```
#import libraries
import pandas as pd
import numpy as np
import seaborn as sns #for data anaysis
import matplotlib.pyplot as plt
```

Load the Data

```
#read data
titanic_data=pd.read_csv('titanic_train.csv')
```

```
len(titanic_data)
```

```
891
```

```
titanic_data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	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

```
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	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200

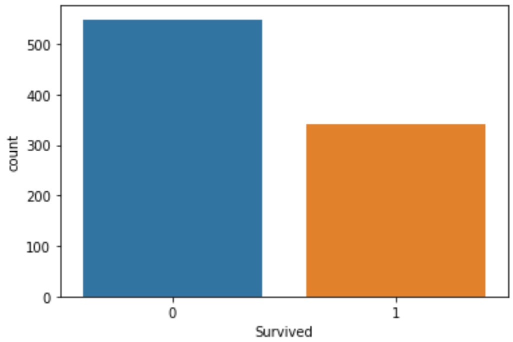
Data Analysis

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)
```

    <AxesSubplot:xlabel='Survived', ylabel='count'>

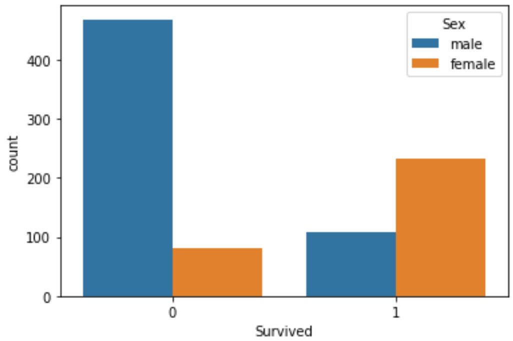


Male vs Female Survival

```
#Male vs Female Survived?

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

    <AxesSubplot: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	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

```
#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
```

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

```
#fill age column

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

We can verify that no more null data exist

we will examine data by isnull mehtod which will return nothing

Double-click (or enter) to edit

```
#verify null value

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

```
0
```

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	Name	Sex	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

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	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	Gender
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S	1
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C	0
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S	0

```
#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	1
1	2	1	1	38.0	1	0	71.2833	0
2	3	1	3	26.0	0	0	7.9250	0
3	4	1	1	35.0	1	0	53.1000	0
4	5	0	3	35.0	0	0	8.0500	1

```
#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

```
#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)
```

```
/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/_logistic.py:814: ConvergenceWarning: lbfgs failed to converge (status=
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	151	24
Actual Yes	37	83

Double-click (or enter) to edit

```
#import classification report

from sklearn.metrics import classification_report

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

```
              precision    recall  f1-score   support

           0       0.80      0.86      0.83       175
           1       0.78      0.69      0.73       120

    accuracy                           0.79       295
   macro avg       0.79      0.78      0.78       295
weighted avg       0.79      0.79      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.

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