```
import numpy as np
import pandas as pd
import sklearn
import scipy
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
from sklearn.svm import OneClassSVM
from pylab import rcParams
rcParams['figure.figsize'] = 14, 8
RANDOM SEED = 42
LABELS = ["Normal", "Fraud"]
from google.colab import drive
drive.mount ('/content/drive')
     Mounted at /content/drive
import pandas as pd
path = "/content/drive/MyDrive/creditcard.csv"
df = pd.read_csv(path)
df.describe
                                                  Time
     <bound method NDFrame.describe of</pre>
                                                               V1
                                                                          V2
                                                                                    1/3
                                                                                              V/A
                                                                                                        V5 \
                 0.0 -1.359807 -0.072781 2.536347 1.378155 -0.338321
                      1.191857
                                  0.266151 0.166480 0.448154 0.060018
                      -1.358354 -1.340163 1.773209 0.379780 -0.503198
     2
                 1.0
                 1.0
     3
                      -0.966272 -0.185226 1.792993 -0.863291 -0.010309
                      -1.158233 0.877737 1.548718 0.403034 -0.407193
                 2.0
     284802 172786.0 -11.881118 10.071785 -9.834783 -2.066656 -5.364473
     284803 172787.0 -0.732789
                                 -0.055080 2.035030 -0.738589 0.868229
                       1.919565 -0.301254 -3.249640 -0.557828 2.630515
     284804 172788.0
                                   7.530483 0.702510 0.689799 -0.377961
                                   .189733 0.703337 -0.506271 -0.012546
 Saved successfully!
                            V7
                                      V8
                                                V9
                                                    ... -0.018307
            0.462388 0.239599 0.098698 0.363787
            -0.082361 -0.078803 0.085102 -0.255425
                                                    ... -0.225775 -0.638672
     1
            1.800499 0.791461 0.247676 -1.514654
                                                    ... 0.247998 0.771679
     2
            1.247203 0.237609 0.377436 -1.387024
                                                    ... -0.108300 0.005274
     3
                                                    ... -0.009431 0.798278
            0.095921 0.592941 -0.270533 0.817739
     4
                                                    ... 0.213454 0.111864
     284802 -2.606837 -4.918215 7.305334 1.914428
     284803 1.058415 0.024330 0.294869
                                         0.584800
                                                         0.214205
                                                                   0.924384
                                                    . . .
                                                                   0.578229
     284804 3.031260 -0.296827 0.708417 0.432454
                                                         0.232045
     284805 0.623708 -0.686180 0.679145
                                          0.392087
                                                         0.265245
                                                                   0.800049
                                                    . . .
     284806 -0.649617 1.577006 -0.414650 0.486180
                                                         0.261057 0.643078
                           V24
                                     V25
                 V23
                                               V26
                                                         V27
                                                                   V28
                                                                        Amount \
     0
            -0.110474 0.066928 0.128539 -0.189115 0.133558 -0.021053
                                                                        149.62
            0.101288 -0.339846 0.167170 0.125895 -0.008983 0.014724
     1
                                                                          2.69
     2
            0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
                                                                        378.66
     3
            -0.190321 -1.175575   0.647376 -0.221929   0.062723   0.061458
                                                                        123.50
            \hbox{-0.137458} \quad \hbox{0.141267} \quad \hbox{-0.206010} \quad \hbox{0.502292} \quad \hbox{0.219422} \quad \hbox{0.215153}
                                                                         69.99
     284802 1.014480 -0.509348 1.436807 0.250034 0.943651 0.823731
                                                                          0.77
                                                    0.068472 -0.053527
     284803 0.012463 -1.016226 -0.606624 -0.395255
     284804 -0.037501 0.640134 0.265745 -0.087371
                                                    0.004455 -0.026561
     284805 -0.163298   0.123205 -0.569159   0.546668   0.108821   0.104533
     Class
     0
                 0
     1
                 0
     2
                 0
     3
                 0
     4
                 0
     284802
     284803
                 0
     284804
                 0
     284805
                 a
     284806
                 0
     [284807 rows x 31 columns]>
df.describe()
```

	Time	V1	V2	V3	V4	V5	V6	V7	
count	284807.000000	2.848070e+05	2.848070e+						
mean	94813.859575	1.168375e-15	3.416908e-16	-1.379537e-15	2.074095e-15	9.604066e-16	1.487313e-15	-5.556467e-16	1.213481e-
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380247e+00	1.332271e+00	1.237094e+00	1.194353e+
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137433e+02	-2.616051e+01	-4.355724e+01	-7.321672e+
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915971e-01	-7.682956e-01	-5.540759e-01	-2.086297e-
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433583e-02	-2.741871e-01	4.010308e-02	2.235804e-
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119264e-01	3.985649e-01	5.704361e-01	3.273459e-
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480167e+01	7.330163e+01	1.205895e+02	2.000721e+

8 rows × 31 columns

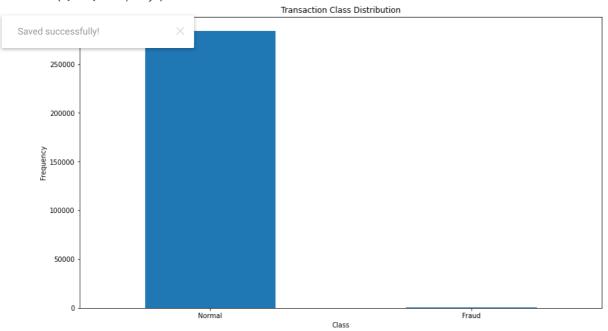


```
df.isnull().values.any()
```

False

```
count_classes = pd.value_counts(df['Class'], sort = True)
count_classes.plot(kind = 'bar', rot=0)
plt.title("Transaction Class Distribution")
plt.xticks(range(2), LABELS)
plt.xlabel("Class")
plt.ylabel("Frequency")
```

Text(0, 0.5, 'Frequency')



1.000000

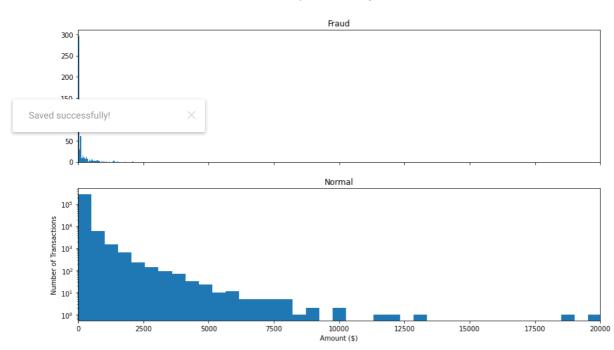
9.250000

25%

50%

```
75%
               105.890000
              2125.870000
     Name: Amount, dtype: float64
normal.Amount.describe()
     count
              284315.000000
                  88.291022
     mean
     std
                 250.105092
     min
                   0.000000
     25%
                   5.650000
     50%
                  22.000000
     75%
                  77.050000
               25691.160000
     max
     Name: Amount, dtype: float64
f, (ax1, ax2) = plt.subplots(2, 1, sharex=True)
f.suptitle('Amount per transaction by class')
bins = 50
ax1.hist(fraud.Amount, bins = bins)
ax1.set_title('Fraud')
ax2.hist(normal.Amount, bins = bins)
ax2.set_title('Normal')
plt.xlabel('Amount ($)')
plt.ylabel('Number of Transactions')
plt.xlim((0, 20000))
plt.yscale('log')
plt.show();
```

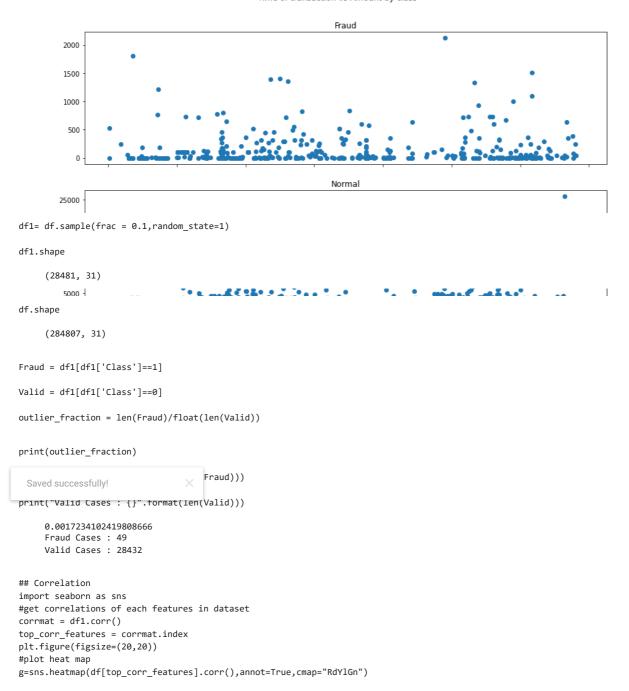
## Amount per transaction by class



# We Will check Do fraudulent transactions occur more often during certain time frame ? Let us find out with a visual representation.

```
f, (ax1, ax2) = plt.subplots(2, 1, sharex=True)
f.suptitle('Time of transaction vs Amount by class')
ax1.scatter(fraud.Time, fraud.Amount)
ax1.set_title('Fraud')
ax2.scatter(normal.Time, normal.Amount)
ax2.set_title('Normal')
plt.xlabel('Time (in Seconds)')
plt.ylabel('Amount')
plt.show()
```

## Time of transaction vs Amount by class



```
0.12 -0.011 -0.42 -0.11 -0.17 -0.0630.0850.0370.00870.031 -0.25 -0.12 -0.0660.099 -0.18 0.012 -0.073 0.09 0.029-0.0510.045 -0.14 0.051-0.016 -0.23 -0.0420.00520.00940.011-0.012
                                                           1e-15.2e-25.2e-168e-167.5e-14e-157.4e-1656e-177.4e-177.1e-175.1e-175.1e-175.e-165.e-177.2e-177.9e-165.2e-177.5e-1467e-175.5e-1463e-1652e-1464e-197.6e-1175.e-175.1e-175.1e-175.e-175.e-175.2e-177.9e-1652e-177.5e-175.2e-177.5e-175.2e-177.9e-1652e-177.5e-175.2e-177.5e-175.2e-177.9e-1652e-177.5e-175.2e-177.5e-175.2e-177.9e-1652e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-177.5e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2e-175.2
                                                                               1161e-1162e-1163e-1161e-1164e-1174e-174e-162e-169.6e-1273e-1167e-116e-17.2e-17.7e-1863e-1161e-1285e-1165e-1165e-1162e-147.5e-1261e-116e-16.1e-1-0.53
                                                                                        e-16.5e-17.5e-14.5e-14.5e-14.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e-17.5e
                     5
                                                                                                    7e-1255e-1461e-167e-169e-1252e-1255e-146e-126e-126e-1254e-1266e-1267e-161e-146-14.9e-1269e-1263e-1272e-126e-1261e-1462e-1462e-12728e-1860e-12728e-1260e-12728e-1260e-12728e-1260e-12728e-1260e-12728e-1260e-12728e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-1260e-
                             - 0.171.8e-19.2e-1665e-117.7e
                                                                                                                    :-1257e-1254e-1254e-1252e-1252e-1254e-1259e-1256e-1257e-1252e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e-1259e
                            -0.0635.5e-1268e-1166e-135.5e-1264e-1
                                                                                                                              2e-116.1e-1461e-1469e-172e-172.4e-1162e-1266e-116.5e-1256e-162e-116.2e-116.9e-1169e-1268e-147.7e-191e-142.1e-1256e-116.4e-1465e-1266e-160.22-40.044
                    -0.085-1e-12.1e-1469e-146.1e-1267e-1162e-1
                                                                                                                                           3e-1161e-176.5e-1174e-178.5e-1188e-177.6e-176-1766e-177.2e-1766e-177.9e-1764e-162e-176.9e-1764e-178.1e-1764e-1
                     4e-1788e-1768e-1789e-1766e-1761e-1763e-1763e-1769e-1769e-1769e-1769e-17664e-1746-17447e-1767e-1766e-1769e-1769e
                     g -0.0081/.5e-1@e-175.6e-1669e-1754e-1461e-1161e-1464e-1
                                                                                                                                                                     6e-1164e-145.1e-1253e-1258e-145.1e-1452e-1151e-145e-145.4e-1253e-1169e-145.1e-1253e-1164e-1258e-145.9e-1259e-125
                                 0.252.1e-1@e-16.6e-135e-1352e-1@e-19.4e-135e-1364e-146.6e-1
                                                                                                                                                                                                4e-1@e-1@-7e-1153e-1158e-1152e-1164e-1154e-1165e-1467e-1768e-1465e-1169e-1-56e-1-6e-1-@.6e-1468e-1060001.0.15
                            - 0.122.1e-156.6e-1573e-156.6e-1764e-126.4e-136.5e-1188e-136.1e-1158e-146.4e-1
                                                                                                                                                                                                             3e-148e-17.4e-153e-156e-16e-17.5e-154e-153e-166e-158e-1464e-15.7e-1264e-1467e-1664e-146.009
                            -0.06@.4e-1673e-1268e-1263e-1269e-126.2e-168e-127.9e-1263e-15.4e-1@e-1@.3e-1
                                                                                                                                                                                                                          2e-1154e-145e-147.6e-1472e-115.9e-1566e-141e-146.7e-177.1e-1154e-1555e-1168e-1467e-1161.e-116.0053D.0046
                            -0.0995e-14.7e-167e-1253e-166e-1256e-1256e-1256e-1256e-1256e-1256e-1257e-1258e-1272e-1
                                                                                                                                                                                                                                       8e-117.4e-1152e-1156e-152e-161.2e-137.4e-1367e-1159e-162e-168.5e-1167e-16e-162.3e-150.034 40.3
                                 0.183.5e-165e-179.1e-1154e-186.7e-1165e-1157e-1461e-115.1e-1558e-1163e-1-15.4e-1154e-1-16.8e-1
                                                                                                                                                                                                                                                    3e-16 6e-1165e-1165e-1263e-1266e-127.2e-1269e-1265e-1262e-1268e-116.1e-1152e-1-50.0030.0042
                            -0.0127.2e-1872e-1873e-1866e-1866e-1859e-1873e-1862e-1855e-1868e-1863e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1862e-1
                                                                                                                                                                                                                                                                 5e-1254e-1153e-1252e-146.7e-1769e-13e-16-3e-146.3e-1753e-1668e-1766e-146.0039-0.
                            -0.0738.9e-1267e-1766e-1267e-1163e-142e-142.2e-1263e-1161e-1255e-138.2e-1266e-1266e-1272e-1266e-1255e-1
                                                                                                                                                                                                                                                                              .9e-1359e-1364e-1352e-1367e-1367e-1364e-1267e-1369e-1361e-1365e-107.0073<mark>-0.33</mark>
 #Create independent and Dependent Features
columns = df.columns.tolist()
# Filter the columns to remove data we do not want
                                                                                                                              ot in ["Class"]]
     Saved successfully!
                                                                                                                               ng
target = "Class"
# Define a random state
state = np.random.RandomState(42)
X = df1[columns]
Y = df1[target]
\label{eq:continuous} $X\_$ outliers = state.uniform(low=0, high=1, size=(X.shape[0], X.shape[1]))$
# Print the shapes of X & Y
print(X.shape)
print(Y.shape)
                   (28481, 30)
                  (28481,)
classifiers = {
               "Isolation Forest":IsolationForest(n_estimators=100, max_samples=len(X),
                                                                                                                                         contamination=outlier fraction, random state=state, verbose=0),
               "Local Outlier Factor":LocalOutlierFactor(n_neighbors=20, algorithm='auto',
                                                                                                                                                                  leaf_size=30, metric='minkowski',
                                                                                                                                                                 p=2, metric_params=None, contamination=outlier_fraction),
              # "Support Vector Machine":OneClassSVM(kernel='rbf', degree=3, gamma=0.1,nu=0.05,
                                                                                                                                                       max_iter=-1, random_state=state)
1
# model = Classifiers(C=1.0, cache_size=200, class_weight=None, coef0=0.0, degree=3,
#
                                                  gamma=0.0, kernel='linear', max_iter=-1, probability=True,
                                                  random_state=None, shrinking=True, tol=0.001, verbose=False)
#
type(classifiers)
                 dict
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_prediction = clf.negative_outlier_factor_
              elif clf_name == "Support Vector Machine":
                            ~1f f:+/v/
```

```
CIL·LT(V)
       y_pred = clf.predict(X)
   else:
       clf.fit(X)
       scores_prediction = clf.decision_function(X)
       y_pred = clf.predict(X)
   \#Reshape the prediction values to 0 for Valid transactions , 1 for Fraud transactions
   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 :")
   print(accuracy_score(Y,y_pred))
   print("Classification Report :")
   print(classification_report(Y,y_pred))
() /usr/local/lib/python3.9/dist-packages/sklearn/base.py:420: UserWarning: X does not have valid feature names, but IsolationForest w
      warnings.warn(
    Isolation Forest: 73
    Accuracy Score :
    0.9974368877497279
    Classification Report :
                  precision
                               recall f1-score
                                                   support
               0
                       1.00
                                 1.00
                                            1.00
                                                     28432
               1
                       0.26
                                 0.27
                                            0.26
                                                        49
                                                     28481
        accuracy
                                            1.00
                                 0.63
                                                     28481
                       0.63
                                            0.63
       macro avg
                                                     28481
    weighted avg
                                 1.00
                                            1.00
                       1.00
    Local Outlier Factor: 97
    Accuracy Score :
    0.9965942207085425
    {\tt Classification} \ {\tt Report} \ :
                  precision
                               recall f1-score
                                                   support
               0
                       1.00
                                  1.00
                                            1.00
                                                     28432
                                 a 02
                                                        49
                                            0.02
Saved successfully!
                                            1.00
                                                     28481
                                  w.51
                                            0.51
                                                     28481
      macro avg
                       0.51
    weighted avg
                       1.00
                                 1.00
                                            1.00
                                                     28481
```

Colab paid products - Cancel contracts here

15s completed at 12:33 AM