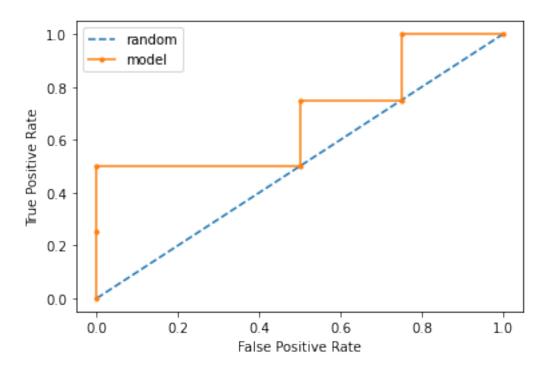
hw3

October 3, 2021

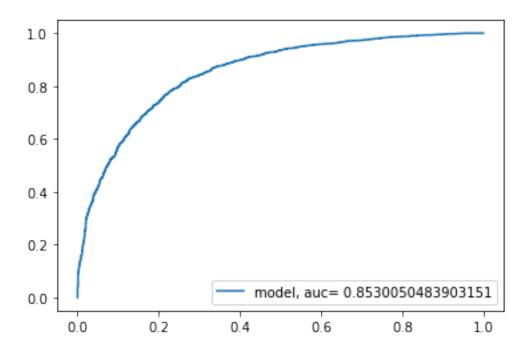
```
[10]: import pandas as pd
      import matplotlib.pyplot as plt
      from sklearn.metrics import roc_auc_score, roc_curve
[11]: model_prob = [0.004, 0.015, 0.448, 0.568, 0.780, 0.879, 0.967, 0.978]
      model_class = [0, 1, 0, 1, 0, 0, 1, 1]
[12]: def plot_roc_curve(model_class, model_prob):
          random_probs = [0 for __ in range(len(model_prob))] # used for linear line_
       \rightarrowto compare to ROC
          #AUC
          model_auc = roc_auc_score(model_class, model_prob)
          #model score
          print("Model: ROC AUC = %.3f" % (model_auc))
          #random model:
          random_false_pos, random_true_pos, __ = roc_curve(model_class, random_probs)
          #actual model:
          model_false_pos, model_true_pos, __ = roc_curve(model_class, model_prob)
          #roc curve plot
          plt.plot(random_false_pos, random_true_pos, linestyle = '--', label = __
       →'random')
          plt.plot(model_false_pos, model_true_pos, marker = '.', label ='model')
          #labels, legend, show
          plt.xlabel('False Positive Rate')
          plt.ylabel('True Positive Rate')
          plt.legend()
          plt.show()
      plot_roc_curve(model_class, model_prob)
```

Model: ROC AUC = 0.688

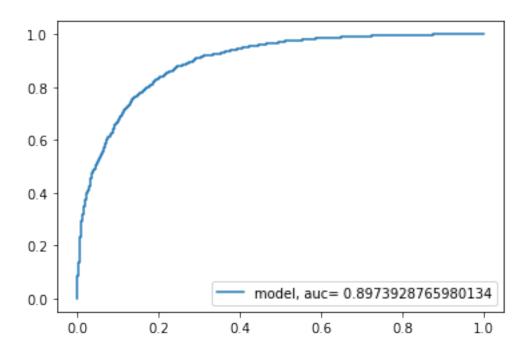


```
[13]: #Part 2: Logistic Regression
      from sklearn.linear_model import LogisticRegression
      from sklearn import metrics
      import numpy as np
      df = pd.read_csv("EE627A_HW3_DataSet1.csv", header = None)
      df.head()
[13]:
            0
                    1
                             2
                                     3
                                             4
                                                      5
                                                              6
                                                                      7
                                                                                    \
         5.5986 5.5986
                         5.5340
                                  5.5340
                                          289.37
                                                  289.82
                                                           289.30
                                                                   289.66
                                                                           289.37
        5.5340
                 5.5521
                         5.5108
                                  5.5185
                                          289.64
                                                  289.89
                                                           289.63
                                                                   289.76
                                                                           289.64
      2
        5.5185
                5.5185
                         5.4566
                                  5.4772
                                          289.86
                                                  290.07
                                                           289.65
                                                                   289.93
                                                                           289.86
        5.4772
                                  5.3894
                                          289.93
                 5.4772
                         5.3894
                                                  290.13
                                                           289.63
                                                                   289.86
                                                                           289.93
         5.3894
                 5.4152
                         5.3868
                                  5.4152
                                          289.85
                                                  290.03
                                                           289.45
                                                                   289.51
                                                                           289.85
            9
                          467
                                  468
                                          469
                                                  470
                                                           471
                                                                   472
                                                                           473
         289.82
                      21.206
                               41.042 42.338
                                               41.042
                                                       42.108
                                                                2.1330
                                                                        2.1744
      0
                 . . .
                               42.108 42.108
                                               41.881
                                                       42.033
         289.89
                      21.258
                                                                2.1175
                                                                        2.1227
      2
         290.07
                      21.268
                               42.033
                                       42.261
                                               41.804
                                                       41.881
                                                                2.1227
                                                                        2.1227
                      21.310
                               42.033
                                               42.033
         290.13
                                       42.186
                                                        42.108
                                                                2.1227
                                                                        2.1227
         290.03
                      21.310
                               42.108
                                       42.186
                                               42.033
                                                                2.0995
                                                                        2.0995
                                                        42.108
            474
                    475
                         476
         2.1175
                2.1175
```

```
1 2.1175 2.1175
      2 2.1124 2.1124
     3 2.0995 2.0995
      4 2.0943 2.0995
      [5 rows x 477 columns]
[14]: predictor = df.iloc[:, 0:476]
      response = df[476]
      response.tail()
[14]: 3995
     3996
     3997
             0
     3998
             1
      3999
             0
     Name: 476, dtype: int64
[15]: #fit and instantiate the model:
      logreg = LogisticRegression(solver='liblinear', C=10.0, random_state=0)
      logreg.fit(predictor, response)
      y_pred_proba = logreg.predict_proba(predictor)[::,1]
      #modeling:
      model_falsepos, model_truepos, __ = roc_curve(response, y_pred_proba)
      auc = roc_auc_score(response, y_pred_proba)
      #plot
      plt.plot(model_falsepos, model_truepos, label = 'model, auc= '+str(auc))
      plt.legend()
      plt.show()
```



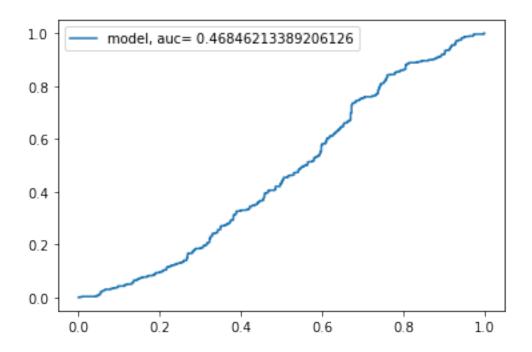
```
[16]: #Task 2
      training_set = df.iloc[0:3000, 0:476]
      validation_set = df.iloc[3000:4000, 0:476]
      response_training = df.iloc[0:3000, 476]
      response_validate = df.iloc[3000:4000, 476]
      \#response\_training = df[np.ix\_([476], [0:3000])]
[17]: #training set date to apply logistic regression
      model_train = LogisticRegression(solver='liblinear', C=10.0, random_state=0)
      model_train.fit(training_set, response_training)
      model_train_proba = model_train.predict_proba(training_set)[::,1]
      training_FP, training_TP, __ = roc_curve(response_training, model_train_proba)
      auc = roc_auc_score(response_training, model_train_proba)
      #plot
      plt.plot(training_FP, training_TP, label ='model, auc= '+str(auc))
      plt.legend()
      plt.show()
```



```
[19]: #validate set
model_validate_proba = model_train.predict_proba(validation_set)[::,1]

validate_FP, validate_TP, __ = roc_curve(response_validate, model_validate_proba)
auc = roc_auc_score(response_validate, model_validate_proba)

plt.plot(validate_FP, validate_TP, label ='model, auc= '+str(auc))
plt.legend()
plt.show()
```



[20]: #The validate auc is 0.468 and the training auc is 0.897, a difference of 0.429

#The validate model is not a good model because it shows that it is predicting

→false positives more than 50% of the time,

#which is worse than guessing. Something is wrong with the model