

```
In [1]: # Import Libraries
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn import preprocessing
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn import svm
from sklearn.metrics import jaccard_score
from sklearn.metrics import f1_score
from sklearn.metrics import log_loss
from sklearn.metrics import confusion_matrix, accuracy_score
import sklearn.metrics as metrics
import matplotlib.pyplot as plt
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
```

```
In [2]: # Read the dataset
df = pd.read_csv("Weather_Data.csv")
df
```

Out[2]:

	Date	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed
0	2/1/2008	19.5	22.4	15.6	6.2	0.0	W	41
1	2/2/2008	19.5	25.6	6.0	3.4	2.7	W	41
2	2/3/2008	21.6	24.5	6.6	2.4	0.1	W	41
3	2/4/2008	20.2	22.8	18.8	2.2	0.0	W	41
4	2/5/2008	19.7	25.7	77.4	4.8	0.0	W	41
...
3266	6/21/2017	8.6	19.6	0.0	2.0	7.8	SSE	37
3267	6/22/2017	9.3	19.2	0.0	2.0	9.2	W	30
3268	6/23/2017	9.4	17.7	0.0	2.4	2.7	W	24
3269	6/24/2017	10.1	19.3	0.0	1.4	9.3	W	43
3270	6/25/2017	7.6	19.3	0.0	3.4	9.4	W	35

3271 rows × 22 columns

```
In [3]: df.head()
```

Out[3]:

	Date	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed	Wii
0	2/1/2008	19.5	22.4	15.6	6.2	0.0	W	41	
1	2/2/2008	19.5	25.6	6.0	3.4	2.7	W	41	
2	2/3/2008	21.6	24.5	6.6	2.4	0.1	W	41	
3	2/4/2008	20.2	22.8	18.8	2.2	0.0	W	41	
4	2/5/2008	19.7	25.7	77.4	4.8	0.0	W	41	

5 rows × 22 columns

```
In [4]: df.describe()
```

Out[4]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed
count	3271.000000	3271.000000	3271.000000	3271.000000	3271.000000	3271.000000	3271.000000
mean	14.877102	23.005564	3.342158	5.175787	7.168970	41.476307	15.000000
std	4.554710	4.483752	9.917746	2.757684	3.815966	10.806951	7.000000
min	4.300000	11.700000	0.000000	0.000000	0.000000	17.000000	0.000000
25%	11.000000	19.600000	0.000000	3.200000	4.250000	35.000000	11.000000
50%	14.900000	22.800000	0.000000	4.800000	8.300000	41.000000	15.000000
75%	18.800000	26.000000	1.400000	7.000000	10.200000	44.000000	20.000000
max	27.600000	45.800000	119.400000	18.400000	13.600000	96.000000	54.000000

```
In [5]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3271 entries, 0 to 3270
Data columns (total 22 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Date                  3271 non-null   object
1   MinTemp               3271 non-null   float64
2   MaxTemp               3271 non-null   float64
3   Rainfall              3271 non-null   float64
4   Evaporation           3271 non-null   float64
5   Sunshine              3271 non-null   float64
6   WindGustDir           3271 non-null   object
7   WindGustSpeed         3271 non-null   int64
8   WindDir9am            3271 non-null   object
9   WindDir3pm            3271 non-null   object
10  WindSpeed9am          3271 non-null   int64
11  WindSpeed3pm          3271 non-null   int64
12  Humidity9am           3271 non-null   int64
13  Humidity3pm           3271 non-null   int64
14  Pressure9am           3271 non-null   float64
15  Pressure3pm           3271 non-null   float64
16  Cloud9am              3271 non-null   int64
17  Cloud3pm              3271 non-null   int64
18  Temp9am               3271 non-null   float64
19  Temp3pm               3271 non-null   float64
20  RainToday             3271 non-null   object
21  RainTomorrow          3271 non-null   object
dtypes: float64(9), int64(7), object(6)
memory usage: 562.3+ KB
```

Data Preprocessing

```
In [6]: ▶ # Convert categorical variables to binary variables
df_dummies = pd.get_dummies(data=df, columns=['RainToday', 'WindGustDir', 'WindDir', 'WindSpeed9kt'])
df_dummies
```

```
Out[6]:
```

	Date	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9kt
0	2/1/2008	19.5	22.4	15.6	6.2	0.0	41	
1	2/2/2008	19.5	25.6	6.0	3.4	2.7	41	
2	2/3/2008	21.6	24.5	6.6	2.4	0.1	41	
3	2/4/2008	20.2	22.8	18.8	2.2	0.0	41	
4	2/5/2008	19.7	25.7	77.4	4.8	0.0	41	
...
3266	6/21/2017	8.6	19.6	0.0	2.0	7.8	37	
3267	6/22/2017	9.3	19.2	0.0	2.0	9.2	30	
3268	6/23/2017	9.4	17.7	0.0	2.4	2.7	24	
3269	6/24/2017	10.1	19.3	0.0	1.4	9.3	43	
3270	6/25/2017	7.6	19.3	0.0	3.4	9.4	35	

3271 rows × 68 columns

```
In [7]: ▶ df_dummies.replace(['No', 'Yes'], [0,1], inplace=True)
```

```
In [8]: ▶ df_dummies.drop('Date',axis=1,inplace=True)
```

```
In [9]: ▶ df_dummies = df_dummies.astype(float)
```

```
In [10]: ▶ features = df_dummies.drop(columns='RainTomorrow', axis=1)
Y = df_dummies['RainTomorrow']
```


1. Linear Regression

Q.1 Use the `train_test_split` function to split the features and Y dataframes with a `test_size` of 0.2 and the `random_state` set to 10

```
In [11]: ▶ # Split the data into train and test sets
x_train, x_test, y_train, y_test = train_test_split(features, Y, test_size = 0.2,
```

Q.2 Create and train a Linear Regression model called `LinearReg` using the training data (`x_train`, `y_train`).

```
In [12]: ▶ # Create model Linear regression
LinearReg = LinearRegression()
```

In [13]:  LinearReg.fit(x_train, y_train)

Out[13]: LinearRegression()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

Q.3 Now use the predict method on the testing data (x_test) and save it to the array predictions.

```
In [57]: ▶ # Predict output for the x_test dataset
          predictions_Linear = LinearReg.predict(x_test)
          predictions_Linear
```

```
Out[57]: array([ 1.31782532e-01,  2.76153564e-01,  9.78088379e-01,  2.87483215e-01,
 1.32377625e-01,  4.60464478e-01,  3.56773376e-01,  8.56460571e-01,
 6.75010681e-01,  3.82766724e-02,  4.82940674e-03,  2.81181335e-01,
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4.18205261e-01,	-1.16004944e-01,	8.70658875e-01,	1.62162781e-01,
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1.56120300e-01,	3.97300720e-01,	5.80154419e-01,	5.03753662e-01,
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1.46217346e-01,	8.24829102e-01,	5.68481445e-01,	-9.56268311e-02,
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5.34416199e-01,	1.42539978e-01,	-1.58424377e-01,	1.00021362e-02,
2.26768494e-01,	3.34747314e-01,	6.04705811e-02,	-2.08816528e-02,
-1.07841492e-01,	3.34335327e-01,	5.10124207e-01,	3.45932007e-01,
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5.81176758e-01,	1.90055847e-01,	5.45578003e-02,	9.38339233e-02,
-6.76956177e-02,	1.05995178e-01,	-2.49252319e-02,	-2.94113159e-02,
6.56051636e-02,	9.61074829e-02,	1.03271484e-01,	1.77772522e-01,

```

1.02096558e-01, 6.64031982e-01, 1.97700500e-01, 1.04774475e-01,
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7.55508423e-01, 2.03941345e-01, 4.90135193e-01, -1.01310730e-01,
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2.73429871e-01, 2.98088074e-01, 1.87126160e-01, 7.19902039e-01,
2.29797363e-01, 3.34632874e-01, 8.51608276e-01, 3.06320190e-02,
-3.72314453e-03, -7.81478882e-02, 7.49839783e-01, 2.04597473e-01,
4.06028748e-01, 3.32359314e-01, 1.81953430e-01, 8.23410034e-01,
5.03158569e-01, 6.34071350e-01, -5.07736206e-02, 4.25796509e-02,
1.11099243e-01, 1.89201355e-01, 6.00975037e-01, 4.09095764e-01,
6.87751770e-01, 2.89863586e-01, -9.21096802e-02, 4.46624756e-02,
1.98905945e-01, 6.18957520e-01, 1.41899109e-01, 6.98921204e-01,
3.11897278e-01, 1.26914978e-01, 8.11447144e-01, 6.24542236e-02,
-1.04484558e-01, 6.60018921e-02, 1.23748779e-01, 5.18707275e-01,
-5.96847534e-02, 6.39770508e-01, -1.30081177e-02, 3.84140015e-02,
-1.04942322e-01, 1.96571350e-01, 3.36097717e-01, 4.87998962e-01,
1.93817139e-01, 7.93266296e-01, 1.69387817e-01, 8.55941772e-02,
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6.09596252e-01, 2.16674805e-02, 1.88301086e-01, -1.35353088e-01,
7.06481934e-01, 4.33082581e-01, -5.83572388e-02, 9.28695679e-01,
5.40626526e-01, -1.65557861e-03, 9.19029236e-01, -2.18505859e-02,
1.65367126e-01, 1.77780151e-01, 4.72900391e-01, -2.81524658e-03,
4.00382996e-01, 1.42211914e-02, 1.95396423e-01, -6.79855347e-02,
5.87219238e-01, 1.92474365e-01, 2.33268738e-01, 2.73651123e-01,
9.40742493e-01, 7.10136414e-01, 1.33438110e-01, 7.37457275e-02,
5.58242798e-02, -2.26371765e-01, 4.10919189e-02, 5.16891479e-02,
3.09066772e-02, 2.93563843e-01, 9.69337463e-01, 7.98675537e-01,
-2.29568481e-02, 5.26657104e-02, 2.64755249e-01, 1.75148010e-01,
7.06344604e-01, 1.73805237e-01, 3.44337463e-01])

```

Q.4 Using the predictions and the y_test dataframe calculate the value for each metric using the appropriate function.

```

In [58]: ▶ # Mean absolute error of linear regression
LinearRegression_MAE = mean_absolute_error(y_test, predictions_Linear)
print("Mean Absolute Error (MAE):", LinearRegression_MAE)

```

Mean Absolute Error (MAE): 0.25631900234076815

```

In [59]: ▶ # Mean absolute error of linear regression
LinearRegression_MSE = mean_squared_error(y_test, predictions_Linear)
print("Mean Absolute Error (MSE):", LinearRegression_MSE)

```

Mean Absolute Error (MSE): 0.11572291759564364

```

In [60]: ▶ # R2 score of linear regression
LinearRegression_R2 = r2_score(y_test, predictions_Linear)
print("R-squared (R2):", LinearRegression_R2)

```

R-squared (R2): 0.4271205492306953

Q.5 Show the MAE, MSE, and R2 in a tabular format using data frame for the linear model

```
In [86]: ▶ # Create a dictionary with metrics
Report_Linear = {
    'Metric': ['Mean Absolute Error (MAE)', 'Mean Squared Error (MSE)', 'R-square'],
    'Value': [LinearRegression_MAE, LinearRegression_MSE, LinearRegression_R2]
}

# Create a DataFrame
Report_Linear_df = pd.DataFrame(Report_Linear)

print(Report_Linear_df)
```

	Metric	Value
0	Mean Absolute Error (MAE)	0.256319
1	Mean Squared Error (MSE)	0.115723
2	R-squared (R2)	0.427121

2. KNN

```
In [19]: ▶ # Split the data into train and test sets
x_train, x_test, y_train, y_test = train_test_split(features, Y, test_size = 0.2,
```

Q.6 Create and train a KNN model called KNN using the training data (x_train, y_train) with the n_neighbors parameter set to 4

```
In [62]: ▶ k = 4

#Train Model and Predict
KNN = KNeighborsClassifier(n_neighbors = k).fit(x_train, y_train)
KNN
```

Out[62]: KNeighborsClassifier(n_neighbors=4)

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Q.7 Now use the predict method on the testing data (x_test) and save it to the array predictions.

```
In [63]: ▶ # Predicting the Test set results
          predictions_KNN = KNN.predict(x_test)
          predictions_KNN
```

```
Out[63]: array([0., 0., 1., 0., 0., 0., 0., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0.,
                0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0.,
                0., 1., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 1., 0., 0.,
                0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 1., 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., 0., 1., 0., 1., 0., 0., 0., 0.,
                1., 0., 1., 1., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
                0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 1., 0.,
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                0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
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                0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0.,
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                1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
                0., 0., 1., 0., 0., 0., 0., 1., 0., 0., 1., 0., 0., 0., 0., 0.,
                0., 0., 0., 1., 0., 0., 0., 1., 1., 0., 0., 0., 0., 0., 0.,
                1., 1., 0., 0., 0., 0., 1., 0., 1.] )
```

Q.8 Using the predictions and the y_test dataframe calculate the value for each metric using the appropriate function.

```
In [64]: ▶ # KNN accuracy score
          KNN_Accuracy_Score = accuracy_score(y_test, predictions_KNN)
          print("KNN accuracy score: ", KNN_Accuracy_Score)
```

```
KNN accuracy score: 0.8183206106870229
```

```
In [65]: ▶ # KNN jaccard index
jaccard_index_KNN = jaccard_score(y_test, predictions_KNN)
print("KNN Jaccard Index:", jaccard_index_KNN)
```

KNN Jaccard Index: 0.4251207729468599

```
In [66]: ▶ # KNN F1 score
f1_KNN = f1_score(y_test, predictions_KNN)
print("KNN F1 Score:", f1_KNN)
```

KNN F1 Score: 0.5966101694915255

```
In [67]: ▶ # Create a dictionary with metrics
Report_KNN = {
    'Metric': ['KNN accuracy score', 'KNN Jaccard Index', 'KNN F1 Score'],
    'Value': [KNN_Accuracy_Score, jaccard_index, f1_KNN]
}

# Create a DataFrame
Report_KNN_df = pd.DataFrame(Report_KNN)

print(Report_KNN_df)
```

	Metric	Value
0	KNN accuracy score	0.818321
1	KNN Jaccard Index	0.425121
2	KNN F1 Score	0.596610

3. Decision Tree

Q.9 Create and train a Decision Tree model called Tree using the training data (x_train, y_train).

```
In [68]: ▶ # Split the data into train and test sets
x_train, x_test, y_train, y_test = train_test_split(features, Y, test_size = 0.2,
```

```
In [31]: ▶ Tree = DecisionTreeClassifier(criterion="entropy", max_depth = 4)
Tree
```

Out[31]: DecisionTreeClassifier(criterion='entropy', max_depth=4)

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```
In [32]: ▶ Tree.fit(x_train, y_train)
```

Out[32]: DecisionTreeClassifier(criterion='entropy', max_depth=4)

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Q.10 Now use the predict method on the testing data (x_test) and save it to the array predictions.

```
In [69]: ▶ predictions_Tree = Tree.predict(x_test)
          predictions_Tree
```

```
Out[69]: array([0., 0., 1., 0., 0., 0., 0., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0.,
                1., 0., 0., 0., 1., 0., 0., 0., 1., 1., 0., 1., 0., 0., 0.,
                0., 1., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 1., 1., 0., 0.,
                0., 0., 0., 0., 0., 0., 1., 1., 0., 0., 0., 1., 1., 0., 0., 1., 0.,
                0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 0., 0., 0., 0., 0.,
                0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 1., 0., 1., 0., 0., 0., 0.,
                1., 0., 1., 1., 0., 1., 0., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0.,
                0., 0., 0., 0., 0., 1., 0., 0., 1., 0., 1., 0., 0., 0., 0., 0.,
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                0., 0., 0., 0., 1., 0., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0.,
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                0., 1., 0., 0., 1., 0., 0., 0., 0., 0., 1., 0., 1., 0., 0., 0., 0.,
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                0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 1., 0., 0., 0.,
                0., 1., 1., 1., 0., 0., 0., 0., 1., 0., 1., 0., 0., 1., 0., 0., 0.,
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                1., 0., 0., 0., 1., 0., 0., 1., 1., 0., 1., 0., 0., 0., 0., 0.,
                0., 0., 0., 1., 0., 0., 0., 1., 1., 0., 0., 0., 0., 0., 0.,
                1., 1., 0., 0., 0., 0., 1., 0., 0.]])
```

Q.11 Using the predictions and the y_test dataframe calculate the value for each metric using the appropriate function.

```
In [37]: ▶ # Tree accuracy score
          Tree_Accuracy_Score = accuracy_score(y_test, predictions_Tree)
          print("Tree accuracy score:", Tree_Accuracy_Score)
```

Tree accuracy score: 0.8183206106870229

```
In [35]: ▶ Tree_JaccardIndex = jaccard_score(y_test, predictions_Tree)
          print("Tree jaccard Index:", Tree_JaccardIndex)
```

Tree jaccard Index: 0.48034934497816595

```
In [36]: ▶ Tree_F1_Score = f1_score(y_test, predictions_Tree)
print("Tree F1 score:", Tree_F1_Score)
```

Tree F1 score: 0.6489675516224188

```
In [38]: ▶ # Create a dictionary with metrics
Report_Tree = {
    'Metric': ['Tree accuracy score', 'Tree jaccard Index', 'Tree F1 score'],
    'Value': [Tree_Accuracy_Score, Tree_JaccardIndex, Tree_F1_Score]
}

# Create a DataFrame
Report_Tree_df = pd.DataFrame(Report_Tree)

print(Report_Tree_df)
```

	Metric	Value
0	Tree accuracy score	0.818321
1	Tree jaccard Index	0.480349
2	Tree F1 score	0.648968

4. Logistic Regression(LR)

Q.12 Use the `train_test_split` function to split the features and Y dataframes with a `test_size` of 0.2 and the `random_state` set to 1

```
In [70]: ▶ # Split the data into train and test sets
x_train, x_test, y_train, y_test = train_test_split(features, Y, test_size = 0.2,
```

Q.13 Create and train a LogisticRegression model called LR using the training data (`x_train`, `y_train`) with the solver parameter set to `liblinear`.

```
In [73]: ▶ # Initialize Logistic Regression model with solver='liblinear'
LR = LogisticRegression(solver='liblinear')
```

```
In [74]: ▶ # Fit the model on training data
LR.fit(x_train, y_train)
```

Out[74]: LogisticRegression(solver='liblinear')

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Q.14 Now, use the predict method on the testing data (x_test) and save it to the array predictions.

```
In [75]: ▶ # Use the predict method on the testing data
          predictions_LR = LR.predict(x_test)
          predictions_LR
```

```
Out[75]: array([[0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 1., 1., 1., 0., 0., 0., 0., 1.,
0., 0., 0., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1.,
1., 1., 1., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1.,
0., 1., 0., 1., 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., 1.,
0., 0., 0., 1., 0., 0., 1., 0., 0., 1., 0., 0., 0., 0., 0., 0., 1.,
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0., 0., 0., 1., 0., 0., 0., 0., 0., 1., 1., 0., 0., 0., 1., 1., 0.,
0., 0., 0., 0., 0., 1., 0., 0., 1., 0., 1., 0., 0., 0., 0., 0., 0.,
0., 1., 1., 0., 0., 1., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0.,
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0., 0., 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.,
1., 0., 0., 0., 1., 0., 1., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0.,
0., 1., 0., 0., 1., 1., 0., 0., 1., 0., 0., 0., 0., 0., 1., 0., 0.,
1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 1., 0., 1.,
0., 0., 0., 0., 0., 1., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0., 1., 1., 0., 1., 0., 0., 1., 0., 0., 0., 0.,
0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 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., 1., 0., 0., 1., 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., 1., 0., 0., 1., 1., 0., 0., 0., 1., 0., 1., 0., 0., 1., 0.,
0., 0., 1., 0., 1., 0., 0., 0., 1.]])
```

Q.15 Using the predictions and the y_test dataframe calculate the value for each metric using the appropriate function.

```
In [76]: ▶ # Calculate Accuracy Score
LR_accuracy_score = accuracy_score(y_test, predictions_LR)
print("LR Accuracy Score:", LR_accuracy_score)
```

LR Accuracy Score: 0.8366412213740458

```
In [77]: ▶ # Calculate Jaccard Index
LR_jaccard_index = jaccard_score(y_test, predictions_LR)
print("LR Jaccard Index:", LR_jaccard_index)
```

LR Jaccard Index: 0.5091743119266054

```
In [78]: ▶ # Calculate F1 Score
LR_f1_score = f1_score(y_test, predictions_LR)
print("LR F1 Score:", LR_f1_score)
```

LR F1 Score: 0.6747720364741641

```
In [79]: ▶ # Calculate Log Loss
LR_log_loss = log_loss(y_test, LR.predict_proba(x_test))
print("LR Log Loss:", LR_log_loss)
```

LR Log Loss: 0.38106374371303714

```
In [80]: ▶ # Create a dictionary with metrics
Report_LR = {
    'Metric': ['LR Accuracy Score', 'LR Jaccard Index', 'LR F1 Score', 'LR Log Lo
    'Value': [LR_accuracy_score, LR_jaccard_index, LR_f1_score, LR_log_loss]
}

# Create a DataFrame
Report_LR_df = pd.DataFrame(Report_LR)

print(Report_LR_df)
```

	Metric	Value
0	LR Accuracy Score	0.836641
1	LR Jaccard Index	0.509174
2	LR F1 Score	0.674772
3	LR Log Loss	0.381064

5. Support Vector Machine(SVM)

Q.16 Create and train a SVM model called SVM using the training data (x_train, y_train).

```
In [81]: ▶ # Split the data into train and test sets
x_train, x_test, y_train, y_test = train_test_split(features, Y, test_size = 0.2,
```

```
In [82]: ▶ svm = SVC(kernel='rbf')
svm.fit(x_train, y_train)
```

Out[82]: SVC()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

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Q.17 Now use the predict method on the testing data (x_test) and save it to the array predictions.

```
In [84]: % # Use the predict method on the testing data
         predictions_SVM = svm.predict(x_test)
         predictions_SVM
```

[illegible]

Q.18 Using the predictions and the y_test dataframe calculate the value for each metric using the appropriate function.

```
In [85]: # Calculate Accuracy Score
SVM_accuracy_score = accuracy_score(y_test, predictions_SVM)
print("SVM Accuracy Score:", SVM_accuracy_score)
```

SVM Accuracy Score: 0.7190839694656489


```
In [54]: ▶ # Calculate Jaccard Index
SVM_jaccard_index = jaccard_score(y_test, predictions_SVM)
print("SVM Jaccard Index:", SVM_jaccard_index)
```

SVM Jaccard Index: 0.0

```
In [55]: ▶ # Calculate F1 Score
SVM_f1_score = f1_score(y_test, predictions_SVM)
print("SVM F1 Score:", SVM_f1_score)
```

SVM F1 Score: 0.0

Report

Q.19 Show the Accuracy, Jaccard Index, F1-Score and LogLoss in a tabular format using data frame for all of the above models.

```
In [93]: ▶ # Create a dictionary with metrics
Report = {
    'Metric': ['Mean Absolute Error(MAE) Linear Regression', 'Mean Squared Error(MSE) Linear Regression', 'R-squared(R2) Linear Regression', 'KNN accuracy score', 'KNN Jaccard Index', 'KNN F1 Score', 'Tree accuracy score', 'Tree jaccard Index', 'Tree F1 score', 'Logistic Regression Accuracy Score', 'Logistic Regression Jaccard Index', 'Logistic Regression F1 Score', 'Logistic Regression Log Loss', 'SVM Accuracy Score', 'SVM Jaccard Index', 'SVM F1 Score'],
    'Value': [LinearRegression_MAE, LinearRegression_MSE, LinearRegression_R2, KNN_accuracy_score, KNN_jaccard_index, KNN_f1_score, Tree_accuracy_score, Tree_jaccard_index, Tree_f1_score, LogisticRegression_Accuracy_Score, LogisticRegression_Jaccard_Index, LogisticRegression_F1_Score, LogisticRegression_Log_Loss, SVM_Accuracy_Score, SVM_Jaccard_Index, SVM_F1_Score]
}

# Create a DataFrame
Report_df = pd.DataFrame(Report)

print(Report_df)
```

	Metric	Value
0	Mean Absolute Error(MAE) Linear Regression	0.256319
1	Mean Squared Error(MSE) Linear Regression	0.115723
2	R-squared(R2) Linear Regression	0.427121
3	KNN accuracy score	0.818321
4	KNN Jaccard Index	0.425121
5	KNN F1 Score	0.596610
6	Tree accuracy score	0.818321
7	Tree jaccard Index	0.480349
8	Tree F1 score	0.648968
9	Logistic Regression Accuracy Score	0.836641
10	Logistic Regression Jaccard Index	0.509174
11	Logistic Regression F1 Score	0.674772
12	Logistic Regression Log Loss	0.381064
13	SVM Accuracy Score	0.719084
14	SVM Jaccard Index	0.000000
15	SVM F1 Score	0.000000

In []: ▶