Analyze and visualize the distribution of various data science roles from a dataset

roles= ['Data Analyst', 'Data Engineer', 'Data Scientist', 'ML Engineer",

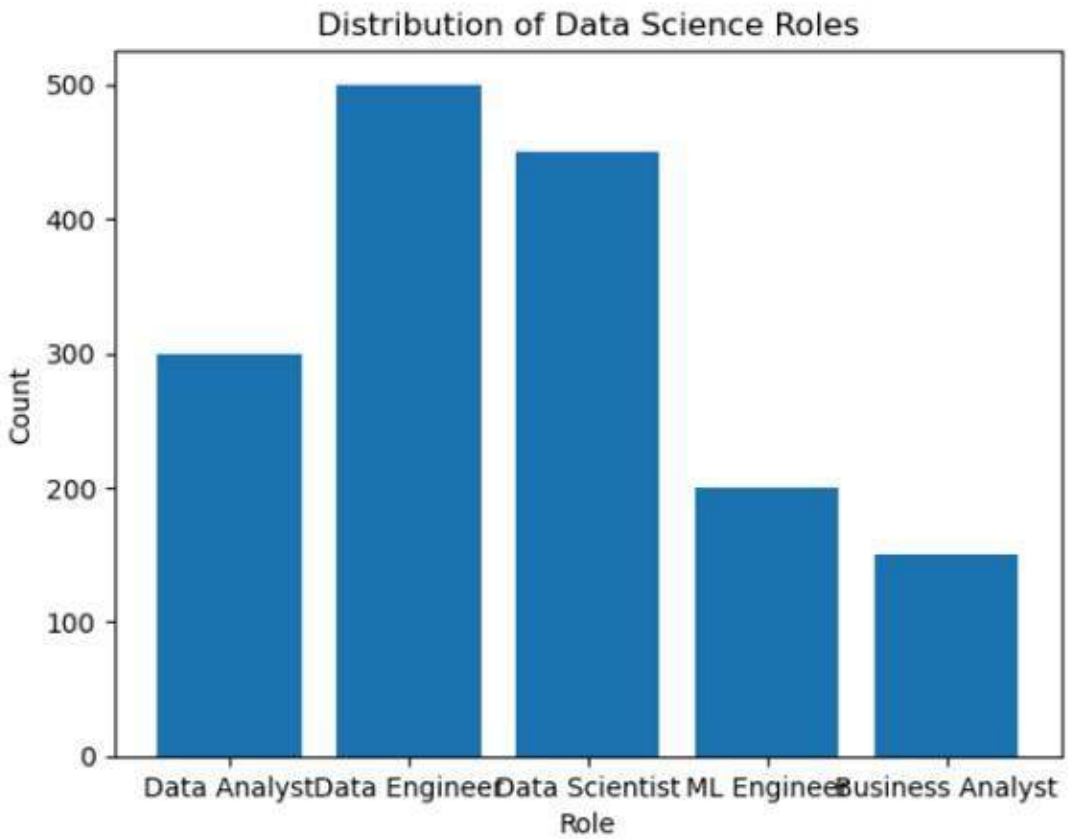
'Business Analyst'] counts =[300, 500, 450,

200, 150] plt.bar(roles, counts)

plt.title('Distribution of Data Science Roles’)

plt.xlabel('Role') plt.ylabel('Count')

plt.show()



CONDUCT AN EXPERIMENT TO ENCRYPT AND DECRYPT GIVEN SENSITIVE DATA.

```
from cryptography.fernet import Fernet
key=Fernet.generate_key()
f=Fernet(key)
token=f.encrypt(b"My name is Dinisha R")
token
b'...'
f.decrypt(token)
b'My name is Dinisha'
key=Fernet.generate_key()
cipher_suite=Fernet(key)
plain_text=b'My name is Dinisha'
cipher_text=cipher_suite.encrypt(plain_text)
decrypt_text=cipher_suite.decrypt(cipher_text)
print("Original Data",plain_text)
print("Encrypted Data",cipher_text)
print("Decrypted Data",decrypt_text)
```

```
Original Data b'My name is Dinisha'
Encrypted Data b'gAAAAABmwrGenCor03j3aGQZW-H0fVnRCA9RQbad5C_jow_zvapDqh71XH-iUq2sRgf1Mpu8PyAx162uK6RdLmBFQhvu3iA6SqPLgv6B9VSzH-XIgPJN8wQ='
Decrypted Data b'My name is Dinisha'
```

Count the frequency of occurrence of a word in a body of text is often needed during text processing.

```
import nltk
from nltk.tokenize import word_tokenize
from nltk.corpus import gutenberg
nltk.download('gutenberg')
nltk.download('punkt')
sample = gutenberg.raw("austen-emma.txt")
token = word_tokenize(sample)
wlist = []
for i in range(50):
 wlist.append(token[i])
wordfreq = [wlist.count(w) for w in wlist]
print("Pairs\n" + str(list(zip(wlist, wordfreq))))
```

```
[nltk_data] Downloading package gutenberg to
[nltk_data]     C:\Users\DELL\AppData\Roaming\nltk_data...
[nltk_data]   Package gutenberg is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\DELL\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

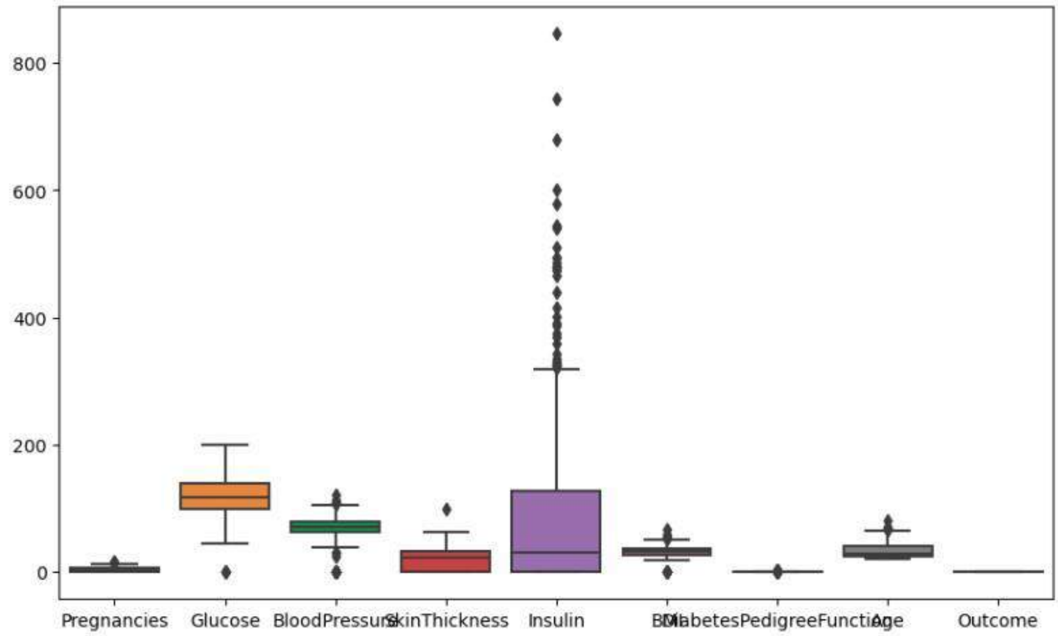
```
Pairs
[('[', 1), ('Emma', 2), ('by', 1), ('Jane', 1), ('Austen', 1), ('1816', 1), (']', 1), ('VOLUME', 1), ('I', 2), ('CHAPTER', 1),
('I', 2), ('Emma', 2), ('Woodhouse', 1), (',', 5), ('handsome', 1), (',', 5), ('clever', 1), (',', 5), ('and', 3), ('rich', 1),
(',', 5), ('with', 2), ('a', 1), ('comfortable', 1), ('home', 1), ('and', 3), ('happy', 1), ('disposition', 1), (',', 5), ('see
med', 1), ('to', 1), ('unite', 1), ('some', 1), ('of', 2), ('the', 2), ('best', 1), ('blessings', 1), ('of', 2), ('existence',
1), (';', 1), ('and', 3), ('had', 1), ('lived', 1), ('nearly', 1), ('twenty-one', 1), ('years', 1), ('in', 1), ('the', 2), ('wo
rld', 1), ('with', 2)]
```

Data Cleaning

```
print(db.isnull())
db.fillna(db.mean(),inplace=True)
print(db.isnull().sum())
```

```
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin    BMI  \
0          False    False          False          False    False  False
1          False    False          False          False    False  False
2          False    False          False          False    False  False
3          False    False          False          False    False  False
4          False    False          False          False    False  False
..           ...      ...            ...            ...      ...    ...
763        False    False          False          False    False  False
764        False    False          False          False    False  False
765        False    False          False          False    False  False
766        False    False          False          False    False  False
767        False    False          False          False    False  False

     DiabetesPedigreeFunction    Age  Outcome
0                       False  False    False
1                       False  False    False
2                       False  False    False
3                       False  False    False
4                       False  False    False
..                        ...    ...      ...
763                     False  False    False
764                     False  False    False
765                     False  False    False
766                     False  False    False
767                     False  False    False

[768 rows x 9 columns]
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

```
import numpy as np
plt.figure(figsize=(10,6))
sns.boxplot(data=db)
plt.show()
from scipy import stats
diabetes_df=db[(np.abs(stats.zscore(db))<3).all(axis=1)]
```



Data Collection and Initial Exploration

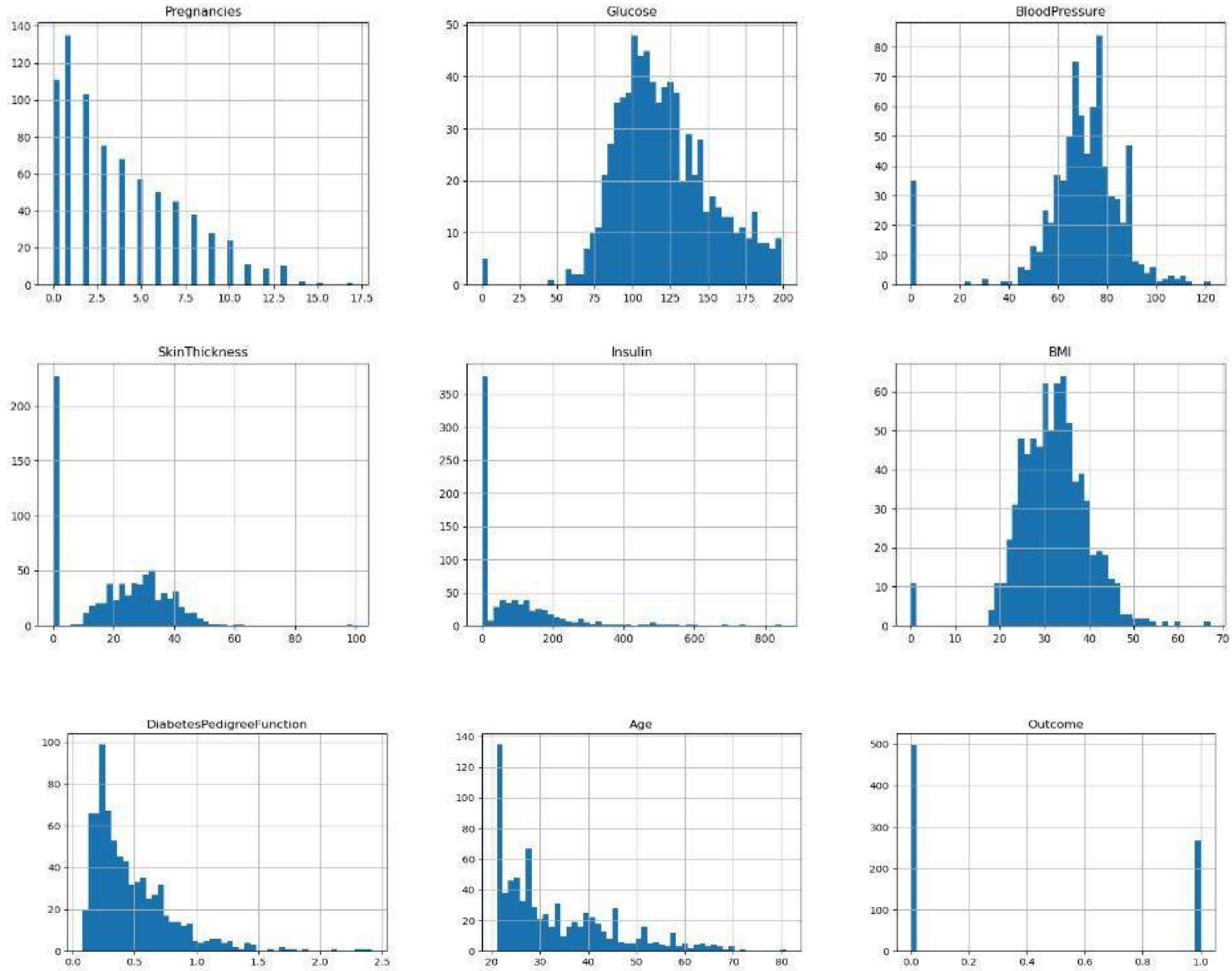
```
import pandas as pd
import matplotlib.pyplot as plt
db = pd.read_csv("diabetes.csv")
print(db.head())
```

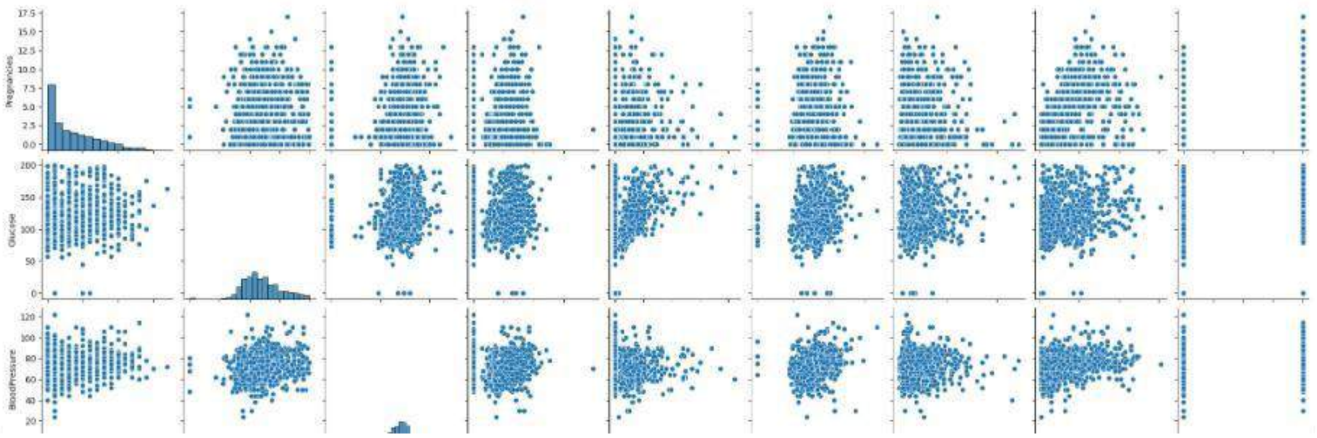
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
```

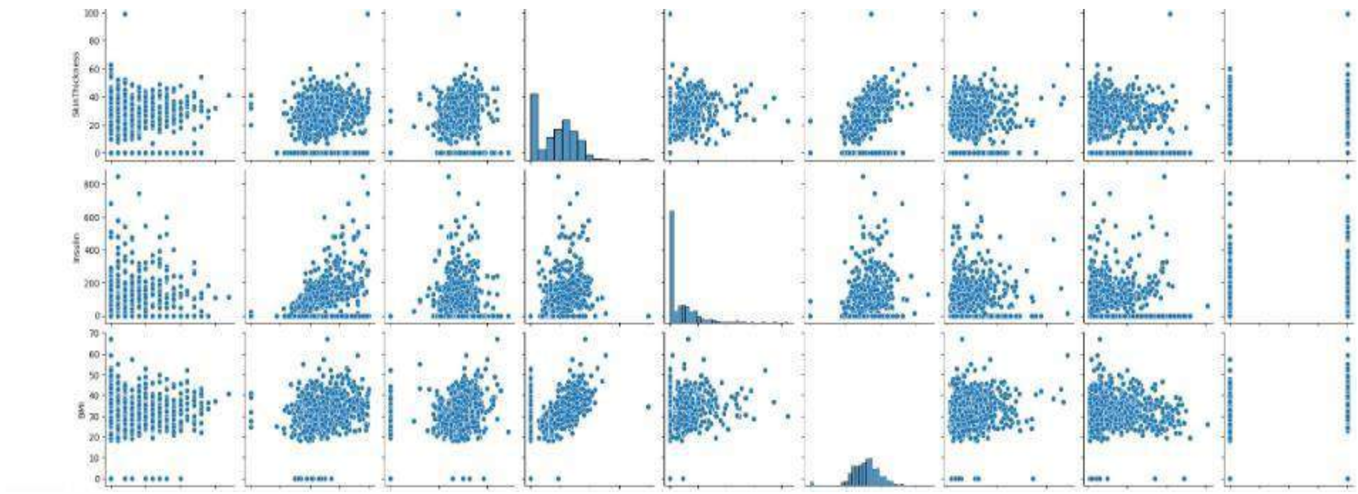
```
print(db.info)
print(db.describe)
import seaborn as sns
db.hist(bins=50,figsize=(20,15))
plt.show()
sns.pairplot(db)
plt.show()
```

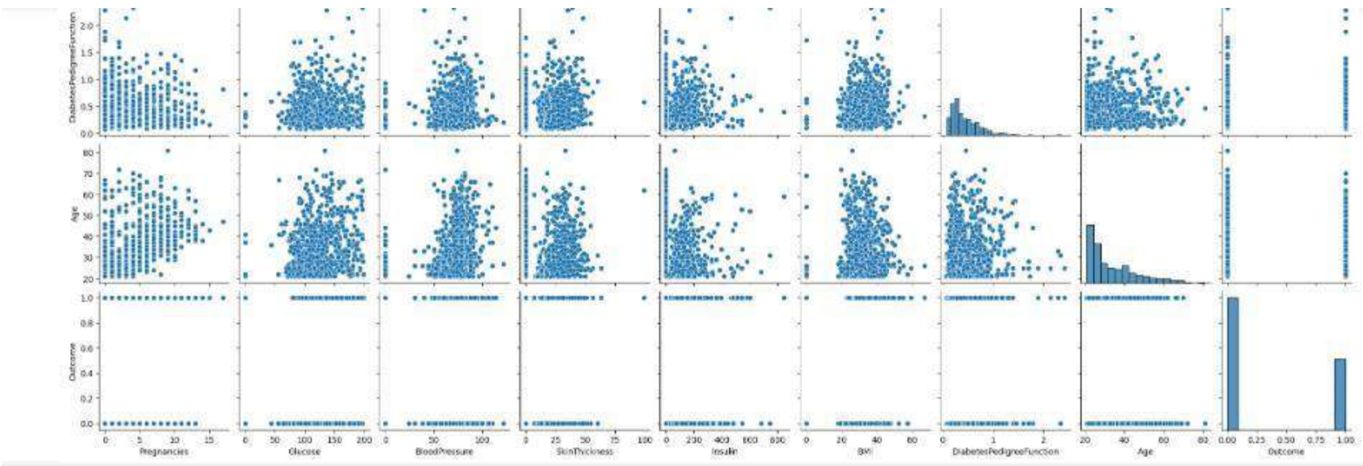
```
<bound method DataFrame.info of      Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              6      148             72             35        0  33.6
1              1       85             66             29        0  26.6
2              8      183             64              0        0  23.3
3              1       89             66             23       94  28.1
4              0      137             40             35      168  43.1
..           ...      ...            ...            ...      ...   ...
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     DiabetesPedigreeFunction  Age  Outcome
0                       0.627   50        1
1                       0.351   31        0
2                       0.672   32        1
3                       0.167   21        0
4                       2.288   33        1
..                        ...  ...      ...
763                     0.171   63        0
764                     0.340   27        0
765                     0.245   30        0
766                     0.349   47        1
767                     0.315   23        0

[768 rows x 9 columns]>
<bound method NDFrame.describe of      Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              6      148             72             35        0  33.6
1              1       85             66             29        0  26.6
2              8      183             64              0        0  23.3
3              1       89             66             23       94  28.1
4              0      137             40             35      168  43.1
..           ...      ...            ...            ...      ...   ...
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4
```

```
     DiabetesPedigreeFunction  Age  Outcome
0                       0.627   50        1
1                       0.351   31        0
2                       0.672   32        1
3                       0.167   21        0
4                       2.288   33        1
..                        ...  ...      ...
763                     0.171   63        0
764                     0.340   27        0
765                     0.245   30        0
766                     0.349   47        1
767                     0.315   23        0

[768 rows x 9 columns]>
```





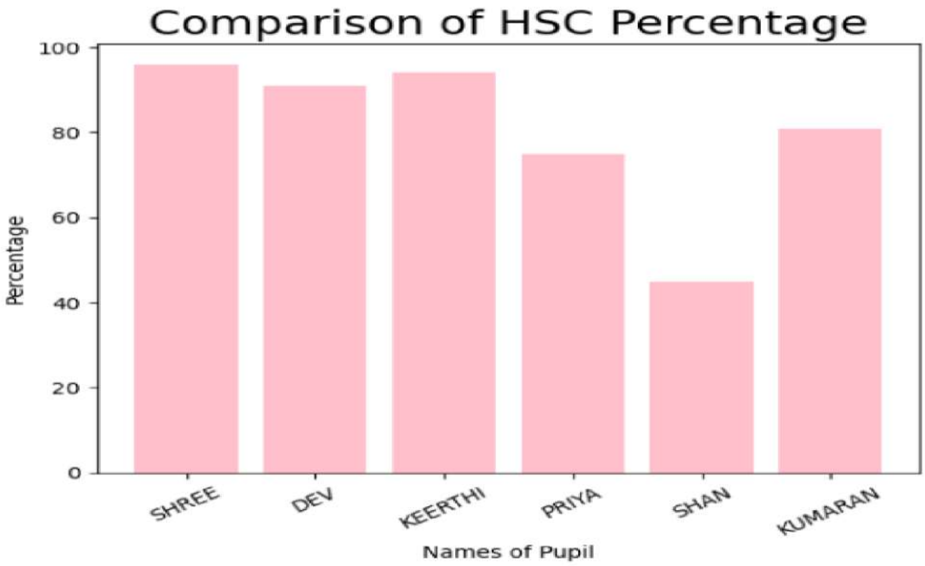

SkinThickness
Insulin
BMI


DiabetesPedigreeFunction
Age
Outcome
Pregnancies
Glucose
BloodPressure
SkinThickness
Insulin
BMI
DiabetesPedigreeFunction
Age
Outcome

Experiment to show data visualization using bar chart

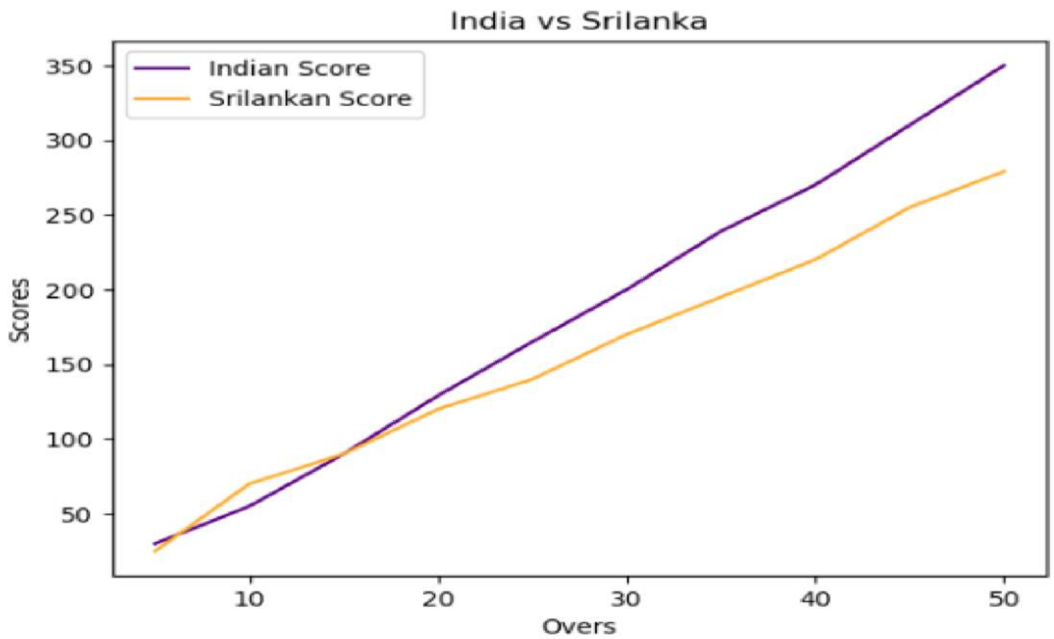
In [1]:

```
import matplotlib.pyplot as hscmark
import numpy as np
Names = ['SHREE', 'DEV', 'KEERTHI','PRIYA','SHAN','KUMARAN']
xaxis = np.arange(len(Names))
Percentage_hsc = [96, 91, 94, 75, 45, 81]
hscmark.bar(Names, Percentage_hsc,color='pink')
hscmark.xticks(xaxis, Names, rotation=30)
hscmark.xlabel('Names of Pupil')
hscmark.ylabel('Percentage')
hscmark.title('Comparison of HSC Percentage', fontsize=20, color='black')
hscmark.show()
```

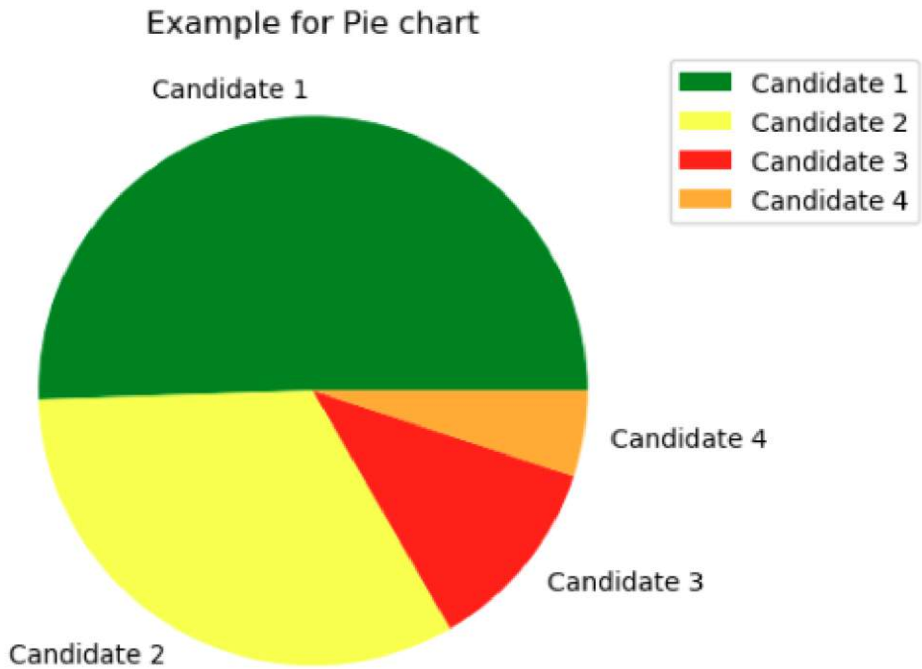


Experiment to show data visualization using line plot

```
In [1]: import matplotlib.pyplot as cricket
        Overs=list(range(5,51,5))
        Indian_Score=[30,55,90,129,165,200,239,270,310,350]
        Srilankan_Score=[25,70,90,120,140,170,195,220,255,279]
        cricket.plot(Overs,Indian_Score,label='Indian Score',color='indigo')
        cricket.plot(Overs,Srilankan_Score,label='Srilankan Score',color='orange')
        cricket.title("India vs Srilanka")
        cricket.xlabel("Overs")
        cricket.ylabel("Scores")
        cricket.legend()
        cricket.show()
```



```
In [1]: import numpy as np
        import matplotlib.pyplot as election
        roles=['Candidate 1','Candidate 2','Candidate 3','Candidate 4']
        count=np.array([100,65,23,10])
        colours = ['green','yellow','red','orange']
        election.pie(count,labels=roles,colors=colours)
        election.legend(loc="upper left",bbox_to_anchor=(1,1))
        election.title("Example for Pie chart")
        election.show()
```



Experiment to show data visualization using pie chart

Experiments on Structured, Unstructured and Semi Structured

import pandas as pd structured_data=pd.DataFrame({

'ID': [1,2,3], 'Name': ['Alice', 'Bob', 'Charlie'], 'Age': [25,30,35]

})

print("Structured data: \n", structured_data)

unstructured_data="This is an example of unstructured data. It can be a piece of text, an image, or a video file." print("Unstructured data: \n", unstructured_data) semi_structured={'ID': 1, 'Name': 'Alice', 'Attributes': {'Height’:165, 'Weight':68}} print("Semi Structed data: \n", semi_structured)

output:

```
Structured data :
    ID     Name  Age
0   1    Alice   25
1   2      Bob   30
2   3  Charlie   35
```

```
Unstructured data :
 This is an example of unstructured data. It can be a piece of text, an image, or a video file.
```

```
Semi Structed data:
 {'ID': 1, 'Name': 'Alice', 'Attributes': {'Height': 165, 'Weight': 68}}
```

Using Pandas for data manipulation and Matplotlib for visualization

Import pandas as pd

Import matplotlib.pyplot as plt

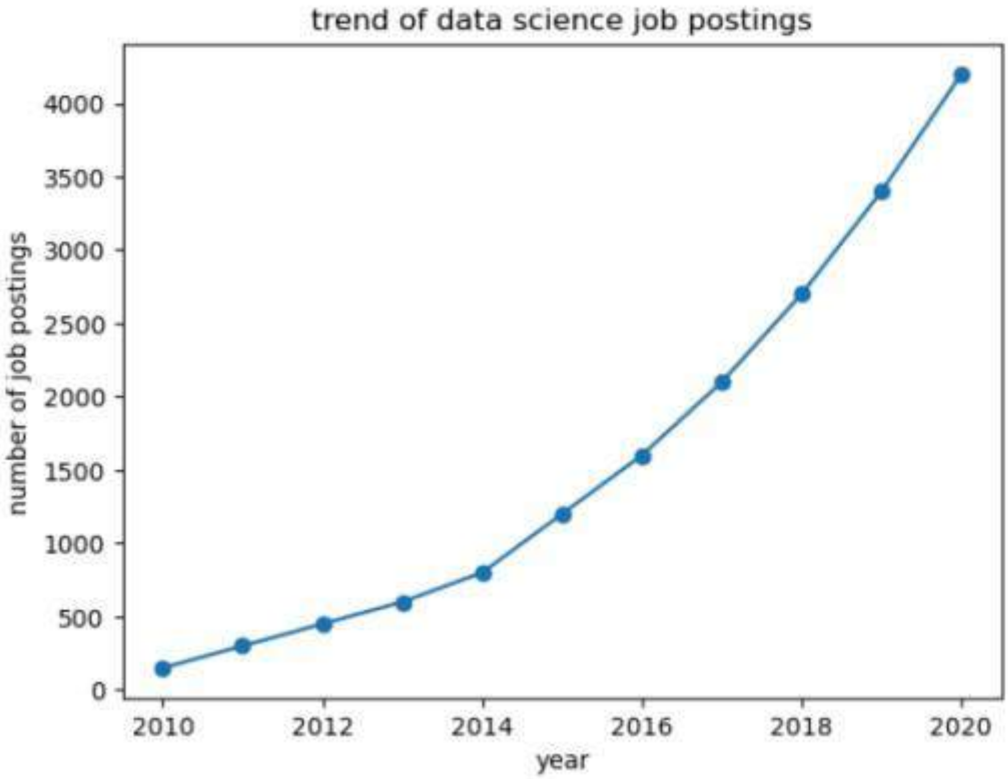
data ={'Year’: list(range (2010,2021)), ‘job posting’: [150, 300, 450, 600, 800, 1200, 1600, 2100, 2700, 3400,4200]} df = pd.DataFrame(data) plt.plot

(df['Year'], df['job posting'], marker='o')

plt.title('trend of data science job postings')

plt.xlabel('year') plt.ylabel('number of job

postings') plt.show()



4: DATA PREPROCESSING

NAME: Gopikrishnan L

ROLL NO: 230701096

```
import pandas as pd import
numpy as np
from sklearn.preprocessing import LabelEncoder, StandardScaler


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


print("Original Dataset:") print(df.head())

df.replace({'Bill': { -1: np.nan, -99999: np.nan, 0: np.nan},
        'NoOfPax': {-1: np.nan, 0: np.nan},
        'EstimatedSalary': {-99999: np.nan, 0: np.nan},
        'Rating(1-5)': { -1: np.nan}},
inplace=True)


df = df.drop_duplicates()


df['Bill'] = df['Bill'].fillna(df['Bill'].mean())
df['NoOfPax'] = df['NoOfPax'].fillna(df['NoOfPax'].mode()[0])  # Mode for categorical-like column
df['EstimatedSalary'] = df['EstimatedSalary'].fillna(df['EstimatedSalary'].mean()) df['Rating(1-5)']
= df['Rating(1-5)'].fillna(df['Rating(1-5)'].mode()[0])

label_encoder = LabelEncoder()
df['Hotel'] = label_encoder.fit_transform(df['Hotel'])
df['FoodPreference'] = label_encoder.fit_transform(df['FoodPreference'])


df = pd.get_dummies(df, columns=['Age_Group'], drop_first=True)
```

```
scaler = StandardScaler()
df[['Bill', 'EstimatedSalary']] = scaler.fit_transform(df[['Bill', 'EstimatedSalary']])

print("\nPreprocessed Dataset:")
print(df.head())

df.to_csv('Preprocessed_Hotel_Dataset.csv', index=False)
```

```
Original Dataset:
   CustomerID Age_Group  Rating(1-5)      Hotel FoodPreference  Bill  NoOfPax  \
0           1     20-25            4       Ibis            veg  1300        2
1           2     30-35            5  LemonTree        Non-Veg  2000        3
2           3     25-30            6     RedFox            Veg  1322        2
3           4     20-25           -1  LemonTree            Veg  1234        2
4           5       35+            3       Ibis     Vegetarian   989        2

   EstimatedSalary Age_Group.1
0            40000       20-25
1            59000       30-35
2            30000       25-30
3           120000       20-25
4            45000         35+
```

```
   EstimatedSalary Age_Group.1
0            40000       20-25
1            59000       30-35
2            30000       25-30
3           120000       20-25
4            45000         35+

Preprocessed Dataset:
   CustomerID  Rating(1-5)  Hotel  FoodPreference      Bill  NoOfPax  \
0           1          4.0      0               4  0.131957      2.0
1           2          5.0      2               0  0.392446      3.0
2           3          6.0      3               1  0.140143      2.0
3           4          3.0      2               1  0.107396      2.0
4           5          3.0      0               2  0.016225      2.0
```

```
Preprocessed Dataset:
   CustomerID  Rating(1-5)  Hotel  FoodPreference      Bill  NoOfPax  \
0           1          4.0      0               4  0.131957      2.0
1           2          5.0      2               0  0.392446      3.0
2           3          6.0      3               1  0.140143      2.0
3           4          3.0      2               1  0.107396      2.0
4           5          3.0      0               2  0.016225      2.0

   EstimatedSalary Age_Group.1  Age_Group_25-30  Age_Group_30-35  \
0        -0.631656       20-25            False            False
1        -0.420194       30-35            False             True
2        -0.742952       25-30             True            False
3         0.258711       20-25            False            False
4        -0.576008         35+            False            False

   Age_Group_35+
0          False
1          False
2          False
3          False
4           True
```

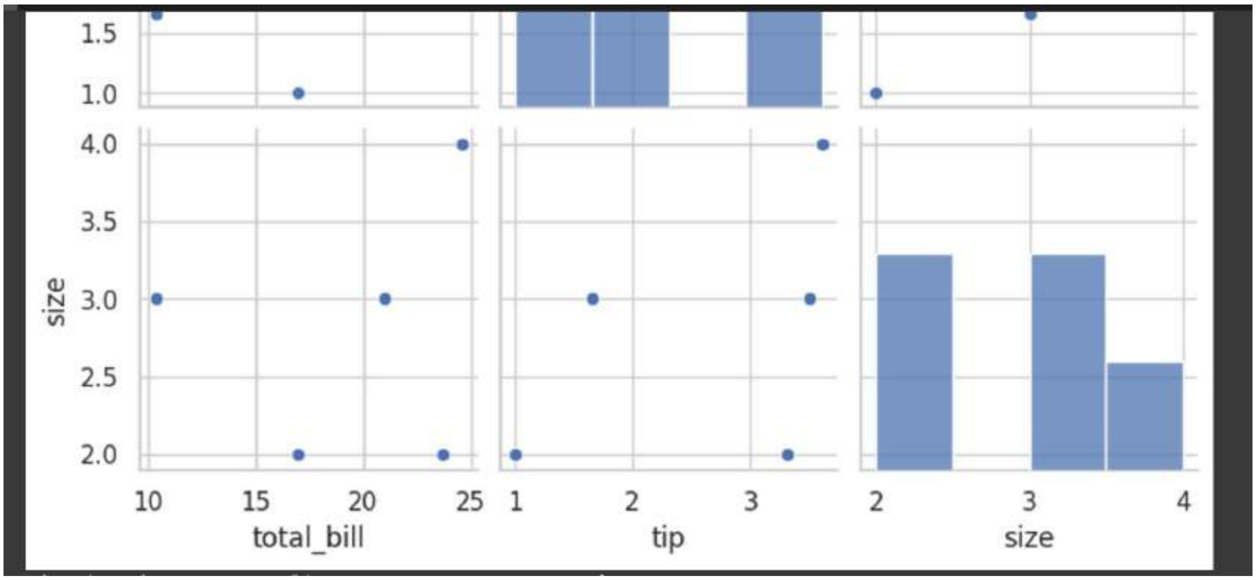
5: EDA quantitative and qualitative plot

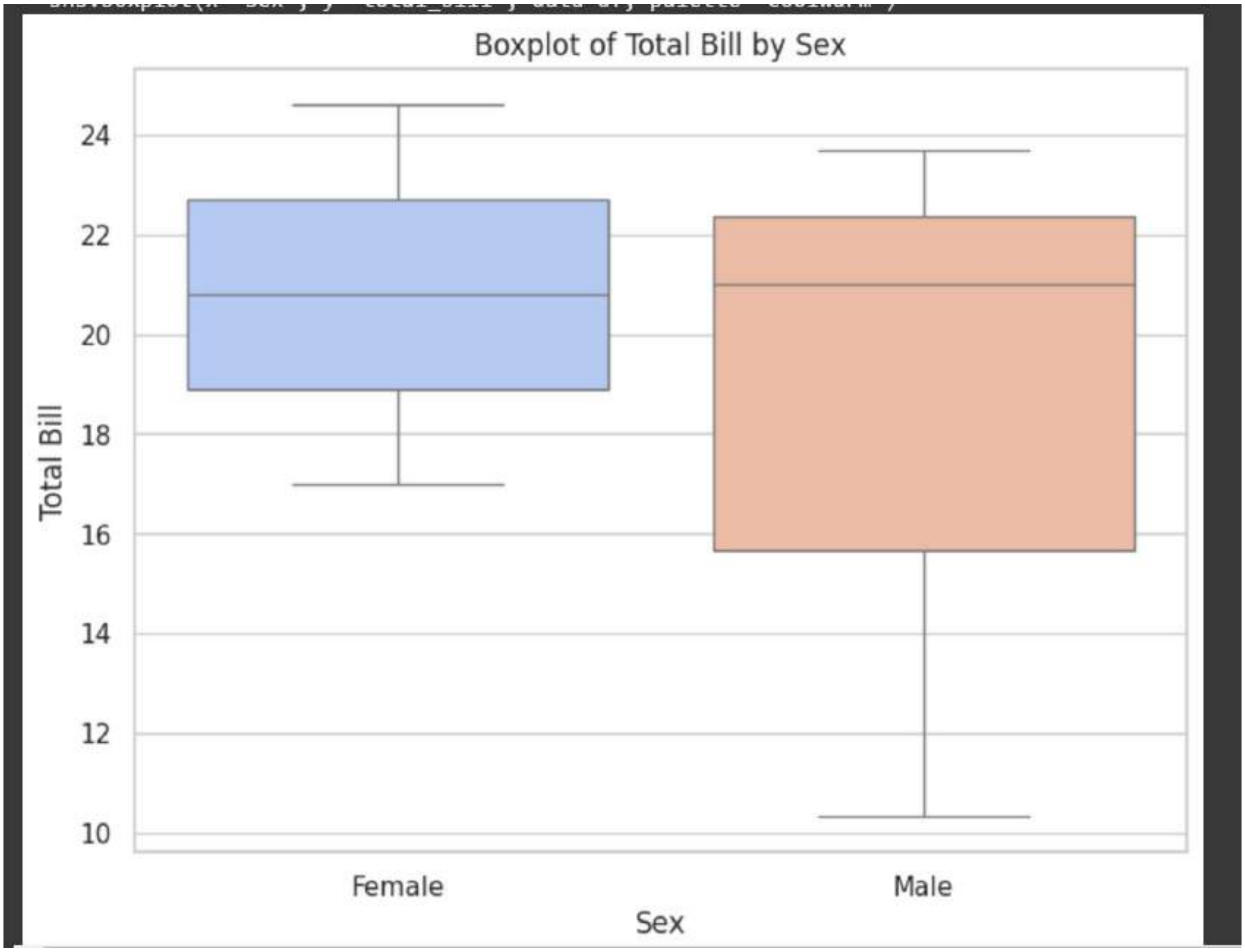
NAME: GOPIKRISHNAN L
ROLL NO :230701096

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


data = {
    'total_bill': [16.99, 10.34, 21.01, 23.68, 24.59],
    'tip': [1.01, 1.66, 3.50, 3.31, 3.61],
    'sex': ['Female', 'Male', 'Male', 'Male', 'Female'],
    'smoker': ['No', 'No', 'No', 'No', 'No'],
    'day': ['Sun', 'Sun', 'Sun', 'Sun', 'Sun'],
    'time': ['Dinner', 'Dinner', 'Dinner', 'Dinner', 'Dinner'],
    'size': [2, 3, 3, 2, 4]
}


df = pd.DataFrame(data)

# Set up Seaborn style for plots
sns.set(style="whitegrid")

# --------------------------
# Quantitative Plots
# --------------------------

plt.figure(figsize=(8, 6))
sns.histplot(df['total_bill'], kde=True, color='blue', bins=10)
plt.title('Distribution of Total Bill')
plt.xlabel('Total Bill')
plt.ylabel('Frequency') plt.show()


plt.figure(figsize=(8, 6))
sns.histplot(df['tip'], kde=True, color='green', bins=10) plt.title('Distribution
of Tip')
plt.xlabel('Tip')
plt.ylabel('Frequency') plt.show()
```

```
plt.figure(figsize=(8, 6)) sns.boxplot(x=df['total_bill'],
color='orange')
plt.title('Boxplot of Total Bill') plt.xlabel('Total
Bill')
plt.show()


plt.figure(figsize=(8, 6))
sns.scatterplot(x=df['total_bill'], y=df['tip'], color='purple')
plt.title('Total Bill vs Tip')
plt.xlabel('Total Bill') plt.ylabel('Tip')
plt.show()

# --------------------------
# Qualitative Plots
# --------------------------

plt.figure(figsize=(8, 6)) sns.countplot(x='sex',
data=df, palette='Set2') plt.title('Count of
Customers by Sex')
plt.xlabel('Sex') plt.ylabel('Count') plt.show()
plt.figure(figsize=(8, 6)) sns.countplot(x='smoker',
data=df, palette='Set3') plt.title('Count of
Smokers vs Non-Smokers')
plt.xlabel('Smoker') plt.ylabel('Count')
plt.show()


plt.figure(figsize=(8, 6)) sns.countplot(x='day',
data=df, palette='muted') plt.title('Count of
Customers by Day')
plt.xlabel('Day')
plt.ylabel('Count') plt.show()
plt.figure(figsize=(8, 6))
sns.countplot(x='time', data=df, palette='pastel') plt.title('Count
of Customers by Time')
plt.xlabel('Time') plt.ylabel('Count')
plt.show()

sns.pairplot(df[['total_bill', 'tip', 'size']])
plt.suptitle('Pairplot: Total Bill, Tip, and Size', y=1.02) plt.show()
```

```
plt.figure(figsize=(8, 6))
sns.boxplot(x='sex', y='total_bill', data=df, palette='coolwarm')
plt.title('Boxplot of Total Bill by Sex')
plt.xlabel('Sex') plt.ylabel('Total Bill')
plt.show()
```





6: RANDOM SAMPLING AND SAMPLING DISTRIBUTION

NAME: GOPIKRISHNAN L
ROLL NO: 230701096

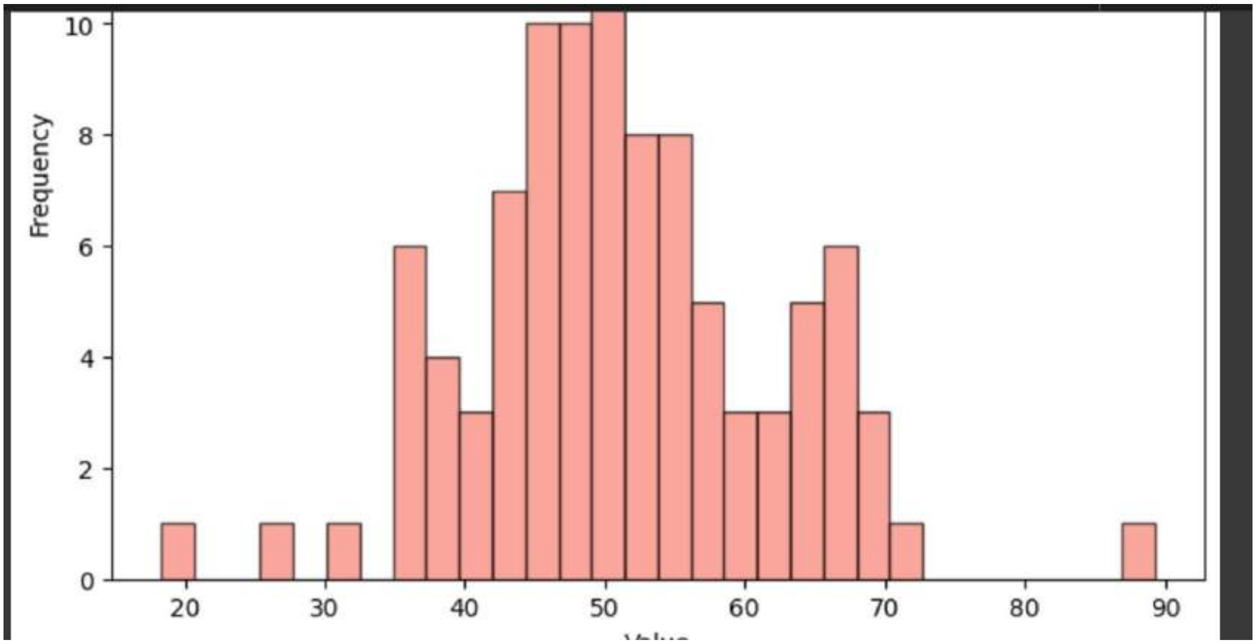
import numpy as np import
matplotlib.pyplot as plt

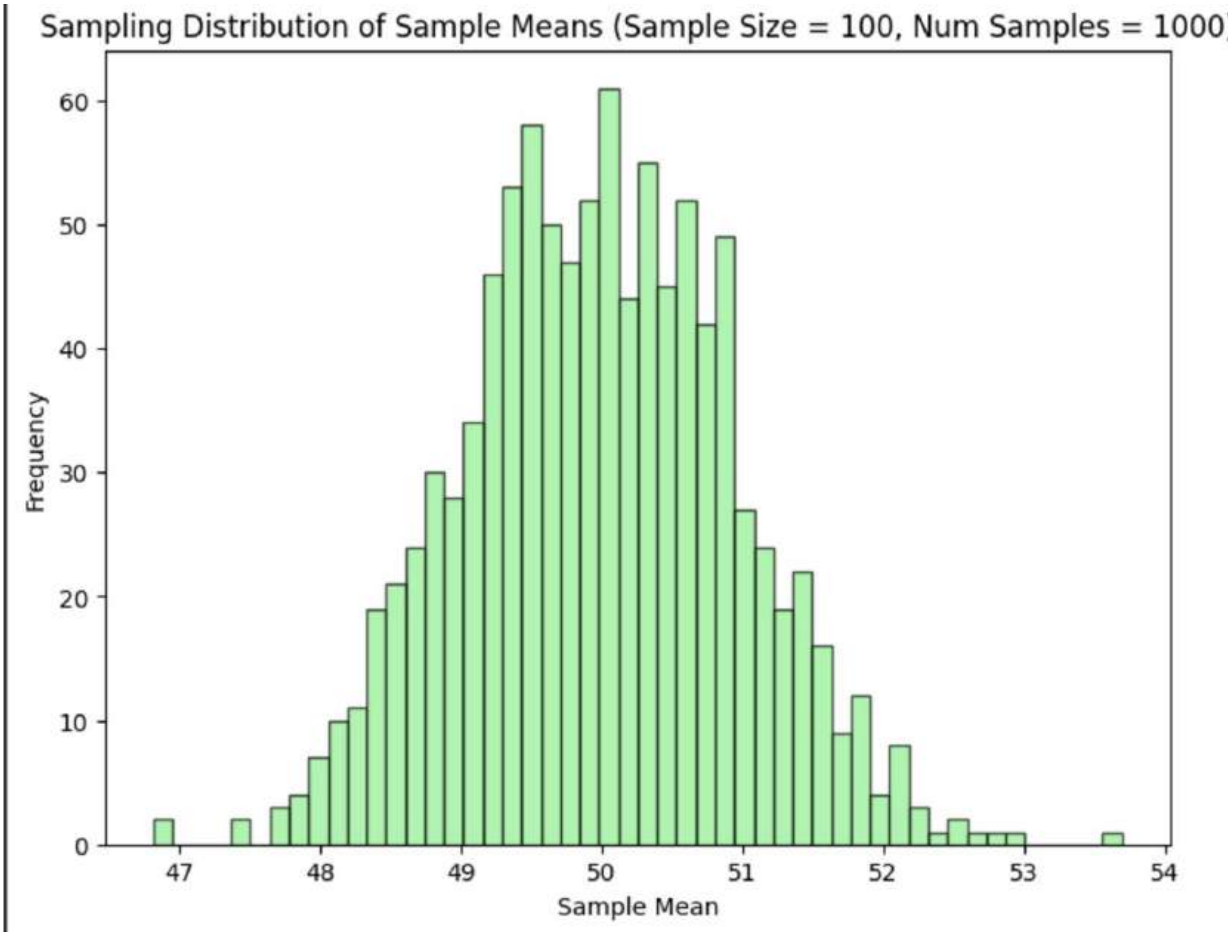
np.random.seed(42)

population = np.random.normal(loc=50, scale=10, size=10000) # Mean=50, SD=10, Population size=10,000

plt.figure(figsize=(8, 6))

```
plt.hist(population, bins=50, color='skyblue', edgecolor='black', alpha=0.7)
plt.title('Population Distribution') plt.xlabel('Value') plt.ylabel('Frequency')
plt.show()


sample_size = 100
random_sample = np.random.choice(population, size=sample_size, replace=False)

plt.figure(figsize=(8, 6))
plt.hist(random_sample, bins=30, color='salmon', edgecolor='black', alpha=0.7)
plt.title(f'Random Sample Distribution (Sample Size = {sample_size})')
plt.xlabel('Value') plt.ylabel('Frequency') plt.show()

num_samples = 1000  # Number of samples to draw sample_means
= []

for _ in range(num_samples):     sample = np.random.choice(population,
size=sample_size, replace=False)
sample_means.append(np.mean(sample))


plt.figure(figsize=(8, 6)) plt.hist(sample_means, bins=50, color='lightgreen',
edgecolor='black', alpha=0.7) plt.title(f'Sampling Distribution of Sample Means
(Sample Size = {sample_size}, Num
Samples = {num_samples})')
plt.xlabel('Sample Mean')
plt.ylabel('Frequency') plt.show()


print(f"Mean of population: {np.mean(population)}") print(f"Mean
of sampling distribution: {np.mean(sample_means)}")
print(f"Standard Deviation of population: {np.std(population)}")
print(f"Standard Deviation of sampling distribution: {np.std(sample_means)}")
```


Frequency
Value


Sampling Distribution of Sample Means (Sample Size = 100, Num Samples = 1000)
Frequency
Sample Mean

7. Z-TEST

NAME : Gopikrishnan

CLASS: CSE-B

ROLL NO : 230701096

CODE:

import numpy as np

import scipy.stats as stats

Define the sample data (hypothetical weights in grams) sample_data

= np.array([152, 148, 151, 149, 147, 153, 150, 148, 152,

149,151, 150, 149, 152, 151, 148, 150, 152, 149, 150,148, 153, 151,

150, 149, 152, 148, 151, 150, 153]) #

Population mean under the null hypothesis

population_mean = 150

Calculate sample statistics

sample_mean = np.mean(sample_data) sample_std = np.std(sample_data,

ddof=1) # Using sample standard deviation

Number of observations n

= len(sample_data)

Calculate the Z-statistic z_statistic = (sample_mean -

population_mean) / (sample_std / np.sqrt(n))

Calculate the p-value

p_value = 2 * (1 - stats.norm.cdf(np.abs(z_statistic))) # Two-tailed test

Print results

print(f"Sample Mean: {sample_mean:.2f}")

print(f"Z-Statistic: {z_statistic:.4f}") print(f"P-Value:

{p_value:.4f}")

Decision based on the significance level

alpha = 0.05 if p_value < alpha:

print("Reject the null hypothesis: The average weight is significantly different from 150 grams.")

else:

print("Fail to reject the null hypothesis: There is no significant difference in average weight from 150 grams.") **OUTPUT:**

```
Sample Mean: 150.20
Z-Statistic: 0.6406
P-Value: 0.5218
Fail to reject the null hypothesis: There is no significant difference in average weight from 150 grams.
```

8. T-TEST

NAME :

GOPIKRISHNAN L

CLASS: CSE-B ROLL NO

: 230701096 CODE:

import numpy as np import

scipy.stats as stats

Set a random seed for reproducibility

np.random.seed(42)

Generate hypothetical sample data (IQ scores)

sample_size = 25

sample_data = np.random.normal(loc=102, scale=15, size=sample_size) # Mean IQ of 102, SD of 15 # Population mean under the null hypothesis

population_mean = 100

Calculate sample statistics sample_mean = np.mean(sample_data) sample_std = np.std(sample_data, ddof=1) n = len(sample_data)

Calculate the T-statistic and p-value t_statistic, p_value = stats.ttest_1samp(sample_data, population_mean)

Print results

print(f"Sample Mean: {sample_mean:.2f}")

print(f"T-Statistic: {t_statistic:.4f}") print(f"P-Value: {p_value:.4f}")

Decision based on the significance level

alpha = 0.05 if p_value < alpha:

print("Reject the null hypothesis: The average IQ score is significantly different from 100.") else:

print("Fail to reject the null hypothesis: There is no significant difference in average IQ score from 100.")

OUTPUT:

```
Sample Mean: 99.55
T-Statistic: -0.1577
P-Value: 0.8760
Fail to reject the null hypothesis: There is no significant difference in average IQ score from 100.
```

10.FEATURE SCALING

NAME : GOPIKRISHNAN L

ROLL NO : 230701096

AIM: To do feature scaling in the given dataset.

import numpy as np import

pandas as pd

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

df.head()

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes

df.Country.fillna(df.Country.mode()[0],inplace=True)

features=df.iloc[:,:-1].values label=df.iloc[:,-1].values

from sklearn.impute import SimpleImputer

age=SimpleImputer(strategy="mean",missing_values=np.nan)

Salary=SimpleImputer(strategy="mean",missing_values=np.nan)

age.fit(features[:,[1]])

```
<ipython-input-5-6281782b3979>:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].meth


  df.Country.fillna(df.Country.mode()[0],inplace=True)
 ▾ SimpleImputer
 SimpleImputer()
```

Salary.fit(features[:,[2]])

```
Salary.fit(features[:,[2]])
```

```
 ▾ SimpleImputer
 SimpleImputer()
```

SimpleImputer()

```
SimpleImputer()
```

```
 ▾ SimpleImputer
 SimpleImputer()
```

features[:,[1]]=age.transform(features[:,[1]])

features[:,[2]]=Salary.transform(features[:,[2]]) features

```
array([['France', 44.0, 72000.0],
       ['Spain', 27.0, 48000.0],
       ['Germany', 30.0, 54000.0],
       ['Spain', 38.0, 61000.0],
       ['Germany', 40.0, 63777.77777777778],
       ['France', 35.0, 58000.0],
       ['Spain', 38.77777777777778, 52000.0],
       ['France', 48.0, 79000.0],
       ['Germany', 50.0, 83000.0],
       ['France', 37.0, 67000.0]], dtype=object)
```

from sklearn.preprocessing import OneHotEncoder oh

= OneHotEncoder(sparse_output=False)

Country=oh.fit_transform(features[:,[0]])

Country

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

final_set=np.concatenate((Country,features[:,[1,2]]),axis=1)

final_set

```
array([[1.0, 0.0, 0.0, 44.0, 72000.0],
       [0.0, 0.0, 1.0, 27.0, 48000.0],
       [0.0, 1.0, 0.0, 30.0, 54000.0],
       [0.0, 0.0, 1.0, 38.0, 61000.0],
       [0.0, 1.0, 0.0, 40.0, 63777.77777777778],
       [1.0, 0.0, 0.0, 35.0, 58000.0],
       [0.0, 0.0, 1.0, 38.77777777777778, 52000.0],
       [1.0, 0.0, 0.0, 48.0, 79000.0],
       [0.0, 1.0, 0.0, 50.0, 83000.0],
       [1.0, 0.0, 0.0, 37.0, 67000.0]], dtype=object)
```

from sklearn.preprocessing import StandardScaler

sc=StandardScaler() sc.fit(final_set)

feat_standard_scaler=sc.transform(final_set) feat_standard_scaler

```
array([[ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
         7.58874362e-01,  7.49473254e-01],
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
        -1.71150388e+00, -1.43817841e+00],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
        -1.27555478e+00, -8.91265492e-01],
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
        -1.13023841e-01, -2.53200424e-01],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
         1.77608893e-01,  6.63219199e-16],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
        -5.48972942e-01, -5.26656882e-01],
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
         0.00000000e+00, -1.07356980e+00],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
         1.34013983e+00,  1.38753832e+00],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
         1.63077256e+00,  1.75214693e+00],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
        -2.58340208e-01,  2.93712492e-01]])
```

from sklearn.preprocessing import MinMaxScaler

mms=MinMaxScaler(feature_range=(0,1)) mms.fit(final_set)

feat_minmax_scaler=mms.transform(final_set)

feat_minmax_scaler

```
array([[1.        , 0.        , 0.        , 0.73913043, 0.68571429],
       [0.        , 0.        , 1.        , 0.        , 0.        ],
       [0.        , 1.        , 0.        , 0.13043478, 0.17142857],
       [0.        , 0.        , 1.        , 0.47826087, 0.37142857],
       [0.        , 1.        , 0.        , 0.56521739, 0.45079365],
       [1.        , 0.        , 0.        , 0.34782609, 0.28571429],
       [0.        , 0.        , 1.        , 0.51207729, 0.11428571],
       [1.        , 0.        , 0.        , 0.91304348, 0.88571429],
       [0.        , 1.        , 0.        , 1.        , 1.        ],
       [1.        , 0.        , 0.        , 0.43478261, 0.54285714]])
```

11.LINEAR REGRESSION

NAME : DINISHA

CLASS: CSE-B

ROLL NO : 230701096

import numpy as np import

pandas as pd

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

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   YearsExperience  30 non-null     float64
 1   Salary           30 non-null     float64
dtypes: float64(2)
memory usage: 608.0 bytes
```

df.dropna(inplace=True)

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   YearsExperience  30 non-null     float64
 1   Salary           30 non-null     float64
dtypes: float64(2)
memory usage: 608.0 bytes
```

df.describe()

	YearsExperience	Salary
count	30.000000	30.000000
mean	5.313333	76003.000000
std	2.837888	27414.429785
min	1.100000	37731.000000
25%	3.200000	56720.750000
50%	4.700000	65237.000000
75%	7.700000	100544.750000
max	10.500000	122391.000000

features=df.iloc[:,[0]].values label=df.iloc[:,[1]].values

from sklearn.model_selection import train_test_split

Assuming `features` and `label` are already defined in your code x_train, x_test, y_train, y_test

= train_test_split(features, label, test_size=0.2, random_state=42)

from sklearn.linear_model import LinearRegression

model=LinearRegression()

model.fit(x_train,y_train)

```
LinearRegression
LinearRegression()
```

model.score(x_train,y_train)

```
0.9645401573418146
```

model.score(x_test,y_test)

```
0.9024461774180497
```

model.coef_

```
array([[9423.81532303]])
```

```
import pickle
pickle.dump(model,open('SalaryPred.model','wb'))
model=pickle.load(open('SalaryPred.model','rb'))
yr_of_exp=float(input("Enter Years of Experience: "))
yr_of_exp_NP=np.array([[yr_of_exp]])
Salary=model.predict(yr_of_exp_NP)
```

```
Enter Years of Experience: 44
```

```
print("Estimated Salary for {} years of experience is {}: " .format(yr_of_exp,Salary))
```

```
Estimated Salary for 44.0 years of experience is [[439969.45722514]]:
```

12. LOGISTIC REGRESSION

NAME : GOPIKRISHNAN L

ROLL NO : 230701096

import numpy as np import pandas as pd

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

df

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
...	...	...	...	...	...
395	15691863	Female	46	41000	1
396	15706071	Male	51	23000	1
397	15654296	Female	50	20000	1
398	15755018	Male	36	33000	0
399	15594041	Female	49	36000	1

400 rows × 5 columns

df.head()

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0

features=df.iloc[:,[2,3]].values

label=df.iloc[:,4].values features

```
       [    38,  65000],
       [    47,  51000],
       [    47, 105000],
       [    41,  63000],
       [    53,  72000],
       [    54, 108000],
       [    39,  77000],
       [    38,  61000],
       [    38, 113000],
       [    37,  75000],
       [    42,  90000],
       [    37,  57000],
       [    36,  99000],
       [    60,  34000],
       [    54,  70000],
       [    41,  72000],
       [    40,  71000],
       [    42,  54000],
       [    43, 129000],
       [    53,  34000],
       [    47,  50000],
       [    42,  79000],
       [    42, 104000],
       [    59,  29000],
       [    58,  47000],
       [    46,  88000],
       [    38,  71000],
       [    54,  26000],
       [    60,  46000],
       [    60,  83000],
```

label

```
label
```

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

from sklearn.model_selection import train_test_split from

sklearn.linear_model import LogisticRegression

for i in range(1, 401):
   # Split the data into training and testing sets   x_train, x_test, y_train, y_test =

train_test_split(features, label, test_size=0.2, random_state=i)

```
    # Initialize the Logistic Regression model
model = LogisticRegression()

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

    # Calculate the train and test scores
train_score = model.score(x_train, y_train)
test_score = model.score(x_test, y_test)

    # Print if test score is greater than train score
if test_score > train_score:
        print("Test {} Train {} Random State {}".format(test_score, train_score, i))
```

```
Test 0.8625 Train 0.8375 Random State 268
Test 0.875 Train 0.840625 Random State 275
Test 0.8625 Train 0.85 Random State 276
Test 0.925 Train 0.8375 Random State 277
Test 0.875 Train 0.846875 Random State 282
Test 0.85 Train 0.846875 Random State 283
Test 0.85 Train 0.84375 Random State 285
Test 0.9125 Train 0.834375 Random State 286
Test 0.85 Train 0.840625 Random State 290
Test 0.85 Train 0.840625 Random State 291
Test 0.85 Train 0.846875 Random State 292
Test 0.8625 Train 0.8375 Random State 294
Test 0.8875 Train 0.828125 Random State 297
Test 0.8625 Train 0.834375 Random State 300
Test 0.8625 Train 0.85 Random State 301
Test 0.8875 Train 0.85 Random State 302
Test 0.875 Train 0.846875 Random State 303
Test 0.8625 Train 0.834375 Random State 305
Test 0.9125 Train 0.8375 Random State 306
Test 0.875 Train 0.846875 Random State 308
Test 0.9 Train 0.84375 Random State 311
Test 0.8625 Train 0.834375 Random State 313
Test 0.9125 Train 0.834375 Random State 314
Test 0.875 Train 0.8375 Random State 315
Test 0.9 Train 0.846875 Random State 317
Test 0.9125 Train 0.821875 Random State 319
Test 0.8625 Train 0.85 Random State 321
Test 0.9125 Train 0.828125 Random State 322
Test 0.85 Train 0.846875 Random State 328
Test 0.85 Train 0.8375 Random State 332
Test 0.8875 Train 0.853125 Random State 336
Test 0.85 Train 0.8375 Random State 337
```

✓ 0s completed at 1:57 PM

Assuming features and label are defined earlier in your code x_train, x_test,

y_train, y_test = train_test_split(features, label, test_size=0.2)

finalModel = LogisticRegression() finalModel.fit(x_train,

y_train)

```
LogisticRegression
LogisticRegression()
```

print(finalModel.score(x_train,y_train)) print(finalModel.score(x_test,y_test))

```
print(finalModel.score(x_test,y_test))
```

```
0.859375
0.8375
```

from sklearn.metrics import classification_report

print(classification_report(label,finalModel.predict(features)))

```
              precision    recall  f1-score   support

           0       0.86      0.92      0.89       257
           1       0.84      0.73      0.78       143

    accuracy                           0.85       400
   macro avg       0.85      0.83      0.84       400
weighted avg       0.85      0.85      0.85       400
```