Credit Card Fraud Detection

```
#Importing necessary algorithms

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.metrics import classification_report, accuracy_score
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor
```

Step 1 : Dataset Loading and Analysis

```
# Load Dataset into a dataframeframe using pandas

df = pd.read_csv('creditcard.csv')
```

```
print("Shape of the Dataset: ", df.shape) # number of rows and columns in our dataset
print("\n\n", df.columns) # columns/features in our Dataset
```

```
Shape of the Dataset:  (284807, 31)


 Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10',
       'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20',
       'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount',
       'Class'],
      dtype='object')
```

```
df.head() # first five records
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533

5 rows × 31 columns

```
df.tail() # last five records
```

	Time	V1	V2	V3	V4	V5	V6	V7
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180
284806	172792.0	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006

5 rows × 31 columns

```
# Print the shape of the dataframe

df = df.sample(frac = 0.3, random_state = 42) # using 30% of our dataset for next steps
print("Shape of the Dataset: ", df.shape)
```

```
Shape of the Dataset:  (85442, 31)
```

```
# Determine number of fraud cases in Dataset

Fraud = df[df['Class'] == 1]
Valid = df[df['Class'] == 0]

outlier_fraction = (len(Fraud)/float(len(Valid)))
print("Outlier_fraction: {0} %".format(outlier_fraction*100))

print('Fraud Cases: {}'.format(len(df[df['Class'] == 1])))
print('Valid Transactions: {}'.format(len(df[df['Class'] == 0])))
```

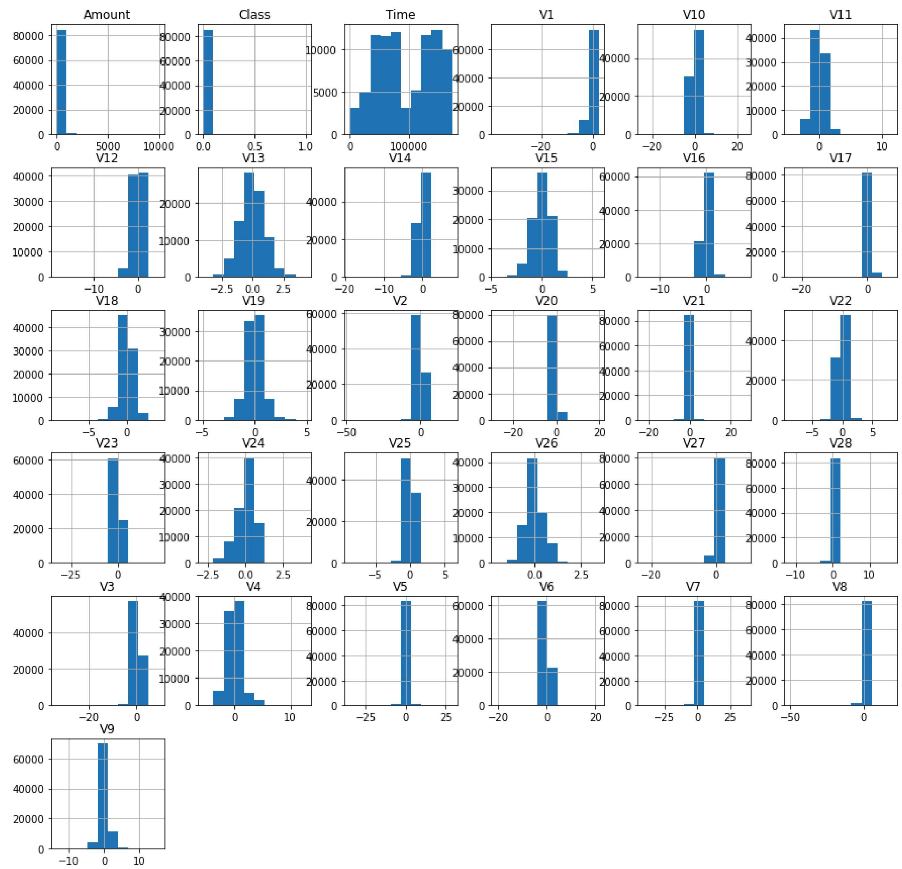
```
Outlier_fraction: 0.15942606616181745 %
Fraud Cases: 136
Valid Transactions: 85306
```

```
# The columns have been encrypted using PCA Dimensionality reduction to protect user identities and sensitive features

print("Description of the Dataset: ", df.describe())
```

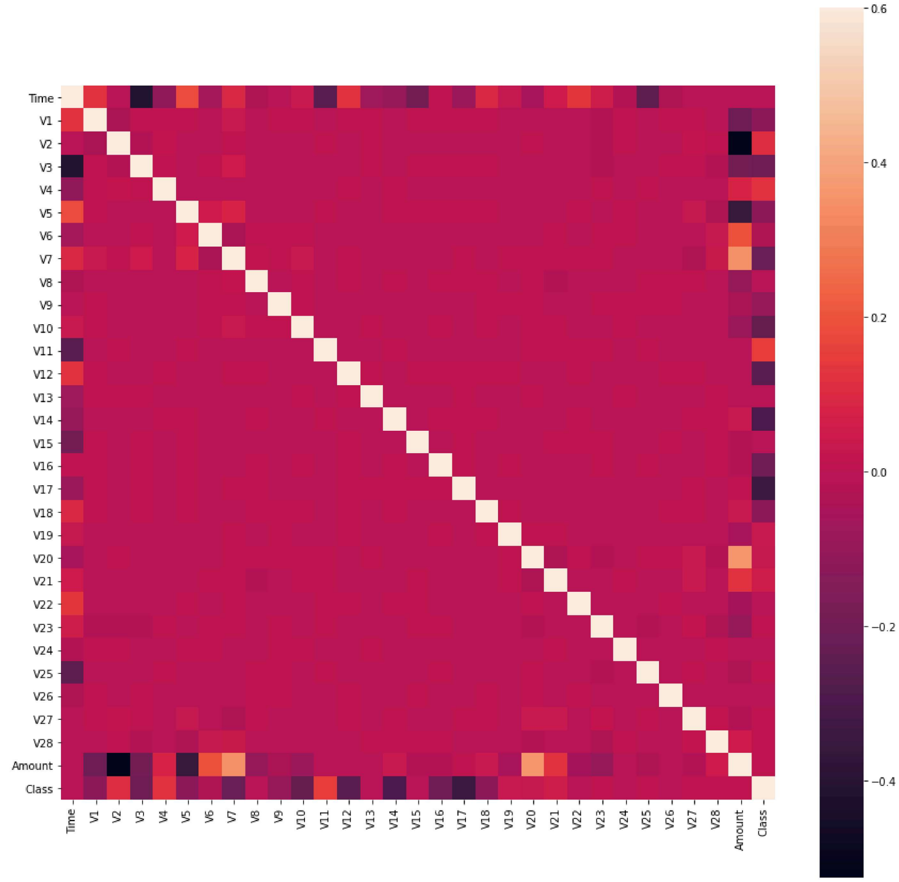
```
Description of the Dataset:                  Time           V1           V2           V3           V4  \
count   85442.000000  85442.000000  85442.000000  85442.000000  85442.000000
mean    94967.874862      0.003465      0.005440     -0.004776      0.002485
std     47520.526676      1.953426      1.611981      1.520529      1.413738
min         0.000000    -37.558067    -48.060856    -33.680984     -5.600607
25%     54257.500000     -0.918861     -0.597627     -0.898758     -0.845937
50%     84962.000000      0.027558      0.063774      0.172342     -0.015543
75%    139498.000000      1.318759      0.804713      1.024434      0.748582
max    172787.000000      2.439207     21.467203      9.382558     12.699542

                 V5           V6           V7           V8           V9  \
count  85442.000000  85442.000000  85442.000000  85442.000000  85442.000000
mean      -0.001153      0.004429     -0.006112      0.002718      0.000754
std        1.349284      1.319968      1.210313      1.208154      1.102415
min      -35.182120    -20.869626    -41.506796    -50.420090    -13.434066
25%       -0.696577     -0.768914     -0.559112     -0.210279     -0.645266
50%       -0.049751     -0.274150      0.033633      0.022630     -0.052660
75%        0.616161      0.408217      0.570121      0.328653      0.596925
max       29.016124     21.550496     36.877368     19.168327     15.594995

       ...           V21           V22           V23           V24  \
count  ...  85442.000000  85442.000000  85442.000000  85442.000000
mean   ...      0.000718      0.004176      0.000418      0.001474
std    ...      0.741520      0.726443      0.603298      0.605319
min    ...    -22.889347     -8.887017    -32.828995     -2.824849
25%    ...     -0.227053     -0.540678     -0.163221     -0.354200
50%    ...     -0.028621      0.010637     -0.012297      0.041341
75%    ...      0.187034      0.534284      0.147358      0.440782
max    ...     27.202839      8.361985     22.083545      3.990646

                V25           V26           V27           V28        Amount  \
count  85442.000000  85442.000000  85442.000000  85442.000000  85442.000000
mean       0.002232     -0.001562      0.001341      0.000050     87.300225
std        0.518783      0.481643      0.397284      0.331885    229.571240
min       -8.696627     -2.068561    -22.565679    -11.710896      0.000000
25%       -0.315966     -0.327504     -0.070385     -0.052708      5.550000
50%        0.020395     -0.055808      0.001562      0.010932     22.000000
75%        0.351311      0.237731      0.090261      0.077683     76.987500
max        6.070850      3.463246      9.200883     16.129609  10000.000000

              Class
count  85442.000000
mean       0.001592
std        0.039865
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000

[8 rows x 31 columns]
```

Step 2 : Data Visualization

```
# Plot histograms for each parameter

df.hist(figsize = (15, 15))
plt.show()
```




```
# Correlation matrix

corrmat = df.corr()
fig = plt.figure(figsize = (15, 15))

#Plotting a heatmap to visualize the correlation matrix and see features
# with strong correlation to the target class
sns.heatmap(corrmat, vmax = .6, square = True) # vmax is the max and min value you want to have for the scale
plt.show()
```




```
1   corrmat['Class']
```

```
Time     -0.008402
V1       -0.121864
V2        0.105051
V3       -0.208042
V4        0.128095
V5       -0.118543
V6       -0.038185
V7       -0.217359
V8       -0.001888
V9       -0.099826
V10      -0.228272
V11       0.153159
V12      -0.256577
V13      -0.012188
V14      -0.294882
V15      -0.006388
V16      -0.205082
V17      -0.345739
V18      -0.121619
V19       0.034440
V20       0.025939
V21       0.052617
V22      -0.003520
V23       0.011271
V24      -0.006823
V25       0.005641
V26      -0.002010
V27       0.013635
V28       0.007974
Amount    0.009849
Class     1.000000
Name: Class, dtype: float64
```

```
len(corrmat['Class'])
```

```
31
```

Step 3 : Feature Selection

```
# getting columns which have correlation score > 0.01 or < -0.01, you can chose a different constant and experiment

cols = corrmat.keys()
cols_to_keep = []

for i in range(len(corrmat)):

    if abs(corrmat['Class'][i]) > 0.01:

        cols_to_keep.append(cols[i])
```

```
len(cols_to_keep) # the final features list we wish to keep
```

```
22
```

```
cols_to_keep
```

```
['V1',
 'V2',
 'V3',
 'V4',
 'V5',
 'V6',
 'V7',
 'V9',
 'V10',
 'V11',
 'V12',
 'V13',
 'V14',
 'V16',
 'V17',
 'V18',
 'V19',
 'V20',
 'V21',
 'V23',
 'V27',
 'Class']
```

```
# removing the 'Class' columnn from the features list, as it is the variable we wish to predict

cols = cols_to_keep[:-1]
```

```
features = df[cols] # records of all transactions, excluding the target class
target = df["Class"] # records of the corresponding label for each record

print(features.shape)
print(target.shape)
```

```
(85442, 21)
(85442,)
```

Step 4 : Model Training and Selection

The machine learning algorithms that we are going to use are:

Local Outlier Factor Isolation Forest We are using them by importing them directly from scikit-learn; however, if you're interested in learning about their theory, you can refer to the two resources mentioned below:

LOF: https://towardsdataframescience.com/local-outlier-factor-for-anomaly-detection-cc0c770d2ebe

IF: https://medium.com/@often_weird/isolation-forest-algorithm-for-anomaly-detection-f88af2d5518d

```
# define random states
state = 1

# define outlier detection tools to be compared
classifiers = {
    "IF": IsolationForest(max_samples = len(features),
                                        contamination = outlier_fraction,
                                        random_state = state),
    "LOF": LocalOutlierFactor(
        n_neighbors = 20,
        contamination = outlier_fraction)}
```

```
# skipping the train, test split step because we wish the model to overfit on these features and learn
# a mathematical function to map the features

n_outliers = len(Fraud)

# Fit the model
for i, (clf_name, clf) in enumerate(classifiers.items()):

    # fit the dataframe and tag outliers
    if clf_name == "LOF":

        y_pred = clf.fit_predict(features)
        scores_pred = clf.negative_outlier_factor_

    else:

        # train/fit classifier on our features
        clf.fit(features)
        # generate predictions
        scores_pred = clf.decision_function(features)
        y_pred = clf.predict(features)

    # Reshape the prediction values to 0 for valid, 1 for fraud.

    y_pred[y_pred == 1] = 0
    y_pred[y_pred == -1] = 1

    n_errors = (y_pred != target).sum()

    # Run classification metrics
    print('Classifier {0}: \nNumber of Errors: {1}'.format(clf_name, n_errors))
    print('Accuracy: {0}%\n'.format(accuracy_score(target, y_pred)*100))
    print(classification_report(target, y_pred))
```

```
Classifier IF:
Number of Errors: 173
Accuracy: 99.797523466211%

              precision    recall  f1-score   support

           0       1.00      1.00      1.00     85306
           1       0.36      0.37      0.37       136

    accuracy                           1.00     85442
   macro avg       0.68      0.68      0.68     85442
weighted avg       1.00      1.00      1.00     85442

Classifier LOF:
Number of Errors: 273
Accuracy: 99.68048500737342%

              precision    recall  f1-score   support

           0       1.00      1.00      1.00     85306
           1       0.00      0.00      0.00       136

    accuracy                           1.00     85442
   macro avg       0.50      0.50      0.50     85442
weighted avg       1.00      1.00      1.00     85442
```