BUSA3020: Advanced Analytics Techniques

Assignment 2: Predictive Analytics

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Import relevant Python packages

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn import linear_model
from sklearn.metrics import r2_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
```

Read the data and show the first 5 columns of the data

In [2]:
```
df = pd.read_csv("TitanicData_AllPassengers.csv")
df.index = np.arange(1,len(df)+1) #Remove 0 (default) indexing on Python
df.head(5)
```

Out[2]:

	Survived	Passenger Class	Name	Gender	Age	No of Siblings or Spouses on Board	No of Parents or Children on Board	Ticket Number	Passenger Fare	Cabin	Port of Embarkation	LifeBoat
1	Yes	First	Allen, Miss. Elisabeth Walton	Female	29.0000	0	0	24160	211.3375	B5	Southampton	2
2	Yes	First	Allison, Master. Hudson Trevor	Male	0.9167	1	2	113781	151.5500	C22 C26	Southampton	11
3	No	First	Allison, Miss. Helen Loraine	Female	2.0000	1	2	113781	151.5500	C22 C26	Southampton	NaN
4	No	First	Allison, Mr. Hudson Joshua Creighton	Male	30.0000	1	2	113781	151.5500	C22 C26	Southampton	NaN

Exploratary Data Analysis (EDA)

In [3]:
```
#Show the list of columns within the data set.
df.columns
```

Out[3]:
```
Index(['Survived', 'Passenger Class', 'Name', 'Gender', 'Age',
       'No of Siblings or Spouses on Board',
       'No of Parents or Children on Board', 'Ticket Number', 'Passenger Fare',
       'Cabin', 'Port of Embarkation', 'LifeBoat'],
      dtype='object')
```

Data Dictionary:

- Survived: It shows whether the passengers have survived in the incident.
- Passenger Class: It shows the ticket class of the passengers.
- Name: The name of the passenger.
- Sex: The gender of the passenger.
- Age: The age of the passenger.
- No of Sibings or Spouses on board: Did the passenger has any sibings/spouses on board in the RMS Titantic.
- No of Parents or Children on board: Did the passenger has any parents/children on board in the RMS Titantic.
- Ticket Number: The ticket number of the passenger.
- Passenger Fare: The price of the passenger fare.
- Cabin: The cabin location of the passneger.

- Port of Embarkatation: The geographic location in a routing scheme from which the passenger depart.
- Lifeboat: Is the passenger in one of the lifeboats available in the RMS Titantic? If so, which one?

It shows that are there are some missing values within both variables 'Cabin' and 'Life Boat'. Further action is needed to resolve such issue.

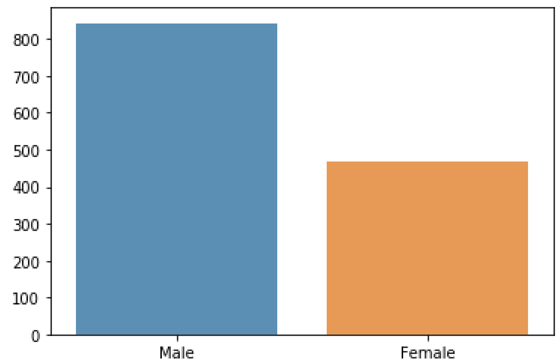
In [4]:
```
#Generate some descriptive statistics of the numerical features.
df.describe()
```

Out[4]:

	Age	No of Siblings or Spouses on Board	No of Parents or Children on Board	Passenger Fare
count	1046.000000	1309.000000	1309.000000	1308.000000
mean	29.881135	0.498854	0.385027	33.295479
std	14.413500	1.041658	0.865560	51.758668
min	0.166700	0.000000	0.000000	0.000000
25%	21.000000	0.000000	0.000000	7.895800
50%	28.000000	0.000000	0.000000	14.454200
75%	39.000000	1.000000	0.000000	31.275000
max	80.000000	8.000000	9.000000	512.329200

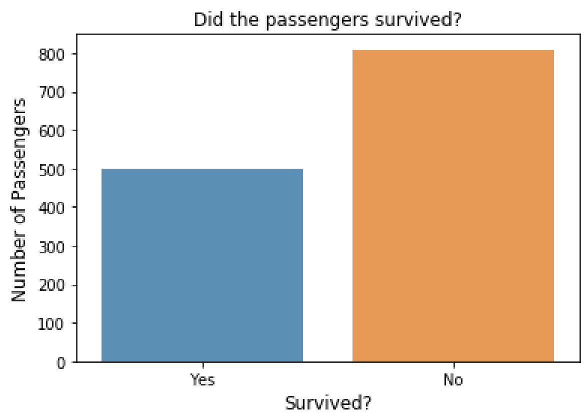
In [5]:
```
gender_count = df['Gender'].value_counts()
gender_count = gender_count[:10,]
sns.barplot(gender_count.index, gender_count.values, alpha=0.8, order=["Male", "Female"])
```

Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x2129a9cb408>



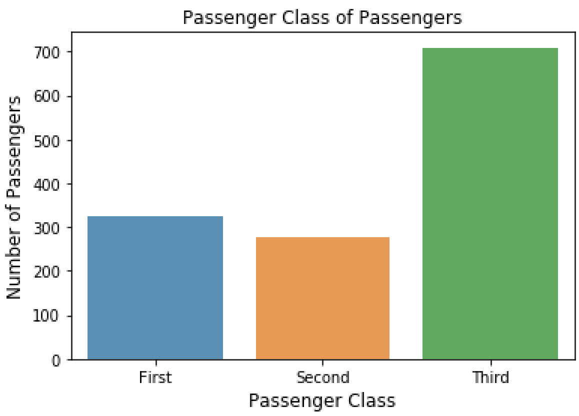
In [6]:
```
survived_count = df['Survived'].value_counts()
survived_count = survived_count[:10,]
sns.barplot(survived_count.index, survived_count.values, alpha=0.8,order=["Yes", "No"])
plt.title('Did the passengers survived?')
plt.ylabel('Number of Passengers', fontsize=12)
plt.xlabel('Survived?', fontsize=12)
```

Out[6]: Text(0.5, 0, 'Survived?')



In [7]:
```
class_count = df['Passenger Class'].value_counts()
class_count = class_count[:10,]
sns.barplot(class_count.index, class_count.values, alpha=0.8, order=["First", "Second","Third"])
plt.title('Passenger Class of Passengers')
plt.ylabel('Number of Passengers', fontsize=12)
plt.xlabel('Passenger Class', fontsize=12)

plt.show()
```



Data Cleansing

Check missing data within the dataset

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
Survived                             0
Passenger Class                      0
Name                                 0
Gender                               0
Age                                263
No of Siblings or Spouses on Board   0
No of Parents or Children on Board   0
Ticket Number                        0
Passenger Fare                       1
Cabin                             1014
Port of Embarkation                  2
LifeBoat                           823
dtype: int64
```

Find out the dimensions of the data (**Before dropping the values**).

In [9]:
```
df.shape
```

Out[9]:
```
(1309, 12)
```

Dealing with Missing Values.

- Drop the missing values of Age column.

In [10]:
```
df = df.dropna(axis=0, subset=['Age'])
```

- The column **Life Boat** is dropped as if the passenger got on a life boat, he/she would likely to survive.
- The column **Cabin** is dropped as it contains many missing values - Hard to deal with.

In [11]:
```
df.drop(['Cabin'], axis = 1, inplace = True)
df.drop(['LifeBoat'], axis = 1, inplace = True)
```

- Drop the missing values of Port of Embrakation and Passenger Fare column.

In [12]:
```
df = df.dropna(axis=0, subset=['Port of Embarkation'])
df = df.dropna(axis=0, subset=['Passenger Fare'])
```

Find out the dimensions of the data (**After dropping the values**).

In [13]:
```
df.shape
```

Out[13]:
```
(1043, 10)
```

Changing the values of different variables.

- Convert the target variable - 'Survived' into a dummy variable.

In [14]:
```
df.replace(to_replace ="Yes", value ="1", inplace = True)
df.replace(to_replace ="No", value ="0", inplace = True)
df["Survived"] = pd.to_numeric(df["Survived"])
df.head()
```

Out[14]:

	Survived	Passenger Class	Name	Gender	Age	No of Siblings or Spouses on Board	No of Parents or Children on Board	Ticket Number	Passenger Fare	Port of Embarkation
1	1	First	Allen, Miss. Elisabeth Walton	Female	29.0000	0	0	24160	211.3375	Southampton
2	1	First	Allison, Master. Hudson Trevor	Male	0.9167	1	2	113781	151.5500	Southampton
3	0	First	Allison, Miss. Helen Loraine	Female	2.0000	1	2	113781	151.5500	Southampton
4	0	First	Allison, Mr. Hudson Joshua Creighton	Male	30.0000	1	2	113781	151.5500	Southampton
5	0	First	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	Female	25.0000	1	2	113781	151.5500	Southampton

- Convert the variable - 'Gender' into a dummy variable.

In [15]:
```
df.replace(to_replace ="Male", value ="0", inplace = True)
df.replace(to_replace ="Female", value ="1", inplace = True)
df["Gender"] = pd.to_numeric(df["Gender"])
df.head()
```

Out[15]:

	Survived	Passenger Class	Name	Gender	Age	No of Siblings or Spouses on Board	No of Parents or Children on Board	Ticket Number	Passenger Fare	Port of Embarkation
1	1	First	Allen, Miss. Elisabeth Walton	1	29.0000	0	0	24160	211.3375	Southampton
2	1	First	Allison, Master. Hudson Trevor	0	0.9167	1	2	113781	151.5500	Southampton
3	0	First	Allison, Miss. Helen Loraine	1	2.0000	1	2	113781	151.5500	Southampton
4	0	First	Allison, Mr. Hudson Joshua Creighton	0	30.0000	1	2	113781	151.5500	Southampton
5	0	First	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	1	25.0000	1	2	113781	151.5500	Southampton

- Replace the values of "First Class", "Second Class" and "Third" into '1', '2' and '3' - for our ease of analysis.

In [16]:
```
df.replace(to_replace ="First", value ="1", inplace = True)
df.replace(to_replace ="Second", value ="2", inplace = True)
df.replace(to_replace ="Third", value ="3", inplace = True)
df["Passenger Class"] = pd.to_numeric(df["Passenger Class"])
df.head()
```

Out[16]:

	Survived	Passenger Class	Name	Gender	Age	No of Siblings or Spouses on Board	No of Parents or Children on Board	Ticket Number	Passenger Fare	Port of Embarkation
1	1	1	Allen, Miss. Elisabeth Walton	1	29.0000	0	0	24160	211.3375	Southampton
2	1	1	Allison, Master. Hudson Trevor	0	0.9167	1	2	113781	151.5500	Southampton
3	0	1	Allison, Miss. Helen Loraine	1	2.0000	1	2	113781	151.5500	Southampton
4	0	1	Allison, Mr. Hudson Joshua Creighton	0	30.0000	1	2	113781	151.5500	Southampton
5	0	1	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	1	25.0000	1	2	113781	151.5500	Southampton

- Creation of age category and replace the values.

In [17]:
```
age_category = pd.cut(df.Age,bins=[0,2,17,65,99],labels=['Toddler/Baby','Child','Adult','Elderly'])
df.insert(5,'Age Group',age_category)
df.replace(to_replace ="Toddler/Baby", value ="1", inplace = True)
df.replace(to_replace ="Child", value ="2", inplace = True)
df.replace(to_replace ="Adult", value ="3", inplace = True)
df.replace(to_replace ="Elderly", value ="4", inplace = True)
df['Age Group'] = pd.to_numeric(df['Age Group'])
```

- Creation of a column called 'Title' with all the titles from the names

In [18]:
```
df['Title'] = df.Name.str.extract('([A-Za-z]+)\.')
display(df.Title.head())
```

```
1      Miss
2    Master
3      Miss
4        Mr
5       Mrs
Name: Title, dtype: object
```

In [19]:
```
display(df.Title.value_counts())
```

```
Mr          580
Miss        209
Mrs         169
Master       53
Rev           8
Dr            7
Col           4
Mlle          2
Major         2
Dona          1
Lady          1
Mme           1
Don           1
Jonkheer      1
Sir           1
Ms            1
Capt          1
Countess      1
Name: Title, dtype: int64
```

In [20]:
```
#Combine the titles 'Dr, Rev, Col, Major, Capt' into one group.
df.Title.replace(to_replace = ['Dr', 'Rev', 'Col', 'Major', 'Capt'], value = 'Officer', inplace = True)

#Combine the titles Dona, Jonkheer, Countess, Sir, Lady, Don in bucket Aristocrat into one group.
df.Title.replace(to_replace = ['Dona', 'Jonkheer', 'Countess', 'Sir', 'Lady', 'Don'], value = 'Aristocrat', i

#Combine the titles Mlle and Ms with Miss. And Mme with Mrs into one group.
df.Title.replace({'Mlle':'Miss', 'Ms':'Miss', 'Mme':'Mrs'}, inplace = True)
```

In [21]:
```
#Preview the new modified titles.
display(df.Title.head())
```

```
1      Miss
2    Master
3      Miss
4        Mr
5       Mrs
Name: Title, dtype: object
```

- Replace the values of the title into a numerical values

In [22]:
```
df.replace(to_replace ="Mr", value ="1", inplace = True)
df.replace(to_replace ="Miss", value ="2", inplace = True)
df.replace(to_replace ="Mrs", value ="3", inplace = True)
df.replace(to_replace ="Master", value ="4", inplace = True)
df.replace(to_replace ="Officer", value ="5", inplace = True)
df.replace(to_replace ="Aristocrat", value ="6", inplace = True)
df['Title'] = pd.to_numeric(df['Title'])
```

Previewing the dataframe the data.

In [23]:
```
df.head()
```

Out[23]:

	Survived	Passenger Class	Name	Gender	Age	Age Group	No of Siblings or Spouses on Board	No of Parents or Children on Board	Ticket Number	Passenger Fare	Port of Embarkation	Title
1	1	1	Allen, Miss. Elisabeth Walton	1	29.0000	3	0	0	24160	211.3375	Southampton	2
2	1	1	Allison, Master. Hudson Trevor	0	0.9167	1	1	2	113781	151.5500	Southampton	4
3	0	1	Allison, Miss. Helen Loraine	1	2.0000	1	1	2	113781	151.5500	Southampton	2
4	0	1	Allison, Mr. Hudson Joshua Creighton	0	30.0000	3	1	2	113781	151.5500	Southampton	1
5	0	1	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	1	25.0000	3	1	2	113781	151.5500	Southampton	3

Dropping Some (More) Variables

I decided to drop my variables as they may not beneficit in our model.

- **Age** is dropped as we already have a new column called 'Age Group'
- **Ticket Number** is dropped because there are already duplicate values within such column therefore it will affect our prediction accuracy. (Ticket Number is also act as an identifier therefore we cannot predict our model based on such field).
- **Passenger Fare** is dropped because it is correlated to Ticket Number therefore we can drop such variable.
- **Port of Embarkation** is dropped because the port of embarkation will NOT affect the survival of the passengers.
- The **Name** of the passengers is also removed due to the creation of the new column **Title**.

In [24]:
```
df.drop(['Age'], axis = 1, inplace = True)
df.drop(['Ticket Number'], axis = 1, inplace = True)
df.drop(['Passenger Fare'], axis = 1, inplace = True)
df.drop(['Port of Embarkation'], axis = 1, inplace = True)
df.drop(['Name'], axis = 1, inplace = True)
df.head()
```

Out[24]:

	Survived	Passenger Class	Gender	Age Group	No of Siblings or Spouses on Board	No of Parents or Children on Board	Title
1	1	1	1	3	0	0	2
2	1	1	0	1	1	2	4
3	0	1	1	1	1	2	2
4	0	1	0	3	1	2	1
5	0	1	1	3	1	2	3

- I have decided to conduct a correlation analysis before conducting any data analysis.

In [25]:
```
df.corr()
```

Out[25]:

	Survived	Passenger Class	Gender	Age Group	No of Siblings or Spouses on Board	No of Parents or Children on Board	Title
Survived	1.000000	-0.317737	0.536332	-0.112768	-0.011403	0.115436	0.394949
Passenger Class	-0.317737	1.000000	-0.141032	-0.186759	0.046333	0.016342	-0.156936
Gender	0.536332	-0.141032	1.000000	-0.088257	0.096464	0.222531	0.486663
Age Group	-0.112768	-0.186759	-0.088257	1.000000	-0.376262	-0.321477	-0.296628
No of Siblings or Spouses on Board	-0.011403	0.046333	0.096464	-0.376262	1.000000	0.373960	0.302026
No of Parents or Children on Board	0.115436	0.016342	0.222531	-0.321477	0.373960	1.000000	0.307252
Title	0.394949	-0.156936	0.486663	-0.296628	0.302026	0.307252	1.000000

Data Modelling

1) Logistic Regression

What is **Logistic Regression**?

Logistic regression is a type of model of probablistic statistical classification. It is used as a binary model to predict binary response (in this case, it is predicting whether the passenger of the Titanic or not), the outcome of a categorical variable (i.e. class label), based on one or more variables.

I have decided to split the dataset into - **80% Training Data and 20% Test Data**. *Note: If we split the data differently, we will create different results.

In [26]:
```
train, test = train_test_split(df, test_size=0.2, random_state=40)
print(train.shape)
print(test.shape)
y = df['Survived']
x = df.drop(['Survived'], axis = 1)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state = 40)
logreg = linear_model.LogisticRegression()
logreg.fit(x_train, y_train)
```

```
(834, 7)
(209, 7)
```

```
D:\Anaconda 3\lib\site-packages\sklearn\linear_model\logistic.py:432: FutureWarning: Default solver will be
changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

Out[26]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```

Generate a confusion matrix and compute the accuracy score by using the **Logistic Regression** metric.

In [27]:
```
y_pred = logreg.predict(x_test)
from sklearn.metrics import accuracy_score
print ("Accuracy score =", accuracy_score(y_test, y_pred))

from sklearn.metrics import confusion_matrix
print("Confusion Matrix = \n", confusion_matrix(y_test, y_pred))
```

```
Accuracy score = 0.8038277511961722
Confusion Matrix =
 [[103  22]
 [ 19  65]]
```

Generate the classification report by using the **Logistic Regression** metric.

In [28]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.82      0.83       125
           1       0.75      0.77      0.76        84

    accuracy                           0.80       209
   macro avg       0.80      0.80      0.80       209
weighted avg       0.81      0.80      0.80       209
```

2) Decision Tree

What is **Decsion Tree**?

Decsion Tree is a type of supervised learning (Algorithm which learn from a training set of labeled example to generalise to the sert of all possible inputs) algorithm where the data is continuously split according to a certain parameter.

In [29]:
```
titanic_tree = DecisionTreeClassifier(random_state=40)

titanic_tree .fit(x_train, y_train)

y_train_predict = titanic_tree.predict(x_train)
y_test_predict = titanic_tree.predict(x_test)

print("Decision Tree Train Accuracy:", accuracy_score(y_train_predict, y_train))
print("Decision Tree Test Accuracy:", accuracy_score(y_test_predict, y_test))
```

```
Decision Tree Train Accuracy: 0.829736211031175
Decision Tree Test Accuracy: 0.84688995215311
```

3) Random Forest

Random Forest

What is **Random Forest Random Forest** is a supervising learning algorithm - which essentially build upon decision trees. Rather than simply averaging the prediction of tress (which we can called a forest), random sampling of training data points when building trees as well as random subsets of features considered when splitting nodes.

In [30]:
```
from sklearn.ensemble import RandomForestClassifier

randomforest = RandomForestClassifier(random_state=40)
randomforest.fit(x_train, y_train)
y_pred = randomforest.predict(x_test)
acc_randomforest = round(accuracy_score(y_pred, y_test) * 100, 2)
print(acc_randomforest)
```

```
85.17

D:\Anaconda 3\lib\site-packages\sklearn\ensemble\forest.py:245: FutureWarning: The default value of n_estim
ators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```