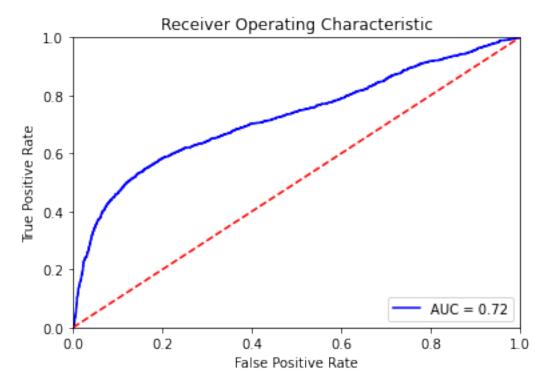
Module4 Tutorial GAMClassification

October 29, 2020

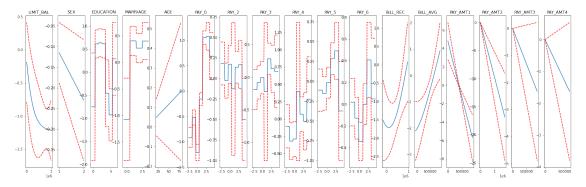
```
[1]: import numpy as np
            import matplotlib.pyplot as plt
            import pandas as pd
            from sklearn.model selection import train test split
            import statsmodels.formula.api as smf
            import statsmodels.api as sm
            from sklearn.metrics import confusion_matrix, roc_curve, auc
            from pygam import LogisticGAM, LinearGAM, GAM, s, f, l
[2]: #Credit Card Defaults, first prep data
[3]: mydata = pd.read_csv('UCI_Credit_Card_prepped.csv', index_col=0)
[4]: train, test = train_test_split(mydata, test_size=0.25)
[5]: #LINEAR MODEL AGAIN
            g1 = smf.glm(formula='default ~ LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + EDUCATION + MARRIAGE + AGE + LIMIT_BAL + SEX + SEX + LIMIT_BAL + SEX + S
               →PAY_0 + PAY_2 + PAY_3 + PAY_4 + PAY_5 + PAY_6 + BILL_REC + BILL_AVG + LI
              →PAY AMT1 + PAY AMT2 + PAY AMT3 + PAY AMT4 + PAY AMT5 + PAY AMT6', ...
              →data=train, family=sm.families.Binomial())
            g1 res = g1.fit()
            g1_pred = g1_res.predict(test)
            g1_pred_labels = np.zeros(len(test))
            g1_pred_labels[g1_pred >0.5] = 1
            confusion_matrix(test['default'], g1_pred_labels)
[5]: array([[5680, 185],
                               [1223, 412]])
[6]: fpr, tpr, threshold = roc curve(test['default'], g1 pred)
            roc_auc = auc(fpr, tpr)
            plt.title('Receiver Operating Characteristic')
            plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
            plt.legend(loc = 'lower right')
            plt.plot([0, 1], [0, 1], 'r--')
            plt.xlim([0, 1])
```

```
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



```
[7]: X_train = train.drop(columns=['default'])
y_train = train['default']
```

plt.show()

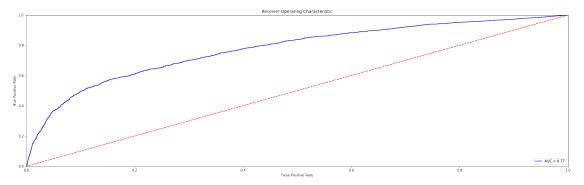


```
[9]: X_test = test.drop(columns=['default'])
y_test = test['default']
gam_preds = gam.predict_proba(X_test)
```

```
[10]: gam_pred_labels = np.zeros(len(test))
gam_pred_labels[gam_preds > 0.5] = 1
confusion_matrix(test['default'], gam_pred_labels)
```

```
[10]: array([[5588, 277], [1051, 584]])
```

```
[11]: fpr, tpr, threshold = roc_curve(y_test, gam_preds)
    roc_auc = auc(fpr, tpr)
    plt.title('Receiver Operating Characteristic')
    plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
    plt.legend(loc = 'lower right')
    plt.plot([0, 1], [0, 1], 'r--')
    plt.xlim([0, 1])
    plt.ylim([0, 1])
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()
```



[]: