Credit Card Fraud Detection

December 31, 2019

1 Import

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn import metrics
```

[2]:
```python
df = pd.read_csv('datasets/creditcard.csv')
```

2 Data Analysis

[3]:
```python
# Let's take a look at the head
df.head()
```

[3]:
```
   Time        V1        V2        V3        V4        V5        V6        V7  \
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
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        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  … -0.108300  0.005274 -0.190321 -1.175575  0.647376
4 -0.270533  0.817739  … -0.009431  0.798278 -0.137458  0.141267 -0.206010

        V26       V27       V28  Amount  Class
0 -0.189115  0.133558 -0.021053  149.62      0
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]
```

[4]:
```
# Check the shape of the dataframe
df.shape
```

[4]:
```
(284807, 31)
```

[5]:
```
# Check for null values, remove rows with null values if they exist
df.dropna(axis=0)
df.shape
```

[5]:
```
(284807, 31)
```

Looking at the data above, we see that this is a classification problem where we are to decide the 'Class' at each row.

[6]:
```
# Check the min, max values of the columns
df.describe()
```

[6]:
```
                Time            V1            V2            V3            V4  \
count  284807.000000  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean    94813.859575  1.165980e-15  3.416908e-16 -1.373150e-15  2.086869e-15
std     47488.145955  1.958696e+00  1.651309e+00  1.516255e+00  1.415869e+00
min         0.000000 -5.640751e+01 -7.271573e+01 -4.832559e+01 -5.683171e+00
25%     54201.500000 -9.203734e-01 -5.985499e-01 -8.903648e-01 -8.486401e-01
50%     84692.000000  1.810880e-02  6.548556e-02  1.798463e-01 -1.984653e-02
75%    139320.500000  1.315642e+00  8.037239e-01  1.027196e+00  7.433413e-01
max    172792.000000  2.454930e+00  2.205773e+01  9.382558e+00  1.687534e+01

                 V5            V6            V7            V8            V9  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean   9.604066e-16  1.490107e-15 -5.556467e-16  1.177556e-16 -2.406455e-15
std    1.380247e+00  1.332271e+00  1.237094e+00  1.194353e+00  1.098632e+00
min   -1.137433e+02 -2.616051e+01 -4.355724e+01 -7.321672e+01 -1.343407e+01
25%   -6.915971e-01 -7.682956e-01 -5.540759e-01 -2.086297e-01 -6.430976e-01
50%   -5.433583e-02 -2.741871e-01  4.010308e-02  2.235804e-02 -5.142873e-02
75%    6.119264e-01  3.985649e-01  5.704361e-01  3.273459e-01  5.971390e-01
max    3.480167e+01  7.330163e+01  1.205895e+02  2.000721e+01  1.559499e+01

       …           V21           V22           V23           V24  \
count  …  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean   …  1.656562e-16 -3.444850e-16  2.578648e-16  4.471968e-15
std    …  7.345240e-01  7.257016e-01  6.244603e-01  6.056471e-01
min    … -3.483038e+01 -1.093314e+01 -4.480774e+01 -2.836627e+00
25%    … -2.283949e-01 -5.423504e-01 -1.618463e-01 -3.545861e-01
```

```
50%    … -2.945017e-02  6.781943e-03 -1.119293e-02  4.097606e-02
75%    …  1.863772e-01  5.285536e-01  1.476421e-01  4.395266e-01
max    …  2.720284e+01  1.050309e+01  2.252841e+01  4.584549e+00

                V25           V26           V27           V28         Amount  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  284807.000000
mean   5.340915e-16  1.687098e-15 -3.666453e-16 -1.220404e-16      88.349619
std    5.212781e-01  4.822270e-01  4.036325e-01  3.300833e-01     250.120109
min   -1.029540e+01 -2.604551e+00 -2.256568e+01 -1.543008e+01       0.000000
25%   -3.171451e-01 -3.269839e-01 -7.083953e-02 -5.295979e-02       5.600000
50%    1.659350e-02 -5.213911e-02  1.342146e-03  1.124383e-02      22.000000
75%    3.507156e-01  2.409522e-01  9.104512e-02  7.827995e-02      77.165000
max    7.519589e+00  3.517346e+00  3.161220e+01  3.384781e+01   25691.160000

               Class
count  284807.000000
mean        0.001727
std         0.041527
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000

[8 rows x 31 columns]
```

[7]:

```python
# Check class sizes
zero = len(df[df['Class']==0])
one = len(df[df['Class']==1])
print ('% of data with class 0 =', round(zero/(zero+one)*100,2))
print ('% of data with class 1 =', round(one/(zero+one)*100,2))
```

```
% of data with class 0 = 99.83
% of data with class 1 = 0.17
```

3 Data Modeling

Looking at our analyses above, we will now perform the following steps, in order, on the data: - remove the 'Time' and 'Amount' columns from our training set as these do not influence the model. - normalize our data by bringing all our data values at the same scale. - split the data into train and test samples. - since class 1 sample is extremely small when compared to class 0, we will use the SMOTE algorithm to balance the data (make class sizes equal).

[8]:

```python
dft = df.drop(axis=1, labels=['Time', 'Amount'])
```

[9]:
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
dfs = pd.DataFrame(scaler.fit_transform(dft), columns=dft.columns)
```

[10]:
```
# split the data into X and y
X = dfs.iloc[:, dfs.columns != 'Class']
y = dfs.iloc[:, dfs.columns == 'Class']

# split into train and test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=0)
```

[11]:
```
# run smote
from imblearn.over_sampling import SMOTE
os = SMOTE(random_state=0)
os_data_X, os_data_y = os.fit_sample(X_train, y_train.values.ravel())
os_data_X = pd.DataFrame(data=os_data_X, columns=X_train.columns )
os_data_y= pd.DataFrame(data=os_data_y, columns=['Class'])

# we can Check the numbers of our data
print("Length of oversampled data =", len(os_data_X))
print("Number of Class 0 in oversampled data =",␣
 ↪len(os_data_y[os_data_y['Class']==0]))
print("Number of Class 1 in oversampled data =",␣
 ↪len(os_data_y[os_data_y['Class']==1]))
print("Proportion of Class 0 in oversampled data =",␣
 ↪len(os_data_y[os_data_y['Class']==0])/len(os_data_X))
print("Proportion of Class 1 in oversampled data =",␣
 ↪len(os_data_y[os_data_y['Class']==1])/len(os_data_X))
```

```
Using TensorFlow backend.
```

```
Length of oversampled data = 454908
Number of Class 0 in oversampled data = 227454
Number of Class 1 in oversampled data = 227454
Proportion of Class 0 in oversampled data = 0.5
Proportion of Class 1 in oversampled data = 0.5
```

3.0.1 Logistic Regression

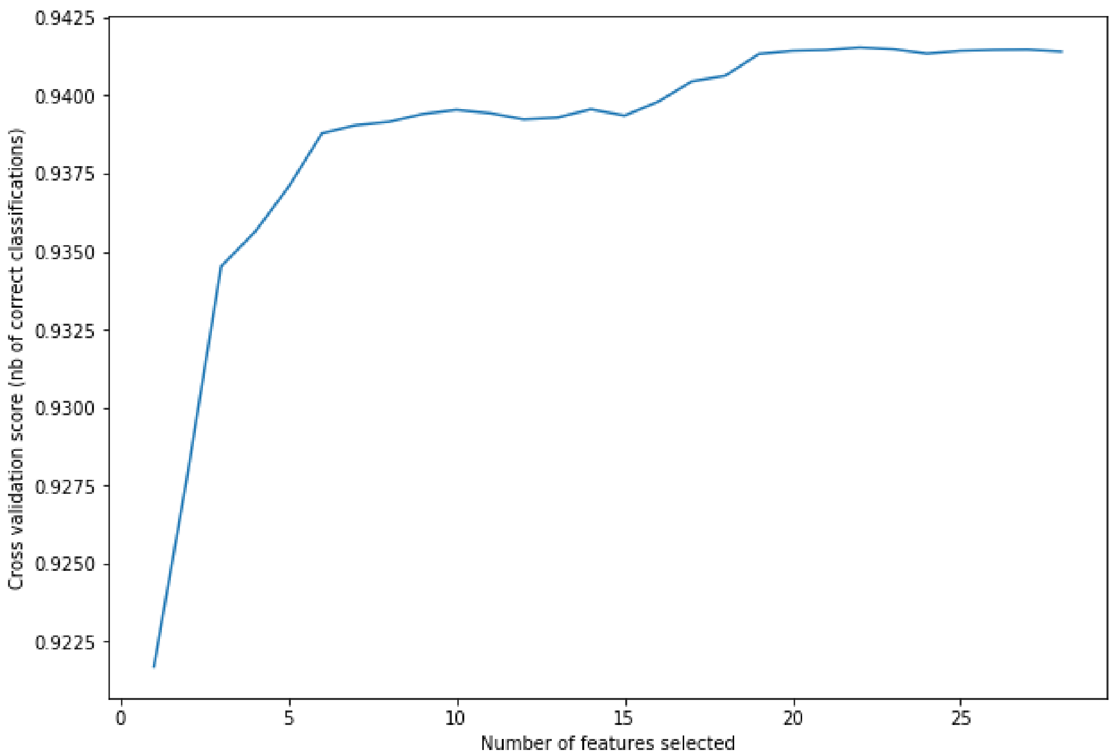
We will use the RFECV function that will select the optimal number of features for training the model.

[12]:
```
# Build a Logistic Regression model
from sklearn.feature_selection import RFECV
from sklearn.linear_model import LogisticRegression
```

```
rfecv = RFECV(estimator=LogisticRegression(solver='liblinear'), step=1, cv=10,␣
 ↪scoring='accuracy')
rfecv.fit(os_data_X, os_data_y.values.ravel())

print('Optimal number of features:', rfecv.n_features_)
print('Selected features:', list(os_data_X.columns[rfecv.support_]))
```

```
Optimal number of features: 22
Selected features: ['V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V10',
'V11', 'V12', 'V13', 'V14', 'V16', 'V18', 'V20', 'V21', 'V22', 'V23', 'V26',
'V27', 'V28']
```

[13]:
```
# Plot number of features vs. cross-validation score
plt.figure(figsize=(10,7))
plt.xlabel("Number of features selected")
plt.ylabel("Cross validation score (nb of correct classifications)")
plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
plt.show()
```



[14]:
```
cols = list(os_data_X.columns[rfecv.support_])
X = os_data_X[cols]
y = os_data_y['Class']
```

[15]:
```python
import statsmodels.api as sm

logit_model = sm.Logit(y,X)
result = logit_model.fit()
print(result.summary2())
```

```
Optimization terminated successfully.
         Current function value: 0.140682
         Iterations 12
                          Results: Logit
=================================================================
Model:              Logit            Pseudo R-squared: 0.797
Dependent Variable: Class            AIC:              128038.6485
Date:               2019-12-31 12:53 BIC:              128281.2612
No. Observations:   454908           Log-Likelihood:   -63997.
Df Model:           21               LL-Null:          -3.1532e+05
Df Residuals:       454886           LLR p-value:      0.0000
Converged:          1.0000           Scale:            1.0000
No. Iterations:     12.0000
-------------------------------------------------------------------
       Coef.    Std.Err.      z       P>|z|     [0.025     0.975]
-------------------------------------------------------------------
V1      5.0176    0.2367    21.1980   0.0000     4.5537     5.4816
V2      0.6550    0.3920     1.6709   0.0947    -0.1133     1.4234
V3     -1.3226    0.2650    -4.9908   0.0000    -1.8421    -0.8032
V4     20.3163    0.1373   147.9260   0.0000    20.0471    20.5855
V5     26.9639    0.6772    39.8138   0.0000    25.6365    28.2913
V6    -17.5979    0.7093   -24.8102   0.0000   -18.9882   -16.2077
V7     24.9813    0.8909    28.0417   0.0000    23.2352    26.7274
V8    -34.1503    0.4573   -74.6817   0.0000   -35.0465   -33.2540
V10   -21.6106    0.4496   -48.0642   0.0000   -22.4918   -20.7293
V11     7.4944    0.1308    57.2816   0.0000     7.2380     7.7508
V12   -15.1398    0.2180   -69.4512   0.0000   -15.5671   -14.7126
V13    -4.0797    0.0958   -42.5945   0.0000    -4.2674    -3.8919
V14   -28.0972    0.2440  -115.1624   0.0000   -28.5754   -27.6190
V16    -3.3026    0.3366    -9.8121   0.0000    -3.9623    -2.6429
V18    -3.5121    0.1699   -20.6712   0.0000    -3.8451    -3.1791
V20    18.2572    0.7407    24.6493   0.0000    16.8055    19.7089
V21    11.7878    0.5381    21.9078   0.0000    10.7333    12.8424
V22     7.3099    0.2497    29.2741   0.0000     6.8205     7.7993
V23    -8.8155    0.4974   -17.7219   0.0000    -9.7904    -7.8405
V26    -1.9630    0.1111   -17.6611   0.0000    -2.1808    -1.7451
V27    30.2315    1.0095    29.9455   0.0000    28.2528    32.2101
V28    25.5525    1.0955    23.3250   0.0000    23.4054    27.6996
=================================================================
```

[16]:
```
# Train the logistic regression model
logreg = LogisticRegression(max_iter=1000)
logreg.fit(X_train, y_train.values.ravel())
```

[16]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=1000,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

[28]:
```
# Print accuracy of the logistic regression model
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.2f}%'.
 ↪format(logreg.score(X_test, y_test)*100))
```

```
Accuracy of logistic regression classifier on test set: 99.91%
```

[18]:
```
# Check the confusion matrix
from sklearn.metrics import confusion_matrix

confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

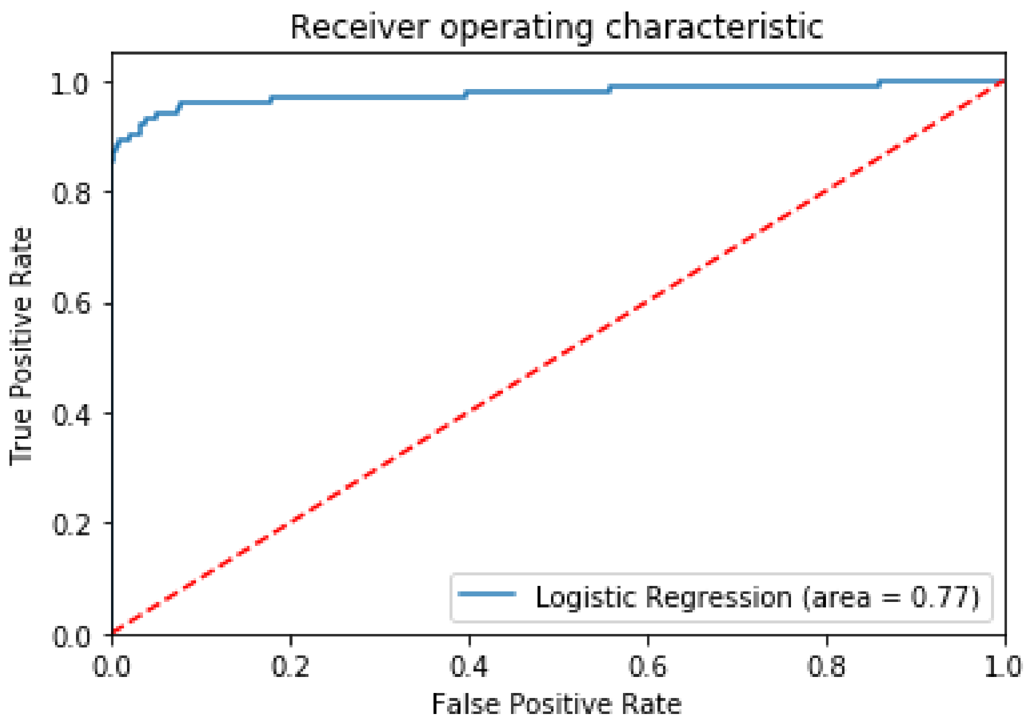
```
[[56853     8]
 [   46    55]]
```

[19]:
```
# Check f1-score
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00     56861
         1.0       0.87      0.54      0.67       101

    accuracy                           1.00     56962
   macro avg       0.94      0.77      0.84     56962
weighted avg       1.00      1.00      1.00     56962
```

[20]:
```
# Check ROC curve
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve

logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:,1])
plt.figure()
```

```
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```



3.0.2 Summary of Logistic Regression

- We balanced the data before training the model
- The accuracy of the model is 99.91%
- From our confusion matrix, we see that the count of total positives and total negatives are very high
- The ROC curve is very from the diagonal which also indicates a good model

3.0.3 Decision Tree

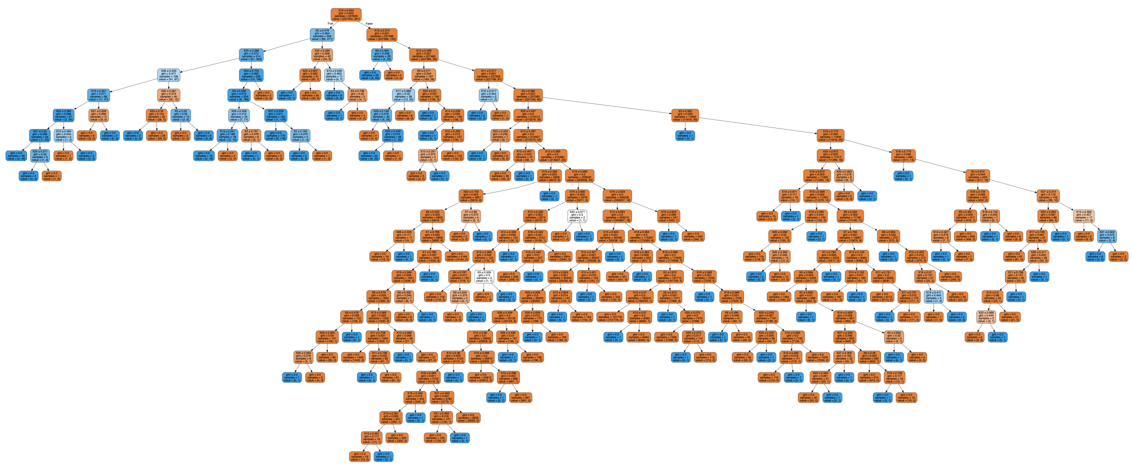
[21]:
```
from sklearn.tree import DecisionTreeClassifier

# Create Decision Tree classifer object
clf = DecisionTreeClassifier()

# Train Decision Tree Classifer
clf = clf.fit(X_train, y_train)

#Predict the response for test dataset
y_pred = clf.predict(X_test)
```

[27]:
```
print("Accuracy of decision tree classifier on test set: {:.2f}%".
 ↪format(metrics.accuracy_score(y_test, y_pred)*100))
```

```
Accuracy of decision tree classifier on test set: 99.92%
```

[24]:
```
from sklearn.tree import export_graphviz
from sklearn.externals.six import StringIO
from IPython.display import Image
import pydotplus

dot_data = StringIO()
export_graphviz(clf, out_file=dot_data, filled=True, rounded=True,␣
 ↪special_characters=True)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```

[24]:



3.0.4 Gradient Boosting

[31]:
```
from sklearn.ensemble import GradientBoostingClassifier

learning_rates = [0.05, 0.1, 0.25, 0.5, 0.75, 1]
for learning_rate in learning_rates:
    gb = GradientBoostingClassifier(n_estimators=20,␣
 ↪learning_rate=learning_rate, random_state = 0)
    gb.fit(X_train, y_train.values.ravel())
    print("Learning rate: ", learning_rate)
    print("Accuracy score (training): {0:.2f}%".format(gb.score(X_train,␣
 ↪y_train)*100))
    print("Accuracy score (validation): {0:.2f}%".format(gb.score(X_test,␣
 ↪y_test)*100))
    print()
```

```
Learning rate:  0.05
Accuracy score (training): 99.95%
Accuracy score (validation): 99.93%

Learning rate:  0.1
Accuracy score (training): 99.93%
Accuracy score (validation): 99.92%

Learning rate:  0.25
Accuracy score (training): 99.94%
Accuracy score (validation): 99.94%

Learning rate:  0.5
Accuracy score (training): 99.86%
Accuracy score (validation): 99.87%

Learning rate:  0.75
Accuracy score (training): 99.83%
Accuracy score (validation): 99.82%

Learning rate:  1
Accuracy score (training): 99.83%
Accuracy score (validation): 99.82%
```

3.0.5 Summary

All three models show very high accuracy on the dataset.

[ ]:
```

```