayesian classifier considering Olivetti Face Data set for training. Compute the accuracy of the classifier, considering a few test data sets. **Book 2: Chapter – 4**
10	Develop a program to implement k-means clustering using Wisconsin Breast Cancer data set and visualize the clustering result. **Book 2: Chapter – 4**

Course outcomes (Course Skill Set):

At the end of the course the student will be able to:

- Illustrate the principles of multivariate data and apply dimensionality reduction techniques.
- Demonstrate similarity-based learning methods and perform regression analysis.
- Develop decision trees for classification and regression problems, and Bayesian models for probabilistic learning.
- Implement the clustering algorithms to share computing resources.

Assessment Details (both CIE and SEE)

The weightage of Continuous Internal Evaluation (CIE) is 50% and for Semester End Exam (SEE) is 50%. The minimum passing mark for the CIE is 40% of the maximum marks (20 marks out of 50) and for the SEE minimum passing mark is 35% of the maximum marks (18 out of 50 marks). A student shall be deemed to have satisfied the academic requirements and earned the credits allotted to each subject/ course if the student secures a minimum of 40% (40 marks out of 100) in the sum total of the CIE (Continuous Internal Evaluation) and SEE (Semester End Examination) taken together

Continuous Internal Evaluation (CIE):

CIE marks for the practical course are **50 Marks**.

The split-up of CIE marks for record/ journal and test are in the ratio **60:40**.

- Each experiment is to be evaluated for conduction with an observation sheet and record write-up. Rubrics for the evaluation of the journal/write-up for hardware/software experiments are designed by the faculty who is handling the laboratory session and are made known to students at the beginning of the practical session.
- Record should contain all the specified experiments in the syllabus and each experiment write-up will be evaluated for 10 marks.
- Total marks scored by the students are scaled down to **30 marks** (60% of maximum marks).
- Weightage to be given for neatness and submission of record/write-up on time.
- Department shall conduct a test of 100 marks after the completion of all the experiments listed in the syllabus.
- In a test, test write-up, conduction of experiment, acceptable result, and procedural knowledge will carry a weightage of 60% and the rest 40% for viva-voce.
- The suitable rubrics can be designed to evaluate each student's performance and learning ability.
- The marks scored shall be scaled down to **20 marks** (40% of the maximum marks).

The Sum of scaled-down marks scored in the report write-up/journal and marks of a test is the total CIE marks scored by the student.

Program 1

Develop a program to create histograms for all numerical features and analyze the distribution of each feature. Generate box plots for all numerical features and identify any outliers. Use California Housing dataset.

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

import warnings
warnings.filterwarnings('ignore')
```

```
df = pd.read_csv(r'C:\Users\vijay\Desktop\Machine Learning Course Batches\FDP_ML_6thSem_VTU\Datasets\housing.csv')
```

```
df.head()
```

```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                41.0        880.0           129.0   
1    -122.22     37.86                21.0       7099.0          1106.0   
2    -122.24     37.85                52.0       1467.0           190.0   
3    -122.25     37.85                52.0       1274.0           235.0   
4    -122.25     37.85                52.0       1627.0           280.0   

   population  households  median_income  median_house_value ocean_proximity  
0       322.0       126.0         8.3252            452600.0        NEAR BAY  
1      2401.0      1138.0         8.3014            358500.0        NEAR BAY  
2       496.0       177.0         7.2574            352100.0        NEAR BAY  
3       558.0       219.0         5.6431            341300.0        NEAR BAY  
4       565.0       259.0         3.8462            342200.0        NEAR BAY  
```

```
df.shape
```

```
(20640, 10)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
```

```
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

```
df.nunique()
```

```
longitude               844
latitude                862
housing_median_age       52
total_rooms            5926
total_bedrooms         1923
population             3888
households             1815
median_income         12928
median_house_value     3842
ocean_proximity           5
dtype: int64
```

Data Cleaning

```
df.isnull().sum()
```

```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
median_house_value      0
ocean_proximity         0
dtype: int64
```

```
df.duplicated().sum()
```

```
0
```

```
df['total_bedrooms'].median()
```

```
435.0
```

```
# Handling missing values
df['total_bedrooms'].fillna(df['total_bedrooms'].median(), inplace=True)
```

Feature Engineering

```
for i in df.iloc[:,2:7]:
    df[i] = df[i].astype('int')
```

```
df.head()
```

```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                  41          880             129   
1    -122.22     37.86                  21         7099            1106   
2    -122.24     37.85                  52         1467             190   
3    -122.25     37.85                  52         1274             235   
4    -122.25     37.85                  52         1627             280   

   population  households  median_income  median_house_value ocean_proximity  
0         322         126         8.3252            452600.0        NEAR BAY  
1        2401        1138         8.3014            358500.0        NEAR BAY  
2         496         177         7.2574            352100.0        NEAR BAY  
3         558         219         5.6431            341300.0        NEAR BAY  
4         565         259         3.8462            342200.0        NEAR BAY  
```

Disciptive Statistics

```
df.describe().T
```

```
                      count           mean            std         min  \
longitude           20640.0    -119.569704       2.003532   -124.3500   
latitude            20640.0      35.631861       2.135952     32.5400   
housing_median_age  20640.0      28.639486      12.585558      1.0000   
total_rooms         20640.0    2635.763081    2181.615252      2.0000   
total_bedrooms      20640.0     536.838857     419.391878      1.0000   
population          20640.0    1425.476744    1132.462122      3.0000   
households          20640.0     499.539680     382.329753      1.0000   
median_income       20640.0       3.870671       1.899822      0.4999   
median_house_value  20640.0  206855.816909  115395.615874  14999.0000   

                            25%          50%           75%          max  
longitude             -121.8000    -118.4900    -118.01000    -114.3100  
latitude                33.9300      34.2600      37.71000      41.9500  
housing_median_age      18.0000      29.0000      37.00000      52.0000  
total_rooms           1447.7500    2127.0000    3148.00000   39320.0000  
total_bedrooms         297.0000     435.0000     643.25000    6445.0000  
population             787.0000    1166.0000    1725.00000   35682.0000  
households             280.0000     409.0000     605.00000    6082.0000  
median_income            2.5634       3.5348       4.74325      15.0001  
median_house_value  119600.0000  179700.0000  264725.00000  500001.0000  
```

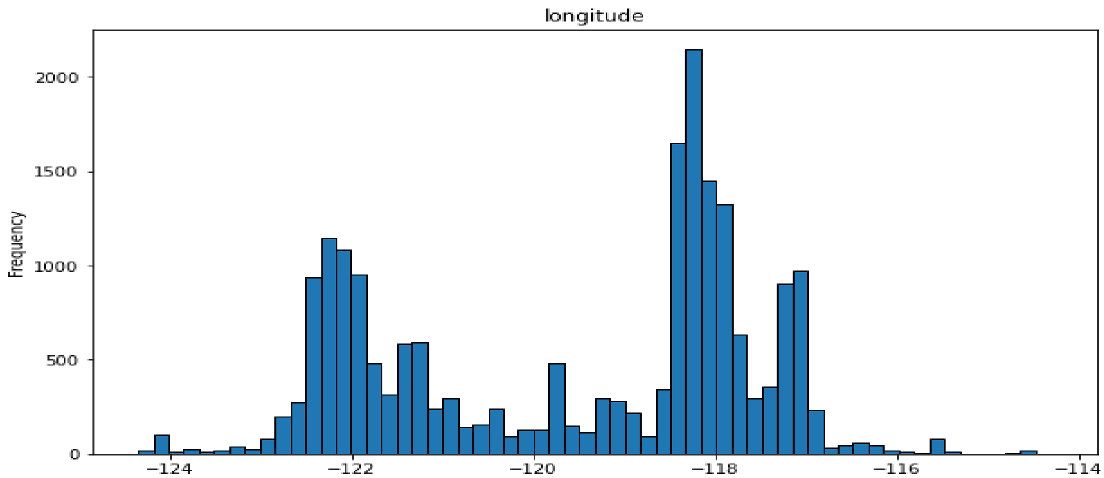
```
Numerical = df.select_dtypes(include=[np.number]).columns
print(Numerical)
```

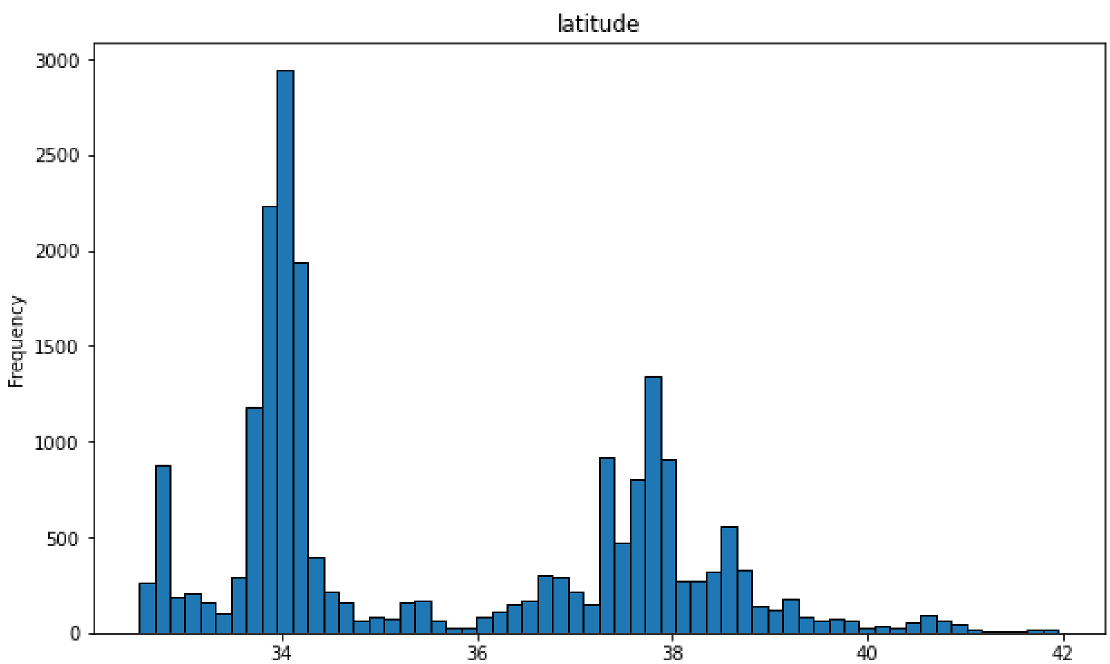
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value'],
      dtype='object')
```

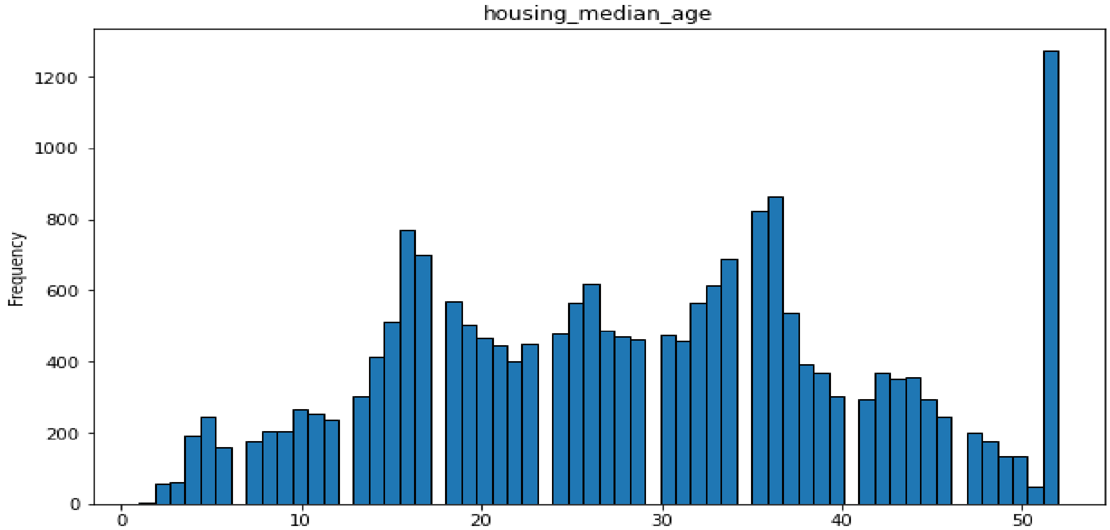
Uni-Variate Analysis

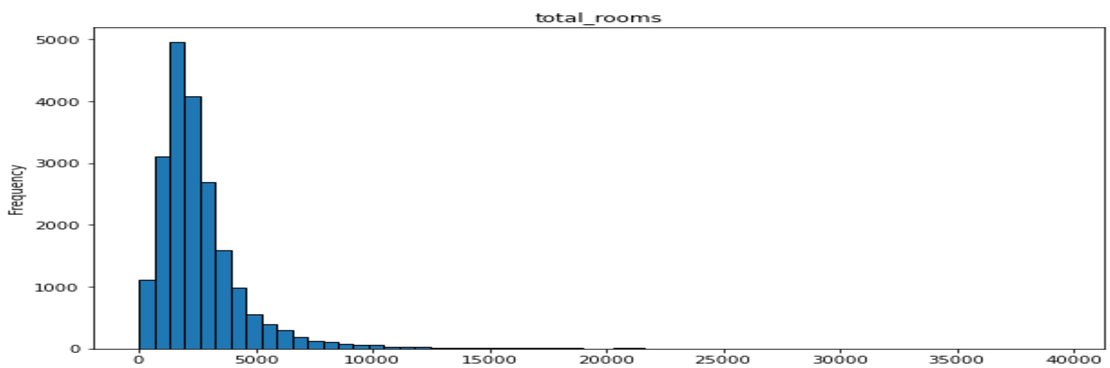
```
for col in Numerical:
    plt.figure(figsize=(10, 6))
```

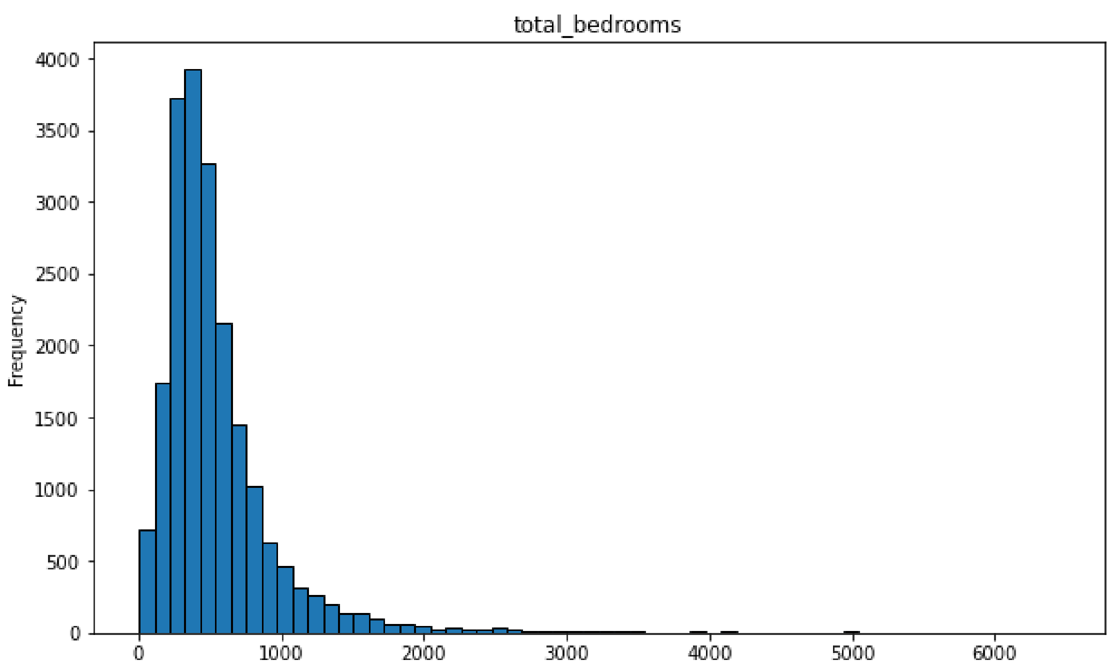
```
df[col].plot(kind='hist', title=col, bins=60, edgecolor='black')
plt.ylabel('Frequency')
plt.show()
```

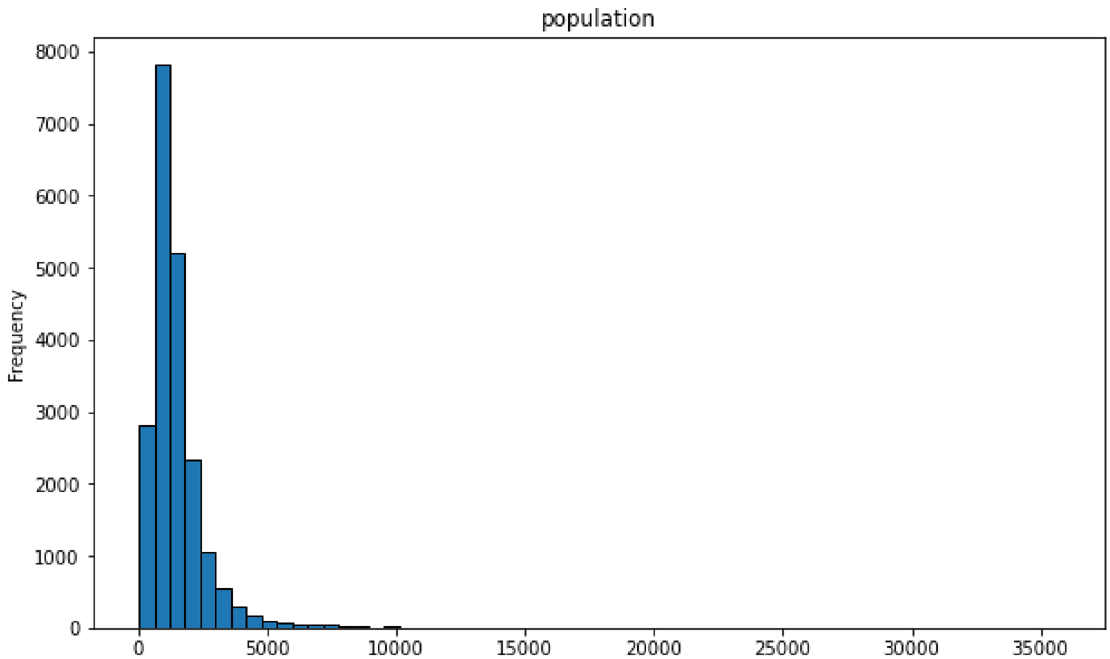


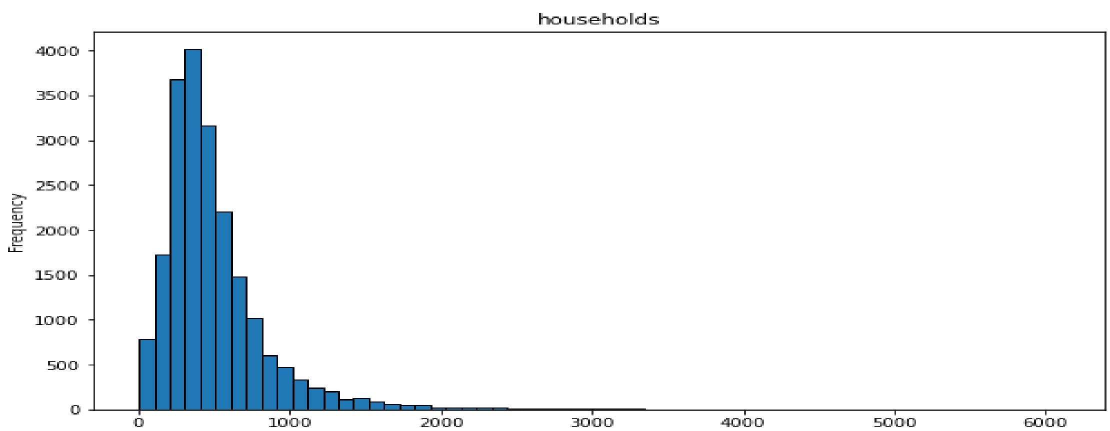



housing_median_age
Frequency
0
200
400
600
800
1000
1200
0
10
20
30
40
50

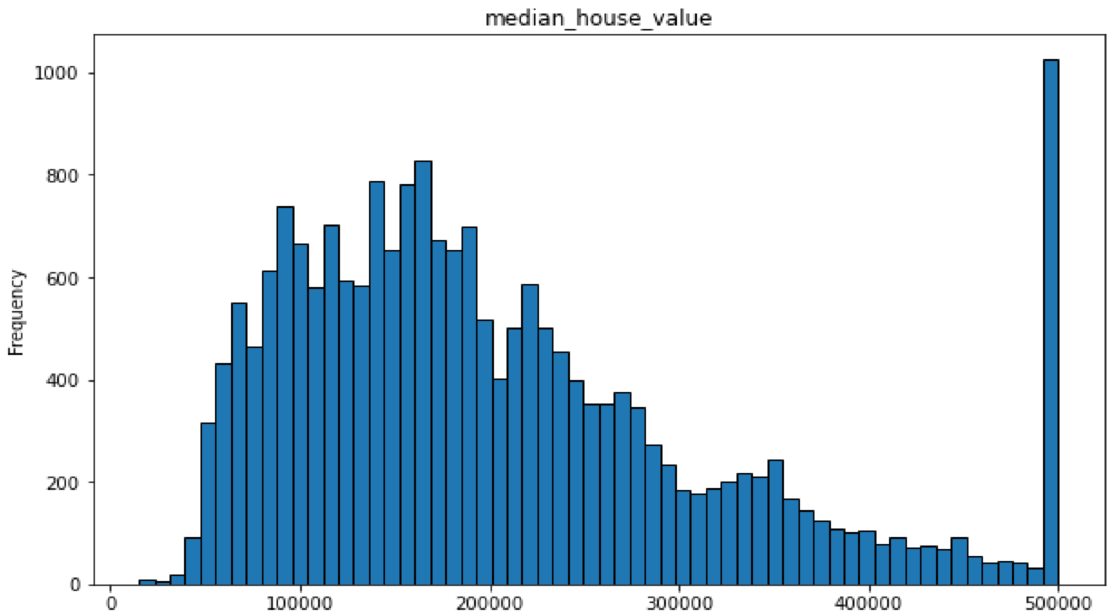

total_rooms
Frequency
0
1000
2000
3000
4000
5000
0
5000
10000
15000
20000
25000
30000
35000
40000


total_bedrooms
Frequency
0
500
1000
1500
2000
2500
3000
3500
4000
0
1000
2000
3000
4000
5000
6000


population
Frequency
8000
7000
6000
5000
4000
3000
2000
1000
0
0
5000
10000
15000
20000
25000
30000
35000


households
Frequency
4000
3500
3000
2500
2000
1500
1000
500
0
0
1000
2000
3000
4000
5000
6000


median_income
Frequency
1400
1200
1000
800
600
400
200
0
0
2
4
6
8
10
12
14



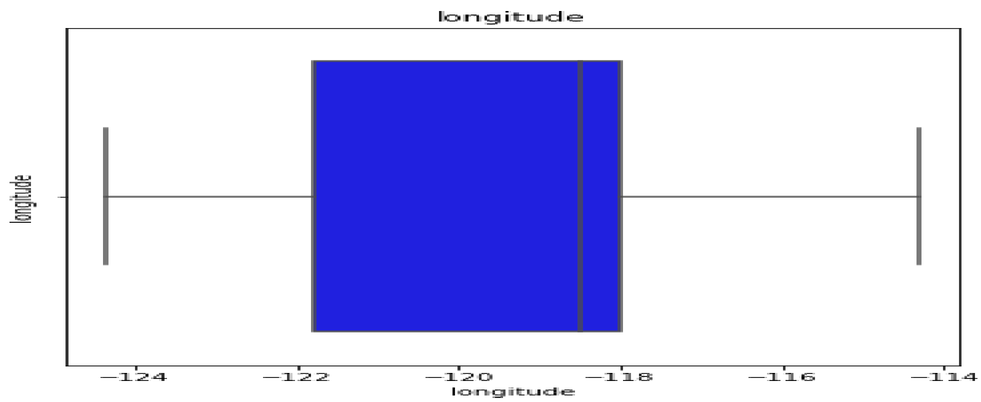
1. Longitude:
2. The dataset contains houses located in specific regions (possibly coastal areas or urban zones) as indicated by the bimodal peaks. Houses are not uniformly distributed across all longitudes.
3. Latitude:
4. Similar to longitude, the latitude distribution shows houses concentrated in particular zones. This suggests geographic clustering, possibly around major cities.
5. Housing Median Age:
6. Most houses are relatively older, with the majority concentrated in a specific range of median ages. This might imply that housing development peaked during certain decades.
7. Total Rooms:
8. The highly skewed distribution shows most houses have a lower total number of rooms. A few properties with a very high number of rooms could represent outliers (e.g., mansions or multi-unit buildings).
9. Median Income:
10. Most households fall within a low-to-mid income bracket. The steep decline after the peak suggests a small proportion of high-income households in the dataset.
11. Population:

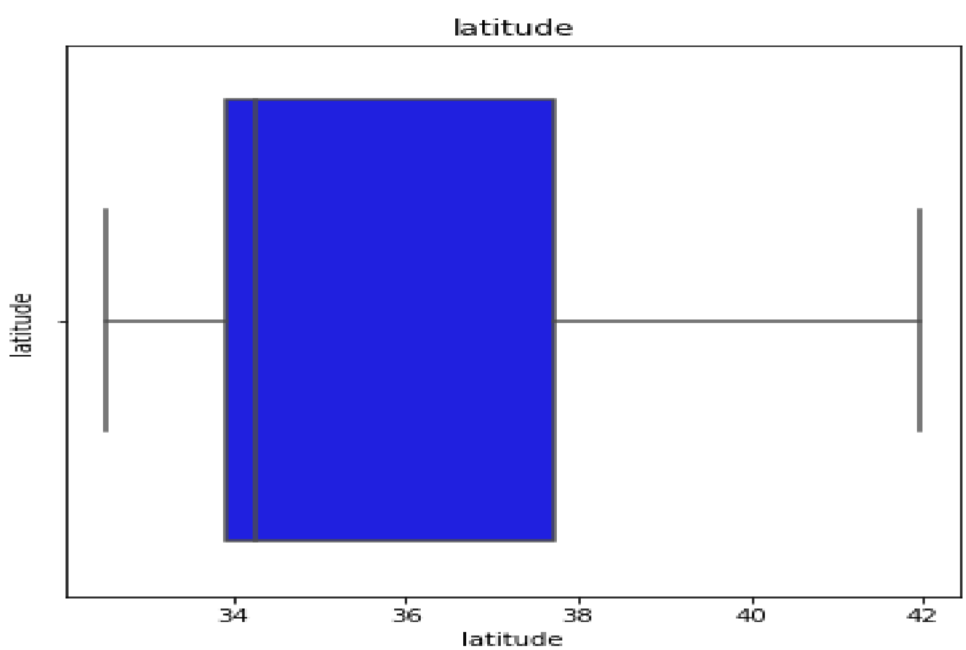
12. Most areas in the dataset have a relatively low population. However, there are some highly populated areas, as evidenced by the long tail. These may represent urban centers.

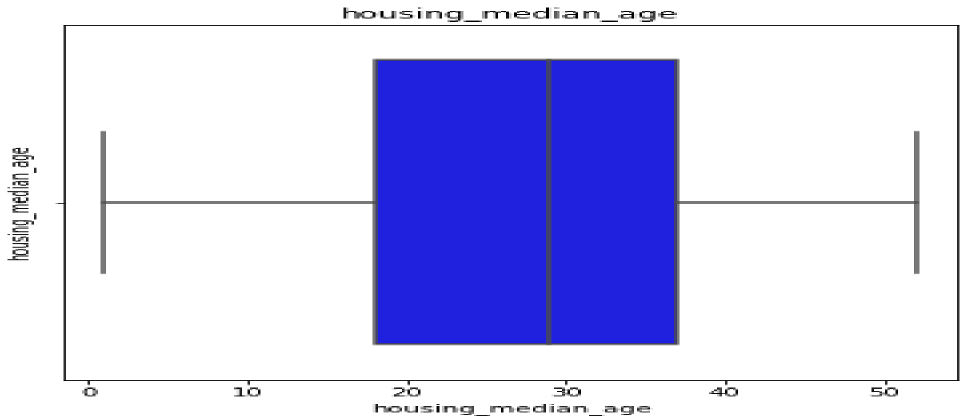
13. Median House Value:

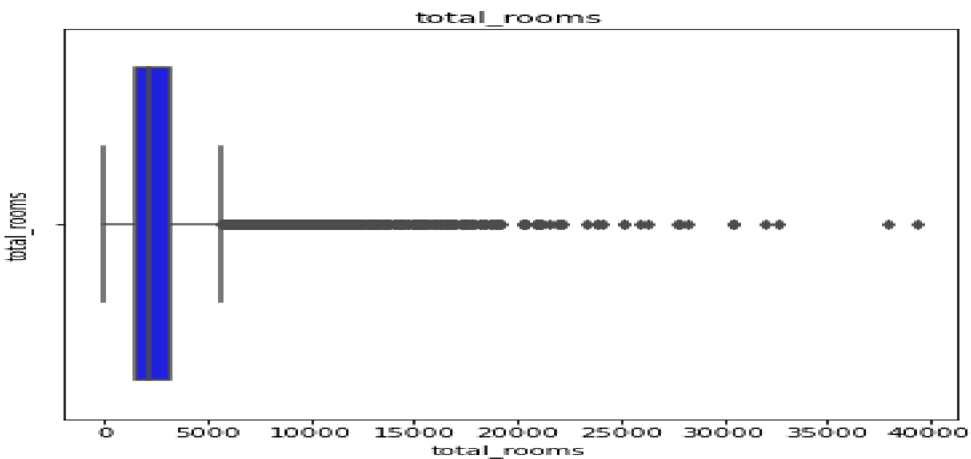
14. The sharp peak at the end of the histogram suggests that house prices in the dataset are capped at a maximum value, which could limit the variability in predictions.

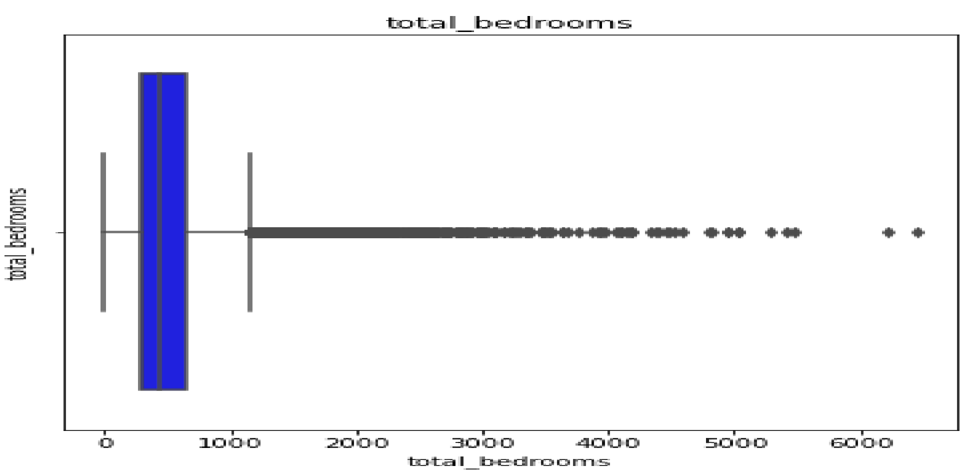
```
for col in Numerical:
    plt.figure(figsize=(6, 6))

    sns.boxplot(df[col], color='blue')
    plt.title(col)
    plt.ylabel(col)

    plt.show()
```

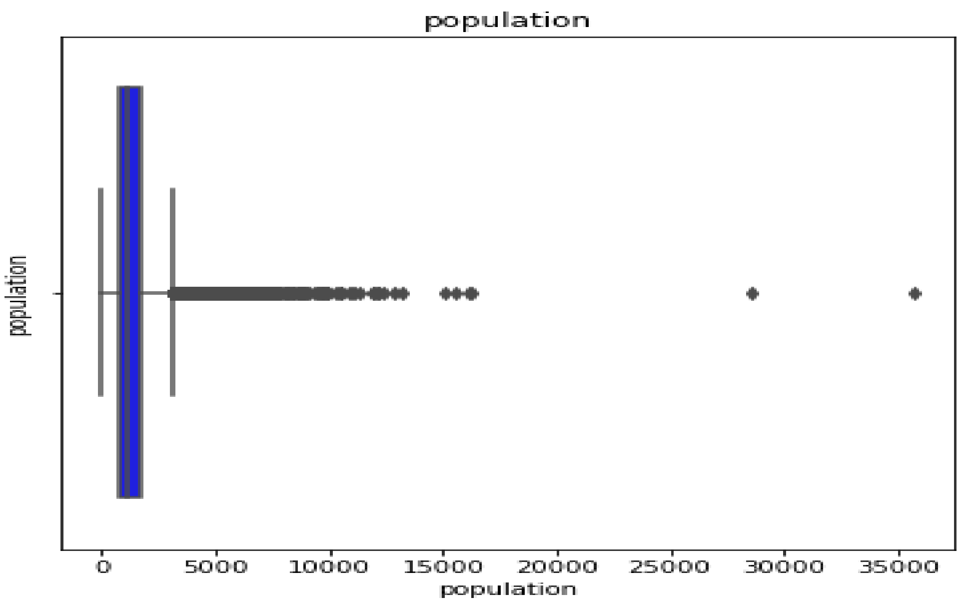


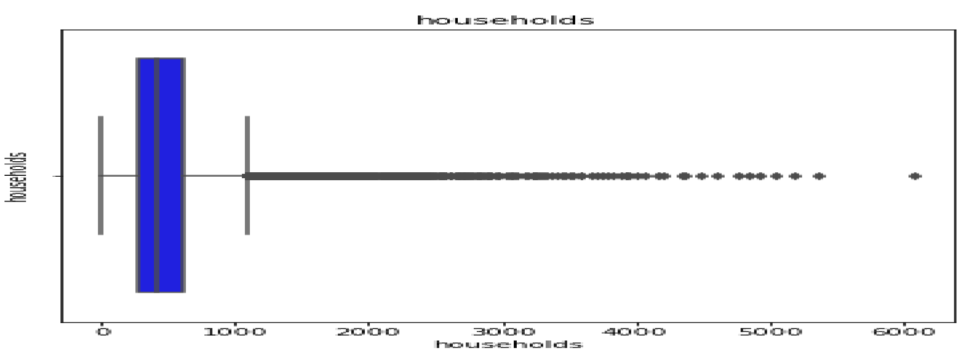


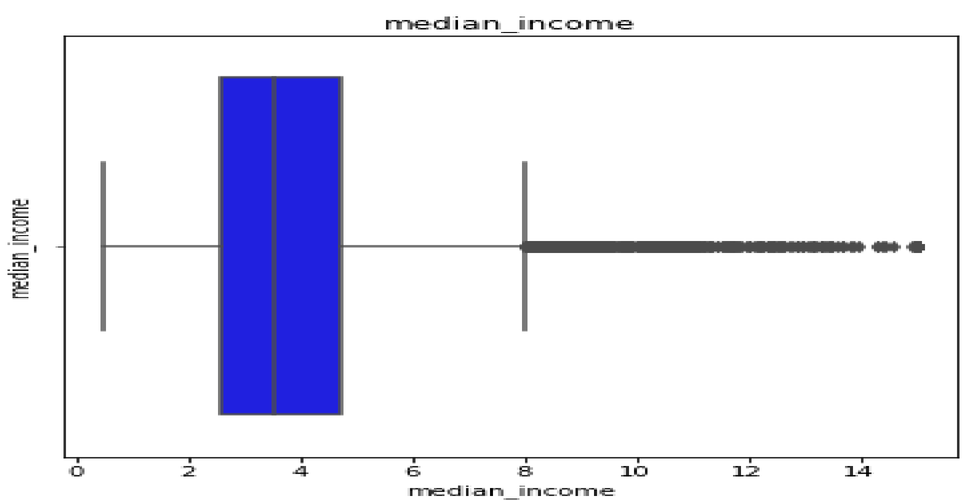

housing_median_age
housing_median_age
0
10
20
30
40
50
housing_median_age

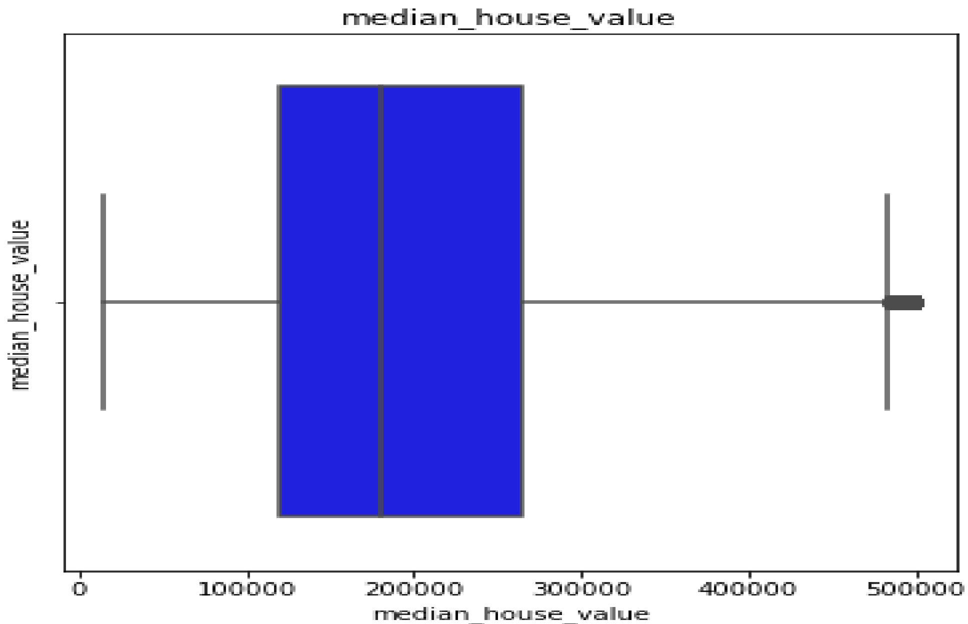

total_rooms
total_rooms
0
5000
10000
15000
20000
25000
30000
35000
40000
total_rooms


total_bedrooms
total_bedrooms
0
1000
2000
3000
4000
5000
6000
total_bedrooms


population
population
0
5000
10000
15000
20000
25000
30000
35000
population


households
households
0
1000
2000
3000
4000
5000
6000
households


median_income
median_income
0
2
4
6
8
10
12
14
median_income



Outlier Analysis for Each Feature:

1. Total Rooms: There are numerous data points above the upper whisker, indicating a significant number of outliers.
2. Total Bedrooms: Numerous data points above the upper whisker indicate a significant presence of outliers with very high total_bedrooms values.
3. Population: There are numerous outliers above the upper whisker, with extreme population values reaching beyond 35,000.
4. Households There is a significant number of outliers above the upper whisker. These values represent areas with an unusually high number of households.
5. Median Income: There are numerous data points above the upper whisker, marked as circles. These are considered potential outliers.
6. Median House Value: A small cluster of outliers is visible near the maximum value of 500,000.

General Actions for Outlier Handling:

1. Transformation: Apply log or square root transformations to reduce skewness for features like total rooms, population, and median income.
2. Removal: If outliers are due to data errors or are not relevant, consider removing them.

Program 2:

Develop a program to Compute the correlation matrix to understand the relationships between pairs of features. Visualize the correlation matrix using a heatmap to know which variables have strong positive/negative correlations. Create a pair plot to visualize pairwise relationships between features. Use California Housing dataset.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import fetch_california_housing

# Load California Housing dataset
data = fetch_california_housing()

# Convert to DataFrame
df = pd.DataFrame(data.data, columns=data.feature_names)
df['Target'] = data.target  # Adding the target variable (median house value)


# Table of Meaning of Each Variable
variable_meaning = {
    "MedInc": "Median income in block group",
    "HouseAge": "Median house age in block group",
    "AveRooms": "Average number of rooms per household",
    "AveBedrms": "Average number of bedrooms per household",
    "Population": "Population of block group",
    "AveOccup": "Average number of household members",
    "Latitude": "Latitude of block group",
    "Longitude": "Longitude of block group",
    "Target": "Median house value (in $100,000s)"
}

variable_df = pd.DataFrame(list(variable_meaning.items()),
columns=["Feature", "Description"])
print("\nVariable Meaning Table:")
print(variable_df)
```

```
Variable Meaning Table:
      Feature                                 Description
0       MedInc                Median income in block group
1     HouseAge             Median house age in block group
2     AveRooms       Average number of rooms per household
3    AveBedrms    Average number of bedrooms per household
4   Population                   Population of block group
5     AveOccup         Average number of household members
6     Latitude                     Latitude of block group
```

```
7   Longitude                  Longitude of block group
8      Target         Median house value (in $100,000s)

# Basic Data Exploration
print("\nBasic Information about Dataset:")
print(df.info())  # Overview of dataset
print("\nFirst Five Rows of Dataset:")
print(df.head())  # Display first few rows


Basic Information about Dataset:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   MedInc      20640 non-null  float64
 1   HouseAge    20640 non-null  float64
 2   AveRooms    20640 non-null  float64
 3   AveBedrms   20640 non-null  float64
 4   Population  20640 non-null  float64
 5   AveOccup    20640 non-null  float64
 6   Latitude    20640 non-null  float64
 7   Longitude   20640 non-null  float64
 8   Target      20640 non-null  float64
dtypes: float64(9)
memory usage: 1.4 MB
None

First Five Rows of Dataset:
   MedInc  HouseAge  AveRooms  AveBedrms  Population  AveOccup  Latitude  \
0  8.3252      41.0  6.984127   1.023810       322.0  2.555556     37.88   
1  8.3014      21.0  6.238137   0.971880      2401.0  2.109842     37.86   
2  7.2574      52.0  8.288136   1.073446       496.0  2.802260     37.85   
3  5.6431      52.0  5.817352   1.073059       558.0  2.547945     37.85   
4  3.8462      52.0  6.281853   1.081081       565.0  2.181467     37.85   

   Longitude  Target  
0    -122.23   4.526  
1    -122.22   3.585  
2    -122.24   3.521  
3    -122.25   3.413  
4    -122.25   3.422  

# Summary Statistics
print("\nSummary Statistics:")
print(df.describe())  # Summary statistics of dataset


Summary Statistics:
```

```
             MedInc      HouseAge      AveRooms     AveBedrms    Population  \
count  20640.000000  20640.000000  20640.000000  20640.000000  20640.000000
mean       3.870671     28.639486      5.429000      1.096675   1425.476744
std        1.899822     12.585558      2.474173      0.473911   1132.462122
min        0.499900      1.000000      0.846154      0.333333      3.000000
25%        2.563400     18.000000      4.440716      1.006079    787.000000
50%        3.534800     29.000000      5.229129      1.048780   1166.000000
75%        4.743250     37.000000      6.052381      1.099526   1725.000000
max       15.000100     52.000000    141.909091     34.066667  35682.000000

           AveOccup      Latitude     Longitude        Target
count  20640.000000  20640.000000  20640.000000  20640.000000
mean       3.070655     35.631861   -119.569704      2.068558
std       10.386050      2.135952      2.003532      1.153956
min        0.692308     32.540000   -124.350000      0.149990
25%        2.429741     33.930000   -121.800000      1.196000
50%        2.818116     34.260000   -118.490000      1.797000
75%        3.282261     37.710000   -118.010000      2.647250
max     1243.333333     41.950000   -114.310000      5.000010
```

```python
# Explanation of Summary Statistics
summary_explanation = """
The summary statistics table provides key percentiles and other descriptive
metrics for each numerical feature:
- **25% (First Quartile - Q1):** This represents the value below which 25% of
the data falls. It helps in understanding the lower bound of typical data
values.
- **50% (Median - Q2):** This is the middle value when the data is sorted. It
provides the central tendency of the dataset.
- **75% (Third Quartile - Q3):** This represents the value below which 75% of
the data falls. It helps in identifying the upper bound of typical values in
the dataset.
- These percentiles are useful for detecting skewness, data distribution, and
identifying potential outliers (values beyond Q1 - 1.5*IQR or Q3 + 1.5*IQR).
"""
print("\nSummary Statistics Explanation:")
print(summary_explanation)
```

```
Summary Statistics Explanation:

The summary statistics table provides key percentiles and other descriptive
metrics for each numerical feature:
- **25% (First Quartile - Q1):** This represents the value below which 25% of
the data falls. It helps in understanding the lower bound of typical data
values.
- **50% (Median - Q2):** This is the middle value when the data is sorted. It
provides the central tendency of the dataset.
- **75% (Third Quartile - Q3):** This represents the value below which 75% of
the data falls. It helps in identifying the upper bound of typical values in
```

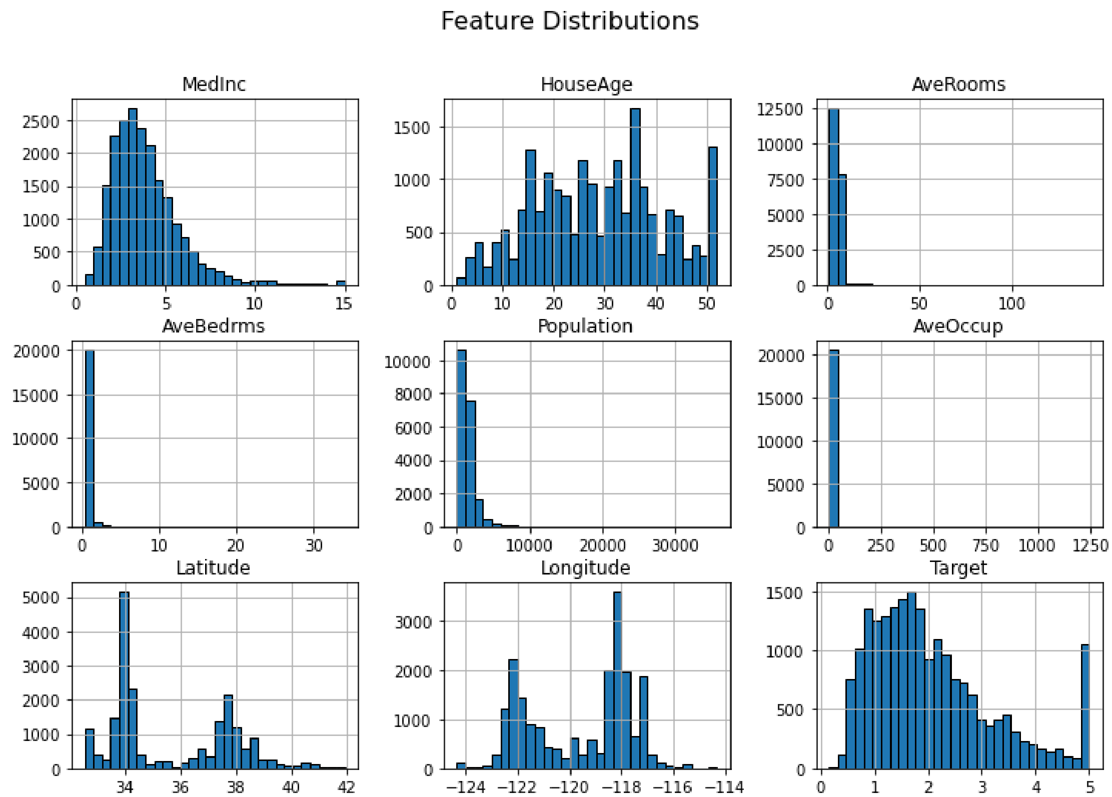
```
the dataset.
- These percentiles are useful for detecting skewness, data distribution, and
identifying potential outliers (values beyond Q1 - 1.5*IQR or Q3 + 1.5*IQR).
```

```
# Check for missing values
print("\nMissing Values in Each Column:")
print(df.isnull().sum())  # Count of missing values
```

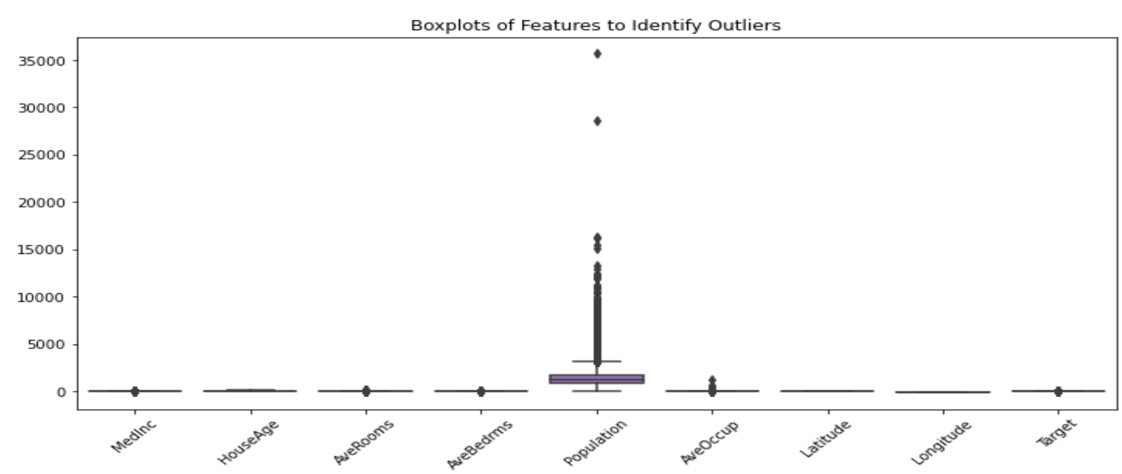
```
Missing Values in Each Column:
MedInc        0
HouseAge      0
AveRooms      0
AveBedrms     0
Population    0
AveOccup      0
Latitude      0
Longitude     0
Target        0
dtype: int64
```

```
# Histograms for distribution of features
plt.figure(figsize=(12, 8))
df.hist(figsize=(12, 8), bins=30, edgecolor='black')
plt.suptitle("Feature Distributions", fontsize=16)
plt.show()
```

```
<Figure size 864x576 with 0 Axes>
```

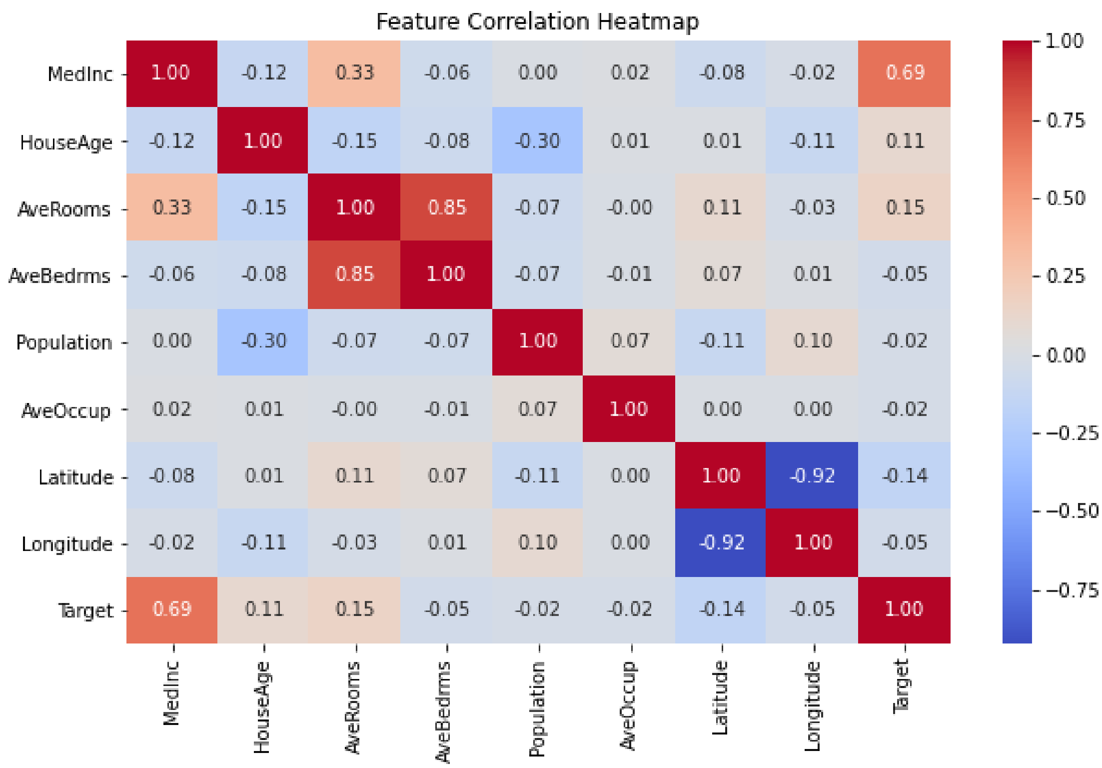



```
# Boxplots for outlier detection
plt.figure(figsize=(12, 6))
sns.boxplot(data=df)
plt.xticks(rotation=45)
plt.title("Boxplots of Features to Identify Outliers")
plt.show()
```

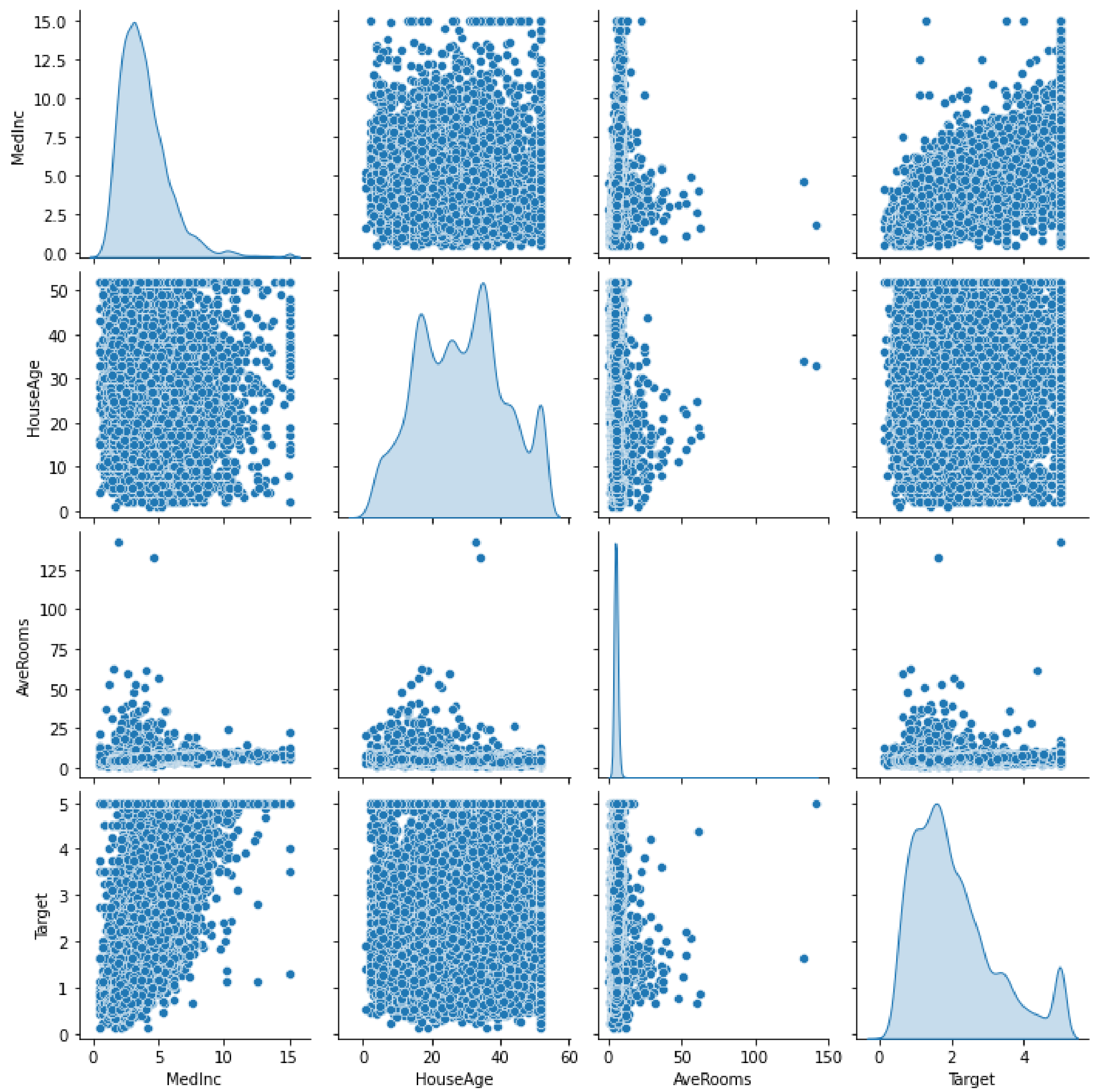



```
# Correlation Matrix
plt.figure(figsize=(10, 6))
corr_matrix = df.corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
```

```
plt.title("Feature Correlation Heatmap")
plt.show()
```




```
# Pairplot to analyze feature relationships (only a subset for clarity)
sns.pairplot(df[['MedInc', 'HouseAge', 'AveRooms', 'Target']],
diag_kind='kde')
plt.show()

# Insights from Data Exploration
print("\nKey Insights:")
print("1. The dataset has", df.shape[0], "rows and", df.shape[1], "columns.")
print("2. No missing values were found in the dataset.")
print("3. Histograms show skewed distributions in some features like
'MedInc'.")
print("4. Boxplots indicate potential outliers in 'AveRooms' and
'AveOccup'.")
print("5. Correlation heatmap shows 'MedInc' has the highest correlation with
house prices.")
```




```
Key Insights:
1. The dataset has 20640 rows and 9 columns.
2. No missing values were found in the dataset.
3. Histograms show skewed distributions in some features like 'MedInc'.
4. Boxplots indicate potential outliers in 'AveRooms' and 'AveOccup'.
5. Correlation heatmap shows 'MedInc' has the highest correlation with house
prices.
```

Program 3

Develop a program to implement Principal Component Analysis (PCA) for reducing the dimensionality of the Iris dataset from 4 features to 2.

```
the Iris dataset from 4 features to 2.

# Introduction to the Iris Dataset
# The Iris dataset is one of the most well-known datasets in machine learning
and statistics.
# It contains 150 samples of iris flowers categorized into three species:
Setosa, Versicolor, and Virginica.

#
# The goal of using PCA in this exercise is to reduce these four features
into two principal components.
# This will help in visualizing the data better and understanding its
underlying structure.
#
# Since humans struggle to visualize data in more than three dimensions,
reducing the data to 2D allows us to
# retain the most important patterns while making it easier to interpret. PCA
helps us achieve this while
# preserving as much variance as possible.
```

Explanation of Features in the Iris Dataset

The Iris dataset consists of 4 features, which represent different physical characteristics of iris flowers:

```
Sepal Length (cm)
Sepal Width (cm)
Petal Length (cm)
Petal Width (cm)
```

These features were chosen because they effectively differentiate between the three iris species (Setosa, Versicolor, and Virginica).

In the 3D visualizations, we select three features for plotting, which are:

```
Feature 1 → Sepal Length
Feature 2 → Sepal Width
Feature 3 → Petal Length
```

These features are chosen arbitrarily for visualization, but all four features are used in the PCA computation. Why is the Iris Dataset Important?

The Iris dataset is a benchmark dataset in machine learning because:

```
It is small yet diverse, making it easy to analyze.
It has clearly separable classes, which makes it ideal for classification
tasks.
It is preloaded in Scikit-learn, making it accessible for learning and
experimentation.
```

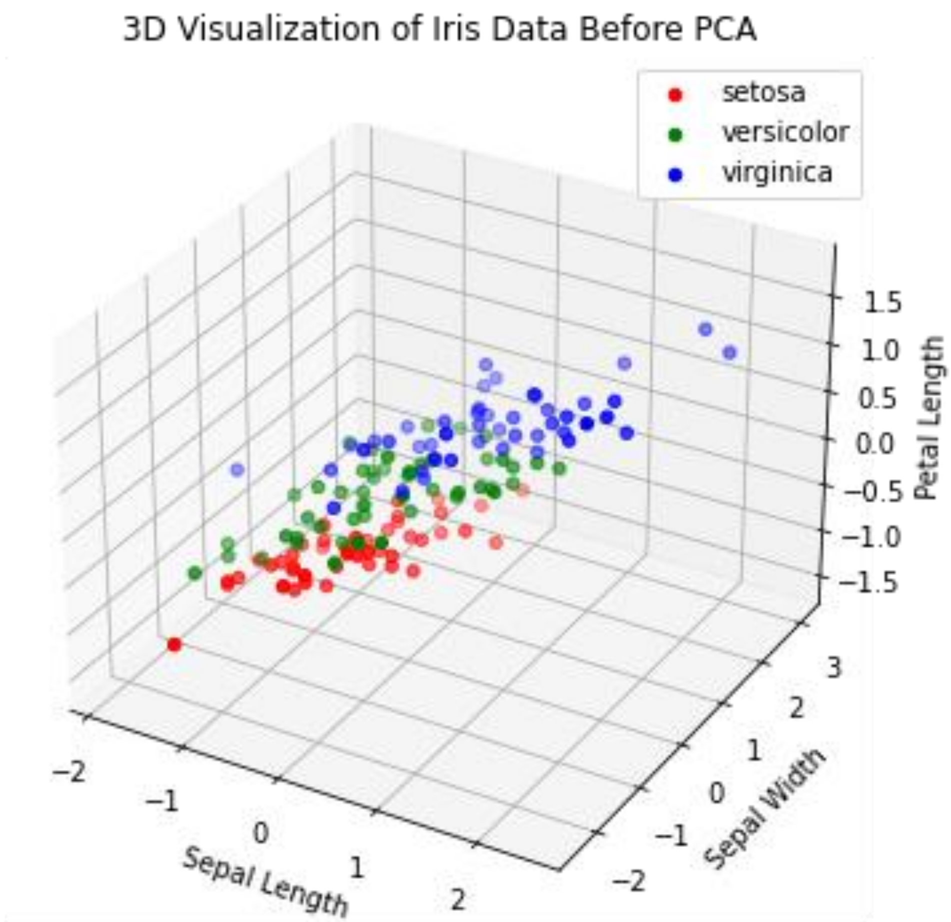
Since the dataset contains three classes (Setosa, Versicolor, and Virginica), PCA helps visualize how well the classes can be separated in a lower-dimensional space.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from sklearn import datasets
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA



# Step 1: Load the Iris Dataset
iris = datasets.load_iris()
X = iris.data  # Extracting feature matrix (4D data)
y = iris.target  # Extracting labels (0, 1, 2 representing three iris
species)

# Step 2: Standardizing the Data
# PCA works best when data is standardized (mean = 0, variance = 1)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Step 3: Calculating Covariance Matrix and Eigenvalues/Eigenvectors
# The foundation of PCA is eigen decomposition of the covariance matrix
cov_matrix = np.cov(X_scaled.T)
print(cov_matrix)
eigenvalues, eigenvectors = np.linalg.eig(cov_matrix)
print("Eigenvalues:", eigenvalues)
print("Eigenvectors:\n", eigenvectors)

# Step 4: Visualizing Data in 3D before PCA
fig = plt.figure(figsize=(8, 6))
ax = fig.add_subplot(111, projection='3d')
colors = ['red', 'green', 'blue']
labels = iris.target_names
for i in range(len(colors)):
    ax.scatter(X_scaled[y == i, 0], X_scaled[y == i, 1], X_scaled[y == i, 2],
color=colors[i], label=labels[i])
ax.set_xlabel('Sepal Length')
ax.set_ylabel('Sepal Width')
ax.set_zlabel('Petal Length')
ax.set_title('3D Visualization of Iris Data Before PCA')
```

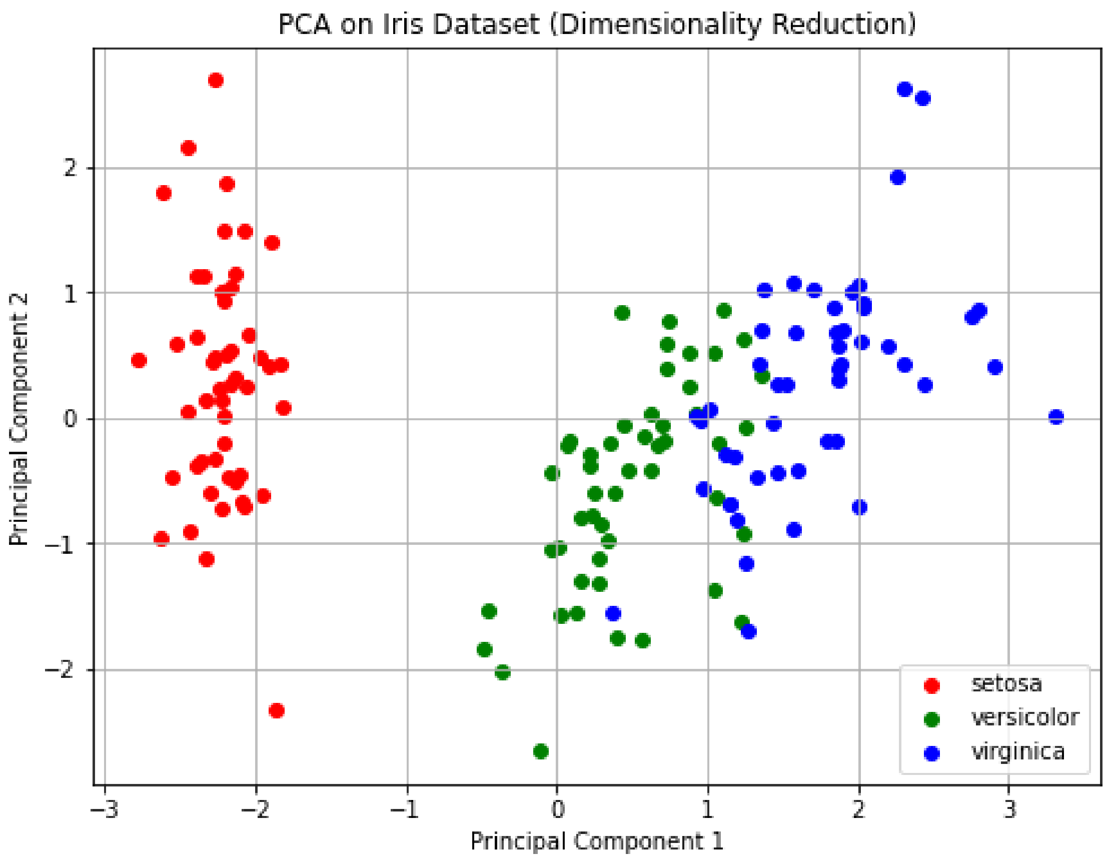
```
plt.legend()
plt.show()

# Step 5: Applying PCA using SVD (Singular Value Decomposition)
# PCA internally relies on SVD, which decomposes a matrix into three parts:
U, S, and V
U, S, Vt = np.linalg.svd(X_scaled, full_matrices=False)
print("Singular Values:", S)

# Step 6: Applying PCA to Reduce Dimensionality to 2D
# We reduce 4D data to 2D for visualization while retaining maximum variance
pca = PCA(n_components=2)  # We choose 2 components because we want to
visualize
X_pca = pca.fit_transform(X_scaled)  # Transform data into principal
components

# Step 7: Understanding Variance Explained
# PCA provides the percentage of variance retained in each principal
component
explained_variance = pca.explained_variance_ratio_
print(f"Explained Variance by PC1: {explained_variance[0]:.2f}")
print(f"Explained Variance by PC2: {explained_variance[1]:.2f}")

# Step 8: Visualizing the Transformed Data
# We plot the 2D representation of the Iris dataset after PCA transformation
plt.figure(figsize=(8, 6))
for i in range(len(colors)):
    plt.scatter(X_pca[y == i, 0], X_pca[y == i, 1], color=colors[i],
label=labels[i])

plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('PCA on Iris Dataset (Dimensionality Reduction)')
plt.legend()
plt.grid()
plt.show()

# Step 9: Visualizing Eigenvectors Superimposed on 3D Data
fig = plt.figure(figsize=(8, 6))
ax = fig.add_subplot(111, projection='3d')
for i in range(len(colors)):
    ax.scatter(X_scaled[y == i, 0], X_scaled[y == i, 1], X_scaled[y == i, 2],
color=colors[i], label=labels[i])
for i in range(3):  # Plot first three eigenvectors
    ax.quiver(0, 0, 0, eigenvectors[i, 0], eigenvectors[i, 1],
eigenvectors[i, 2], color='black', length=1)
ax.set_xlabel('Sepal Length')
ax.set_ylabel('Sepal Width')
ax.set_zlabel('Petal Length')
ax.set_title('3D Data with Eigenvectors')
```

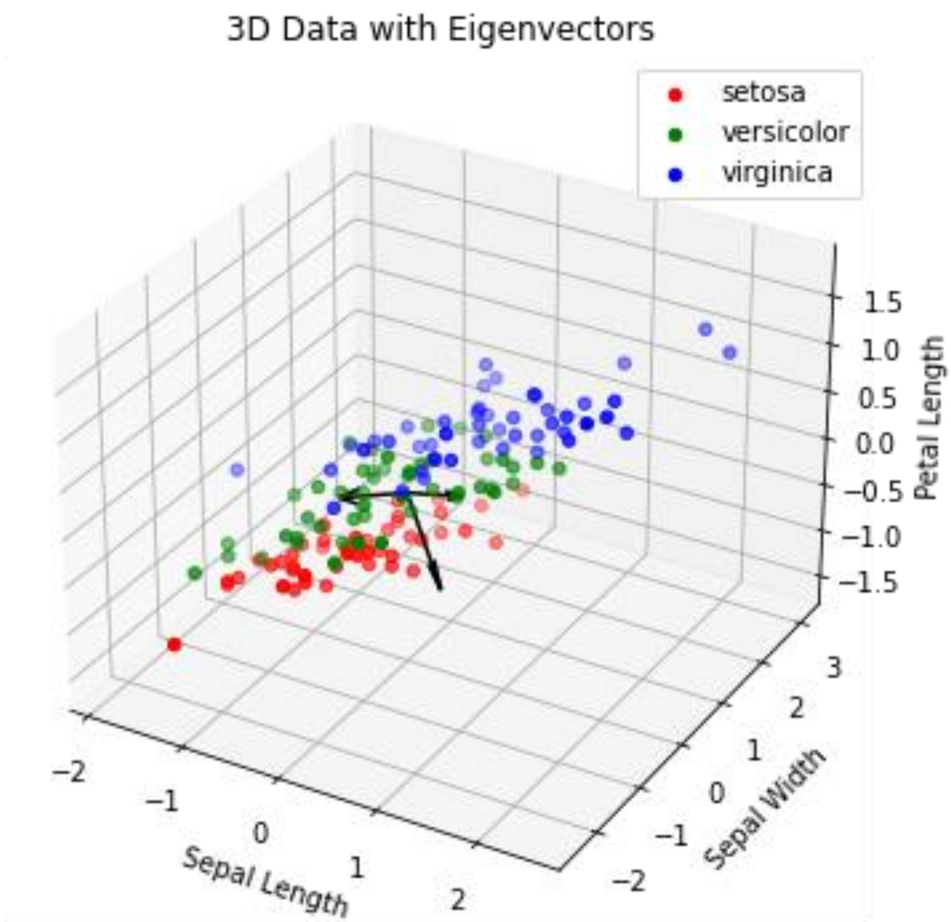
```
plt.legend()
plt.show()

# Recap:
# - The Iris dataset is historically important for testing classification
models.
# - We standardized the data to ensure fair comparison across features.
# - We calculated the covariance matrix, eigenvalues, and eigenvectors.
# - PCA is built on SVD, which decomposes data into important components.
# - We visualized the original 3D data and superimposed eigenvectors.
# - We applied PCA to reduce the dimensionality from 4D to 2D.
# - Finally, we visualized the transformed data in 2D space.
```

```
[[ 1.00671141 -0.11835884  0.87760447  0.82343066]
 [-0.11835884  1.00671141 -0.43131554 -0.36858315]
 [ 0.87760447 -0.43131554  1.00671141  0.96932762]
 [ 0.82343066 -0.36858315  0.96932762  1.00671141]]
Eigenvalues: [2.93808505 0.9201649  0.14774182 0.02085386]
Eigenvectors:
 [[ 0.52106591 -0.37741762 -0.71956635  0.26128628]
 [-0.26934744 -0.92329566  0.24438178 -0.12350962]
 [ 0.5804131  -0.02449161  0.14212637 -0.80144925]
 [ 0.56485654 -0.06694199  0.63427274  0.52359713]]
```




```
Singular Values: [20.92306556 11.7091661   4.69185798  1.76273239]
Explained Variance by PC1: 0.73
Explained Variance by PC2: 0.23
```


PCA on Iris Dataset (Dimensionality Reduction)
Principal Component 2
Principal Component 1
2
1
0
−1
−2
−3
−2
−1
0
1
2
3
setosa
versicolor
virginica


3D Data with Eigenvectors
setosa
versicolor
virginica
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
Petal Length
3
2
1
0
−1
−2
Sepal Width
−2
−1
0
1
2
Sepal Length

Program 4

For a given set of training data examples stored in a .CSV file, implement and demonstrate the Find-S algorithm to output a description of the set of all hypotheses consistent with the training examples.

For a given set of training data examples stored in a .CSV file, implement and demonstrate the Find-S

algorithm to output a description of the set of all hypotheses consistent with the training examples.

Understanding Find-S Algorithm and Hypothesis Concept

The Find-S algorithm is a simple machine-learning algorithm used in concept learning. It finds the most specific hypothesis that is consistent with all positive examples in a given training dataset. The algorithm assumes:

```
The target concept is represented in a binary classification (yes/no,
true/false, etc.).
The hypothesis space uses conjunctive attributes (each attribute in a
hypothesis must match exactly).
There is at least one positive example in the dataset.
```

```
import pandas as pd

data = pd.read_csv(r"C:\Users\vijay\Desktop\Machine Learning Course
Batches\FDP_ML_6thSem_VTU\Experiment_4_FindS\training_data.csv")

print(data)
```

```
  Experience Qualification   Skill  Age Hired
0        Yes       Masters  Python   30   Yes
1        Yes     Bachelors  Python   25   Yes
2         No     Bachelors    Java   28    No
3        Yes       Masters    Java   40   Yes
4         No       Masters  Python   35    No
```

```
def find_s_algorithm(data):
    """Implements the Find-S algorithm to find the most specific
hypothesis."""
    # Extract feature columns and target column
    attributes = data.iloc[:, :-1].values  # All columns except last
    target = data.iloc[:, -1].values  # Last column (class labels)

    # Step 1: Initialize hypothesis with first positive example
    for i in range(len(target)):
        if target[i] == "Yes":  # Consider only positive examples
            hypothesis = attributes[i].copy()
            break
```

```python
    # Step 2: Update hypothesis based on other positive examples
    for i in range(len(target)):
        if target[i] == "Yes":
            for j in range(len(hypothesis)):
                if hypothesis[j] != attributes[i][j]:
                    hypothesis[j] = '?'  # Generalize inconsistent attributes

    return hypothesis



# Run Find-S Algorithm
final_hypothesis = find_s_algorithm(data)

# Print the learned hypothesis
print("Most Specific Hypothesis:", final_hypothesis)
```

```
Most Specific Hypothesis: ['Yes' '?' '?' '?']
```

Program 5:

Develop a program to implement k-Nearest Neighbour algorithm to classify the randomly generated 100 values of x in the range of [0,1]. Perform the following based on dataset generated.

3. Label the first 50 points {x1,......,x50} as follows: if (xi ≤ 0.5), then xi ∊ Class1, else xi ∊ Class1
4. Classify the remaining points, x51,......,x100 using KNN. Perform this for k=1,2,3,4,5,20,30

```
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.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

import warnings
warnings.filterwarnings('ignore')

# Step 1: Generate dataset
np.random.seed(42)
values = np.random.rand(100)

labels = []

for i in values[:50]:
    if i <=0.5:
        labels.append('Class1')
    else:
        labels.append('Class2')


labels += [None] * 50

print(labels)

['Class1', 'Class2', 'Class2', 'Class2', 'Class1', 'Class1', 'Class1',
'Class2', 'Class2', 'Class2', 'Class1', 'Class2', 'Class2', 'Class1',
'Class1', 'Class1', 'Class1', 'Class2', 'Class1', 'Class1', 'Class2',
'Class1', 'Class1', 'Class1', 'Class1', 'Class2', 'Class1', 'Class2',
'Class2', 'Class1', 'Class2', 'Class1', 'Class1', 'Class2', 'Class2',
'Class2', 'Class1', 'Class1', 'Class2', 'Class1', 'Class1', 'Class1',
'Class1', 'Class2', 'Class1', 'Class2', 'Class1', 'Class2', 'Class2',
'Class1', None, None, None, None, None, None, None, None, None, None, None,
None, None, None, None, None, None, None, None, None, None, None, None, None,
None, None, None, None, None, None, None, None, None, None, None, None, None,
None, None, None, None, None, None, None, None, None, None, None, None, None]

data = {
    "Point": [f"x{i+1}" for i in range(100)],
```

```
    "Value": values,
    "Label": labels
}

print(data)
type(data)
```

```
{'Point': ['x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7', 'x8', 'x9', 'x10',
'x11', 'x12', 'x13', 'x14', 'x15', 'x16', 'x17', 'x18', 'x19', 'x20', 'x21',
'x22', 'x23', 'x24', 'x25', 'x26', 'x27', 'x28', 'x29', 'x30', 'x31', 'x32',
'x33', 'x34', 'x35', 'x36', 'x37', 'x38', 'x39', 'x40', 'x41', 'x42', 'x43',
'x44', 'x45', 'x46', 'x47', 'x48', 'x49', 'x50', 'x51', 'x52', 'x53', 'x54',
'x55', 'x56', 'x57', 'x58', 'x59', 'x60', 'x61', 'x62', 'x63', 'x64', 'x65',
'x66', 'x67', 'x68', 'x69', 'x70', 'x71', 'x72', 'x73', 'x74', 'x75', 'x76',
'x77', 'x78', 'x79', 'x80', 'x81', 'x82', 'x83', 'x84', 'x85', 'x86', 'x87',
'x88', 'x89', 'x90', 'x91', 'x92', 'x93', 'x94', 'x95', 'x96', 'x97', 'x98',
'x99', 'x100'], 'Value': array([0.37454012, 0.95071431, 0.73199394,
0.59865848, 0.15601864,
       0.15599452, 0.05808361, 0.86617615, 0.60111501, 0.70807258,
       0.02058449, 0.96990985, 0.83244264, 0.21233911, 0.18182497,
       0.18340451, 0.30424224, 0.52475643, 0.43194502, 0.29122914,
       0.61185289, 0.13949386, 0.29214465, 0.36636184, 0.45606998,
       0.78517596, 0.19967378, 0.51423444, 0.59241457, 0.04645041,
       0.60754485, 0.17052412, 0.06505159, 0.94888554, 0.96563203,
       0.80839735, 0.30461377, 0.09767211, 0.68423303, 0.44015249,
       0.12203823, 0.49517691, 0.03438852, 0.9093204 , 0.25877998,
       0.66252228, 0.31171108, 0.52006802, 0.54671028, 0.18485446,
       0.96958463, 0.77513282, 0.93949894, 0.89482735, 0.59789998,
       0.92187424, 0.0884925 , 0.19598286, 0.04522729, 0.32533033,
       0.38867729, 0.27134903, 0.82873751, 0.35675333, 0.28093451,
       0.54269608, 0.14092422, 0.80219698, 0.07455064, 0.98688694,
       0.77224477, 0.19871568, 0.00552212, 0.81546143, 0.70685734,
       0.72900717, 0.77127035, 0.07404465, 0.35846573, 0.11586906,
       0.86310343, 0.62329813, 0.33089802, 0.06355835, 0.31098232,
       0.32518332, 0.72960618, 0.63755747, 0.88721274, 0.47221493,
       0.11959425, 0.71324479, 0.76078505, 0.5612772 , 0.77096718,
       0.4937956 , 0.52273283, 0.42754102, 0.02541913, 0.10789143]), 'Label':
['Class1', 'Class2', 'Class2', 'Class2', 'Class1', 'Class1', 'Class1',
'Class2', 'Class2', 'Class2', 'Class1', 'Class2', 'Class2', 'Class1',
'Class1', 'Class1', 'Class1', 'Class2', 'Class1', 'Class1', 'Class2',
'Class1', 'Class1', 'Class1', 'Class1', 'Class2', 'Class1', 'Class2',
'Class2', 'Class1', 'Class2', 'Class1', 'Class1', 'Class2', 'Class2',
'Class2', 'Class1', 'Class1', 'Class2', 'Class1', 'Class1', 'Class1',
'Class1', 'Class2', 'Class1', 'Class2', 'Class1', 'Class2', 'Class2',
'Class1', None, None, None, None, None, None, None, None, None, None, None,
None, None, None, None, None, None, None, None, None, None, None, None, None,
None, None, None, None, None, None, None, None, None, None, None, None, None,
None, None, None, None, None, None, None, None, None, None, None, None,
None]}

dict
```

```
df = pd.DataFrame(data)
df.head()
```

```
  Point     Value   Label
0    x1  0.374540  Class1
1    x2  0.950714  Class2
2    x3  0.731994  Class2
3    x4  0.598658  Class2
4    x5  0.156019  Class1
```

```
df.nunique()
```

```
Point    100
Value    100
Label      2
dtype: int64
```

```
df.shape
```

```
(100, 3)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Point   100 non-null    object
 1   Value   100 non-null    float64
 2   Label   50 non-null     object
dtypes: float64(1), object(2)
memory usage: 2.5+ KB
```

```
df.describe().T
```

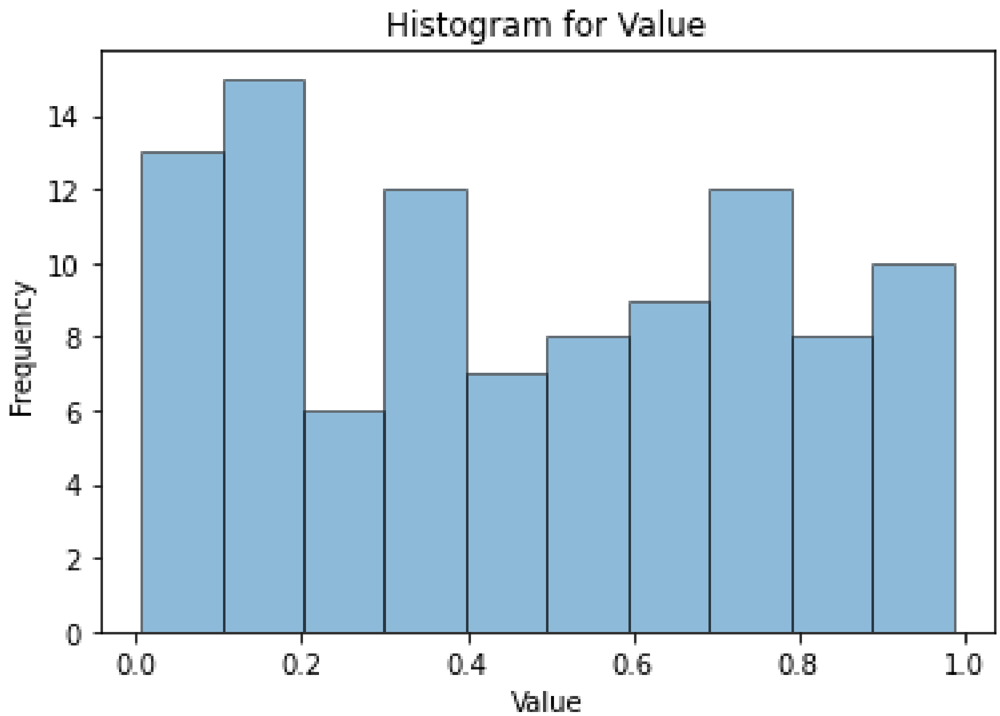
```
       count      mean       std       min       25%       50%       75%  \
Value  100.0  0.470181  0.297489  0.005522  0.193201  0.464142  0.730203

            max
Value  0.986887
```

```
df.isnull().sum()
```

```
Point     0
Value     0
Label    50
dtype: int64
```

```
num_col = df.select_dtypes(include=['int', 'float']).columns
for col in num_col:
    df[col].hist(bins=10, alpha=0.5, edgecolor='black',grid=False)
    plt.title(f'Histogram for {col}')
```

```
    plt.xlabel(col)
    plt.ylabel('Frequency')
    plt.show()
```




```
# Split data into labeled and unlabeled
labeled_df = df[df["Label"].notna()]
X_train = labeled_df[["Value"]]
y_train = labeled_df["Label"]

unlabeled_df = df[df["Label"].isna()]
X_test = unlabeled_df[["Value"]]

# Generate true labels for testing (for accuracy calculation)
true_labels = ["Class1" if x <= 0.5 else "Class2" for x in values[50:]]

# Step 2: Perform KNN classification for different values of k
k_values = [1, 2, 3, 4, 5, 20, 30]
results = {}
accuracies = {}

for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    predictions = knn.predict(X_test)
    results[k] = predictions

    # Calculate accuracy
    accuracy = accuracy_score(true_labels, predictions) * 100
    accuracies[k] = accuracy
```

```
    print(f"Accuracy for k={k}: {accuracy:.2f}%")

    # Assign predictions back to the DataFrame for this k
    unlabeled_df[f"Label_k{k}"] = predictions
```

```
Accuracy for k=1: 100.00%
Accuracy for k=2: 100.00%
Accuracy for k=3: 98.00%
Accuracy for k=4: 98.00%
Accuracy for k=5: 98.00%
Accuracy for k=20: 98.00%
Accuracy for k=30: 100.00%
```

```
print(predictions)
```

```
['Class2' 'Class2' 'Class2' 'Class2' 'Class2' 'Class2' 'Class1' 'Class1'
 'Class1' 'Class1' 'Class1' 'Class1' 'Class2' 'Class1' 'Class1' 'Class2'
 'Class1' 'Class2' 'Class1' 'Class2' 'Class2' 'Class1' 'Class1' 'Class2'
 'Class2' 'Class2' 'Class2' 'Class1' 'Class1' 'Class1' 'Class2' 'Class2'
 'Class1' 'Class1' 'Class1' 'Class1' 'Class2' 'Class2' 'Class2' 'Class1'
 'Class1' 'Class2' 'Class2' 'Class2' 'Class2' 'Class1' 'Class2' 'Class1'
 'Class1' 'Class1']
```

```
df1 = unlabeled_df.drop(columns=['Label'], axis=1)
df1
```

```
   Point     Value Label_k1 Label_k2 Label_k3 Label_k4 Label_k5 Label_k20  \
50   x51  0.969585   Class2   Class2   Class2   Class2   Class2    Class2   
51   x52  0.775133   Class2   Class2   Class2   Class2   Class2    Class2   
52   x53  0.939499   Class2   Class2   Class2   Class2   Class2    Class2   
53   x54  0.894827   Class2   Class2   Class2   Class2   Class2    Class2   
54   x55  0.597900   Class2   Class2   Class2   Class2   Class2    Class2   
55   x56  0.921874   Class2   Class2   Class2   Class2   Class2    Class2   
56   x57  0.088493   Class1   Class1   Class1   Class1   Class1    Class1   
57   x58  0.195983   Class1   Class1   Class1   Class1   Class1    Class1   
58   x59  0.045227   Class1   Class1   Class1   Class1   Class1    Class1   
59   x60  0.325330   Class1   Class1   Class1   Class1   Class1    Class1   
60   x61  0.388677   Class1   Class1   Class1   Class1   Class1    Class1   
61   x62  0.271349   Class1   Class1   Class1   Class1   Class1    Class1   
62   x63  0.828738   Class2   Class2   Class2   Class2   Class2    Class2   
63   x64  0.356753   Class1   Class1   Class1   Class1   Class1    Class1   
64   x65  0.280935   Class1   Class1   Class1   Class1   Class1    Class1   
65   x66  0.542696   Class2   Class2   Class2   Class2   Class2    Class2   
66   x67  0.140924   Class1   Class1   Class1   Class1   Class1    Class1   
67   x68  0.802197   Class2   Class2   Class2   Class2   Class2    Class2   
68   x69  0.074551   Class1   Class1   Class1   Class1   Class1    Class1   
69   x70  0.986887   Class2   Class2   Class2   Class2   Class2    Class2   
70   x71  0.772245   Class2   Class2   Class2   Class2   Class2    Class2   
71   x72  0.198716   Class1   Class1   Class1   Class1   Class1    Class1   
72   x73  0.005522   Class1   Class1   Class1   Class1   Class1    Class1   
73   x74  0.815461   Class2   Class2   Class2   Class2   Class2    Class2   
```

```
74   x75  0.706857   Class2   Class2   Class2   Class2   Class2    Class2
75   x76  0.729007   Class2   Class2   Class2   Class2   Class2    Class2
76   x77  0.771270   Class2   Class2   Class2   Class2   Class2    Class2
77   x78  0.074045   Class1   Class1   Class1   Class1   Class1    Class1
78   x79  0.358466   Class1   Class1   Class1   Class1   Class1    Class1
79   x80  0.115869   Class1   Class1   Class1   Class1   Class1    Class1
80   x81  0.863103   Class2   Class2   Class2   Class2   Class2    Class2
81   x82  0.623298   Class2   Class2   Class2   Class2   Class2    Class2
82   x83  0.330898   Class1   Class1   Class1   Class1   Class1    Class1
83   x84  0.063558   Class1   Class1   Class1   Class1   Class1    Class1
84   x85  0.310982   Class1   Class1   Class1   Class1   Class1    Class1
85   x86  0.325183   Class1   Class1   Class1   Class1   Class1    Class1
86   x87  0.729606   Class2   Class2   Class2   Class2   Class2    Class2
87   x88  0.637557   Class2   Class2   Class2   Class2   Class2    Class2
88   x89  0.887213   Class2   Class2   Class2   Class2   Class2    Class2
89   x90  0.472215   Class1   Class1   Class1   Class1   Class1    Class1
90   x91  0.119594   Class1   Class1   Class1   Class1   Class1    Class1
91   x92  0.713245   Class2   Class2   Class2   Class2   Class2    Class2
92   x93  0.760785   Class2   Class2   Class2   Class2   Class2    Class2
93   x94  0.561277   Class2   Class2   Class2   Class2   Class2    Class2
94   x95  0.770967   Class2   Class2   Class2   Class2   Class2    Class2
95   x96  0.493796   Class1   Class1   Class2   Class2   Class2    Class2
96   x97  0.522733   Class2   Class2   Class2   Class2   Class2    Class2
97   x98  0.427541   Class1   Class1   Class1   Class1   Class1    Class1
98   x99  0.025419   Class1   Class1   Class1   Class1   Class1    Class1
99  x100  0.107891   Class1   Class1   Class1   Class1   Class1    Class1

   Label_k30
50    Class2
51    Class2
52    Class2
53    Class2
54    Class2
55    Class2
56    Class1
57    Class1
58    Class1
59    Class1
60    Class1
61    Class1
62    Class2
63    Class1
64    Class1
65    Class2
66    Class1
67    Class2
68    Class1
69    Class2
70    Class2
71    Class1
```

```
72    Class1
73    Class2
74    Class2
75    Class2
76    Class2
77    Class1
78    Class1
79    Class1
80    Class2
81    Class2
82    Class1
83    Class1
84    Class1
85    Class1
86    Class2
87    Class2
88    Class2
89    Class1
90    Class1
91    Class2
92    Class2
93    Class2
94    Class2
95    Class1
96    Class2
97    Class1
98    Class1
99    Class1
```

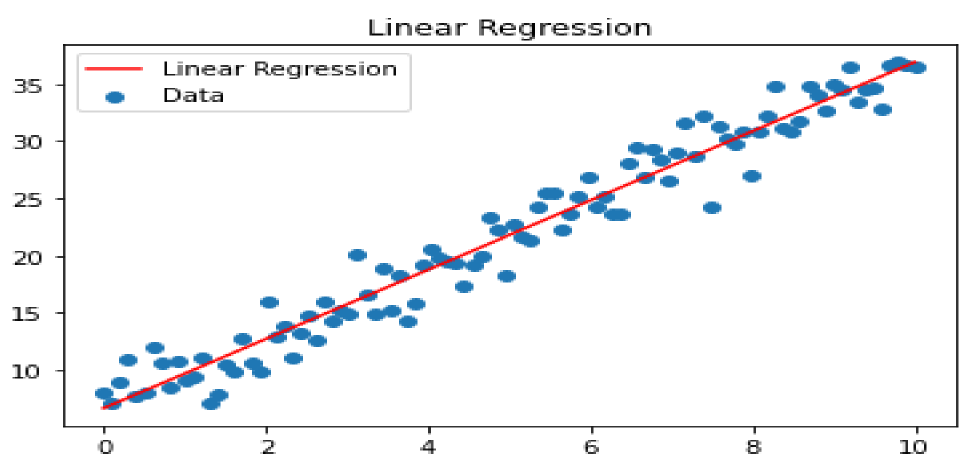
```python
# Display accuracies
print("\nAccuracies for different k values:")
for k, acc in accuracies.items():
    print(f"k={k}: {acc:.2f}%")
```

```
Accuracies for different k values:
k=1: 100.00%
k=2: 100.00%
k=3: 98.00%
k=4: 98.00%
k=5: 98.00%
k=20: 98.00%
k=30: 100.00%
```

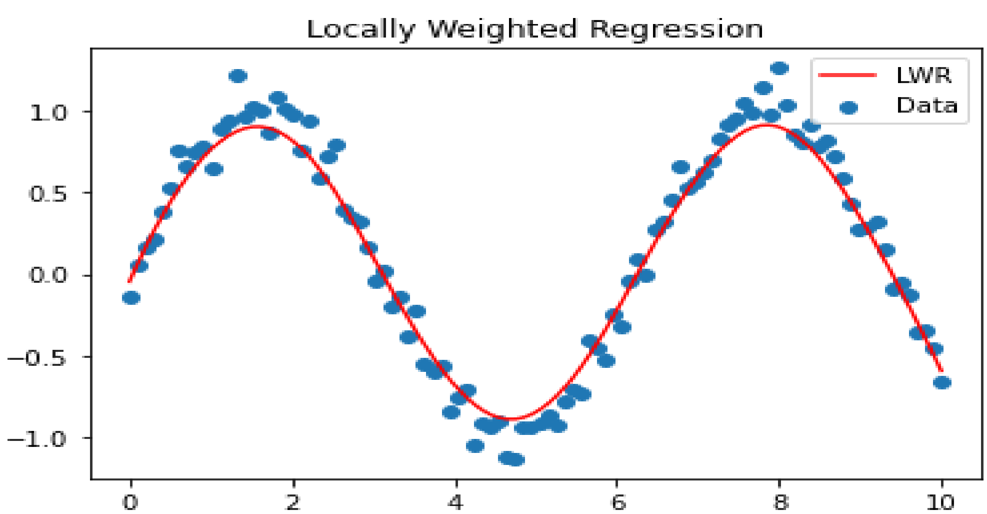
Program 6

Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
from scipy.spatial.distance import cdist

# Load datasets
df_linear = pd.read_csv("linear_dataset.csv")
df_lwr = pd.read_csv("lwr_dataset.csv")
df_poly = pd.read_csv("polynomial_dataset.csv")

# Linear Regression
def linear_regression(df):
    X, y = df[['X']], df['Y']
    model = LinearRegression()
    model.fit(X, y)
    y_pred = model.predict(X)
    plt.scatter(X, y, label='Data')
    plt.plot(X, y_pred, color='red', label='Linear Regression')
    plt.legend()
    plt.title("Linear Regression")
    plt.show()

linear_regression(df_linear)
```

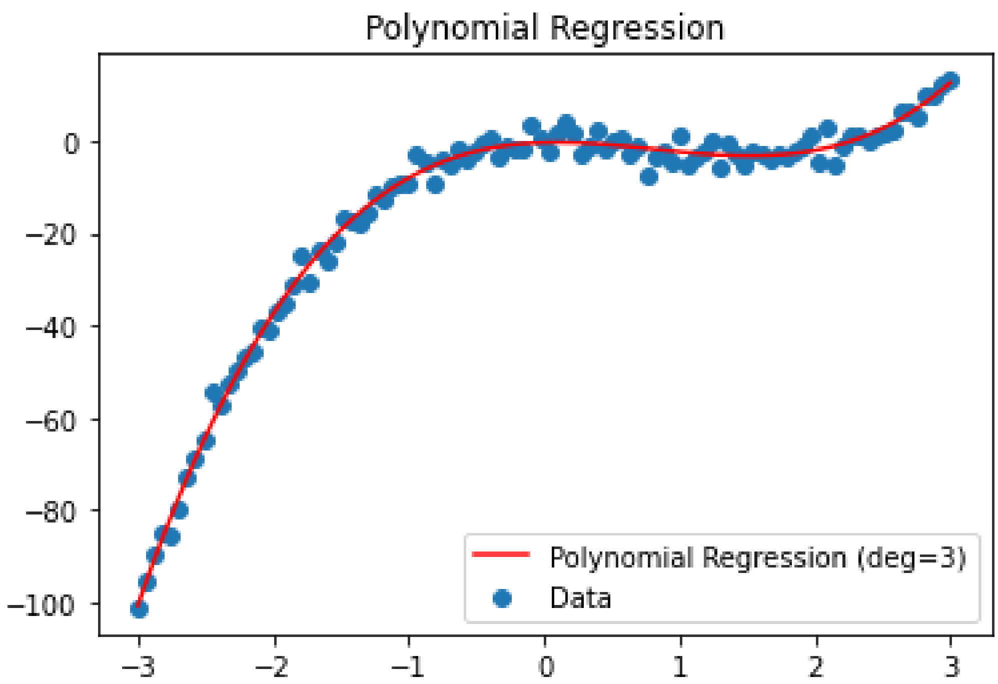


```
 # Locally Weighted Regression (LWR)
def gaussian_kernel(x, X, tau):
    return np.exp(-cdist([[x]], X, 'sqeuclidean') / (2 * tau**2))

def locally_weighted_regression(X_train, y_train, tau=0.5):
    X_train = np.hstack([np.ones((X_train.shape[0], 1)), X_train])  # Add
intercept
    X_range = np.linspace(X_train[:, 1].min(), X_train[:, 1].max(), 100)
    y_pred = []

    for x in X_range:
        x_vec = np.array([1, x])  # Intercept term
        weights = gaussian_kernel(x, X_train[:, 1:], tau).flatten()
        W = np.diag(weights)

        theta = np.linalg.pinv(X_train.T @ W @ X_train) @ (X_train.T @ W @
y_train)
        y_pred.append(x_vec @ theta)  # Use dot product for prediction

    plt.scatter(X_train[:, 1], y_train, label='Data')
    plt.plot(X_range, y_pred, color='red', label='LWR')
    plt.legend()
    plt.title("Locally Weighted Regression")
    plt.show()


# Run the models

locally_weighted_regression(df_lwr[['X']].values, df_lwr['Y'].values)
```




```
# Polynomial Regression
def polynomial_regression(df, degree=3):
    X, y = df[['X']], df['Y']
```

```
    model = make_pipeline(PolynomialFeatures(degree), LinearRegression())
    model.fit(X, y)
    y_pred = model.predict(X)
    plt.scatter(X, y, label='Data')
    plt.plot(X, y_pred, color='red', label=f'Polynomial Regression
(deg={degree})')
    plt.legend()
    plt.title("Polynomial Regression")
    plt.show()

polynomial_regression(df_poly, degree=3)
```



Program 7:

Develop a program to demonstrate the working of Linear Regression and Polynomial Regression. Use Boston Housing Dataset for Linear Regression and Auto MPG Dataset (for vehicle fuel efficiency prediction) for Polynomial Regression.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler

import warnings
warnings.filterwarnings('ignore')
```

```
data = pd.read_csv(r"C:\Users\Admin\OneDrive\Documents\Machine Learning Lab\Datasets\Boston housing dataset.csv")
```

5. CRIM: Per capita crime rate by town.
6. ZN: Proportion of residential land zoned for lots over 25,000 square feet.
7. INDUS: Proportion of non-retail business acres per town.
8. CHAS: Charles River dummy variable (1 if tract bounds river; 0 otherwise).
9. NOX: Nitric oxide concentration (parts per 10 million).
10. RM: Average number of rooms per dwelling.
11. AGE: Proportion of owner-occupied units built before 1940.
12. DIS: Weighted distances to five Boston employment centers.
13. RAD: Index of accessibility to radial highways.
14. TAX: Full-value property-tax rate per $10,000.
15. PTRATIO: Pupil-teacher ratio by town.
16. B: $1000(Bk - 0.63)2$, where Bk is the proportion of Black residents by town.
17. LSTAT: Percentage of the lower status of the population.
18. MEDV: Median value of owner-occupied homes in $1000s.

```
data.head()
```

```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD  TAX  PTRATIO  \
0  0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900    1  296     15.3
1  0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671    2  242     17.8
2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671    2  242     17.8
3  0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622    3  222     18.7
4  0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622    3  222     18.7

        B  LSTAT  MEDV
0  396.90   4.98  24.0
1  396.90   9.14  21.6
```

```
2  392.83   4.03  34.7
3  394.63   2.94  33.4
4  396.90    NaN  36.2
```

```
data.shape
```

```
(506, 14)
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   CRIM     486 non-null    float64
 1   ZN       486 non-null    float64
 2   INDUS    486 non-null    float64
 3   CHAS     486 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      486 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    int64  
 9   TAX      506 non-null    int64  
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    486 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
```

19. The dataset contains 506 entries and 14 columns, with 6 columns (CRIM, ZN, INDUS, CHAS, AGE, LSTAT) having 20 missing values each.
20. Most columns are continuous (float64), while RAD and TAX are discrete (int64).
21. MEDV (median home value) is the target variable, likely influenced by features like RM (average rooms) and LSTAT (lower-status population).
22. Missing values need to be addressed through imputation or by dropping rows with missing data.
23. Exploratory analysis and modeling can help understand feature relationships and predict MEDV.

```
data.nunique()
```

```
CRIM       484
ZN          26
INDUS       76
CHAS         2
NOX         81
RM         446
AGE        348
```

```
DIS        412
RAD          9
TAX         66
PTRATIO     46
B          357
LSTAT      438
MEDV       229
dtype: int64
```

```
data.CHAS.unique()
```

```
array([ 0., nan,  1.])
```

```
data.ZN.unique()
```

```
array([ 18. ,   0. ,  12.5,  75. ,  21. ,  90. ,  85. , 100. ,  25. ,
        17.5,  80. ,   nan,  28. ,  45. ,  60. ,  95. ,  82.5,  30. ,
        22. ,  20. ,  40. ,  55. ,  52.5,  70. ,  34. ,  33. ,  35. ])
```

Data Cleaning

Checking Null values

data.isnull() - Returns a DataFrame of the same shape as data, where each element is True if it's NaN and False otherwise.

.sum() - Sums up the True values (which are treated as 1 in Python) column-wise, giving the total count of missing values for each column.

```
data.isnull().sum()
```

```
CRIM       20
ZN         20
INDUS      20
CHAS       20
NOX         0
RM          0
AGE        20
DIS         0
RAD         0
TAX         0
PTRATIO     0
B           0
LSTAT      20
MEDV        0
dtype: int64
```

```
data.duplicated().sum()
```

```
np.int64(0)
```

```
df = data.copy()
```

```python
df['CRIM'].fillna(df['CRIM'].mean(), inplace=True)
df['ZN'].fillna(df['ZN'].mean(), inplace=True)
df['CHAS'].fillna(df['CHAS'].mode()[0], inplace=True)
df['INDUS'].fillna(df['INDUS'].mean(), inplace=True)
df['AGE'].fillna(df['AGE'].median(), inplace=True)  # Median is often
preferred for skewed distributions
df['LSTAT'].fillna(df['LSTAT'].median(), inplace=True)
```

```python
df.isnull().sum()
```

```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
MEDV       0
dtype: int64
```

```python
df.head()
```

```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD  TAX  PTRATIO  
\
0  0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900    1  296     15.3   
1  0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671    2  242     17.8   
2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671    2  242     17.8   
3  0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622    3  222     18.7   
4  0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622    3  222     18.7   

        B  LSTAT  MEDV  
0  396.90   4.98  24.0  
1  396.90   9.14  21.6  
2  392.83   4.03  34.7  
3  394.63   2.94  33.4  
4  396.90  11.43  36.2  
```

```python
df['CHAS'] = df['CHAS'].astype('int')
```

```python
df.describe().T
```

```
         count       mean        std      min       25%       50%  \
CRIM     506.0   3.611874   8.545770  0.00632  0.083235   0.29025   
ZN       506.0  11.211934  22.921051  0.00000  0.000000   0.00000   
INDUS    506.0  11.083992   6.699165  0.46000  5.190000   9.90000   
CHAS     506.0   0.067194   0.250605  0.00000  0.000000   0.00000   
```

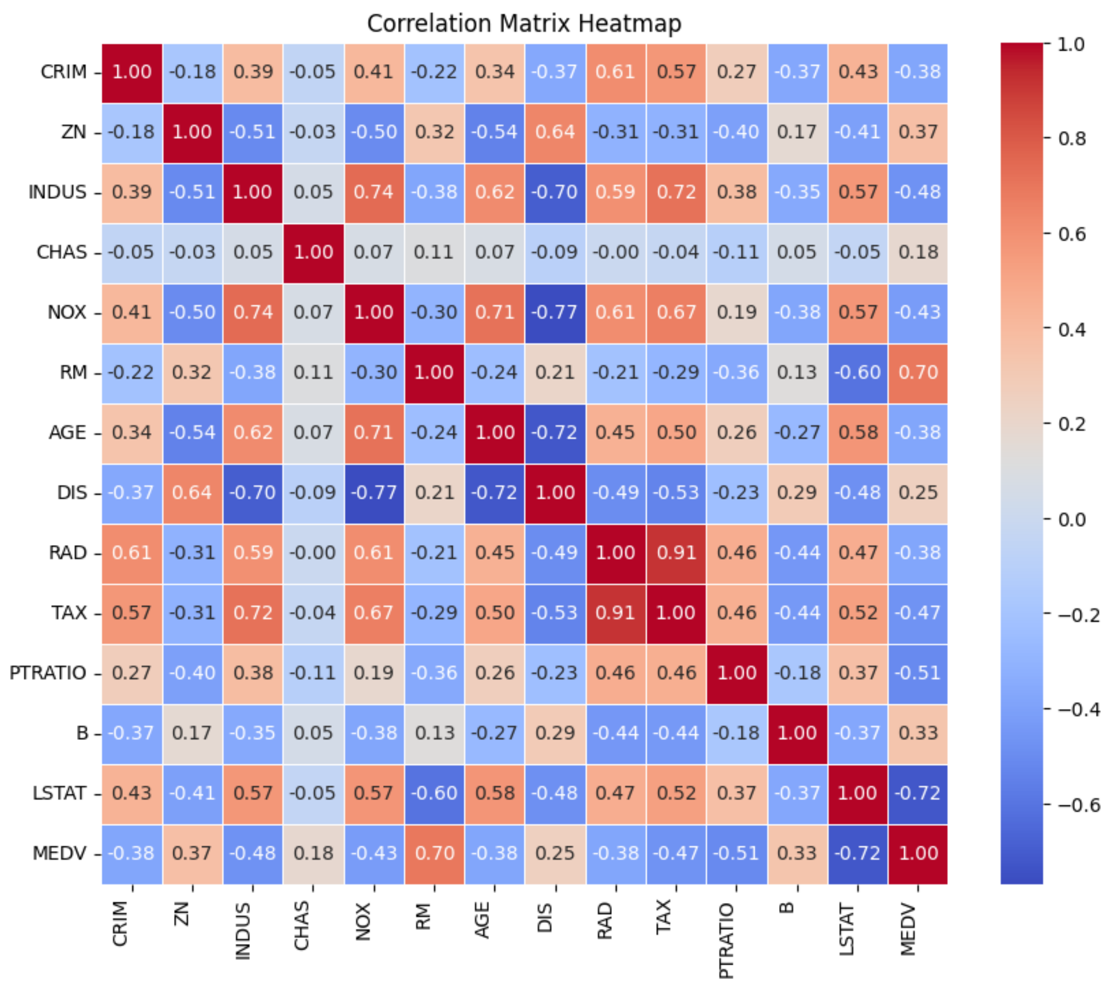
```
NOX      506.0    0.554695    0.115878    0.38500    0.449000    0.53800
RM       506.0    6.284634    0.702617    3.56100    5.885500    6.20850
AGE      506.0   68.845850   27.486962    2.90000   45.925000   76.80000
DIS      506.0    3.795043    2.105710    1.12960    2.100175    3.20745
RAD      506.0    9.549407    8.707259    1.00000    4.000000    5.00000
TAX      506.0  408.237154  168.537116  187.00000  279.000000  330.00000
PTRATIO  506.0   18.455534    2.164946   12.60000   17.400000   19.05000
B        506.0  356.674032   91.294864    0.32000  375.377500  391.44000
LSTAT    506.0   12.664625    7.017219    1.73000    7.230000   11.43000
MEDV     506.0   22.532806    9.197104    5.00000   17.025000   21.20000

                75%       max
CRIM       3.611874   88.9762
ZN        11.211934  100.0000
INDUS     18.100000   27.7400
CHAS       0.000000    1.0000
NOX        0.624000    0.8710
RM         6.623500    8.7800
AGE       93.575000  100.0000
DIS        5.188425   12.1265
RAD       24.000000   24.0000
TAX      666.000000  711.0000
PTRATIO   20.200000   22.0000
B        396.225000  396.9000
LSTAT     16.570000   37.9700
MEDV      25.000000   50.0000
```

```python
for i in df.columns:
    plt.figure(figsize=(6,3))

    plt.subplot(1, 2, 1)
    df[i].hist(bins=20, alpha=0.5, color='b',edgecolor='black')
    plt.title(f'Histogram of {i}')
    plt.xlabel(i)
    plt.ylabel('Frequency')

    plt.subplot(1, 2, 2)
    plt.boxplot(df[i], vert=False)
    plt.title(f'Boxplot of {i}')

    plt.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-1-72aa2831224b> in <module>
----> 1 for i in df.columns:
      2     plt.figure(figsize=(6,3))
      3
      4     plt.subplot(1, 2, 1)
      5     df[i].hist(bins=20, alpha=0.5, color='b',edgecolor='black')
```

```
NameError: name 'df' is not defined
```

```python
corr = df.corr(method='pearson')

plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, cmap="coolwarm", fmt=".2f", linewidths=0.5)
plt.xticks(rotation=90, ha='right')
plt.yticks(rotation=0)
plt.title("Correlation Matrix Heatmap")
plt.show()
```




```python
X = df.drop('MEDV', axis=1)  # All columns except 'MEDV'
y = df['MEDV']  # Target variable
```

Why Use StandardScaler?

24. Improved model performance: Linear models assume that features are normally distributed around the mean. Scaling the data can make the algorithm converge faster and produce more accurate predictions.
25. Prevents bias due to feature magnitude: Features with larger numeric ranges (like TAX or CRIM) may dominate the model if not scaled properly, especially in

regularized models. While standard linear regression may not be heavily affected, scaling ensures more consistent results.

```
# Scale the features
scale = StandardScaler()
X_scaled  = scale.fit_transform(X)

# Split the data into training (80%) and testing (20%) sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled , y,
test_size=0.2, random_state=42)

# Initialize the linear regression model
model = LinearRegression()

# Fit the model on the training data
model.fit(X_train, y_train)

LinearRegression()

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

array([28.99719439, 36.56606809, 14.51022803, 25.02572187, 18.42885474,
       23.02785726, 17.95437605, 14.5769479 , 22.14430832, 20.84584632,
       25.15283588, 18.55925182, -5.69168071, 21.71242445, 19.06845707,
       25.94275348, 19.70991322,  5.85916505, 40.9608103 , 17.21528576,
       25.36124981, 30.26007975, 11.78589412, 23.48106943, 17.35338161,
       15.13896898, 21.61919056, 14.51459386, 23.17246824, 19.40914754,
       22.56164985, 25.21208496, 25.88782605, 16.68297496, 16.44747174,
       16.65894826, 31.10314158, 20.25199803, 24.38567686, 23.09800032,
       14.47721796, 32.36053979, 43.01157914, 17.61473728, 27.60723089,
       16.43366912, 14.25719607, 26.0854729 , 19.75853278, 30.15142187,
       21.01932313, 33.72128781, 16.39180467, 26.36438908, 39.75793372,
       22.02419633, 18.39453126, 32.81854401, 25.370573  , 12.82224665,
       22.76128341, 30.73955199, 31.34386371, 16.27681305, 20.36945226,
       17.23156773, 20.15406451, 26.15613066, 30.92791361, 11.42177654,
       20.89590447, 26.58633798, 11.01176073, 12.76831709, 23.73870867,
        6.37180464, 21.6922679 , 41.74800223, 18.64423785,  8.82325704,
       20.96406016, 13.20179007, 20.99146149,  9.17404063, 23.0011185 ,
       32.41062673, 18.99778065, 25.56204885, 28.67383635, 19.76918944,
       25.94842754,  5.77674362, 19.514431  , 15.22571165, 10.87671123,
       20.08359505, 23.77725749,  0.05985008, 13.56333825, 16.1215622 ,
       22.74200442, 24.36218289])

# Calculate Mean Squared Error
mse = mean_squared_error(y_test, y_pred)

# Calculate Root Mean Squared Error (RMSE)
rmse = np.sqrt(mse)

# Calculate R-squared value
```

```
r2 = r2_score(y_test, y_pred)

print(f'Mean Squared Error: {mse}')
print(f'Root Mean Squared Error: {rmse}')
print(f'R-squared: {r2}')
```

```
Mean Squared Error: 24.944071172175562
Root Mean Squared Error: 4.994403985679929
R-squared: 0.6598556613717499
```

Program 8:

Develop a program to demonstrate the working of the decision tree algorithm. Use Breast Cancer Data set for building the decision tree and apply this knowledge to classify a new sample.

```
# Importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix

from sklearn.tree import export_graphviz
from IPython.display import Image
import pydotplus

import warnings
warnings.filterwarnings('ignore')

data = pd.read_csv(r'C:\Users\Admin\OneDrive\Documents\Machine Learning
Lab\Datasets\Breast Cancer Dataset.csv')

pd.set_option('display.max_columns', None)

data.head()
```

```
         id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean
\
0    842302         M        17.99         10.38          122.80     1001.0
1    842517         M        20.57         17.77          132.90     1326.0
2  84300903         M        19.69         21.25          130.00     1203.0
3  84348301         M        11.42         20.38           77.58      386.1
4  84358402         M        20.29         14.34          135.10     1297.0

   smoothness_mean  compactness_mean  concavity_mean  concave_points_mean  \
0          0.11840           0.27760          0.3001              0.14710
1          0.08474           0.07864          0.0869              0.07017
2          0.10960           0.15990          0.1974              0.12790
3          0.14250           0.28390          0.2414              0.10520
4          0.10030           0.13280          0.1980              0.10430

   symmetry_mean  fractal_dimension_mean  radius_se  texture_se  perimeter_se
\
0         0.2419                 0.07871     1.0950      0.9053         8.589
1         0.1812                 0.05667     0.5435      0.7339         3.398
2         0.2069                 0.05999     0.7456      0.7869         4.585
```

```
3       0.2597                  0.09744     0.4956      1.1560         3.445
4       0.1809                  0.05883     0.7572      0.7813         5.438

   area_se  smoothness_se  compactness_se  concavity_se  concave_points_se  \
0   153.40       0.006399         0.04904       0.05373            0.01587
1    74.08       0.005225         0.01308       0.01860            0.01340
2    94.03       0.006150         0.04006       0.03832            0.02058
3    27.23       0.009110         0.07458       0.05661            0.01867
4    94.44       0.011490         0.02461       0.05688            0.01885

   symmetry_se  fractal_dimension_se  radius_worst  texture_worst  \
0      0.03003              0.006193         25.38          17.33
1      0.01389              0.003532         24.99          23.41
2      0.02250              0.004571         23.57          25.53
3      0.05963              0.009208         14.91          26.50
4      0.01756              0.005115         22.54          16.67

   perimeter_worst  area_worst  smoothness_worst  compactness_worst  \
0           184.60      2019.0            0.1622             0.6656
1           158.80      1956.0            0.1238             0.1866
2           152.50      1709.0            0.1444             0.4245
3            98.87       567.7            0.2098             0.8663
4           152.20      1575.0            0.1374             0.2050

   concavity_worst  concave_points_worst  symmetry_worst  \
0           0.7119                0.2654          0.4601
1           0.2416                0.1860          0.2750
2           0.4504                0.2430          0.3613
3           0.6869                0.2575          0.6638
4           0.4000                0.1625          0.2364

   fractal_dimension_worst
0                  0.11890
1                  0.08902
2                  0.08758
3                  0.17300
4                  0.07678
```

```
data.shape
```

```
(569, 32)
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 32 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   id                       569 non-null    int64
 1   diagnosis                569 non-null    object
```

```
 2   radius_mean              569 non-null    float64
 3   texture_mean             569 non-null    float64
 4   perimeter_mean           569 non-null    float64
 5   area_mean                569 non-null    float64
 6   smoothness_mean          569 non-null    float64
 7   compactness_mean         569 non-null    float64
 8   concavity_mean           569 non-null    float64
 9   concave_points_mean      569 non-null    float64
 10  symmetry_mean            569 non-null    float64
 11  fractal_dimension_mean   569 non-null    float64
 12  radius_se                569 non-null    float64
 13  texture_se               569 non-null    float64
 14  perimeter_se             569 non-null    float64
 15  area_se                  569 non-null    float64
 16  smoothness_se            569 non-null    float64
 17  compactness_se           569 non-null    float64
 18  concavity_se             569 non-null    float64
 19  concave_points_se        569 non-null    float64
 20  symmetry_se              569 non-null    float64
 21  fractal_dimension_se     569 non-null    float64
 22  radius_worst             569 non-null    float64
 23  texture_worst            569 non-null    float64
 24  perimeter_worst          569 non-null    float64
 25  area_worst               569 non-null    float64
 26  smoothness_worst         569 non-null    float64
 27  compactness_worst        569 non-null    float64
 28  concavity_worst          569 non-null    float64
 29  concave_points_worst     569 non-null    float64
 30  symmetry_worst           569 non-null    float64
 31  fractal_dimension_worst  569 non-null    float64
dtypes: float64(30), int64(1), object(1)
memory usage: 142.4+ KB
```

```
data.diagnosis.unique()
```

```
array(['M', 'B'], dtype=object)
```

Data Preprocessing

Data Cleaning

```
data.isnull().sum()
```

```
id                         0
diagnosis                  0
radius_mean                0
texture_mean               0
perimeter_mean             0
area_mean                  0
smoothness_mean            0
compactness_mean           0
concavity_mean             0
```

```
concave_points_mean        0
symmetry_mean              0
fractal_dimension_mean     0
radius_se                  0
texture_se                 0
perimeter_se               0
area_se                    0
smoothness_se              0
compactness_se             0
concavity_se               0
concave_points_se          0
symmetry_se                0
fractal_dimension_se       0
radius_worst               0
texture_worst              0
perimeter_worst            0
area_worst                 0
smoothness_worst           0
compactness_worst          0
concavity_worst            0
concave_points_worst       0
symmetry_worst             0
fractal_dimension_worst    0
dtype: int64
```

```
data.duplicated().sum()
```

```
np.int64(0)
```

```
df = data.drop(['id'], axis=1)
```

```
df['diagnosis'] = df['diagnosis'].map({'M':1, 'B':0}) # Malignant:1, Benign:0
```

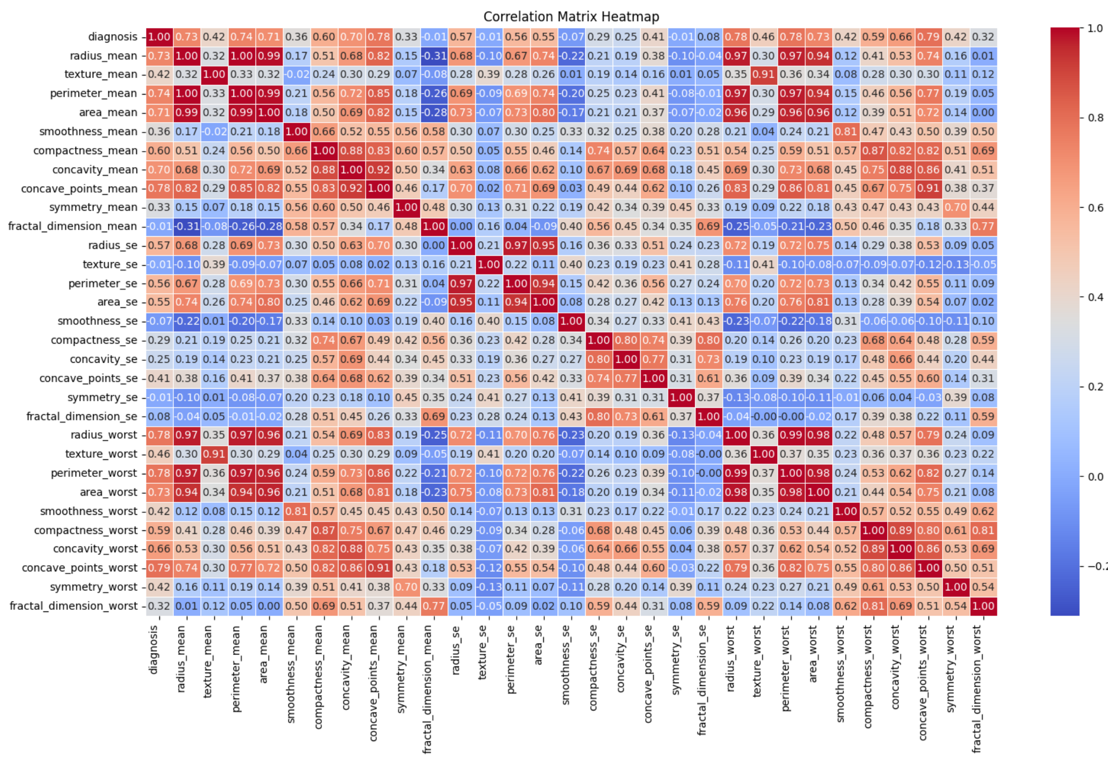
Discriptive Statistics

```
df.describe().T
```

```
                         count        mean         std         min  \
diagnosis                569.0    0.372583    0.483918    0.000000
radius_mean              569.0   14.127292    3.524049    6.981000
texture_mean             569.0   19.289649    4.301036    9.710000
perimeter_mean           569.0   91.969033   24.298981   43.790000
area_mean                569.0  654.889104  351.914129  143.500000
smoothness_mean          569.0    0.096360    0.014064    0.052630
compactness_mean         569.0    0.104341    0.052813    0.019380
concavity_mean           569.0    0.088799    0.079720    0.000000
concave_points_mean      569.0    0.048919    0.038803    0.000000
symmetry_mean            569.0    0.181162    0.027414    0.106000
fractal_dimension_mean   569.0    0.062798    0.007060    0.049960
radius_se                569.0    0.405172    0.277313    0.111500
texture_se               569.0    1.216853    0.551648    0.360200
perimeter_se             569.0    2.866059    2.021855    0.757000
```

```
area_se                  569.0   40.337079   45.491006    6.802000
smoothness_se            569.0    0.007041    0.003003    0.001713
compactness_se           569.0    0.025478    0.017908    0.002252
concavity_se             569.0    0.031894    0.030186    0.000000
concave_points_se        569.0    0.011796    0.006170    0.000000
symmetry_se              569.0    0.020542    0.008266    0.007882
fractal_dimension_se     569.0    0.003795    0.002646    0.000895
radius_worst             569.0   16.269190    4.833242    7.930000
texture_worst            569.0   25.677223    6.146258   12.020000
perimeter_worst          569.0  107.261213   33.602542   50.410000
area_worst               569.0  880.583128  569.356993  185.200000
smoothness_worst         569.0    0.132369    0.022832    0.071170
compactness_worst        569.0    0.254265    0.157336    0.027290
concavity_worst          569.0    0.272188    0.208624    0.000000
concave_points_worst     569.0    0.114606    0.065732    0.000000
symmetry_worst           569.0    0.290076    0.061867    0.156500
fractal_dimension_worst  569.0    0.083946    0.018061    0.055040

                                25%         50%          75%         max
diagnosis                  0.000000    0.000000     1.000000     1.00000
radius_mean               11.700000   13.370000    15.780000    28.11000
texture_mean              16.170000   18.840000    21.800000    39.28000
perimeter_mean            75.170000   86.240000   104.100000   188.50000
area_mean                420.300000  551.100000   782.700000  2501.00000
smoothness_mean            0.086370    0.095870     0.105300     0.16340
compactness_mean           0.064920    0.092630     0.130400     0.34540
concavity_mean             0.029560    0.061540     0.130700     0.42680
concave_points_mean        0.020310    0.033500     0.074000     0.20120
symmetry_mean              0.161900    0.179200     0.195700     0.30400
fractal_dimension_mean     0.057700    0.061540     0.066120     0.09744
radius_se                  0.232400    0.324200     0.478900     2.87300
texture_se                 0.833900    1.108000     1.474000     4.88500
perimeter_se               1.606000    2.287000     3.357000    21.98000
area_se                   17.850000   24.530000    45.190000   542.20000
smoothness_se              0.005169    0.006380     0.008146     0.03113
compactness_se             0.013080    0.020450     0.032450     0.13540
concavity_se               0.015090    0.025890     0.042050     0.39600
concave_points_se          0.007638    0.010930     0.014710     0.05279
symmetry_se                0.015160    0.018730     0.023480     0.07895
fractal_dimension_se       0.002248    0.003187     0.004558     0.02984
radius_worst              13.010000   14.970000    18.790000    36.04000
texture_worst             21.080000   25.410000    29.720000    49.54000
perimeter_worst           84.110000   97.660000   125.400000   251.20000
area_worst               515.300000  686.500000  1084.000000  4254.00000
smoothness_worst           0.116600    0.131300     0.146000     0.22260
compactness_worst          0.147200    0.211900     0.339100     1.05800
concavity_worst            0.114500    0.226700     0.382900     1.25200
concave_points_worst       0.064930    0.099930     0.161400     0.29100
symmetry_worst             0.250400    0.282200     0.317900     0.66380
fractal_dimension_worst    0.071460    0.080040     0.092080     0.20750
```

```python
corr = df.corr(method='pearson')

plt.figure(figsize=(18, 10))
sns.heatmap(corr, annot=True, cmap="coolwarm", fmt=".2f", linewidths=0.5)
plt.xticks(rotation=90, ha='right')
plt.yticks(rotation=0)
plt.title("Correlation Matrix Heatmap")
plt.show()
```




```python
X = df.drop('diagnosis', axis=1)  # Drop the 'diagnosis' column (target)
y = df['diagnosis']

# Split the dataset into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Fit the decision tree model
model = DecisionTreeClassifier(criterion='entropy') #criteria = gini, entropy
model.fit(X_train, y_train)
model
```

```
DecisionTreeClassifier(criterion='entropy')
```

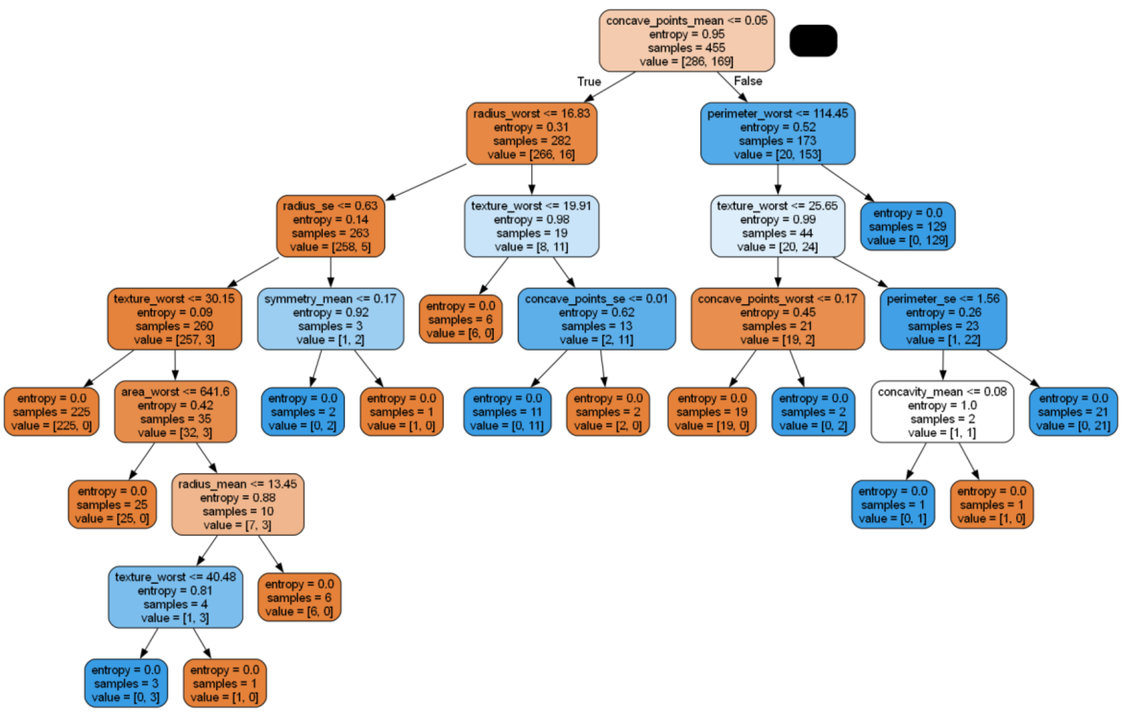
```python
import math

# Function to calculate entropy
def entropy(column):
    counts = column.value_counts()
    probabilities = counts / len(column)
```

```
    return -sum(probabilities * probabilities.apply(math.log2))

# Function to calculate conditional entropy
def conditional_entropy(data, X, target):
    feature_values = data[X].unique()  # Corrected: use .unique() on the
series
    weighted_entropy = 0
    for value in feature_values:
        subset = data[data[feature] == value]
        weighted_entropy += (len(subset) / len(data)) *
entropy(subset[target])
    return weighted_entropy

# Function to calculate information gain
def information_gain(data, X, target):
    total_entropy = entropy(data[target])
    feature_conditional_entropy = conditional_entropy(data, X, target)
    return total_entropy - feature_conditional_entropy


# Calculate information gain for each feature

for feature in X:
    ig = information_gain(df,feature,'diagnosis')
    print(f"Information Gain for {feature}: {ig}")
```

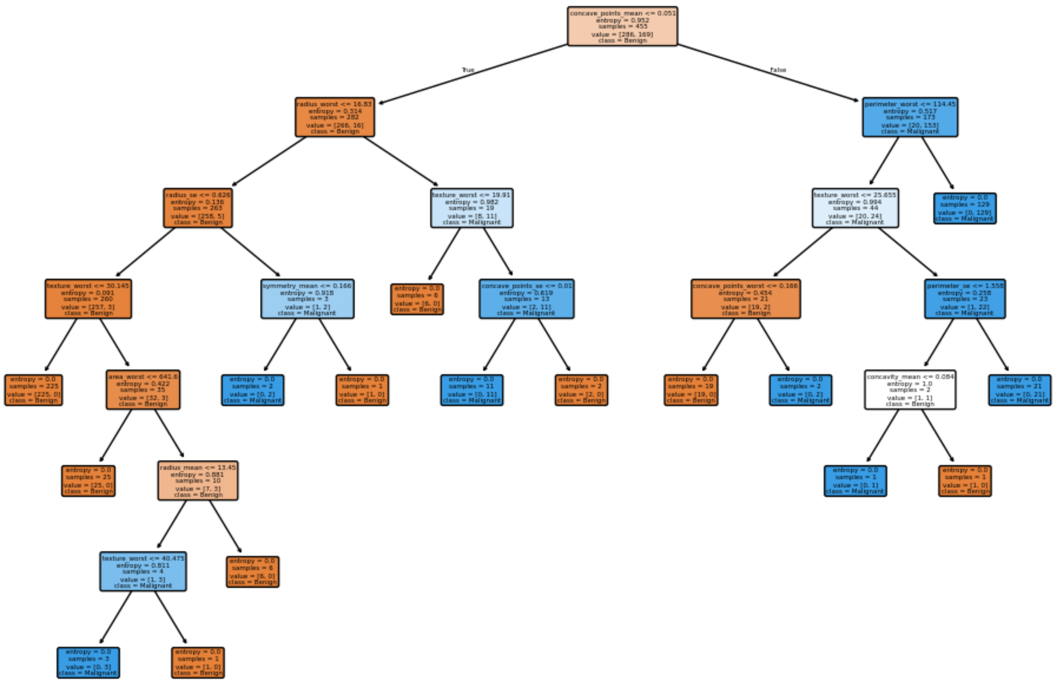
```
Information Gain for radius_mean: 0.8607815854835991
Information Gain for texture_mean: 0.8357118798482908
Information Gain for perimeter_mean: 0.9267038614138748
Information Gain for area_mean: 0.9280305529818247
Information Gain for smoothness_mean: 0.7761788341876101
Information Gain for compactness_mean: 0.9091291689709926
Information Gain for concavity_mean: 0.9350604299589776
Information Gain for concave_points_mean: 0.9420903069361305
Information Gain for symmetry_mean: 0.735036638169654
Information Gain for fractal_dimension_mean: 0.8361770160635639
Information Gain for radius_se: 0.9337337383910278
Information Gain for texture_se: 0.8642965239721755
Information Gain for perimeter_se: 0.9315454914704012
Information Gain for area_se: 0.925377169845925
Information Gain for smoothness_se: 0.9350604299589776
Information Gain for compactness_se: 0.9231889229252984
Information Gain for concavity_se: 0.9280305529818247
Information Gain for concave_points_se: 0.8585933385629725
Information Gain for symmetry_se: 0.8181371874054084
Information Gain for fractal_dimension_se: 0.9174857375160954
Information Gain for radius_worst: 0.9003074642106167
Information Gain for texture_worst: 0.8634349686194988
Information Gain for perimeter_worst: 0.8985843535052632
Information Gain for area_worst: 0.9350604299589776
```

```
Information Gain for smoothness_worst: 0.7197189097252679
Information Gain for compactness_worst: 0.9183472928687721
Information Gain for concavity_worst: 0.9302187999024514
Information Gain for concave_points_worst: 0.9148323543801957
Information Gain for symmetry_worst: 0.8453951399613433
Information Gain for fractal_dimension_worst: 0.8915544765281104
```

```python
# Export the tree to DOT format
dot_data = export_graphviz(model, out_file=None,
                           feature_names=X_train.columns,
                           rounded=True, proportion=False,
                           precision=2, filled=True)

# Convert DOT data to a graph
graph = pydotplus.graph_from_dot_data(dot_data)

# Display the graph
Image(graph.create_png())
```




```python
# Visualize the Decision Tree (optional)
plt.figure(figsize=(12, 8))
plot_tree(model, filled=True, feature_names=X.columns, class_names=['Benign',
'Malignant'], rounded=True)
plt.show()
```



```
y_pred = model.predict(X_test)
y_pred
```

```
array([0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0,
       1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 1])
```

```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred) * 100
classification_rep = classification_report(y_test, y_pred)

# Print the results
print("Accuracy:", accuracy)
print("Classification Report:\n", classification_rep)
```

```
Accuracy: 94.73684210526315
Classification Report:
               precision    recall  f1-score   support

           0       0.93      0.99      0.96        71
           1       0.97      0.88      0.93        43

    accuracy                           0.95       114
   macro avg       0.95      0.93      0.94       114
```

```
weighted avg       0.95      0.95      0.95       114
```

```
df.head(1)
```

```
   diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0          1        17.99         10.38           122.8     1001.0   

   smoothness_mean  compactness_mean  concavity_mean  concave_points_mean  \
0           0.1184            0.2776          0.3001               0.1471   

   symmetry_mean  fractal_dimension_mean  radius_se  texture_se  perimeter_se  
\
0         0.2419                 0.07871      1.095      0.9053         8.589   

   area_se  smoothness_se  compactness_se  concavity_se  concave_points_se  \
0    153.4       0.006399         0.04904       0.05373            0.01587   

   symmetry_se  fractal_dimension_se  radius_worst  texture_worst  \
0      0.03003              0.006193         25.38          17.33   

   perimeter_worst  area_worst  smoothness_worst  compactness_worst  \
0            184.6      2019.0            0.1622             0.6656   

   concavity_worst  concave_points_worst  symmetry_worst  \
0           0.7119                0.2654          0.4601   

   fractal_dimension_worst  
0                   0.1189  
```

```
new = [[12.5, 19.2, 80.0, 500.0, 0.085, 0.1, 0.05, 0.02, 0.17, 0.06,
     0.4, 1.0, 2.5, 40.0, 0.006, 0.02, 0.03, 0.01, 0.02, 0.003,
     16.0, 25.0, 105.0, 900.0, 0.13, 0.25, 0.28, 0.12, 0.29, 0.08]]
y_pred = model.predict(new)

# Output the prediction (0 = Benign, 1 = Malignant)
if y_pred[0] == 0:
    print("Prediction: Benign")
else:
    print("Prediction: Malignant")
```

```
Prediction: Benign
```

Program 9:

Develop a program to implement the Naive Bayesian classifier considering Olivetti Face Data set for training. Compute the accuracy of the classifier, considering a few test data set.

The Olivetti Face Dataset is a collection of images of faces, used primarily for face recognition tasks. The dataset contains 400 images of 40 different individuals, with 10 images per person. The dataset was created for research in machine learning and pattern recognition, especially in the context of facial recognition.

The Olivetti dataset provides the following key features:

*400 Images: Each image is a grayscale photo of a person's face.

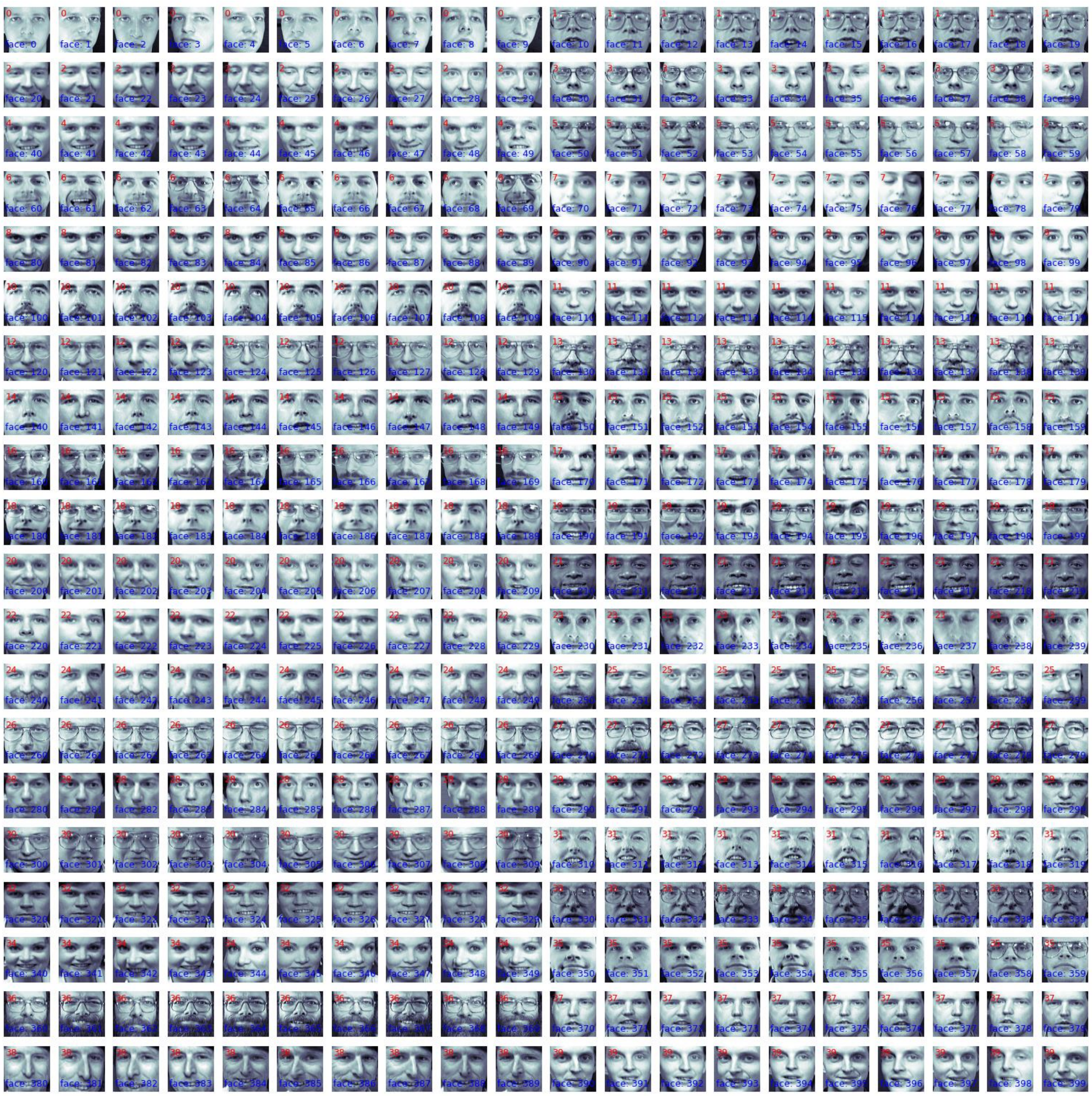
40 People: The dataset contains 40 different individuals, and each individual Has 10 different images.

*Image Size: Each image is 64x64 pixels, resulting in 4096 features (flattened vector) per image.

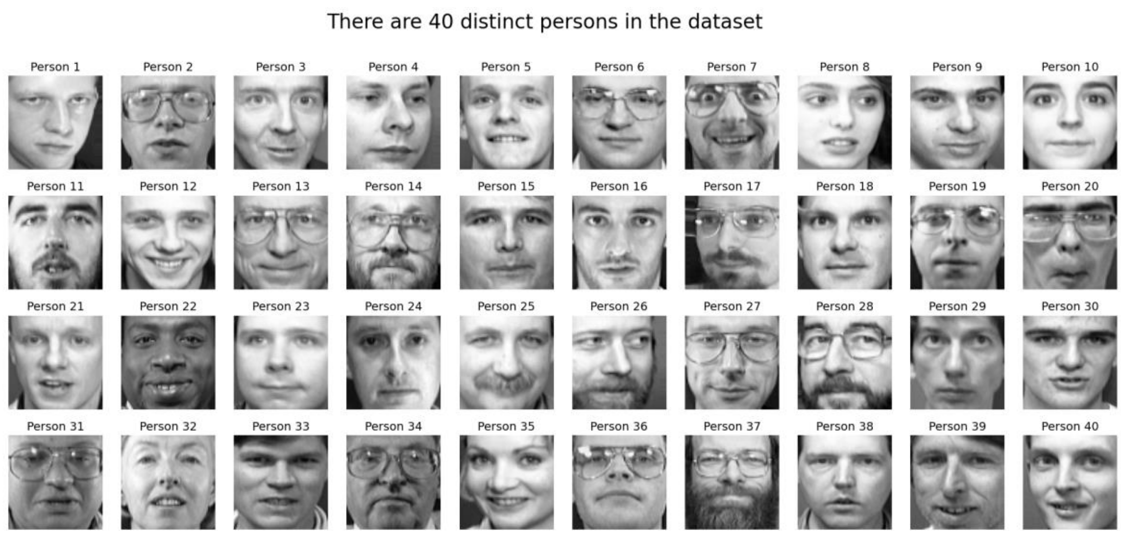
*Target Labels: Each image is associated with a label representing the individual (0 to 39).

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

from sklearn.datasets import fetch_olivetti_faces
data = fetch_olivetti_faces()

data.keys()

dict_keys(['data', 'images', 'target', 'DESCR'])

print("Data Shape:", data.data.shape)
print("Target Shape:", data.target.shape)
print("There are {} unique persons in the
dataset".format(len(np.unique(data.target))))
print("Size of each image is
{}x{}".format(data.images.shape[1],data.images.shape[1]))

Data Shape: (400, 4096)
Target Shape: (400,)
There are 40 unique persons in the dataset
Size of each image is 64x64

def print_faces(images, target, top_n):
    # Ensure the number of images does not exceed available data
    top_n = min(top_n, len(images))

    # Set up figure size based on the number of images
    grid_size = int(np.ceil(np.sqrt(top_n)))
    fig, axes = plt.subplots(grid_size, grid_size, figsize=(15, 15))
```

```
    fig.subplots_adjust(left=0, right=1, bottom=0, top=1, hspace=0.2,
wspace=0.2)

    for i, ax in enumerate(axes.ravel()):
        if i < top_n:
            ax.imshow(images[i], cmap='bone')
            ax.axis('off')
            ax.text(2, 12, str(target[i]), fontsize=9, color='red')
            ax.text(2, 55, f"face: {i}", fontsize=9, color='blue')
        else:
            ax.axis('off')

    plt.show()

print_faces(data.images,data.target,400)
```



```
#let us extract unique charaters present in dataset
def display_unique_faces(pics):
    fig = plt.figure(figsize=(24, 10))  # Set figure size
    columns, rows = 10, 4  # Define grid dimensions

    # Loop through grid positions and plot each image
    for i in range(1, columns * rows + 1):
        img_index = 10 * i - 1  # Calculate the image index
        if img_index < pics.shape[0]:  # Check for valid image index
            img = pics[img_index, :, :]
            ax = fig.add_subplot(rows, columns, i)
            ax.imshow(img, cmap='gray')
            ax.set_title(f"Person {i}", fontsize=14)
            ax.axis('off')

    plt.suptitle("There are 40 distinct persons in the dataset", fontsize=24)
    plt.show()

display_unique_faces(data.images)
```




```
from sklearn.model_selection import train_test_split
X = data.data
Y = data.target
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size = 0.3,
random_state=46)

print("x_train: ",x_train.shape)
print("x_test: ",x_test.shape)
```

```
x_train:  (280, 4096)
x_test:  (120, 4096)
```

```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix, accuracy_score
```

```
# Train the model
nb = GaussianNB()
nb.fit(x_train, y_train)

# Predict the test set results
y_pred = nb.predict(x_test)

# Calculate accuracy
nb_accuracy = round(accuracy_score(y_test, y_pred) * 100, 2)

# Display the confusion matrix
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(cm)

# Display accuracy result
print(f"Naive Bayes Accuracy: {nb_accuracy}%")
```

```
Confusion Matrix:
[[3 0 0 ... 0 0 0]
 [0 1 0 ... 0 0 0]
 [0 0 1 ... 0 0 0]
 ...
 [0 0 0 ... 2 0 0]
 [0 0 0 ... 0 3 0]
 [1 0 0 ... 0 0 1]]
Naive Bayes Accuracy: 73.33%
```

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import confusion_matrix, accuracy_score,
classification_report

# Initialize and fit Multinomial Naive Bayes
nb = MultinomialNB()
nb.fit(x_train, y_train)

# Predict the test set results
y_pred = nb.predict(x_test)

# Calculate accuracy
accuracy = round(accuracy_score(y_test, y_pred) * 100, 2)
print(f"Multinomial Naive Bayes Accuracy: {accuracy}%")
```

```
Multinomial Naive Bayes Accuracy: 85.83%
```

```
# Calculate the number of misclassified images
misclassified_idx = np.where(y_pred != y_test)[0]
num_misclassified = len(misclassified_idx)
```

```
# Print the number of misclassified images and accuracy
print(f"Number of misclassified images: {num_misclassified}")
print(f"Total images in test set: {len(y_test)}")
print(f"Accuracy: {round((1 - num_misclassified / len(y_test)) * 100, 2)}%")

# Visualize some of the misclassified images
n_misclassified_to_show = min(num_misclassified, 5)  # Show up to 5
misclassified images
plt.figure(figsize=(10, 5))
for i in range(n_misclassified_to_show):
    idx = misclassified_idx[i]
    plt.subplot(1, n_misclassified_to_show, i + 1)
    plt.imshow(x_test[idx].reshape(64, 64), cmap='gray')
    plt.title(f"True: {y_test[idx]}, Pred: {y_pred[idx]}")
    plt.axis('off')
plt.show()
```

```
Number of misclassified images: 17
Total images in test set: 120
Accuracy: 85.83%
```


```
from sklearn.preprocessing import label_binarize
from sklearn.metrics import roc_auc_score

# Binarize the test labels
y_test_bin = label_binarize(y_test, classes=np.unique(y_test))

# Get predicted probabilities for each class
y_pred_prob = nb.predict_proba(x_test)

# Calculate and print AUC for each class
for i in range(y_test_bin.shape[1]):
    roc_auc = roc_auc_score(y_test_bin[:, i], y_pred_prob[:, i])
    print(f"Class {i} AUC: {roc_auc:.2f}")
```

```
Class 0 AUC: 0.92
Class 1 AUC: 1.00
Class 2 AUC: 1.00
Class 3 AUC: 1.00
Class 4 AUC: 1.00
Class 5 AUC: 1.00
Class 6 AUC: 1.00
```

```
Class 7 AUC: 1.00
Class 8 AUC: 1.00
Class 9 AUC: 1.00
Class 10 AUC: 1.00
Class 11 AUC: 1.00
Class 12 AUC: 0.87
Class 13 AUC: 1.00
Class 14 AUC: 1.00
Class 15 AUC: 1.00
Class 16 AUC: 0.65
Class 17 AUC: 0.16
Class 18 AUC: 0.36
Class 19 AUC: 0.89
Class 20 AUC: 0.52
Class 21 AUC: 0.81
Class 22 AUC: 0.13
Class 23 AUC: 0.34
Class 24 AUC: 0.64
Class 25 AUC: 0.55
Class 26 AUC: 0.48
Class 27 AUC: 0.38
Class 28 AUC: 0.62
Class 29 AUC: 0.73
Class 30 AUC: 0.55
Class 31 AUC: 0.17
Class 32 AUC: 0.47
Class 33 AUC: 0.67
Class 34 AUC: 0.31
Class 35 AUC: 0.03
Class 36 AUC: 0.91
Class 37 AUC: 0.87
Class 38 AUC: 0.47
```

Program 10:

Develop a program to implement k-means clustering using Wisconsin Breast Cancer data set and visualize the clustering result.

Steps to Implement K-Means Clustering

1. **Load the dataset –** Use sklearn.datasets to fetch the Wisconsin Breast Cancer dataset.
2. **Preprocess the data –** Normalize features for better clustering.
3. **Apply K-Means algorithm –** Use KMeans from sklearn.cluster.
4. **Evaluate clustering performance –** Compare with actual labels using ARI or silhouette score.
5. **Visualize clusters –** Use PCA for dimensionality reduction and plot clusters.

1. Install and Import Required Libraries

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.datasets import load_breast_cancer

from sklearn.preprocessing import StandardScaler

from sklearn.cluster import KMeans

from sklearn.decomposition import PCA

from sklearn.metrics import silhouette_score, adjusted_rand_score
```

2. Load the Wisconsin Breast Cancer Dataset

```
# Load dataset

data = load_breast_cancer()

X = data.data

y = data.target  # Ground truth labels (0 - Malignant, 1 - Benign)

feature_names = data.feature_names


# Convert to DataFrame for better visualization
```

```
df = pd.DataFrame(X, columns=feature_names)
df['target'] = y  # Add target labels
df.head()
```

3. Normalize the Data

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)  # Standardize features
```

4. Apply K-Means Clustering

```
# Choose number of clusters (K=2 as we have benign/malignant labels)
kmeans = KMeans(n_clusters=2, random_state=42, n_init=10)
y_pred = kmeans.fit_predict(X_scaled)

# Add cluster labels to DataFrame
df['cluster'] = y_pred
```

5. Evaluate Clustering Performance

```
# Compare predicted clusters with actual labels
ari_score = adjusted_rand_score(y, y_pred)
silhouette_avg = silhouette_score(X_scaled, y_pred)

print(f"Adjusted Rand Index: {ari_score:.3f}")
print(f"Silhouette Score: {silhouette_avg:.3f}")
```

6. Visualize Clusters using PCA (2D Projection)

```
# Reduce data to 2D using PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
```

```
# Plot the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x=X_pca[:, 0], y=X_pca[:, 1], hue=y_pred, palette='coolwarm', alpha=0.7)
plt.title("K-Means Clustering on Breast Cancer Dataset (PCA Projection)")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.legend(title="Cluster")
plt.show()
```

Results & Insights

1.The **Adjusted Rand Index (ARI)** measures how well the clustering matches the actual labels (closer to 1 means better clustering).

2.The **Silhouette Score** measures how well-separated the clusters are.

3.The **PCA scatter plot** provides a 2D visualization of the clusters.