# **Classification on Titanic Dataset**

# 1)Importing Libraries

```
In [1]:
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

# 2)Importing Dataset

```
In [2]:
```

```
df = pd.read_csv('test_s.csv')
df.head()
```

#### Out[2]:

	Passengerld	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embari
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	
1	2	1	1	Cumings, Mrs. John Bradley\r(Florence Briggs T	female	38.0	1	0	PC 17599	71.2833	C85	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2.\r3101282	7.9250	NaN	
3	4	1	1	Futrelle, Mrs. Jacques Heath\r(Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	
4												· ·

# 3) Data Preprocessing

```
In [3]:
```

```
df.describe()
```

# Out[3]:

assengerld	Survived	Pclass	Age	SibSp	Parch	Fare
876.000000	876.000000	876.000000	701.000000	876.000000	876.000000	876.000000
445.929224	0.384703	2.304795	29.719215	0.528539	0.385845	32.391794
257.600137	0.486803	0.836059	14.583577	1.110102	0.809645	50.020501
1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
222.750000	0.000000	2.000000	20.000000	0.000000	0.000000	7.917700
446.500000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
	876.000000 445.929224 257.600137 1.000000 222.750000	876.000000 876.000000 445.929224 0.384703 257.600137 0.486803 1.000000 0.000000 222.750000 0.000000	876.000000 876.000000 876.000000 445.929224 0.384703 2.304795 257.600137 0.486803 0.836059 1.000000 0.000000 1.000000 222.750000 0.000000 2.000000	876.000000 876.000000 876.000000 701.0000000 445.929224 0.384703 2.304795 29.719215 257.600137 0.486803 0.836059 14.583577 1.000000 0.000000 1.000000 0.420000 222.750000 0.000000 2.000000 20.000000	876.000000 876.000000 876.000000 701.000000 876.000000 445.929224 0.384703 2.304795 29.719215 0.528539 257.600137 0.486803 0.836059 14.583577 1.110102 1.000000 0.000000 1.000000 0.420000 0.0000000 222.750000 0.000000 2.000000 20.000000 0.0000000	876.000000 876.000000 876.000000 701.000000 876.000000 876.000000 445.929224 0.384703 2.304795 29.719215 0.528539 0.385845 257.600137 0.486803 0.836059 14.583577 1.110102 0.809645 1.000000 0.000000 1.000000 0.420000 0.000000 0.000000 0.000000 0.000000

```
75% Passengerid
                                          38.000000
                                                                            31.068750
                                                      1.000000
                    $000000
                                                                  6.000000 512.329200
      891.000000
                    1.000000
                               3.000000
                                         80.000000
                                                      8.000000
max
```

## In [4]:

df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 876 entries, 0 to 875 Data columns (total 12 columns): # Column Non-Null Count Dtype \_\_\_ -----O PassengerId 876 non-null int64 1 Survived 876 non-null int64 2 Pclass 876 non-null int64 3 Name 876 non-null object 876 non-null object 4 Sex 5 Age 701 non-null float64 6 SibSp 876 non-null int64 876 non-null 7 Parch int64 object float64 8 Ticket 876 non-null 9 Fare 876 non-null 10 Cabin object object 202 non-null

memory usage: 82.2+ KB

## In [5]:

df[df.isnull().any(axis=1)]

11 Embarked 874 non-null

dtypes: float64(2), int64(5), object(5)

# Out[5]:

	Passengerld	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Eml
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2.\r3101282	7.9250	NaN	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	
869	885	0	3	Sutehall, Mr. Henry Jr	male	25.0	0	0	SOTON/OQ\r392076	7.0500	NaN	
870	886	0	3	Rice, Mrs. William (Margaret\rNorton)	female	39.0	0	5	382652	29.1250	NaN	
871	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	
873	889	0	3	Johnston, Miss. Catherine Helen∖r"Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	
875	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	

#### 695 rows × 12 columns

In [6]:

4

df.isnull().values.any()

Out[6]:

Trup

1 L U C

#### In [7]:

```
df.isnull().sum()
```

#### Out[7]:

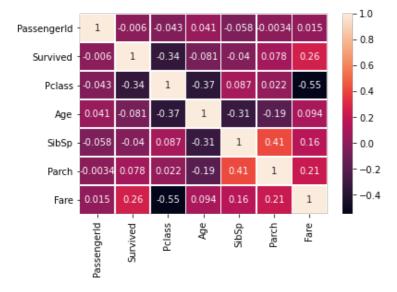
PassengerId 0 Survived 0 Pclass 0 0 Name Sex 0 175 Age 0 SibSp 0 Parch Ticket 0 Fare 0 Cabin 674 Embarked 2 dtype: int64

# In [8]:

sns.heatmap(df.corr(), annot=True, linewidth = 0.5)

### Out[8]:

<matplotlib.axes. subplots.AxesSubplot at 0x132ca76e9c8>

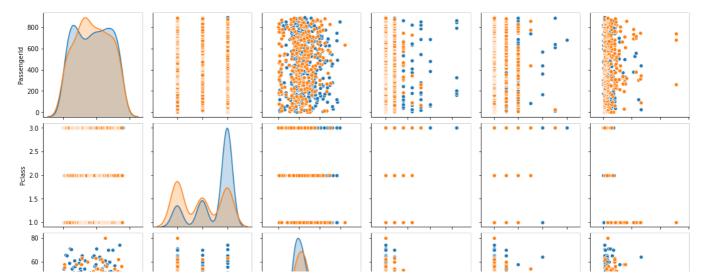


# In [9]:

sns.pairplot(df,hue = 'Survived',dropna = True)

# Out[9]:

<seaborn.axisgrid.PairGrid at 0x132caae98c8>



```
∯ 40
  20
 500
  400
  300
                                                    2.5
SibSp
        Passengerld
In [10]:
df.drop(['PassengerId', 'Name', 'Ticket', 'Cabin'],axis = 1,inplace = True)
In [11]:
df = df.dropna(subset =['Embarked', 'Age'])
In [12]:
df.isnull().sum()
Out[12]:
Survived
Pclass
Sex
             0
             0
Age
             0
SibSp
Parch
Fare
Embarked
dtype: int64
In [13]:
df.isnull().values.any()
Out[13]:
False
In [14]:
IQR Age = df['Age'].quantile(0.75) - df['Age'].quantile(0.25)
print(IQR Age)
Upper_OutlierLimit_Age = df['Age'].quantile(0.75) + 1.5*IQR_Age
Lower OutlierLimit Age = df['Age'].quantile(0.25) - 1.5*IQR Age
```

print(Upper\_OutlierLimit\_Age)
print(Lower OutlierLimit Age)

OutlierValues Age

'Age']<=Lower\_OutlierLimit\_Age)]</pre>

OutlierValues Age = df[(df['Age']>=Upper OutlierLimit Age) | (df[

```
18.0
65.0
-7.0
```

### Out[14]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
33	0	2	male	66.0	0	0	10.5000	s
53	0	1	male	65.0	0	1	61.9792	С
95	0	1	male	71.0	0	0	34.6542	С
114	0	3	male	70.5	0	0	7.7500	Q
276	0	3	male	65.0	0	0	7.7500	Q
448	0	1	male	65.0	0	0	26.5500	s
485	0	1	male	71.0	0	0	49.5042	С
619	1	1	male	80.0	0	0	30.0000	s
661	0	2	male	70.0	0	0	10.5000	s
732	0	1	male	70.0	1	1	71.0000	s
836	0	3	male	74.0	0	0	7.7750	S

#### In [15]:

```
df.loc[df.Age > 54.5, 'Age'] = df['Age'].quantile(0.95)
df.loc[df.Age < 2.5, 'Age'] = df['Age'].quantile(0.05)</pre>
```

### In [16]:

```
IQR_Fare = df['Fare'].quantile(0.75) - df['Fare'].quantile(0.25)
print(IQR_Fare)
Upper_OutlierLimit_Fare = df['Fare'].quantile(0.75) + 1.5*IQR_Fare
Lower_OutlierLimit_Fare = df['Fare'].quantile(0.25) - 1.5*IQR_Fare
print(Upper_OutlierLimit_Fare)
print(Lower_OutlierLimit_Fare)
OutlierValues_Fare = df[(df['Fare']>=Upper_OutlierLimit_Fare) | (df['Fare']<=Lower_OutlierLimit_Fare)]
OutlierValues_Fare</pre>
```

24.95 70.425

-29.374999999999996

#### Out[16]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked
1	1	1	female	38.0	1	0	71.2833	С
27	0	1	male	19.0	3	2	263.0000	s
34	0	1	male	28.0	1	0	82.1708	С
61	0	1	male	45.0	1	0	83.4750	s
71	0	2	male	21.0	0	0	73.5000	s
788	1	1	male	11.0	1	2	120.0000	s
806	1	1	female	52.0	1	1	93.5000	s
821	1	1	female	39.0	1	1	83.1583	С
841	1	1	female	45.0	1	1	164.8667	s
864	1	1	female	56.0	0	1	83.1583	С

#### 94 rows × 8 columns

```
In [17]:
df.loc[df.Fare > 65.795325, 'Fare'] = df['Fare'].quantile(0.95)
df.loc[df.Fare < -26.808875000000004, 'Fare'] = df['Fare'].quantile(0.05)</pre>
In [18]:
obj = df.dtypes == np.object
df.columns[obj]
Out[18]:
Index(['Sex', 'Embarked'], dtype='object')
In [19]:
dummydf = pd.DataFrame()
for i in df.columns[obj]:
    dummy = pd.get_dummies(df[i], drop_first=True)
    dummydf = pd.concat([dummydf, dummy], axis=1)
print(dummydf)
     male Q S
0
       1 0 1
1
        0 0 0
2
        0 0
             1
3
       0 0 1
4
       1
          0 1
      . . .
          . .
870
      0 1
             0
871
       1
          0
             1
872
       0
          0
              1
874
       1 0
             0
875
       1 1 0
[699 rows x 3 columns]
In [20]:
df = pd.concat([df,dummydf], axis=1)
In [21]:
dataset = df[['Pclass','Age','SibSp','Parch','Fare','male','Q','S','Survived']]
In [22]:
dataset.head(10)
Out[22]:
```

	Pclass	Age	SibSp	Parch	Fare	male	Q	S	Survived
0	3	22.0	1	0	7.2500	1	0	1	0
1	1	38.0	1	0	120.0000	0	0	0	1
2	3	26.0	0	0	7.9250	0	0	1	1
3	1	35.0	1	0	53.1000	0	0	1	1
4	3	35.0	0	0	8.0500	1	0	1	0
6	1	54.0	0	0	51.8625	1	0	1	0
7	3	4.0	3	1	21.0750	1	0	1	0
8	3	27.0	0	2	11.1333	0	0	1	1
9	2	14.0	1	0	30.0708	0	0	0	1
10	3	4.0	1	1	16.7000	0	0	1	1

```
In [23]:
dataset.shape
Out[23]:
(699, 9)
4) Creating X and Y variables
In [24]:
X = dataset.iloc[:,:-1].values
Out[24]:
array([[ 3., 22., 1., ...,
                            1.,
                                  0., 1.],
       [ 1., 38.,
                             0.,
                                  0.,
                  1., ...,
                                      0.],
       [ 3., 26.,
                             0.,
                                  0.,
                  0., ...,
                                       1.],
       [ 1., 19.,
                  0., ...,
                             0.,
                                  0.,
                                     1.],
       [1., 26., 0., ..., 1., 0., 0.],
       [ 3., 32., 0., ..., 1.,
                                 1.,
In [25]:
y = dataset.iloc[:,-1].values
У
Out[25]:
\texttt{array}([0,\ 1,\ 1,\ 1,\ 0,\ 0,\ 0,\ 1,\ 1,\ 1,\ 1,\ 0,\ 0,\ 0,\ 1,\ 0,\ 0,\ 1,\ 1,\ 1,\ 0,
       1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0,
       0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1,
       0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0,
       0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0,
       0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0,
       1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1,
       1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0,
       0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1,
                                                                      1.
       0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0,
       0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1,
                                                                      1,
       1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1,
       0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0,
       1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0,
       0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0,
       0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0,
       0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
       1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0,
       0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0,
       1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1,
       0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1,
       0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0], dtype=int64)
```

# 5) Splitting into Train & Test Data

In [26]:

```
from sklearn.model selection import train test split
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state
In [27]:
X train
Out [27]:
array([[ 3., 3.,
                   3., ...,
                             0.,
      [ 2., 17.,
                   0., ...,
                             0.,
                                  0.,
                                       1.],
                             1.,
       [ 2., 56.,
                   0., ...,
                                  1.,
                                       0.],
       . . . ,
       [ 3., 31.,
                   0., ...,
                             1.,
                                  0.,
                                      1.],
       [ 2., 27.,
                             0.,
                                  0.,
                  0., ...,
                                      1.],
       [ 2., 28.,
                             0.,
                                  0.,
                  1., ...,
                                      0.]])
In [28]:
y train
Out[28]:
array([0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0,
       0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0,
       1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
       1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0,
       1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0,
       0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0,
      1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0,
      1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1,
      0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0,
      0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0,
      1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1,
      0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
      0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1,
      0, 1,
            1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1,
      0, 0,
               0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1,
            1,
      0, 1,
               0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1,
            Ο,
                                                          0, 0, 0,
      0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0,
      1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0,
       0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0,
       1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0,
       1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1,
       0, 1, 0, 1, 0, 0, 0, 1, 1], dtype=int64)
In [29]:
X test
Out[29]:
array([[ 3., 26.,
                   1., ...,
                             0.,
                                  0.,
                                       1.],
                                  0.,
       [ 2., 25.,
                             1.,
                                       0.],
                   1., ...,
       [ 2., 21.,
                   0., ...,
                             0.,
                                  0.,
                                       1.],
                             1.,
                                       1.],
       [ 3., 18.,
                   0., ...,
                                  0.,
       [ 1., 27.,
                  0., ..., 1.,
                                  0.,
       [ 1., 45.,
                  1., ..., 1., 0.,
In [30]:
y_test
Out[30]:
array([0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1,
       0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1,
       0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0,
```

```
0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 1, 1, 0, 1, 0], dtype=int64)
In [31]:
from sklearn.preprocessing import StandardScaler
sc X = StandardScaler()
X train = sc X.fit transform(X train)
X test = sc X.transform(X test)
In [32]:
X train
Out[32]:
array([[ 0.89943714, -1.92529953, 2.7498332 , ..., -1.35556758,
        -0.21180135, 0.52837127],
       [-0.29482738, -0.90840042, -0.55825165, ..., -1.35556758,
       -0.21180135, 0.52837127],
       [-0.29482738, 1.92438996, -0.55825165, ..., 0.73769838,
        4.72140516, -1.89260857],
       [0.89943714, 0.10849869, -0.55825165, ..., 0.73769838,
       -0.21180135, 0.52837127],
       [-0.29482738, -0.18204391, -0.55825165, ..., -1.35556758,
       -0.21180135, 0.52837127],
       [-0.29482738, -0.10940826, 0.5444433, ..., -1.35556758,
       -0.21180135, -1.89260857]])
In [33]:
X test
Out[33]:
array([[ 0.89943714, -0.25467956, 0.5444433 , ..., -1.35556758,
       -0.21180135, 0.52837127],
       [-0.29482738, -0.32731521, 0.5444433, ..., 0.73769838,
       -0.21180135, -1.89260857],
       [-0.29482738, -0.61785782, -0.55825165, ..., -1.35556758,
       -0.21180135, 0.52837127],
       [0.89943714, -0.83576477, -0.55825165, ..., 0.73769838,
       -0.21180135, 0.52837127],
       [-1.4890919, -0.18204391, -0.55825165, ..., 0.73769838,
       -0.21180135, 0.52837127],
       [-1.4890919 , 1.1253978 , 0.5444433 , ..., 0.73769838,
        -0.21180135, 0.52837127]])
6) Building the Model and Testing Accuracy
a)Logistic Regression
In [34]:
from sklearn.linear model import LogisticRegression
lr = LogisticRegression()
lr.fit(X train, y train)
Out[34]:
LogisticRegression()
```

In [35]:

y pred = lr.predict(X test)

```
y_pred
Out[35]:
array([1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1,
       0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0,
       0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0,
       1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0,
       1, 1, 1, 1, 0, 0, 1, 0], dtype=int64)
In [36]:
y_test
Out[36]:
array([0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1,
       0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1,
       0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0,
       0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0,
       0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 1, 1, 1, 0, 1, 0], dtype=int64)
In [37]:
from sklearn.metrics import confusion matrix
confusion = confusion matrix(y test, y pred)
print(confusion)
[[69 7]
 [15 49]]
In [38]:
from sklearn import metrics
metrics.accuracy_score(y_test, y_pred)
Out[38]:
0.8428571428571429
Accuracy of Logistic Regression Model: 0.8428571428571429
```

# b)K Nearest Neighbours Classification

```
In [39]:
```

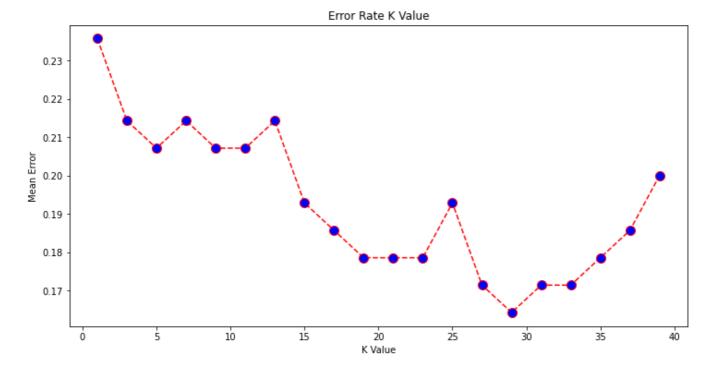
```
from sklearn.neighbors import KNeighborsClassifier
error = []
accuracy = []

# Calculating error for K values between 1 and 40
for i in range(1,40,2):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train, y_train)
    pred_i = knn.predict(X_test)
    error.append(np.mean(pred_i != y_test))
    accuracy.append(metrics.accuracy_score(y_test, pred_i))
```

#### In [40]:

# Out[40]:

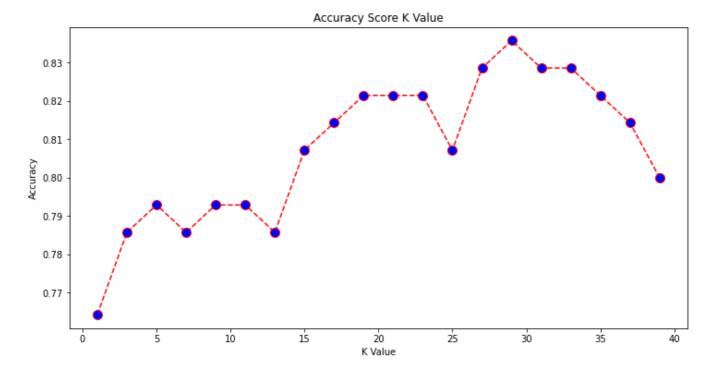
Text(0, 0.5, 'Mean Error')



# In [41]:

#### Out[41]:

Text(0, 0.5, 'Accuracy')



## In [42]:

```
knn = KNeighborsClassifier(n_neighbors = 30, metric = 'minkowski', p = 2)
knn.fit(X_train, y_train)
```

### Out[42]:

KNeighborsClassifier(n neighbors=30)

```
y pred = knn.predict(X_test)
y pred
Out[43]:
array([0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1,
       1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0,
       0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0,
       1, 1, 1, 1, 0, 0, 0], dtype=int64)
In [44]:
confusion matrix(y_test, y_pred)
Out[44]:
array([[69, 7],
       [18, 46]], dtype=int64)
In [45]:
print(metrics.classification_report(y_test, y_pred))
              precision recall f1-score support
                   0.79
                            0.91
                                                   76
           0
                                       0.85
           1
                   0.87
                             0.72
                                       0.79
                                                   64
                                       0.82
                                                 140
   accuracy
                                      0.82
   macro avg
                  0.83
                             0.81
                                                 140
weighted avg
                  0.83
                             0.82
                                      0.82
                                                 140
In [46]:
metrics.accuracy score(y test, y pred)
Out[46]:
0.8214285714285714
Accuracy of KNN Classification Model: 0.8214285714285714
c)Decision Tree Classifier
In [47]:
from sklearn.tree import DecisionTreeClassifier
clf = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)
clf.fit(X_train, y_train)
y pred = clf.predict(X test)
y pred
Out[47]:
array([0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1,
       0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1,
       1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0,
       0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0,
       1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0,
       1, 1, 1, 1, 0, 0, 1, 1], dtype=int64)
```

In [43]:

Tn [481.

```
Out[48]:
array([[65, 11],
      [18, 46]], dtype=int64)
In [49]:
import graphviz
from sklearn import tree
from PIL import Image
dot data = tree.export graphviz(clf,
                                 out file=None,
                                 filled=True,
                                 rounded=True,
                                 max depth = 6,
                                 special characters=True,
                                feature names = ['Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'm
ale','Q','S'])
graph = graphviz.Source(dot_data, format = "png")
graph.render('sample', view=True)
graph
Out[49]:
In [50]:
print(metrics.classification_report(y_test, y_pred))
              precision recall f1-score support
           0
                   0.78
                             0.86
                                        0.82
                                                    76
           1
                   0.81
                             0.72
                                        0.76
                                                    64
                                        0.79
    accuracy
                                                   140
                             0.79
   macro avg
                   0.80
                                        0.79
                                                   140
                   0.79
                             0.79
                                        0.79
                                                   140
weighted avg
In [51]:
metrics.accuracy_score(y_test, y_pred)
Out[51]:
0.7928571428571428
Accuracy of Decision Tree Classification Model: 0.7928571428571428
d)Random Forest Classifier
In [52]:
from sklearn.ensemble import RandomForestClassifier
clf =RandomForestClassifier(n estimators = 20, criterion = 'entropy', random state = 0)
clf.fit(X train, y train)
y pred = clf.predict(X test)
y_pred
Out[52]:
array([1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1,
       0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0,
       0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0,
```

\_\_\_\_\_.

confusion matrix (y test, y pred)

```
1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0], dtype=int64)
```

### In [53]:

```
confusion_matrix(y_test, y_pred)
```

### Out[53]:

```
array([[62, 14], [19, 45]], dtype=int64)
```

## In [54]:

print(metrics.classification report(y test, y pred))

	precision	recall	f1-score	support
0	0.77	0.82	0.79	76
1	0.76	0.70	0.73	64
accuracy			0.76	140
macro avg	0.76	0.76	0.76	140
weighted avg	0.76	0.76	0.76	140

### In [55]:

```
metrics.accuracy score(y test, y pred)
```

#### Out[55]:

0.7642857142857142

Accuracy of Random Forest Classification Model: 0.7642857142857142

# **CONCLUSION:**

From the above observations, it is obvious that Logistic Regression performs well on the titanic dataset model and gives the highest accuracy of 84%. So, LOGISTIC REGRESSION IS THE BEST MODEL