Task 1: Titanic Survival Prediction

Importing Required Libraries

We are using the following libraries to complete the task of titanic survival prediction:

- Numpy
- Pandas
- re: To work with regular expressions
- Seaborn
- Matplotlib
- Skelarn etc.

```
import numpy as np
import pandas as pd
import re
import warnings
warnings.filterwarnings('ignore')

#For data visualization
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Saved successfully!

Reading Dataset and Data preprocessing

The importing of data is an important step in the process. Also data pre-processing is neccessary .Data Pre-Processing refers to the cleaning, transforming, and integrating of data in order to make it ready for analysis. The goal of data preprocessing is to improve the quality of the data and to make it more suitable for the specific task.

```
train = pd.read_csv('/titanic-training-data.csv')
test = pd.read_csv('/tested.csv')

# To know number of columns and rows
train.shape
# (891, 12)
```

```
(891, 12)
```

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

```
#lets take a look at our training data
train.head()
```

	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
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

```
# Now the test dataset
test.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S

Saved successfully!

```
#list of all the columns in our training dataset
train.columns
```

```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

```
# summary statistics of data
train.describe()
```

	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

```
train.describe(include='O')
```

	Name	Sex	Ticket	Cabin	Embarked
count	891	891	891	204	889

```
#percantage of missing values in train dataset
train.isnull().sum()/ len(train) *100
```

```
PassengerId     0.000000
Survived        0.000000
Pclass          0.000000
Name            0.000000
Sex             0.000000
Age            19.865320
SibSp           0.000000
Parch           0.000000
Ticket          0.000000
Fare            0.000000
Cabin          77.104377
Embarked        0.224467
dtype: float64
```

```
#Finding the Null values in test dataset
test.isnull().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
```

Saved successfully!

```
Cabin          327
Embarked         0
dtype: int64
```

```
train['Sex'].value_counts()
```

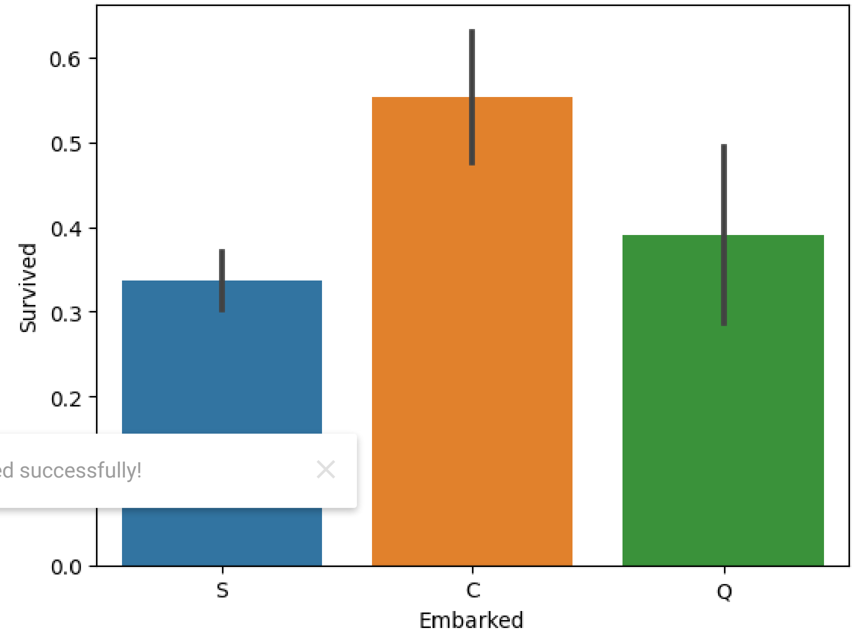
```
male      577
female    314
Name: Sex, dtype: int64
```

```
#Comparing the Sex and Survived feature
sns.barplot(x='Sex',y='Survived',data=train)
train.groupby('Sex',as_index=False).Survived.mean()
```

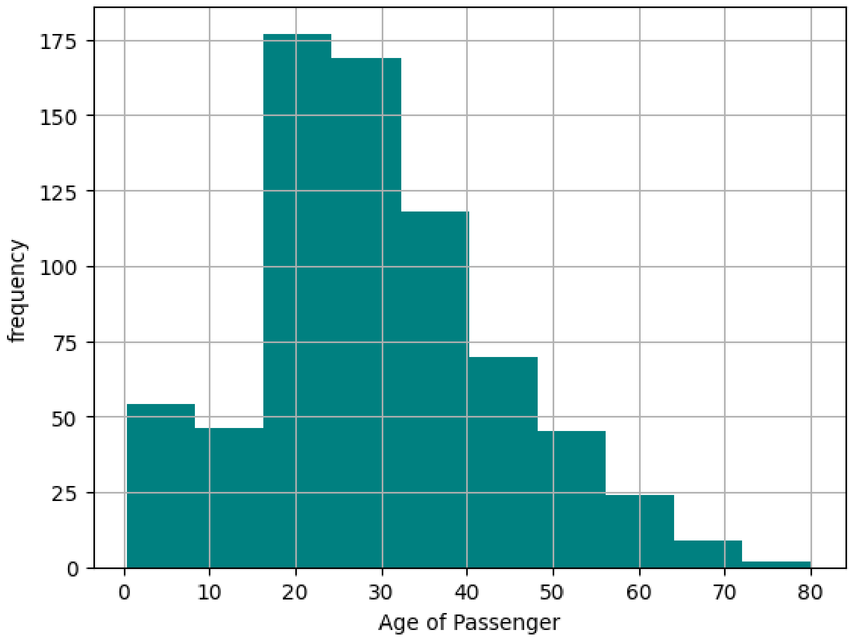
	Sex	Survived
0	female	0.742038

```
#Comparing the Embarked feature against Survived
sns.barplot(x='Embarked',y='Survived',data=train)
train[["Embarked", "Survived"]].groupby(['Embarked'], as_index=False).mean().sort_values(by='Survived', ascending=False)
```

	Embarked	Survived
0	C	0.553571
1	Q	0.389610
2	S	0.336957



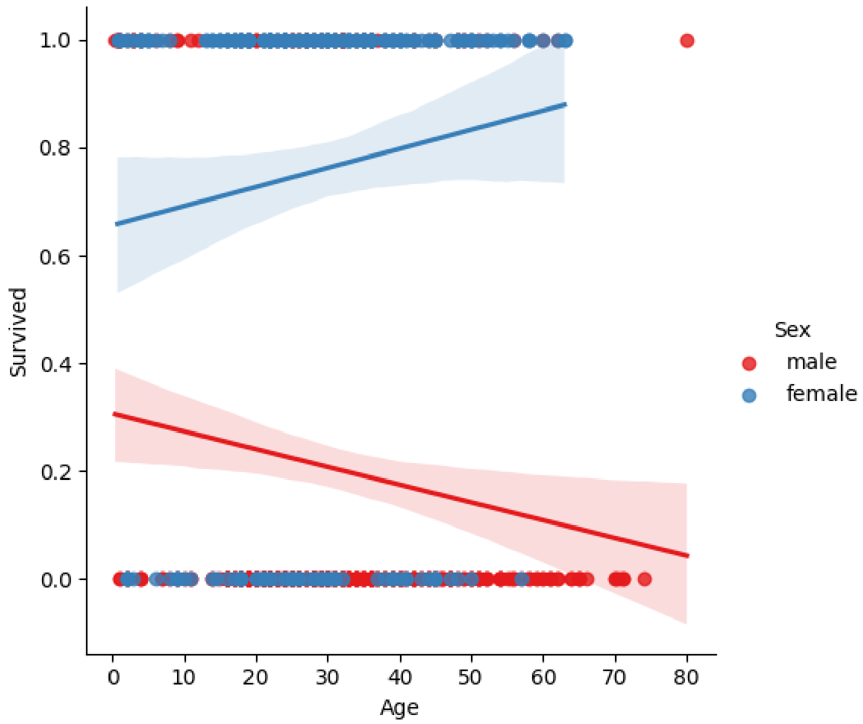

```
train.Age.hist(bins=10,color='teal')
plt.xlabel('Age of Passenger')
plt.ylabel('frequency')
plt.show()
print("Median age of passengers :", int(train.Age.median()))
print("Standard Deviation of age of passengers :", int(train.Age.std()))
```




```
Median age of passengers : 28
Standard Deviation of age of passengers : 14
```

```
sns.lmplot(x='Age',y='Survived',data=train,hue='Sex',palette='Set1')
```

<seaborn.axisgrid.FacetGrid at 0x7d437e10bd00>

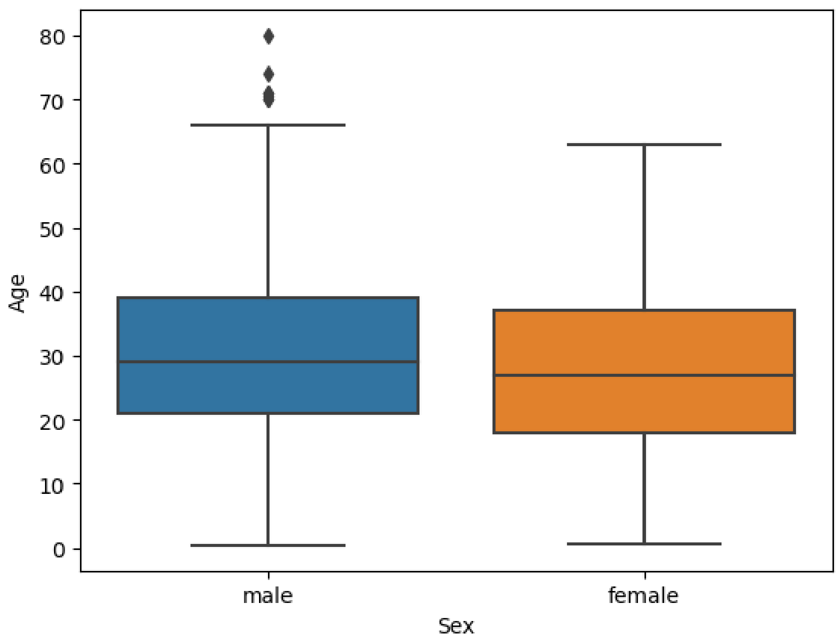


Saved successfully!

```
outliers in Age data
ain)
```

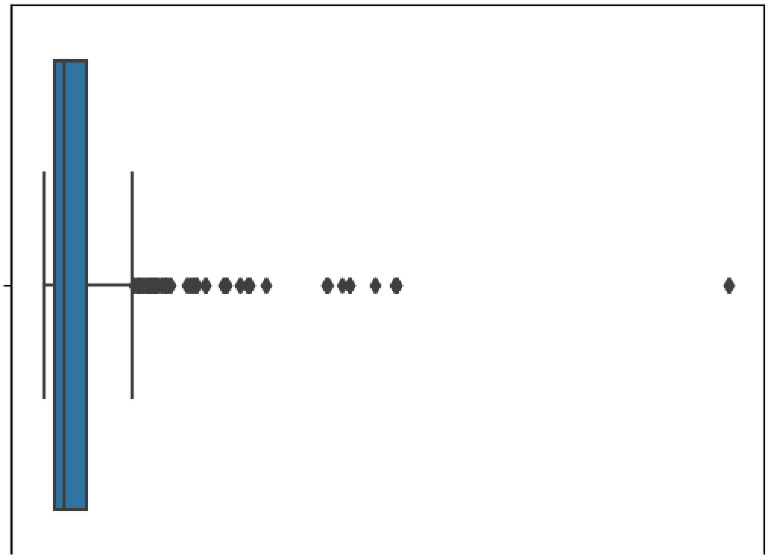
```
#getting the median age according to Sex
train.groupby('Sex',as_index=False)['Age'].median()
```

	Sex	Age
0	female	27.0
1	male	29.0




```
#plotting the Fare column to see the spread of data
sns.boxplot(x="Fare",data=train)
```

<Axes: xlabel='Fare'>



```
#dropping the coulmns, no more required
drop_list=['Cabin','Ticket']

train_1 = train.drop(drop_list,axis=1)
test_passenger = pd.DataFrame(test.PassengerId)
test_1 = test.drop(drop_list,axis=1)

test_passenger.head()
test_1.head()
```

Saved successfully!

			ss	Name	Sex	Age	SibSp	Parch	Fare	Embarked
0	892	0	3	Kelly, Mr. James	male	34.5	0	0	7.8292	Q
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	7.0000	S
2	894	0	2	Myles, Mr. Thomas Francis	male	62.0	0	0	9.6875	Q
3	895	0	3	Wirz, Mr. Albert	male	27.0	0	0	8.6625	S
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	12.2875	S

```
#filling the missing values in Embarked column in train and test datasets
train_1.Embarked.fillna('S',inplace=True)
train_1.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	7.9250	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	53.1000	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	8.0500	S

```
#filling the missing values in the Age column
train_1.Age.fillna(28, inplace=True)
test_1.Age.fillna(28, inplace=True)
train_1.tail()
```

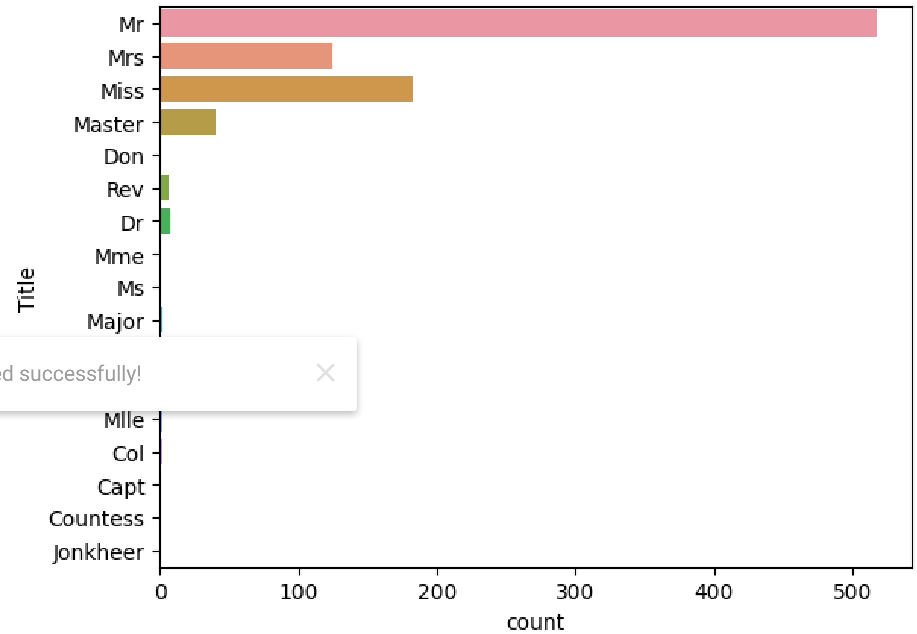
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Fare	Embarked
				Johnston, Miss. Catherine Helen						

```
#Filling the null values in Fare values with median in test dataset
test_1.Fare.fillna(test.Fare.median(), inplace=True)
```

```
#combining train and test dataframes
Concat_data = [train_1, test_1]
```

```
#extracting the various title in Names
for dataset in Concat_data:
    dataset['Title'] = dataset.Name.str.extract(' ([A-Za-z]+)\.', expand=False)

#Plotting the various titles
sns.countplot(y='Title',data=train_1)
```

```
<Axes: xlabel='count', ylabel='Title'>
```



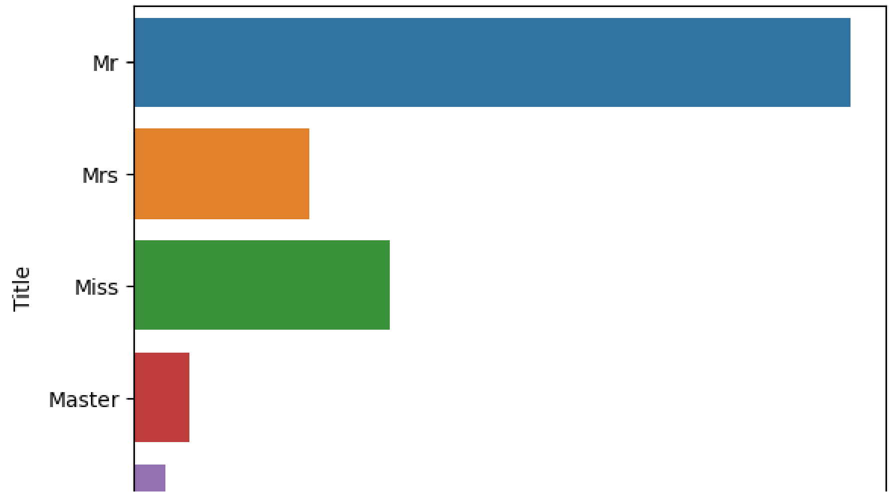
Saved successfully!

```
#Refining the title
for dataset in Concat_data:
    dataset['Title'] = dataset['Title'].replace(['Lady', 'Countess','Capt', 'Col',\
    'Don', 'Dr', 'Major', 'Rev', 'Sir', 'Jonkheer', 'Dona'], 'Special')

    dataset['Title'] = dataset['Title'].replace({'Mlle':'Miss','Ms':'Miss','Mme':'Mrs'})

train_1.groupby('Title',as_index=False)['Survived'].mean().sort_values(by='Survived',ascending=False)
```

	Title	Survived
3	Mrs	0.793651
1	Miss	0.702703
0	Master	0.575000
4	Special	0.347826
2	Mr	0.156673

```
#Now lets see the distribution of the title feature
sns.countplot(y='Title',data=train_1)
```

```
<Axes: xlabel='count', ylabel='Title'>
```




```
#Mapping the title names to numeric values
title_mapping = {"Mr": 1, "Miss": 2, "Mrs": 3, "Master": 4, "Special": 5}
for dataset in Concat_data:
    dataset['Title'] = dataset.Title.map(title_mapping)
    dataset['Title'] = dataset.Title.fillna(0)


#dropping the Name,SibSP and Parch columns
for dataset in Concat_data:
    dataset.drop(['SibSp','Parch','Name'],axis=1,inplace=True)
```

Saved successfully!

```
ge']>50)&(train_1['Sex']=='female')
d_Female'].astype(int)

test_1['Old_Female'] = (test_1['Age']>50)&(test_1['Sex']=='female')
test_1['Old_Female'] = test_1['Old_Female'].astype(int)


#Converting categorical variables into numerical ones
train_2 = pd.get_dummies(train_1,columns=['Pclass','Sex','Embarked'],drop_first=True)
test_2 = pd.get_dummies(test_1,columns=['Pclass','Sex','Embarked'],drop_first=True)
train_2.head()
```

	PassengerId	Survived	Age	Fare	Title	Old_Female	Pclass_2	Pclass_3	Sex_ma
0	1	0	22.0	7.2500	1	0	0	1	
1	2	1	38.0	71.2833	3	0	0	0	
2	3	1	26.0	7.9250	2	0	0	1	
3	4	1	35.0	53.1000	3	0	0	0	
4	5	0	35.0	8.0500	1	0	0	1	

```
train_2.head()
#sns.barplot('AgeBands','Survived',data=train_df2)
```

	PassengerId	Survived	Age	Fare	Title	Old_Female	Pclass_2	Pclass_3	Sex_ma
0	1	0	22.0	7.2500	1	0	0	1	
1	2	1	38.0	71.2833	3	0	0	0	
2	3	1	26.0	7.9250	2	0	0	1	
3	4	1	35.0	53.1000	3	0	0	0	
4	5	0	35.0	8.0500	1	0	0	1	

```
test_2.head()
```

	PassengerId	Survived	Age	Fare	Title	Old_Female	Pclass_2	Pclass_3	Sex_ma
0	892	0	34.5	7.8292	1	0	0	1	
1	893	1	47.0	7.0000	3	0	0	1	
2	894	0	62.0	9.6875	1	0	1	0	
3	895	0	27.0	8.6625	1	0	0	1	
4	896	1	22.0	12.2875	3	0	0	1	

Fitting a model

Model fitting is a measure of how well a machine learning model generalizes to similar data to that on which it was trained. Each machine learning algorithm has a basic set of parameters that can be changed to improve its accuracy. During the fitting process, you run an algorithm on data for which you know the target variable, known as “labeled” data, and produce a machine learning model.In this project we are fitting a decision tree .

```
#importing the required ML libraries for model fitting
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.metrics import accuracy_score
```

```
#Splitting training data into features and target
X = train_2.drop("Survived",axis=1)
y = train_2["Survived"]
```

Saved successfully!

```
in train and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,random_state=2)
X_train.head()
```

	PassengerId	Age	Fare	Title	Old_Female	Pclass_2	Pclass_3	Sex_male	Embarked_Q	Embarked_S	AgeBands
451	452	28.0	19.9667	1	0	0	1	1	0	1	1
345	346	24.0	13.0000	2	0	1	0	0	0	1	1
687	688	19.0	10.1708	1	0	0	1	1	0	1	0
279	280	35.0	20.2500	3	0	0	1	0	0	1	2
742	743	21.0	262.3750	2	0	0	0	0	0	0	0

```
#Fitting a decision tree
#Decision Tree Classifier

decisiontree = DecisionTreeClassifier()
dep = np.arange(1,10)
param_grid = {'max_depth' : dep}
clsft_cv = GridSearchCV(decisiontree, param_grid=param_grid, cv=5)
clsft_cv.fit(X, y)
clsft_cv.best_params_,clsft_cv.best_score_*100
print('Best score:',clsft_cv.best_score_*100)
```

```
Best score: 82.48948590797816
```

Model Evaluation

```
from sklearn.tree import DecisionTreeClassifier
clf = DecisionTreeClassifier(criterion='entropy', max_depth=3, random_state=0)
clf.fit(X_train, y_train)
y_pred_train=clf.predict(X_train)
accuracy_train=accuracy_score(y_pred_train,y_train)
y_predicted = clf.predict(X_test)
```

```
accuracy_test=accuracy_score(y_predicted,y_test)
```

```
accuracy_train
```

```
0.8475120385232745
```

```
accuracy_test
```

```
0.8097014925373134
```

Saved successfully!

0s completed at 6:38 PM