```
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In this notebook, We will implement Logistic Regression and Understand how we can CHANGE THRESHOLD for classification

Logistic Regression Demonstration

In [4]:

```python
import pandas as pd
import numpy as np
```

In [70]:

```python
df = pd.read_csv("Dataset/KNN/data_cleaned.csv")
df.head()

# using Titanic Survival Dataset which has been already cleaned and encoded for usage
```

Out[70]:

	Survived	Age	Fare	Pclass_1	Pclass_2	Pclass_3	Sex_female	Sex_male	SibSp_0	SibSp_1	...	Parch_0	Parch_1	Parch_2	Parch_3	Parch_4	P
0	0	22.0	7.2500	0	0	1	0	1	0	1	...	1	0	0	0	0	
1	1	38.0	71.2833	1	0	0	1	0	0	1	...	1	0	0	0	0	
2	1	26.0	7.9250	0	0	1	1	0	1	0	...	1	0	0	0	0	
3	1	35.0	53.1000	1	0	0	1	0	0	1	...	1	0	0	0	0	
4	0	35.0	8.0500	0	0	1	0	1	1	0	...	1	0	0	0	0	

5 rows × 25 columns

Separating Independent & Target Features

In [6]:

```python
x = df.drop(['Survived'], axis=1)
y = df['Survived']
x.shape, y.shape
```

Out[6]:

```
((891, 24), (891,))
```

In [10]:

```python
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x,y, random_state=9, stratify=y)

x_train.shape, x_test.shape
```

Out[10]:

```
((668, 24), (223, 24))
```

Scaling Features

using Min Max scalar

In [16]:

```python
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

train_x_scaled = scaler.fit_transform(x_train)
train_x_scaled = pd.DataFrame(train_x_scaled, columns=x_train.columns)
train_x_scaled.head()
```

Out[16]:

	Age	Fare	Pclass_1	Pclass_2	Pclass_3	Sex_female	Sex_male	SibSp_0	SibSp_1	SibSp_2	...	Parch_0	Parch_1	Parch_2	Parch_3	Parch_
0	0.044986	0.032596	0.0	0.0	1.0	1.0	0.0	0.0	1.0	0.0	...	0.0	1.0	0.0	0.0	0
1	0.346569	0.025374	0.0	1.0	0.0	1.0	0.0	1.0	0.0	0.0	...	1.0	0.0	0.0	0.0	0
2	0.367921	0.030254	0.0	0.0	1.0	1.0	0.0	0.0	1.0	0.0	...	1.0	0.0	0.0	0.0	0
3	0.258608	0.015127	0.0	0.0	1.0	1.0	0.0	1.0	0.0	0.0	...	1.0	0.0	0.0	0.0	0
4	0.233476	0.019852	0.0	0.0	1.0	0.0	1.0	1.0	0.0	0.0	...	1.0	0.0	0.0	0.0	0

5 rows × 24 columns

In [17]:

```
test_x_scaled = scaler.transform(x_test)
test_x_scaled = pd.DataFrame(test_x_scaled, columns=x_test.columns)
test_x_scaled.head()
```

Out[17]:

	Age	Fare	Pclass_1	Pclass_2	Pclass_3	Sex_female	Sex_male	SibSp_0	SibSp_1	SibSp_2	...	Parch_0	Parch_1	Parch_2	Parch_3	Parch_
0	0.648153	0.059532	1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	...	1.0	0.0	0.0	0.0	0
1	0.296306	0.096626	1.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	...	1.0	0.0	0.0	0.0	0
2	0.346569	0.051822	1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	...	1.0	0.0	0.0	0.0	0
3	0.585323	0.049943	1.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	...	1.0	0.0	0.0	0.0	0
4	0.258608	0.016461	0.0	0.0	1.0	0.0	1.0	1.0	0.0	0.0	...	1.0	0.0	0.0	0.0	0

5 rows × 24 columns

Implementing Logistic Regression

In [1]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
```

In [26]:

```
# creating instance of Logictic Regression class
LogisticReg = LogisticRegression(max_iter=500)

# Training / Fitting the model
LogisticReg.fit(x_train, y_train)
```

Out[26]:

```
LogisticRegression(max_iter=500)
```

We are aware of the fact that each feature has a coefficient associated with its equation.

Lets check them out

In [28]:

```
pd.DataFrame({
    'Feature' : x_train.columns,
    'Coefficients' : LogisticReg.coef_.flatten()
}).sort_values(by = 'Coefficients')
```

Out[28]:

	Feature	Coefficients
6	Sex_male	-1.291244
4	Pclass_3	-0.938834
10	SibSp_3	-0.899003
18	Parch_4	-0.801684
19	Parch_5	-0.698865
13	SibSp_8	-0.452825
12	SibSp_5	-0.232781
11	SibSp_4	-0.193704
23	Embarked_S	-0.159248
0	Age	-0.031875
22	Embarked_Q	-0.002438

> We could clearlt see that `Probability of Surviving` is Minimal with sex_male, 3rd class passangers and so on... (having smallest coefficient) and Maximum with sex_female, 1st class passangers and so on ... (having highest coefficient)

Predictions

In [37]:

```
train_pred = LogisticReg.predict(x_train)
train_pred[:10]

# these are the hard tags for survival (sliced out only 10 predictions for better visibility)
```

Out[37]:

```
array([1, 1, 1, 1, 0, 0, 1, 0, 0, 0], dtype=int64)
```

Predicting over Train set

In [39]:

```
# calculating f1_score for train set
train_f1_score = f1_score(y_train, train_pred)
print('Training F1 Score : ',train_f1_score)

# remeber this score is with the default 50% Threshold
```

```
Training F1 Score :  0.7398373983739838
```

Predicting over Test set

In [40]:

```
test_pred = LogisticReg.predict(x_test)
test_pred[:10]
```

Out[40]:

```
array([0, 1, 0, 0, 0, 0, 0, 1, 1, 1], dtype=int64)
```

In [42]:

```
# calculating f1_score for test set
test_f1_score = f1_score(test_pred, y_test)
print('Test F1 Score : ',test_f1_score)

# remeber this score is with the default 50% Threshold
```

```
Test F1 Score :  0.7349397590361445
```

We could say model is not overfitting here and the scores are descent enough

---

As seen earlier in this notebook , the predictions predicted by .predict() are `Hard Tags`

In order to generate the `Soft Tags` , we will use .predict_proba()

Predicting Soft Tags

In [53]:

```
train_pred_soft = LogisticReg.predict_proba(x_train)
train_pred_soft[:10]

# the output here is the COLUMNS equal to the number of CLASSES in TARGET
# and EACH COLUMN CONTAINS PROBABILITY OF THAT DATA POINT BELONGING TO THAT CLASS

# the below data shows the probability of each data point for 1st 10 records belonging to class 0 & 1 respectively
```

Out[53]:

```
array([[0.16079452, 0.83920548],
       [0.21442751, 0.78557249],
       [0.35700362, 0.64299638],
       [0.33732195, 0.66267805],
       [0.8810176 , 0.1189824 ],
       [0.88812343, 0.11187657],
       [0.22680276, 0.77319724],
       [0.91303642, 0.08696358],
       [0.60869506, 0.39130494],
       [0.88404956, 0.11595044]])
```

In [51]:

```
# we can check and validiate the sum across the axis will always be 1 (total probability)
train_pred_soft.sum(axis=1)[:10]
```

Out[51]:

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

The best part about having probabilities is that we can set our own `Thresholds` to seggregate between classes ¶

In [54]:

```
# seggeregating survived column from probabilities
train_pred_soft_survived = train_pred_soft[:, 1]
train_pred_soft_survived[:10]
```

Out[54]:

```
array([0.83920548, 0.78557249, 0.64299638, 0.66267805, 0.1189824 ,
       0.11187657, 0.77319724, 0.08696358, 0.39130494, 0.11595044])
```

In [55]:

```
# setting up threshold of 0.55 and separating

for i in range(len(train_pred_soft_survived)):

    if(train_pred_soft_survived[i] > 0.55):
        train_pred_soft_survived[i] = 1
    else:
        train_pred_soft_survived[i] = 0
```

In [57]:

```
# checking how they look now
train_pred_soft_survived[:10]
```

Out[57]:

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

In [59]:

```
# calculating F1 Score

train_f1_score_soft = f1_score(y_train, train_pred_soft_survived)
print('Training F1 Score (soft) : ',train_f1_score_soft)

# remeber this score is with the custom 55% Threshold

# notice the change in accuracy
```

```
Training F1 Score (soft) :  0.7375
```

Creating Confusion Matrix

In [61]:

```
from sklearn.metrics import confusion_matrix, log_loss

confusion_mat = confusion_matrix(y_test, test_pred)
print(confusion_mat)
```

```
[[118  19]
 [ 25  61]]
```

Generating Classification Report

In [62]:

```
from sklearn.metrics import classification_report as report
print(report(y_test, test_pred))
```

```
              precision    recall  f1-score   support

           0       0.83      0.86      0.84       137
           1       0.76      0.71      0.73        86

    accuracy                           0.80       223
   macro avg       0.79      0.79      0.79       223
weighted avg       0.80      0.80      0.80       223
```

```
Support => shows that how many data points are belonging to that particular class
maxro avg => shows the average of above two entities irrespective of class
weighted avg => average calculated by their respective weights (weights are the points available in the support of that     class)
```

Visualizing the coefficients

In [63]:

```
LogisticReg.coef_
```

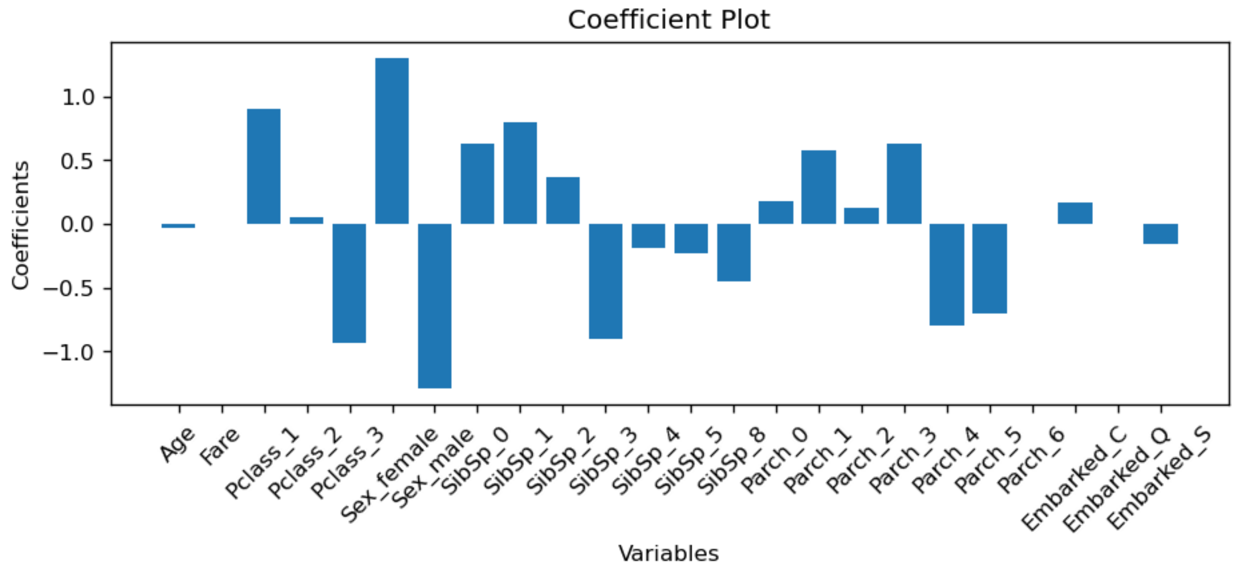
Out[63]:

```
array([[-0.03187542,  0.00261003,  0.89636692,  0.05059092, -0.93883372,
         1.29936852, -1.2912444 ,  0.62758533,  0.79778733,  0.36106487,
        -0.89900305, -0.19370445, -0.23278051, -0.45282541,  0.17803249,
         0.57647513,  0.12804463,  0.62612123, -0.80168393, -0.69886542,
         0.        ,  0.16981082, -0.00243845, -0.15924825]])
```

In [67]:

```python
import matplotlib.pyplot as plt

plt.figure(figsize = (9,3), dpi=120, facecolor='w', edgecolor='b')
x = x_train.columns
y = LogisticReg.coef_.reshape(-1)
plt.bar(x,y)
plt.xlabel('Variables')
plt.ylabel('Coefficients')
plt.title('Coefficient Plot')
plt.xticks(rotation = 45)
plt.show()
```



In [ ]:

```
 
```