In [1]: 1 import pandas as pd
In [2]: 1 data=pd.read_csv("/home/placement/Downloads/Titanic Dataset.csv")#reading csv file
In [3]: 1 data.describe()

Out[3]:

	Passengerld	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
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [4]: 1 data.head(10)#display top 10 rows

Out[4]:

	Passengerld	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	С
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
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S
9	10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN	С

In [5]:

1 data

Out[5]:

	Passengerld	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	С
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
				•••								
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	С
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	Q

891 rows × 12 columns

```
In [6]:
            data.info()#null values shows
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 891 entries, 0 to 890
        Data columns (total 12 columns):
             Column
                           Non-Null Count Dtype
                                            _ _ _ _
              -----
             PassengerId 891 non-null
                                            int64
             Survived
                           891 non-null
         1
                                            int64
          2
             Pclass
                           891 non-null
                                           int64
          3
                           891 non-null
                                           obiect
             Name
                           891 non-null
         4
                                           obiect
              Sex
          5
             Age
                           714 non-null
                                           float64
                           891 non-null
                                           int64
         6
             SibSp
                                           int64
         7
             Parch
                           891 non-null
         8
                           891 non-null
                                           object
             Ticket
          9
             Fare
                           891 non-null
                                           float64
             Cabin
                           204 non-null
         10
                                           obiect
         11 Embarked
                           889 non-null
                                            object
        dtypes: float64(2), int64(5), object(5)
        memory usage: 83.7+ KB
          1 data.isna().sum()#no.of null values
In [7]:
Out[7]: PassengerId
                          0
        Survived
                          0
        Pclass
                          0
        Name
                          0
        Sex
                          0
                        177
        Age
        SibSp
                          0
        Parch
                          0
        Ticket
                          0
        Fare
                          0
        Cabin
                        687
        Embarked
                          2
```

dtype: int64

```
1 data['Pclass'].unique()#unique values
In [8]:
 Out[8]: array([3, 1, 2])
          1 data['Survived'].unique()
In [9]:
 Out[9]: array([0, 1])
In [10]:
          1 data['SibSp'].unique()
Out[10]: array([1, 0, 3, 4, 2, 5, 8])
In [11]:
          1 data['Age'].unique()
                                           nan, 54. , 2. , 27. , 14. ,
Out[11]: array([22. , 38. , 26. , 35. ,
                   , 58.
                                , 39. , 55. , 31.
                4.
                          , 20.
                                                   , 34.
                                                           , 15.
                          , 40. , 66. , 42. , 21.
                                                    , 18.
                                                    , 45.
                         , 65. , 28.5 , 5. , 11.
                                                           , 17.
               16. . 25.
                         , 0.83, 30. , 33. , 23.
                                                    , 24.
                                                           , 46.
               71. , 37. , 47. , 14.5 , 70.5 , 32.5 , 12.
               51. , 55.5 , 40.5 , 44. , 1. , 61.
                                                    , 56.
                                                           , 50.
               45.5 , 20.5 , 62. , 41. , 52. , 63. , 23.5 , 0.92, 43. ,
               60. , 10. , 64. , 13. , 48. , 0.75, 53. , 57. , 80. ,
               70. , 24.5 , 6. , 0.67, 30.5 , 0.42, 34.5 , 74. 1)
            datal=data.drop(['Cabin','Name','PassengerId','Ticket','SibSp','Parch'],axis=1)#deleting columns
In [12]:
```

In [13]:

1 data1

Out[13]:

	Survived	Pclass	Sex	Age	Fare	Embarked
0	0	3	male	22.0	7.2500	S
1	1	1	female	38.0	71.2833	С
2	1	3	female	26.0	7.9250	S
3	1	1	female	35.0	53.1000	S
4	0	3	male	35.0	8.0500	S
886	0	2	male	27.0	13.0000	S
887	1	1	female	19.0	30.0000	S
888	0	3	female	NaN	23.4500	S
889	1	1	male	26.0	30.0000	С
890	0	3	male	32.0	7.7500	Q

891 rows × 6 columns

In [14]:

1 data1.isna().sum()#finding null values
2

Out[14]: Survived

Survived 0
Pclass 0
Sex 0
Age 177
Fare 0
Embarked 2
dtype: int64

```
In [15]: 1 data1.shape#no of rows and columns
Out[15]: (891, 6)
In [16]: 1 data1['Sex']=data1['Sex'].map({'male':1,'female':0})#assinging 1 to male and 0 to female using map
In [17]: 1 data1
Out[17]:
```

	Survived	Pclass	Sex	Age	Fare	Embarked
0	0	3	1	22.0	7.2500	S
1	1	1	0	38.0	71.2833	С
2	1	3	0	26.0	7.9250	S
3	1	1	0	35.0	53.1000	S
4	0	3	1	35.0	8.0500	S
886	0	2	1	27.0	13.0000	S
887	1	1	0	19.0	30.0000	S
888	0	3	0	NaN	23.4500	S
889	1	1	1	26.0	30.0000	С
890	0	3	1	32.0	7.7500	Q

891 rows × 6 columns

```
In [43]: 1 datal=datal.fillna(datal.mean())#fill null values using mean
2
```

In [19]:

1 data1

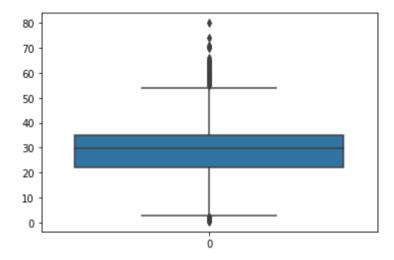
Out[19]:

	Survived	Pclass	Sex	Age	Fare	Embarked
0	0	3	1	22.000000	7.2500	S
1	1	1	0	38.000000	71.2833	С
2	1	3	0	26.000000	7.9250	S
3	1	1	0	35.000000	53.1000	S
4	0	3	1	35.000000	8.0500	S
886	0	2	1	27.000000	13.0000	S
887	1	1	0	19.000000	30.0000	S
888	0	3	0	29.699118	23.4500	S
889	1	1	1	26.000000	30.0000	С
890	0	3	1	32.000000	7.7500	Q

891 rows × 6 columns

In [20]: 1 import seaborn as sns
2 import matplotlib.pyplot as mp
3 sns.boxplot(data1.Age)#plotting for age

Out[20]: <AxesSubplot:>



200

100

1 mp.hist(data1['Fare'])#histograam for fare In [21]: Out[21]: (array([732., 106., 31., 2., 11., 6., 0., 0., 0., 3.]), array([0. , 51.23292, 102.46584, 153.69876, 204.93168, 256.1646 , 307.39752, 358.63044, 409.86336, 461.09628, 512.3292]), <BarContainer object of 10 artists>) 700 600 500 400 300 200 100 0

300

400

500

1 mp.hist(data1['Sex']) In [23]: Out[23]: (array([314., 0., 0., 0., 0., 0., 0., 0., 577.]), array([0., 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.]), <BarContainer object of 10 artists>) 600 500 400 300 200 100 0.2 0.4 0.6 0.8 1.0 0.0

```
1 data1['Age'].unique()
In [24]:
Out[24]: array([22.
                                            , 26.
                                                          , 35.
                                                                        , 29.69911765,
                              , 38.
                 54.
                              , 2.
                                            , 27.
                                                          , 14.
                                                                        , 4.
                 58.
                              , 20.
                                            , 39.
                                                          , 55.
                                                                        , 31.
                 34.
                              , 15.
                                            , 28.
                                                          , 8.
                                                                          19.
                              , 66.
                                            , 42.
                                                          , 21.
                 40.
                                                                        , 18.
                                            , 49.
                  3.
                                                          , 29.
                                                                          65.
                 28.5
                                5.
                                            , 11.
                                                          , 45.
                                                                        , 17.
                                            , 25.
                 32.
                                                          , 0.83
                              , 16.
                                                                          30.
                               23.
                                            , 24.
                 33.
                                                          , 46.
                                                                          59.
                 71.
                              , 37.
                                            , 47.
                                                          , 14.5
                                                                        , 70.5
                                            , 9.
                 32.5
                              , 12.
                                                          , 36.5
                                                                          51.
                 55.5
                              , 40.5
                                            , 44.
                                                          , 1.
                                                                        , 61.
                 56.
                              , 50.
                                            , 36.
                                                          , 45.5
                                                                        , 20.5
                 62.
                               41.
                                            , 52.
                                                          , 63.
                                                                          23.5
                                            , 60.
                  0.92
                              , 43.
                                                          , 10.
                                                                        , 64.
                 13.
                               48.
                                            , 0.75
                                                          , 53.
                                                                        , 57.
                 80.
                              , 70.
                                            , 24.5
                                                          , 6.
                                                                           0.67
                              , 0.42
                                            , 34.5
                                                          , 74.
                 30.5
                                                                        ])
```

Survived Pclass Sex Fare Embarked

In [25]: 1 data1.groupby(['Age']).count()#no of ages can be printed

Out[25]:

Age					
0.42	1	1	1	1	1
0.67	1	1	1	1	1
0.75	2	2	2	2	2
0.83	2	2	2	2	2
0.92	1	1	1	1	1
70.00	2	2	2	2	2
70.50	1	1	1	1	1
71.00	2	2	2	2	2
74.00	1	1	1	1	1
80.00	1	1	1	1	1

89 rows × 5 columns

```
In [26]: 1 data1['Pclass']=data1['Pclass'].map({1:'F',2:'S',3:'t'})#assigning values
```

In [27]:

1 data1

Out[27]:

	Survived	Pclass	Sex	Age	Fare	Embarked
0	0	t	1	22.000000	7.2500	S
1	1	F	0	38.000000	71.2833	С
2	1	t	0	26.000000	7.9250	S
3	1	F	0	35.000000	53.1000	S
4	0	t	1	35.000000	8.0500	S
886	0	S	1	27.000000	13.0000	S
887	1	F	0	19.000000	30.0000	S
888	0	t	0	29.699118	23.4500	S
889	1	F	1	26.000000	30.0000	С
890	0	t	1	32.000000	7.7500	Q

891 rows × 6 columns

In [28]:

data2=pd.get_dummies(data1)#where the pclass it shows"1" other pclass it shows "0" data2

Out[28]:

	Survived	Sex	Age	Fare	Pclass_F	Pclass_S	Pclass_t	Embarked_C	Embarked_Q	Embarked_S
0	0	1	22.000000	7.2500	0	0	1	0	0	1
1	1	0	38.000000	71.2833	1	0	0	1	0	0
2	1	0	26.000000	7.9250	0	0	1	0	0	1
3	1	0	35.000000	53.1000	1	0	0	0	0	1
4	0	1	35.000000	8.0500	0	0	1	0	0	1
								•••	•••	
886	0	1	27.000000	13.0000	0	1	0	0	0	1
887	1	0	19.000000	30.0000	1	0	0	0	0	1
888	0	0	29.699118	23.4500	0	0	1	0	0	1
889	1	1	26.000000	30.0000	1	0	0	1	0	0
890	0	1	32.000000	7.7500	0	0	1	0	1	0

891 rows × 10 columns

In [29]:

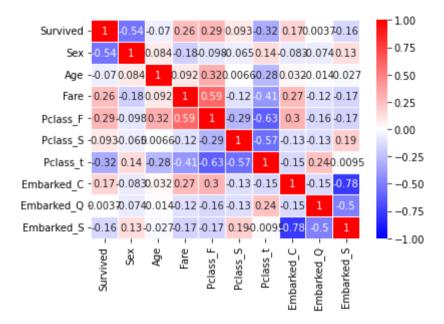
1 cor_mat=data2.corr()#correlation
2 cor_mat

Out[29]:

	Survived	Sex	Age	Fare	Pclass_F	Pclass_S	Pclass_t	Embarked_C	Embarked_Q	Embarked_S
Survived	1.000000	-0.543351	-0.069809	0.257307	0.285904	0.093349	-0.322308	0.168240	0.003650	-0.155660
Sex	-0.543351	1.000000	0.084153	-0.182333	-0.098013	-0.064746	0.137143	-0.082853	-0.074115	0.125722
Age	-0.069809	0.084153	1.000000	0.091566	0.319916	0.006589	-0.281004	0.032024	-0.013855	-0.027121
Fare	0.257307	-0.182333	0.091566	1.000000	0.591711	-0.118557	-0.413333	0.269335	-0.117216	-0.166603
Pclass_F	0.285904	-0.098013	0.319916	0.591711	1.000000	-0.288585	-0.626738	0.296423	-0.155342	-0.170379
Pclass_S	0.093349	-0.064746	0.006589	-0.118557	-0.288585	1.000000	-0.565210	-0.125416	-0.127301	0.192061
Pclass_t	-0.322308	0.137143	-0.281004	-0.413333	-0.626738	-0.565210	1.000000	-0.153329	0.237449	-0.009511
Embarked_C	0.168240	-0.082853	0.032024	0.269335	0.296423	-0.125416	-0.153329	1.000000	-0.148258	-0.778359
Embarked_Q	0.003650	-0.074115	-0.013855	-0.117216	-0.155342	-0.127301	0.237449	-0.148258	1.000000	-0.496624
Embarked_S	-0.155660	0.125722	-0.027121	-0.166603	-0.170379	0.192061	-0.009511	-0.778359	-0.496624	1.000000

In [30]: 1 import seaborn as reddy#plotting correlation
2 sns.heatmap(cor_mat,vmax=1,vmin=-1,annot=True,linewidth=.5,cmap='bwr')

Out[30]: <AxesSubplot:>



In [31]: 1 data2.groupby(['Survived']).count()

Out[31]:

Sex Age Fare Pclass_F Pclass_S Pclass_t Embarked_C Embarked_Q Embarked_S Survived 549 342 342

In [32]: 1 y=data2['Survived']
2 x=data2.drop('Survived',axis=1)

In [33]: 1 x

Out[33]:

	Sex	Age	Fare	Pclass_F	Pclass_S	Pclass_t	Embarked_C	Embarked_Q	Embarked_S
0	1	22.000000	7.2500	0	0	1	0	0	1
1	0	38.000000	71.2833	1	0	0	1	0	0
2	0	26.000000	7.9250	0	0	1	0	0	1
3	0	35.000000	53.1000	1	0	0	0	0	1
4	1	35.000000	8.0500	0	0	1	0	0	1
886	1	27.000000	13.0000	0	1	0	0	0	1
887	0	19.000000	30.0000	1	0	0	0	0	1
888	0	29.699118	23.4500	0	0	1	0	0	1
889	1	26.000000	30.0000	1	0	0	1	0	0
890	1	32.000000	7.7500	0	0	1	0	1	0

891 rows × 9 columns

```
In [34]:
          1 y
Out[34]: 0
                0
         2
                1
                0
         886
                0
         887
                1
         888
         889
                1
         890
         Name: Survived, Length: 891, dtype: int64
In [35]:
          1 from sklearn.model_selection import train_test_split#training and testing data
          2 x train,x test,y train,y test=train test split(x,y,test size=0.33,random state=42)
In [42]:
          1 from sklearn.linear model import LogisticRegression
          2 classifier = LogisticRegression()#logistic regression
             classifier.fit(x_train, y_train)
Out[42]: LogisticRegression()
          1 y pred=classifier.predict(x test)
In [37]:
```

```
In [38]:
          1 y pred
Out[38]: array([0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0,
                1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0,
                1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1,
                0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
                1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0,
                0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1,
                0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0,
                0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0,
                1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0,
                0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1,
                0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0,
                0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
                1, 0, 0, 0, 0, 0, 1, 1, 0])
In [39]:
          1 from sklearn.metrics import confusion matrix#confusing matrix
          2 confusion matrix(y test,y pred)
Out[39]: array([[154, 21],
                [ 37, 83]])
          1 from sklearn.metrics import accuracy_score#accuracy
In [40]:
          2 accuracy score(y test,y pred)
Out[40]: 0.8033898305084746
In [ ]:
```