EDA with Python and applying Logistic Regression

Problem statement : Exploring titanic dataset & explore about the people,both who survived and did not survive. What factors made people more likely to survive the sinking of the titanic?

Import Libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sb
import matplotlib.pyplot as plt
import math
%matplotlib inline
```

Collecting Data

Reading in the titanic_dataset.csv file into a pandas dataframe.

In [2]:
```
A = pd.read_csv("C:/Users/aksha/OneDrive/Desktop/titanic_dataset.csv")
```

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

Out[3]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

In [4]:
```
print("Number of passengers in original data: " +str(len(A.index)))
```

```
Number of passengers in original data: 891
```

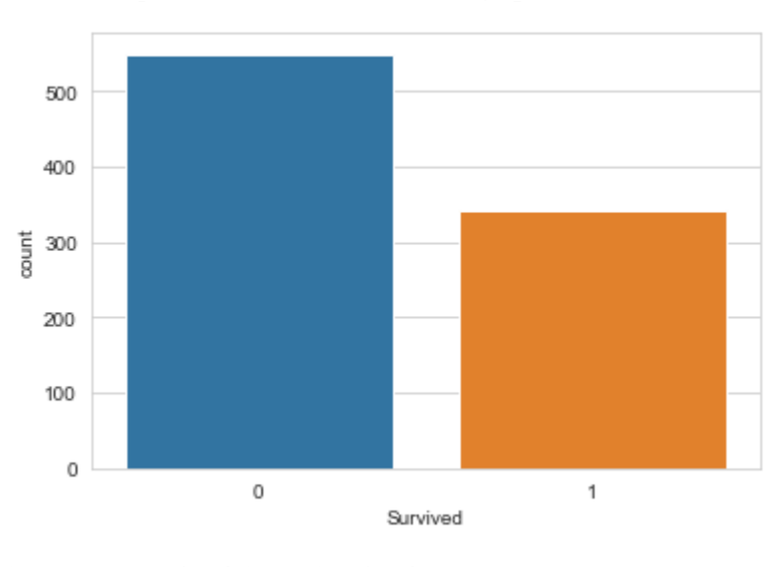
Exploratory Data Analysis

Analyzing Data

Creating different plots to check the relationship between variables. Simply explore the data by using various columns

In [5]:
```
sb.set_style("whitegrid")
sb.countplot(x = "Survived", data=A)
```

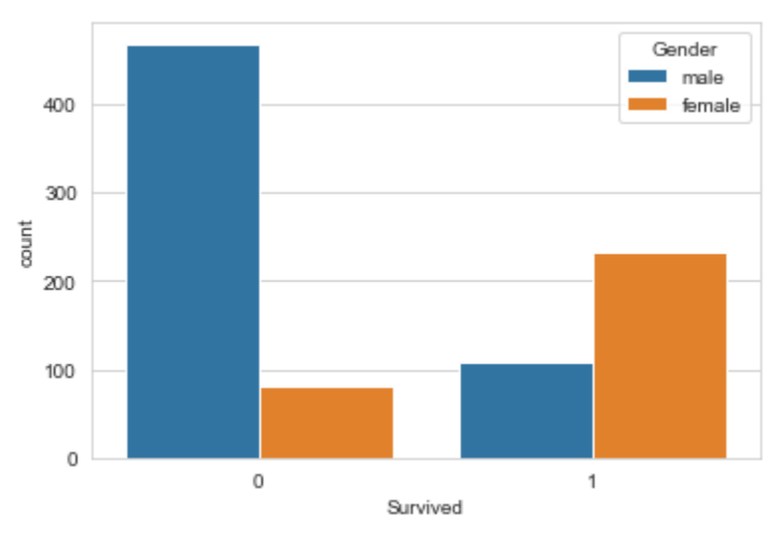
Out[5]: <AxesSubplot:xlabel='Survived', ylabel='count'>



0 --> Not survived 1 --> Survived

In [6]:
```
#To check how many were men and how many were women
sb.set_style("whitegrid")
sb.countplot(x = "Survived", hue = "Gender", data=A)
```

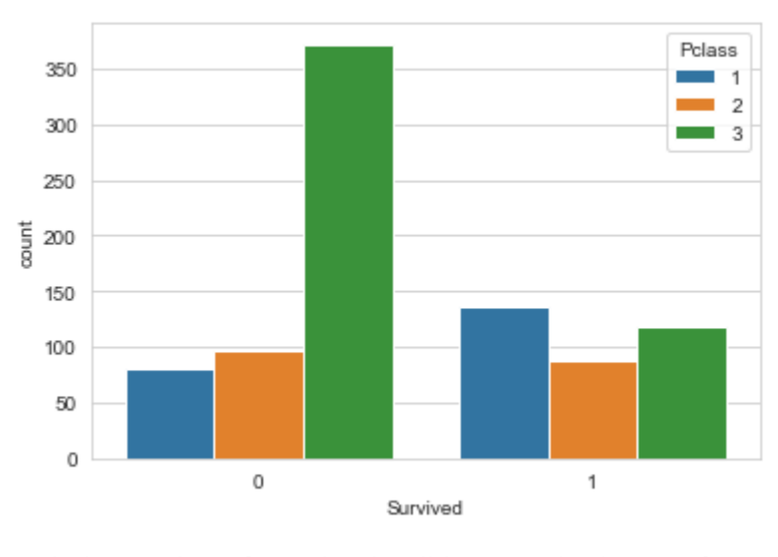
Out[6]: <AxesSubplot:xlabel='Survived', ylabel='count'>



Analysis: The number of men who did not survive is more as compared to women.

In [7]:
```
#To check the class of passengers who did not survive
sb.set_style("whitegrid")
sb.countplot(x = "Survived", hue="Pclass" ,data=A)
```

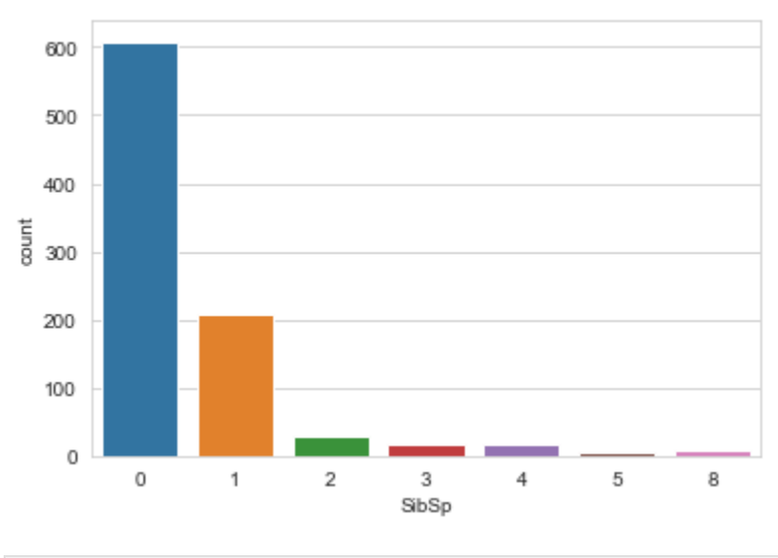
Out[7]: <AxesSubplot:xlabel='Survived', ylabel='count'>



Analysis: Number of people who did not survive is more from Class 3.

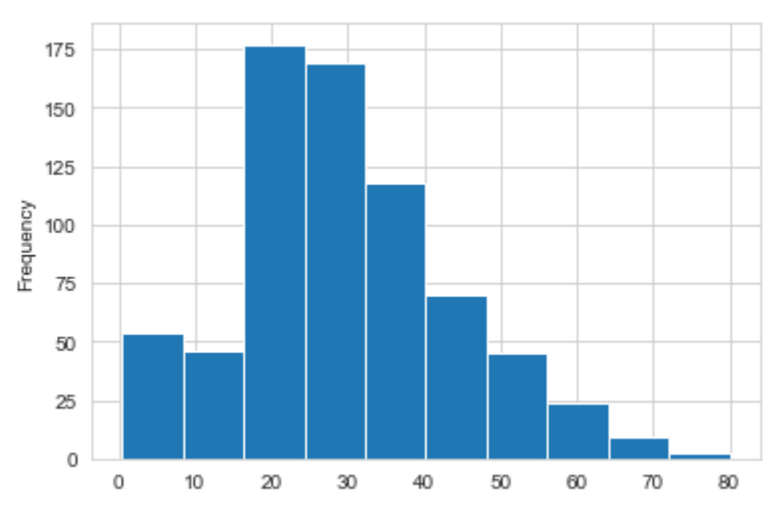
In [8]:
```
#To check SibSp
sb.set_style("whitegrid")
sb.countplot(x = "SibSp" ,data=A)
```

Out[8]: <AxesSubplot:xlabel='SibSp', ylabel='count'>



In [9]:
```
#to check the age of passengers travelling in titanic
sb.set_style("whitegrid")
A["Age"].plot.hist()
```

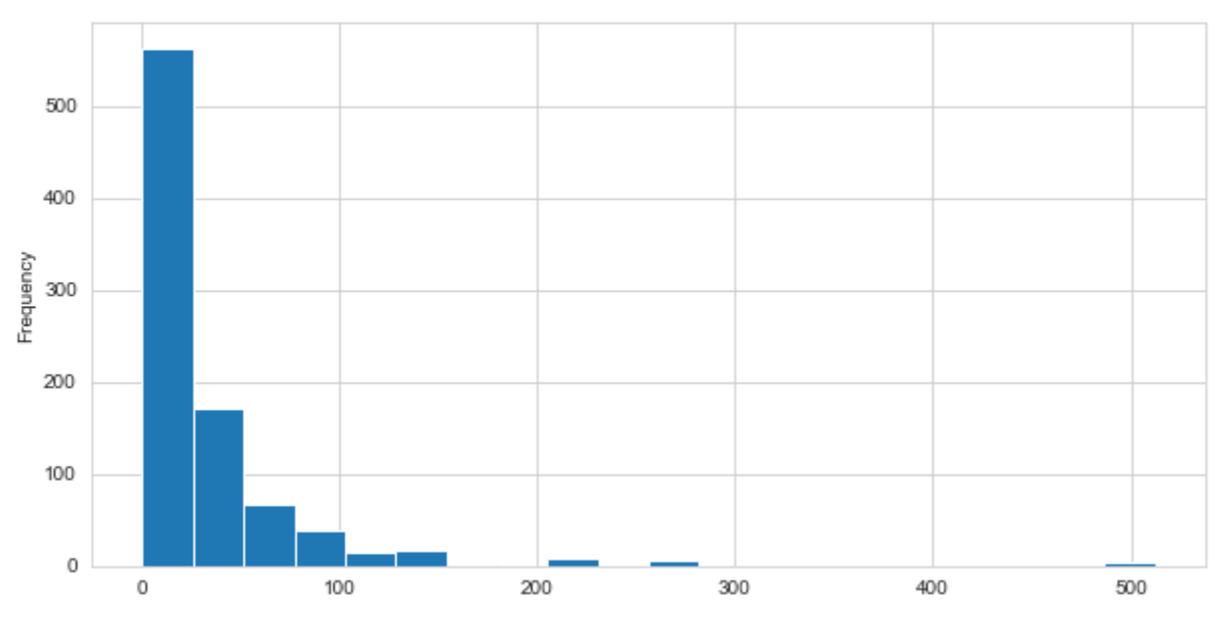
Out[9]: <AxesSubplot:ylabel='Frequency'>



Analysis: People of age ranging 20-30 is more

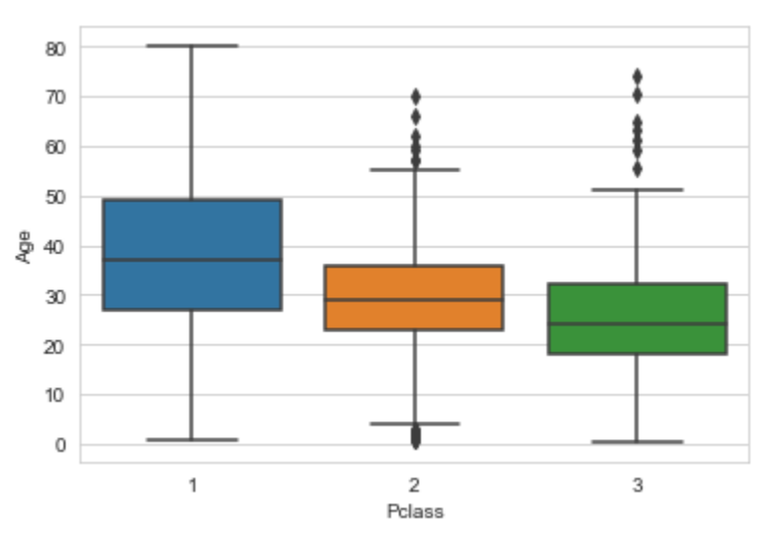
In [10]:
```
#To check the average fare of the people who have bought the ticket
sb.set_style("whitegrid")
A["Fare"].plot.hist(bins=20 , figsize = (10,5))
```

Out[10]: <AxesSubplot:ylabel='Frequency'>



In [11]:
```
sb.set_style("whitegrid")
sb.boxplot(x = "Pclass", y = "Age",data=A)
```

Out[11]: <AxesSubplot:xlabel='Pclass', ylabel='Age'>



Analysis: Passengers in class 1 & 2 are older than in class 3.

In [13]:
```
A.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Gender       891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

Missing Data Treatment

Cleaning the data by removing NaN values and unnecessary columns from the dataset.

In [14]:
```
A.isnull()    #True -- If it is null
              #False -- If it is not null
```

Out[14]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	False	False	False	False	False	False	False	False	False	False	True	False
1	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	True	False
3	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	True	False
...	...	...	...	...	...	...	...	...	...	...	...	...
886	False	False	False	False	False	False	False	False	False	False	True	False
887	False	False	False	False	False	False	False	False	False	False	False	False
888	False	False	False	False	False	True	False	False	False	False	True	False
889	False	False	False	False	False	False	False	False	False	False	False	False
890	False	False	False	False	False	False	False	False	False	False	True	False

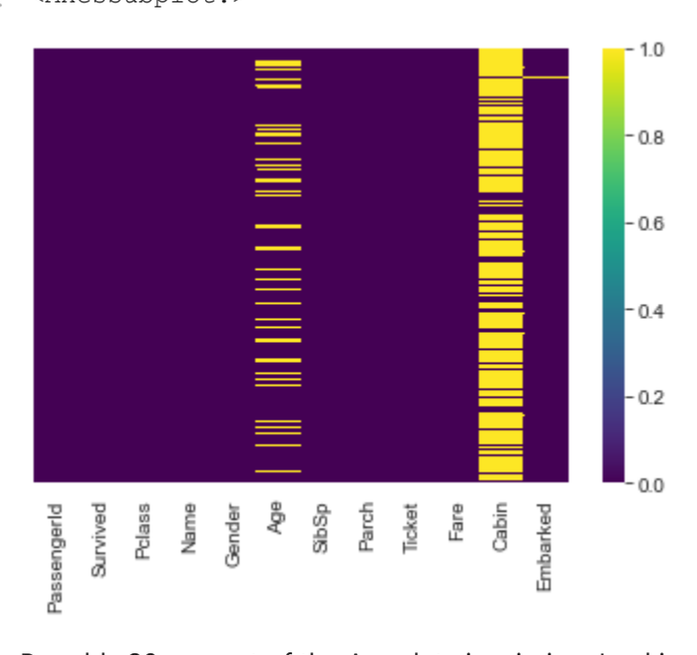
891 rows × 12 columns

In [15]:
```
A.isnull().sum()     #age,cabin,embarked columns have missing values in them.
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Gender           0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [16]:
```
#To analyze them visually, use seaborn to create a simple heatmap to see where is the data missing.
sb.heatmap(A.isnull(), yticklabels = False , cmap = "viridis")
```

Out[16]: <AxesSubplot:>



Roughly 20 percent of the Age data is missing. Looking at the cabin column,it looks like too much data is missing.

In order to remove these columns- Either drop them or replace them and put dummy values to it.

In [17]:
```
A.head()
```

Out[17]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

In [18]:
```
A.drop("Cabin", axis=1, inplace=True)      #drop the cabin column
A.head()
```

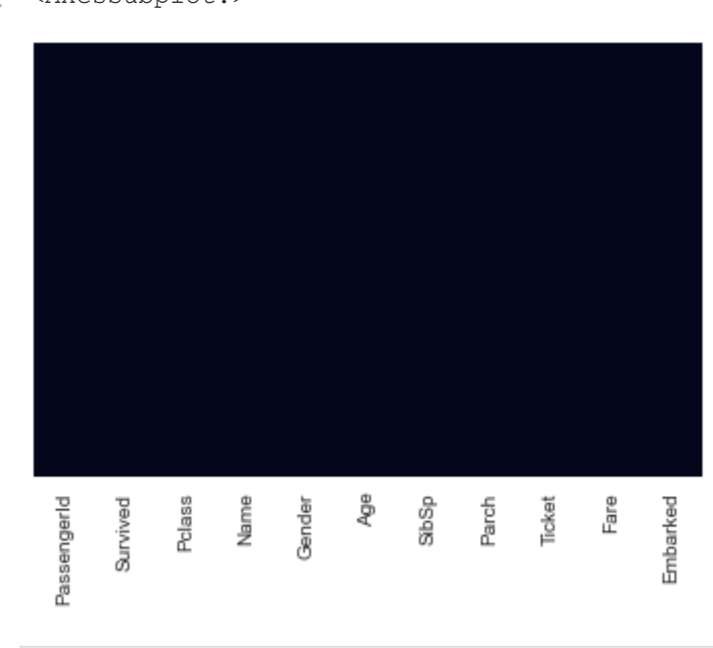
Out[18]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	S

In [19]:
```
A.dropna(inplace=True)      #drop Na values
```

In [20]:
```
#to check if the values have been removed or not.
sb.heatmap(A.isnull(), yticklabels=False , cbar = False)
```

Out[20]: <AxesSubplot:>



In [21]:
```
A.isnull().sum()
```

```
PassengerId    0
Survived       0
Pclass         0
Name           0
Gender         0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

All 0's tell us that the dataset does not contain any null value.

Coverting Categorical Features

In [22]:
```
A.head(2)
```

Out[22]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C

The data has lot of string values.Have to convert categorical featues to dummy variables using pandas. Otherwise the machine learning algorithm won't be able to directly take in those features as input.

In [23]:
```
G = pd.get_dummies(A["Gender"],drop_first=True)
G
```

Out[23]:

	male
0	1
1	0
2	0
3	0
4	1
...	...
885	0
886	1
887	0
889	1
890	1

712 rows × 1 columns

In [24]:
```
E= pd.get_dummies(A["Embarked"], drop_first=True)
E
```

Out[24]:

	Q	S
0	0	1
1	0	0
2	0	1
3	0	1
4	0	1
...	...	...
885	1	0
886	0	1
887	0	1
889	0	0
890	1	0

712 rows × 2 columns

In [25]:
```
Pcl = pd.get_dummies(A["Pclass"],drop_first=True)
Pcl
```

Out[25]:

	2	3
0	0	1
1	0	0
2	0	1
3	0	0
4	0	1
...	...	...
885	0	1
886	1	0
887	0	0
889	0	0
890	0	1

712 rows × 2 columns

In [26]:
```
#concatenate all the new rows into the dataset
A = pd.concat([A,G,E,Pcl],axis=1)
A.head()
```

Out[26]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Embarked	male	Q	S	2	3
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S	1	0	1	0	1
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C	0	0	0	0	0
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S	0	0	1	0	1
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S	0	0	1	0	0
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	S	1	0	1	0	1

In [27]:
```
#drop unnecessary columns from the dataset
A.drop(["PassengerId","Pclass","Name","Gender","Ticket","Embarked"],axis=1,inplace=True)
A.head()
```

Out[27]:

	Survived	Age	SibSp	Parch	Fare	male	Q	S	2	3
0	0	22.0	1	0	7.2500	1	0	1	0	1
1	1	38.0	1	0	71.2833	0	0	0	0	0
2	1	26.0	0	0	7.9250	0	0	1	0	1
3	1	35.0	1	0	53.1000	0	0	1	0	0
4	0	35.0	0	0	8.0500	1	0	1	0	1

Building a Logistic Regression Model

Splitting the data into training set and testing set.

Train Test Split

In [28]:
```
X = A.drop("Survived",axis=1)
Y = A[["Survived"]]
```

In [29]:
```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest = train_test_split(X,Y,test_size=0.2,random_state=31)
```

In [30]:
```
from warnings import filterwarnings
filterwarnings("ignore")

from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lrmodel = lr.fit(xtrain,ytrain)
```

In [31]:
```
pred = lrmodel.predict(xtest)
```

In [32]:
```
pred
```

Out[32]:
```
array([0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0,
       1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 1, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1,
       1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0], dtype=int64)
```

Accuracy Check

calculate accuracy to check how accurate the results are.

In [33]:
```
#to calculate classification report
from sklearn.metrics import classification_report
classification_report(ytest,pred)
```

Out[33]:
```
'              precision    recall  f1-score   support\n\n           0       0.81      0.85      0.83        84\n           1       0.76      0.71      0.74        59\n\n    accuracy                           0.79       143\n   macro avg       0.79      0.78      0.78       143\nweighted avg       0.79      0.79      0.79       143\n'
```

In [34]:
```
#to calculate accuracy using confusion matrix
from sklearn.metrics import confusion_matrix
confusion_matrix(ytest,pred)
```

Out[34]:
```
array([[71, 13],
       [17, 42]], dtype=int64)
```

In [37]:
```
#accuracy score calculated from
(71+42)/(71+13+17+42)
```

Out[37]: 0.7902097902097902

In [38]:
```
#to calculate accuracy score
from sklearn.metrics import accuracy_score
accuracy_score(ytest,pred)
```

Out[38]: 0.7902097902097902

Therefore,accuracy is 0.79 i.e. 79%

In [40]:
```
ytest["Predicted"] = pred
ytest
```

Out[40]:

	Survived	Predicted
4	0	0
523	1	1
102	0	1
544	0	0
874	1	1
...	...	...
412	1	1
797	1	1
679	1	1
164	0	0
54	0	0

143 rows × 2 columns