Assignment - 23 - MACHINE LEARNING - 4

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Problem Statement - Predicting Survival in the Titanic Data Set

We will be using a decision tree to make predictions about the Titanic data set from Kaggle. This data set provides information on the Titanic passengers and can be used to predict whether a passenger survived or not.

Solution:

In [108]:

```
# Loading Data and modules
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt
import sklearn
from pandas import Series, DataFrame
from pylab import rcParams

from sklearn import tree, metrics, model_selection, preprocessing
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
import pydotplus as pydotplus
from IPython.display import Image
from sklearn.externals.six import StringIO
from sklearn.tree import export_graphviz
import collections
```

In [90]:

```
# Create Datsframe from the URL
url= 'https://raw.githubusercontent.com/BigDataGal/Python-for-Data-Science/master/titanic-train.csv'
titanic = pd.read_csv(url)
titanic.columns =['PassengerId','Survived','Pclass','Name','Sex','Age','SibSp','Parch','Ticket','Fare','Cabin','Embark
ed']
titanic.head(2)
```

Out[90]:

	PassengerId	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	C

Description of Titanic Dataset:

Survival:	Survival 0 = No, 1 = Yes
Pclass:	Ticket class 1 = 1st, 2 = 2nd, 3 = 3rd
Sex:	Gender of passangers
Age:	Age of passangers(Age in years)
SibSp:	# of siblings / spouses aboard the Titanic
Parch:	# of parents / children aboard the Titanic
Ticket:	Ticket number
Fare:	Passenger fare
Cabin:	Cabin number
Embarked:	Port of Embarkation C = Cherbourg, Q = Queenstown, S = Southampton

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Data Exploration

- Structure of data

In [91]:
```
titanic.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: 83.6+ KB
```

In [92]:
```
# Calculation Null/NA values present in titanic dataset
titanic.isna().sum()
```

Out[92]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [93]:
```
# Statictical observation
titanic.describe()
```

Out[93]:

	PassengerId	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

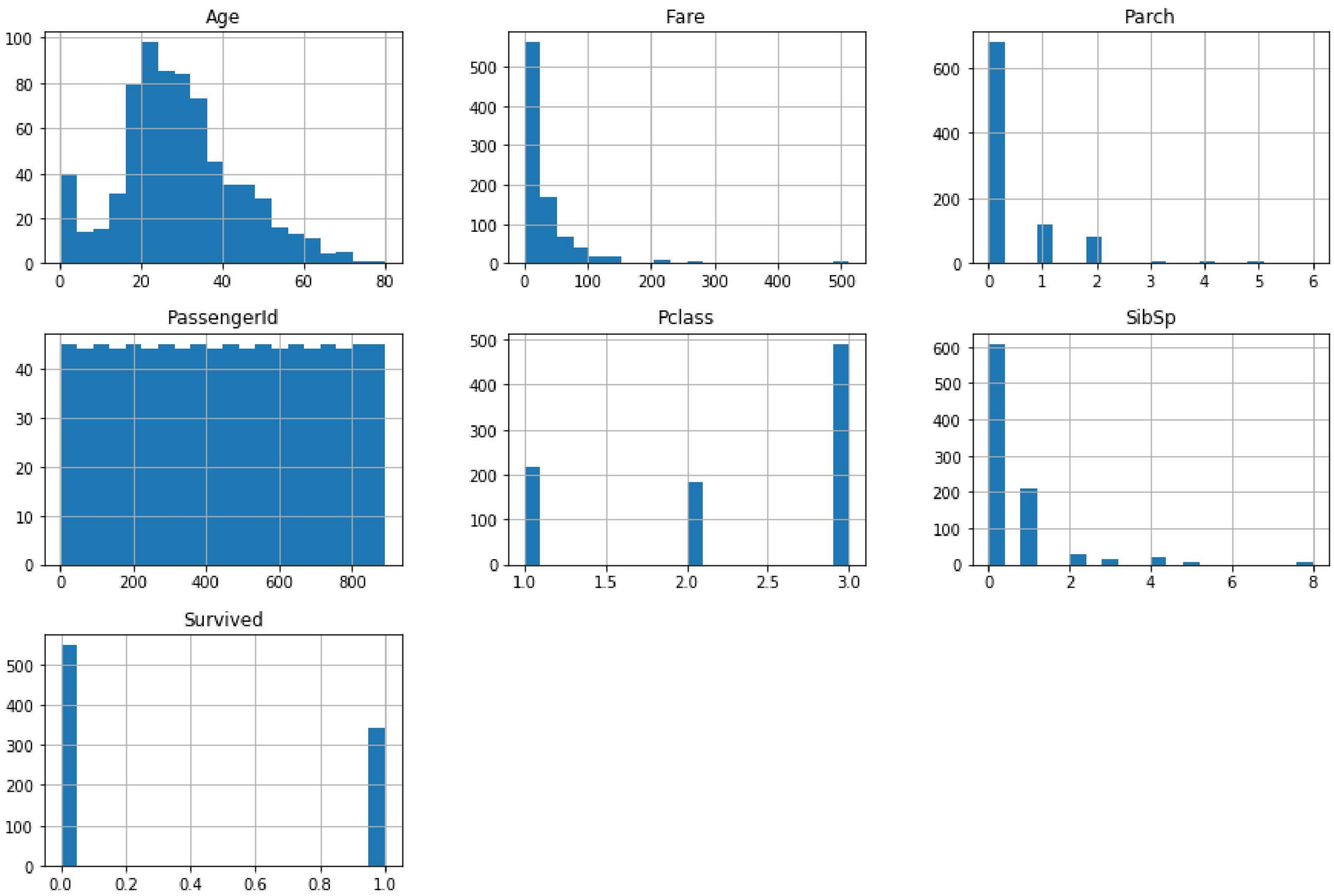
In [94]:
```
# Analyze the Survival based on raw data
titanic.groupby(['Survived']).count()
```

Out[94]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
Survived											
0	549	549	549	549	424	549	549	549	549	68	549
1	342	342	342	342	290	342	342	342	342	136	340

Data Visualisation

In [100]:
```
titanic.hist(bins=20, figsize=(15,10))
plt.show()
```



Data Exploration

Use only Pclass, Sex, Age, SibSp (Siblings aboard), Parch (Parents/children aboard), and Fare to predict whether a passenger survived

In [101]:
```python
# Cretae dataframe with given features
# Decide Independant and Dependnat variables and clean data
df = titanic[['Survived','Pclass', 'Sex', 'Age', 'SibSp','Parch','Fare']]
df.head(2)
```

Out[101]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
0	0	3	male	22.0	1	0	7.2500
1	1	1	female	38.0	1	0	71.2833

In [102]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 7 columns):
Survived    891 non-null int64
Pclass      891 non-null int64
Sex         891 non-null object
Age         714 non-null float64
SibSp       891 non-null int64
Parch       891 non-null int64
Fare        891 non-null float64
dtypes: float64(2), int64(4), object(1)
memory usage: 48.8+ KB
```

In [103]:
```
# Fill NA/NULL values with Mean for numerical datatatype features
df=df.fillna(df.mean())

# Convert Sex to Bironary or numaric Data
df['Sex'] = pd.get_dummies(df['Sex'])

df.info()
```

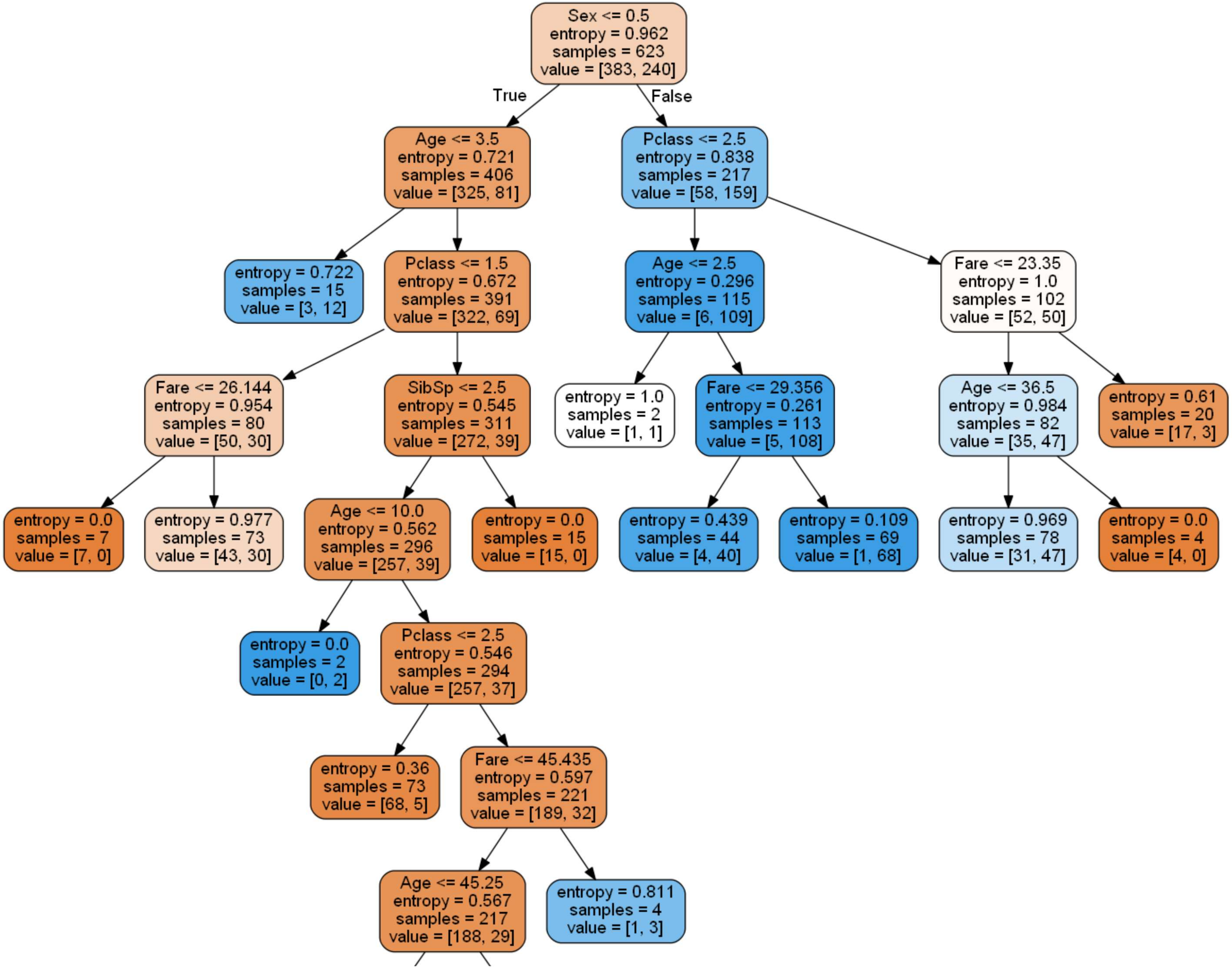
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 7 columns):
Survived    891 non-null int64
Pclass      891 non-null int64
Sex         891 non-null uint8
Age         891 non-null float64
SibSp       891 non-null int64
Parch       891 non-null int64
Fare        891 non-null float64
dtypes: float64(2), int64(4), uint8(1)
memory usage: 42.7 KB
```

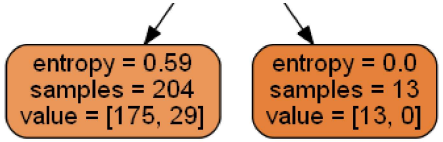
Decision Tree Model

In [104]:
```
# Target or Dependant variables
df_features=df[['Pclass','Sex','Age','SibSp','Parch','Fare']]
df_target=df['Survived']

#Split the Train and Test Data
X_train, X_test, y_train, y_test = train_test_split(df_features,df_target, test_size = 0.30)

#Initiate Decision Tree Classifier and Fit
clf = DecisionTreeClassifier(criterion = 'entropy',
                             splitter='best',
                             min_samples_split=80,
                             max_depth=8,
                             random_state=1)
clf.fit(X_train, y_train)
```

Out[104]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=8,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=80,
            min_weight_fraction_leaf=0.0, presort=False, random_state=1,
            splitter='best')
```

In [105]:
```
#Show in the tree graphice to evaluate the model
dot_data = tree.export_graphviz(clf,
                                out_file=None,
                                filled=True,
                                rounded=True,
                                feature_names=['Pclass','Sex','Age','SibSp','Parch','Fare'])
graph = pydotplus.graph_from_dot_data(dot_data)

#graph = pydotplus.graph_from_dot_data(dot_data)
display(Image(graph.create_png()))
```


Sex <= 0.5
entropy = 0.962
samples = 623
value = [383, 240]
True
False
Age <= 3.5
entropy = 0.721
samples = 406
value = [325, 81]
Pclass <= 2.5
entropy = 0.838
samples = 217
value = [58, 159]
entropy = 0.722
samples = 15
value = [3, 12]
Pclass <= 1.5
entropy = 0.672
samples = 391
value = [322, 69]
Age <= 2.5
entropy = 0.296
samples = 115
value = [6, 109]
Fare <= 23.35
entropy = 1.0
samples = 102
value = [52, 50]
Fare <= 26.144
entropy = 0.954
samples = 80
value = [50, 30]
SibSp <= 2.5
entropy = 0.545
samples = 311
value = [272, 39]
entropy = 1.0
samples = 2
value = [1, 1]
Fare <= 29.356
entropy = 0.261
samples = 113
value = [5, 108]
Age <= 36.5
entropy = 0.984
samples = 82
value = [35, 47]
entropy = 0.61
samples = 20
value = [17, 3]
entropy = 0.0
samples = 7
value = [7, 0]
entropy = 0.977
samples = 73
value = [43, 30]
Age <= 10.0
entropy = 0.562
samples = 296
value = [257, 39]
entropy = 0.0
samples = 15
value = [15, 0]
entropy = 0.439
samples = 44
value = [4, 40]
entropy = 0.109
samples = 69
value = [1, 68]
entropy = 0.969
samples = 78
value = [31, 47]
entropy = 0.0
samples = 4
value = [4, 0]
entropy = 0.0
samples = 2
value = [0, 2]
Pclass <= 2.5
entropy = 0.546
samples = 294
value = [257, 37]
entropy = 0.36
samples = 73
value = [68, 5]
Fare <= 45.435
entropy = 0.597
samples = 221
value = [189, 32]
Age <= 45.25
entropy = 0.567
samples = 217
value = [188, 29]
entropy = 0.811
samples = 4
value = [1, 3]



In [106]:
```
# Print Decision Tree Cross Validation Score for Train Data
print('Train Set :',clf.score(X_train, y_train))

# Print Decision Tree Score for Test Data
print('Test Set:  ',clf.score(X_test, y_test))
```

```
Train Set : 0.826645264847512
Test Set:   0.8507462686567164
```

Now, we will make prediction based on the Decision Tree Model

In [107]:
```
# For the inut feature we are getting feature of an random passanger and passing the feature
# to get the Predicted Survival (later we can compare with actual as we it is known here)
predicted_survival=clf.predict(np.array(df_features[1:2]))

print('Predicted Survival:\t\t', predicted_survival)
print('Actual Survival(from Dataset):\t', df['Survived'][1:2].values[0])
```

```
Predicted Survival:             [1]
Actual Survival(from Dataset):  1
```