TITANIC DATA ANALYSIS AND MODEL TRAINING

In [182]:

```
# STEPS FOR DOING THIS PROJECT ARE : DATA ACQUISITION , DATA ANALYSIS, DATA CLEANING, MODEL
```

In [126]:

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

In [127]:

```
titanic_data = pd.read_csv(r'D:\machine learning practice\titanic\data.csv')
```

In [128]:

```
titanic_data.head()
```

Out[128]:

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

In [129]:

```
'''
pclass = passenger class
sibsb = no of siblings
parch = parents
embarled = place from passenger arrive to ship
'''
```

Out[129]:

```
'\npclass = passenger class\nsibsb = no of siblings\nparch = parents\nembarl
ed = place\n'
```

In [130]:

```
#total no. of passengers
print('the total no. of passengers present in titanic data set are : ' + str(len(titanic_da
```

```
the total no. of passengers present in titanic data set are : 891
```

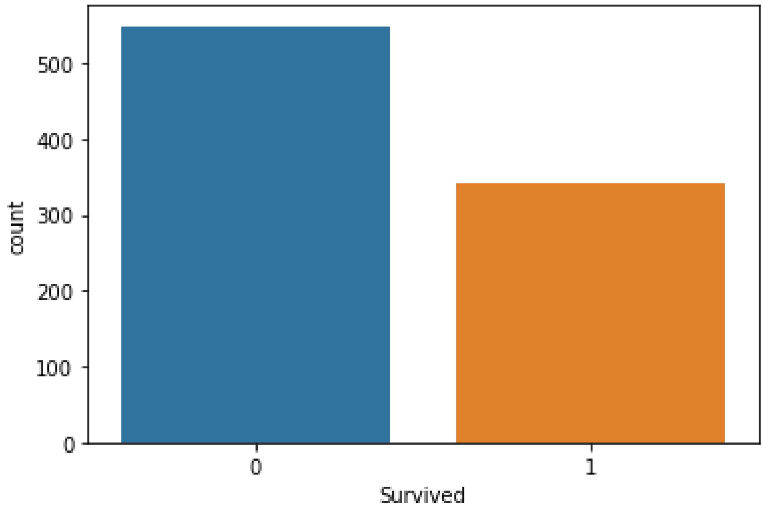
ANALYZE DATA

In [131]:

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

Out[131]:

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

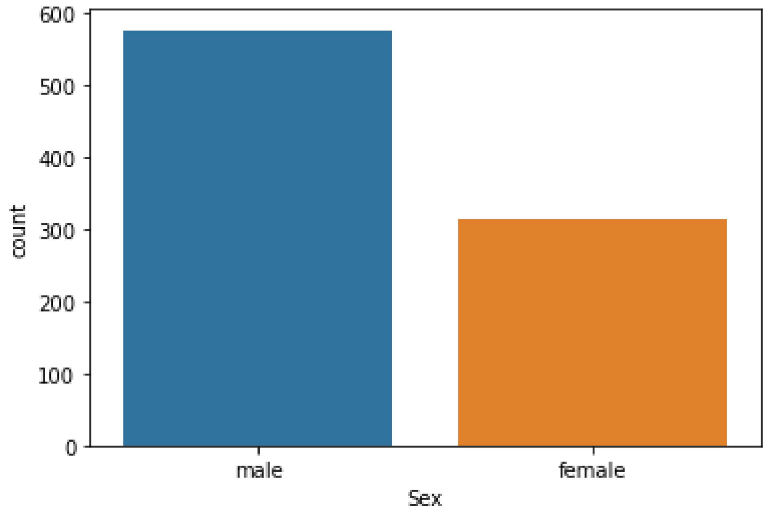


In [132]:

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

Out[132]:

```
<AxesSubplot:xlabel='Sex', ylabel='count'>
```

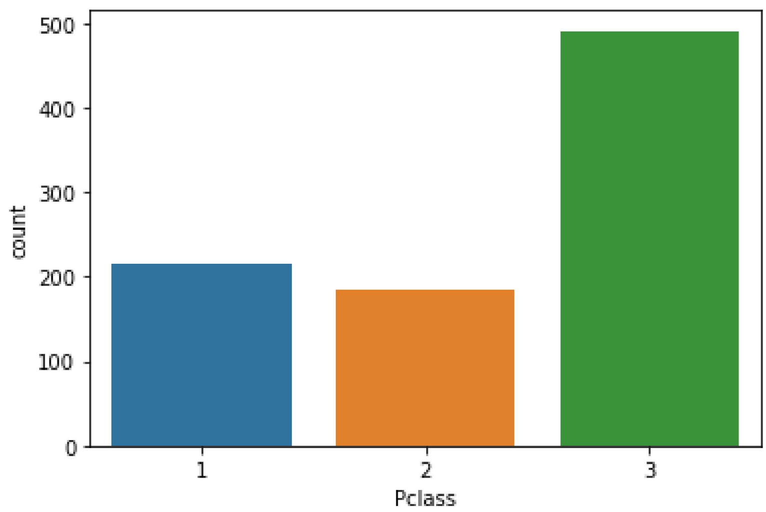


In [133]:

```
sns.countplot(x ='Pclass', data = titanic_data)
```

Out[133]:

```
<AxesSubplot:xlabel='Pclass', ylabel='count'>
```



In [134]:

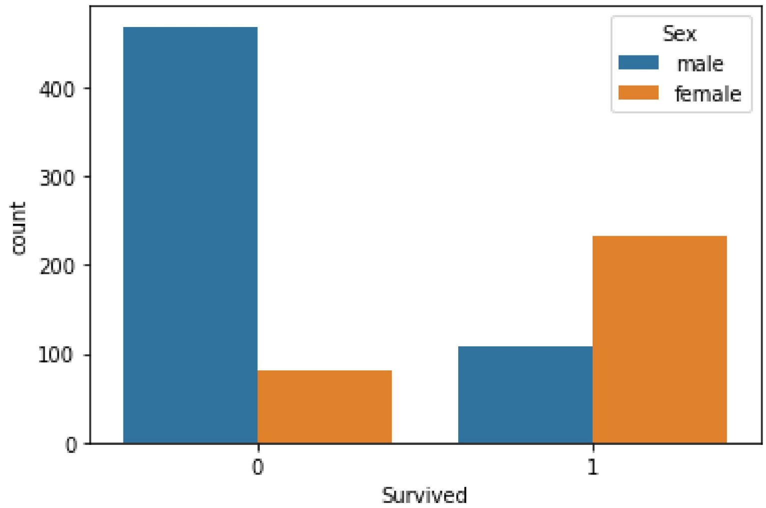
```
# now we plot same sns.countplot(x ='Survived', data = titanic_data) this one but on the ba
```

In [135]:

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

Out[135]:

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

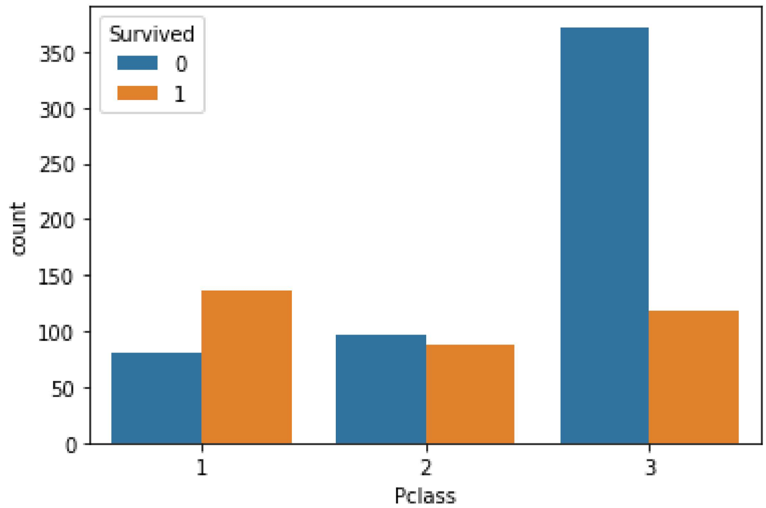


In [136]:

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

Out[136]:

```
<AxesSubplot:xlabel='Pclass', ylabel='count'>
```

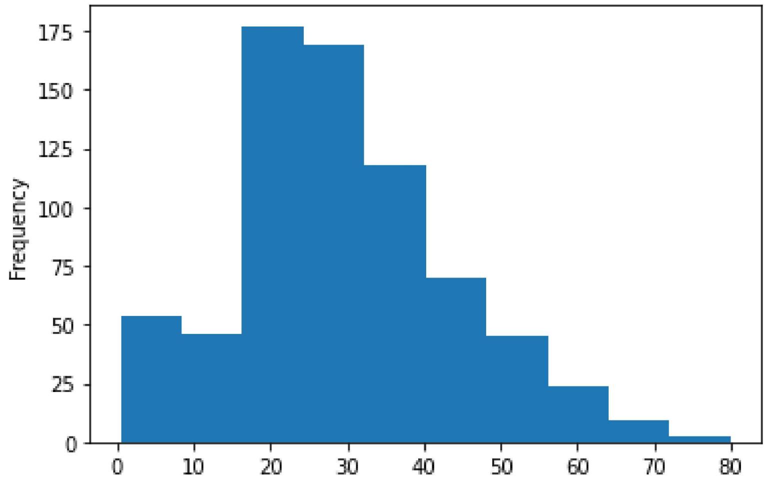


In [137]:

```
titanic_data['Age'].plot.hist()
```

Out[137]:

<AxesSubplot:ylabel='Frequency'>



In [138]:

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

Out[138]:

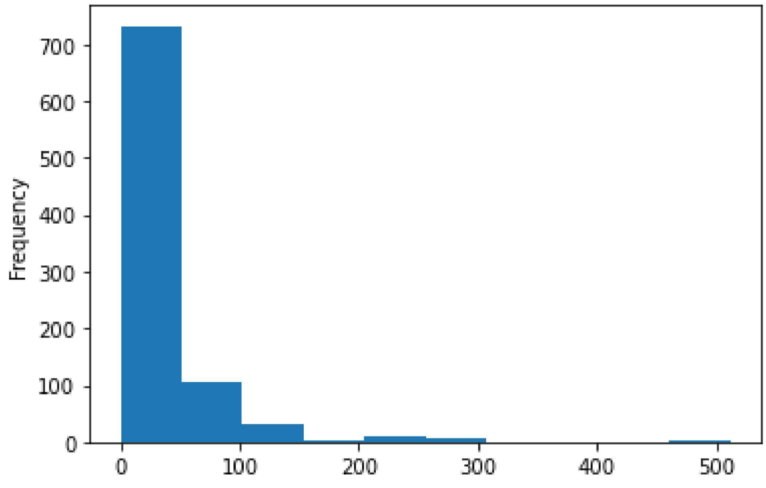
29.69911764705882

In [139]:

```
titanic_data['Fare'].plot.hist()
```

Out[139]:

<AxesSubplot:ylabel='Frequency'>

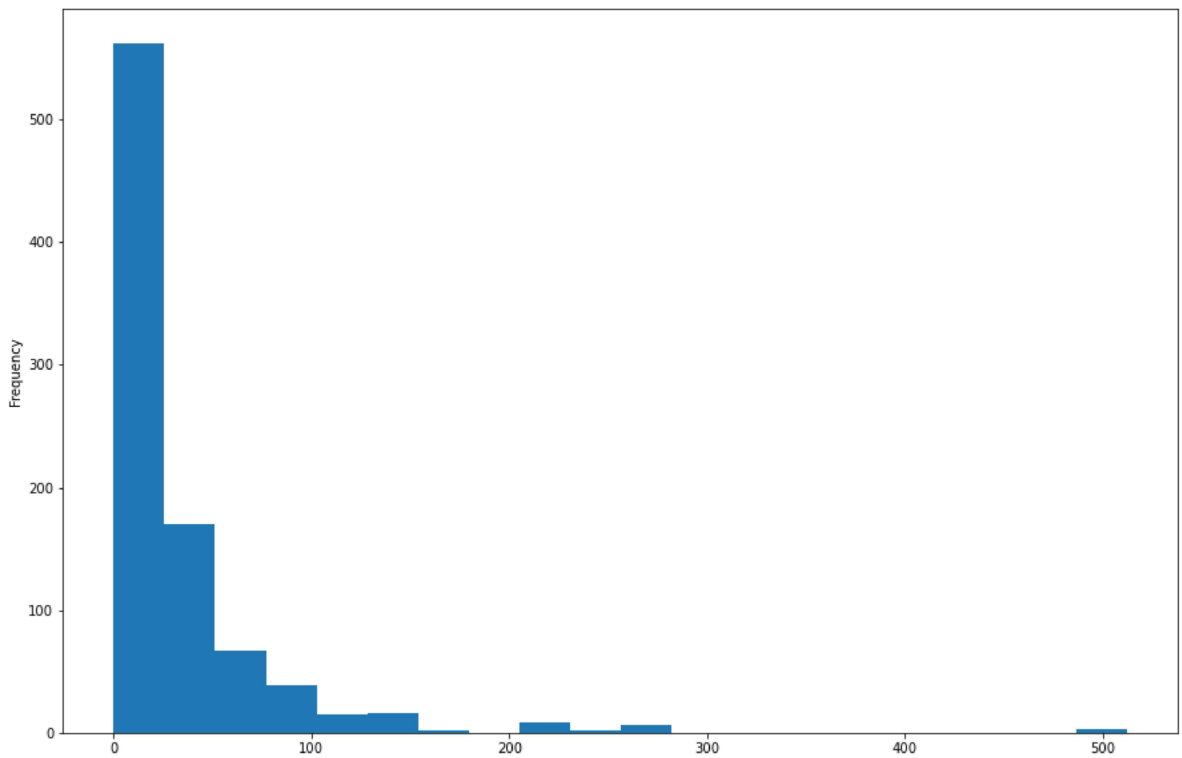


In [140]:

```
titanic_data['Fare'].plot.hist(bins=20,figsize=(15,10))
```

Out[140]:

<AxesSubplot:ylabel='Frequency'>



DATA WRANGLING OR DATA CLEANING

In [141]:

```
# FIRST WE CHECK THAT OUR DATA IS NULL OR NOT
```

In [142]:

```
titanic_data.isnull()
```

Out[142]:

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

891 rows × 12 columns

In [143]:

```
# true means null, false means not null
```

In [144]:

```
titanic_data.isnull().sum()
```

Out[144]:

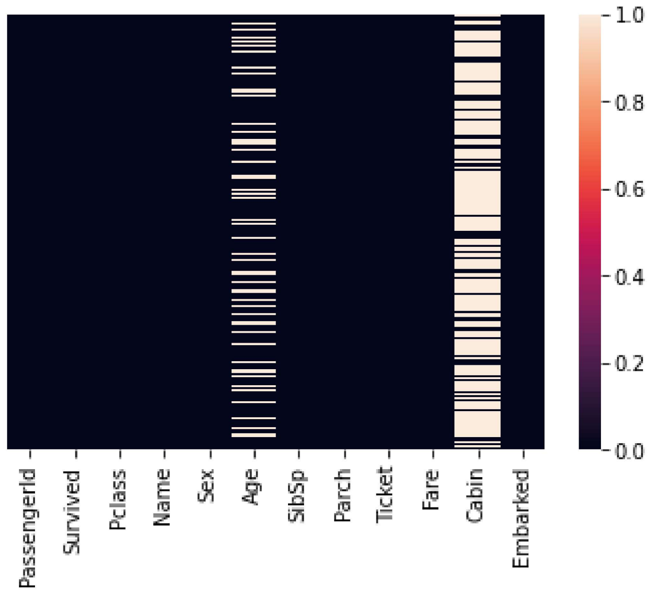
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [145]:

```
sns.heatmap(titanic_data.isnull(), yticklabels =False)
```

Out[145]:

<AxesSubplot:>



In [146]:

```
# from the above diagram you can see that 20% age data are emply are thee are large number
# we have to remove the Cabin column as there are 687 empty values

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

In [147]:

```
titanic_data.head()
```

Out[147]:

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

In [148]:

```
# we can see after all processes we can apply logistic regression to the survival column so
```

In [149]:

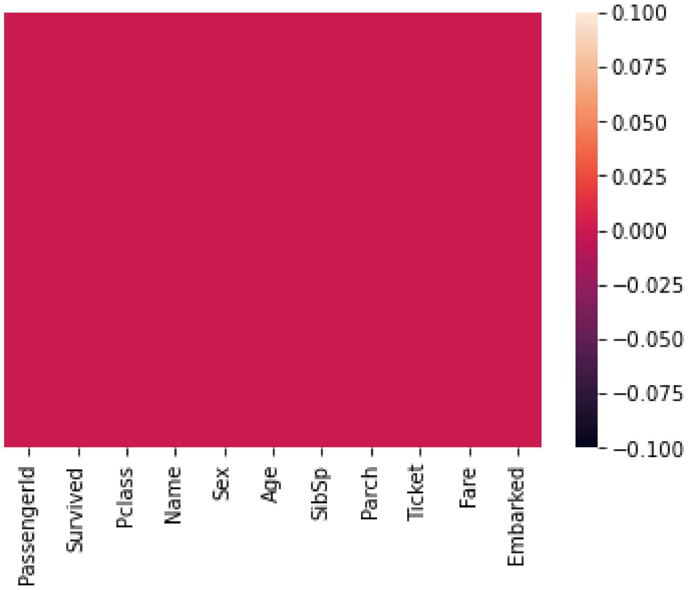
```
#we have to drop na values
titanic_data.dropna(inplace=True)
```

In [150]:

```
sns.heatmap(titanic_data.isnull(),yticklabels = False)
```

Out[150]:

```
<AxesSubplot:>
```



In [151]:

```
#now there is no null value
titanic_data.isnull().sum()
```

Out[151]:

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

In [152]:

```
titanic_data.describe()
```

Out[152]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	712.000000	712.000000	712.000000	712.000000	712.000000	712.000000	712.000000
mean	448.589888	0.404494	2.240169	29.642093	0.514045	0.432584	34.567251
std	258.683191	0.491139	0.836854	14.492933	0.930692	0.854181	52.938648
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	222.750000	0.000000	1.000000	20.000000	0.000000	0.000000	8.050000
50%	445.000000	0.000000	2.000000	28.000000	0.000000	0.000000	15.645850
75%	677.250000	1.000000	3.000000	38.000000	1.000000	1.000000	33.000000
max	891.000000	1.000000	3.000000	80.000000	5.000000	6.000000	512.329200

In [153]:

```
titanic_data.shape
```

Out[153]:

(712, 11)

In [154]:

```
# now you can see that data is reduced to 712 from 891, this is because we have dropped the
# whenever you train model by machine learning make sure that you have no string values bec
```

In [155]:

```
# we have to basically split sex column into male and female , lets do it
# we have inbuilt function "dummy variable" in pandas lets implement it
```

In [156]:

```
pd.get_dummies(titanic_data['Sex'])
```

Out[156]:

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

712 rows × 2 columns

In [157]:

```
# we can identify only one column to see weather it is male or female, so lets drop first c
```

In [158]:

```
sex = pd.get_dummies(titanic_data['Sex'],drop_first=True)
sex.head()
```

Out[158]:

	male
0	1
1	0
2	0
3	0
4	1

In [159]:

```
embark = pd.get_dummies(titanic_data['Embarked'],drop_first=True)
embark.head()
#we are dropping first because both 0-0 means that it is (C)
```

Out[159]:

	Q	S
0	0	1
1	0	0
2	0	1
3	0	1
4	0	1

In [160]:

```
Pcl = pd.get_dummies(titanic_data['Pclass'],drop_first=True)
Pcl.head()
#we are dropping first because both 0-0 means that it is (1)
```

Out[160]:

	2	3
0	0	1
1	0	0
2	0	1
3	0	0
4	0	1

In [161]:

```
#  NOW OUR NEXT STEP IS TO CONCATINATE ALL THESE VALUE INTO OUR DATASET
```

In [162]:

```
titanic_data = pd.concat([titanic_data,sex,Pcl,embark],axis = 1)
titanic_data.head()
```

Out[162]:

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

In [163]:

```
titanic_data.drop(['Pclass','Sex','Embarked','PassengerId','Name','Ticket'],axis=1,inplace=
```

In [164]:

```
titanic_data.head()
```

Out[164]:

	Survived	Age	SibSp	Parch	Fare	male	2	3	Q	S
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	0	0	1
4	0	35.0	0	0	8.0500	1	0	1	0	1

Train Data

In [165]:

```
X=titanic_data.drop('Survived',axis=1)
y=titanic_data['Survived']
# inplace is not used here because we are creating variable x and we have to return data in
# inplace true is used on same data set operation
# When inplace = True is used, it performs operation on data and nothing is returned. df.so
```

In [166]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

In [167]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)
```

In [168]:

```
#now we will create the instance og logistic regression
```

In [169]:

```
logmodel = LogisticRegression()
```

In [170]:

```
#now we will fit the data in our logistic model
```

In [171]:

```
logmodel.fit(X_train,y_train)
```

```
C:\Users\verma\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.p
y:763: 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 (https://scik
it-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-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)
  n_iter_i = _check_optimize_result(
```

Out[171]:

```
LogisticRegression()
```

In [172]:

```
predictions = logmodel.predict(X_test)
```

In [176]:

```
from sklearn.metrics import classification_report
```

In [177]:

```
classification_report(y_test,predictions)
```

Out[177]:

```
'              precision    recall  f1-score   support\n\n           0
0.79      0.82      0.81       136\n           1       0.74      0.71
0.73        99\n\n    accuracy                           0.77       235\n
macro avg       0.77      0.77      0.77       235\nweighted avg       0.77
0.77      0.77       235\n'
```

In [178]:

```
from sklearn.metrics import confusion_matrix
```

In [179]:

```
confusion_matrix(y_test,predictions)
```

Out[179]:

```
array([[112,  24],
       [ 29,  70]], dtype=int64)
```

In [180]:

```
#we can also check accuracy from confusion metrics but we have an inbuilt function in pytho
from sklearn.metrics import accuracy_score
```

In [181]:

```
accuracy_score(y_test,predictions)
```

Out[181]:

```
0.774468085106383
```