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CREDIT CARD FRAUDULENT TRANSACTION PREDICTION USING LOCAL OUTLIER FACTOR & ISOLATION FOREST
ALGORITHM
```

Throughout the financial sector, machine learning algorithms are being developed to detect fraudulent transactions. In this project, that is exactly what I am going to do as well. Using a dataset of of nearly 28,500 credit card transactions and multiple unsupervised anomaly detection algorithms, we are going to identify transactions with a high probability of being credit card fraud. In this project, we will build and deploy the following two machine learning algorithms: Local Outlier Factor (LOF) and Isolation Forest Algorithm Furthermore, using metrics suchs as precision, recall, and F1-scores, I will investigate why the classification accuracy for these algorithms can be misleading. In addition, I will explore the use of data visualization techniques common in data science, such as parameter histograms and correlation matrices, to gain a better understanding of the underlying distribution of data in our data set.

1.we will start with importing necessary libraries.

In [9]:

```
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/creditcardfraud/creditcard.csv
```

In [6]:

```
import sys
import numpy
import pandas
import matplotlib
import seaborn
import scipy
```

In [7]:

```
#importing necessary packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

1. I will import the dataset from a .csv file as a Pandas DataFrame. Furthermore, we will begin exploring the dataset to gain an understanding of the type, quantity, and distribution of data in our dataset. For this purpose, I will use Pandas' built-in describe feature, as well as parameter histograms and a correlation matrix

In [10]:

```
# Load the dataset from the csv file using pandas
data = pd.read_csv("/kaggle/input/creditcardfraud/creditcard.csv")
```

In [11]:

```
# Start exploring the dataset
print(data.columns)
```

```
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')
```

In [12]:

```
# Print the shape of the data
data = data.sample(frac=0.1, random_state = 1)
print(data.shape)
print(data.describe())

# V1 - V28 are the results of a PCA Dimensionality reduction to protect user identities and sensit
ive features
```

```
(28481, 31)
                Time            V1            V2            V3            V4  \
count   28481.000000  28481.000000  28481.000000  28481.000000  28481.000000
mean    94705.035216     -0.001143     -0.018290      0.000795      0.000350
std     47584.727034      1.994661      1.709050      1.522313      1.420003
min         0.000000    -40.470142    -63.344698    -31.813586     -5.266509
25%     53924.000000     -0.908809     -0.610322     -0.892884     -0.847370
50%     84551.000000      0.031139      0.051775      0.178943     -0.017692
75%    139392.000000      1.320048      0.792685      1.035197      0.737312
max    172784.000000      2.411499     17.418649      4.069865     16.715537

                 V5            V6            V7            V8            V9  \
count  28481.000000  28481.000000  28481.000000  28481.000000  28481.000000
mean      -0.015666      0.003634     -0.008523     -0.003040      0.014536
std        1.395552      1.334985      1.237249      1.204102      1.098006
min      -42.147898    -19.996349    -22.291962    -33.785407     -8.739670
25%       -0.703986     -0.765807     -0.562033     -0.208445     -0.632488
50%       -0.068037     -0.269071      0.028378      0.024696     -0.037100
75%        0.603574      0.398839      0.559428      0.326057      0.621093
max       28.762671     22.529298     36.677268     19.587773      8.141560

       ...           V21           V22           V23           V24  \
count  ...  28481.000000  28481.000000  28481.000000  28481.000000
mean   ...      0.004740      0.006719     -0.000494     -0.002626
std    ...      0.744743      0.728209      0.645945      0.603968
min    ...    -16.640785    -10.933144    -30.269720     -2.752263
25%    ...     -0.224842     -0.535877     -0.163047     -0.360582
50%    ...     -0.029075      0.014337     -0.012678      0.038383
75%    ...      0.189068      0.533936      0.148065      0.434851
max    ...     22.588989      6.090514     15.626067      3.944520

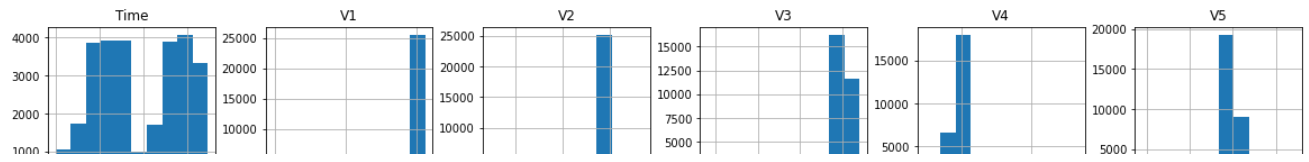
                V25           V26           V27           V28        Amount  \
count  28481.000000  28481.000000  28481.000000  28481.000000  28481.000000
mean      -0.000917      0.004762     -0.001689     -0.004154     89.957884
std        0.520679      0.488171      0.418304      0.321646    270.894630
min       -7.025783     -2.534330     -8.260909     -9.617915      0.000000
25%       -0.319611     -0.328476     -0.071712     -0.053379      5.980000
50%        0.015231     -0.049750      0.000914      0.010753     22.350000
75%        0.351466      0.253580      0.090329      0.076267     78.930000
max        5.541598      3.118588     11.135740     15.373170  19656.530000

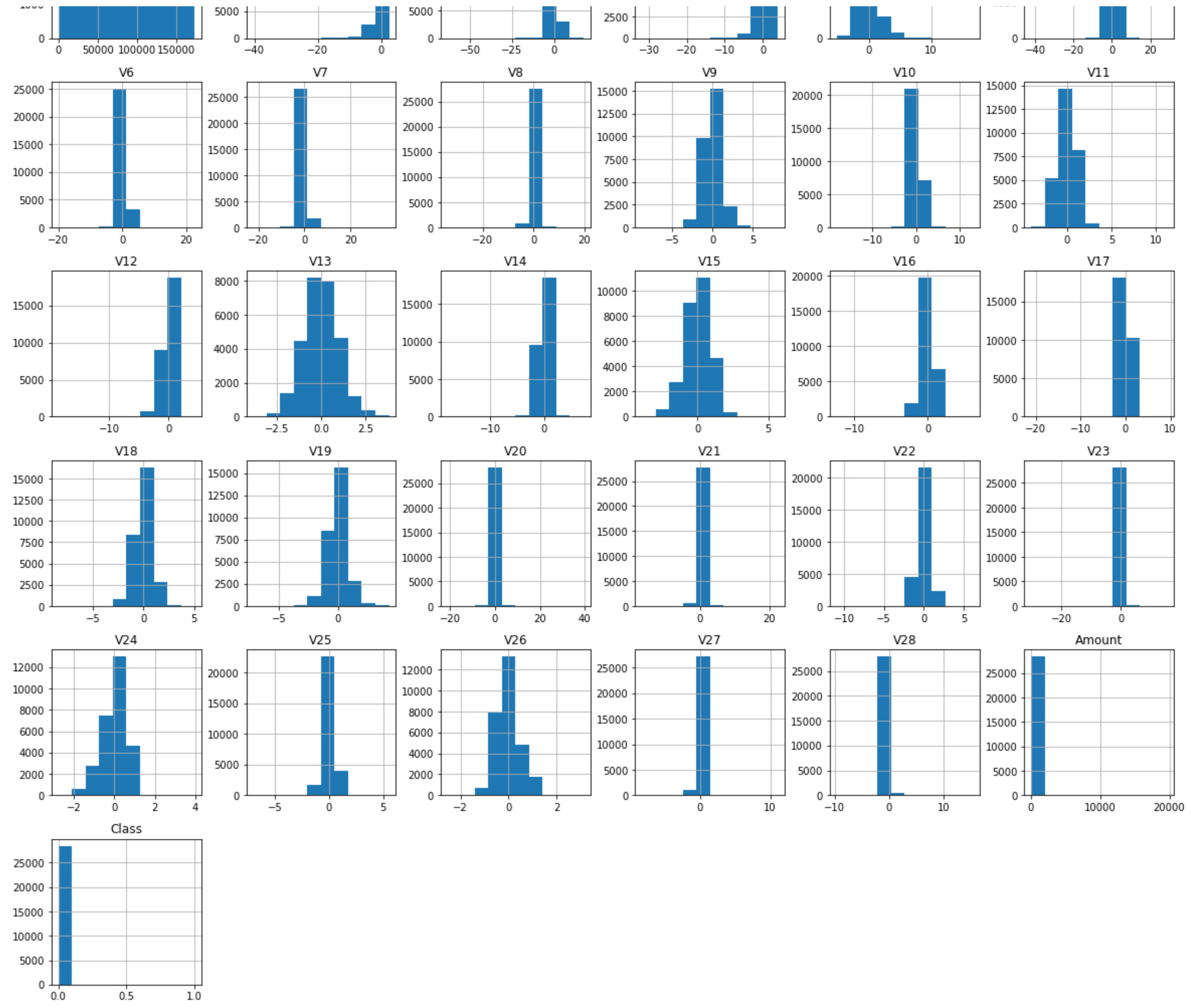
              Class
count  28481.000000
mean       0.001720
std        0.041443
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000

[8 rows x 31 columns]
```

In [13]:

```
# Plot histograms of each parameter
data.hist(figsize = (20, 20))
plt.show()
```





In [14]:

```
# Determine number of fraud cases in dataset

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

outlier_fraction = len(Fraud)/float(len(Valid))
print(outlier_fraction)

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

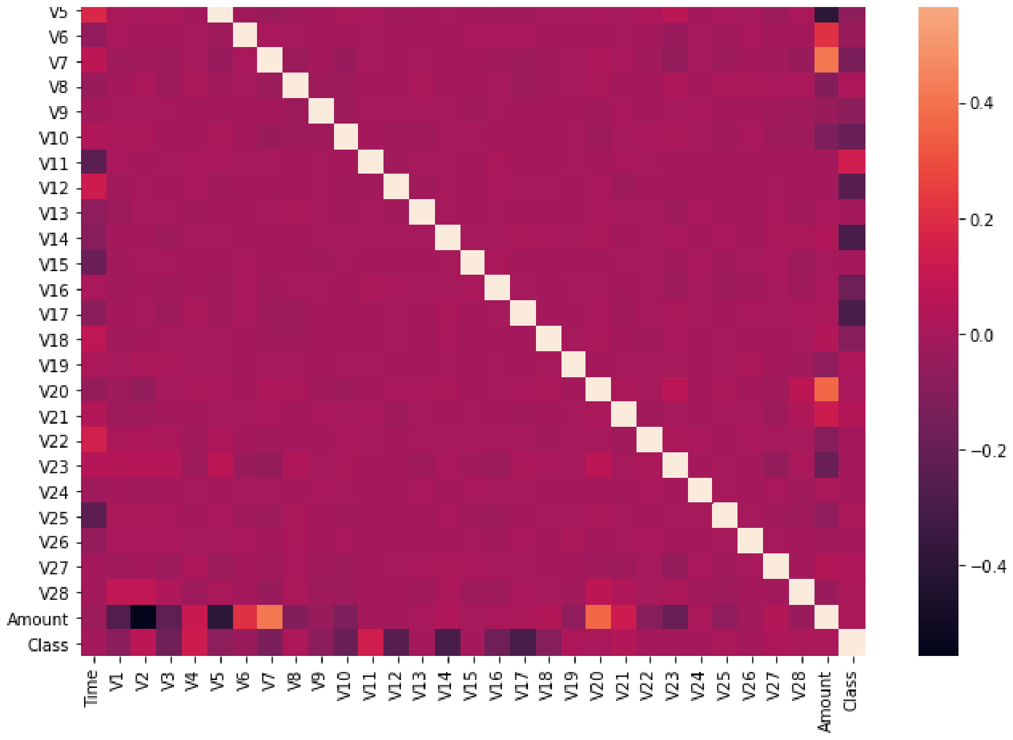
```
0.0017234102419808666
Fraud Cases: 49
Valid Transactions: 28432
```

In [15]:

```
# Correlation matrix
corrmat = data.corr()
fig = plt.figure(figsize = (12, 9))

sns.heatmap(corrmat, vmax = .8, square = True)
plt.show()
```

Time
V1
V2
V3
V4
0.8
0.6



In [16]:

```python
# Get all the columns from the dataFrame
columns = data.columns.tolist()

# Filter the columns to remove data we do not want
columns = [c for c in columns if c not in ["Class"]]

# Store the variable we'll be predicting on
target = "Class"

X = data[columns]
Y = data[target]

# Print shapes
print(X.shape)
print(Y.shape)
```

```
(28481, 30)
(28481,)
```

I have already processed my data and now I can start deploying our machine learning algorithms. I will use the following techniques: Local Outlier Factor (LOF)-> The anomaly score of each sample is called Local Outlier Factor. It measures the local deviation of density of a given sample with respect to its neighbors. It is local in that the anomaly score depends on how isolated the object is with respect to the surrounding neighborhood. Isolation Forest Algorithm ->The IsolationForest 'isolates' observations by randomly selecting a feature and then randomly selecting a split value between the maximum and minimum values of the selected feature. Since recursive partitioning can be represented by a tree structure, the number of splittings required to isolate a sample is equivalent to the path length from the root node to the terminating node. This path length, averaged over a forest of such random trees, is a measure of normality and our decision function. Random partitioning produces noticeably shorter paths for anomalies. Hence, when a forest of random trees collectively produce shorter path lengths for particular samples, they are highly likely to be anomalies.

In [17]:

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

# define random states
state = 1

# define outlier detection tools to be compared
classifiers = {
    "Isolation Forest": IsolationForest(max_samples=len(X),
                                        contamination=outlier_fraction,
                                           random_state=state),
    "Local Outlier Factor": LocalOutlierFactor(
        n_neighbors=20,
        contamination=outlier_fraction)}
```

In [19]:

```
# Fit the model
import warnings
warnings.filterwarnings('ignore')

n_outliers = len(Fraud)


for i, (clf_name, clf) in enumerate(classifiers.items()):

    # fit the data and tag outliers
    if clf_name == "Local Outlier Factor":
        y_pred = clf.fit_predict(X)
        scores_pred = clf.negative_outlier_factor_
    else:
        clf.fit(X)
        scores_pred = clf.decision_function(X)
        y_pred = clf.predict(X)

    # 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 != Y).sum()

    # Run classification metrics
    print('{}: {}'.format(clf_name, n_errors))
    print(accuracy_score(Y, y_pred))
    print(classification_report(Y, y_pred))
```

```
Isolation Forest: 71
0.99750711000316
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28432
           1       0.28      0.29      0.28        49

    accuracy                           1.00     28481
   macro avg       0.64      0.64      0.64     28481
weighted avg       1.00      1.00      1.00     28481

Local Outlier Factor: 97
0.9965942207085425
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28432
           1       0.02      0.02      0.02        49

    accuracy                           1.00     28481
   macro avg       0.51      0.51      0.51     28481
weighted avg       1.00      1.00      1.00     28481
```

So, we can see isolation forest shows better accuracy in terms of FRAUDULENT TRANSACTION PREDICTION. so, now i will tabulate the works and outcomes of my project. Understood data type, features, quantity, distribution using histogram and correlation matrix with pandas. Preprocessed and scaled the data for standardization and screened for extreme values. LOF algorithm & Isolation Forest applied for classification on the dataset, Isolation forest showed better accuracy, 64% F1-Score