Titanic_CaseStudy_18BCS6033

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1 Case Study on Titanic: Machine Learning from Disaster.

1.1 Karan Trehan

1.1.1 18BCS6033

1.1.2 18AITAIML1 - Group B

[1]:
```
# Supress Warnings
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```python
#Data analysis
import pandas as pd
import numpy as np

#Statistical Libraries
from sklearn.preprocessing import MinMaxScaler
import statsmodels.api as sm
import scipy.stats as st
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.feature_selection import RFE
from sklearn.svm import SVR

from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score

#Machine Learning
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier

#Data Visualization
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set_palette('bright')
sns.set_style("darkgrid")
```

[3]:
```python
#Reading the Datasets into two separate DataFrames 'train_df' and 'test_df'
train_df = pd.read_csv('train.csv')
test_df = pd.read_csv('test.csv')
```

[4]:
```python
#Taking a look at the first 5 rows of training data.
train_df.head()
```

[4]:
```
   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
```

[5]:
```
#Taking a look at the first 5 rows of testing data.
test_df.head()
```

[5]:
```
   PassengerId  Pclass                                          Name     Sex  \
0          892       3                              Kelly, Mr. James    male
1          893       3              Wilkes, Mrs. James (Ellen Needs)  female
2          894       2                     Myles, Mr. Thomas Francis    male
3          895       3                              Wirz, Mr. Albert    male
4          896       3  Hirvonen, Mrs. Alexander (Helga E Lindqvist)  female

    Age  SibSp  Parch   Ticket     Fare Cabin Embarked
0  34.5      0      0   330911   7.8292   NaN        Q
1  47.0      1      0   363272   7.0000   NaN        S
2  62.0      0      0   240276   9.6875   NaN        Q
3  27.0      0      0   315154   8.6625   NaN        S
4  22.0      1      1  3101298  12.2875   NaN        S
```

[6]:
```
#Checking information about the Training DataFrame
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId    891 non-null int64
Survived       891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            714 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Cabin          204 non-null object
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

[7]:
```
#Checking information about the Testing DataFrame
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
PassengerId    418 non-null int64
Pclass         418 non-null int64
Name           418 non-null object
Sex            418 non-null object
Age            332 non-null float64
SibSp          418 non-null int64
Parch          418 non-null int64
Ticket         418 non-null object
Fare           417 non-null float64
Cabin          91 non-null object
Embarked       418 non-null object
dtypes: float64(2), int64(4), object(5)
memory usage: 36.0+ KB
```

[8]:

```python
#Viewing the Statistical Measures/Details of the Training DataFrame
train_df.describe()
```

[8]:

```
       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
```

[9]:

```python
#Viewing the Statistical Measures/Details of the Testing DataFrame
test_df.describe()
```

[9]:

```
       PassengerId      Pclass         Age       SibSp       Parch        Fare
count   418.000000  418.000000  332.000000  418.000000  418.000000  417.000000
mean   1100.500000    2.265550   30.272590    0.447368    0.392344   35.627188
std     120.810458    0.841838   14.181209    0.896760    0.981429   55.907576
min     892.000000    1.000000    0.170000    0.000000    0.000000    0.000000
```

```
25%     996.250000    1.000000   21.000000    0.000000    0.000000    7.895800
50%    1100.500000    3.000000   27.000000    0.000000    0.000000   14.454200
75%    1204.750000    3.000000   39.000000    1.000000    0.000000   31.500000
max    1309.000000    3.000000   76.000000    8.000000    9.000000  512.329200
```

1.2 Checking for Missing and Duplicated Values

[10]:
```
#Checking for duplicacy in both the DataFrames using '.duplicated()' method and␣
↪then checking the number of rows using
# '.shape[0]'
print("Number of Duplicate Rows in Training DataFrame:" , train_df[train_df.
↪duplicated()].shape[0])
print("Number of Duplicate Rows in Testing DataFrame:" , test_df[test_df.
↪duplicated()].shape[0])
```

```
Number of Duplicate Rows in Training DataFrame: 0
Number of Duplicate Rows in Testing DataFrame: 0
```

[11]:
```
#Checking the Percentage of Columns having Missing Values in both the DataFrames
print('-+-'*10)
print('Training Data')
print(round(train_df.isnull().sum()/len(train_df)*100,2))
print('-+-'*10)
print('Testing Data')
print(round(test_df.isnull().sum()/len(test_df)*100,2))
print('-+-'*10)
```

```
-+--+--+--+--+--+--+--+--+--+-
Training Data
PassengerId     0.00
Survived        0.00
Pclass          0.00
Name            0.00
Sex             0.00
Age            19.87
SibSp           0.00
Parch           0.00
Ticket          0.00
Fare            0.00
Cabin          77.10
Embarked        0.22
dtype: float64
-+--+--+--+--+--+--+--+--+--+-
Testing Data
PassengerId     0.00
Pclass          0.00
Name            0.00
Sex             0.00
```

```
Age            20.57
SibSp           0.00
Parch           0.00
Ticket          0.00
Fare            0.24
Cabin          78.23
Embarked        0.00
dtype: float64
-+--+--+--+--+--+--+--+--+--+-
```

[12]:
```
#Dropping 'cabin' variable because it has 77.10% and 78.23% missing values in␣
 ↪'train_df' and 'test_df' respectively
train_df.drop(columns=['Cabin'],axis=1,inplace=True)
test_df.drop(columns=['Cabin'],axis=1,inplace=True)
```

[13]:
```
#Grouping the DataFrames according to their 'Pclass' and their 'Sex'.
#After Grouping, calculating the median 'Age' based on the above mentioned␣
 ↪features.
print('-+-'*10)
print('Training Data')
print(train_df.groupby(['Pclass', 'Sex']).median()['Age'])
print('-+-'*10)
print('Testing Data')
print(test_df.groupby(['Pclass', 'Sex']).median()['Age'])
print('-+-'*10)
```

```
-+--+--+--+--+--+--+--+--+--+-
Training Data
Pclass  Sex
1       female    35.0
        male      40.0
2       female    28.0
        male      30.0
3       female    21.5
        male      25.0
Name: Age, dtype: float64
-+--+--+--+--+--+--+--+--+--+-
Testing Data
Pclass  Sex
1       female    41.0
        male      42.0
2       female    24.0
        male      28.0
3       female    22.0
        male      24.0
Name: Age, dtype: float64
-+--+--+--+--+--+--+--+--+--+-
```

[14]:
```
#Filling the Missing Values in 'Age' column based on the median values␣
↪calculated in the above cell.
train_df['Age'] = train_df.groupby(['Pclass', 'Sex'])['Age'].apply(lambda a:a.
↪fillna(a.median()))
test_df['Age'] = test_df.groupby(['Pclass', 'Sex'])['Age'].apply(lambda a:a.
↪fillna(a.median()))

#Filling the Missing Values in 'Embarked' column based on the mode value.
mode = train_df['Embarked'].mode()
train_df['Embarked'] = train_df['Embarked'].fillna(str(mode[0]))

#Filling the Missing Values in 'Fare' column based on the median value.
test_df['Fare'] = test_df['Fare'].fillna(test_df['Fare'].median())
```

[15]:
```
#Again Checking the Percentage of Columns having Missing Values in case all the␣
↪values have not been imputed.
print('-+-'*10)
print('Training Data')
print(round(train_df.isnull().sum()/len(train_df)*100,2))
print('-+-'*10)
print('Testing Data')
print(round(test_df.isnull().sum()/len(test_df)*100,2))
print('-+-'*10)
```

```
-+--+--+--+--+--+--+--+--+--+-
Training Data
PassengerId    0.0
Survived       0.0
Pclass         0.0
Name           0.0
Sex            0.0
Age            0.0
SibSp          0.0
Parch          0.0
Ticket         0.0
Fare           0.0
Embarked       0.0
dtype: float64
-+--+--+--+--+--+--+--+--+--+-
Testing Data
PassengerId    0.0
Pclass         0.0
Name           0.0
Sex            0.0
Age            0.0
SibSp          0.0
Parch          0.0
```

```
Ticket          0.0
Fare            0.0
Embarked        0.0
dtype: float64
-+--+--+--+--+--+--+--+--+--+-
```

1.3 Data Cleaning and Wrangling

[16]:
```python
#Dropping 'Ticket' and 'Name' columns.
train_df.drop(columns=['Ticket','Name'],axis=1,inplace=True)
test_df.drop(columns=['Ticket','Name'],axis=1,inplace=True)
```

- Dropping the column 'Ticket' because it has both numeric and categorical values and is of no use. It will not yield good results.
- Dropping 'Name' because we have unique values in it and is not of much use. 'Sex' variable will be more handy in this scenario

[17]:
```python
#Combining the 'SibSp' , 'Parch' and the person's own count to create a new␣
 ↪'Family' variable.
train_df['Family'] = train_df['SibSp'] + train_df['Parch'] + 1
test_df['Family'] = test_df['SibSp'] + test_df['Parch'] + 1
```

[18]:
```python
#Calculating Fare Per Person
train_df['FarePP'] = train_df['Fare']/train_df['Family']
test_df['FarePP'] = test_df['Fare']/test_df['Family']
```

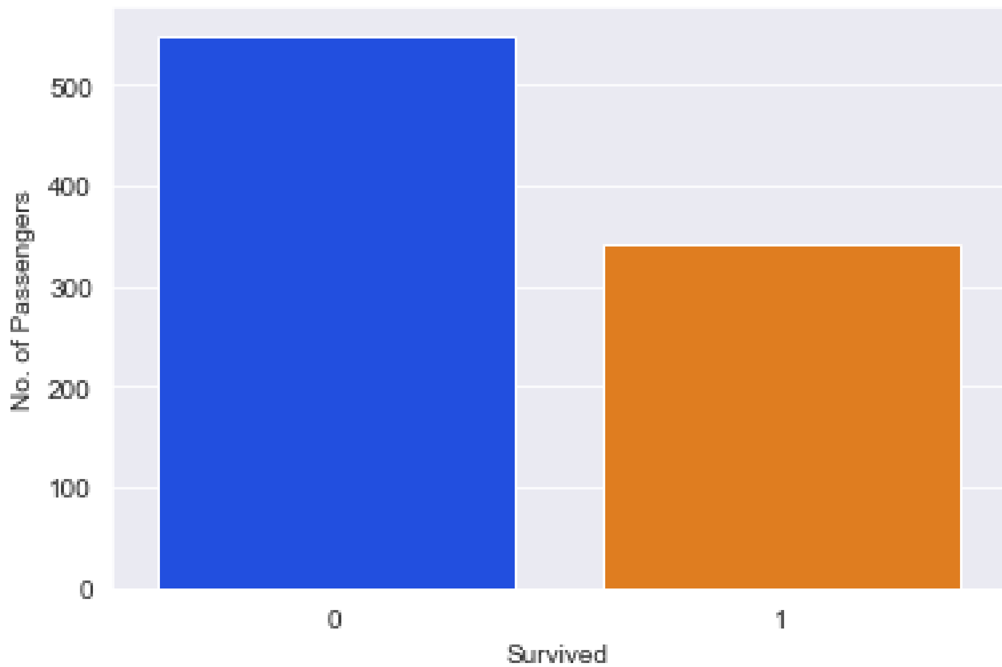
[19]:
```python
#Dropping 'SibSp','Parch' and 'Fare' columns as new columns have been created.
train_df.drop(columns=['SibSp','Parch','Fare'],axis=1,inplace=True)
test_df.drop(columns=['SibSp','Parch','Fare'],axis=1,inplace=True)
```

1.4 Exploratory Data Analysis

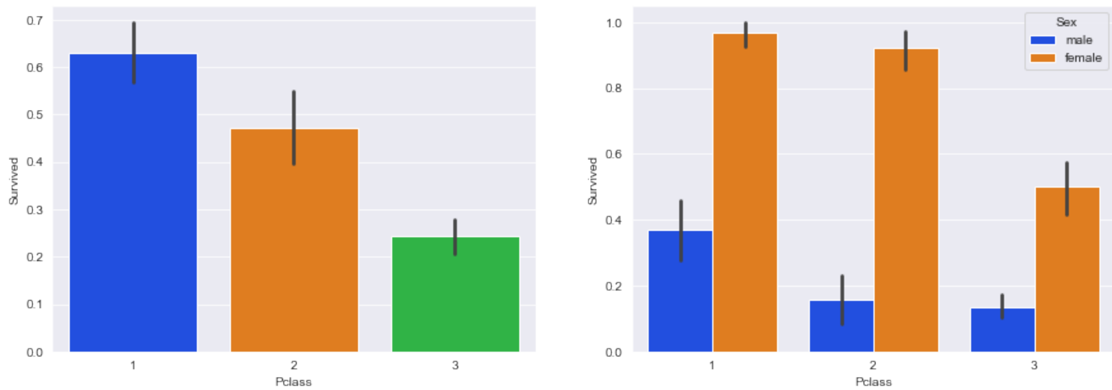
[20]:
```python
#Plotting PairPlot to check the relations among the Variables
sns.pairplot(data=train_df,hue='Survived')
plt.show()
```

- Fare and Age are continuous in Nature.
- PassengerId is discrete in Nature.
- Family and Pclass are ordinal in nature.
- Sex and Embarked are categorical in Nature.
- Survived is the Dependent Variable

[21]:
```
#Creating a Dataframe based on the number of people who survived and who did not.
sur = train_df.groupby('Survived')['Survived'].count().to_frame()
sur.rename(columns={'Survived' : 'No. of Passengers'} , inplace = True)
sns.barplot(data=sur, x=sur.index , y = 'No. of Passengers')
plt.show()
```



[22]:
```
#Plotting 'Pclass' vs 'Survived' Graph to see how many people survived from each␣
↪class.
fig, axs = plt.subplots(1,2,figsize = (15,5))
sns.barplot(data=train_df,x='Pclass',y='Survived',ax=axs[0])
sns.barplot(data=train_df,x='Pclass',y='Survived',hue='Sex',ax=axs[1])
plt.show()
```



- From First Plot, People belonging to class 1 had more chances of survival than people of class 2 followed by class 3.
- From Second Plot, Females from every class had better chances of survival.

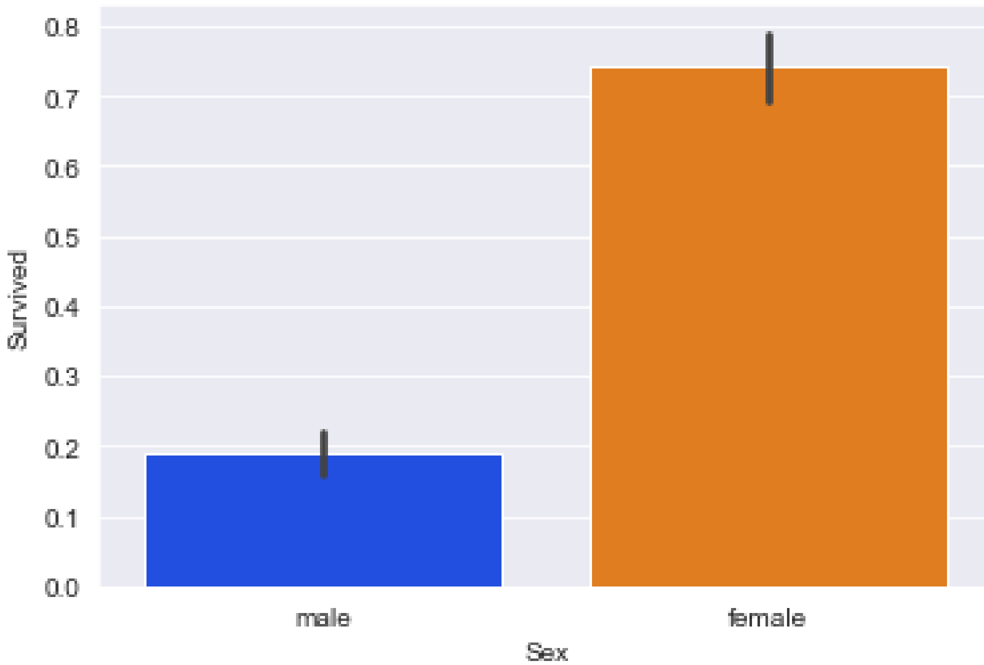
[23]:
```python
#Confirming the above plots Statistically
psur = round(train_df[['Survived','Pclass']].groupby('Pclass').mean()*100 , 2)
psur = pd.DataFrame(psur)
psur
```

[23]:
```
        Survived
Pclass
1          62.96
2          47.28
3          24.24
```

[24]:
```python
psurse = round(train_df[['Survived','Pclass','Sex']].groupby(['Sex','Pclass']).
 ↪mean()*100 , 2)
psurse = pd.DataFrame(psurse)
psurse
```

[24]:
```
               Survived
Sex    Pclass
female 1          96.81
       2          92.11
       3          50.00
male   1          36.89
       2          15.74
       3          13.54
```

[25]:
```python
#Plotting 'Sex' vs 'Survived' Graph to see how many people survived based on␣
 ↪Gender.
sns.barplot(data=train_df,x='Sex',y='Survived')
plt.show()
```



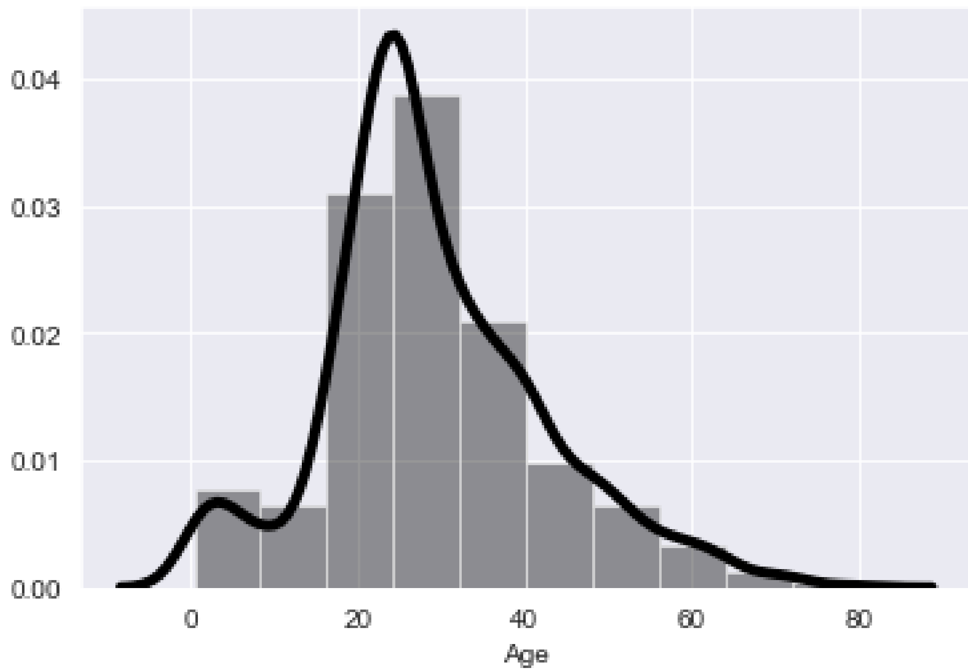
- Evident that Females survived more than Males

[26]:
```
#Confirming the above plot Statistically
agesur = round(train_df[['Survived','Sex']].groupby('Sex').mean()*100 , 2)
agesur = pd.DataFrame(agesur)
agesur
```

[26]:
```
        Survived
Sex
female     74.20
male       18.89
```

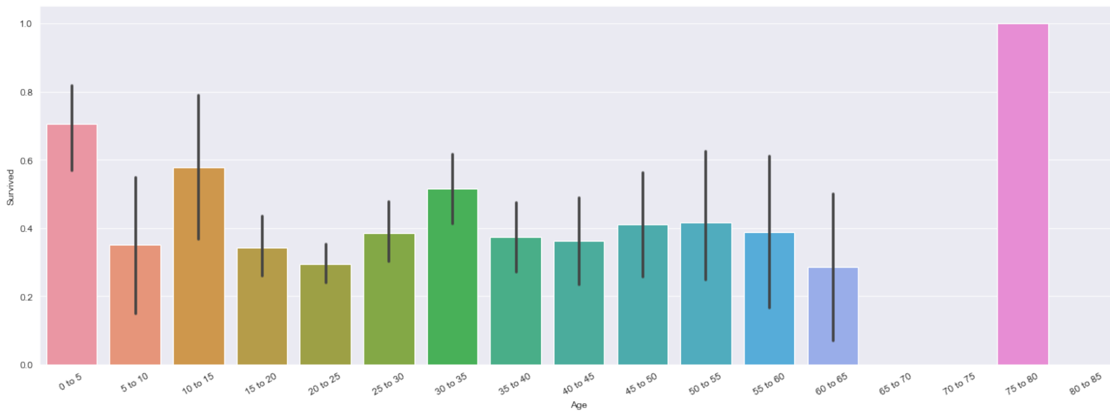
- We can observe that the percentage of Females Surviving was very high as compared to Males.

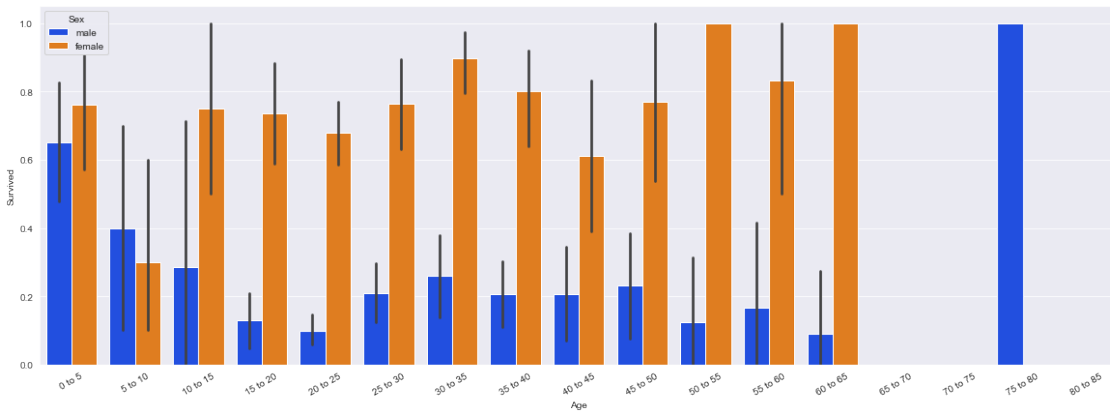
[27]:
```
#Checking the Distribution Plot of 'Age' to see ranges of people present on the␣
↪ship.
sns.distplot(train_df['Age'],color='k',bins=10,kde_kws=dict(linewidth=4))
plt.show()
```



- 20 to 40 year olds had the maximum count
- Infants followed after the age range mentioned above.

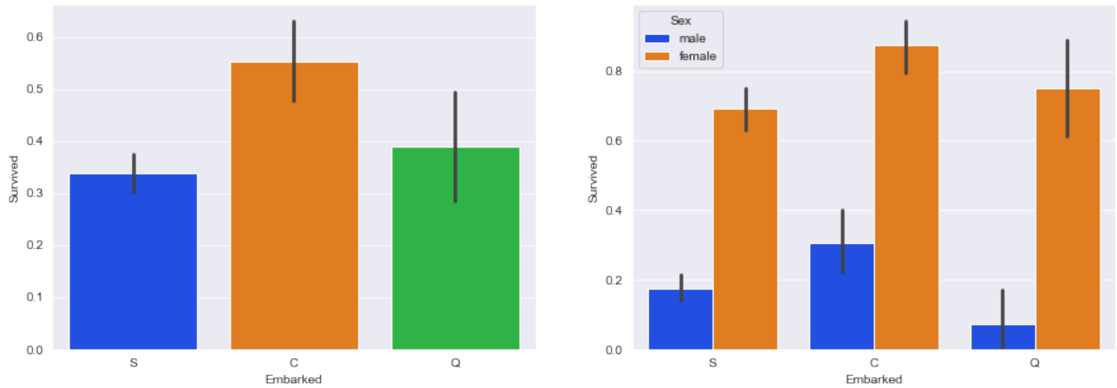
[28]:
```
#Creating Binned Age and Plotting the graph of 'Age' vs 'Survived'
binnedAge = pd.cut(train_df['Age'], bins=list(range(0,90,5)),␣
 ↪include_lowest=True)
labels = [str(i) + ' to ' + str(j) for i , j in zip(range(0,90,5) ,␣
 ↪range(5,95,5))]


fig, axs = plt.subplots(2,1,figsize = (20,15))
sns.barplot(data=train_df,x=binnedAge,y='Survived',ax=axs[0])
sns.barplot(data=train_df,x=binnedAge,y='Survived',hue='Sex',ax=axs[1])
axs[0].set_xticklabels(labels,rotation=30)
axs[1].set_xticklabels(labels,rotation=30)
plt.show()
```





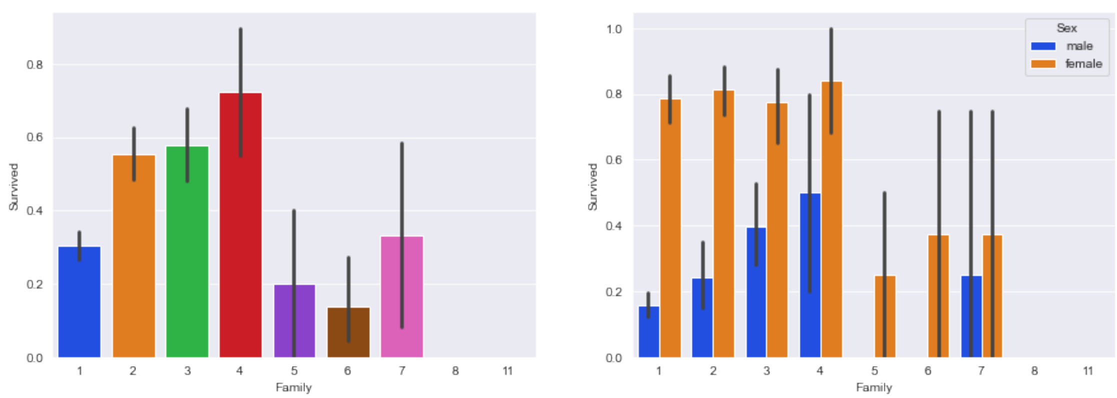
- We can infer that the children of age 0 to 5 and 10 to 15 had higher chances of survival
- Also young people of age 20 to 25 had the least chances of survival
- Old people, 75 to 80, also had a very good chances of survival
- In every age range, we can clearly see that Females had far better chances of survival than Males

[29]:
```
#Plotting 'Embarked' vs 'Survived' Graph to see how many people had the chance␣
↪to survive based on the Port they boarded from.
fig, axs = plt.subplots(1,2,figsize = (15,5))
sns.barplot(data=train_df,x='Embarked',y='Survived',ax=axs[0])
sns.barplot(data=train_df,x='Embarked',y='Survived',hue='Sex',ax=axs[1])
plt.show()
```



- People who embarked from Cherbourg had more chances of survival than Queenstown and Southampton

[30]:
```
#Plotting 'Family' vs 'Survived' Graph to see how many people survived based on␣
↪Family Count.
fig, axs = plt.subplots(1,2,figsize = (15,5))
sns.barplot(data=train_df,x='Family',y='Survived',ax=axs[0])
sns.barplot(data=train_df,x='Family',y='Survived',hue='Sex',ax=axs[1])
plt.show()
```

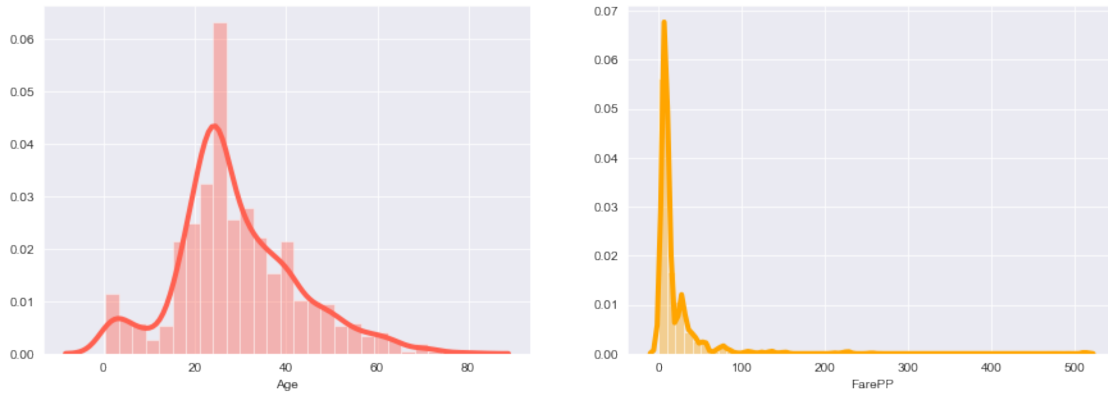


- Nothing Concrete can be said from the above graphs

[31]:
```
#Creating separate Lists for Numerical and Categorical Features
num_features=[i for i in train_df.columns if train_df[i].dtypes!='O']
cat_features=[i for i in train_df.columns if train_df[i].dtypes=='O']
```

[32]:
```
#Checking Skewness of the Continuous Variables 'Age' and 'FarePP'
fig, axs = plt.subplots(1,2,figsize = (15,5))
sns.distplot(train_df['Age'],color='#FF6050',kde_kws=dict(linewidth=4),ax=axs[0])
```

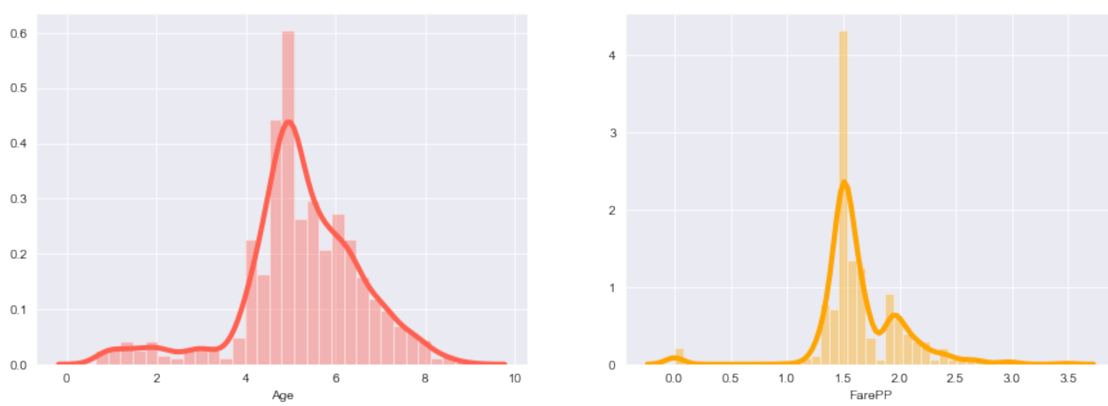
```
sns.
 ↪distplot(train_df['FarePP'],color='orange',kde_kws=dict(linewidth=4),ax=axs[1])
plt.show()
```



[33]:
```
#Calculating Skewness using the Skew function from the scipy.stats library
print('Age = ' , st.skew(train_df['Age']) , ' FarePP = ',st.
 ↪skew(train_df['FarePP']))
```

```
Age =  0.5331838972036701  FarePP =  7.7525153713575365
```

[34]:
```
#Removing Skewness from the Variables and then checking there distribution plots.
age_train = np.sqrt(train_df['Age'])
farepp_train = np.power(train_df['FarePP'],0.20)

fig, axs = plt.subplots(1,2,figsize = (15,5))
sns.distplot(age_train,color='#FF6050',kde_kws=dict(linewidth=4),ax=axs[0])
sns.distplot(farepp_train,color='orange',kde_kws=dict(linewidth=4),ax=axs[1])
plt.show()
print('Age = ' , st.skew(age_train) , ' FarePP = ',st.skew(farepp_train))
```



```
Age =  -0.6508369087687663  FarePP =  -0.2306287355826746
```

- Such Transformation can add a huge bias so we will ignore it.

[35]:
```python
#Mapping 'Sex' to 0 and 1
# Male=0 and Female=1
train_df['Sex'] = train_df['Sex'].map({'male':1, 'female':0})
test_df['Sex'] = test_df['Sex'].map({'male':1, 'female':0})
```

[36]:
```python
#Mapping 'Embarked' to 0 and 1
# Q=0 , S=1 and C=0
train_df['Embarked'] = train_df['Embarked'].map({'Q':2, 'S':1, 'C':0})
test_df['Embarked'] = test_df['Embarked'].map({'Q':2, 'S':1, 'C':0})
```

[37]:
```python
#Dropping PassengerId because it contains unique discrete values, like an index.
train_df.drop(columns=['PassengerId'] , axis=1 , inplace = True)
train_df
```

[37]:

	Survived	Pclass	Sex	Age	Embarked	Family	FarePP
0	0	3	1	22.0	1	2	3.62500
1	1	1	0	38.0	0	2	35.64165
2	1	3	0	26.0	1	1	7.92500
3	1	1	0	35.0	1	2	26.55000
4	0	3	1	35.0	1	1	8.05000
..	...	...	...	...	...	...	...
886	0	2	1	27.0	1	1	13.00000
887	1	1	0	19.0	1	1	30.00000
888	0	3	0	21.5	1	4	5.86250
889	1	1	1	26.0	0	1	30.00000
890	0	3	1	32.0	2	1	7.75000

[891 rows x 7 columns]

[38]:
```python
#Removing 'PassengerId' from and storing it in test_pid because we will use it␣
↪later
test_pid = test_df.pop('PassengerId')
test_df
```

[38]:

	Pclass	Sex	Age	Embarked	Family	FarePP
0	3	1	34.5	2	1	7.829200
1	3	0	47.0	1	2	3.500000
2	2	1	62.0	2	1	9.687500
3	3	1	27.0	1	1	8.662500
4	3	0	22.0	1	3	4.095833
..	...	...	...	...	...	...
413	3	1	24.0	1	1	8.050000
414	1	0	39.0	0	1	108.900000
415	3	1	38.5	1	1	7.250000

```
416        3    1   24.0          1        1     8.050000
417        3    1   24.0          0        3     7.452767

[418 rows x 6 columns]
```

[39]:
```python
#Removing the features mentioned below because 1 has been removed and 2 are␣
↪Ordinal
num_features.remove('PassengerId')
num_features.remove('Pclass')
num_features.remove('Survived')
```

[40]:
```python
#Scaling the Features between 0 - 1, for easier and efficient performance by the␣
↪Model
scaler = MinMaxScaler()
train_df[num_features] = scaler.fit_transform(train_df[num_features])
test_df[num_features] = scaler.fit_transform(test_df[num_features])

print('-+-'*25)
print('Training Data')
print(train_df.describe())
print('-+-'*25)
print('Testing Data')
print(test_df.describe())
print('-+-'*25)
```

```
-+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+-
Training Data
         Survived      Pclass         Sex         Age    Embarked      Family  \
count  891.000000  891.000000  891.000000  891.000000  891.000000  891.000000
mean     0.383838    2.308642    0.647587    0.360548    0.897868    0.090460
std      0.486592    0.836071    0.477990    0.167183    0.514624    0.161346
min      0.000000    1.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000    2.000000    0.000000    0.264891    1.000000    0.000000
50%      0.000000    3.000000    1.000000    0.321438    1.000000    0.000000
75%      1.000000    3.000000    1.000000    0.447097    1.000000    0.100000
max      1.000000    3.000000    1.000000    1.000000    2.000000    1.000000

           FarePP
count  891.000000
mean     0.038874
std      0.069957
min      0.000000
25%      0.014151
50%      0.016201
75%      0.046194
max      1.000000
-+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+-
Testing Data
```

```
          Pclass         Sex         Age    Embarked      Family      FarePP
count  418.000000  418.000000  418.000000  418.000000  418.000000  418.000000
mean     2.265550    0.636364    0.384120    0.866029    0.083971    0.083036
std      0.841838    0.481622    0.171949    0.580452    0.151907    0.135679
min      1.000000    0.000000    0.000000    0.000000    0.000000    0.000000
25%      1.000000    0.000000    0.287881    1.000000    0.000000    0.029097
50%      3.000000    1.000000    0.327443    1.000000    0.000000    0.033016
75%      3.000000    1.000000    0.477450    1.000000    0.100000    0.099029
max      3.000000    1.000000    1.000000    2.000000    1.000000    1.000000
-+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+--+-
```

[41]:
```
#Splitting into Training and Testing Variables. Separating the Dependent Variable
y_train = train_df.pop('Survived')
X_train = train_df.copy()

X_test  = test_df.copy()

#Checking Shape of the Variables
X_train.shape, y_train.shape, X_test.shape
```

[41]:
```
((891, 6), (891,), (418, 6))
```

1.5 GLM Model based Classification

[42]:
```
#Adding a constant manually because GLM otherwise fits the line through the␣
 ↪origin
X_train_sm = sm.add_constant(X_train)

#Create a first fitted model
logglm = sm.GLM(y_train,X_train_sm,family=sm.families.Binomial()).fit()

#Viewing Summary
print(logglm.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:               Survived   No. Observations:                  891
Model:                            GLM   Df Residuals:                      884
Model Family:                Binomial   Df Model:                            6
Link Function:                  logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -392.80
Date:                Wed, 26 Aug 2020   Deviance:                       785.60
Time:                        00:08:05   Pearson chi2:                     905.
No. Iterations:                     5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
```

```
const          5.4663      0.569      9.604      0.000       4.351       6.582
Pclass        -1.1906      0.143     -8.332      0.000      -1.471      -0.911
Sex           -2.7652      0.200    -13.842      0.000      -3.157      -2.374
Age           -3.4791      0.648     -5.367      0.000      -4.750      -2.208
Embarked      -0.1823      0.184     -0.993      0.321      -0.542       0.177
Family        -2.2763      0.653     -3.487      0.000      -3.556      -0.997
FarePP         1.3372      1.666      0.803      0.422      -1.928       4.602
==============================================================================
```

[43]:
```
#Defining a function which will calculate the VIF values and store them in a␣
↪DataFrame
#High VIF Means High Multicollinearity
def calculateVIF(X_train_lm):
    vif = pd.DataFrame()
    vif['Features'] = X_train_lm.columns
    vif['VIF'] = [variance_inflation_factor(X_train_lm.values, i) for i in␣
↪range(X_train_lm.shape[1])]
    vif['VIF'] = round(vif['VIF'], 2)
    vif = vif.sort_values(by = "VIF", ascending = False).reset_index()
    vif = vif.drop(columns = ['index'],axis = 1)
    return vif
```

[44]:
```
#Calculating VIF
vif = calculateVIF(X_train_sm.drop(columns=['const'],axis=1))
vif
```

[44]:

	Features	VIF
0	Pclass	6.12
1	Embarked	4.38
2	Age	4.04
3	Sex	3.02
4	FarePP	1.39
5	Family	1.34

1.6 GLM Model based Classification after removal of high P values

[45]:
```
X_train_sm1 = sm.add_constant(X_train[X_train_sm.
↪drop(columns=['const','Embarked','FarePP'],axis=1).columns])
logglm1 = sm.GLM(y_train,X_train_sm1,family=sm.families.Binomial()).fit()
print(logglm1.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:               Survived   No. Observations:                  891
Model:                            GLM   Df Residuals:                      886
Model Family:                Binomial   Df Model:                            4
Link Function:                  logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -393.80
```

```
Date:                  Wed, 26 Aug 2020   Deviance:                       787.60
Time:                          00:08:06   Pearson chi2:                     921.
No. Iterations:                       5
Covariance Type:              nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          5.5485      0.512     10.840      0.000       4.545       6.552
Pclass        -1.2744      0.128     -9.971      0.000      -1.525      -1.024
Sex           -2.7550      0.198    -13.905      0.000      -3.143      -2.367
Age           -3.5219      0.646     -5.452      0.000      -4.788      -2.256
Family        -2.2743      0.648     -3.509      0.000      -3.545      -1.004
==============================================================================
```

1.7 GLM Model based Classification with Recursive Feature Elimination.

[46]:
```
#Fitting the Training Data to RFE model
estimator = SVR(kernel="linear")
rfe = RFE(estimator,3, step=1)
rfe = rfe.fit(X_train, y_train)
```

[47]:
```
#checking the listing of the features that got selected
list(zip(X_train.columns,rfe.support_,rfe.ranking_))
```

[47]:
```
[('Pclass', False, 3),
 ('Sex', True, 1),
 ('Age', False, 2),
 ('Embarked', False, 4),
 ('Family', True, 1),
 ('FarePP', True, 1)]
```

[48]:
```
col = X_train.columns[rfe.support_]
col #Printing the list of Columns that are selected by RFE
```

[48]:
```
Index(['Sex', 'Family', 'FarePP'], dtype='object')
```

[49]:
```
#Again building a GLM Model
X_train_rfe = X_train[col]
X_train_rfe = sm.add_constant(X_train_rfe)
logglmrfe = sm.GLM(y_train,X_train_rfe,family=sm.families.Binomial()).fit()
print(logglmrfe.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:               Survived   No. Observations:                  891
Model:                            GLM   Df Residuals:                      887
Model Family:                Binomial   Df Model:                            3
Link Function:                  logit   Scale:                          1.0000
```

```
Method:                          IRLS   Log-Likelihood:                -434.41
Date:                Wed, 26 Aug 2020   Deviance:                       868.83
Time:                        00:08:06   Pearson chi2:                     903.
No. Iterations:                     6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.8552      0.179      4.786      0.000       0.505       1.205
Sex           -2.6360      0.184    -14.333      0.000      -2.996      -2.276
Family        -1.4377      0.572     -2.514      0.012      -2.559      -0.317
FarePP        11.5381      2.449      4.711      0.000       6.738      16.339
==============================================================================
```

[50]:

```python
#Defining a function print_matrix that will print the Confusion Matrix
import sklearn.metrics as sklm #For Performance Measures
def print_matrix(labels, scores):
    metrics = sklm.precision_recall_fscore_support(labels,scores)
    conf = sklm.confusion_matrix(labels,scores)
    fig, (ax1,ax2) = plt.subplots(figsize=(15,7), ncols=2, nrows=1)

    left   =  0.125  # the left side of the subplots of the figure
    right  =  0.9    # the right side of the subplots of the figure
    bottom =  0.1    # the bottom of the subplots of the figure
    top    =  0.9    # the top of the subplots of the figure
    wspace =  .5     # the amount of width reserved for blank space between␣
 ↪subplots
    hspace =  1.1    # the amount of height reserved for white space between␣
 ↪subplots

    # This function actually adjusts the sub plots using the above paramters
    plt.subplots_adjust(
            left    =  left,
            bottom  =  bottom,
            right   =  right,
            top     =  top,
            wspace  =  wspace,
            hspace  =  hspace
    )

    sns.set(font_scale=1.4)#for label size

    ax1.set_title('Confusion Matrix\n')
    axes = ['Positive' , 'Negative']
    g1 = sns.heatmap(conf, cmap="Greens", annot=True,annot_kws={"size": 16} ,␣
 ↪xticklabels = axes , yticklabels = axes , ax=ax1)# font size
    g1.set_ylabel('Actual Label')
```

```
    g1.set_xlabel('Predicted Label')

    print('\nAccuracy :  %0.2f' % sklm.accuracy_score(labels, scores) , '\n')␣
 ↪#Printing Accuracy Of the Model

    ax2.set_title('Performance Measure\n')
    xaxes = ['Positive' , 'Negative']
    yaxes = ['Precision' , 'Recall' , 'F-Score' , 'NumCase']
    g2 = sns.heatmap(metrics, cmap="Greens", annot=True,annot_kws={"size": 16} ,␣
 ↪xticklabels = xaxes , yticklabels = yaxes , ax=ax2)

    plt.yticks(rotation=0)
    plt.show()
```

1.8 Sk-learn Logistic Regression

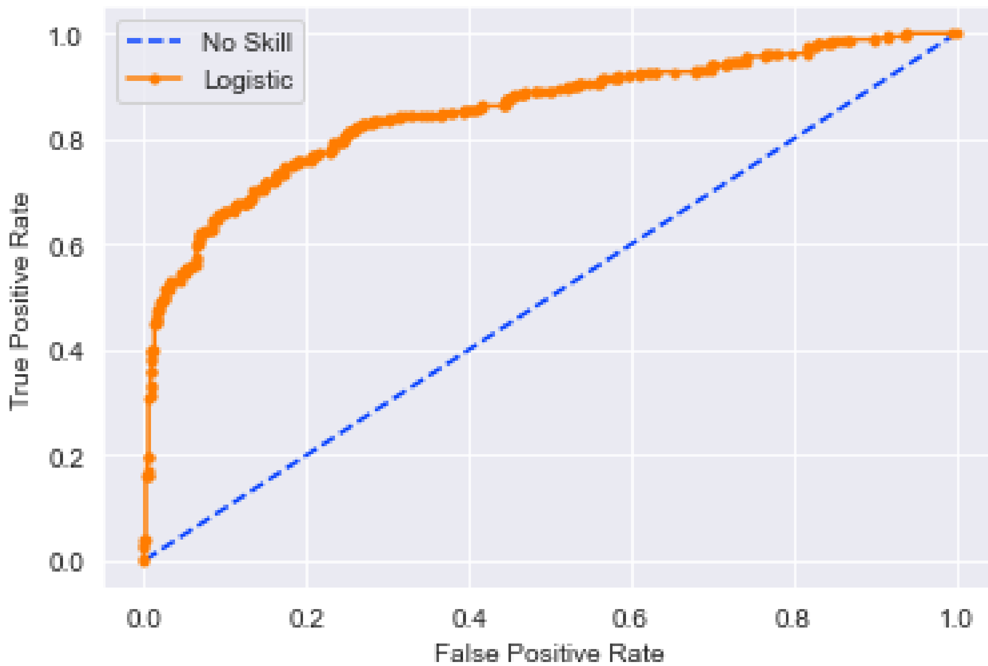
[51]:
```
#Creating an instance of LogisticRegression
logreg = LogisticRegression()

#Fitting the data.
logreg.fit(X_train, y_train)
logreg_Y_pred=logreg.predict(X_test)

#Storing the values predicted on training Data
logreg_Y_pred_train=logreg.predict(X_train)

#Checking the Accuracy
logreg_accuracy=logreg.score(X_train,y_train)
logreg_accuracy
```

[51]: 0.7991021324354658

[52]:
```
#Plotting the ROC Curve

# generate a no skill prediction (majority class)
ns_probs = [0 for _ in range(len(y_train))]
lr_probs = logreg.predict_proba(X_train)
# keep probabilities for the positive outcome only
lr_probs = lr_probs[:, 1]
# calculate scores
ns_auc = roc_auc_score(y_train, ns_probs)
lr_auc = roc_auc_score(y_train, lr_probs)
# summarize scores
print('No Skill: ROC AUC=%.3f' % (ns_auc))
print('Logistic: ROC AUC=%.3f' % (lr_auc))
# calculate roc curves
ns_fpr, ns_tpr, _ = roc_curve(y_train, ns_probs)
```

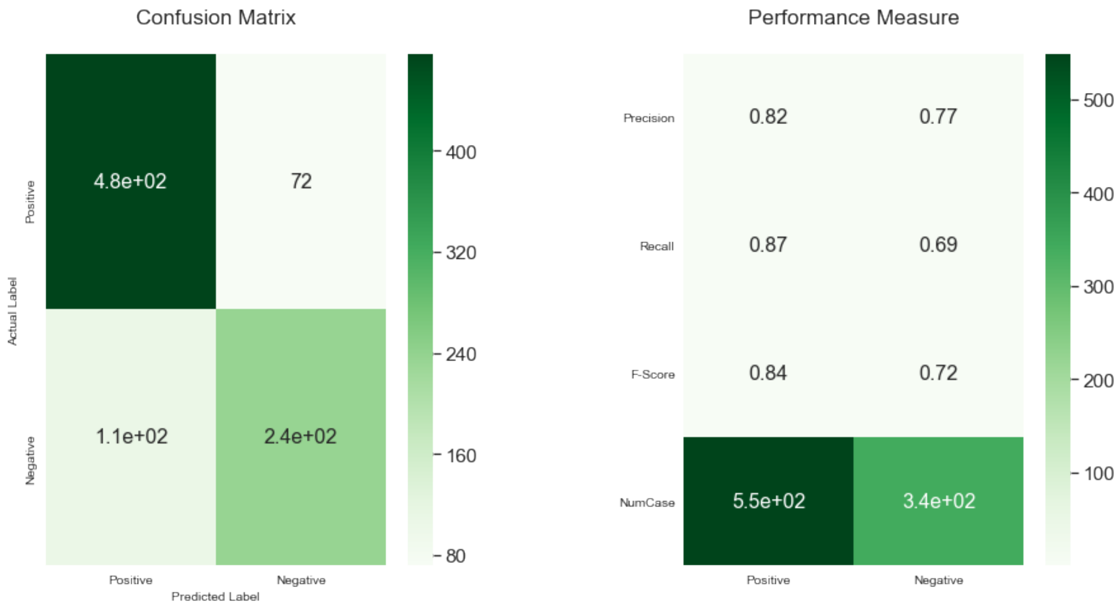
```
lr_fpr, lr_tpr, _ = roc_curve(y_train, lr_probs)
# plot the roc curve for the model
plt.plot(ns_fpr, ns_tpr, linestyle='--', label='No Skill')
plt.plot(lr_fpr, lr_tpr, marker='.', label='Logistic')
# axis labels
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
# show the legend
plt.legend()
# show the plot
plt.show()
```

```
No Skill: ROC AUC=0.500
Logistic: ROC AUC=0.853
```



[53]:
```
print_matrix(y_train,logreg_Y_pred_train) #displaying the produced analysis in␣
↪confusion matrix
```

```
Accuracy :  0.80
```



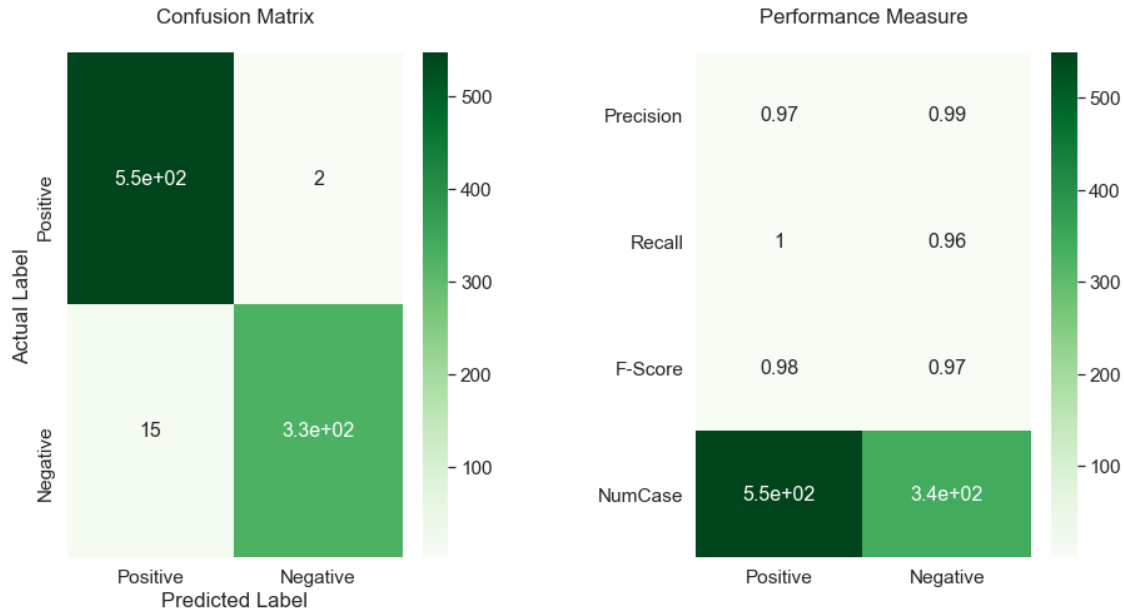
1.9 Decision Tree based Classification

[54]:
```
#Creating an instance of DecisionTreeClassifier
decision_tree = DecisionTreeClassifier()

#Fitting the data.
decision_tree.fit(X_train, y_train)
decision_tree_Y_pred = decision_tree.predict(X_test)

#Storing the values predicted on training Data
decision_tree_Y_pred_train = decision_tree.predict(X_train)

#Checking the accuracy
decision_tree_accuracy = decision_tree.score(X_train, y_train)
decision_tree_accuracy
```

[54]: 0.9809203142536476

[55]:
```
print_matrix(y_train,decision_tree_Y_pred_train) #displaying the produced␣
↪analysis in confusion matrix
```

```
Accuracy :  0.98
```



1.10 Random Forest based Classification

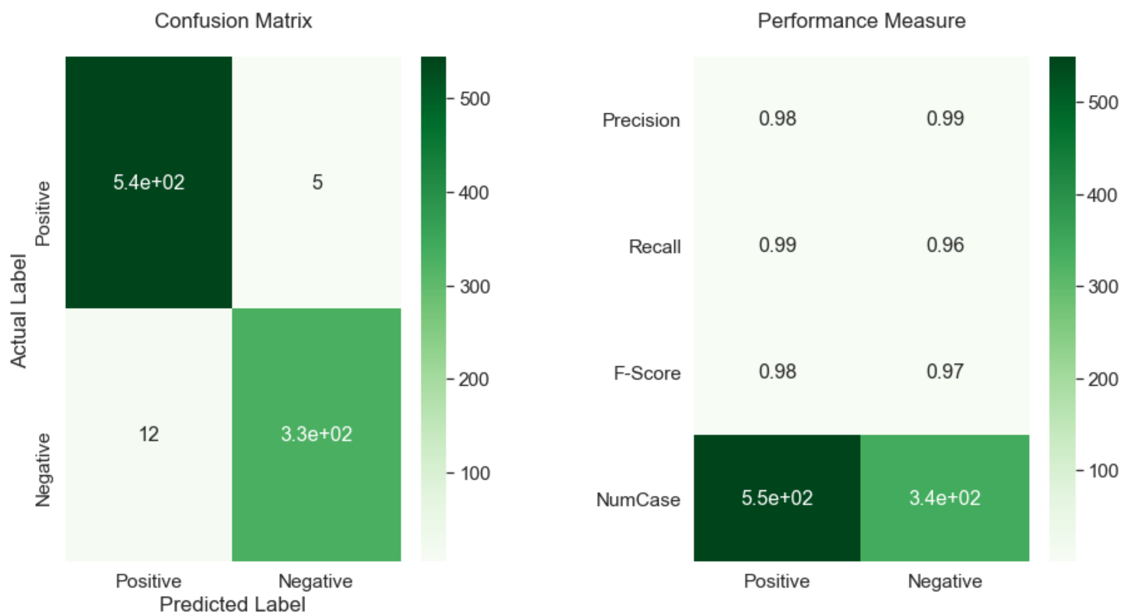
[56]:
```
#Creating an instance of RandomForestClassifier
random_forest = RandomForestClassifier(n_estimators=100)

#Fitting the data.
random_forest.fit(X_train, y_train)
random_forest_Y_pred = random_forest.predict(X_test)

#Storing the values predicted on training Data
random_forest_Y_pred_train = random_forest.predict(X_train)

#Checking the accuracy
random_forest.score(X_train, y_train)
random_forest_accuracy = random_forest.score(X_train, y_train)
print(random_forest_accuracy)

#Feature Importance
random_forest.feature_importances_
```

```
0.9809203142536476
```

[56]:
```
array([0.07193574, 0.26885973, 0.26747397, 0.03695173, 0.07817132,
       0.27660752])
```

[57]:
```
print_matrix(y_train,random_forest_Y_pred_train) #displaying the produced␣
↪analysis in confusion matrix
```

```
Accuracy :  0.98
```



[58]:
```python
#Creating the Model DataFrame based on accuracy
models = pd.DataFrame({
    'Model': ['Logistic Regression','Decision Tree','Random Forest'],
    'Score': [logreg_accuracy,decision_tree_accuracy, random_forest_accuracy]})
models.sort_values(by='Score', ascending=False)
```

[58]:

	Model	Score
1	Decision Tree	0.980920
2	Random Forest	0.980920
0	Logistic Regression	0.799102

[59]:
```python
#Creating submission file from each model
logreg_submission = pd.DataFrame({"PassengerId": test_pid, "Survived":␣
 ↪logreg_Y_pred})
logreg_submission.to_csv('logreg_submission.csv', index=False)

decision_tree_submission = pd.DataFrame({"PassengerId": test_pid, "Survived":␣
 ↪decision_tree_Y_pred})
decision_tree_submission.to_csv('decision_tree_submission.csv', index=False)

random_forest_submission = pd.DataFrame({"PassengerId": test_pid, "Survived":␣
 ↪random_forest_Y_pred})
random_forest_submission.to_csv('random_forest_submission.csv', index=False)
```