VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
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B.M.S. College of Engineering,

Bull Temple Road, Bangalore 560019

(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled "Machine Learning (23CS6PCMAL)" carried out by **Polu Rajeswari Vinuthna(1BM22CS193),** who is a bonafide student of **B.M.S. College of Engineering.** It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum. The Lab report has been approved as it satisfies the academic requirements in respect of an Machine Learning (23CS6PCMAL) work prescribed for the said degree.

Lab Faculty Incharge Name: **Ms. Saritha A N** Assistant Professor Department of CSE, BMSCE	 **Dr. Kavitha Sooda** Professor & HOD Department of CSE, BMSCE

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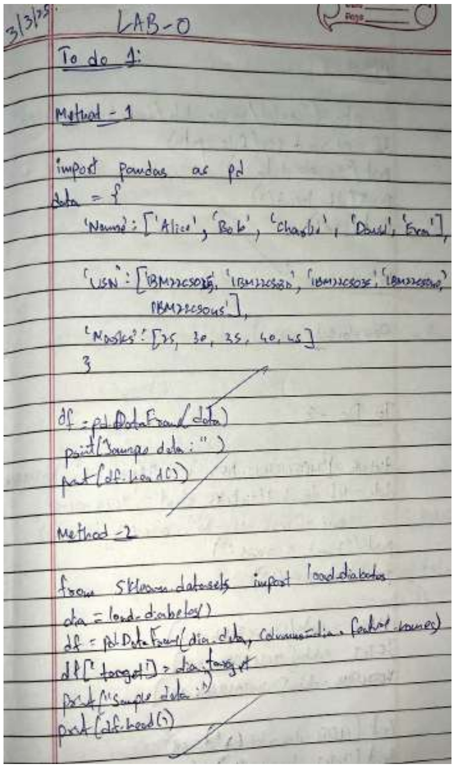
Github Link:
https://github.com/VINUTHNA193/ML

Program 1

Write a python program to import and export data using Pandas library functions

Screenshots



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LAB-0

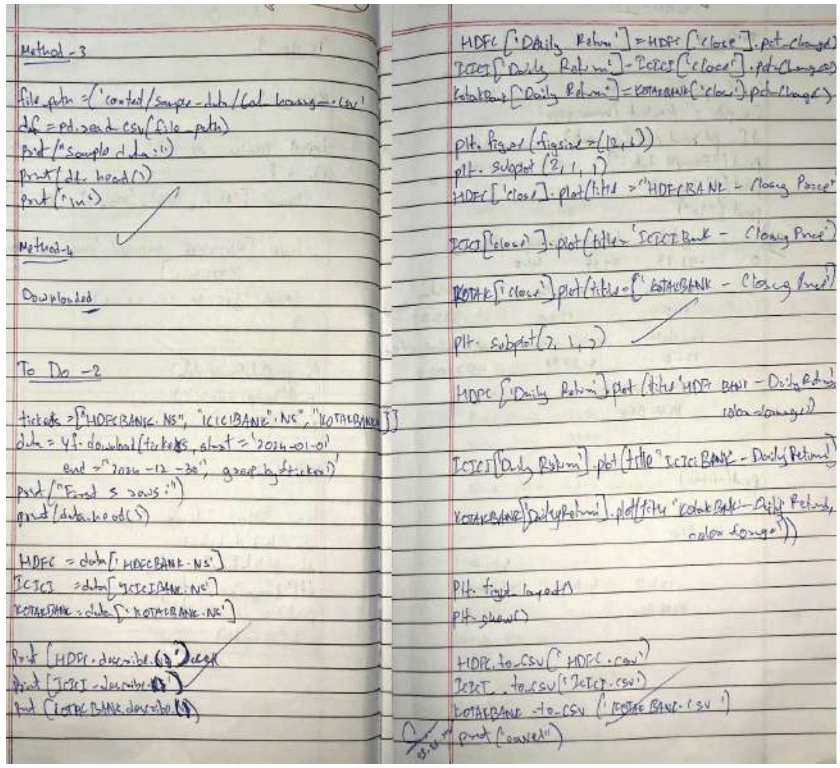
To do 1:

Method - 1

```
import pandas as pd
data = {
    'Name': ['Alice', 'Bob', 'Charlie', 'David', 'Eva'],
    'USN': ['1BM22CS0__', '1BM22CS0__', '1BM22CS0__', '1BM22CS0__', '1BM22CS0__'],
    'Marks': [25, 30, 35, 40, 45]
}
df = pd.DataFrame(data)
print("Sample data:")
print(df.head())
```

Method - 2

```
from sklearn.datasets import load_diabetes
dia = load_diabetes()
df = pd.DataFrame(dia.data, columns=dia.feature_names)
df['target'] = dia.target
print("Sample data:")
print(df.head())
```



Method - 3

```
file_path = ('content/sample_data/cal_housing_....csv')
df = pd.read_csv(file_path)
print("Sample data:")
print(df.head())
print("\n")
```

Method - 4

Downloaded

To Do - 2

```
tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK"]
data = yf.download(tickers, start='2024-01-01',
        end="2024-12-30", group_by='ticker')
print("First 5 rows:")
print(data.head())

HDFC = data['HDFCBANK.NS']
ICICI = data['ICICIBANK.NS']
KOTAKBANK = data['KOTAKBANK.NS']

print(HDFC.describe())
print(ICICI.describe())
print(KOTAKBANK.describe())

HDFC['Daily Return'] = HDFC['close'].pct_change()
ICICI['Daily Return'] = ICICI['close'].pct_change()
KotakBank['Daily Return'] = KOTAKBANK['close'].pct_change()

plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
HDFC['close'].plot(title="HDFCBANK - Closing Price")

ICICI['close'].plot(title='ICICI Bank - Closing Price')

KOTAK['close'].plot(title=('KOTAKBANK - Closing Price')

plt.subplot(2, 1, 2)
HDFC['Daily Return'].plot(title='HDFC BANK - Daily Return',
        color='orange')

ICICI['Daily Return'].plot(title="ICICI BANK - Daily Return")

KOTAKBANK['Daily Return'].plot(title="Kotak Bank - Daily Return",
        color='orange'))

plt.tight_layout()
plt.show()

HDFC.to_csv('HDFC.csv')
ICICI.to_csv('ICICI.csv')
KOTAKBANK.to_csv('KOTAKBANK.csv')
print("saved")
```

Code:

import pandas as pd

Create a DataFrame directly from a dictionary

data = {

'Name': ['Alice', 'Bob', 'Charlie', 'David'],

'Age': [25, 30, 35, 40],

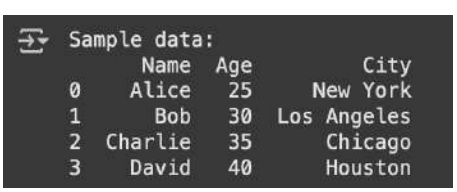
'City': ['New York', 'Los Angeles', 'Chicago', 'Houston']

}

df = pd.DataFrame(data)

print("Sample data:")

print(df.head())



```
Sample data:
      Name  Age         City
0    Alice   25     New York
1      Bob   30  Los Angeles
2  Charlie   35      Chicago
3    David   40      Houston
```

```
from sklearn.datasets import load_iris
iris = load_iris()
df = pd.DataFrame(iris.data, columns=iris.feature_names)
df['target'] = iris.target
print("Sample data:")
print(df.head())
```

```
Sample data:
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2

   target
0       0
1       0
2       0
3       0
4       0
```

```
# Load data from a CSV file (replace 'data.csv' with your file path)
file_path = '/content/industry.csv'
# Ensure the file exists in the same directory
df = pd.read_csv(file_path)
print("Sample data:")
print(df.head())
print("\n")
```

```
Sample data:
                         Industry
0              Accounting/Finance
1  Advertising/Public Relations
2              Aerospace/Aviation
3  Arts/Entertainment/Publishing
4                      Automotive
```

```
import pandas as pd
# Reading data from a CSV file
data = {
'Name': ['Alice', 'Bob', 'Charlie', 'David', 'Evangline'],
'USN': ['1BM22CS025', '1BM22CS030', '1BM22CS035', '1BM22CS040', '1BM22CS045'],
'Marks': [25, 30, 35, 40, 45]
}
df = pd.DataFrame(data)
print("Sample data:")
print(df.head())
```

```
Sample data:
        Name        USN  Marks
0      Alice  1BM22CS025     25
1        Bob  1BM22CS030     30
2    Charlie  1BM22CS035     35
3      David  1BM22CS040     40
4  Evangline  1BM22CS045     45
```

from sklearn.datasets import load_diabetes

dia = load_diabetes()

df = pd.DataFrame(dia.data, columns=dia.feature_names)

df['target'] = dia.target

print("Sample data:")

print(df.head())

```
Sample data:
        age       sex       bmi        bp        s1        s2        s3  \
0  0.038076  0.050680  0.061696  0.021872 -0.044223 -0.034821 -0.043401
1 -0.001882 -0.044642 -0.051474 -0.026328 -0.008449 -0.019163  0.074412
2  0.085299  0.050680  0.044451 -0.005670 -0.045599 -0.034194 -0.032356
3 -0.089063 -0.044642 -0.011595 -0.036656  0.012191  0.024991 -0.036038
4  0.005383 -0.044642 -0.036385  0.021872  0.003935  0.015596  0.008142

         s4        s5        s6  target
0 -0.002592  0.019907 -0.017646   151.0
1 -0.039493 -0.068332 -0.092204    75.0
2 -0.002592  0.002861 -0.025930   141.0
3  0.034309  0.022688 -0.009362   206.0
4 -0.002592 -0.031988 -0.046641   135.0
```

Load data from a CSV file (replace 'data.csv' with your file path)

file_path = '/content/sample_data/california_housing_train.csv' # Ensure the file exists in the same directory

df = pd.read_csv(file_path)

print("Sample data:")

print(df.head())

print("\n")

```
Sample data:
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -114.31     34.19                15.0       5612.0          1283.0
1    -114.47     34.40                19.0       7650.0          1901.0
2    -114.56     33.69                17.0        720.0           174.0
3    -114.57     33.64                14.0       1501.0           337.0
4    -114.57     33.57                20.0       1454.0           326.0

   population  households  median_income  median_house_value
0      1015.0       472.0         1.4936             66900.0
1      1129.0       463.0         1.8200             80100.0
2       333.0       117.0         1.6509             85700.0
3       515.0       226.0         3.1917             73400.0
4       624.0       262.0         1.9250             65500.0
```

Load data from a CSV file (replace 'data.csv' with your file path)

downloading and loading

file_path = '/content/Dataset of Diabetes .csv' # Ensure the file exists in the same directory

df = pd.read_csv(file_path)

print("Sample data:")

print(df.head())

print("\n")

```
Sample data:
    ID  No_Pation Gender  AGE  Urea  Cr  HbA1c  Chol   TG  HDL  LDL  VLDL  \
0  502      17975      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
1  735      34221      M   26   4.5  62    4.9   3.7  1.4  1.1  2.1   0.6
2  420      47975      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
3  680      87656      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
4  504      34223      M   33   7.1  46    4.9   4.9  1.0  0.8  2.0   0.4

    BMI CLASS
0  24.0     N
1  23.0     N
2  24.0     N
3  24.0     N
4  21.0     N
```

import pandas as pd

Reading data from a CSV file

df =pd.read_csv('/content/sample_data/california_housing_test.csv')

Displaying the first few rowsof the DataFrame

print(df.head())

Writing the DataFrame to a CSV file

df.to_csv('output.csv',index=False)

print("Data saved tooutput.csv")

```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.05     37.37                27.0       3885.0           661.0
1    -118.30     34.26                43.0       1510.0           310.0
2    -117.81     33.78                27.0       3589.0           507.0
3    -118.36     33.82                28.0         67.0            15.0
4    -119.67     36.33                19.0       1241.0           244.0

   population  households  median_income  median_house_value
0      1537.0       606.0         6.6085            344700.0
1       809.0       277.0         3.5990            176500.0
2      1484.0       495.0         5.7934            270500.0
3        49.0        11.0         6.1359            330000.0
4       850.0       237.0         2.9375             81700.0
Data saved tooutput.csv
```

Reading sales data from a CSV file

california_df =pd.read_csv('/content/sample_data/california_housing_test.csv')

Displaying the first fewrows of the dataset

print("First few rows of the california_housing_test data:")

print(california_df.head())

```
First few rows of the california_housing_test data:
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.05     37.37                27.0       3885.0           661.0
1    -118.30     34.26                43.0       1510.0           310.0
2    -117.81     33.78                27.0       3589.0           507.0
3    -118.36     33.82                28.0         67.0            15.0
4    -119.67     36.33                19.0       1241.0           244.0

   population  households  median_income  median_house_value
0      1537.0       606.0         6.6085            344700.0
1       809.0       277.0         3.5990            176500.0
2      1484.0       495.0         5.7934            270500.0
3        49.0        11.0         6.1359            330000.0
4       850.0       237.0         2.9375             81700.0
```

Grouping by Region and calculating total sales

california =california_df.groupby('total_rooms')['total_bedrooms'].sum()

print("\nTotal housing by region:")

print(california)

```
Total housing by region:
total_rooms
6.0          2.0
16.0         4.0
18.0         3.0
19.0        19.0
21.0         7.0
            ...
21988.0   4055.0
23915.0   4135.0
24121.0   4522.0
27870.0   5027.0
30450.0   5033.0
Name: total_bedrooms, Length: 2215, dtype: float64
```

Grouping by Product and calculating total quantity sold

best_selling_homes =

california_df.groupby('housing_median_age')['households'].sum().sort_values(ascending=False)

print("\nBest-selling products by quantity:")

print(best_selling_homes)

```
Best-selling products by quantity:
housing_median_age
52.0    64943.0
17.0    58184.0
16.0    49321.0
19.0    47612.0
35.0    45376.0
25.0    44133.0
34.0    42328.0
26.0    42320.0
18.0    42040.0
24.0    41335.0
36.0    40843.0
15.0    40482.0
32.0    39534.0
29.0    38879.0
33.0    38627.0
27.0    38492.0
20.0    37554.0
5.0     37454.0
21.0    37112.0
4.0     35466.0
30.0    35027.0
22.0    34291.0
14.0    33256.0
37.0    31574.0
28.0    30872.0
12.0    28560.0
23.0    28165.0
11.0    25067.0
```

```python
# Saving the sales by region data to a CSV file
california.to_csv('california.csv')
# Saving the best-selling products data to a CSV file
best_selling_homes.to_csv('best_selling_homes.csv')
print("\nAnalysis results saved to CSV files.")
```

```
Analysis results saved to CSV files.
```

import yfinance as yf

import pandas as pd

import matplotlib.pyplot as plt

Step 2: Downloading Stock Market Data

Define the ticker symbols for Indian companies

Example: Reliance Industries (RELIANCE.NS), TCS (TCS.NS), Infosys (INFY.NS)

tickers = ["RELIANCE.NS", "TCS.NS", "INFY.NS"]

Fetch historical data for the last 1 year

data = yf.download(tickers, start="2022-10-01", end="2023-10-01",

group_by='ticker')

Display the first 5 rows of the dataset

print("First 5 rows of the dataset:")

print(data.head())

```
YF.download() has changed argument auto_adjust default to True
[*********************100%***********************]  3 of 3 completedFirst 5 rows of the dataset:
Ticker      RELIANCE.NS                                                       \
Price              Open         High          Low        Close    Volume
Date
2022-10-03  1096.071886  1107.736072  1083.009806  1085.988892  11852723
2022-10-04  1098.959251  1108.217280  1095.453061  1106.017334   8948850
2022-10-06  1113.258819  1122.883445  1108.285998  1110.096313  13352162
2022-10-07  1106.681897  1120.087782  1106.681897  1114.794189   7714340
2022-10-10  1102.259136  1108.034009  1094.467737  1102.625854   6329527

Ticker           TCS.NS                                                      \
Price              Open         High          Low        Close   Volume
Date
2022-10-03  2894.197635  2919.032606  2873.904430  2884.485840  1763331
2022-10-04  2927.970939  2993.730628  2921.254903  2987.111084  2145875
2022-10-06  3006.293304  3018.855764  2988.367592  2997.547852  1790816
2022-10-07  2993.150777  3000.495078  2955.173685  2961.744629  1939879
2022-10-10  2908.692292  3021.754418  2903.860578  3013.588867  3064063

Ticker          INFY.NS
Price              Open         High          Low        Close   Volume
Date
2022-10-03  1337.743240  1337.743240  1313.110574  1320.453003  4943169
2022-10-04  1345.038201  1356.928245  1339.638009  1354.228149  6631341
2022-10-06  1369.007786  1383.029504  1368.155094  1378.624023  6180672
2022-10-07  1370.286797  1381.182015  1364.412900  1374.881714  3994466
2022-10-10  1351.338576  1387.956005  1351.338576  1385.729614  5274677
```

Step 3: Basic Data Exploration

Check the shape of the dataset

print("\nShape of the dataset:")

print(data.shape)

Check column names

print("\nColumn names:")

print(data.columns)

Summary statistics for a specific stock (e.g., Reliance)

reliance_data = data['RELIANCE.NS']

print("\nSummary statistics for Reliance Industries:")

print(reliance_data.describe())

Calculate daily returns

Create a copy of the Reliance data to avoid modifying a slice of the original dataframe

reliance_data = data['RELIANCE.NS'].copy()

Now, apply the calculation

reliance_data['Daily Return'] = reliance_data['Close'].pct_change()

```
Shape of the dataset:
(247, 15)

Column names:
MultiIndex([('RELIANCE.NS',   'Open'),
            ('RELIANCE.NS',   'High'),
            ('RELIANCE.NS',    'Low'),
            ('RELIANCE.NS',  'Close'),
            ('RELIANCE.NS', 'Volume'),
            (     'TCS.NS',   'Open'),
            (     'TCS.NS',   'High'),
            (     'TCS.NS',    'Low'),
            (     'TCS.NS',  'Close'),
            (     'TCS.NS', 'Volume'),
            (    'INFY.NS',   'Open'),
            (    'INFY.NS',   'High'),
            (    'INFY.NS',    'Low'),
            (    'INFY.NS',  'Close'),
            (    'INFY.NS', 'Volume')],
           names=['Ticker', 'Price'])

Summary statistics for Reliance Industries:
Price         Open         High          Low        Close        Volume
count   247.000000   247.000000   247.000000   247.000000  2.470000e+02
mean   1155.033899  1163.758985  1144.612976  1154.002433  1.316652e+07
std      65.890843    66.876907    65.755901    66.726021  6.754099e+06
min    1015.178443  1017.470038   999.137216  1008.876526  3.370033e+06
25%    1106.532938  1111.081861  1092.347974  1104.997559  8.717141e+06
50%    1155.424265  1163.078198  1146.716157  1155.240967  1.158959e+07
75%    1202.667031  1209.102783  1193.235594  1201.447937  1.530302e+07
max    1297.045129  1308.961472  1281.920577  1302.476196  5.708188e+07
```

Plot the closing price and daily returns

plt.figure(figsize=(12, 6))

plt.subplot(2, 1, 1)

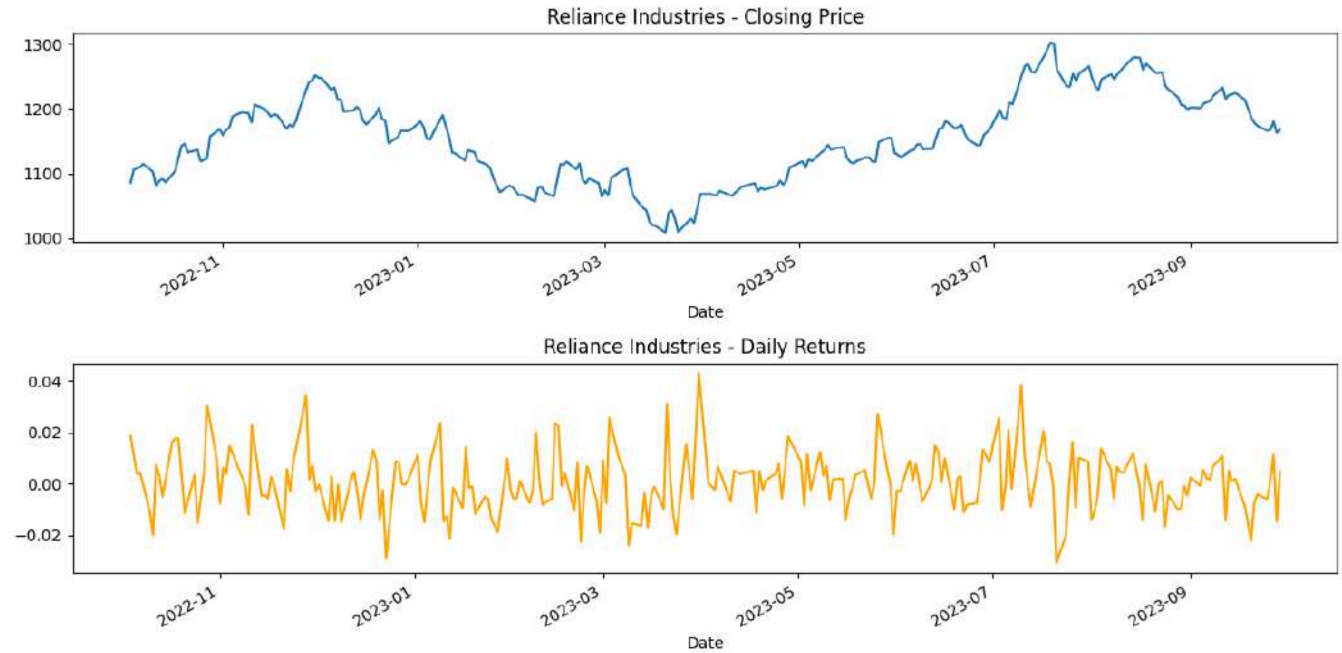
reliance_data['Close'].plot(title="Reliance Industries - Closing Price")

plt.subplot(2, 1, 2)

reliance_data['Daily Return'].plot(title="Reliance Industries - Daily Returns", color='orange')

plt.tight_layout()

plt.show()




```
# Step 4: Saving the Processed Data to a New CSV File
# Save the Reliance data to a CSV file
reliance_data.to_csv('reliance_stock_data.csv')
print("\nReliance stock data saved to 'reliance_stock_data.csv'.")
```

```
Reliance stock data saved to 'reliance_stock_data.csv'.
```

```
tickers = ["HDFCBANK.NS", "ICICIBANK.NS", "KOTAKBANK.NS"]
data = yf.download(tickers, start="2024-01-01", end="2024-12-30",
group_by='ticker')
# Display the first 5 rows of the dataset
print("First 5 rows of the dataset:")
print(data.head())
```

```
[*********************100%***********************]  3 of 3 completed
First 5 rows of the dataset:
Ticker      ICICIBANK.NS                                                   \
Price               Open        High         Low       Close    Volume
Date
2024-01-01    983.086778  996.273246  982.541485  990.869812   7683792
2024-01-02    988.490253  989.134730  971.883221  973.866150  16263825
2024-01-03    976.295294  979.567116  966.777197  975.650818  16826752
2024-01-04    977.980767  980.707295  973.519176  978.724365  22789140
2024-01-05    979.567084  989.779158  975.402920  985.218445  14875499

Ticker      HDFCBANK.NS                                                      \
Price              Open         High          Low        Close    Volume
Date
2024-01-01  1683.017598  1686.125187  1669.206199  1675.223999   7119843
2024-01-02  1675.914685  1679.860799  1665.950651  1676.210571  14621046
2024-01-03  1679.071480  1681.735059  1646.466666  1650.363525  14194881
2024-01-04  1655.394910  1672.116520  1648.193203  1668.071777  13367028
2024-01-05  1664.421596  1681.932477  1645.628180  1659.538208  15944735

Ticker     KOTAKBANK.NS
Price              Open         High          Low        Close   Volume
Date
2024-01-01  1906.909954  1916.899006  1891.027338  1907.059814  1425902
2024-01-02  1905.911108  1905.911108  1858.063525  1863.008179  5120796
2024-01-03  1861.959234  1867.952665  1845.627158  1863.857178  3781515
2024-01-04  1869.451068  1869.451068  1858.513105  1861.559692  2865766
2024-01-05  1863.457575  1867.852782  1839.383985  1845.577148  7799341
```

```
HDFC = data['HDFCBANK.NS']
print("\nSummary statistics for HDFC:")
print(HDFC.describe())
# Calculate daily returns
# Create a copy of the Reliance data to avoid modifying a slice of the original dataframe
HDFC = data['HDFCBANK.NS'].copy()
# Now, apply the calculation
HDFC['Daily Return'] = HDFC['Close'].pct_change()
```

```
Summary statistics for HDFC:
Price         Open         High          Low        Close        Volume
count   244.000000   244.000000   244.000000   244.000000  2.440000e+02
mean   1601.375295  1615.443664  1588.221245  1601.898968  2.119658e+07
std     134.648125   134.183203   132.796819   133.748372  2.133860e+07
min    1357.463183  1372.754374  1345.180951  1365.404785  8.798460e+05
25%    1475.316358  1494.072805  1460.259509  1474.564087  1.274850e+07
50%    1627.724976  1638.350037  1616.000000  1625.950012  1.686810e+07
75%    1696.474976  1711.425018  1679.250000  1697.062531  2.295014e+07
max    1877.699951  1880.000000  1858.550049  1871.750000  2.226710e+08
```

```
ICICI = data['ICICIBANK.NS']
print("\nSummary statistics for ICICI:")
print(ICICI.describe())
# Calculate daily returns
# Create a copy of the Reliance data to avoid modifying a slice of the original dataframe
ICICI = data['ICICIBANK.NS'].copy()
# Now, apply the calculation
```

ICICI['Daily Return'] = ICICI['Close'].pct_change()

```
Summary statistics for ICICI:
Price         Open         High          Low        Close        Volume
count   244.000000   244.000000   244.000000   244.000000  2.440000e+02
mean   1161.723560  1173.687900  1151.318979  1162.751791  1.539172e+07
std     104.905646   105.668229   105.083015   105.520481  9.503609e+06
min     965.637027   979.567116   961.869473   971.387512  1.007022e+06
25%    1073.818215  1085.368782  1067.386038  1075.107086  1.014533e+07
50%    1169.443635  1178.450012  1157.361521  1165.470703  1.291768e+07
75%    1248.512512  1261.399994  1236.649963  1250.812531  1.755770e+07
max    1344.900024  1362.349976  1340.050049  1346.099976  7.325777e+07
```

KOTAKBANK = data['KOTAKBANK.NS']

print("\nSummary statistics for KOTAKBANK:")

print(KOTAKBANK.describe())

Calculate daily returns

Create a copy of the Reliance data to avoid modifying a slice of the original dataframe

KOTAKBANK = data['KOTAKBANK.NS'].copy()

Now, apply the calculation

KOTAKBANK['Daily Return'] = KOTAKBANK['Close'].pct_change()

```
Summary statistics for KOTAKBANK:
Price         Open         High          Low        Close        Volume
count   244.000000   244.000000   244.000000   244.000000  2.440000e+02
mean   1771.245907  1787.548029  1754.395105  1770.792347  5.736598e+06
std      62.189675    61.978802    62.765980    62.594747  5.388927e+06
min    1581.266899  1586.161558  1542.159736  1545.006592  1.824890e+05
25%    1733.974927  1754.131905  1719.028421  1736.297058  3.300380e+06
50%    1769.500000  1789.450012  1758.099976  1773.681030  4.307680e+06
75%    1809.925018  1826.998164  1789.912506  1808.155670  6.159475e+06
max    1935.000000  1942.000000  1909.599976  1934.699951  6.617908e+07
```

Plot the closing price and daily returns

plt.figure(figsize=(12, 6))

plt.subplot(2, 1, 1)

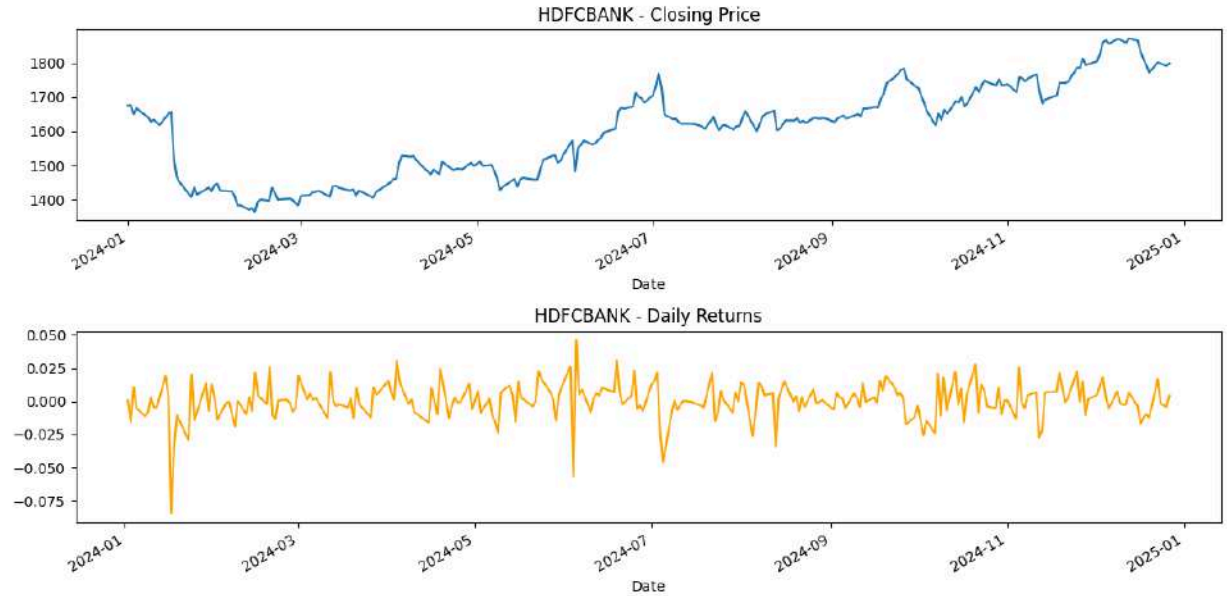
HDFC['Close'].plot(title="HDFCBANK - Closing Price")

plt.subplot(2, 1, 2)

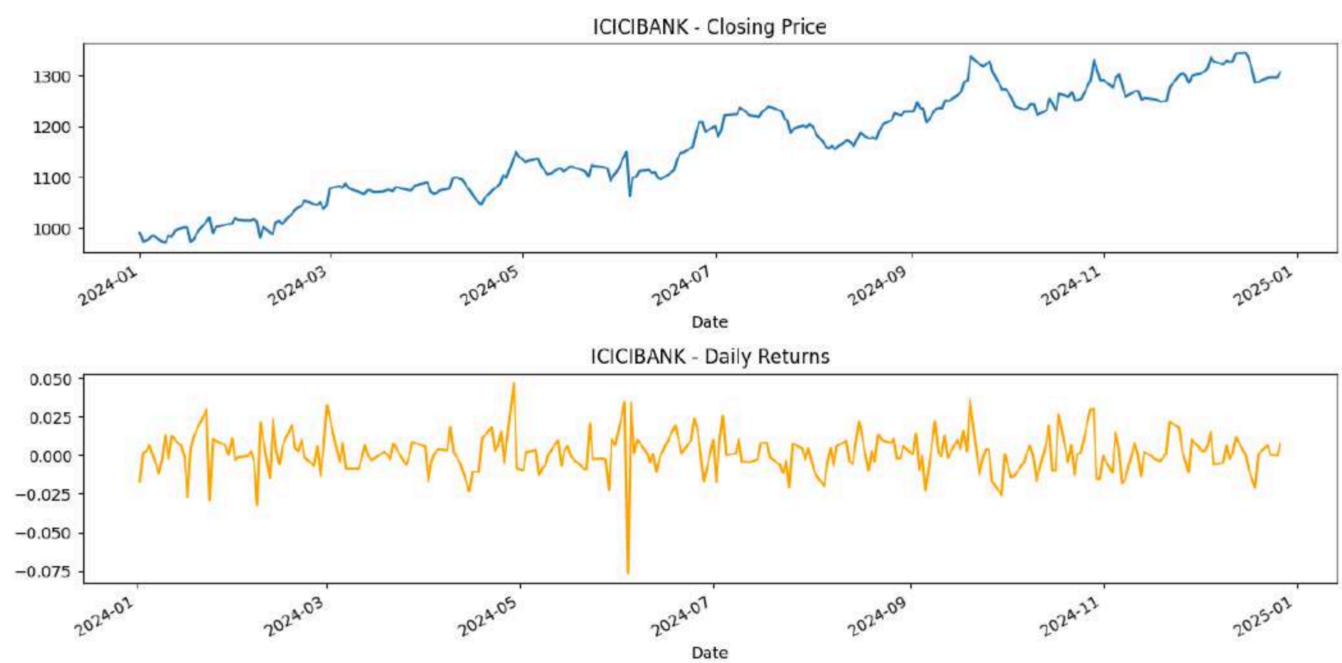
HDFC['Daily Return'].plot(title="HDFCBANK - Daily Returns", color='orange')

plt.tight_layout()

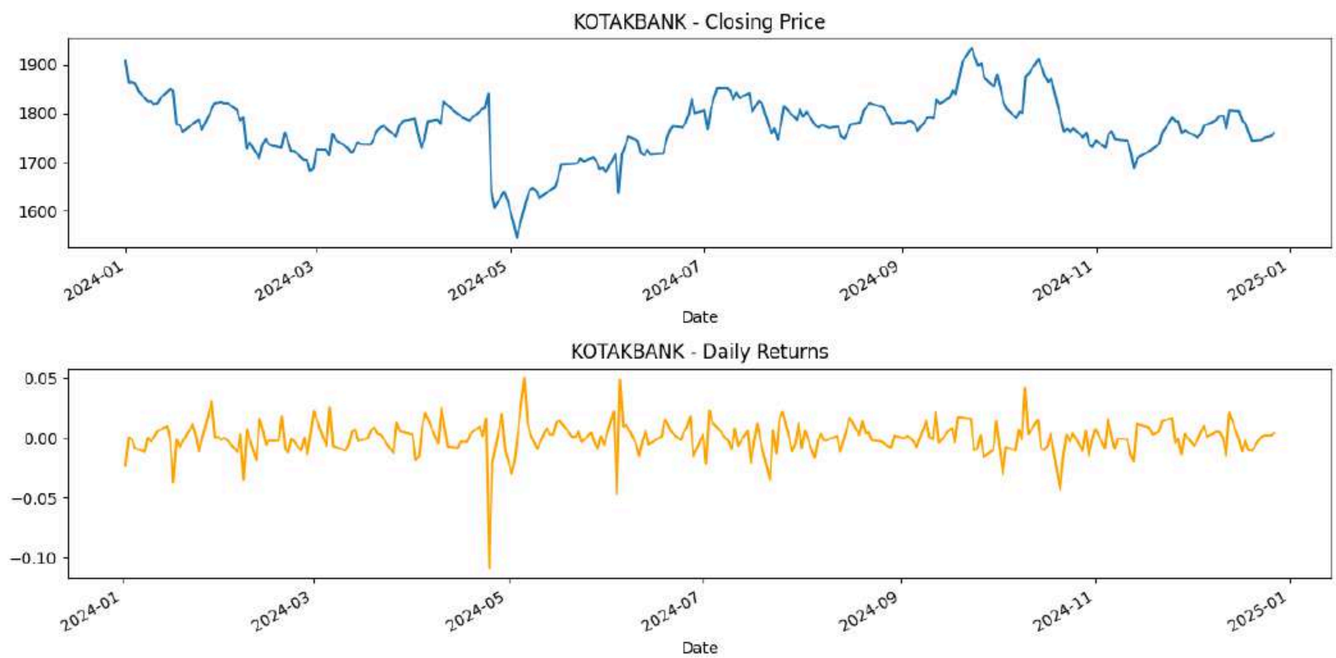
plt.show()

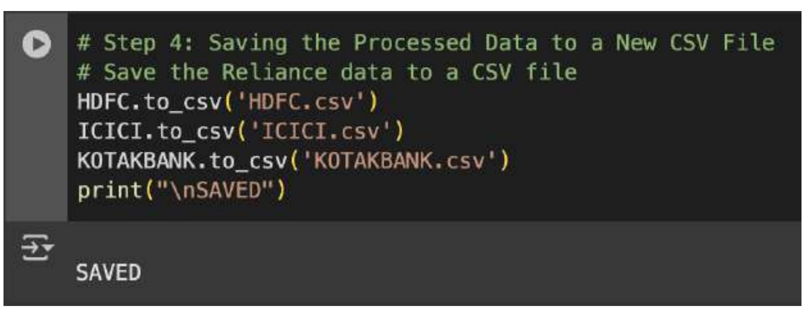



```
# Plot the closing price and daily returns
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
ICICI['Close'].plot(title="ICICIBANK - Closing Price")
plt.subplot(2, 1, 2)
ICICI['Daily Return'].plot(title="ICICIBANK - Daily Returns", color='orange')
plt.tight_layout()
plt.show()
```



# Plot the closing price and daily returns
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
KOTAKBANK['Close'].plot(title="KOTAKBANK - Closing Price")
plt.subplot(2, 1, 2)
KOTAKBANK['Daily Return'].plot(title="KOTAKBANK - Daily Returns", color='orange')
plt.tight_layout()
plt.show()





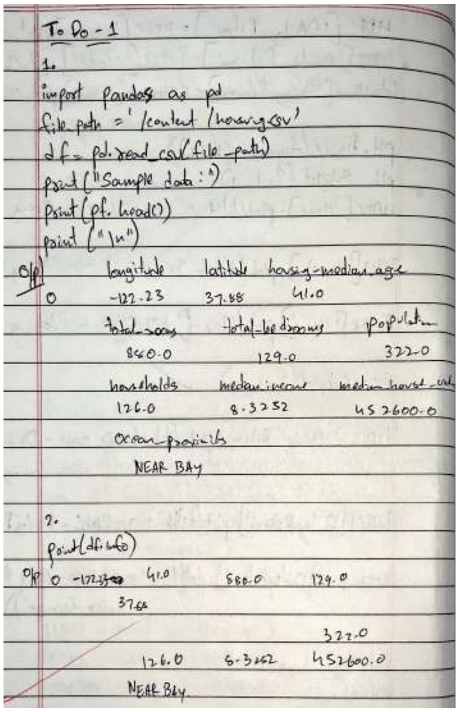
```
# Step 4: Saving the Processed Data to a New CSV File
# Save the Reliance data to a CSV file
HDFC.to_csv('HDFC.csv')
ICICI.to_csv('ICICI.csv')
KOTAKBANK.to_csv('KOTAKBANK.csv')
print("\nSAVED")
```

```
SAVED
```

Program 2

Demonstrate various data pre-processing techniques for a given dataset.

Screenshots



To Do - 1

1.

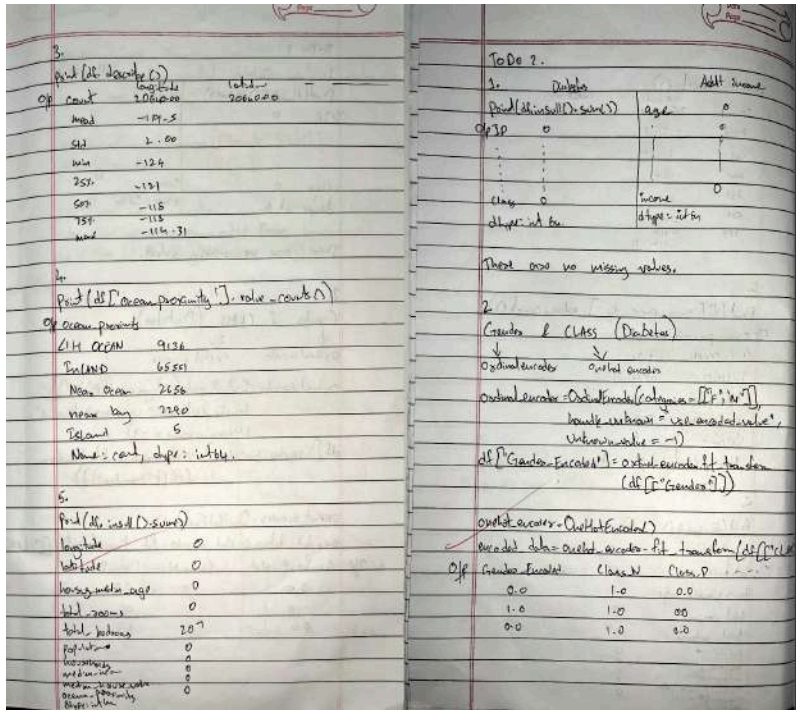
import pandas as pd
file_path = '/content/housing.csv'
df = pd.read_csv(file_path)
print("Sample data:")
print(df.head())
print("\n")

O/P longitude latitude housing_median_age
0 -122.23 37.88 41.0
total_rooms total_bedrooms population
880.0 129.0 322.0
households median_income median_house_value
126.0 8.3252 452600.0
ocean_proximity
NEAR BAY

2.

print(df.info)

O/P 0 -122.23 41.0 880.0 129.0
37.88
322.0
126.0 8.3252 452600.0
NEAR BAY



3.

print(df.describe())

	longitude	total_
O/P count	20640.00	20640.00
mean	-119.5	
std	2.00	
min	-124	
25%	-121	
50%	-118	
75%	-118	
max	-114.31	

4.

print(df['ocean_proximity'].value_counts())

O/P ocean_proximity
<1H OCEAN 9136
INLAND 6551
Near Ocean 2658
near bay 2290
Island 5
Name: count, dtype: int64.

5.

print(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

ToDo 2.

1. Diabetes | Adult income

print(df.isnull().sum()) | age 0

O/P ID 0 | income 0
Class 0 | dtype: int64
dtype: int64

There are no missing values.

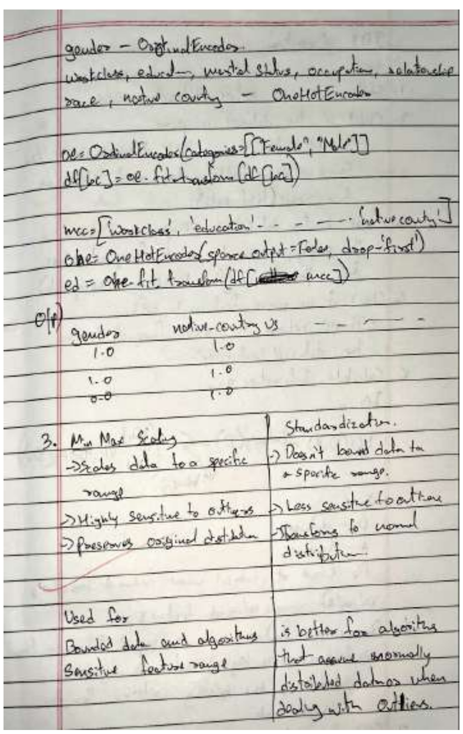
2

Gender & CLASS (Diabetes)
Ordinal encoder Onehot encoder

ordinal_encoder = OrdinalEncoder(categories=[['F','M']],
handle_unknown='use_encoded_value',
unknown_value=-1)
df['Gender_Encoded'] = ordinal_encoder.fit_transform(df[['Gender']])

onehot_encoder = OneHotEncoder()
encoded_data = onehot_encoder.fit_transform(df[['CLASS']])

O/P Gender_Encoded	Class_N	Class_P
0.0	1.0	0.0
1.0	1.0	0.0
0.0	1.0	0.0



gender - OrdinalEncoder
workclass, education, marital status, occupation, relationship, race, native country - OneHotEncoder

oe = OrdinalEncoder(categories=[["Female", "Male"]])
df[oc] = oe.fit_transform(df[oc])

mcc = ['workclass', 'education' - - - 'native country']
ohe = OneHotEncoder(sparse_output=False, drop='first')
ed = ohe.fit_transform(df[mcc])

O/P gender	native-country US
1.0	1.0
1.0	1.0
0.0	1.0

3. Min Max Scaling	Standardization.
-> Scales data to a specific range	-> Doesn't bound data to a specific range.
-> Highly sensitive to outliers	-> Less sensitive to outliers
-> Preserves original distribution	-> Transforms to normal distribution
Used for Bounded data and algorithms sensitive feature range	is better for algorithms that assume normally distributed data or when dealing with outliers.

Code:

import pandas as pd

file_path = '/content/housing.csv'

df = pd.read_csv(file_path)

print("Sample data:")

print(df.head())

print("\n")

```
Sample data:
   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
```

#To display information of all columns

print(df.info)

```
<bound method DataFrame.info of        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
...          ...       ...                 ...          ...             ...
20635    -121.09     39.48                25.0       1665.0           374.0
20636    -121.21     39.49                18.0        697.0           150.0
20637    -121.22     39.43                17.0       2254.0           485.0
20638    -121.32     39.43                18.0       1860.0           409.0
20639    -121.24     39.37                16.0       2785.0           616.0

       population  households  median_income  median_house_value  \
0           322.0       126.0         8.3252            452600.0
1          2401.0      1138.0         8.3014            358500.0
2           496.0       177.0         7.2574            352100.0
3           558.0       219.0         5.6431            341300.0
4           565.0       259.0         3.8462            342200.0
...           ...         ...            ...                 ...
20635       845.0       330.0         1.5603             78100.0
20636       356.0       114.0         2.5568             77100.0
20637      1007.0       433.0         1.7000             92300.0
20638       741.0       349.0         1.8672             84700.0
20639      1387.0       530.0         2.3886             89400.0

      ocean_proximity
0            NEAR BAY
1            NEAR BAY
2            NEAR BAY
3            NEAR BAY
4            NEAR BAY
...               ...
20635          INLAND
20636          INLAND
20637          INLAND
20638          INLAND
20639          INLAND

[20640 rows x 10 columns]>
```

#To display statistical information of all numerical

print(df.describe())

```
         longitude      latitude  housing_median_age   total_rooms  \
count  20640.000000  20640.000000        20640.000000  20640.000000
mean    -119.569704     35.631861           28.639486   2635.763081
std        2.003532      2.135952           12.585558   2181.615252
min     -124.350000     32.540000            1.000000      2.000000
25%     -121.800000     33.930000           18.000000   1447.750000
50%     -118.490000     34.260000           29.000000   2127.000000
75%     -118.010000     37.710000           37.000000   3148.000000
max     -114.310000     41.950000           52.000000  39320.000000

       total_bedrooms    population    households  median_income  \
count    20433.000000  20640.000000  20640.000000   20640.000000
mean       537.870553   1425.476744    499.539680       3.870671
std        421.385070   1132.462122    382.329753       1.899822
min          1.000000      3.000000      1.000000       0.499900
25%        296.000000    787.000000    280.000000       2.563400
50%        435.000000   1166.000000    409.000000       3.534800
75%        647.000000   1725.000000    605.000000       4.743250
max       6445.000000  35682.000000   6082.000000      15.000100

       median_house_value
count        20640.000000
mean        206855.816909
std         115395.615874
min          14999.000000
25%         119600.000000
50%         179700.000000
75%         264725.000000
max         500001.000000
```

#To display the count of unique labels for “Ocean Proximity” column

print(df['ocean_proximity'].value_counts())

```
ocean_proximity
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: count, dtype: int64
```

#To display which attributes (columns) in a dataset have missing values count greater than zero

print(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
```

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.impute import SimpleImputer

from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder

```
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from scipy import stats
def createdata():
 data = {
    'Age': np.random.randint(18, 70, size=20),
    'Salary': np.random.randint(30000, 120000, size=20),
    'Purchased': np.random.choice([0, 1], size=20),
    'Gender': np.random.choice(['Male', 'Female'], size=20),
    'City': np.random.choice(['New York', 'San Francisco', 'Los Angeles'], size=20)
 }

 df = pd.DataFrame(data)
 return df
Vdf = createdata()
df.head(10)
```

	Age	Salary	Purchased	Gender	City
0	67	95582	0	Female	Los Angeles
1	58	75108	1	Female	San Francisco
2	64	94631	1	Male	New York
3	42	71454	0	Female	New York
4	44	108391	1	Male	San Francisco
5	20	106194	1	Male	New York
6	37	82085	0	Male	New York
7	27	110483	1	Female	New York
8	42	57678	1	Female	San Francisco
9	63	59239	0	Female	San Francisco

```
df.shape
(20, 5)
```

```
# Introduce some missing values for demonstration
df.loc[5, 'Age'] = np.nan
df.loc[10, 'Salary'] = np.nan
df.head(10)
```

	Age	Salary	Purchased	Gender	City
0	67.0	95582.0	0	Female	Los Angeles
1	58.0	75108.0	1	Female	San Francisco
2	64.0	94631.0	1	Male	New York
3	42.0	71454.0	0	Female	New York
4	44.0	108391.0	1	Male	San Francisco
5	NaN	106194.0	1	Male	New York
6	37.0	82085.0	0	Male	New York
7	27.0	110483.0	1	Female	New York
8	42.0	57678.0	1	Female	San Francisco
9	63.0	59239.0	0	Female	San Francisco

```
# Basic information about the dataset
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20 entries, 0 to 19
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Age        19 non-null     float64
 1   Salary     19 non-null     float64
 2   Purchased  20 non-null     int64
 3   Gender     20 non-null     object
 4   City       20 non-null     object
dtypes: float64(2), int64(1), object(2)
memory usage: 932.0+ bytes
None
```

```
# Summary statistics
print(df.describe())
```

```
             Age         Salary  Purchased
count  19.000000      19.000000  20.000000
mean   45.947368   78821.315789   0.550000
std    15.356771   24850.883175   0.510418
min    19.000000   37052.000000   0.000000
25%    33.500000   58458.500000   0.000000
50%    42.000000   77139.000000   1.000000
75%    60.500000  101866.000000   1.000000
max    68.000000  112223.000000   1.000000
```

```
#Code to Find Missing Values
# Check for missing values in each column
missing_values = df.isnull().sum()
# Display columns with missing values
print(missing_values[missing_values > 0])
```

```
Age       1
Salary    1
dtype: int64
```

```
#Set the values to some value (zero, the mean, the median, etc.).
# Step 1: Create an instance of SimpleImputer with the median strategy for Age and mean stratergy for Salary
imputer1 = SimpleImputer(strategy="median")
imputer2 = SimpleImputer(strategy="mean")
df_copy=df
# Step 2: Fit the imputer on the "Age" and "Salary"column
# Note: SimpleImputer expects a 2D array, so we reshape the column
imputer1.fit(df_copy[["Age"]])
imputer2.fit(df_copy[["Salary"]])
# Step 3: Transform (fill) the missing values in the "Age" and "Salary"c column
df_copy["Age"] = imputer1.transform(df[["Age"]])
df_copy["Salary"] = imputer2.transform(df[["Salary"]])
# Verify that there are no missing values left
print(df_copy["Age"].isnull().sum())
print(df_copy["Salary"].isnull().sum())
```

```
0
0
```

```
#Handling Categorical Attributes
#Using Ordinal Encoding for gender COlumn and One-Hot Encoding for City Column
# Initialize OrdinalEncoder
ordinal_encoder = OrdinalEncoder(categories=[["Male", "Female"]])
# Fit and transform the data
df_copy["Gender_Encoded"] = ordinal_encoder.fit_transform(df_copy[["Gender"]])
# Initialize OneHotEncoder
onehot_encoder = OneHotEncoder()
# Fit and transform the "City" column
encoded_data = onehot_encoder.fit_transform(df[["City"]])
# Convert the sparse matrix to a dense array
encoded_array = encoded_data.toarray()
# Convert to DataFrame for better visualization
encoded_df = pd.DataFrame(encoded_array,
```

columns=onehot_encoder.get_feature_names_out(["City"]))

df_encoded = pd.concat([df_copy, encoded_df], axis=1)

df_encoded.drop("Gender", axis=1, inplace=True)

df_encoded.drop("City", axis=1, inplace=True)

print(df_encoded. head())

```
    Age    Salary  Purchased  Gender_Encoded  City_Los Angeles  City_New York  \
0  67.0   95582.0          0             1.0               1.0            0.0
1  58.0   75108.0          1             1.0               0.0            0.0
2  64.0   94631.0          1             0.0               0.0            1.0
3  42.0   71454.0          0             1.0               0.0            1.0
4  44.0  108391.0          1             0.0               0.0            0.0

   City_San Francisco
0                 0.0
1                 1.0
2                 0.0
3                 0.0
4                 1.0
```

#Data Transformation

Min-Max Scaler/Normalization (range 0-1)

#Pros: Keeps all data between 0 and 1; ideal for distance-based models.

#Cons: Can distort data distribution, especially with extreme outliers.

normalizer = MinMaxScaler()

df_encoded[['Salary']] = normalizer.fit_transform(df_encoded[['Salary']])

df_encoded.head()

	Age	Salary	Purchased	Gender_Encoded	City_Los Angeles	City_New York	City_San Francisco
0	67.0	0.778625	0	1.0	1.0	0.0	0.0
1	58.0	0.506259	1	1.0	0.0	0.0	1.0
2	64.0	0.765974	1	0.0	0.0	1.0	0.0
3	42.0	0.457650	0	1.0	0.0	1.0	0.0
4	44.0	0.949023	1	0.0	0.0	0.0	1.0

Standardization (mean=0, variance=1)

#Pros: Works well for normally distributed data; suitable for many models.

#Cons: Sensitive to outliers.

scaler = StandardScaler()

df_encoded[['Age']] = scaler.fit_transform(df_encoded[['Age']])

df_encoded.head()

	Age	Salary	Purchased	Gender_Encoded	City_Los Angeles	City_New York	City_San Francisco
0	1.456069	0.778625	0	1.0	1.0	0.0	0.0
1	0.839381	0.506259	1	1.0	0.0	0.0	1.0
2	1.250506	0.765974	1	0.0	0.0	1.0	0.0
3	-0.256953	0.457650	0	1.0	0.0	1.0	0.0
4	-0.119912	0.949023	1	0.0	0.0	0.0	1.0

#Removing Outliers

Outlier Detection and Treatment using IQR

#Pros: Simple and effective for mild outliers.

#Cons: May overly reduce variation if there are many extreme outliers.

df_encoded_copy1=df_encoded

df_encoded_copy2=df_encoded

df_encoded_copy3=df_encoded

Q1 = df_encoded_copy1['Salary'].quantile(0.25)

Q3 = df_encoded_copy1['Salary'].quantile(0.75)

IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR

upper_bound = Q3 + 1.5 * IQR

df_encoded_copy1['Salary'] = np.where(df_encoded_copy1['Salary'] > upper_bound, upper_bound,

np.where(df_encoded_copy1['Salary'] < lower_bound, lower_bound,

df_encoded_copy1['Salary']))

print(df_encoded_copy1.head())

```
        Age    Salary  Purchased  Gender_Encoded  City_Los Angeles  \
0  1.456069  0.778625          0             1.0               1.0
1  0.839381  0.506259          1             1.0               0.0
2  1.250506  0.765974          1             0.0               0.0
3 -0.256953  0.457650          0             1.0               0.0
4 -0.119912  0.949023          1             0.0               0.0

   City_New York  City_San Francisco
0            0.0                 0.0
1            0.0                 1.0
2            1.0                 0.0
3            1.0                 0.0
4            0.0                 1.0
```

#Removing Outliers

Z-score method

#Pros: Good for normally distributed data.

#Cons: Not suitable for non-normal data; may miss outliers in skewed distributions.

df_encoded_copy2['Salary_zscore'] = stats.zscore(df_encoded_copy2['Salary']) df_encoded_copy2['Salary'] = np.where(df_encoded_copy2['Salary_zscore'].abs() > 3, np.nan, df_encoded_copy2['Salary']) # Replace outliers with NaN

print(df_encoded_copy2.head())

```
        Age    Salary  Purchased  Gender_Encoded  City_Los Angeles  \
0  1.456069  0.778625          0             1.0               1.0
1  0.839381  0.506259          1             1.0               0.0
2  1.250506  0.765974          1             0.0               0.0
3 -0.256953  0.457650          0             1.0               0.0
4 -0.119912  0.949023          1             0.0               0.0

   City_New York  City_San Francisco  Salary_zscore
0            0.0                 0.0       0.710933
1            0.0                 1.0      -0.157507
2            1.0                 0.0       0.670595
3            1.0                 0.0      -0.312497
4            0.0                 1.0       1.254249
```

#Removing Outliers

Median replacement for outliers

#Pros: Keeps distribution shape intact, useful when capping isn’t feasible.

#Cons: May distort data if outliers represent real phenomena.

df_encoded_copy3['Salary_zscore'] = stats.zscore(df_encoded_copy3['Salary'])

median_salary = df_encoded_copy3['Salary'].median()

df_encoded_copy3['Salary'] = np.where(df_encoded_copy3['Salary_zscore'].abs() > 3, median_salary, df_encoded_copy3['Salary'])

print(df_encoded_copy3.head())

```
        Age    Salary  Purchased  Gender_Encoded  City_Los Angeles  \
0  1.456069  0.778625          0             1.0               1.0
1  0.839381  0.506259          1             1.0               0.0
2  1.250506  0.765974          1             0.0               0.0
3 -0.256953  0.457650          0             1.0               0.0
4 -0.119912  0.949023          1             0.0               0.0

   City_New York  City_San Francisco  Salary_zscore
0            0.0                 0.0       0.710933
1            0.0                 1.0      -0.157507
2            1.0                 0.0       0.670595
3            1.0                 0.0      -0.312497
4            0.0                 1.0       1.254249
```

➔ **Diabetes**

import pandas as pd

file_path = '/content/Dataset of Diabetes .csv'

df = pd.read_csv(file_path)

print("Sample data:")

print(df.head())

print("\n")

```
Sample data:
    ID  No_Pation Gender  AGE  Urea  Cr  HbA1c  Chol   TG  HDL  LDL  VLDL  \
0  502      17975      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
1  735      34221      M   26   4.5  62    4.9   3.7  1.4  1.1  2.1   0.6
2  420      47975      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
3  680      87656      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
4  504      34223      M   33   7.1  46    4.9   4.9  1.0  0.8  2.0   0.4

    BMI CLASS
0  24.0     N
1  23.0     N
2  24.0     N
3  24.0     N
4  21.0     N
```

#1. Which columns in the dataset had missing values? How did you handle them ?

print(df.isnull().sum())

```
ID           0
No_Pation    0
Gender       0
AGE          0
Urea         0
Cr           0
HbA1c        0
Chol         0
TG           0
HDL          0
LDL          0
VLDL         0
BMI          0
CLASS        0
dtype: int64
```

#2. Which categorical columns did you identify in the dataset? How did you encode them ?

print(df.info)

```
<bound method DataFrame.info of       ID  No_Pation Gender  AGE  Urea  Cr  HbA1c  Chol   TG  HDL  LDL  VLDL  \
0    502      17975      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
1    735      34221      M   26   4.5  62    4.9   3.7  1.4  1.1  2.1   0.6
2    420      47975      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
3    680      87656      F   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5
4    504      34223      M   33   7.1  46    4.9   4.9  1.0  0.8  2.0   0.4
..   ...        ...    ...  ...   ...  ..    ...   ...  ...  ...  ...   ...
995  200     454317      M   71  11.0  97    7.0   7.5  1.7  1.2  1.8   0.6
996  671     876534      M   31   3.0  60   12.3   4.1  2.2  0.7  2.4  15.4
997  669      87654      M   30   7.1  81    6.7   4.1  1.1  1.2  2.4   8.1
998   99      24004      M   38   5.8  59    6.7   5.3  2.0  1.6  2.9  14.0
999  248      24054      M   54   5.0  67    6.9   3.8  1.7  1.1  3.0   0.7

      BMI CLASS
0    24.0     N
1    23.0     N
2    24.0     N
3    24.0     N
4    21.0     N
..    ...   ...
995  30.0    Y
996  37.2    Y
997  27.4    Y
998  40.5    Y
999  33.0    Y

[1000 rows x 14 columns]>
```

Clean the Gender column: Convert all values to uppercase

df["Gender"] = df["Gender"].str.upper()

Initialize OrdinalEncoder for Gender

ordinal_encoder = OrdinalEncoder(categories=[["F", "M"]], handle_unknown="use_encoded_value", unknown_value=-1)

Fit and transform the Gender column

df["Gender_Encoded"] = ordinal_encoder.fit_transform(df[["Gender"]])

Initialize OneHotEncoder for CLASS

onehot_encoder = OneHotEncoder()

Fit and transform the CLASS column

encoded_data = onehot_encoder.fit_transform(df[["CLASS"]])

Convert the sparse matrix to a dense array

encoded_array = encoded_data.toarray()

Convert to DataFrame for better visualization

encoded_df = pd.DataFrame(encoded_array, columns=onehot_encoder.get_feature_names_out(["CLASS"]))

df_encoded = pd.concat([df, encoded_df], axis=1)

Drop the original Gender and CLASS columns

df_encoded.drop("Gender", axis=1, inplace=True)

df_encoded.drop("CLASS", axis=1, inplace=True)

print(df_encoded.head())

```
    ID  No_Pation  AGE  Urea  Cr  HbA1c  Chol   TG  HDL  LDL  VLDL   BMI  \
0  502      17975   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5  24.0
1  735      34221   26   4.5  62    4.9   3.7  1.4  1.1  2.1   0.6  23.0
2  420      47975   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5  24.0
3  680      87656   50   4.7  46    4.9   4.2  0.9  2.4  1.4   0.5  24.0
4  504      34223   33   7.1  46    4.9   4.9  1.0  0.8  2.0   0.4  21.0

   Gender_Encoded  CLASS_N  CLASS_N   CLASS_P  CLASS_Y  CLASS_Y
0             0.0      1.0       0.0      0.0      0.0       0.0
1             1.0      1.0       0.0      0.0      0.0       0.0
2             0.0      1.0       0.0      0.0      0.0       0.0
3             0.0      1.0       0.0      0.0      0.0       0.0
4             1.0      1.0       0.0      0.0      0.0       0.0
```

➔ **ADULT INCOME DATA**

import pandas as pd

file_path = '/content/adult.csv'

df = pd.read_csv(file_path)

print("Sample data:")

print(df.head())

print("\n")

```
Sample data:
   age workclass  fnlwgt     education  educational-num      marital-status  \
0   25   Private  226802          11th                7       Never-married
1   38   Private   89814       HS-grad                9  Married-civ-spouse
2   28 Local-gov  336951    Assoc-acdm               12  Married-civ-spouse
3   44   Private  160323  Some-college               10  Married-civ-spouse
4   18         ?  103497  Some-college               10       Never-married

          occupation relationship   race  gender  capital-gain  capital-loss  \
0  Machine-op-inspct    Own-child  Black    Male             0             0
1    Farming-fishing      Husband  White    Male             0             0
2    Protective-serv      Husband  White    Male             0             0
3  Machine-op-inspct      Husband  Black    Male          7688             0
4                  ?    Own-child  White  Female             0             0

   hours-per-week native-country income
0              40  United-States  <=50K
1              50  United-States  <=50K
2              40  United-States   >50K
3              40  United-States   >50K
4              30  United-States  <=50K
```

print(df.isnull().sum())

```
age                0
workclass          0
fnlwgt             0
education          0
educational-num    0
marital-status     0
occupation         0
relationship       0
race               0
gender             0
capital-gain       0
capital-loss       0
hours-per-week     0
native-country     0
income             0
dtype: int64
```

print(df.info)

```
<bound method DataFrame.info of        age     workclass  fnlwgt     education  educational-num  \
0       25       Private  226802          11th                7
1       38       Private   89814       HS-grad                9
2       28     Local-gov  336951    Assoc-acdm               12
3       44       Private  160323  Some-college               10
4       18             ?  103497  Some-college               10
...    ...           ...     ...           ...              ...
48837   27       Private  257302    Assoc-acdm               12
48838   40       Private  154374       HS-grad                9
48839   58       Private  151910       HS-grad                9
48840   22       Private  201490       HS-grad                9
48841   52  Self-emp-inc  287927       HS-grad                9

           marital-status         occupation relationship   race  gender  \
0           Never-married  Machine-op-inspct    Own-child  Black    Male
1      Married-civ-spouse    Farming-fishing      Husband  White    Male
2      Married-civ-spouse    Protective-serv      Husband  White    Male
3      Married-civ-spouse  Machine-op-inspct      Husband  Black    Male
4           Never-married                  ?    Own-child  White  Female
...                   ...                ...          ...    ...     ...
48837  Married-civ-spouse       Tech-support         Wife  White  Female
48838  Married-civ-spouse  Machine-op-inspct      Husband  White    Male
48839             Widowed       Adm-clerical    Unmarried  White  Female
48840       Never-married       Adm-clerical    Own-child  White    Male
48841  Married-civ-spouse    Exec-managerial         Wife  White  Female

       capital-gain  capital-loss  hours-per-week native-country income
0                 0             0              40  United-States  <=50K
1                 0             0              50  United-States  <=50K
2                 0             0              40  United-States   >50K
3              7688             0              40  United-States   >50K
4                 0             0              30  United-States  <=50K
...             ...           ...             ...            ...    ...
48837             0             0              38  United-States  <=50K
48838             0             0              40  United-States   >50K
48839             0             0              40  United-States  <=50K
48840             0             0              20  United-States  <=50K
48841         15024             0              40  United-States   >50K

[48842 rows x 15 columns]>
```

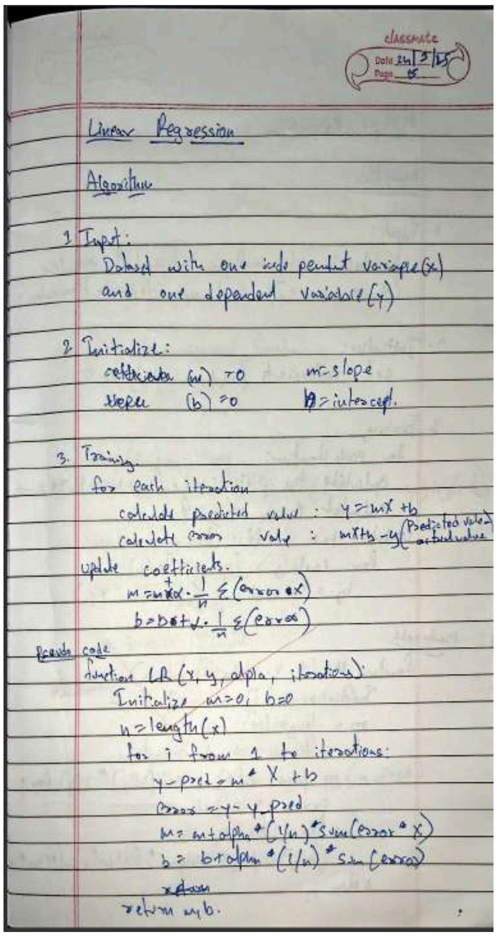
```
# Encode binary categorical columns (e.g., gender) using OrdinalEncoder
binary_columns = ['gender']
# Initialize OrdinalEncoder for binary columns
ordinal_encoder = OrdinalEncoder(categories=[["Female", "Male"]],
handle_unknown="use_encoded_value", unknown_value=-1)
df[binary_columns] = ordinal_encoder.fit_transform(df[binary_columns])
# Encode multi-category columns using OneHotEncoder
multi_category_columns = ['workclass', 'education', 'marital-status', 'occupation', 'relationship', 'race',
'native-country']
onehot_encoder = OneHotEncoder(sparse_output=False, drop='first')  # Drop first column to avoid
multicollinearity
encoded_data = onehot_encoder.fit_transform(df[multi_category_columns])
# Convert encoded data to DataFrame
encoded_df = pd.DataFrame(encoded_data,
columns=onehot_encoder.get_feature_names_out(multi_category_columns))
# Concatenate encoded data with the original DataFrame
df_encoded = pd.concat([df.drop(multi_category_columns, axis=1), encoded_df], axis=1)
# Display the encoded DataFrame
print("\nEncoded DataFrame:")
print(df_encoded.head())
```

```
Encoded DataFrame:
   age  fnlwgt  educational-num  gender  capital-gain  capital-loss  \
0   25  226802                7     1.0             0             0
1   38   89814                9     1.0             0             0
2   28  336951               12     1.0             0             0
3   44  160323               10     1.0          7688             0
4   18  103497               10     0.0             0             0

   hours-per-week income  workclass_Federal-gov  workclass_Local-gov  ...  \
0              40  <=50K                    0.0                  0.0  ...
1              50  <=50K                    0.0                  0.0  ...
2              40   >50K                    0.0                  1.0  ...
3              40   >50K                    0.0                  0.0  ...
4              30  <=50K                    0.0                  0.0  ...

   native-country_Portugal  native-country_Puerto-Rico  \
0                      0.0                         0.0
1                      0.0                         0.0
2                      0.0                         0.0
3                      0.0                         0.0
4                      0.0                         0.0

   native-country_Scotland  native-country_South  native-country_Taiwan  \
0                      0.0                   0.0                    0.0
1                      0.0                   0.0                    0.0
2                      0.0                   0.0                    0.0
3                      0.0                   0.0                    0.0
4                      0.0                   0.0                    0.0

   native-country_Thailand  native-country_Trinadad&Tobago  \
0                      0.0                             0.0
1                      0.0                             0.0
2                      0.0                             0.0
3                      0.0                             0.0
4                      0.0                             0.0

   native-country_United-States  native-country_Vietnam  \
0                           1.0                     0.0
1                           1.0                     0.0
2                           1.0                     0.0
3                           1.0                     0.0
4                           1.0                     0.0

   native-country_Yugoslavia
0                        0.0
1                        0.0
2                        0.0
3                        0.0
4                        0.0

[5 rows x 101 columns]
```

Program 3

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Screenshots



classmate
Date 24/5/25
Page 15

Linear Regression

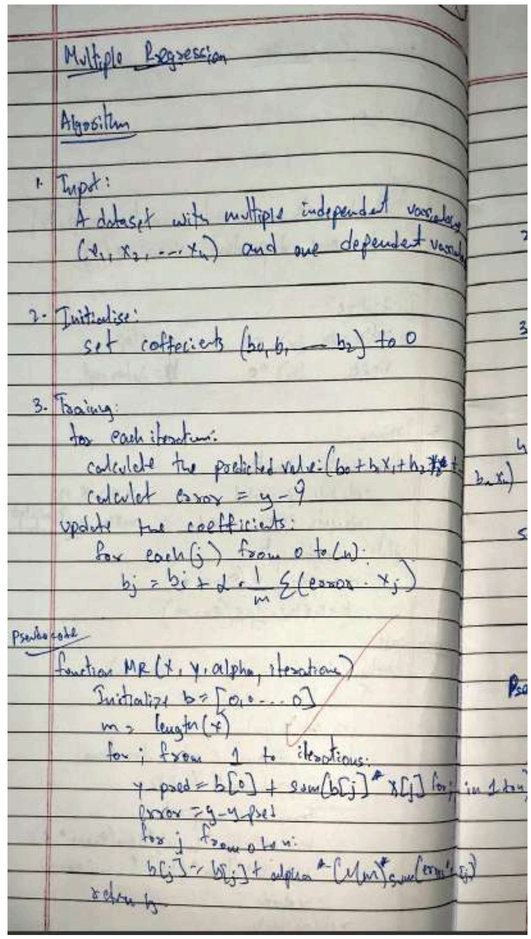
Algorithm

1. Input:
Dataset with one independent variable (x)
and one dependent variable (y)

2. Initialize:
coefficients (m) = 0 m = slope
slope (b) = 0 b = intercept.

3. Training
for each iteration
calculate predicted value : y = mX + b
calculate error value : mX+b - y (predicted value, actual value)
update coefficients.
$m = m + \alpha \cdot \frac{1}{n} \Sigma(error \cdot x)$
$b = b + \alpha \cdot \frac{1}{n} \Sigma(error)$

Pseudo code
function LR(x, y, alpha, iterations):
Initialize m=0, b=0
n = length(x)
for i from 1 to iterations:
y_pred = m * X + b
error = y - y_pred
m = m + alpha * (1/n) * sum(error * x)
b = b + alpha * (1/n) * sum(error)
return m, b.



Multiple Regression

Algorithm

1. Input:
A dataset with multiple independent variables
$(x_1, x_2, \ldots, x_n)$ and one dependent variable

2. Initialise:
set coefficients $(b_0, b_1, \ldots b_n)$ to 0

3. Training:
for each iteration:
calculate the predicted value: $(b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_n x_n)$
calculate error = $y - \hat{y}$
update the coefficients:
for each (j) from 0 to (n):
$b_j = b_j + \alpha \cdot \frac{1}{m} \Sigma(error \cdot x_j)$

Pseudocode
function MR(X, y, alpha, iterations)
Initialize b = [0, 0 ... 0]
m = length(y)
for i from 1 to iterations:
y_pred = b[0] + sum(b[j] * x[j] for j in 1 to n)
error = y - y_pred
for j from 0 to n:
b[j] = b[j] + alpha * (1/m) * sum(error * x_j)
return b

Code:

Linear Regression:

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.datasets import fetch_california_housing
# Load the California Housing dataset
california_housing = fetch_california_housing()
# Assign the data (features) and target (house prices)
```

```
X = pd.DataFrame(california_housing.data, columns=california_housing.feature_names)
y = pd.Series(california_housing.target)
# Select features for Linear Regression
X = X[['MedInc', 'AveRooms']]
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Create and train the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)
# Make predictions
y_pred = model.predict(X_test)
# Print the actual vs predicted values
results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print("Linear Regression Results:")
print(results.head())
```

```
Linear Regression Results:
        Actual  Predicted
20046  0.47700   1.162302
3024   0.45800   1.499135
15663  5.00001   1.955731
20484  2.18600   2.852755
9814   2.78000   2.001677
```

Multiple Regression:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.datasets import fetch_california_housing
california_housing = fetch_california_housing()
X = pd.DataFrame(california_housing.data, columns=california_housing.feature_names)
y = pd.Series(california_housing.target)
X = X[['MedInc', 'AveRooms']]
```

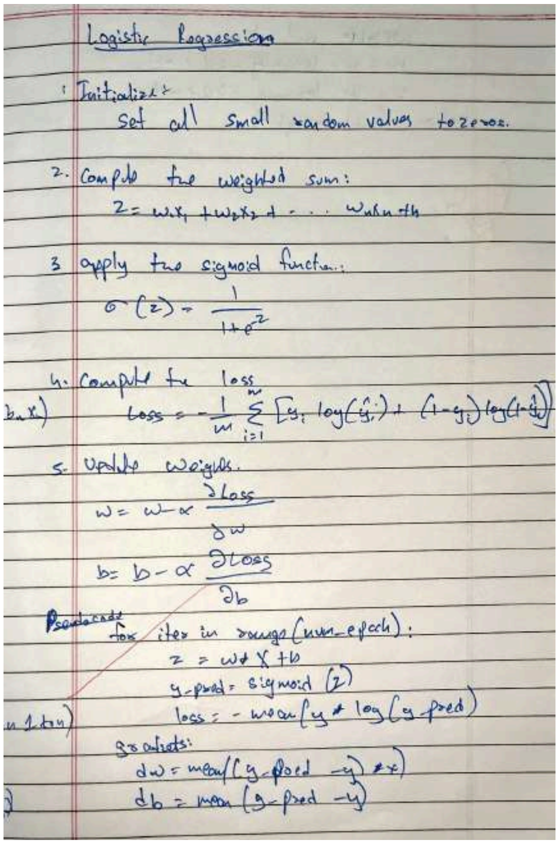
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
# Print the actual vs predicted values
results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print(results.head())
```

```
        Actual  Predicted
20046  0.47700   1.162302
3024   0.45800   1.499135
15663  5.00001   1.955731
20484  2.18600   2.852755
9814   2.78000   2.001677
```

Program 4

Build Logistic Regression Model for a given dataset

Screenshots



Logistic Regression

1. Initialize:
set all small random values to zeros.

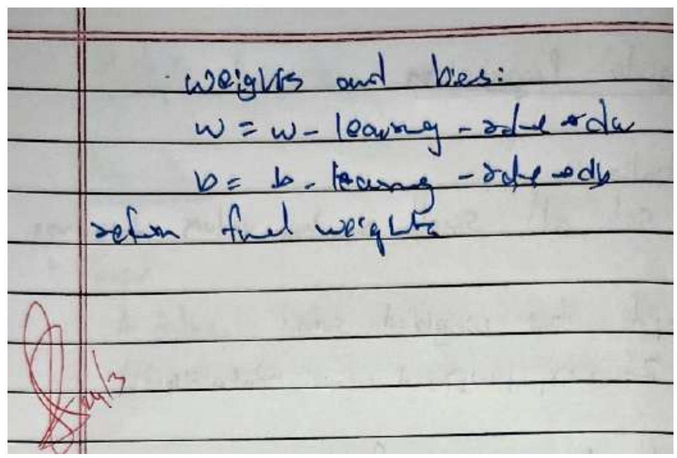
2. Compute the weighted sum:
$z = w_1x_1 + w_2x_2 + \dots w_nx_n + b$

3. apply the sigmoid function:
$\sigma(z) = \frac{1}{1+e^{-z}}$

4. Compute the loss
$Loss = -\frac{1}{m}\sum_{i=1}^{m}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)]$

5. Update weights.
$w = w - \alpha \frac{\partial Loss}{\partial w}$
$b = b - \alpha \frac{\partial Loss}{\partial b}$

Pseudocode
for iter in range(num_epoch):
z = w * X + b
y_pred = sigmoid(z)
loss = - mean(y * log(y_pred))
gradients:
dw = mean((y_pred - y) * x)
db = mean(y_pred - y)



weights and bias:
w = w - learning_rate * dw
b = b - learning_rate * db
return final weights

Code:

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.datasets import load_iris
# Load the Iris dataset
iris = load_iris()
# Assign the data (features) and target (species)
X = pd.DataFrame(iris.data, columns=iris.feature_names)
y = pd.Series(iris.target)
# For simplicity, we will classify only two classes (0 and 1)
X = X[y.isin([0, 1])]  # Select only classes 0 and 1
```

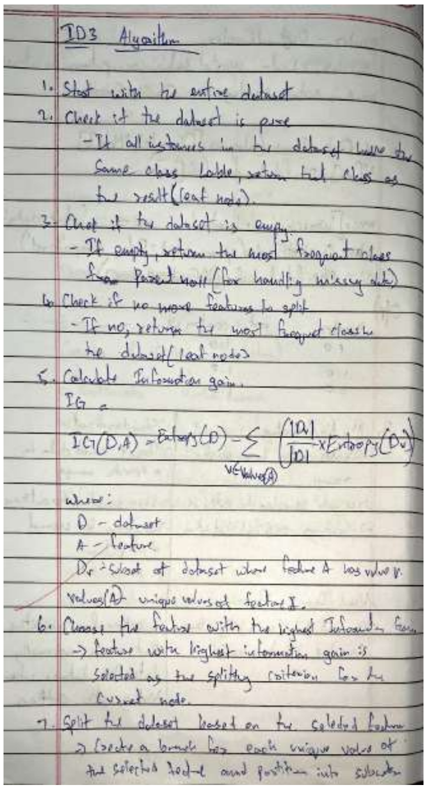
```
y = y[y.isin([0, 1])]
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Create and train the Logistic Regression model
model = LogisticRegression()
model.fit(X_train, y_train)
# Make predictions
y_pred = model.predict(X_test)
# Print the actual vs predicted values
results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
print("Logistic Regression Results:")
print(results.head())
```

```
Logistic Regression Results:
    Actual  Predicted
83       1          1
53       1          1
70       1          1
45       0          0
44       0          0
```

Program 5

Use an appropriate data set for building the decision tree (ID3) and apply this knowledge to classify a new sample

Screenshots



ID3 Algorithm

1. Start with the entire dataset
2. Check if the dataset is pure
   - If all instances in the dataset have the same class lable, return that class as the result (leaf node).
3. Check if the dataset is empty
   - If empty, return the most frequent class from parent node (for handling missing data)
4. Check if no more features to split
   - If no, return the most frequent class in the dataset (leaf node)
5. Calculate Information gain.

IG =

$$IG(D,A) = Entropy(D) - \sum_{v \in Values(A)} \left(\frac{|D_v|}{|D|} \times Entropy(D_v)\right)$$

where:

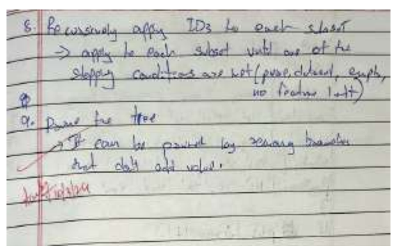
D - dataset

A - feature

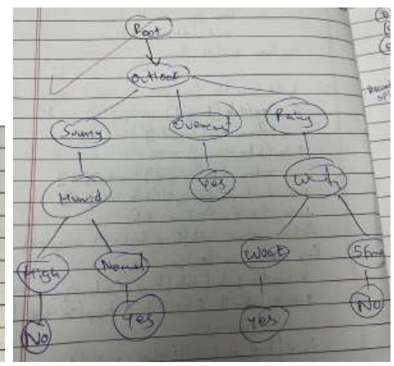
D_v - subset of dataset where feature A has value v.

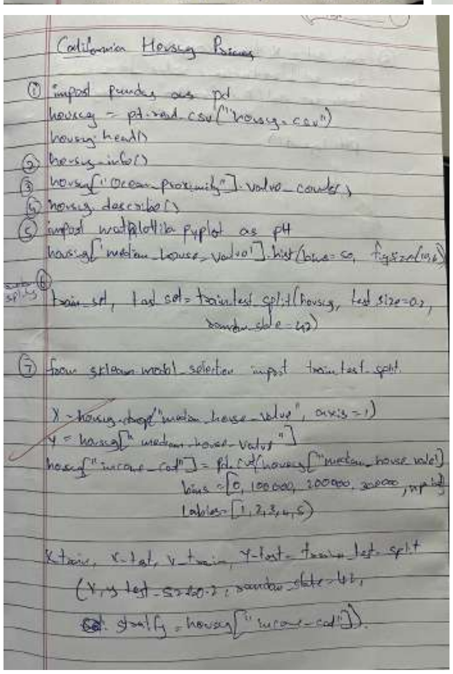
Values(A) - unique values of feature A.

6. Choose the feature with the highest Information Gain
   -> feature with highest information gain is selected as the splitting criterion for the current node.
7. Split the dataset based on the selected feature
   -> Create a branch for each unique value of the selected feature and partition into subsets



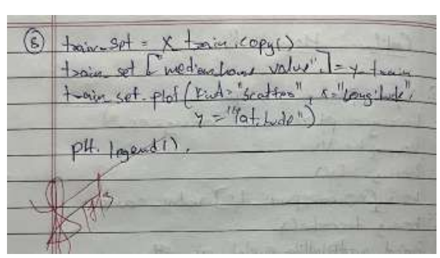
8. Recursively apply ID3 to each subset
   -> apply to each subset until one of the stopping conditions are met (pure dataset, empty, no feature left)
9. Prune the tree
   -> It can be pruned by removing branches that don't add value.





California Housing Prices

① import pandas as pd
housing = pd.read_csv("housing.csv")
housing.head()
② housing.info()
③ housing["ocean_proximity"].value_counts()
④ housing.describe()
⑤ import matplotlib.pyplot as plt
housing['median_house_value'].hist(bins=50, figsize=(12,8))
⑥ train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)
⑦ from sklearn.model_selection import train_test_split
X = housing.drop("median_house_value", axis=1)
y = housing["median_house_value"]
housing["income_cat"] = pd.cut(housing["median_house_value"], bins=[0, 100000, 200000, 300000, np.inf], labels=[1,2,3,4,5])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=housing["income_cat"])



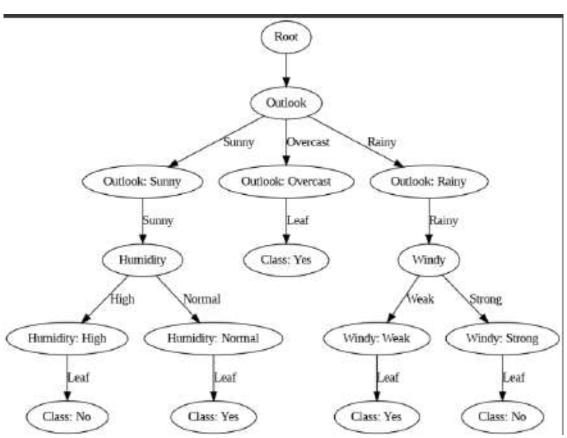
⑧ train_set = X_train.copy()
train_set["median_house_value"] = y_train
train_set.plot(kind="scatter", x="longitude", y="latitude")
plt.legend().

Code:

```
import pandas as pd
data = {
    'Outlook': ['Sunny', 'Sunny', 'Overcast', 'Rainy', 'Rainy', 'Rainy', 'Overcast', 'Sunny', 'Sunny',
'Rainy', 'Sunny', 'Overcast', 'Overcast', 'Rainy'],
    'Temperature': ['Hot', 'Hot', 'Hot', 'Mild', 'Cool', 'Cool', 'Cool','Mild', 'Cool','Mild', 'Mild', 'Mild',
'Hot', 'Mild'],
    'Humidity': ['High', 'High', 'High', 'High', 'Normal', 'Normal', 'Normal', 'High', 'Normal', 'Normal',
'Normal', 'High', 'Normal', 'High'],
    'Windy': ['Weak', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong',
'Strong', 'Weak', 'Strong'],
    'PlayTennis': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No']
}
df = pd.DataFrame(data)
import math
def entropy(data):
    total = len(data)
    counts = data.value_counts()
    entropy_value = 0
    for count in counts:
        probability = count / total
        entropy_value -= probability * math.log2(probability)
    return entropy_value
def information_gain(data, feature, target):
    total_entropy = entropy(data[target])
    feature_values = data[feature].unique()
    weighted_entropy = 0
    for value in feature_values:
        subset = data[data[feature] == value]
        weighted_entropy += (len(subset) / len(data)) * entropy(subset[target])
    return total_entropy - weighted_entrop
def best_split(data, target):
```

```
    features = data.drop(columns=[target]).columns
    best_feature = None
    best_gain = -1
    for feature in features:
        gain = information_gain(data, feature, target)
        if gain > best_gain:
            best_gain = gain
            best_feature = feature
    return best_feature
def best_split(data, target):
    features = data.drop(columns=[target]).columns
    best_feature = None
    best_gain = -1
    for feature in features:
        gain = information_gain(data, feature, target)
        if gain > best_gain:
            best_gain = gain
            best_feature = feature
    return best_feature
# Build the decision tree using the dataset
tree = build_tree(df, target='PlayTennis')
print(tree)
```

```
{'Outlook': {'Sunny': {'Humidity': {'High': 'No', 'Normal': 'Yes'}}, 'Overcast': 'Yes', 'Rainy': {'Windy': {'Weak': 'Yes', 'Strong': 'No'}}}}
```



➔ **California Housing Prices (Splitting)**

import pandas as pd

housing = pd.read_csv("housing.csv")

housing.head()

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

```
housing.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
```

```
housing["ocean_proximity"].value_counts()
```

ocean_proximity	count
<1H OCEAN	9136
INLAND	6551
NEAR OCEAN	2658
NEAR BAY	2290
ISLAND	5

dtype: int64

```
housing.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	3.870671	206855.816909
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	1.899822	115395.615874
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	0.499900	14999.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	2.563400	119600.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	3.534800	179700.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	4.743250	264725.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	15.000100	500001.000000

import matplotlib.pyplot as plt

Plot a histogram of median house values

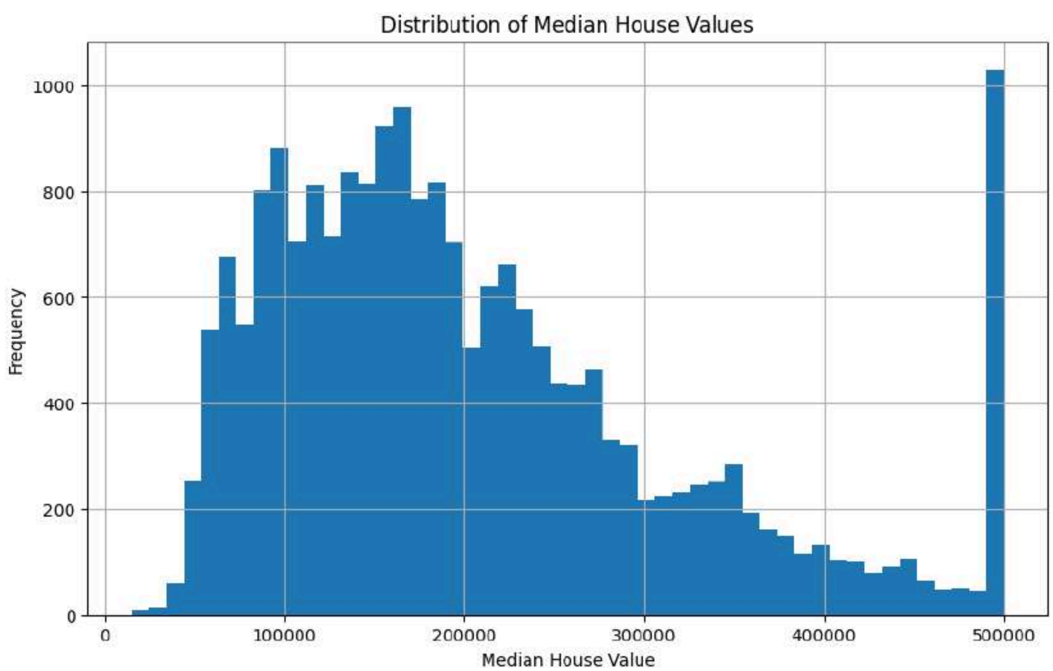
housing['median_house_value'].hist(bins=50, figsize=(10, 6))

plt.xlabel("Median House Value")

plt.ylabel("Frequency")

plt.title("Distribution of Median House Values")

plt.show()



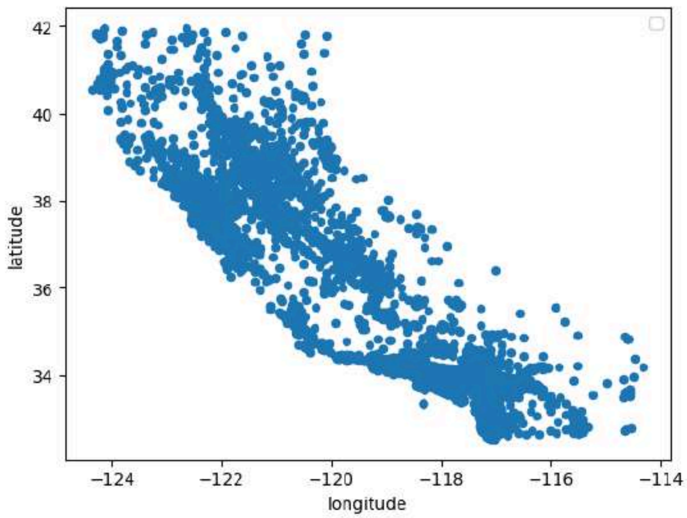
import pandas as pd

from sklearn.model_selection import train_test_split

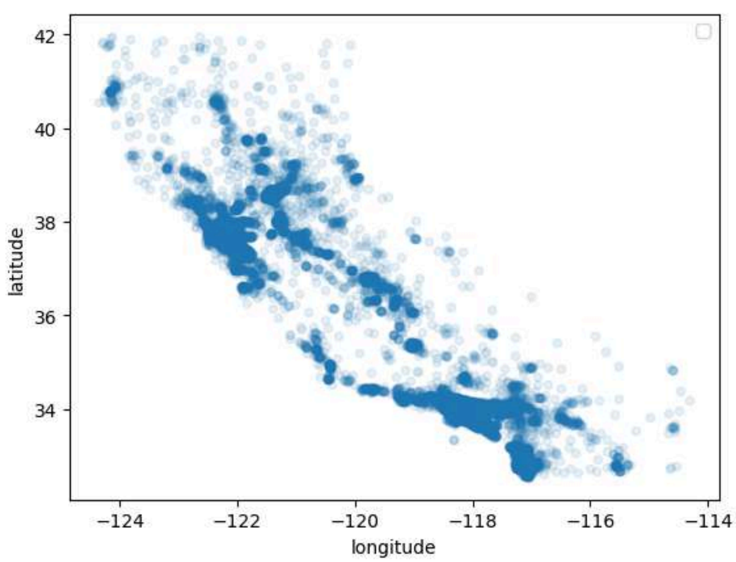
housing = pd.read_csv("housing.csv")

Random sampling

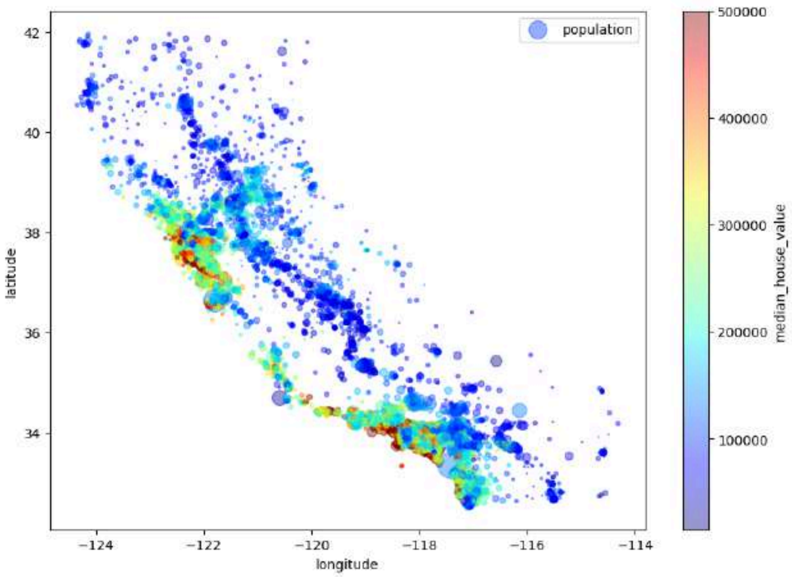
```
train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
# Separate into features (X) and target (y)
X = housing.drop("median_house_value", axis=1)  # Features (all columns except the target)
y = housing["median_house_value"]  # Target variable
# Split into train and test sets with stratification
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
import pandas as pd
from sklearn.model_selection import train_test_split
# Separate into features (X) and target (y)
X = housing.drop("median_house_value", axis=1)  # Features (all columns except the target)
y = housing["median_house_value"]  # Target variable
# Create categories for the target variable
housing["income_cat"] = pd.cut(housing["median_house_value"],
                               bins=[0, 100000, 200000, 300000, 400000, np.inf],
                               labels=[1, 2, 3, 4, 5])
# Split into train and test sets with stratification
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42,
stratify=housing["income_cat"])
import matplotlib.pyplot as plt
# Add the target variable back to the training set for visualization
train_set = X_train.copy()
train_set["median_house_value"] = y_train
# Plot the training set
train_set.plot(kind="scatter", x="longitude", y="latitude")
plt.legend()
```




```
import matplotlib.pyplot as plt
# Add the target variable back to the training set for visualization
train_set = X_train.copy()
train_set["median_house_value"] = y_train
# Plot the training set
train_set.plot(kind="scatter", x="longitude", y="latitude",alpha=0.1)
plt.legend()
```




```
train_set.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4, s=train_set["population"]/100,
label="population", figsize=(10,7), c="median_house_value", cmap=plt.get_cmap("jet"), colorbar=True)
```



Select only numerical columns (excluding categorical columns like 'ocean_proximity')

numerical_columns = housing.select_dtypes(include=['float64', 'int64'])

Calculate the correlation matrix

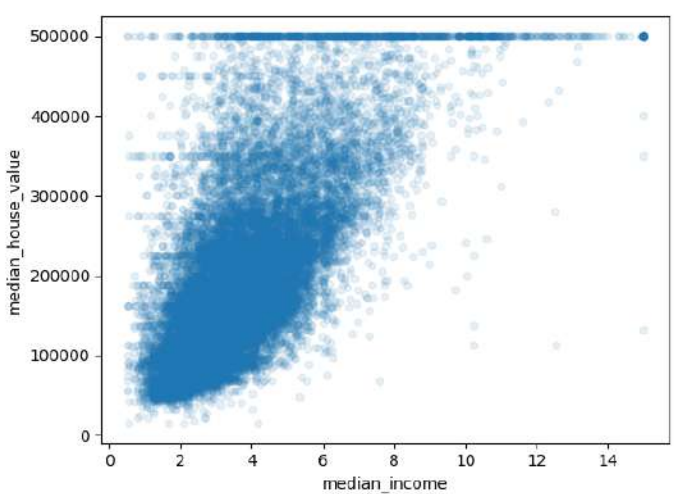
correlation_matrix = numerical_columns.corr()

Display the correlation of 'median_house_value' with other numerical columns

print(correlation_matrix["median_house_value"].sort_values(ascending=False))

```
median_house_value    1.000000
median_income         0.688075
total_rooms           0.134153
housing_median_age    0.105623
households            0.065843
total_bedrooms        0.049686
population           -0.024650
longitude            -0.045967
latitude             -0.144160
Name: median_house_value, dtype: float64
```

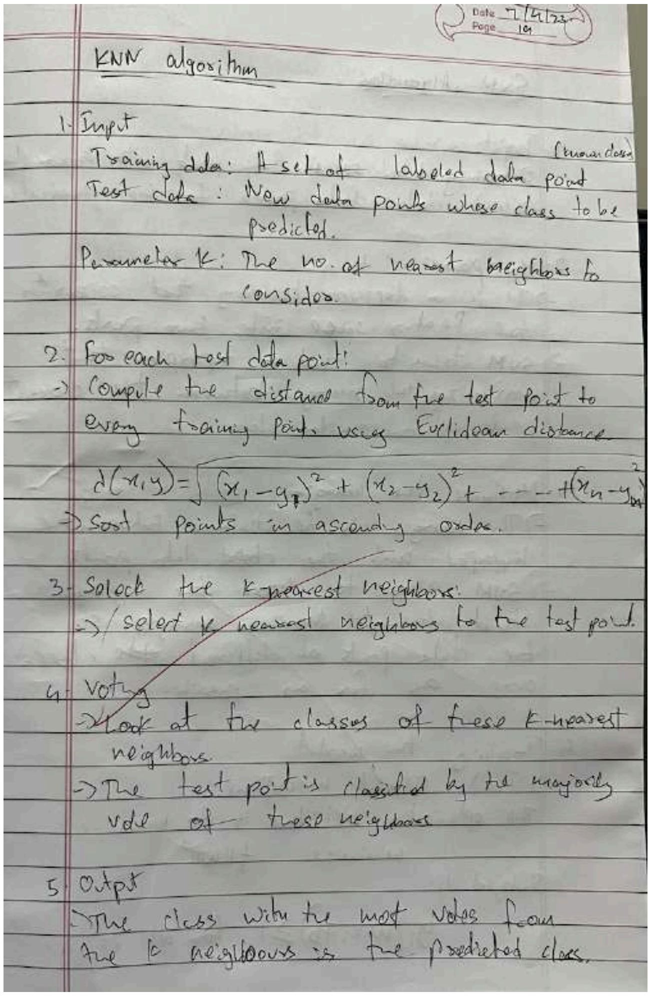
housing.plot(kind="scatter", x="median_income", y="median_house_value", alpha=0.1)



Program 6

Build KNN Classification model for a given dataset

Screenshots



KNN algorithm

1. Input

Training data: A set of labeled data point (known class)

Test data: New data points whose class to be predicted.

Parameter K: The no. of nearest neighbors to consider.

2. For each test data point:

-> Compute the distance from the test point to every training point using Euclidean distance

$d(x,y) = \sqrt{(x_1-y_1)^2 + (x_2-y_2)^2 + \cdots + (x_n-y_n)^2}$

-> Sort points in ascending order.

3. Select the K-nearest neighbors:

-> Select K nearest neighbors to the test point.

4. Voting

-> Look at the classes of these K-nearest neighbors.

-> The test point is classified by the majority vote of these neighbors

5. Output

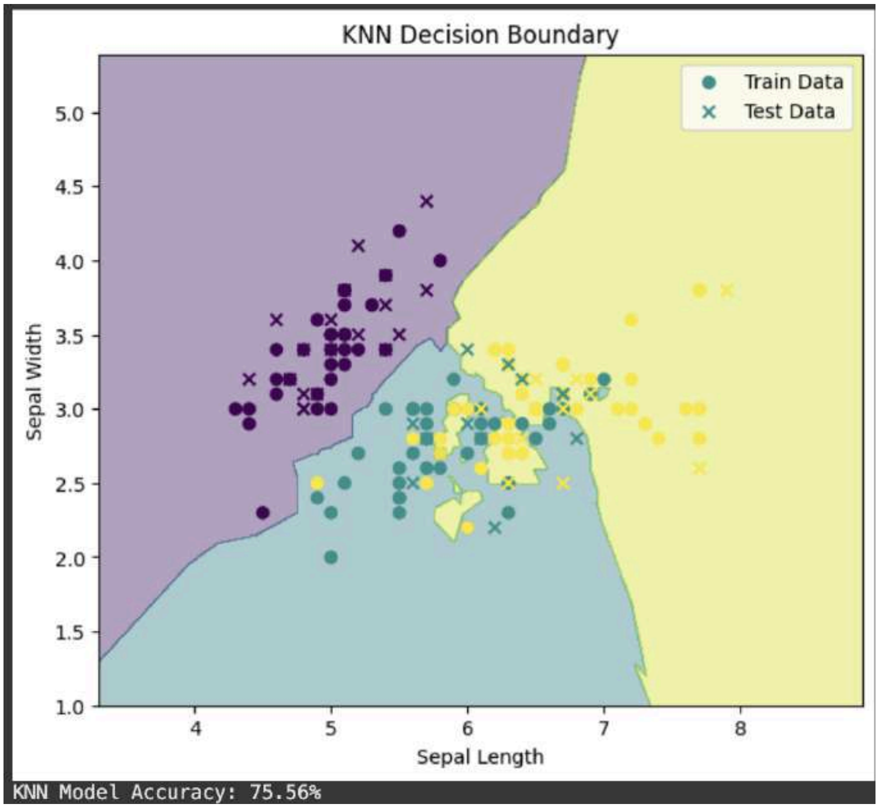
-> The class with the most votes from the K neighbours is the predicted class.

Code:

Using Iris Dataset and visualizing:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
# Load the Iris dataset
iris = datasets.load_iris()
```

```
X = iris.data[:, :2]  # Only use the first two features (sepal length and sepal width)
y = iris.target  # Target labels
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
# Create the KNN classifier (k=3 for this example)
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)
y_pred_knn = knn.predict(X_test)
# Create a mesh grid for plotting decision boundaries
x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
                     np.arange(y_min, y_max, 0.01))
# Plotting the decision boundaries for KNN
plt.figure(figsize=(7, 6))
Z_knn = knn.predict(np.c_[xx.ravel(), yy.ravel()])
Z_knn = Z_knn.reshape(xx.shape)
plt.contourf(xx, yy, Z_knn, alpha=0.4)
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, marker='o', label="Train Data")
plt.scatter(X_test[:, 0], X_test[:, 1], c=y_test, marker='x', label="Test Data")
plt.title("KNN Decision Boundary")
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.legend()
plt.show()
# Print accuracy
accuracy_knn = accuracy_score(y_test, y_pred_knn)
print(f"KNN Model Accuracy: {accuracy_knn * 100:.2f}%")
```

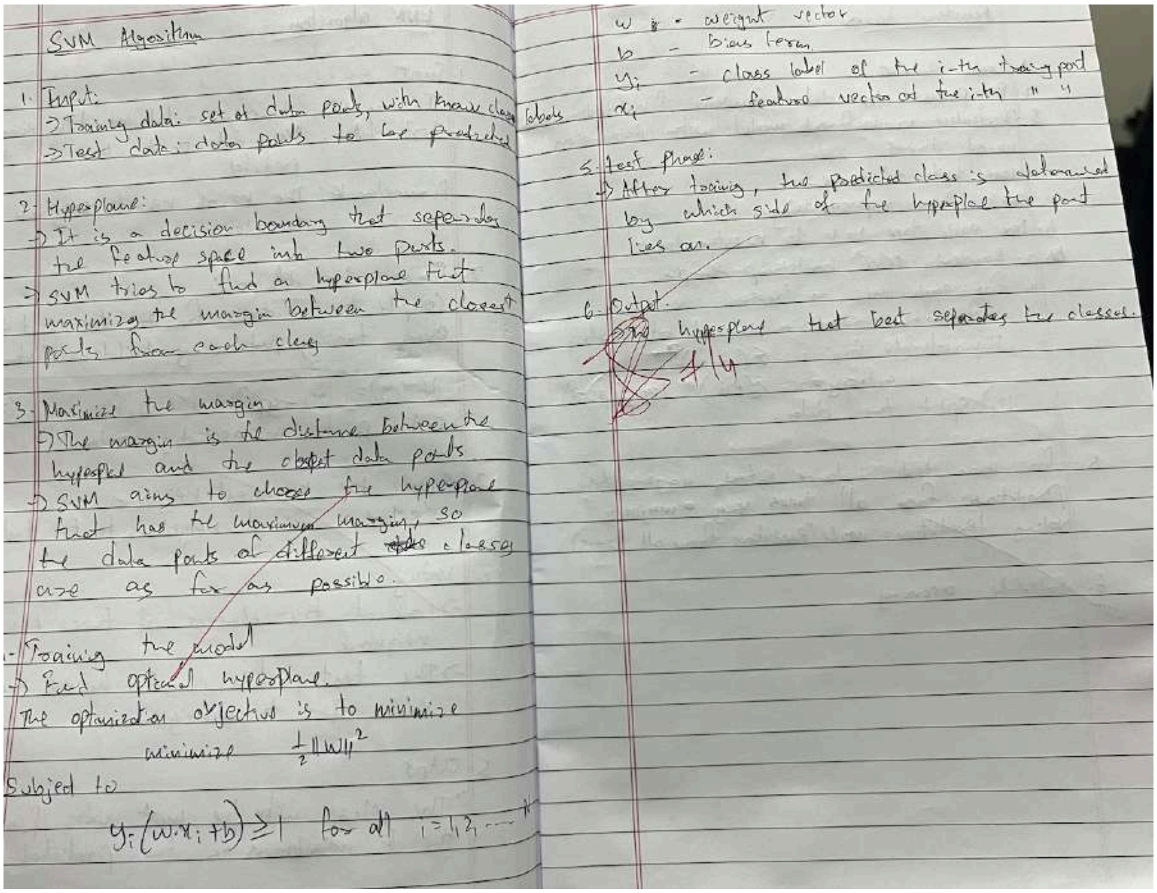


KNN Decision Boundary
Train Data
Test Data
Sepal Width
Sepal Length
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
4
5
6
7
8
KNN Model Accuracy: 75.56%

Program 7

Build Support vector machine model for a given dataset

Screenshots



SVM Algorithm

1. Input:
-> Training data: set of data points, with known class labels
-> Test data: data points to be predicted

2. Hyperplane:
-> It is a decision boundary that separates the feature space into two parts.
-> SVM tries to find a hyperplane that maximizes the margin between the closest points from each class

3. Maximize the margin
-> The margin is the distance between the hyperplane and the closest data points
-> SVM aims to choose the hyperplane that has the maximum margin, so the data points of different classes are as far as possible.

4. Training the model
-> Find optimal hyperplane.
The optimization objective is to minimize

minimize $\frac{1}{2}\|w\|^2$

Subject to

$y_i(w.x_i + b) \geq 1$ for all $i = 1, 2, \ldots n$

w - weight vector
b - bias term
y_i - class label of the i-th training point
x_i - feature vector of the i-th " "

5. Test phase:
-> After training, the predicted class is determined by which side of the hyperplane the point lies on.

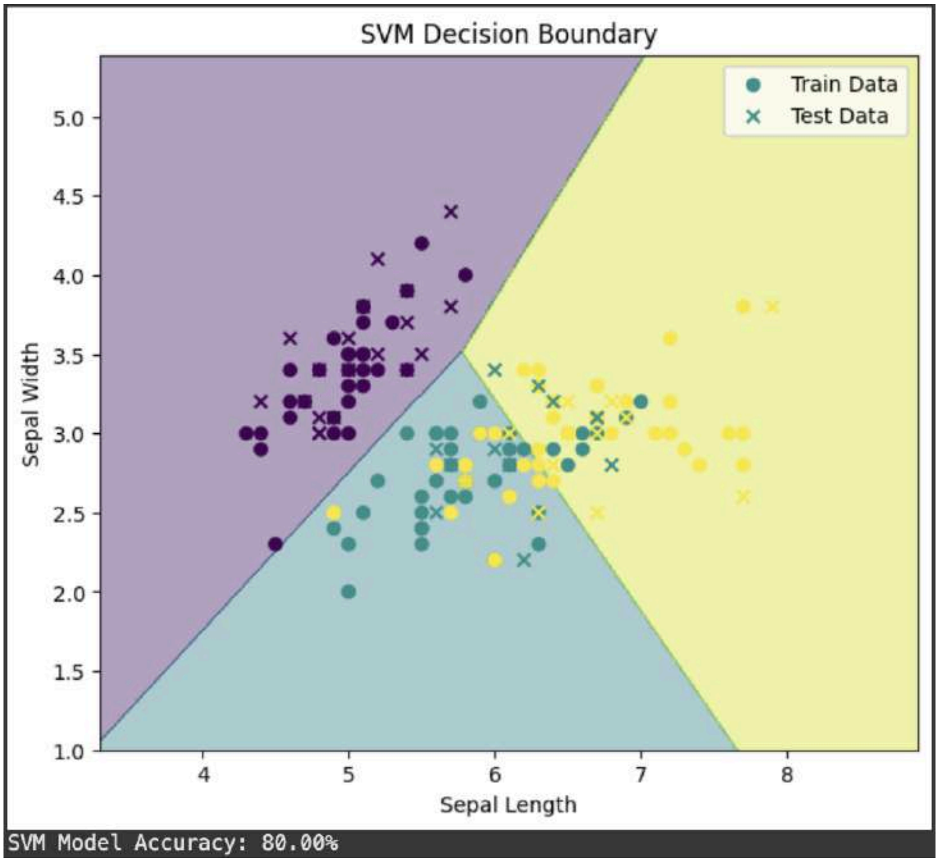
6. Output:
The hyperplane that best separates the classes.

Code:

Using Iris Dataset and visualizing:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
# Load the Iris dataset
iris = datasets.load_iris()
X = iris.data[:, :2]  # Only use the first two features (sepal length and sepal width)
y = iris.target  # Target labels
```

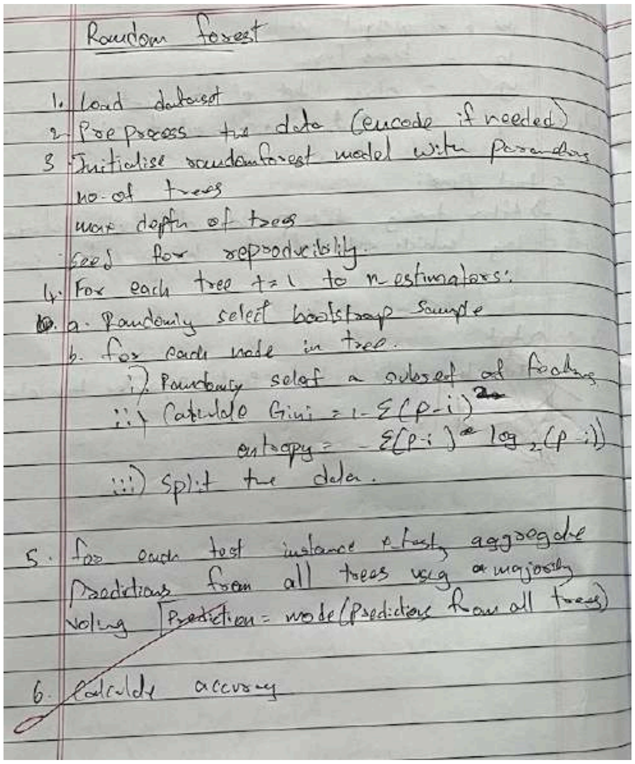
```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
# Create the SVM classifier (using a linear kernel for this example)
svm = SVC(kernel='linear')
svm.fit(X_train, y_train)
y_pred_svm = svm.predict(X_test)
# Create a mesh grid for plotting decision boundaries
x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
                     np.arange(y_min, y_max, 0.01))
# Plotting the decision boundaries for SVM
plt.figure(figsize=(7, 6))
Z_svm = svm.predict(np.c_[xx.ravel(), yy.ravel()])
Z_svm = Z_svm.reshape(xx.shape)
plt.contourf(xx, yy, Z_svm, alpha=0.4)
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, marker='o', label="Train Data")
plt.scatter(X_test[:, 0], X_test[:, 1], c=y_test, marker='x', label="Test Data")
plt.title("SVM Decision Boundary")
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.legend()
plt.show()
# Print accuracy
accuracy_svm = accuracy_score(y_test, y_pred_svm)
print(f"SVM Model Accuracy: {accuracy_svm * 100:.2f}%")
```


SVM Decision Boundary
Train Data
Test Data
Sepal Width
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
4
5
6
7
8
Sepal Length
SVM Model Accuracy: 80.00%

Program 8

Implement Random forest ensemble method on a given dataset.

Screenshots



Random forest

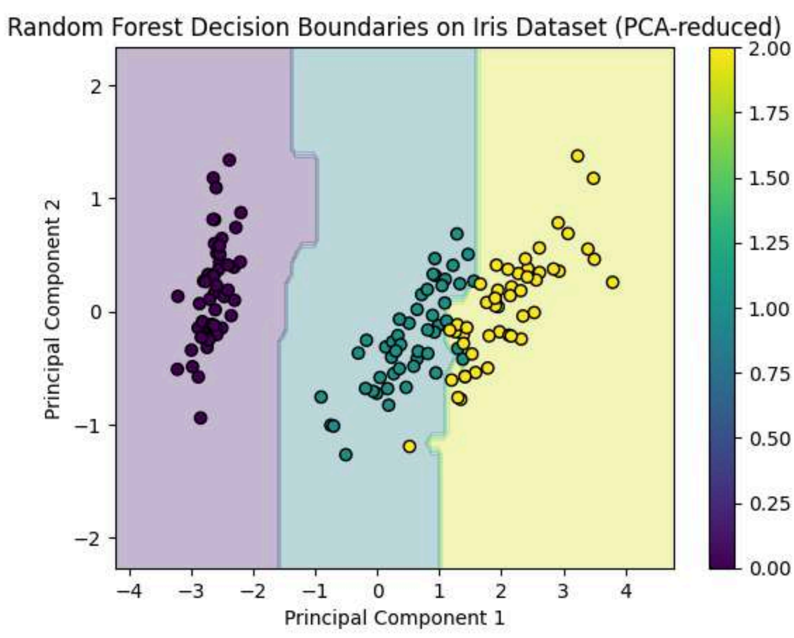
1. Load dataset
2. Preprocess the data (encode if needed)
3. Initialise randomforest model with parameters
no. of trees
max depth of trees
seed for reproducibility.
4. For each tree $t=1$ to n_estimators:
a. Randomly select bootstrap sample
b. for each node in tree.
i) Randomly select a subset of features
ii) Calculate Gini $= 1 - \Sigma(p_i)^2$
entropy $= -\Sigma(p_i) \log_2(p_i)$
iii) Split the data.
5. for each test instance x_test, aggregate predictions from all trees using a majority voting Prediction = mode(Predictions from all trees)
6. Calculate accuracy

Code:

Using Iris Dataset and visualizing:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.ensemble import RandomForestClassifier
from sklearn.decomposition import PCA
# Load Iris dataset
iris = load_iris()
X = iris.data
y = iris.target
# Apply PCA for 2D visualization (reduce to 2 components)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)
```

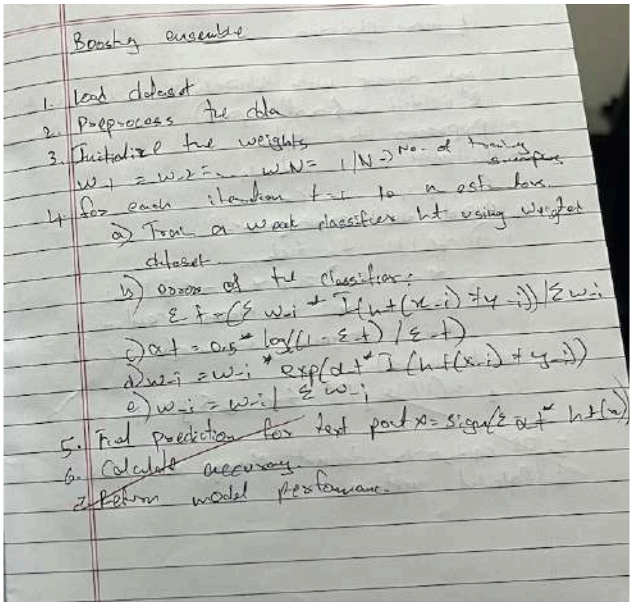
```
# Initialize Random Forest Classifier
clf = RandomForestClassifier(n_estimators=100, random_state=42)
# Train the model
clf.fit(X_pca, y)
# Create a mesh grid to plot decision boundaries
x_min, x_max = X_pca[:, 0].min() - 1, X_pca[:, 0].max() + 1
y_min, y_max = X_pca[:, 1].min() - 1, X_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                     np.arange(y_min, y_max, 0.1))
# Predict on mesh grid
Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
# Plot decision boundaries
plt.contourf(xx, yy, Z, alpha=0.3, cmap='viridis')
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, edgecolors='k', cmap='viridis')
plt.title('Random Forest Decision Boundaries on Iris Dataset (PCA-reduced)')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar()
plt.show()
```



Program 9

Implement Boosting ensemble method on a given dataset.

Screenshots



Boosting ensemble

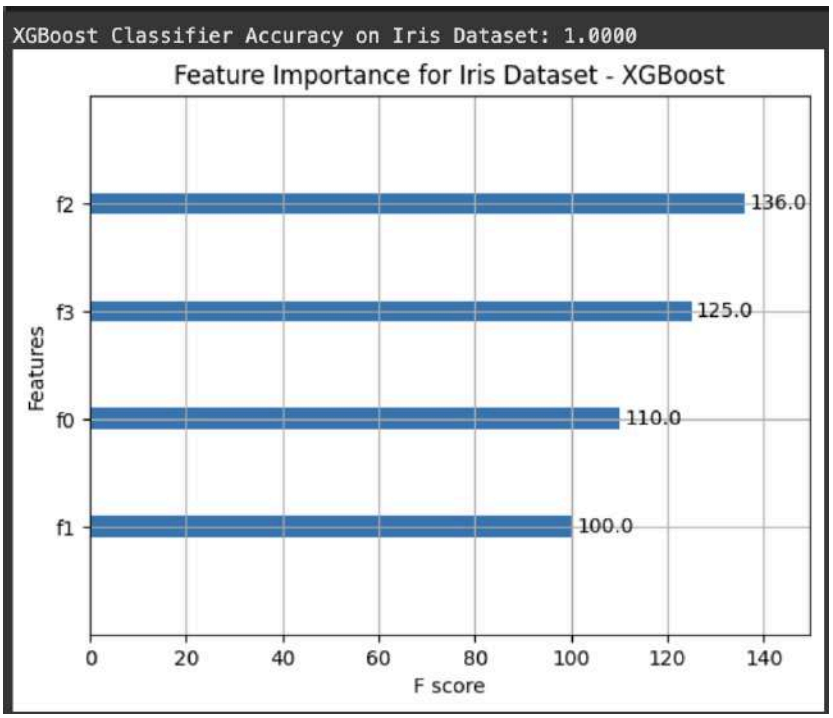
1. Load dataset
2. Preprocess the data
3. Initialize the weights
   w_1 = w_2 = ... w_N = 1/N → No. of training examples
4. for each iteration t = 1 to n_estimators.
   a) Train a weak classifier h_t using weighted dataset.
   b) error of the classifier:
   ε_t = (Σ w_i * I(h_t(x_i) ≠ y_i)) / Σ w_i
   c) α_t = 0.5 * log((1 - ε_t) / ε_t)
   d) w_i = w_i * exp(α_t * I(h_t(x_i) ≠ y_i))
   e) w_i = w_i / Σ w_i
5. Final prediction for test point x = sign(Σ α_t * h_t(x))
6. Calculate accuracy.
7. Return model performance.

Code:

Using Iris Dataset and visualizing:

```
# XGBoost on Iris Dataset with Feature Importance Visualization
import matplotlib.pyplot as plt
import xgboost as xgb
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
# Load Iris dataset
iris = load_iris()
X = iris.data
y = iris.target
# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
# Initialize XGBoost Classifier
xgb_clf = xgb.XGBClassifier(n_estimators=100, random_state=42)
# Train the model
xgb_clf.fit(X_train, y_train)
```

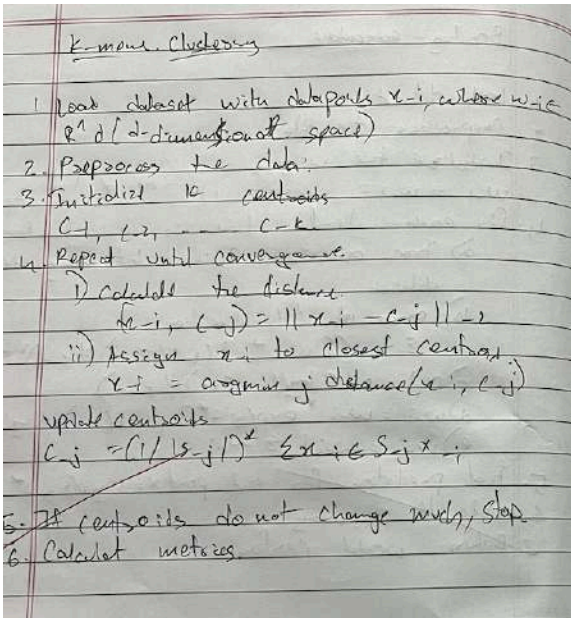
```
# Make predictions
y_pred = xgb_clf.predict(X_test)
# Calculate accuracy
accuracy = (y_pred == y_test).mean()
print(f'XGBoost Classifier Accuracy on Iris Dataset: {accuracy:.4f}')
# Feature importance visualization
xgb.plot_importance(xgb_clf, importance_type='weight', max_num_features=10)
plt.title('Feature Importance for Iris Dataset - XGBoost')
plt.show()
```



Program 10

Build k-Means algorithm to cluster a set of data stored in a .CSV file.

Screenshots

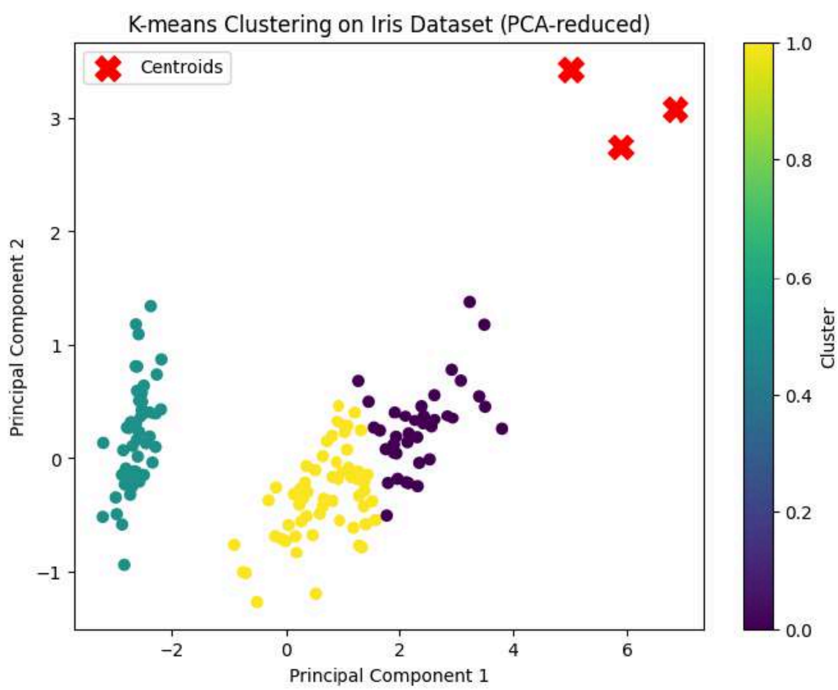

K-means Clustering

1. Load dataset with datapoints x_i, where x_i ∈ R^d (d-dimensional space)
2. Preprocess the data.
3. Initialize k centroids c_1, c_2, ... c_k
4. Repeat until convergence.
   i) Calculate the distance d(x_i, c_j) = ||x_i − c_j||_2
   ii) Assign x_i to closest centroid
   x_i = argmin_j distance(x_i, c_j)
   update centroids
   c_j = (1/|S_j|) Σ x_i ∈ S_j x_i
5. If centroids do not change much, stop.
6. Calculate metrics.

Code:

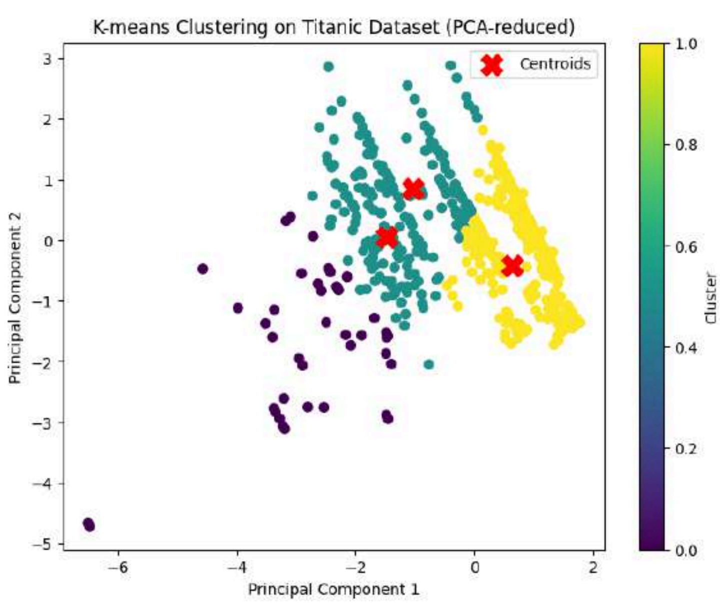
```
# K-means on Iris Dataset with Visualization
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
# Load Iris dataset
iris = load_iris()
X = iris.data
y = iris.target
# Apply PCA for 2D visualization (reduce to 2 components)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)
# Perform K-means clustering (3 clusters for 3 species in Iris)
kmeans = KMeans(n_clusters=3, random_state=42)
y_kmeans = kmeans.fit_predict(X)
# Visualize the clustering result in 2D (PCA-reduced space)
```

```
plt.figure(figsize=(8, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y_kmeans, cmap='viridis')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s=200, c='red', marker='X',
label='Centroids')
plt.title('K-means Clustering on Iris Dataset (PCA-reduced)')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='Cluster')
plt.legend()
plt.show()
```




```
# K-means on Kaggle Titanic Dataset with Visualization
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
# Load Titanic dataset (You can replace the URL with your own Kaggle dataset link)
url = "https://raw.githubusercontent.com/datasciencedojo/datasets/master/titanic.csv"
data = pd.read_csv(url)
# Preprocessing: Selecting relevant features and dropping missing values
```

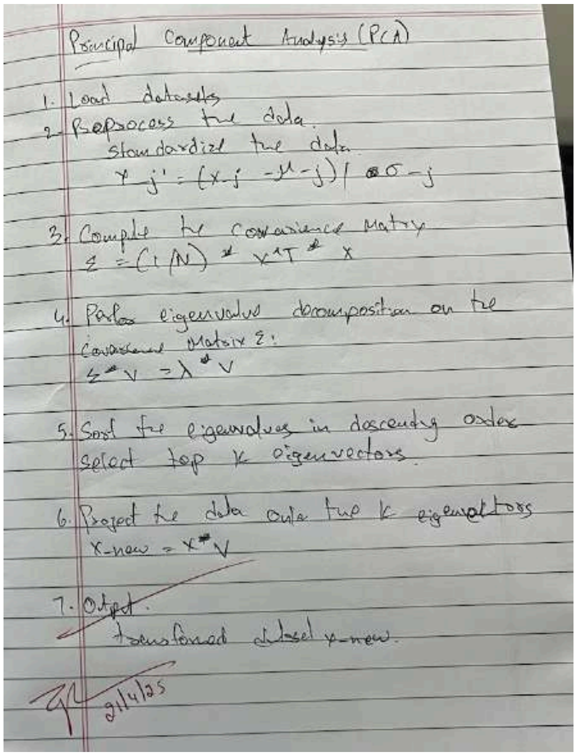
```
data = data.dropna(subset=['Pclass', 'Age', 'Fare'])
X = data[['Pclass', 'Age', 'Fare']]
# Normalize the data (optional, but helps with clustering)
X = (X - X.mean()) / X.std()
# Apply K-means clustering (let's assume we use 3 clusters for this example)
kmeans = KMeans(n_clusters=3, random_state=42)
y_kmeans = kmeans.fit_predict(X)
# Apply PCA for 2D visualization (reduce to 2 components)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)
# Plot the clusters in 2D
plt.figure(figsize=(8, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y_kmeans, cmap='viridis')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s=200, c='red', marker='X',
label='Centroids')
plt.title('K-means Clustering on Titanic Dataset (PCA-reduced)')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='Cluster')
plt.legend()
plt.show()
```



Program 11

Implement Dimensionality reduction using Principal Component Analysis (PCA) method.

Screenshots


Principal Component Analysis (PCA)

1. Load datasets
2. Preprocess the data.
   Standardize the data
   $X\_j' = (X\_j - \mu\_j) / \sigma\_j$
3. Compute the covariance Matrix
   $\Sigma = (1/N) * X^T * X$
4. Perform eigenvalue decomposition on the covariance Matrix Σ:
   $\Sigma * V = \lambda * V$
5. Sort the eigenvalues in descending order
   select top k eigenvectors.
6. Project the data onto the k eigenvectors
   $X\_new = X * V$
7. Output:
   transformed dataset X_new.

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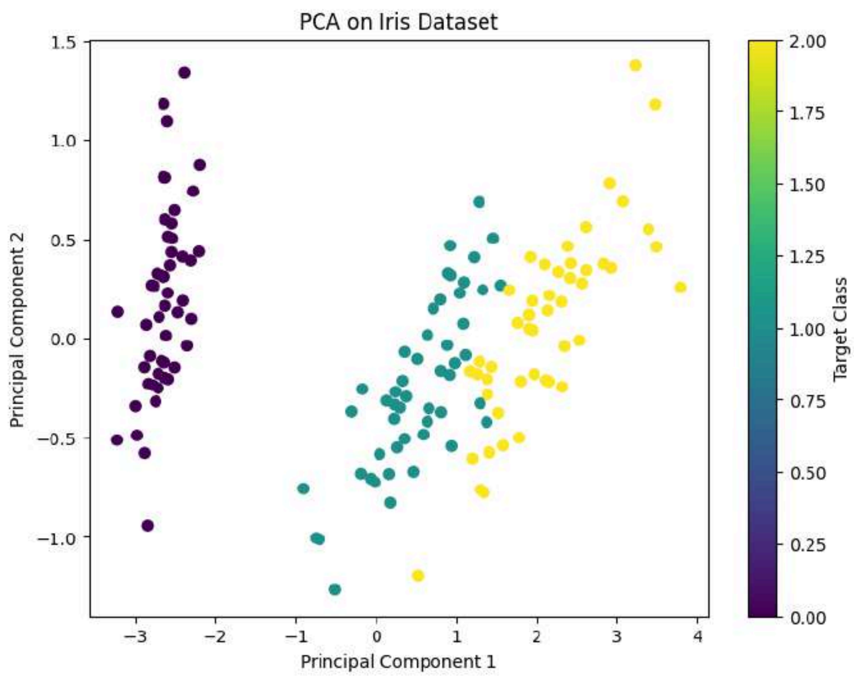
Code:

Using Iris Dataset and visualizing:

```
# PCA on Iris Dataset with Visualization
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.decomposition import PCA
# Load Iris dataset
iris = load_iris()
X = iris.data
y = iris.target
# Apply PCA to reduce data to 2D
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)
# Plot the PCA-reduced data
```

```
plt.figure(figsize=(8, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='viridis')
plt.title('PCA on Iris Dataset')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='Target Class')
plt.show()
```



Using Kaggle Titanic Dataset and visualizing:

```
# PCA on Kaggle Titanic Dataset with Visualization
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.preprocessing import LabelEncoder
# Load Titanic dataset (Replace with your dataset URL or local file path)
url = "https://raw.githubusercontent.com/datasciencedojo/datasets/master/titanic.csv"
data = pd.read_csv(url)
# Preprocess the dataset: Handle missing values and encode categorical features
data = data.dropna(subset=['Pclass', 'Age', 'Fare'])
data['Sex'] = LabelEncoder().fit_transform(data['Sex'])
```

```
# Select relevant features
X = data[['Pclass', 'Age', 'Fare']]
y = data['Survived']
# Apply PCA to reduce data to 2D
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)
# Plot the PCA-reduced data
plt.figure(figsize=(8, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='coolwarm')
plt.title('PCA on Titanic Dataset')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='Survived (0=No, 1=Yes)')
plt.show()
```