In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from pylab import rcParams
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve, roc_a
uc_score
from sklearn.tree import DecisionTreeClassifier, export_graphviz
```

In [2]:
```
url= 'https://raw.githubusercontent.com/BigDataGal/Python-for-Data Science/mas
ter/titanic-train.csv'
titanic = pd.read_csv('train.csv')
```

titanic.columns = ['PassengerId','Survived','Pclass','Name','Sex','Age','SibSp','Parch','Ti cket','Fare','Cabin','E mbarked'] You use only Pclass, Sex, Age, SibSp (Siblings aboard), Parch (Parents/children aboard), and Fare to predict whether a passenger survived.

In [3]:
```
titanic.head()
```

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
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	C
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	

In [4]:
```
titanic = titanic[['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Survive
d']]
```

In [5]:
```
titanic.head()
```

Out[5]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Survived
0	3	male	22.0	1	0	7.2500	0
1	1	female	38.0	1	0	71.2833	1
2	3	female	26.0	0	0	7.9250	1
3	1	female	35.0	1	0	53.1000	1
4	3	male	35.0	0	0	8.0500	0

In [6]:
```
titanic.isna().sum()
```

Out[6]:
```
Pclass        0
Sex           0
Age         177
SibSp         0
Parch         0
Fare          0
Survived      0
dtype: int64
```

Analysing the distribution of data

In [7]:
```
titanic.describe()
```

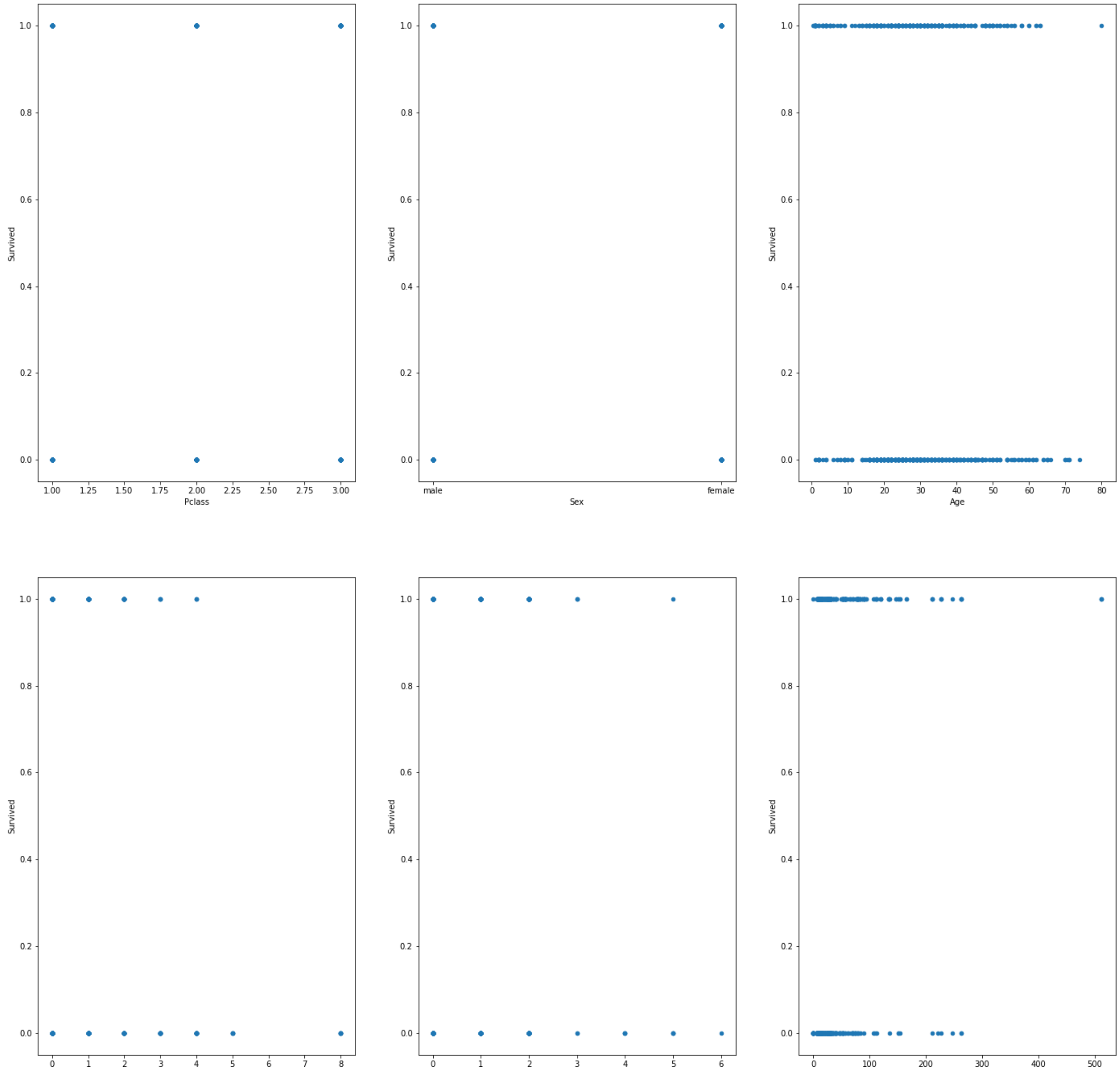
Out[7]:

	Pclass	Age	SibSp	Parch	Fare	Survived
count	891.000000	714.000000	891.000000	891.000000	891.000000	891.000000
mean	2.308642	29.699118	0.523008	0.381594	32.204208	0.383838
std	0.836071	14.526497	1.102743	0.806057	49.693429	0.486592
min	1.000000	0.420000	0.000000	0.000000	0.000000	0.000000
25%	2.000000	20.125000	0.000000	0.000000	7.910400	0.000000
50%	3.000000	28.000000	0.000000	0.000000	14.454200	0.000000
75%	3.000000	38.000000	1.000000	0.000000	31.000000	1.000000
max	3.000000	80.000000	8.000000	6.000000	512.329200	1.000000

In [8]:
```
titanic.info()
```

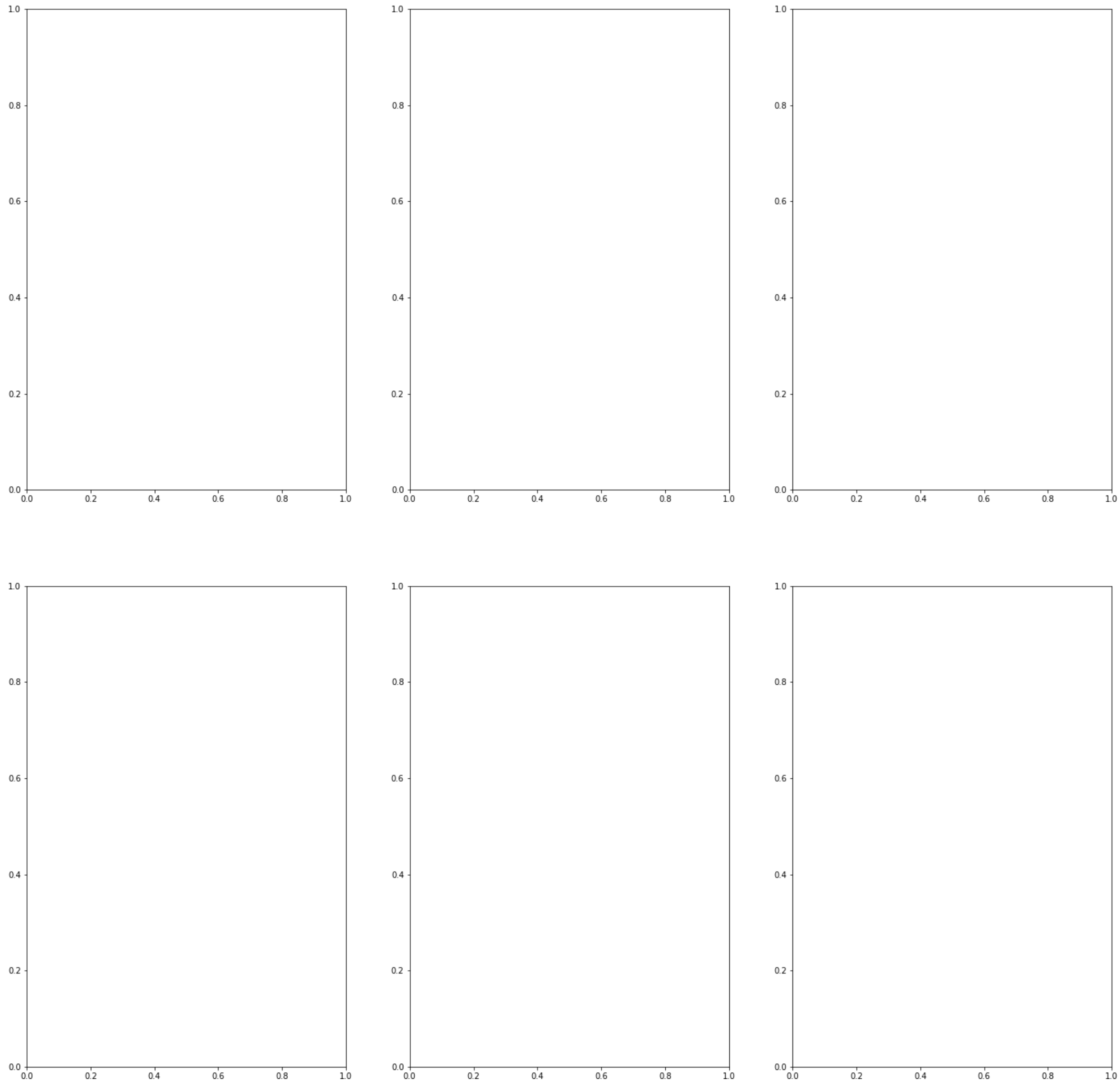
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Pclass    891 non-null    int64  
 1   Sex       891 non-null    object 
 2   Age       714 non-null    float64
 3   SibSp     891 non-null    int64  
 4   Parch     891 non-null    int64  
 5   Fare      891 non-null    float64
 6   Survived  891 non-null    int64  
dtypes: float64(2), int64(4), object(1)
memory usage: 48.9+ KB
```

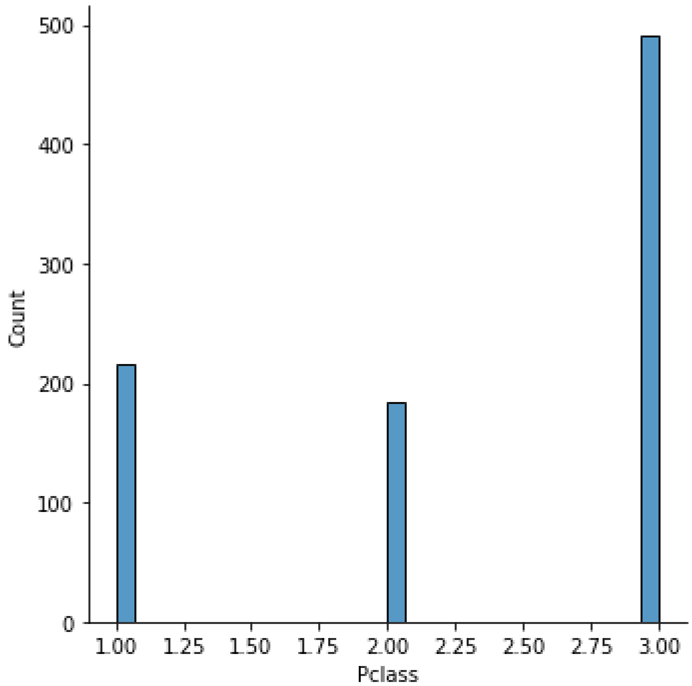
In [9]:
```
# visualize the relationship between independent variable and the dependent va
riable using scatterplot
fig, axs = plt.subplots(2, 3, figsize = (24, 24))
# unpack all the axes subplots
axe = axs.ravel()
for i in range(len(titanic.drop(columns='Survived').columns)):
    titanic.plot(kind = 'scatter', x = titanic.columns[i], y = 'Survived', ax
= axe[i])
    plt.xlabel(titanic.columns[i])
```



In [10]:
```
# visualize the distribution of data
fig, axs = plt.subplots(2, 3, figsize = (24, 24))
# unpack all the axes subplots
axe = axs.ravel()
col = ['Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'Survived']
for i in range(len(col)):
    #sns.set(rc={'figure.figsize':(11.7,8.27)})
    sns.displot(titanic[col[i]], bins=30, ax = axe[i])
    plt.show()
```

```
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\distribut
ions.py:2163: UserWarning: `displot` is a figure-level function and does not
accept the ax= paramter. You may wish to try histplot.
  warnings.warn(msg, UserWarning)
```






```
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\distribut
ions.py:2163: UserWarning: `displot` is a figure-level function and does not
accept the ax= paramter. You may wish to try histplot.
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```

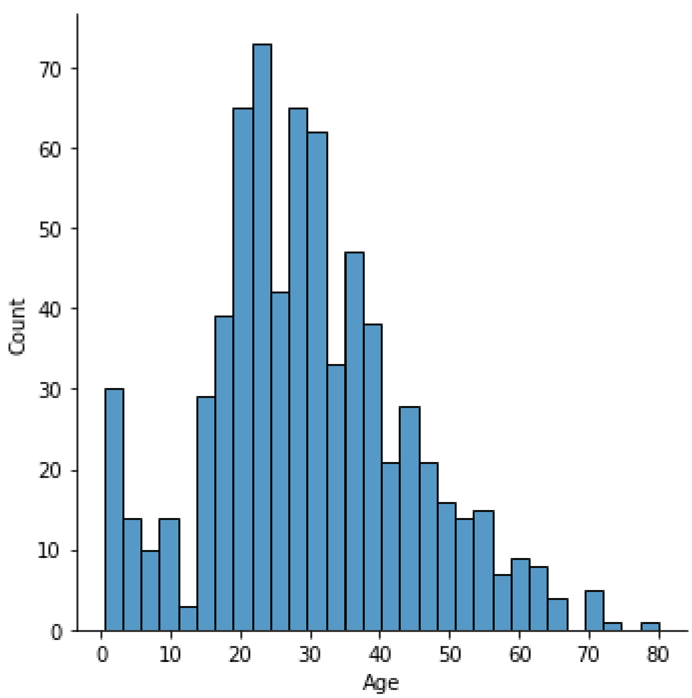


```
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\distribut
ions.py:2163: UserWarning: `displot` is a figure-level function and does not
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  warnings.warn(msg, UserWarning)
```
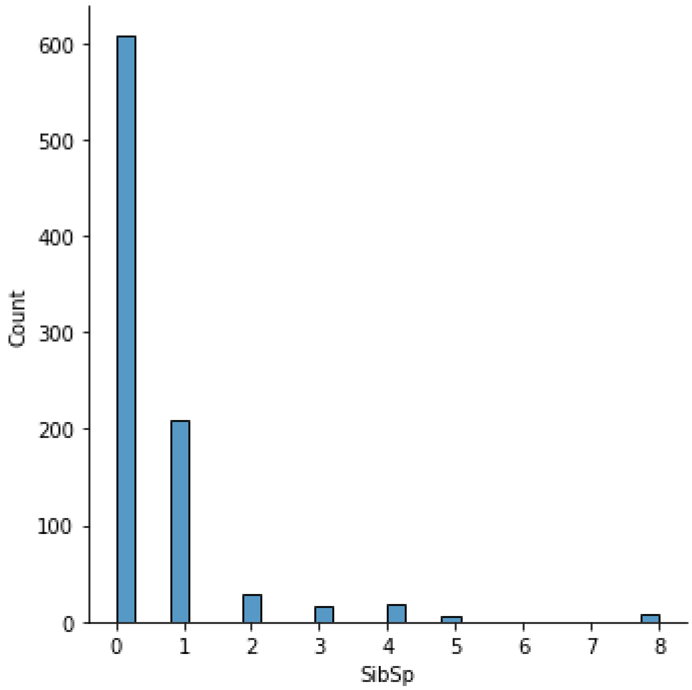
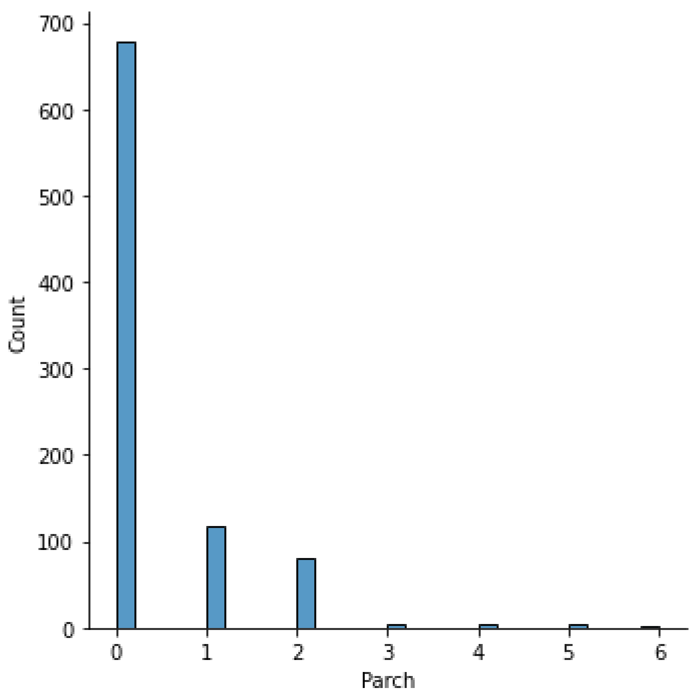
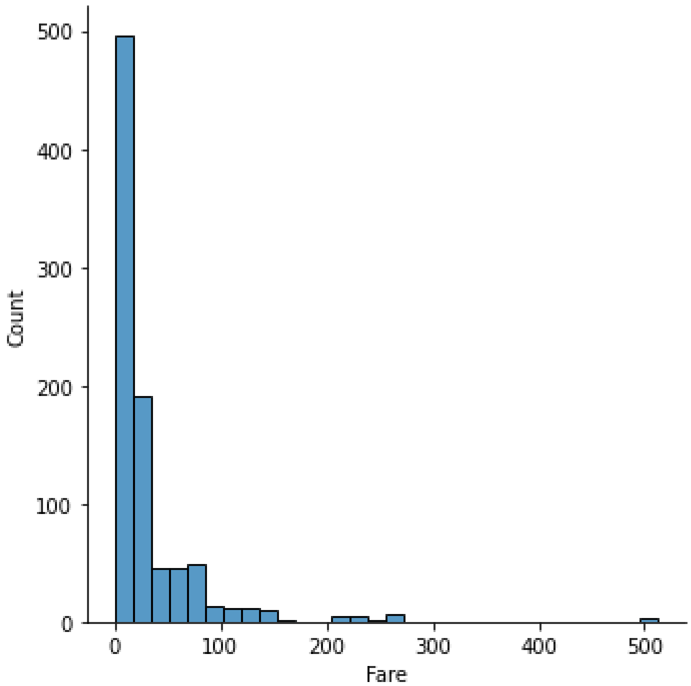



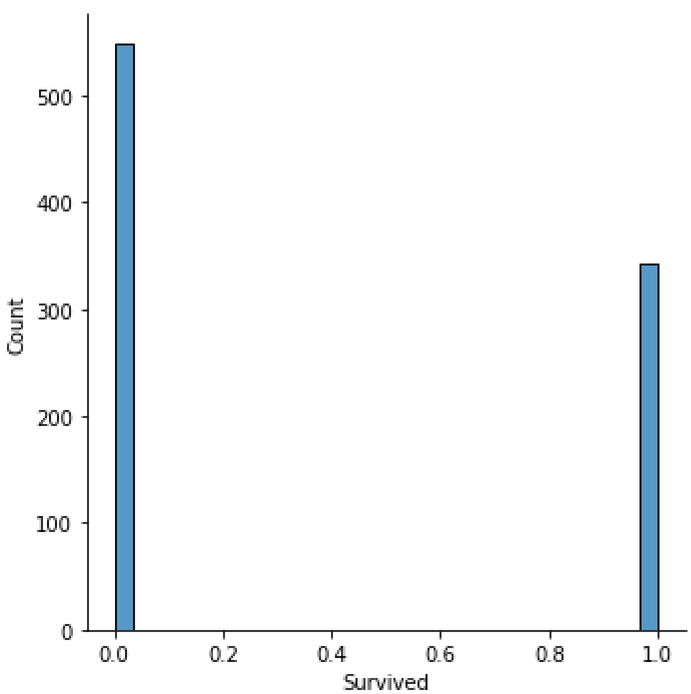

```
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\distribut
ions.py:2163: UserWarning: `displot` is a figure-level function and does not
accept the ax= paramter. You may wish to try histplot.
  warnings.warn(msg, UserWarning)
```




```
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\distribut
ions.py:2163: UserWarning: `displot` is a figure-level function and does not
accept the ax= paramter. You may wish to try histplot.
  warnings.warn(msg, UserWarning)
```




```
C:\Users\Urvi\AppData\Roaming\Python\Python37\site-packages\seaborn\distribut
ions.py:2163: UserWarning: `displot` is a figure-level function and does not
accept the ax= paramter. You may wish to try histplot.
  warnings.warn(msg, UserWarning)
```



In [11]:
```
# Fill missing values, as age is almost normally distributed, will replace the values with mean
# titanic[(titanic['Age'].isna()) & (titanic.Sex == 'male')]['Age'] = titanic[titanic.Sex == 'male']['Age'].mean()
# titanic[(titanic['Age'].isna()) & (titanic.Sex == 'female')]['Age'] = titanic[titanic.Sex == 'female']['Age'].mean()

titanic.loc[(titanic.Age.isnull()) & (titanic.Sex=='male'), 'Age'] = titanic.groupby('Sex')['Age'].mean()[1]
titanic.loc[(titanic.Age.isnull()) & (titanic.Sex=='female'), 'Age'] = titanic.groupby('Sex')['Age'].mean()[0]
```

In [12]:
```
titanic.isna().sum()
```

Out[12]:
```
Pclass      0
Sex         0
Age         0
SibSp       0
Parch       0
Fare        0
Survived    0
dtype: int64
```

In [13]:
```
titanic.groupby('Sex')['Age'].mean()[1]
```

Out[13]:
```
30.7266445916115
```

In [14]:
```
titanic.groupby('Sex')['Age'].mean()
```

Out[14]:
```
Sex
female    27.915709
male      30.726645
Name: Age, dtype: float64
```

In [15]:
```
# Convert categorical data into numerical
titanic['Sex'] = titanic['Sex'].map({'female': 1, 'male': 0}).astype(int)
```

In [16]:
```
X = titanic.drop(columns='Survived')
y = titanic.Survived
```

In [17]:
```
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state = 123)
```

In [18]:
```
#let's first visualize the tree on the data
clf = DecisionTreeClassifier()
clf.fit(x_train, y_train)
```

Out[18]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=Non
e,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

In [19]:
```
clf.score(x_train,y_train)
```

Out[19]:
```
0.9865269461077845
```

In [20]:
```
y_pred = clf.predict(x_test)
```

In [21]:
```
# accuracy of our classification tree
clf.score(x_test,y_test)
```

Out[21]:
```
0.7802690582959642
```

In [22]:
```
accuracy = accuracy_score(y_test,y_pred)
accuracy
```

Out[22]:
```
0.7802690582959642
```

In [23]:
```
conf_mat = confusion_matrix(y_test, y_pred)
conf_mat
```

Out[23]:
```
array([[114,  25],
       [ 24,  60]], dtype=int64)
```

In [24]:
```
tp = conf_mat[0][0]
fp = conf_mat[0][1]
fn = conf_mat[1][0]
tn = conf_mat[1][1]
```

In [25]:
```
precision = tp/(tp+fp)
precision
```

Out[25]:
```
0.8201438848920863
```

In [26]:
```
recall = tp/(tp+fn)
recall
```

Out[26]:
```
0.8260869565217391
```

In [27]:
```
f1_score = (2*precision*recall)/(precision+recall)
f1_score
```

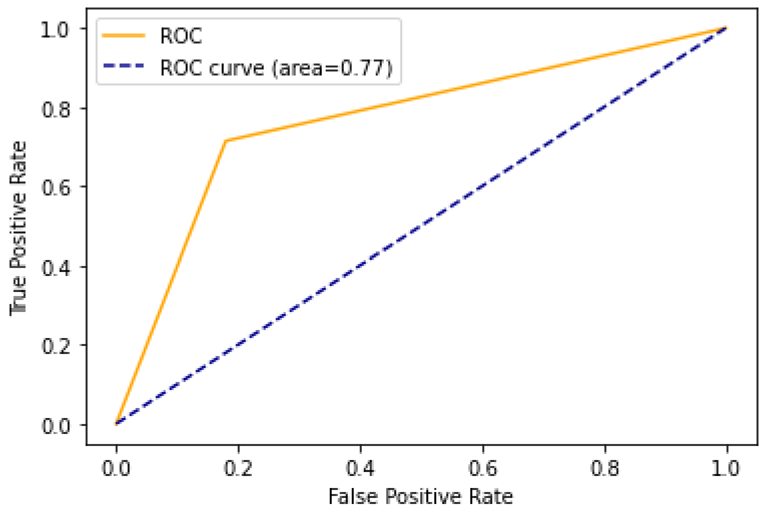
Out[27]:
```
0.8231046931407943
```

In [28]:
```
auc = roc_auc_score(y_test, y_pred)
auc
```

Out[28]: 0.7672147995889004

In [29]:
```
fpr, tpr, thresholds = roc_curve(y_test, y_pred)
```

In [30]:
```
plt.plot(fpr, tpr, color='orange', label='ROC')
plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--', label='ROC curve (area=%0.2f)' % auc)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```



Using Grid Search

In [31]:
```
# we are tuning 5 hyperparameters right now, we are passing the different values for the parameters
grid_param = {
    'criterion': ['gini', 'entropy'],
    'max_depth' : range(2,32,1),
    'min_samples_leaf' : range(1,10,1),
    'min_samples_split': range(2,10,1),
    'splitter' : ['best', 'random']
}
```

In [32]:
```
grid_search = GridSearchCV(estimator=clf, param_grid=grid_param, cv = 5, n_jobs = -1)
```

In [33]:
```
grid_search.fit(x_train, y_train)
```

Out[33]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=DecisionTreeClassifier(ccp_alpha=0.0, class_weight=Non
e,
                                              criterion='gini', max_depth=Non
e,
                                              max_features=None,
                                              max_leaf_nodes=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              presort='deprecated',
                                              random_state=None,
                                              splitter='best'),
             iid='deprecated', n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': range(2, 32),
                         'min_samples_leaf': range(1, 10),
                         'min_samples_split': range(2, 10),
                         'splitter': ['best', 'random']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

In [34]:
```
grid_search.best_params_
```

Out[34]:
```
{'criterion': 'entropy',
 'max_depth': 7,
 'min_samples_leaf': 2,
 'min_samples_split': 2,
 'splitter': 'best'}
```

In [35]:
```
clf_grid = DecisionTreeClassifier(criterion = 'entropy', max_depth = 7, min_sa
mples_leaf = 2, min_samples_split = 8, splitter = 'best')
clf_grid.fit(x_train, y_train)
```

Out[35]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                       max_depth=7, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=2, min_samples_split=8,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

In [36]:
```
clf_grid.score(x_train, y_train)
```

Out[36]:
```
0.8712574850299402
```

In [37]:
```
y_pred_grid = clf_grid.predict(x_test)
```

In [38]:
```
# accuracy of our classification tree
clf_grid.score(x_test,y_test)
```
Out[38]:
```
0.7847533632286996
```

In [39]:
```
accuracy = accuracy_score(y_test, y_pred_grid)
accuracy
```
Out[39]:
```
0.7847533632286996
```

In [40]:
```
conf_mat_grid = confusion_matrix(y_test, y_pred_grid)
conf_mat_grid
```
Out[40]:
```
array([[124,  15],
       [ 33,  51]], dtype=int64)
```

In [41]:
```
tp_grid = conf_mat_grid[0][0]
fp_grid = conf_mat_grid[0][1]
fn_grid = conf_mat_grid[1][0]
tn_grid = conf_mat_grid[1][1]
```

In [42]:
```
precision_grid = tp_grid/(tp_grid+fp_grid)
precision_grid
```
Out[42]:
```
0.8920863309352518
```

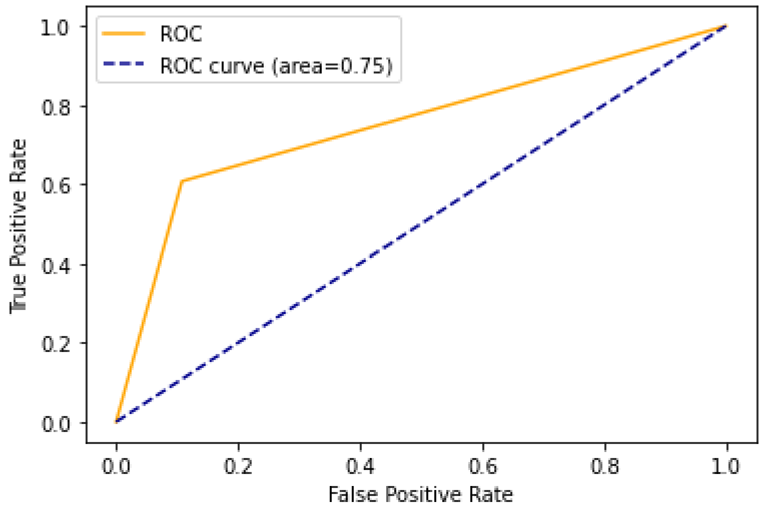
In [43]:
```
recall_grid = tp_grid/(tp_grid+fn_grid)
recall_grid
```
Out[43]:
```
0.7898089171974523
```

In [44]:
```
f1_score_grid = (2*precision_grid*recall_grid)/(precision_grid+recall_grid)
f1_score_grid
```
Out[44]:
```
0.8378378378378379
```

In [45]:
```
auc_grid = roc_auc_score(y_test, y_pred_grid)
auc_grid
```
Out[45]:
```
0.7496145940390545
```

In [46]:
```
fpr_grid, tpr_grid, thresholds_grid = roc_curve(y_test, y_pred_grid)
```

In [47]:
```
plt.plot(fpr_grid, tpr_grid, color='orange', label='ROC')
plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--', label='ROC curve (a
rea=%0.2f)' % auc_grid)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```



Project Done By: Urvi Gadda

mailto: urvigada96@gmail.com

In [ ]: