eneskemal_PredModel

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1 Prediction Model

Course: Data Mining

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Implementing the logistic regression model on the Titanic data to predict the likelyhood of the events. I will be using binary outcome classification.

1.1 Data introduction:

- **Survival**: This refers to the survival of the passengers (0 = No and 1 = Yes)
- **Pclass**: This refers to the passenger class (1 = 1st, 2 = 2nd, and 3 = 3rd)
- **Name**: This refers to the names of the passengers
- **Sex**: This refers to the gender of the passenger
- **Age**: This refers to the age of the passengers
- **Sibsp**: This refers to the number of siblings/spouses aboard
- **Parch**: This refers to the number of parents/children aboard
- **Ticket**: This refers to the ticket number
- **Fare**: This refers to the passenger fares
- **Cabin**: This refers to the cabin
- **Embarked**: This refers to the port of embarkation (C = Cherbourg, Q = Queenstown, and S = Southampton)

1.2 Data Preparation and Cleaning

In [8]:
```
# Libraries used in the notebook
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from patsy import dmatrices # descriptive statistical models (similar to R

# Inline plotting
%matplotlib inline
```

```
In [9]: df = pd.read_csv('./eneskemal_PredModel.csv')
        df.count(0) # Counting missing values in the data
        # I am going to get rid of cabin(almost empty), Ticket(just an id),
        #  and Name(I don't need names of passengers) columns
```

```
Out[9]: PassengerId    891
        Survived       891
        Pclass         891
        Name           891
        Sex            891
        Age            714
        SibSp          891
        Parch          891
        Ticket         891
        Fare           891
        Cabin          204
        Embarked       889
        dtype: int64
```

```
In [10]: # Applying axis as 1 to remove the columns with the following labels
         df = df.drop(['Ticket','Cabin','Name'], axis=1)
         # Remove missing values
         df = df.dropna()
```

```
In [11]: df.count()
```

```
Out[11]: PassengerId    712
         Survived       712
         Pclass         712
         Sex            712
         Age            712
         SibSp          712
         Parch          712
         Fare           712
         Embarked       712
         dtype: int64
```

1.3 Data Seperation

```
In [12]: # Creating a formula that specifies numerical, categorical variables and
         #  their dependencies
         formula = 'Survived ~ C(Pclass) + C(Sex) + Age + SibSp + C(Embarked) + Par
         df_train = df.iloc[ 0: 600, : ]
         df_test = df.iloc[ 600: , : ]

         # Splitting the data into dependent and independent variables
         y_train,x_train = dmatrices(formula, data=df_train, return_type='dataframe
         y_test,x_test = dmatrices(formula, data=df_test, return_type='dataframe')
```

1.4 Model Building and Evaluation

In [13]:
```
from sklearn.linear_model import LogisticRegression
# instantiate a logistic regression model, and fit with X and y
model = LogisticRegression()
model = model.fit(x_train, y_train.Survived)
```

In [16]:
```
# examine the coefficients
pd.DataFrame(list(zip(x_train.columns, np.transpose(model.coef_))))
# The first column contains our dependent variable name and the second co
#  contains the coefficient values.
```

Out[16]:
```
                   0                  1
0          Intercept     [1.76714885294]
1     C(Pclass)[T.2]   [-0.855297665892]
2     C(Pclass)[T.3]    [-2.05150890647]
3     C(Sex)[T.male]    [-2.36757593644]
4   C(Embarked)[T.Q]   [-0.268544547557]
5   C(Embarked)[T.S]   [-0.265577528299]
6                Age  [-0.0309255780811]
7              SibSp    [-0.26002373595]
8              Parch  [-0.0967816203051]
```

In [17]:
```
# how our precision and recall are performing:
y_pred = model.predict_proba(x_test)
y_pred_flag = y_pred[:,1] > 0.7

pd.crosstab(y_test.Survived ,y_pred_flag ,
             rownames = ['Actual'] ,colnames = ['Predicted'])
```

Out[17]:
```
Predicted  False  True
Actual
0.0           66     1
1.0           21    24
```

In [20]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred_flag))
```

```
             precision    recall  f1-score   support

        0.0       0.76      0.99      0.86        67
        1.0       0.96      0.53      0.69        45

avg / total       0.84      0.80      0.79       112
```

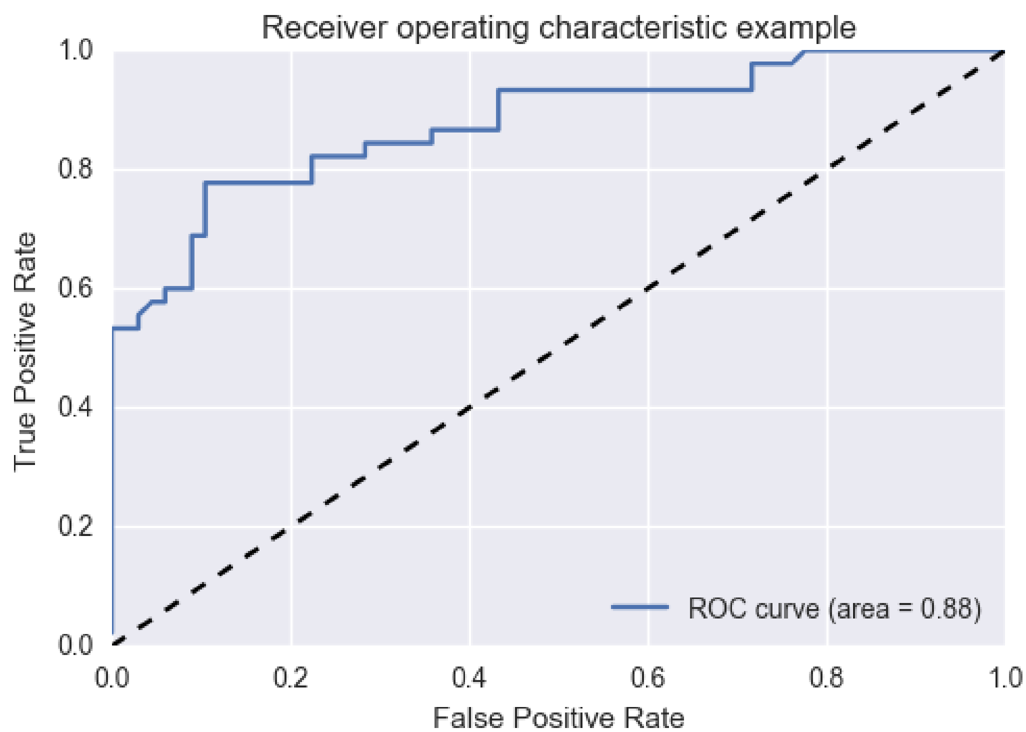
In [23]:
```
from sklearn.metrics import roc_curve, auc
# ROC and area under the curve:
```

```
fpr, tpr, thresholds = roc_curve(y_test, y_pred[:,1])
roc_auc = auc(fpr, tpr)
print("Area under the ROC curve : %f" % roc_auc)
```

```
Area under the ROC curve : 0.877944
```

What is ROC Curve: The ROC curve is a fundamental tool for diagnostic test evaluation. In a ROC curve the true positive rate (Sensitivity) is plotted in function of the false positive rate (100-Specificity) for different cut-off points of a parameter.

```
In [24]: # Plot ROC curve
         plt.clf()
         plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_auc)
         plt.plot([0, 1], [0, 1], 'k--')
         plt.xlim([0.0, 1.0])
         plt.ylim([0.0, 1.0])
         plt.xlabel('False Positive Rate')
         plt.ylabel('True Positive Rate')
         plt.title('Receiver operating characteristic example')
         plt.legend(loc="lower right")
         plt.show()
```




```
In [ ]:
```