

1 Probability

a. Calculating Simple probabilities

#Import necessary libraries

```
import pandas as pd
```

Load your dataset

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

Calculate probability of an event

```
probability_event = df['Survived'].value_counts() / len(df['Survived'])
```

```
print(probability_event)
```

OUTPUT

Survived

0 0.616162

1 0.383838

Name: count, dtype: float64

b.Applications of Probability Distributions

Import necessary libraries

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
from scipy.stats import norm
```

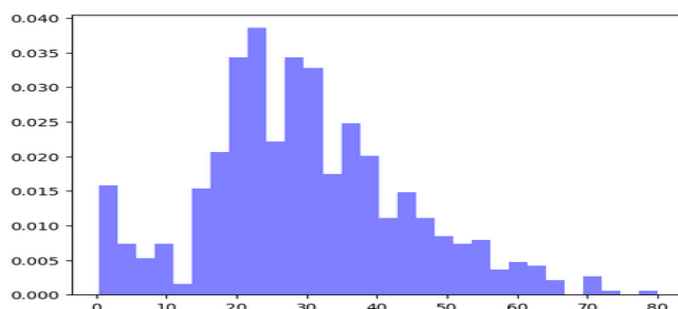
Drop missing values in the 'Age' column for simplicity

```
titanic_data = df.dropna(subset=['Age'])
```

Plot the histogram

```
plt.hist(df['Age'], bins=30, density=True, alpha=0.5, color='b',label='Age Distribution')
```

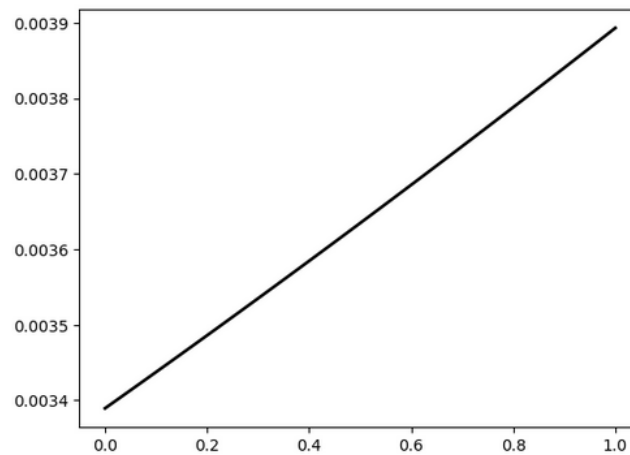
```
Out[8]: (array([0.01583946, 0.00739175, 0.00527982, 0.00739175, 0.00158395,
0.01531148, 0.0205913 , 0.03431883, 0.03854269, 0.02217524,
0.03431883, 0.03273488, 0.01742341, 0.02481515, 0.02006332,
0.01108762, 0.0147835 , 0.01108762, 0.00844771, 0.00739175,
0.00791973, 0.00369587, 0.00475184, 0.00422386, 0.00211193,
0.00263991, 0.00052798, 0.00052798]),
array([ 0.42, 3.07266667, 5.72533333, 8.378 , 11.03066667,
13.68333333, 16.336 , 18.98866667, 21.64133333, 24.294 ,
26.94666667, 29.59933333, 32.252 , 34.90466667, 37.55733333,
40.21 , 42.86266667, 45.51533333, 48.168 , 50.82066667,
53.47333333, 56.126 , 58.77866667, 61.43133333, 64.084 ,
66.73666667, 69.38933333, 72.042 , 74.69466667, 77.34733333,
80. ]),
<BarContainer object of 30 artists>)
```



Fit a normal distribution to the data

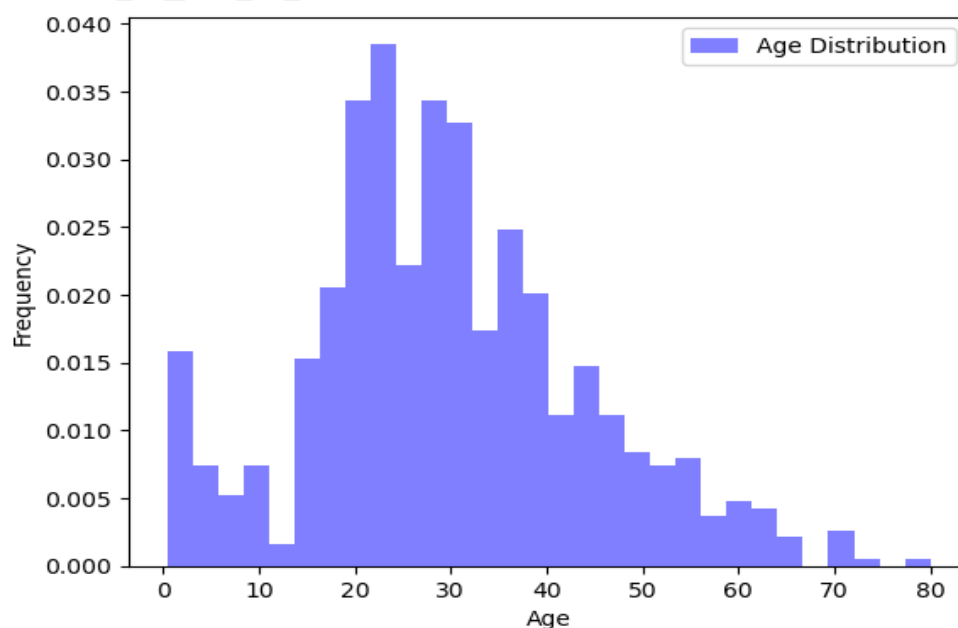
```
mu, std = norm.fit(titanic_data['Age'])  
xmin, xmax = plt.xlim()  
x = np.linspace(xmin, xmax, 100)  
p = norm.pdf(x, mu, std)  
plt.plot(x, p, 'k', linewidth=2)
```

Out[10]: [



Display the plot

```
plt.hist(df['Age'], bins=30, density=True, alpha=0.5, color='b', label='Age Distribution')  
plt.xlabel('Age')  
plt.ylabel('Frequency')  
plt.legend()  
plt.show()
```



2 Test of Significance

a. t-Test: one sample, two independent samples and Paired

```
from scipy.stats import ttest_ind
```

Load the dataset

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

Separate data for male and female students

```
from scipy.stats import ttest_ind
```

```
import pandas as pd
```

Separate data for male students

```
male_scores = df[df['gender'] == 'male']['math score']
```

```
male_scores
```

OUTPUT

```
3      47
4      76
7      40
8      64
10     58
```

```
..
985    57
987    81
990    86
994    63
996    62
```

```
Name: math score, Length: 482, dtype: int64
```

Separate data for female students

```
female_scores = df[df['gender'] == 'female']['math score']
```

```
female_scores
```

```
0      72
1      69
2      90
5      71
6      88
```

```
..
993    62
995    88
997    59
998    68
999    77
```

```
Name: math score, Length: 518, dtype: int64
```

Perform independent two-sample t-test

```
t_statistic, p_value = ttest_ind(male_scores, female_scores)
```

Print the results

```
print(f'T-Statistic: {t_statistic}')
```

```
print(f'P-Value: {p_value}')
```

OUTPUT

```
T-Statistic: 5.383245869828983
```

```
P-Value: 9.120185549328822e-08
```

Interpret the results

```
alpha = 0.05
```

```
if p_value < alpha:
```

```
    print("There is a significant difference in math scores between male and female students.")
```

```
else:
```

```
    print("There is no significant difference in math scores between male and female students.")
```

OUTPUT

There is a significant difference in math scores between male and female students.

ANOVA: Comparing Multiple Groups (e.g., Ethnicity)

```
from scipy.stats import f_oneway
```

Load the dataset

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

Extract math scores for each ethnicity_groups

```
ethnicity_groups = df['ethnicity'].unique()
```

```
ethnicity_groups
```

OUTPUT

```
array(['group B', 'group C', 'group A', 'group D', 'group E'],  
      dtype=object)
```

Extract math scores for each ethnicity_data

```
ethnicity_data = {ethnicity: df[df['ethnicity'] == ethnicity]['math score'] for ethnicity in ethnicity_groups}
ethnicity_data
```

OUTPUT

```
{'group B': 0      72
 2      90
 5      71
 6      88
 7      40
 ..
969     75
976     60
980      8
982     79
991     65
Name: math score, Length: 190, dtype: int64,
'group C': 1      69
 4      76
10     58
15     69
16     88
 ..
979     91
984     74
986     40
996     62
997     59
Name: math score, Length: 319, dtype: int64,
'group A': 3      47
13     78
14     50
25     73
46     55
 ..
974     54
983     78
985     57
988     44
994     63
Name: math score, Length: 89, dtype: int64,
'group D': 8      64
11     40
20     66
22     44
24     74
 ..
989     67
992     55
993     62
998     68
999     77
Name: math score, Length: 262, dtype: int64,
'group E': 32     56
34     97
35     81
44     50
50     53
```

```
...
962    100
968     68
987     81
990     86
995     88
Name: math score, Length: 140, dtype: int64}
```

Perform one-way ANOVA

```
f_statistic, p_value_anova = f_oneway(*ethnicity_data.values())
```

Print the results

```
print(f'F-Statistic: {f_statistic}')
print(f'P-Value (ANOVA): {p_value_anova}')
```

OUTPUT

```
F-Statistic: 14.593885166332637
P-Value (ANOVA): 1.3732194030370688e-11
```

Interpret the results

```
if p_value_anova < alpha:
    print("There is a significant difference in math scores among different ethnicities.")
else:
    print("There is no significant difference in math scores among different ethnicities.")
```

OUTPUT

There is a significant difference in math scores among different ethnicities.

3. Correlation and Regression Analysis

a. Scatter Diagram, Calculating of Correlation coefficient

#Importing necessary libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.metrics import mean_squared_error, r2_score, accuracy_score,
confusion_matrix
```

Load the Housedata dataset

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

#To display the Columns in dataset

```
df.columns
```

Display the first five rows of the dataset

```
print(df.head())
```

```
date      price  bedrooms  bathrooms  sqft_living  sqft_lot  \
0  2014-05-02 00:00:00  313000.0      3.0      1.50      1340      7912
1  2014-05-02 00:00:00  2384000.0     5.0      2.50      3650      9050
2  2014-05-02 00:00:00  342000.0      3.0      2.00      1930     11947
3  2014-05-02 00:00:00  420000.0      3.0      2.25      2000      8030
4  2014-05-02 00:00:00  550000.0      4.0      2.50      1940     10500

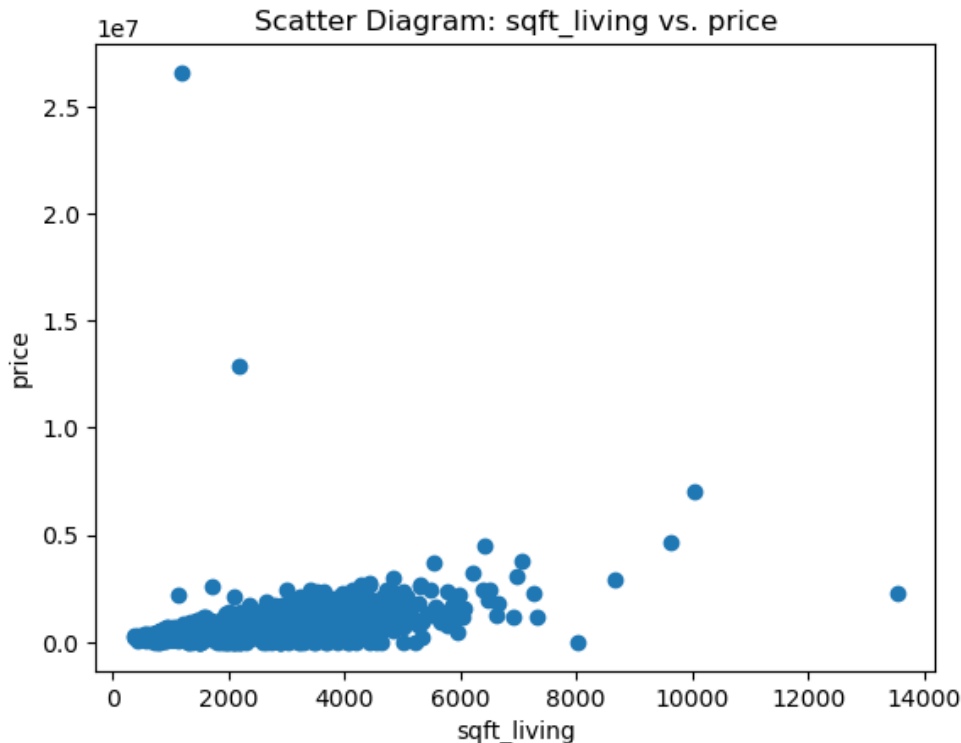
floors  waterfront  view  condition  sqft_above  sqft_basement  yr_built  \
0      1.5          0     0          3      1340          0      1955
1      2.0          0     4          5      3370          280     1921
2      1.0          0     0          4      1930          0     1966
3      1.0          0     0          4      1000         1000     1963
4      1.0          0     0          4      1140          800     1976

yr_renovated  street  city  statezip  country
0      2005      18810 Densmore Ave N  Shoreline  WA 98133  USA
1      0      709 W Blaine St  Seattle  WA 98119  USA
2      0  26206-26214 143rd Ave SE  Kent  WA 98042  USA
3      0      857 170th Pl NE  Bellevue  WA 98008  USA
4      1992      9105 170th Ave NE  Redmond  WA 98052  USA
```

a. Scatter Diagram

Scatter diagram for two variables (e.g., sqft_living vs. price)

```
plt.scatter(df['sqft_living'], df['price'])  
plt.title('Scatter Diagram: sqft_living vs. price')  
plt.xlabel('sqft_living')  
plt.ylabel('price')  
plt.show()
```



Calculate the correlation coefficient

```
correlation_coefficient = df['sqft_living'].corr(df['price'])  
print(f'Correlation Coefficient (sqft_living vs. price): {correlation_coefficient}')
```

OUTPUT

```
Correlation Coefficient (sqft_living vs. price): 0.43041002543262824
```

b. Linear Regression: Fitting, Testing Model Adequacy, and Prediction (Simple and Multiple)

Simple Linear Regression

```
X_simple = sm.add_constant(df[['sqft_living']])  
y_simple = df['price']  
model_simple = sm.OLS(y_simple, X_simple).fit()
```


Summary of the simple linear regression

```
print(model_simple.summary())
```

OUTPUT

OLS Regression Results

```
=====
Dep. Variable:                price    R-squared:                0.185
Model:                        OLS      Adj. R-squared:           0.185
Method:                      Least Squares  F-statistic:             1045.
Date:                        Fri, 24 Nov 2023  Prob (F-statistic):    7.55e-207
Time:                        17:00:16    Log-Likelihood:          -66971.
No. Observations:            4600      AIC:                    1.339e+05
Df Residuals:                4598      BIC:                    1.340e+05
Df Model:                    1
Covariance Type:              nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	1.295e+04	1.83e+04	0.709	0.479	-2.29e+04	4.88e+04
sqft_living	251.9501	7.792	32.334	0.000	236.674	267.227

```
=====
Omnibus:                    12550.690    Durbin-Watson:           1.980
Prob(Omnibus):              0.000      Jarque-Bera (JB):        504349454.972
Skew:                      33.420      Prob(JB):                0.00
Kurtosis:                   1623.778    Cond. No.:               5.72e+03
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 5.72e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Multiple Linear Regression

```
X_multi = sm.add_constant(df[['sqft_living', 'bedrooms', 'bathrooms']])
```

```
y_multi = df['price']
```

```
model_multi = sm.OLS(y_multi, X_multi).fit()
```

```
# Summary of the multiple linear regression
```

```
print(model_multi.summary())
```

OUTPUT

OLS Regression Results

```
=====
Dep. Variable:                price    R-squared:                0.190
Model:                        OLS      Adj. R-squared:           0.190
Method:                      Least Squares  F-statistic:             359.8
Date:                        Fri, 24 Nov 2023  Prob (F-statistic):    6.78e-210
Time:                        17:00:49    Log-Likelihood:          -66957.
No. Observations:            4600      AIC:                    1.339e+05
Df Residuals:                4596      BIC:                    1.339e+05
Df Model:                    3
Covariance Type:              nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
--	------	---------	---	------	--------	--------

```

-----
const          1.232e+05    3.02e+04    4.080    0.000    6.4e+04    1.82e+05
sqft_living    274.6629    12.692    21.641    0.000    249.781    299.545
bedrooms      -5.514e+04    1.04e+04    -5.296    0.000    -7.56e+04    -3.47e+04
bathrooms     1.33e+04    1.5e+04    0.889    0.374    -1.6e+04    4.26e+04
=====
Omnibus:                12588.478    Durbin-Watson:                1.978
Prob(Omnibus):          0.000    Jarque-Bera (JB):            516518988.559
Skew:                   33.683    Prob(JB):                     0.00
Kurtosis:               1643.227    Cond. No.:                   9.83e+03
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 9.83e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Prediction

```
predictions_simple = model_simple.predict(X_simple)
```

```
predictions_simple
```

OUTPUT

```

0      350567.418016
1      932572.220763
2      499217.995341
3      516854.504515
4      501737.496651

```

```

...
4595    393398.940296
4596    380801.433743
4597    771324.136885
4598    539530.016310
4599    388359.937675

```

```
Length: 4600, dtype: float64
```

Prediction

```
X_multi = sm.add_constant(df[['sqft_living', 'bedrooms', 'bathrooms']])
```

```
y_multi = df['price']
```

```
model_multi = sm.OLS(y_multi, X_multi).fit()
```

```
predictions_multi = model_multi.predict(X_multi)
```

```
predictions_multi
```

```
predictions_multi
```

OUTPUT

```

0      345726.155445
1      883214.890294
2      514428.895515
3      536981.112223
4      468684.238234

```

```

...
4595    395744.662521
4596    391988.957691
4597    817716.458384
4598    503232.046882
4599    400228.844801

```

```
Length: 4600, dtype: float64
```

c. Fitting of Linear regression

Assuming 'waterfront' is a binary variable indicating waterfront or not

```
X_logistic = df[['sqft_living', 'waterfront']]
```

```
y_logistic = (df['price'] > df['price'].median()).astype(int)
```

Binary target variable

```
X_train_log, X_test_log, y_train_log, y_test_log = train_test_split(X_logistic, y_logistic, test_size=0.2, random_state=42)
```

```
print(X_logistic)
```

```
print(y_logistic)
```

OUTPUT

X_logistic:

	sqft_living	waterfront
0	1340	0
1	3650	0
2	1930	0
3	2000	0
4	1940	0
...
4595	1510	0
4596	1460	0
4597	3010	0
4598	2090	0
4599	1490	0

[4600 rows x 2 columns]

y_logistic:

0	0
1	1
2	0
3	0
4	1
...	...
4595	0
4596	1
4597	0
4598	0
4599	0

Name: price, Length: 4600, dtype: int32

Logistic Regression

```
logreg = LogisticRegression()
```

```
logreg.fit(X_train_log, y_train_log)
```

OUTPUT

▼ LogisticRegression

LogisticRegression()

,

Predictions

```
y_pred_log = logreg.predict(X_test_log)
```

```
y_pred_log
```

OUTPUT

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

Model Evaluation

```
accuracy_log = accuracy_score(y_test_log, y_pred_log)
```

```
conf_matrix_log = confusion_matrix(y_test_log, y_pred_log)
```

```
print(f'Accuracy (Logistic Regression): {accuracy_log}')
```

```
print(f'Confusion Matrix (Logistic Regression): \n{conf_matrix_log}')
```

OUTPUT

```
Accuracy (Logistic Regression): 0.7184782608695652
```

```
Confusion Matrix (Logistic Regression):
```

```
[[351 119]
 [140 310]]
```