Fraud Detection using Logistic Regression

December 8, 2022

```
[1]: import pandas as pd
    df = pd.read_csv('data/card_data.csv')
   df.head()
[2]:
                  V1
                            V2
                                     V3
                                               ۷4
                                                        V5
                                                                  V6
                                                                           ۷7
    0
        0.0 -1.359807 -0.072781
                                2.536347
                                         1.378155 -0.338321
                                                            0.462388
                                                                     0.239599
    1
        0.0 1.191857 0.266151
                               0.166480
                                         0.448154 0.060018 -0.082361 -0.078803
        1.0 -1.358354 -1.340163
                               1.773209
                                        0.379780 -0.503198
                                                            1.800499
                                                                     0.791461
        1.0 -0.966272 -0.185226 1.792993 -0.863291 -0.010309
    3
                                                            1.247203
                                                                     0.237609
        0.095921
                                                                     0.592941
             ٧8
                      V9
                                  V21
                                           V22
                                                    V23
                                                              V24
                                                                       V25
    0 0.098698 0.363787
                          ... -0.018307
                                      0.277838 -0.110474 0.066928
                                                                   0.128539
    1 0.085102 -0.255425
                          ... -0.225775 -0.638672 0.101288 -0.339846
                                                                  0.167170
    2 0.247676 -1.514654
                          ... 0.247998
                                      0.771679
                                               0.909412 -0.689281 -0.327642
    3 0.377436 -1.387024
                                      0.005274 -0.190321 -1.175575  0.647376
                          ... -0.108300
    4 -0.270533 0.817739
                          ... -0.009431
                                      V26
                     V27
                               V28
                                   Amount
    0 -0.189115
                0.133558 -0.021053
                                   149.62
    1 0.125895 -0.008983
                          0.014724
                                     2.69
                                               0
    2 -0.139097 -0.055353 -0.059752
                                   378.66
                                               0
    3 -0.221929 0.062723
                          0.061458
                                   123.50
                                               0
    4 0.502292 0.219422
                          0.215153
                                    69.99
                                               0
    [5 rows x 31 columns]
[3]: df['Class'].value_counts()
[3]: 0
         284315
    1
            492
    Name: Class, dtype: int64
[4]: df = df.sample(frac = 1, random_state = 1)
    df = df.reset_index(drop = True)
```

```
df.head()
[4]:
                                  ۷2
            Time
                        V1
                                            VЗ
                                                       ۷4
                                                                 V5
                                                                           ۷6
     0 119907.0 -0.611712 -0.769705 -0.149759 -0.224877
                                                           2.028577 -2.019887
        78340.0 -0.814682 1.319219 1.329415 0.027273 -0.284871 -0.653985
     1
         82382.0 -0.318193 1.118618 0.969864 -0.127052 0.569563 -0.532484
     3
         31717.0 -1.328271 1.018378 1.775426 -1.574193 -0.117696 -0.457733
         80923.0 1.276712 0.617120 -0.578014 0.879173 0.061706 -1.472002
              ۷7
                        8V
                                  ۷9
                                               V21
                                                         V22
                                                                   V23
                                                                             V24 \
     0 \quad 0.292491 \quad -0.523020 \quad 0.358468 \quad ... \quad -0.075208 \quad 0.045536 \quad 0.380739 \quad 0.023440
     1 0.321552 0.435975 -0.704298 ... -0.128619 -0.368565 0.090660
                                                                        0.401147
     2 0.706252 -0.064966 -0.463271
                                     ... -0.305402 -0.774704 -0.123884 -0.495687
     3 0.681867 -0.031641 0.383872
                                     ... -0.220815 -0.419013 -0.239197 0.009967
     4 0.373692 -0.287204 -0.084482
                                      ... -0.160161 -0.430404 -0.076738 0.258708
             V25
                       V26
                                           V28 Amount Class
                                 V27
     0 -2.220686 -0.201146  0.066501  0.221180
                                                   1.79
                                                             0
     1 -0.261034 0.080621 0.162427 0.059456
                                                   1.98
                                                             0
     2 -0.018148  0.121679  0.249050  0.092516
                                                   0.89
                                                             0
     3 0.232829 0.814177 0.098797 -0.004273
                                                  15.98
                                                             0
     4 0.552170 0.370701 -0.034255 0.041709
                                                   0.76
                                                             0
     [5 rows x 31 columns]
[5]: as_np = df.to_numpy()
     index = int(len(as np) * .92)
     X_train, y_train = as_np[:index, :-1], as_np[:index, -1]
     X_test, y_test = as_np[index:, :-1], as_np[index:, -1]
     (X_train.shape, y_train.shape), (X_test.shape, y_test.shape)
[5]: (((262022, 30), (262022,)), ((22785, 30), (22785,)))
[6]: from sklearn.preprocessing import StandardScaler
     scaler = StandardScaler().fit(X_train)
     X_train = scaler.transform(X_train)
     X_test = scaler.transform(X_test)
     X_test[0]
[6]: array([ 0.14097956, 0.53955733, -1.15153973, -0.47041404, 0.57191953,
            -0.85362208, -0.27419086, -0.03159233, -0.25697594, 2.43387034,
            -0.75622807, -0.03956163, -1.77401948, 2.41251471, 1.26340856,
```

```
-0.24099657, 0.16722599, 0.24463032, 0.56588687, -0.53397987, 1.02654979, 0.4423462, 0.47928779, -0.49696321, -0.14435544, -0.64466426, 0.08065479, -0.24695714, 0.11458447, 1.64640304])
```

[7]: from sklearn.linear_model import LogisticRegression

model = LogisticRegression().fit(X_train, y_train)
 test_predictions = model.predict(X_test)

pd.value_counts(test_predictions)

[7]: 0.0 22757 1.0 28 dtype: int64

[8]: from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

cm = confusion_matrix(y_test, test_predictions, labels = [0, 1])

disp = ConfusionMatrixDisplay(confusion_matrix = cm,

display_labels = ['Not Fraud', 'Fraud'])

disp.plot()

[8]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x173812d02b0>



```
[9]: tn, fp, fn, tp = cm.ravel()
     s = '''
     True negatives: {0}
     False Positives: {1}
     False Negatives: {2}
     True Positives: {3}'''.format(tn, fp, fn, tp)
     print(s)
     True negatives: 22741
     False Positives: 8
     False Negatives: 16
     True Positives: 20
[10]: \# accuracy = (tp+tn)/(tp+tn+fp+fn)
     def accuracy(tn, fp, fn, tp):
         return ((tp+tn)/(tp+tn+fp+fn))
     "Accuracy: {0}".format(accuracy(tn, fp, fn, tp))
[10]: 'Accuracy: 0.9989466754443713'
[11]: \# recall = sensitivity = true positive rate = tp/(tp+fn)
     def tpr(tn, fp, fn, tp):
         return (tp / (tp + fn))
     "True positive Rate: {0}".format(tpr(tn, fp, fn, tp))
[11]: 'True positive Rate: 0.55555555555555556'
[12]: # false negative rate = fn/(tp+fn)
     def fpr(tn, fp, fn, tp):
         return (fn / (tp + fn))
     "False Negative Rate: {0}".format(fpr(tn, fp, fn, tp))
[13]: # specificity = true negative rate = tn/(tn+fp)
     def tnr(tn, fp, fn, tp):
         return (tn / (tn + fp))
```

```
"True Negative Rate: {0}".format(tnr(tn, fp, fn, tp))
[13]: 'True Negative Rate: 0.9996483361906018'
[14]: # false positive rate = fp/(tn+fp)
      def fpr(tn, fp, fn, tp):
          return (fp / (tn + fp))
      "False Positive Rate: {0}".format(fpr(tn, fp, fn, tp))
[14]: 'False Positive Rate: 0.00035166380939821533'
[15]: # precision = positive predictive value = tp/(tp+fp)
      def ppv(tn, fp, fn, tp):
          return (tp / (tp + fp))
      "Positive Predictive Value: {0}".format(ppv(tn, fp, fn, tp))
[15]: 'Positive Predictive Value: 0.7142857142857143'
[16]: | # negative predictive value = tn/(tn+fn)
      def npv(tn, fp, fn, tp):
          return (tn / (tn + fn))
      "Negative Predictive Value: {0}".format(npv(tn, fp, fn, tp))
[16]: 'Negative Predictive Value: 0.9992969196291251'
[17]: \# balanced accuracy = (tpr+tnr)/2
      def balanced_accuracy(tn, fp, fn, tp):
          return (tpr(tn, fp, fn, tp) + tnr(tn, fp, fn, tp)) / 2
      "Balanced Accuracy: {0}".format(balanced_accuracy(tn, fp, fn, tp))
[17]: 'Balanced Accuracy: 0.7776019458730787'
[18]: \# f1 \ score = 2 \ x \ (precision \ x \ recall)/(precision + recall)
      def f1(tn, fp, fn, tp):
          p = ppv(tn, fp, fn, tp)
          r = tpr(tn, fp, fn, tp)
          return (2*p*r)/(p+r)
      "F1 Score: {0}".format(f1(tn, fp, fn, tp))
```

```
[18]: 'F1 Score: 0.6250000000000001'
[19]: probabilities = model.predict_proba(X_test)[:, 1]
      probabilities
[19]: array([0.00012139, 0.0003532, 0.00030147, ..., 0.00473659, 0.00017273,
             0.00171865])
[20]: pd.value_counts(probabilities > 0.5)
[20]: False
               22757
      True
                  28
      dtype: int64
[21]: import numpy as np
      thresholds = np.linspace(0, 1, num = 2000).astype(np.float16)
      thresholds
[21]: array([0.000e+00, 5.002e-04, 1.000e-03, ..., 9.990e-01, 9.995e-01,
             1.000e+00], dtype=float16)
[22]: all_predictions = np.array([(probabilities > t).astype(int) for t in_
       →thresholds])
      all_predictions.shape
[22]: (2000, 22785)
[23]: all_predictions[-4]
[23]: array([0, 0, 0, ..., 0, 0, 0])
[24]: pd.value_counts(all_predictions[-4])
[24]: 0
           22776
      dtype: int64
[25]: confusion_matrices = [confusion_matrix(y_test, predictions) for predictions in__
       →all_predictions]
      tn_fp_fn_tps = [cm.ravel() for cm in confusion_matrices]
      tprs = [tpr(tn, fp, fn, tp) for tn, fp, fn, tp in tn_fp_fn_tps]
      fprs = [fpr(tn, fp, fn, tp) for tn, fp, fn, tp in tn_fp_fn_tps]
```

```
[26]: import plotly.express as px
      px.scatter(x = fprs, y = tprs, color = thresholds, labels = dict(x = 'False_{ll})
       ⊖Positive Rate', y = 'True Positive Rate', color = 'Threshold'), title = 'ROC⊔

Gurve')
[27]: from sklearn.metrics import auc
      auc(fprs, tprs)
[27]: 0.9810064911278153
[28]: # classification report
      from sklearn.metrics import classification_report
      print(classification_report(y_test, test_predictions, labels = [0, 1],__
       starget_names = ['Not Fraud', 'Fraud']))
                                 recall f1-score
                                                      support
                    precision
        Not Fraud
                          1.00
                                    1.00
                                               1.00
                                                        22749
            Fraud
                         0.71
                                    0.56
                                               0.63
                                                           36
                                               1.00
                                                        22785
         accuracy
        macro avg
                         0.86
                                    0.78
                                               0.81
                                                        22785
     weighted avg
                         1.00
                                    1.00
                                               1.00
                                                        22785
[29]: # matthews correlation coefficient = (tp \ x \ tn) - (fp \ x \ fn) / sqroot((tp + fp) \ x_{\perp})
       \hookrightarrow (tp + fn) x (tn + fp) x (tn + fn))
      import math as mt
      def mcc(tn, fp, fn, tp):
          return (((tp*tn) - (fp*fn))/mt.sqrt((tp + fp)*(tp + fn)*(tn + fp)*(tn + _{\sqcup}
       ⊶fn)))
      "Matthews Correlation Coefficient: {0}".format(mcc(tn, fp, fn, tp))
[29]: 'Matthews Correlation Coefficient: 0.6294313746803477'
```

[]: