Titanic Disaster Survival Using Logistic Regression

```
# import libraries

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

Load the Data

```
#load data

titanic_data=pd.read_csv('titanic_train.csv')

len(titanic_data)

891
```

View the data using head function which returns top rows

```
titanic_data.head()

   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age
SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0
1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
1
2                             Heikkinen, Miss. Laina  female  26.0
0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
4                           Allen, Mr. William Henry    male  35.0
0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S

titanic_data.index
```

```
RangeIndex(start=0, stop=891, step=1)
```

```
titanic_data.columns
```

```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age',
'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

```
titanic_data.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   Sex          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
```

```
titanic_data.dtypes
```

```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

```
titanic_data.describe()
```

```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
```

```
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

Explaining Dataset

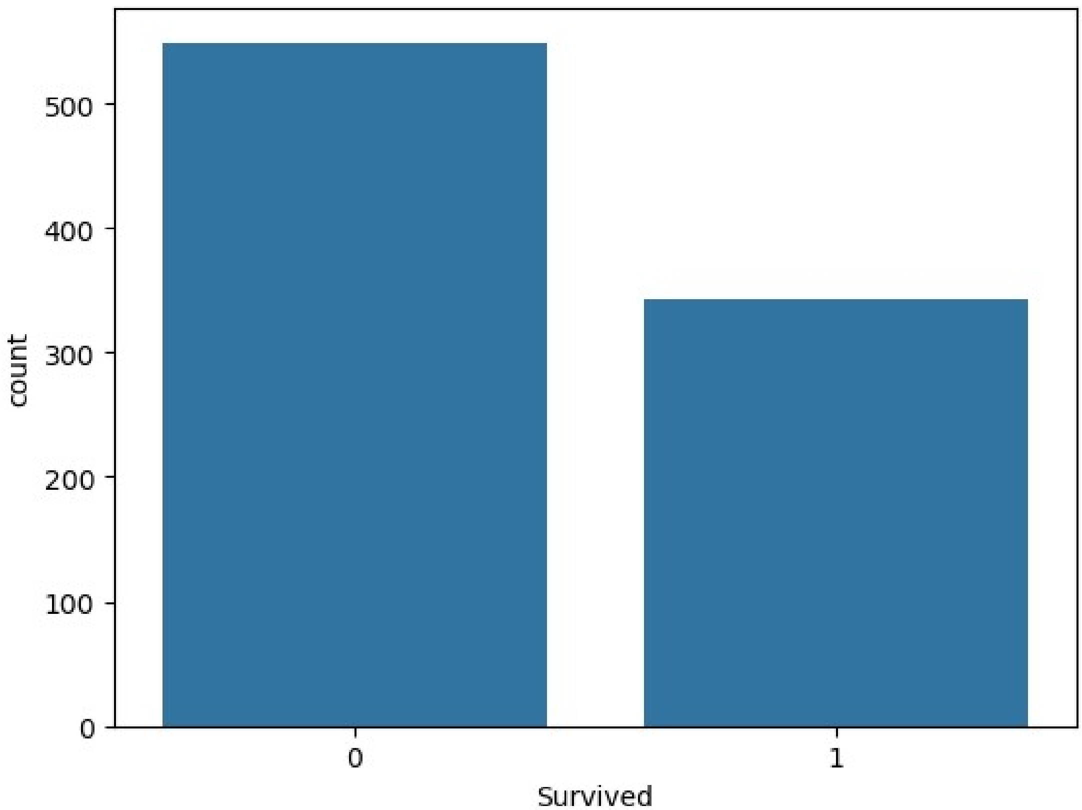
survival : Survival 0 = No, 1 = Yes pclass : Ticket class 1 = 1st, 2 = 2nd, 3 = 3rd sex : Sex Age : Age in years sibsp : Number of siblings / spouses aboard the Titanic parch # of parents / children aboard the Titanic ticket : Ticket number fare Passenger fare cabin Cabin number embarked : Port of Embarkation C = Cherbourg, Q = Queenstown, S = Southampton

Data Analysis

Import Seaborn for visually analysing the data

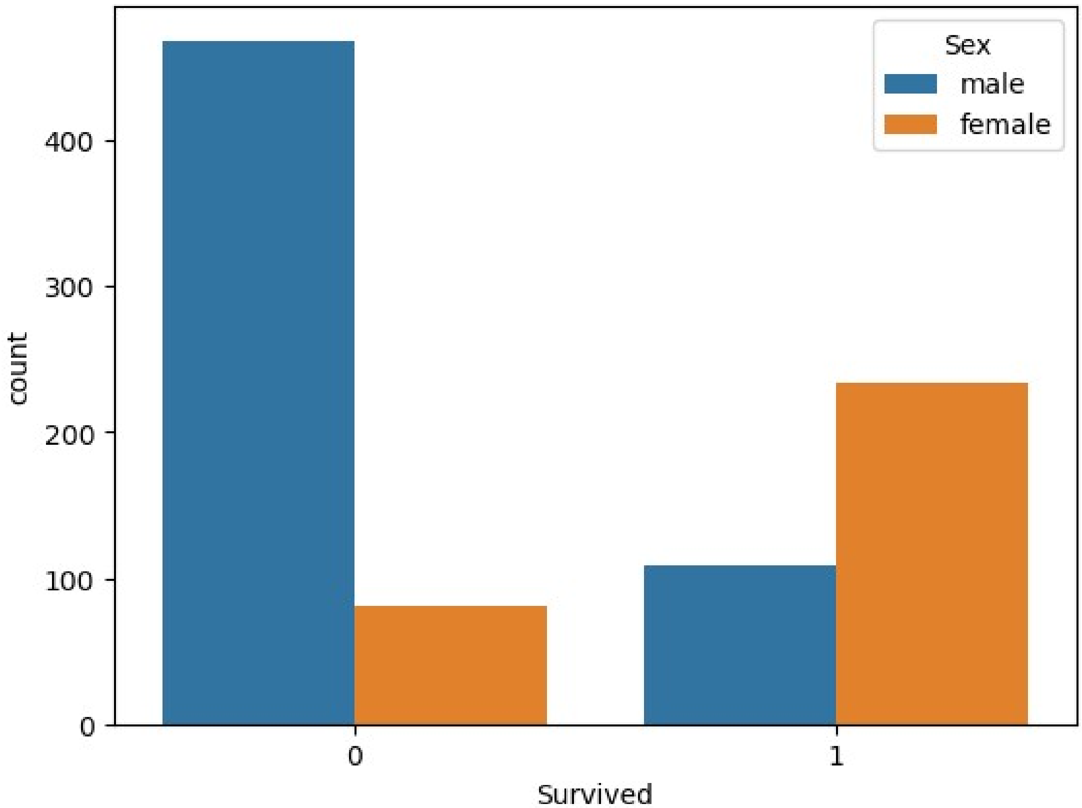
Find out how many survived vs Died using countplot method of seaboarn

```
#countplot of subrvived vs not  survived

sns.countplot(x='Survived',data=titanic_data)

<Axes: xlabel='Survived', ylabel='count'>
```



Male vs Female Survival

```
#Male vs Female Survived?

sns.countplot(x='Survived',data=titanic_data,hue='Sex')

<Axes: xlabel='Survived', ylabel='count'>
```



See age group of passengeres travelled

Note: We will use displot method to see the histogram. However some records does not have age hence the method will throw an error. In order to avoid that we will use dropna method to eliminate null values from graph

```
#Check for null

titanic_data.isna()

     PassengerId  Survived  Pclass   Name    Sex    Age  SibSp  Parch
Ticket  \
0          False     False   False  False  False  False  False  False
False
1          False     False   False  False  False  False  False  False
False
2          False     False   False  False  False  False  False  False
False
3          False     False   False  False  False  False  False  False
False
4          False     False   False  False  False  False  False  False
False
..           ...       ...     ...    ...    ...    ...    ...    ...
...
886        False     False   False  False  False  False  False  False
```

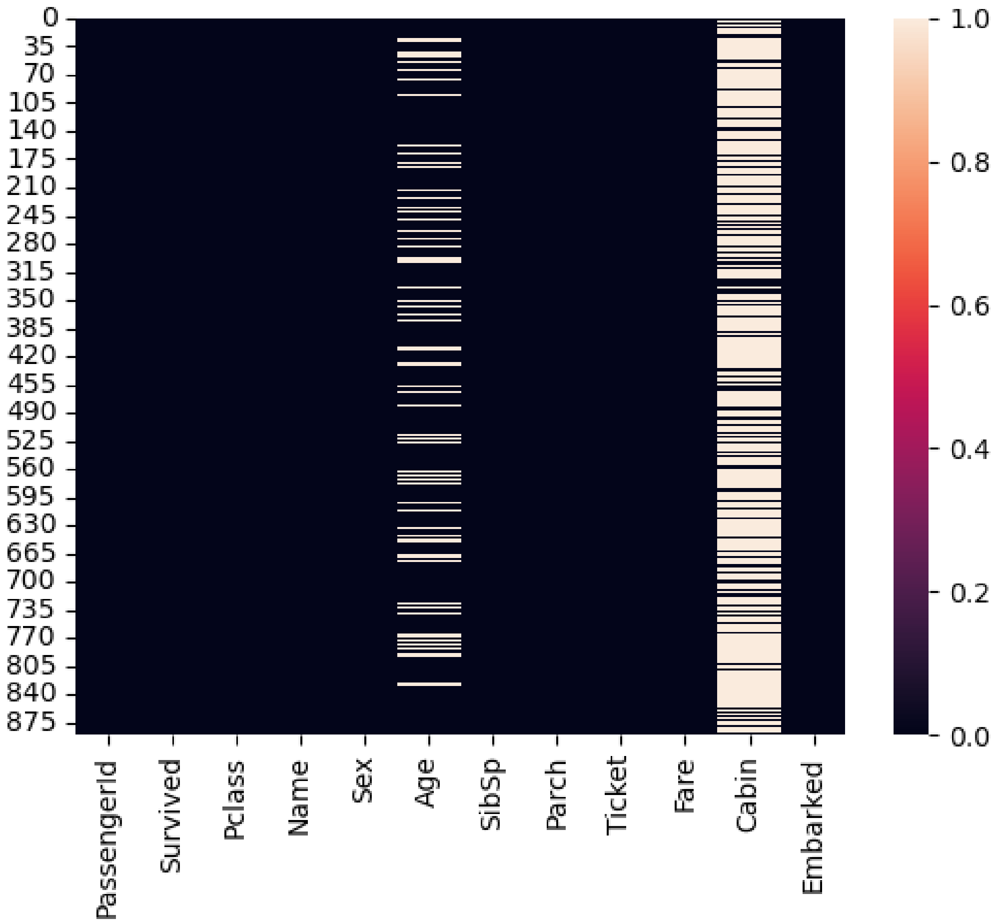
```
False
887       False     False   False  False  False  False  False  False
False
888       False     False   False  False  False   True  False  False
False
889       False     False   False  False  False  False  False  False
False
890       False     False   False  False  False  False  False  False
False

      Fare  Cabin  Embarked
0    False   True     False
1    False  False     False
2    False   True     False
3    False  False     False
4    False   True     False
..     ...    ...       ...
886  False   True     False
887  False  False     False
888  False   True     False
889  False  False     False
890  False   True     False

[891 rows x 12 columns]
```

```
#Check how many values are null

titanic_data.isna().sum()
```

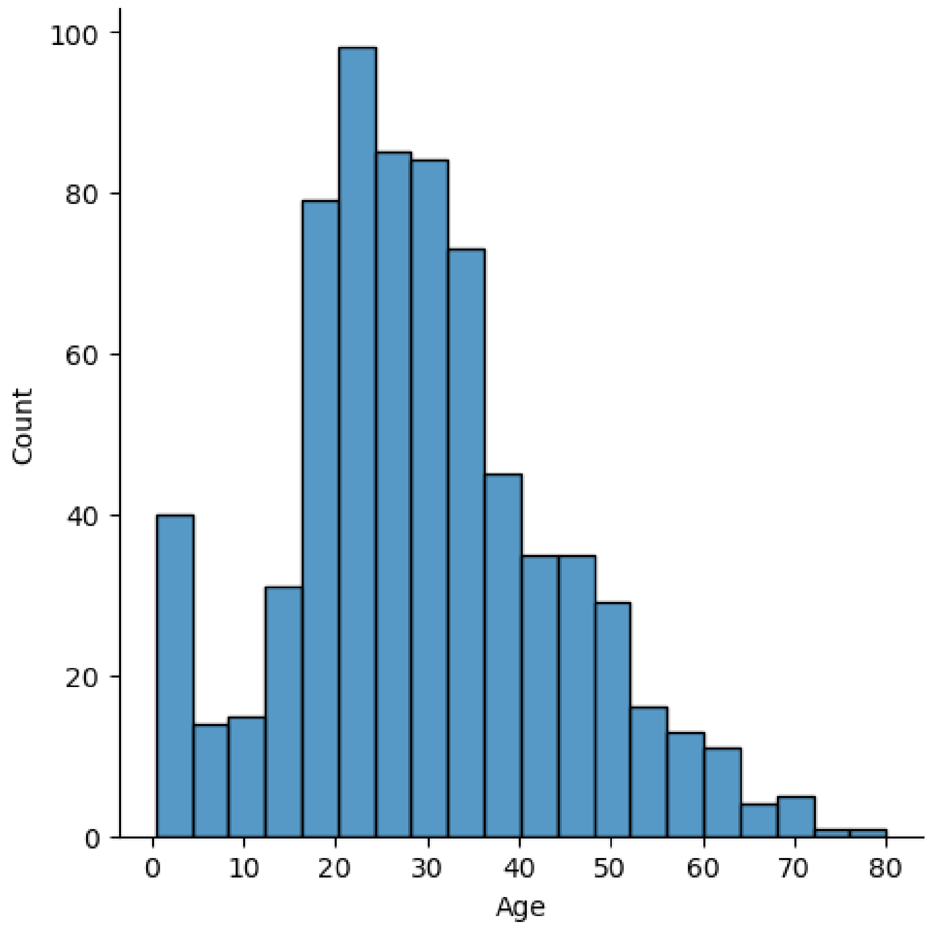
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

```
#Visualize null values

sns.heatmap(titanic_data.isna())
```

```
<Axes: >
```




```
#find the % of null values in age column
(titanic_data['Age'].isna().sum()/len(titanic_data['Age']))*100
19.865319865319865
#find the % of null values in cabin column
(titanic_data['Cabin'].isna().sum()/len(titanic_data['Cabin']))*100
77.10437710437711
#find the distribution for the age column
sns.displot(x='Age',data=titanic_data)
<seaborn.axisgrid.FacetGrid at 0x2760a11deb0>
```



Data Cleaning

Fill the missing values we will fill the missing values for age. In order to fill missing values we use fillna method. For now we will fill the missing age by taking average of all age

```
titanic_data['Age'] =
titanic_data['Age'].fillna(titanic_data['Age'].mean())
```

We can verify that no more null data exist we will examine data by isnull mehtod which will return nothing

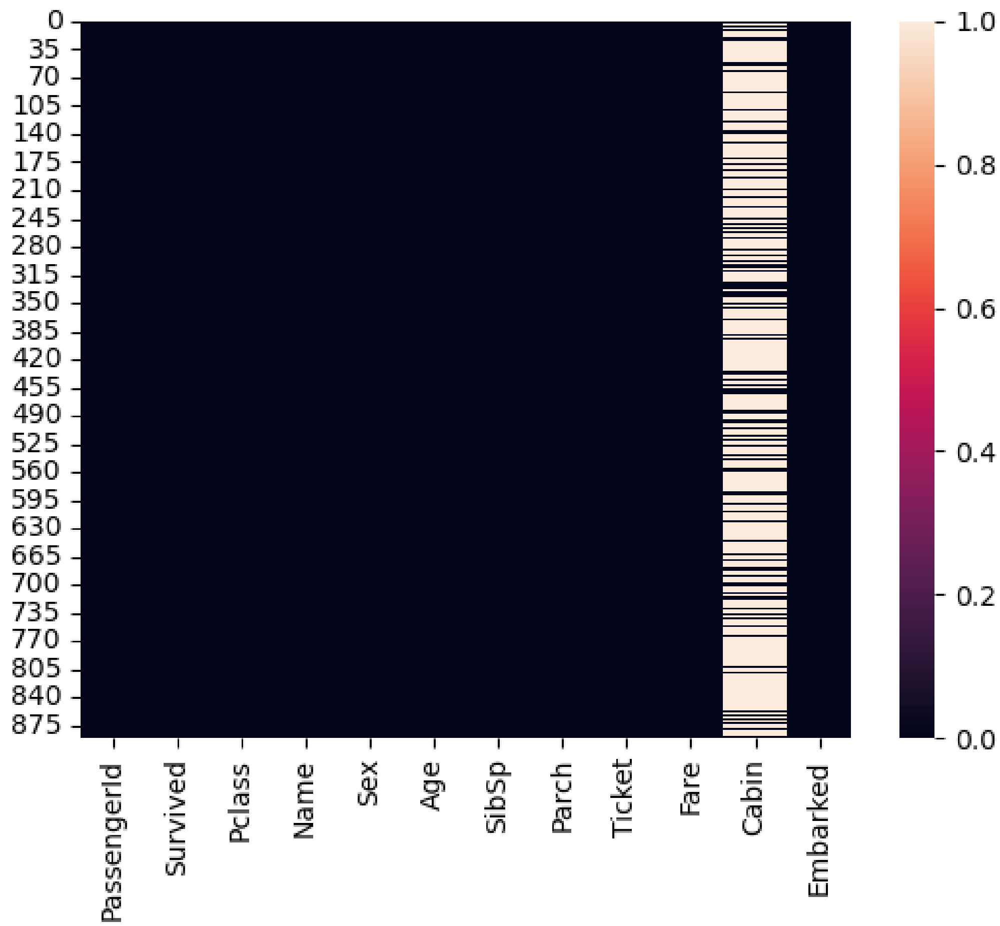
```
#verify null value

titanic_data['Age'].isna().sum()

0
```

Alternatively we will visualise the null value using heatmap

we will use heatmap method by passing only records which are null.

```
sns.heatmap(titanic_data.isna())
```

```
<Axes: >
```



We can see cabin column has a number of null values, as such we can not use it for prediction. Hence we will drop it

```
#Drop cabin column

titanic_data.drop('Cabin',axis=1,inplace=True)

#see the contents of the data

titanic_data.head()
```

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
```

```
2            3          1        3
3            4          1        1
4            5          0        3

                                                Name     Sex   Age
SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0
1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
1
2                             Heikkinen, Miss. Laina  female  26.0
0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
4                           Allen, Mr. William Henry    male  35.0
0

   Parch            Ticket     Fare Embarked
0      0         A/5 21171   7.2500        S
1      0          PC 17599  71.2833        C
2      0  STON/O2. 3101282   7.9250        S
3      0            113803  53.1000        S
4      0            373450   8.0500        S
```

Preaparing Data for Model

No we will require to convert all non-numerical columns to numeric. Please note this is required for feeding data into model. Lets see which columns are non numeric info describe method

```
#Check for the non-numeric column

titanic_data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 11 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   Sex          891 non-null    object
 5   Age          891 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  Embarked     889 non-null    object
```

```
dtypes: float64(2), int64(5), object(4)
memory usage: 76.7+ KB
```

```
titanic_data.dtypes
```

```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Embarked        object
dtype: object
```

We can see, Name, Sex, Ticket and Embarked are non-numerical.It seems Name,Embarked and Ticket number are not useful for Machine Learning Prediction hence we will eventually drop it. For Now we would convert Sex Column to dummies numerical values

```
#convert sex column to numerical values

gender=pd.get_dummies(titanic_data['Sex'],drop_first=True)

titanic_data['Gender']=gender

titanic_data.head()
```

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age
SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0
1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
1
2                             Heikkinen, Miss. Laina  female  26.0
0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
1
4                           Allen, Mr. William Henry    male  35.0
```

```
0
```

	Parch	Ticket	Fare	Embarked	Gender
0	0	A/5 21171	7.2500	S	True
1	0	PC 17599	71.2833	C	False
2	0	STON/O2. 3101282	7.9250	S	False
3	0	113803	53.1000	S	False
4	0	373450	8.0500	S	True

```python
#drop the columns which are not required

titanic_data.drop(['Name','Sex','Ticket','Embarked'],axis=1,inplace=True)

titanic_data.head()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare	Gender
0	1	0	3	22.0	1	0	7.2500	True
1	2	1	1	38.0	1	0	71.2833	False
2	3	1	3	26.0	0	0	7.9250	False
3	4	1	1	35.0	1	0	53.1000	False
4	5	0	3	35.0	0	0	8.0500	True

```python
#Seperate Dependent and Independent variables

x=titanic_data[['PassengerId','Pclass','Age','SibSp','Parch','Fare','Gender']]
y=titanic_data['Survived']

y
```

```
0      0
1      1
2      1
3      1
4      0
      ..
886    0
887    1
888    0
889    1
890    0
Name: Survived, Length: 891, dtype: int64
```

Data Modelling

Building Model using Logestic Regression

Build the model

```python
#import train test split method
```

```
from sklearn.model_selection import train_test_split

#train test split

x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.33, random_state=42)

#import Logistic  Regression

from sklearn.linear_model import LogisticRegression

#Fit  Logistic Regression

lr=LogisticRegression()
lr.fit(x_train,y_train)
```

```
C:\Users\NITISH\anaconda3\Lib\site-packages\sklearn\linear_model\
_logistic.py:469: ConvergenceWarning: lbfgs failed to converge
(status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

LogisticRegression()
```

```
#predict

predict=lr.predict(x_test)
```

Testing

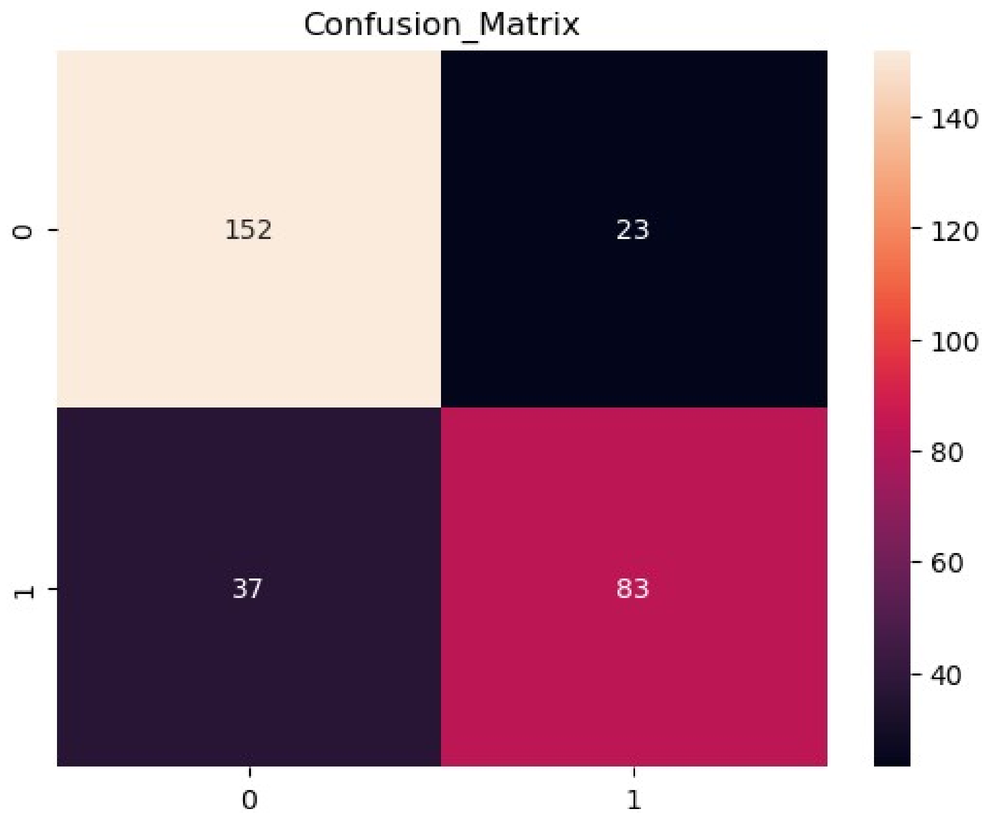
See how our model is performing

```
#print confusion matrix
from sklearn.metrics import confusion_matrix

pd.DataFrame(confusion_matrix(y_test,predict),columns=['Predicted
No','Predicted Yes'],index=['Actual No','Actual Yes'])
```

	Predicted No	Predicted Yes
Actual No	152	23
Actual Yes	37	83

```
sns.heatmap(confusion_matrix(y_test,predict),annot=True,fmt='d')
plt.title('Confusion_Matrix')
plt.show
```

```
<function matplotlib.pyplot.show(close=None, block=None)>
```




```
#import classification report
from sklearn.metrics import classification_report

print(classification_report(y_test,predict))
```

```
              precision    recall  f1-score   support

           0       0.80      0.87      0.84       175
           1       0.78      0.69      0.73       120

    accuracy                           0.80       295
   macro avg       0.79      0.78      0.78       295
weighted avg       0.80      0.80      0.79       295
```

Precision is fine considering Model Selected and Available Data. Accuracy can be increased by further using more features (which we dropped earlier) and/or by using other model

Note: Precision : Precision is the ratio of correctly predicted positive observations to the total predicted positive observations Recall : Recall is the ratio of correctly predicted positive observations to the all observations in actual class F1 score - F1 Score is the weighted average of Precision and Recall.