

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
data = pd.read_csv('creditcard.csv')
data.head()
```

Out[2]:

|   | Time     | V1        | V2        | V3        | V4        | V5        | V6        | V7        | V8        | V9        | ... | V21       |
|---|----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----|-----------|
| 0 | 51435.0  | 1.197490  | -0.352125 | -0.135904 | 0.222100  | 0.231128  | 1.086617  | -0.420363 | 0.391464  | 0.672499  | ... | -0.337999 |
| 1 | 78049.0  | 0.976047  | -0.289947 | 1.465321  | 1.300002  | -1.382887 | -0.479586 | -0.632572 | 0.064533  | 0.710743  | ... | 0.322829  |
| 2 | 157168.0 | -1.395302 | 0.478266  | -0.584911 | -1.201527 | 0.928544  | -0.743618 | 0.755504  | -0.141397 | -2.118499 | ... | 0.282803  |
| 3 | 69297.0  | 1.276014  | -0.672705 | -0.425494 | -0.777398 | -0.582088 | -0.880396 | -0.103505 | -0.203036 | -1.241653 | ... | 0.256003  |
| 4 | 144504.0 | -0.312745 | -1.202565 | 2.249806  | -0.297210 | -0.963389 | 1.207532  | -0.837776 | -0.057654 | 1.121421  | ... | -0.274386 |

5 rows × 31 columns

In [3]:

```
data.shape
```

Out[3]:

```
(186000, 31)
```

In [4]:

```
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 186000 entries, 0 to 185999
Data columns (total 31 columns):
 #   Column      Non-Null Count  Dtype
---  -
 0   Time        186000 non-null float64
 1   V1          186000 non-null float64
 2   V2          186000 non-null float64
 3   V3          186000 non-null float64
 4   V4          186000 non-null float64
 5   V5          186000 non-null float64
 6   V6          186000 non-null float64
 7   V7          186000 non-null float64
 8   V8          186000 non-null float64
```

```

9   V9          186000 non-null float64
10  V10         186000 non-null float64
11  V11         186000 non-null float64
12  V12         186000 non-null float64
13  V13         186000 non-null float64
14  V14         186000 non-null float64
15  V15         186000 non-null float64
16  V16         186000 non-null float64
17  V17         186000 non-null float64
18  V18         186000 non-null float64
19  V19         186000 non-null float64
20  V20         186000 non-null float64
21  V21         186000 non-null float64
22  V22         186000 non-null float64
23  V23         186000 non-null float64
24  V24         186000 non-null float64
25  V25         186000 non-null float64
26  V26         186000 non-null float64
27  V27         186000 non-null float64
28  V28         186000 non-null float64
29  Amount      186000 non-null float64
30  Class       186000 non-null int64

```

```

dtypes: float64(30), int64(1)
memory usage: 44.0 MB

```

In [5]:

```
data.describe()
```

Out[5]:

|       | Time          | V1            | V2            | V3            | V4            | V5            |               |
|-------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|
| count | 186000.000000 | 186000.000000 | 186000.000000 | 186000.000000 | 186000.000000 | 186000.000000 | 186000.000000 |
| mean  | 94829.405134  | -0.003211     | 0.001000      | 0.000697      | -0.000765     | 0.001546      | 0.000522      |
| std   | 47498.820375  | 1.960298      | 1.658303      | 1.510441      | 1.412797      | 1.401870      | 1.342198      |
| min   | 0.000000      | -56.407510    | -72.715728    | -48.325589    | -5.683171     | -113.743307   | -26.160500    |
| 25%   | 54169.000000  | -0.921761     | -0.594771     | -0.888268     | -0.846676     | -0.690550     | -0.767943     |
| 50%   | 84669.500000  | 0.012918      | 0.069063      | 0.179846      | -0.023288     | -0.053598     | -0.274187     |
| 75%   | 139336.000000 | 1.313242      | 0.807190      | 1.028361      | 0.740716      | 0.615143      | 0.396718      |
| max   | 172792.000000 | 2.454930      | 19.167239     | 9.382558      | 16.875344     | 34.801666     | 73.301626     |

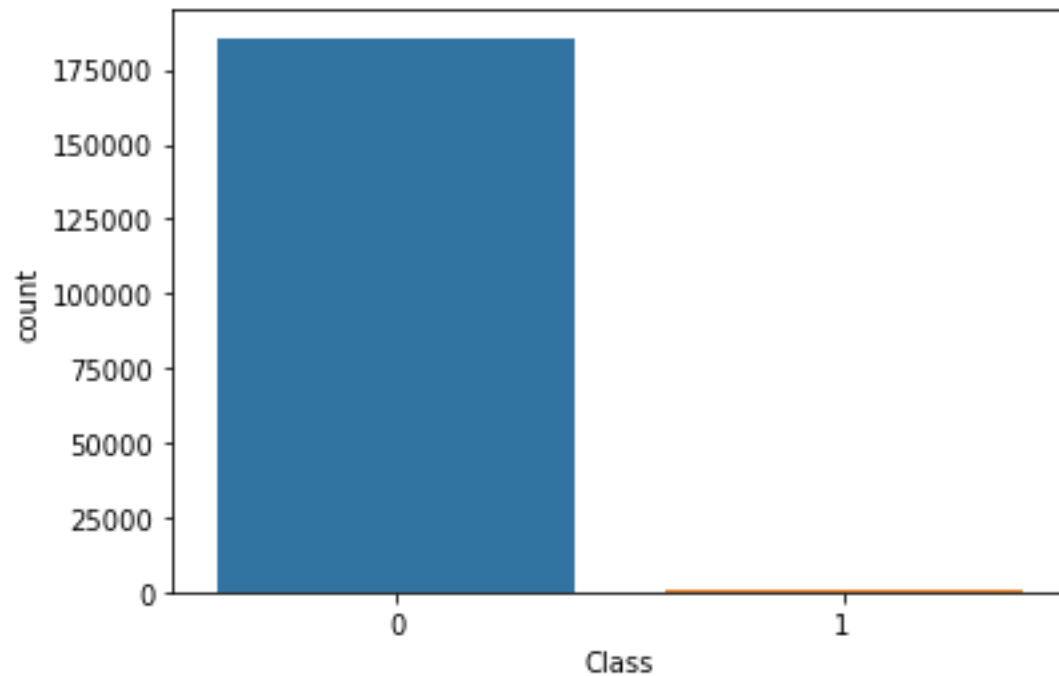
8 rows × 31 columns

In [6]:

```

sns.countplot(x='Class', data=data)
print("Fraud: ",data.Class.sum()/data.Class.count())
Fraud:  0.001586021505376344

```

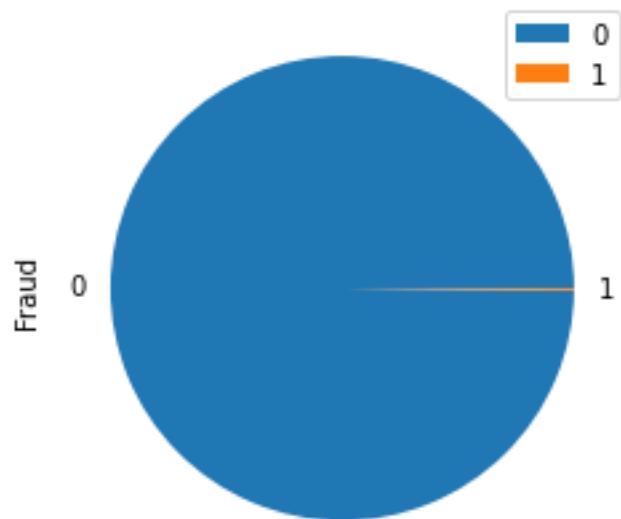


In [7]:

```
Fraud_class = pd.DataFrame({'Fraud': data['Class']})
Fraud_class.apply(pd.value_counts).plot(kind='pie', subplots=True)
```

Out[7]:

```
array([<AxesSubplot:ylabel='Fraud'>], dtype=object)
```



In [8]:

```
fraud = data[data['Class'] == 1]
valid = data[data['Class'] == 0]
```

In [9]:

```
fraud.Amount.describe()
```

Out[9]:

```
count      295.000000
mean       126.596983
std        251.386390
min         0.000000
25%        1.000000
50%        14.460000
75%        112.015000
max        1809.680000
Name: Amount, dtype: float64
```

In [12]:

```
plt.figure(figsize=(20,20))
plt.title('Correlation Matrix', y=1.05, size=15)
sns.heatmap(data.astype(float).corr(),linewidths=0.1,vmax=1.0,
            square=True, linecolor='white', annot=True)
```

Out[12]:

```
<AxesSubplot:title={'center':'Correlation Matrix'}>
```

Correlation Ma

|      |         |         |         |        |        |        |        |        |        |        |        |        |        |        |        |        |        |
|------|---------|---------|---------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Time | 1       | 0.11    | -0.0099 | -0.42  | -0.11  | 0.17   | -0.061 | 0.083  | 0.037  | 0.008  | 0.028  | -0.25  | 0.12   | -0.066 | 0.099  | -0.18  | 0.011  |
| V1   | 0.11    | 1       | 0.013   | 0.0018 | 0.0005 | 0.0028 | 0.0006 | 0.016  | 0.0023 | 0.003  | 0.012  | 0.0026 | 0.0074 | 0.0028 | 0.0029 | 0.0027 | 0.01   |
| V2   | -0.0099 | 0.013   | 1       | 0.012  | 0.0074 | 0.0033 | 0.002  | 0.0058 | 0.0064 | 0.0016 | 0.0046 | 0.0047 | 0.0042 | 0.0016 | 0.0029 | 0.0038 | 0.002  |
| V3   | -0.42   | 0.0018  | 0.012   | 1      | 0.0046 | 0.0015 | 0.0099 | 0.029  | 0.0032 | 0.0064 | 0.0096 | 0.0067 | -0.01  | 0.0099 | 0.0078 | 0.0019 | 0.01   |
| V4   | -0.11   | 0.0005  | 0.0074  | 0.0046 | 1      | 0.0031 | 0.001  | 0.0077 | 0.0034 | 0.0002 | 0.0069 | 0.0028 | 0.0046 | 0.001  | 0.005  | 0.0007 | 0.007  |
| V5   | 0.17    | -0.0028 | 0.0033  | 0.0015 | 0.0031 | 1      | -0.021 | -0.045 | 0.009  | 0.0034 | 0.0031 | 0.0024 | 0.0029 | 0.0019 | 0.003  | 0.002  | -0.01  |
| V6   | -0.06   | 0.0006  | 0.002   | 0.0099 | 0.001  | 0.021  | 1      | 0.023  | 0.0047 | 0.0002 | 0.0016 | 0.0039 | 0.0039 | 0.0014 | 0.0056 | 0.0043 | 0.002  |
| V7   | 0.083   | 0.016   | 0.0058  | 0.029  | 0.0077 | 0.045  | 0.023  | 1      | 0.024  | 0.0064 | 0.019  | 0.008  | -0.013 | 0.0027 | 0.012  | 0.0024 | 0.000  |
| V8   | -0.037  | 0.0028  | 0.0064  | 0.0032 | 0.0039 | 0.009  | 0.0047 | 0.024  | 1      | 0.0048 | 0.0078 | 0.0039 | 0.0067 | 0.0039 | 0.0094 | 0.0038 | 0.0003 |
| V9   | -0.008  | 0.0037  | 0.0014  | 0.0064 | 0.0002 | 0.0037 | 0.0002 | 0.0064 | 0.0048 | 1      | 0.0008 | 0.004  | 0.0049 | 0.0014 | 0.0076 | 0.0014 | 0.003  |
| V10  | -0.028  | 0.012   | 0.0046  | 0.0096 | 0.0069 | 0.0034 | 0.001  | 0.019  | 0.0078 | 0.0008 | 1      | 0.0064 | 0.006  | 0.0006 | 0.014  | 0.0024 | 0.007  |
| V11  | -0.25   | 0.0026  | 0.0049  | 0.0067 | 0.0028 | 0.0024 | 0.0039 | 0.008  | 0.0039 | 0.004  | 0.0064 | 1      | 0.0062 | 0.0007 | 0.0046 | 0.0017 | 0.005  |
| V12  | 0.12    | -0.007  | 0.0042  | -0.01  | 0.0046 | 0.0029 | 0.0034 | 0.013  | 0.0067 | 0.0049 | 0.0062 | 0.0062 | 1      | 0.0009 | 0.0096 | 0.0013 | 0.006  |
| V13  | -0.066  | 0.0028  | 0.0018  | 0.0009 | 0.001  | 0.0019 | 0.0016 | 0.0027 | 0.0039 | 0.0014 | 0.0006 | 0.0007 | 0.0009 | 1      | 0.001  | 0.0015 | 0.001  |
| V14  | -0.099  | 0.0029  | 0.0029  | 0.0078 | 0.0057 | 0.0038 | 0.0058 | 0.012  | 0.0094 | 0.0076 | 0.014  | 0.0046 | 0.0096 | 0.0011 | 1      | 0.0009 | 0.007  |
| V15  | -0.18   | 0.0027  | 0.0039  | 0.0019 | 0.0007 | 0.002  | 0.0049 | 0.0024 | 0.0038 | 0.0014 | 0.0024 | 0.0019 | 0.0013 | 0.0015 | 0.0009 | 1      | 0.0002 |
| V16  | -0.011  | -0.01   | 0.002   | 0.011  | 0.007  | -0.01  | 0.0024 | 0.0003 | 0.0003 | 0.0038 | 0.0076 | 0.0059 | 0.0069 | 0.001  | 0.0078 | 0.0002 | 1      |
| V17  | -0.076  | -0.01   | 0.0084  | 0.016  | 0.0036 | 0.007  | 0.0037 | 0.02   | 0.0049 | 0.0058 | 0.012  | 0.0086 | -0.01  | 0.0037 | 0.011  | 0.0014 | 0.01   |
| V18  | -0.09   | -0.0017 | 0.0058  | 0.0079 | 0.0005 | 0.002  | 0.0032 | 0.0088 | 0.0014 | 0.0038 | 0.0058 | 0.001  | 0.0062 | 0.0008 | 0.0027 | 0.0003 | 0.002  |
| V19  | -0.029  | 0.0016  | 0.0005  | 0.0009 | 0.0019 | 0.0002 | 0.001  | 0.0009 | 0.0045 | 0.0007 | 0.0018 | 0.0028 | 0.0013 | 0.0006 | 0.0042 | 0.0013 | 0.0008 |
| V20  | -0.05   | 0.013   | 0.0032  | 0.013  | 0.0046 | 0.022  | 0.018  | 0.016  | 0.021  | 0.0003 | 0.0039 | 0.004  | 0.001  | 0.0014 | 0.0019 | 0.0029 | 0.008  |

In [13]:

```
from sklearn.preprocessing import RobustScaler
rs = RobustScaler()

data['Amount'] = rs.fit_transform(data['Amount'].values.reshape(-1, 1))
data['Time'] = rs.fit_transform(data['Time'].values.reshape(-1, 1))
```

In [14]:

```
X = data.drop(['Class'], axis = 1)
Y = data["Class"]
```

In [15]:

```
from sklearn.model_selection import train_test_split
# Split the data into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2,
random_state = 1)
```

In [16]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.tree import DecisionTreeClassifier

from sklearn.metrics import classification_report, accuracy_score,
precision_score, recall_score, f1_score
from sklearn.metrics import confusion_matrix, precision_recall_curve,
roc_auc_score
```

In [17]:

```
def evaluate(Y_pred, Y_pred_prob):
    print("Accuracy: ",accuracy_score(Y_test, Y_pred))
    print("Precision: ",precision_score(Y_test, Y_pred))
    print("Recall: ",recall_score(Y_test, Y_pred))
    print("F1-Score: ",f1_score(Y_test, Y_pred))
    print("AUC score: ",roc_auc_score(Y_test, Y_pred))

    print(classification_report(Y_test, Y_pred, target_names = ['Normal',
'Fraud']))

    conf_matrix = confusion_matrix(Y_test, Y_pred)
    plt.figure(figsize =(6, 6))
    sns.heatmap(conf_matrix, xticklabels = ['Normal', 'Fraud'],
                yticklabels = ['Normal', 'Fraud'], annot = True, fmt ="d");
    plt.title("Confusion matrix")
    plt.ylabel('True class')
    plt.xlabel('Predicted class')
    plt.show()

p, r, t = precision_recall_curve(Y_test, Y_pred_prob)
```

```

plt.plot(p, r)
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision Recall Curve')

```

In [18]:

```

#logistic regression

lr = LogisticRegression()
lr.fit(X_train, Y_train)
Y_pred_lr_i = lr.predict(X_test)

Y_pred_prob_lr_i = lr.predict_proba(X_test)[:,:1]

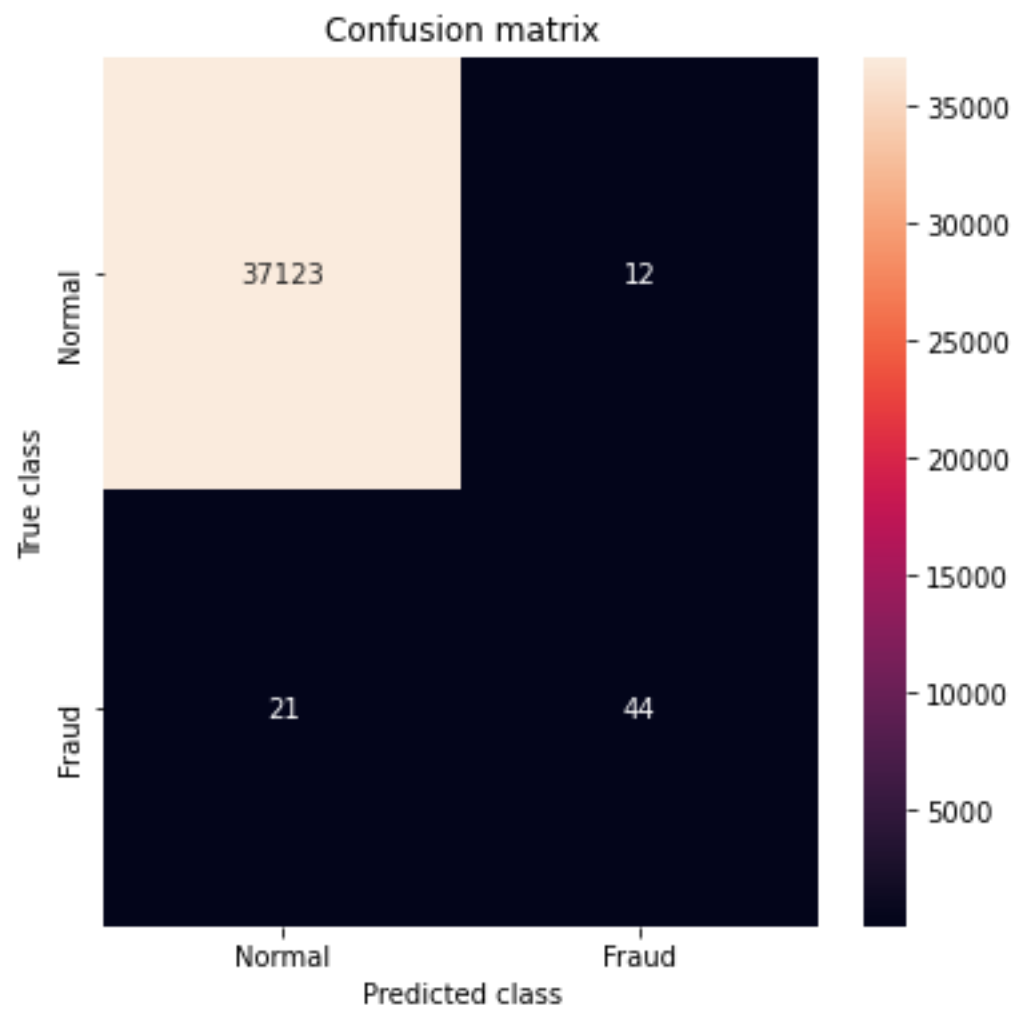
evaluate(Y_pred_lr_i, Y_pred_prob_lr_i)
Accuracy:  0.9991129032258065
Precision:  0.7857142857142857
Recall:  0.676923076923077
F1-Score:  0.7272727272727272
AUC score:  0.8382999658211723

```

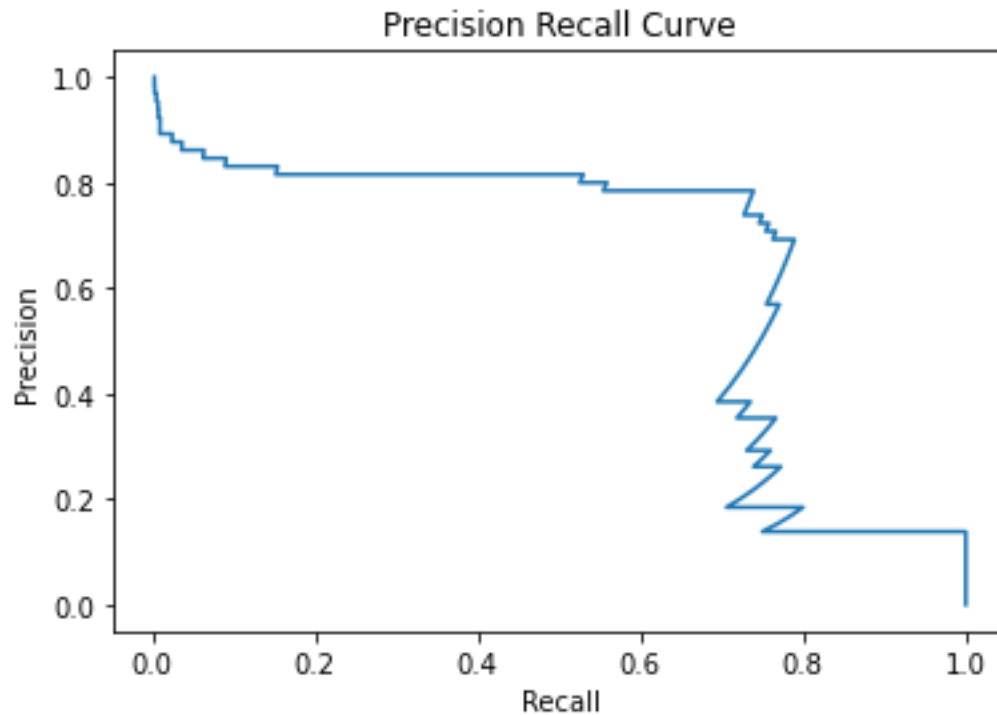
In [19]:

In [20]:

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Normal       | 1.00      | 1.00   | 1.00     | 37135   |
| Fraud        | 0.79      | 0.68   | 0.73     | 65      |
| accuracy     |           |        | 1.00     | 37200   |
| macro avg    | 0.89      | 0.84   | 0.86     | 37200   |
| weighted avg | 1.00      | 1.00   | 1.00     | 37200   |







In [21]:

```
# random forest model creation
rfc = RandomForestClassifier()
rfc.fit(X_train, Y_train)
# predictions
Y_pred_rf_i = rfc.predict(X_test)
```

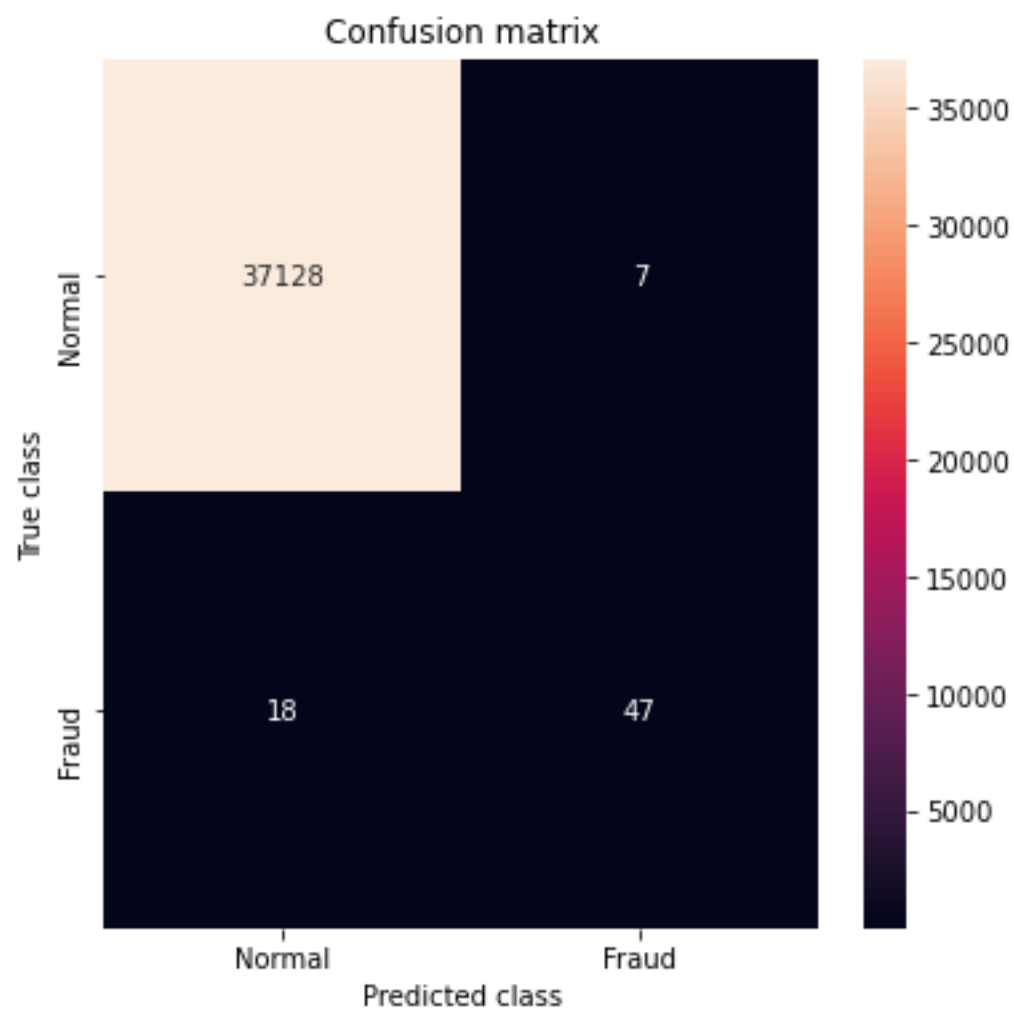
In [22]:

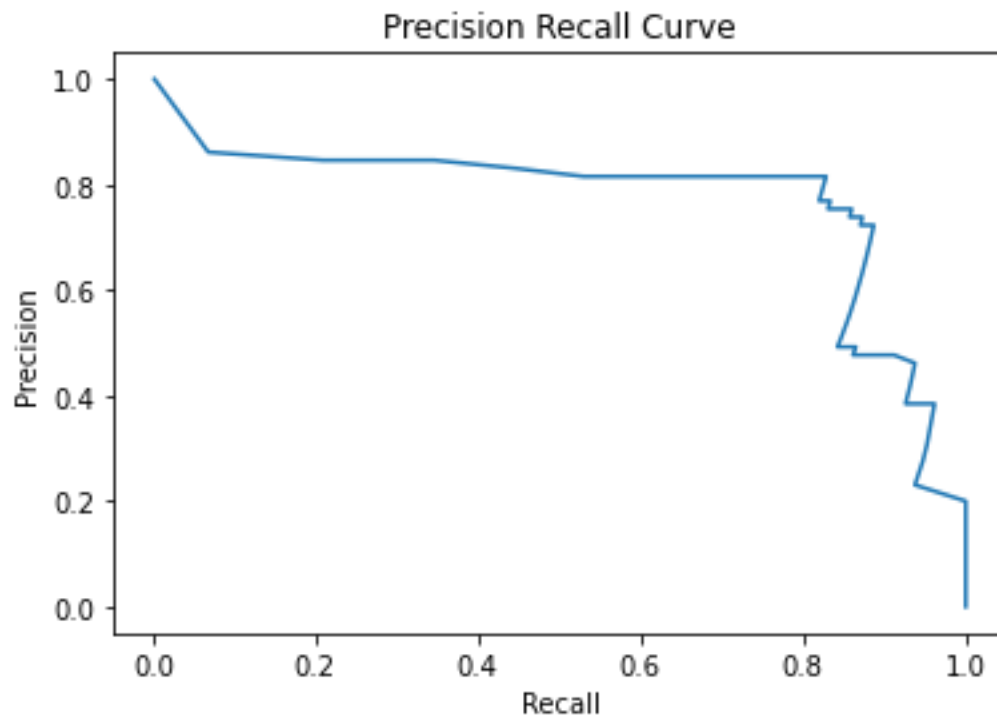
```
Y_pred_prob_rf_i = rfc.predict_proba(X_test)[: ,1]
```

In [23]:

```
evaluate(Y_pred_rf_i, Y_pred_prob_rf_i)
Accuracy:  0.9993279569892473
Precision:  0.8703703703703703
Recall:    0.7230769230769231
F1-Score:  0.7899159663865546
AUC score: 0.8614442108315813
```

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Normal       | 1.00      | 1.00   | 1.00     | 37135   |
| Fraud        | 0.87      | 0.72   | 0.79     | 65      |
| accuracy     |           |        | 1.00     | 37200   |
| macro avg    | 0.93      | 0.86   | 0.89     | 37200   |
| weighted avg | 1.00      | 1.00   | 1.00     | 37200   |





In [24]:

```
# decision tree model creation
dtc = DecisionTreeClassifier()
dtc.fit(X_train, Y_train)
# predictions
Y_pred_dt_i = dtc.predict(X_test)
```

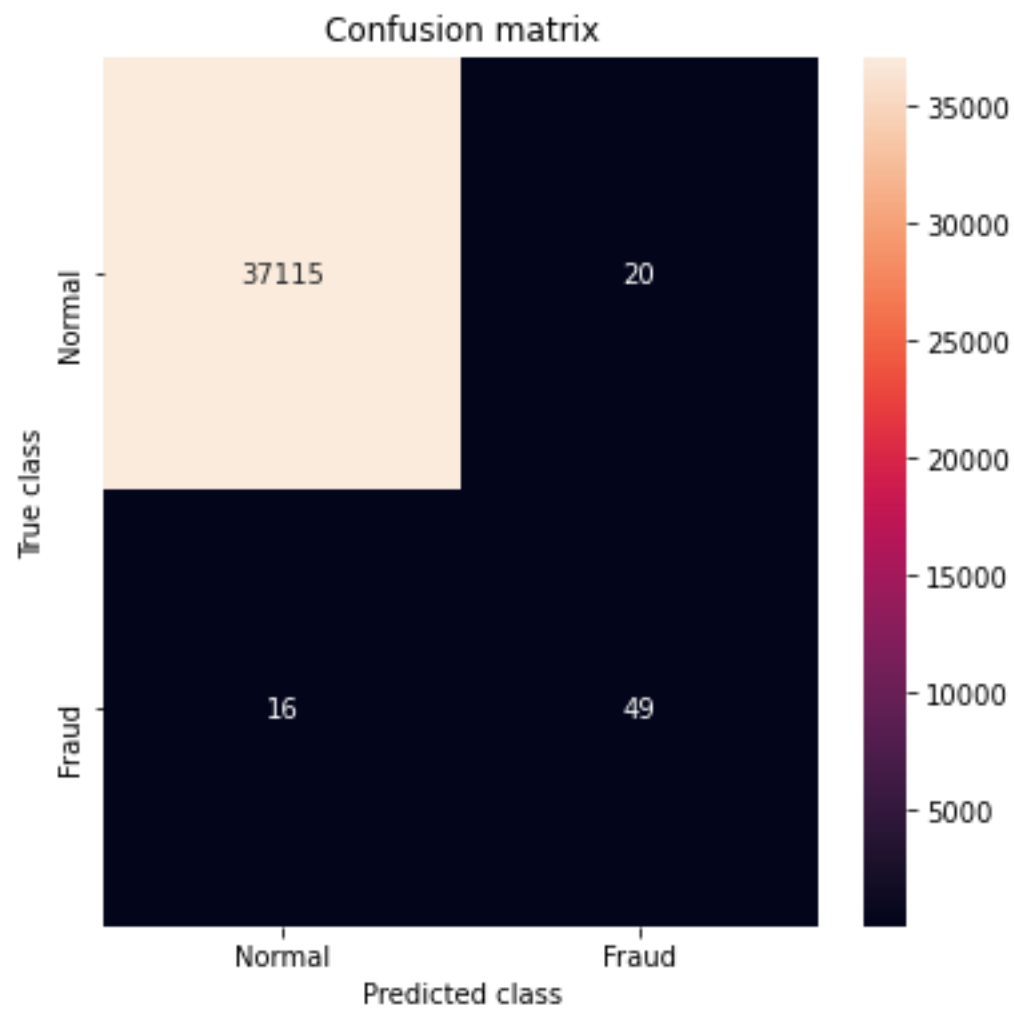
In [25]:

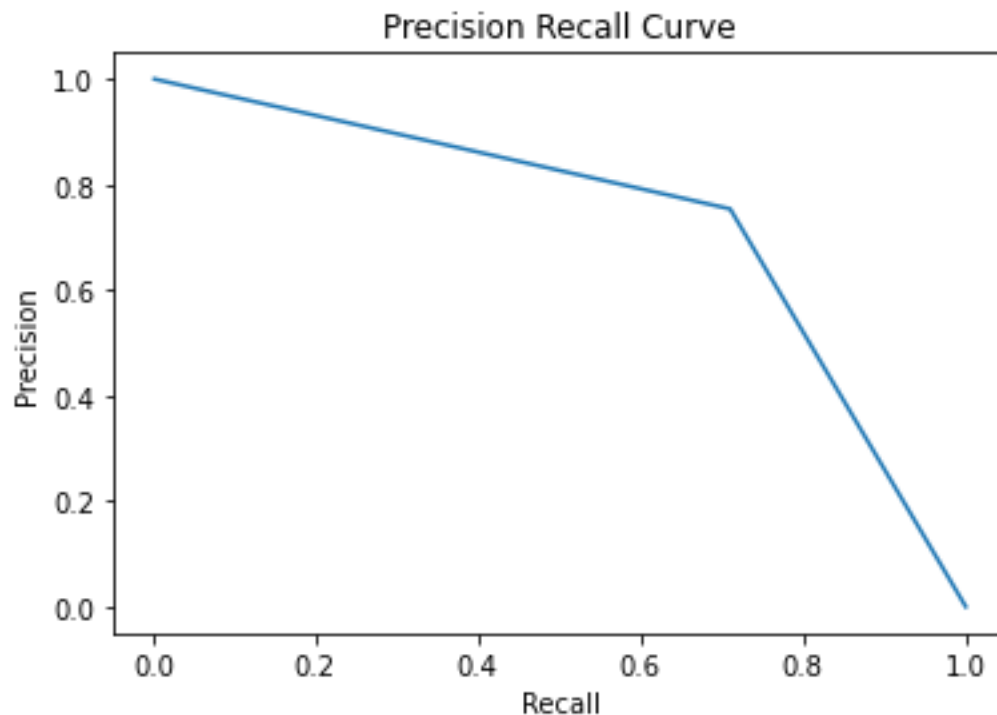
```
Y_pred_prob_dt_i = dtc.predict_proba(X_test)[:,1]
```

In [26]:

```
evaluate(Y_pred_dt_i, Y_pred_prob_dt_i)
Accuracy:  0.9990322580645161
Precision:  0.7101449275362319
Recall:     0.7538461538461538
F1-Score:   0.7313432835820897
AUC score:  0.8766537891891332
```

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Normal       | 1.00      | 1.00   | 1.00     | 37135   |
| Fraud        | 0.71      | 0.75   | 0.73     | 65      |
| accuracy     |           |        | 1.00     | 37200   |
| macro avg    | 0.85      | 0.88   | 0.87     | 37200   |
| weighted avg | 1.00      | 1.00   | 1.00     | 37200   |





In [27]:

```
#random forest balanced weights
from sklearn.ensemble import RandomForestClassifier
# random forest model creation
rfb = RandomForestClassifier(class_weight='balanced')
rfb.fit(X_train, Y_train)
# predictions
Y_pred_rf_b = rfb.predict(X_test)
```

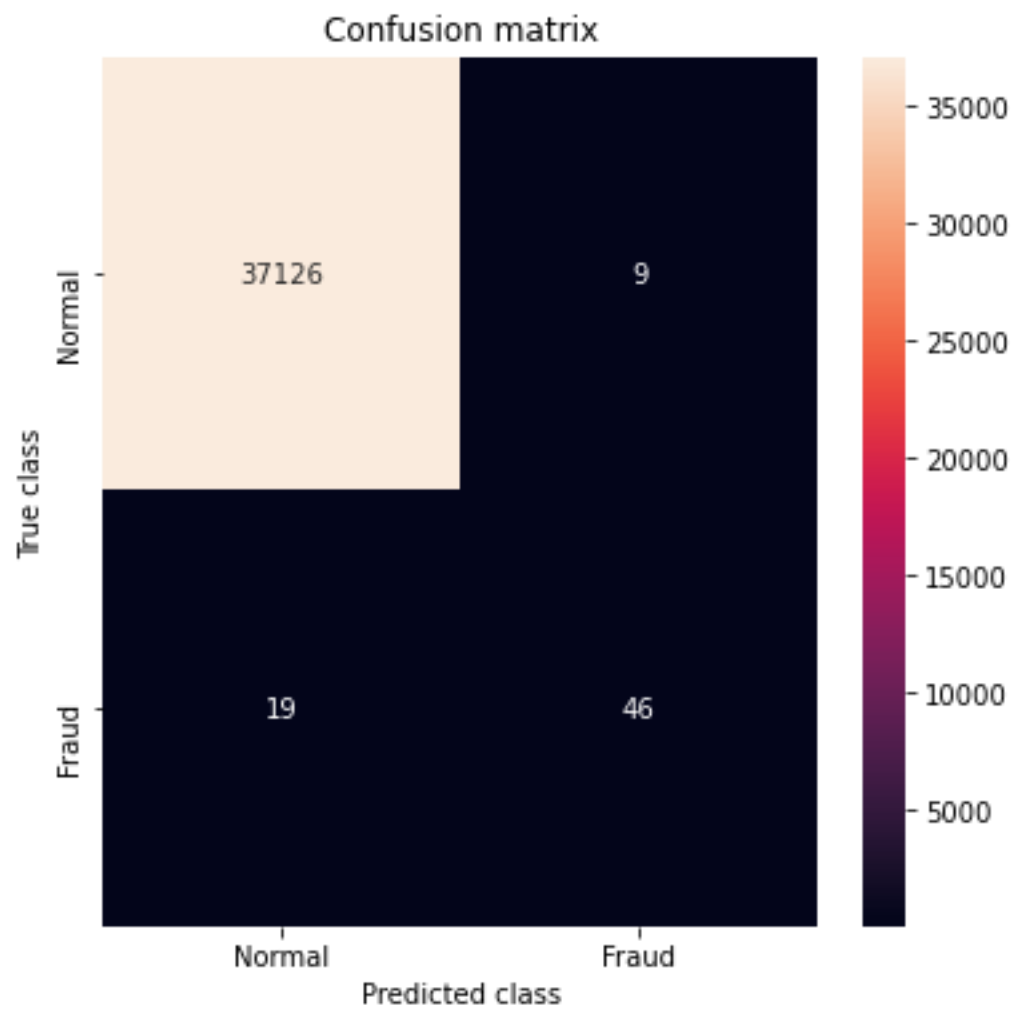
In [28]:

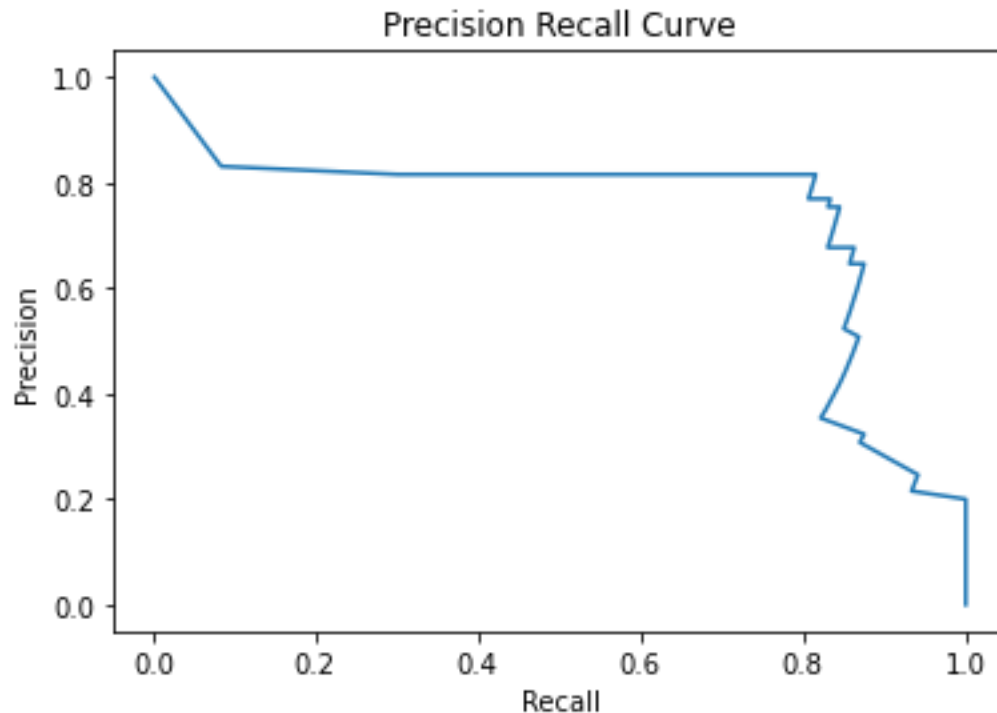
```
Y_pred_prob_rf_b = rfb.predict_proba(X_test)[: ,1]
```

In [29]:

```
evaluate(Y_pred_rf_b, Y_pred_prob_rf_b)
Accuracy:  0.999247311827957
Precision:  0.8363636363636363
Recall:    0.7076923076923077
F1-Score:  0.7666666666666666
AUC score: 0.8537249743658792
```

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Normal       | 1.00      | 1.00   | 1.00     | 37135   |
| Fraud        | 0.84      | 0.71   | 0.77     | 65      |
| accuracy     |           |        | 1.00     | 37200   |
| macro avg    | 0.92      | 0.85   | 0.88     | 37200   |
| weighted avg | 1.00      | 1.00   | 1.00     | 37200   |





In [31]:

```

pip install -U imbalanced-learn
Collecting imbalanced-learn
  Downloading imbalanced_learn-0.7.0-py3-none-any.whl (167 kB)
Requirement already satisfied, skipping upgrade: numpy>=1.13.3 in
c:\users\revan\anaconda3\lib\site-packages (from imbalanced-learn) (1.19.2)
Requirement already satisfied, skipping upgrade: joblib>=0.11 in
c:\users\revan\anaconda3\lib\site-packages (from imbalanced-learn) (0.17.0)
Requirement already satisfied, skipping upgrade: scikit-learn>=0.23 in
c:\users\revan\anaconda3\lib\site-packages (from imbalanced-learn) (0.23.2)
Requirement already satisfied, skipping upgrade: scipy>=0.19.1 in
c:\users\revan\anaconda3\lib\site-packages (from imbalanced-learn) (1.5.2)
Requirement already satisfied, skipping upgrade: threadpoolctl>=2.0.0 in
c:\users\revan\anaconda3\lib\site-packages (from scikit-learn>=0.23-
>imbalanced-learn) (2.1.0)
Installing collected packages: imbalanced-learn
Successfully installed imbalanced-learn-0.7.0
Note: you may need to restart the kernel to use updated packages.

```

In [32]:

```

from imblearn.over_sampling import SMOTE

```

In [33]:

```

smote = SMOTE(random_state=56)
smote_X, smote_Y = smote.fit_resample(X, Y)

```

In [34]:

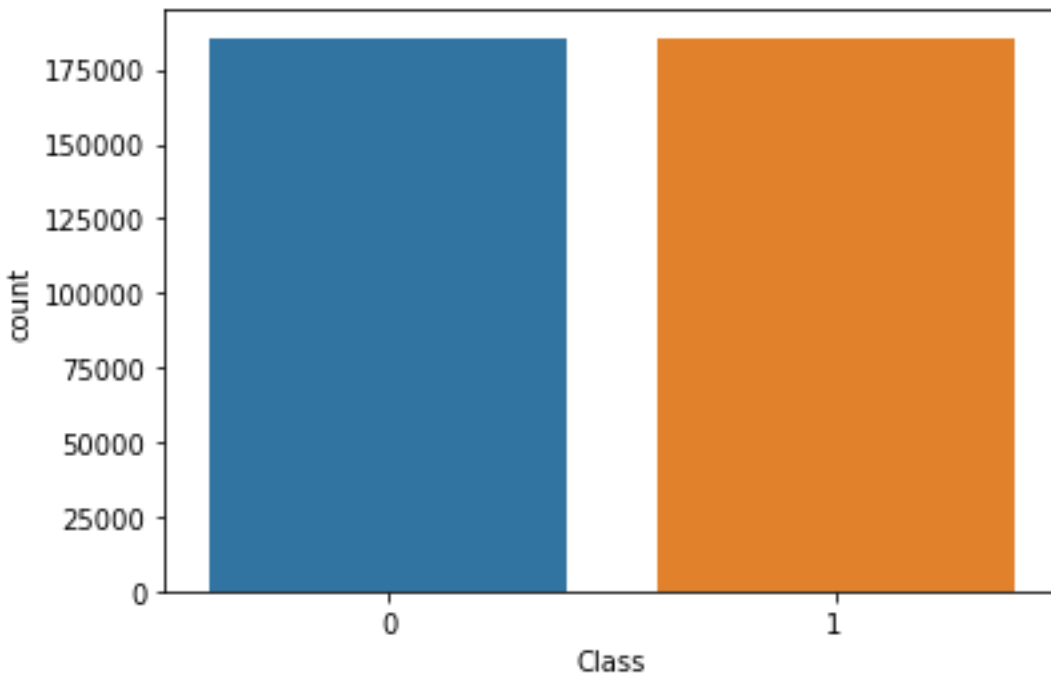
```

sns.countplot(smote_Y)

```

Out[34]:

```
<AxesSubplot:xlabel='Class', ylabel='count'>
```



In [35]:

```
X_train, X_test, Y_train, Y_test = train_test_split(smote_X, smote_Y,  
test_size=0.2, random_state=1)
```

In [36]:

```
#using smote  
lr_smote = LogisticRegression()  
lr_smote.fit(X_train, Y_train)  
Y_pred_lr_smote = lr_smote.predict(X_test)
```

In [37]:

```
Y_pred_prob_lr_smote = lr_smote.predict_proba(X_test)[: ,1]
```

In [38]:

```
evaluate(Y_pred_lr_smote, Y_pred_prob_lr_smote)
```

```
Accuracy:  0.9483993430440752
```

```
Precision:  0.9761665758453552
```

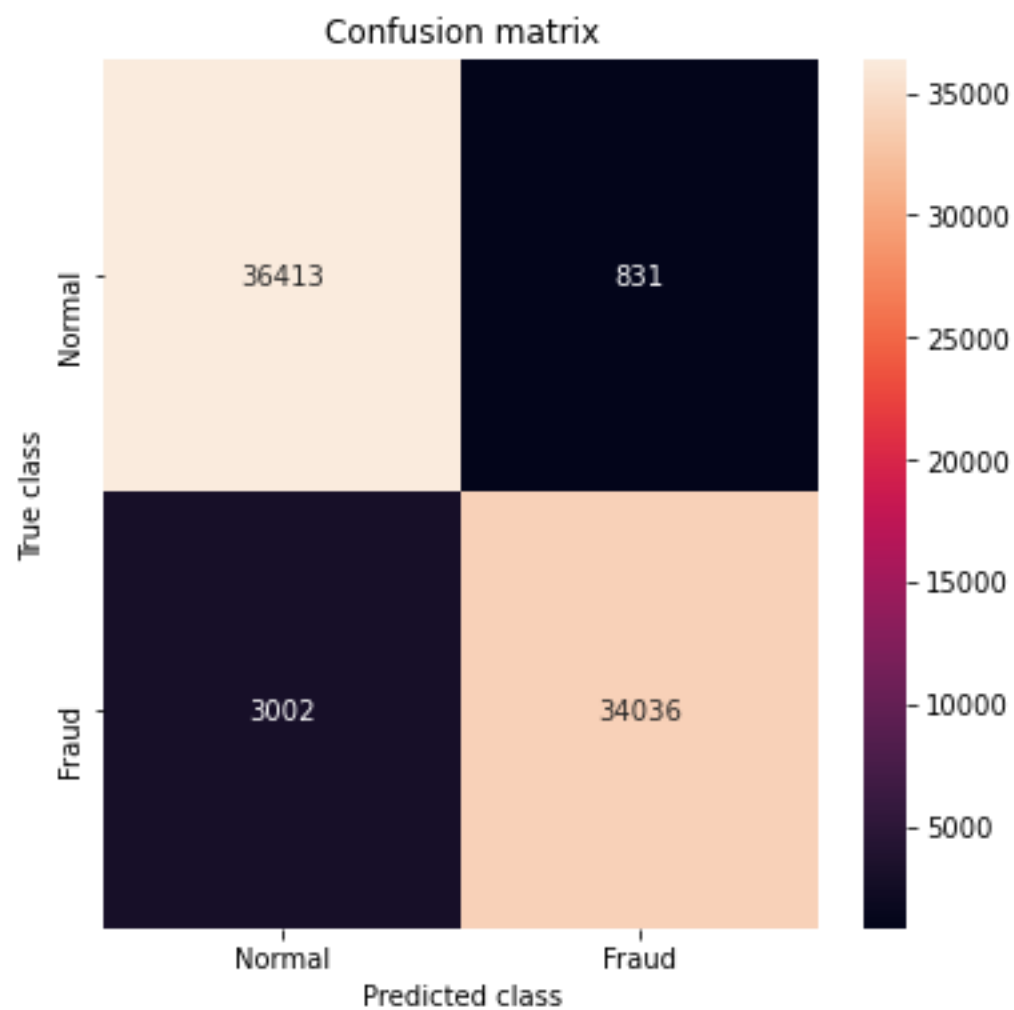
```
Recall:  0.918948107349209
```

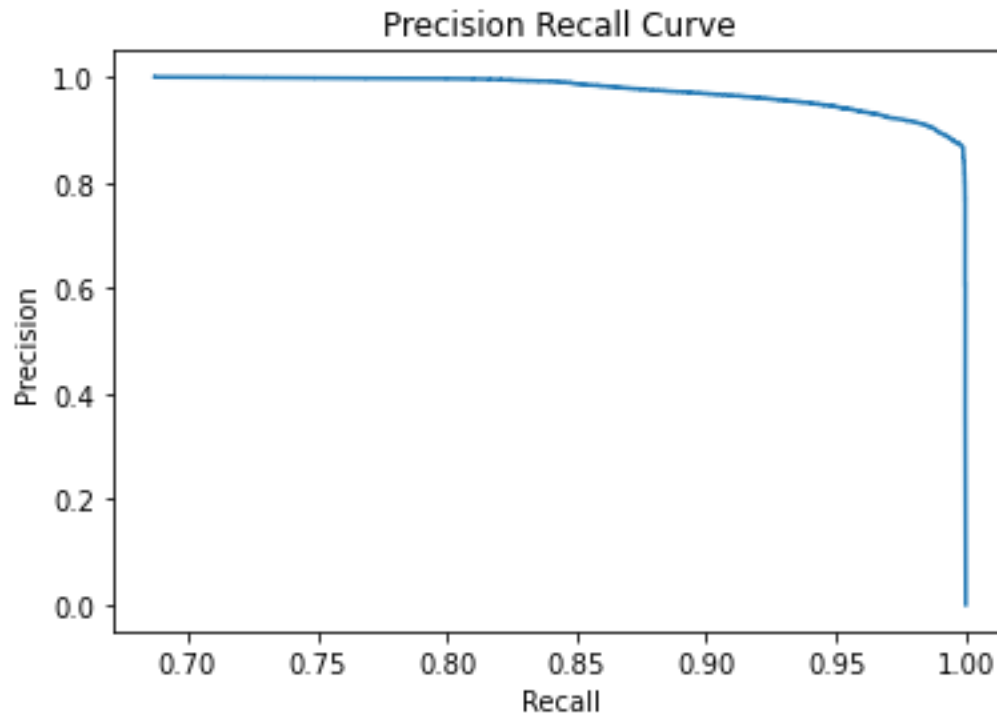
```
F1-Score:  0.9466935539948543
```

```
AUC score:  0.9483178942932277
```

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Normal       | 0.92      | 0.98   | 0.95     | 37244   |
| Fraud        | 0.98      | 0.92   | 0.95     | 37038   |
| accuracy     |           |        | 0.95     | 74282   |
| macro avg    | 0.95      | 0.95   | 0.95     | 74282   |
| weighted avg | 0.95      | 0.95   | 0.95     | 74282   |







In [39]:

```
#using randomforest
rf_smote = RandomForestClassifier()
rf_smote.fit(X_train, Y_train)
Y_pred_rf_smote = rf_smote.predict(X_test)
```

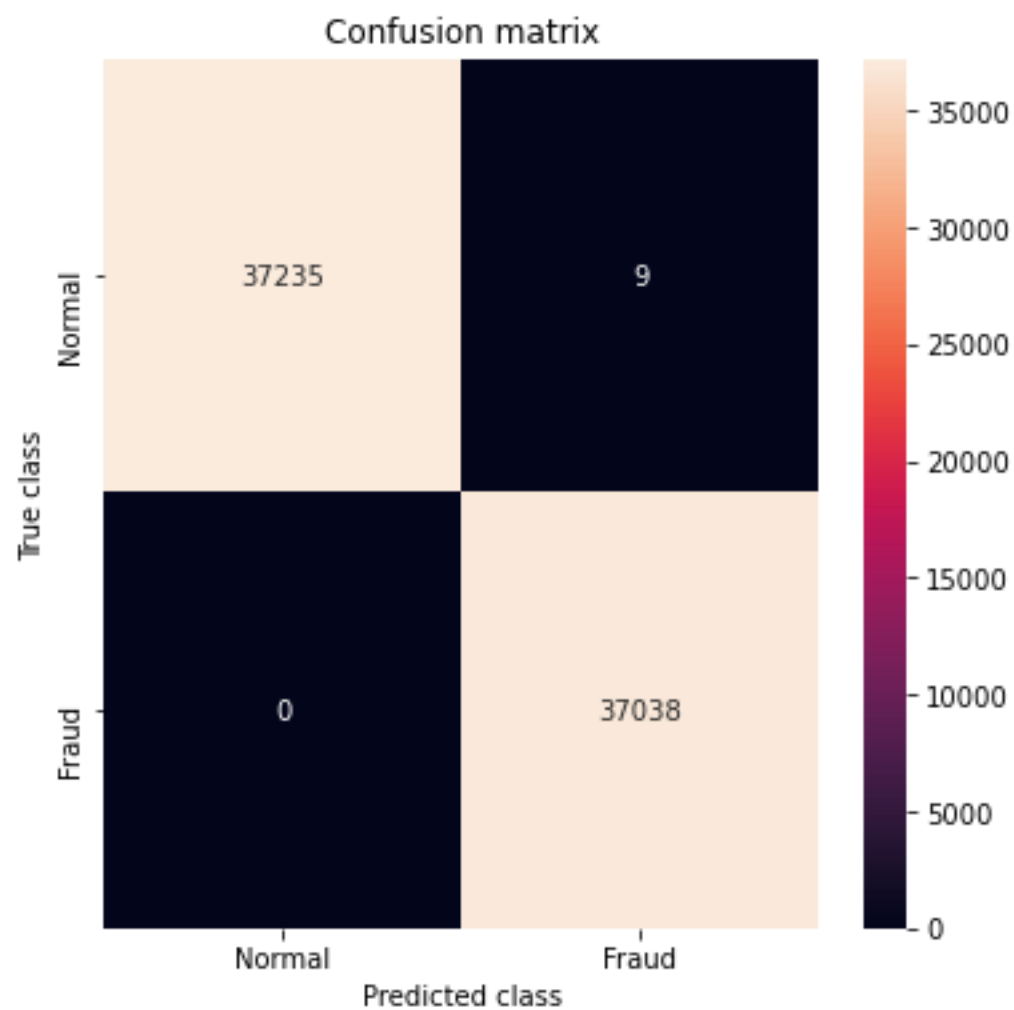
In [40]:

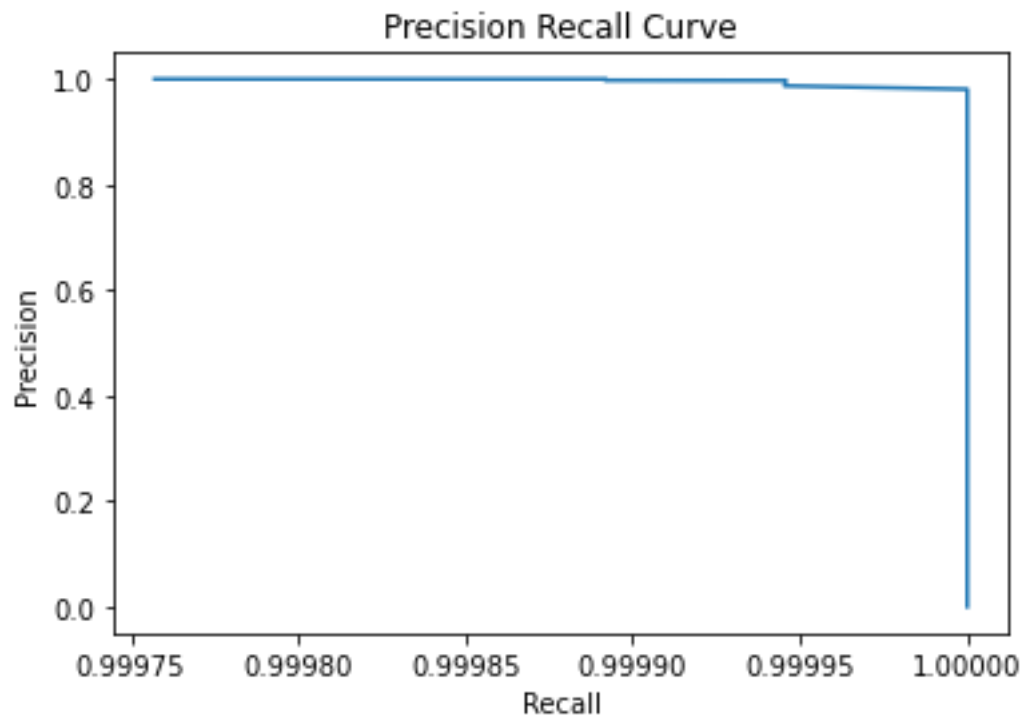
```
Y_pred_prob_rf_smote = rf_smote.predict_proba(X_test)[:,-1]
```

In [41]:

```
evaluate(Y_pred_rf_smote, Y_pred_prob_rf_smote)
Accuracy:  0.9998788400958509
Precision:  0.999757065349421
Recall:    1.0
F1-Score:  0.999878517918607
AUC score: 0.9998791751691547
```

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Normal       | 1.00      | 1.00   | 1.00     | 37244   |
| Fraud        | 1.00      | 1.00   | 1.00     | 37038   |
| accuracy     |           |        | 1.00     | 74282   |
| macro avg    | 1.00      | 1.00   | 1.00     | 74282   |
| weighted avg | 1.00      | 1.00   | 1.00     | 74282   |





In [43]:

```
#using decision tree
dt_smote = DecisionTreeClassifier()
dt_smote.fit(X_train, Y_train)
Y_pred_dt_smote = dt_smote.predict(X_test)
```

In [45]:

```
Y_pred_prob_dt_smote = dt_smote.predict_proba(X_test)[:,1]
```

In [46]:

```
evaluate(Y_pred_dt_smote, Y_pred_prob_dt_smote)
```

```
Accuracy: 0.9985326189386392
```

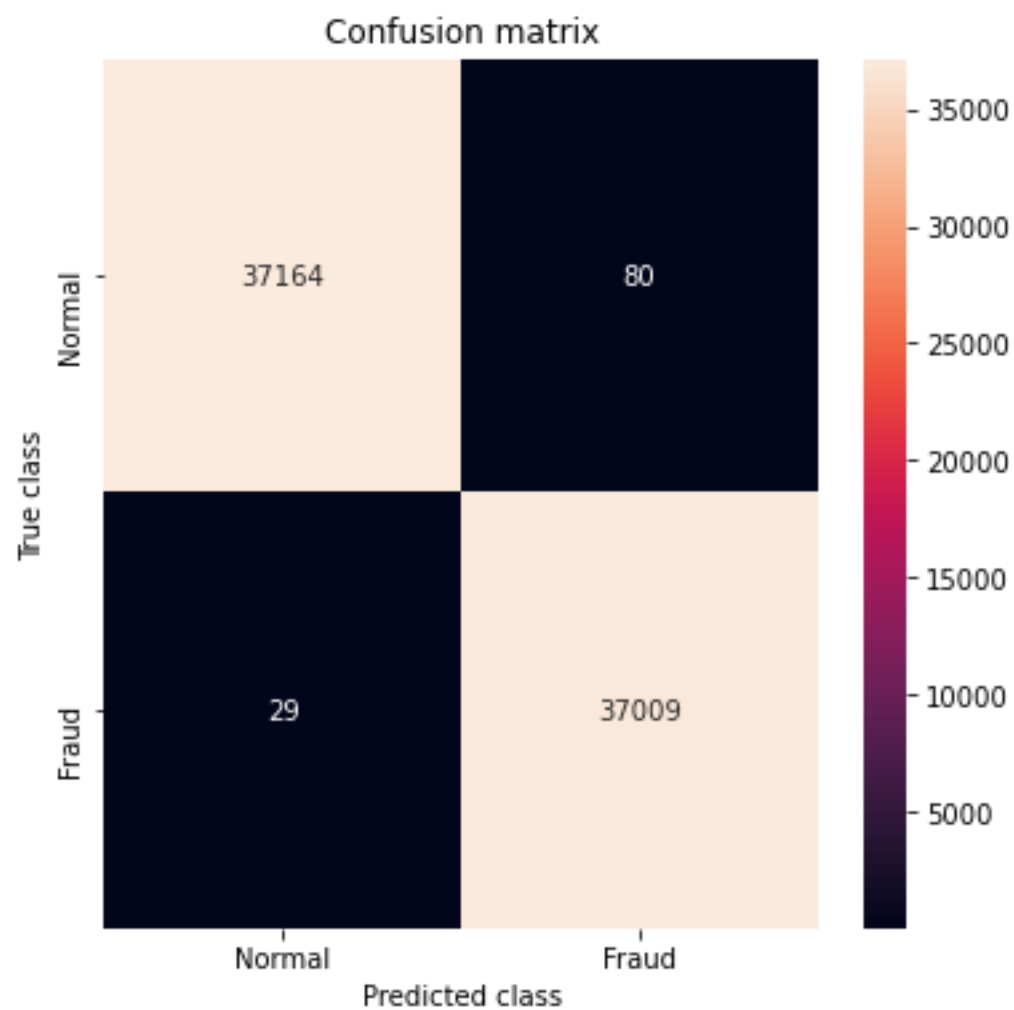
```
Precision: 0.9978430262341934
```

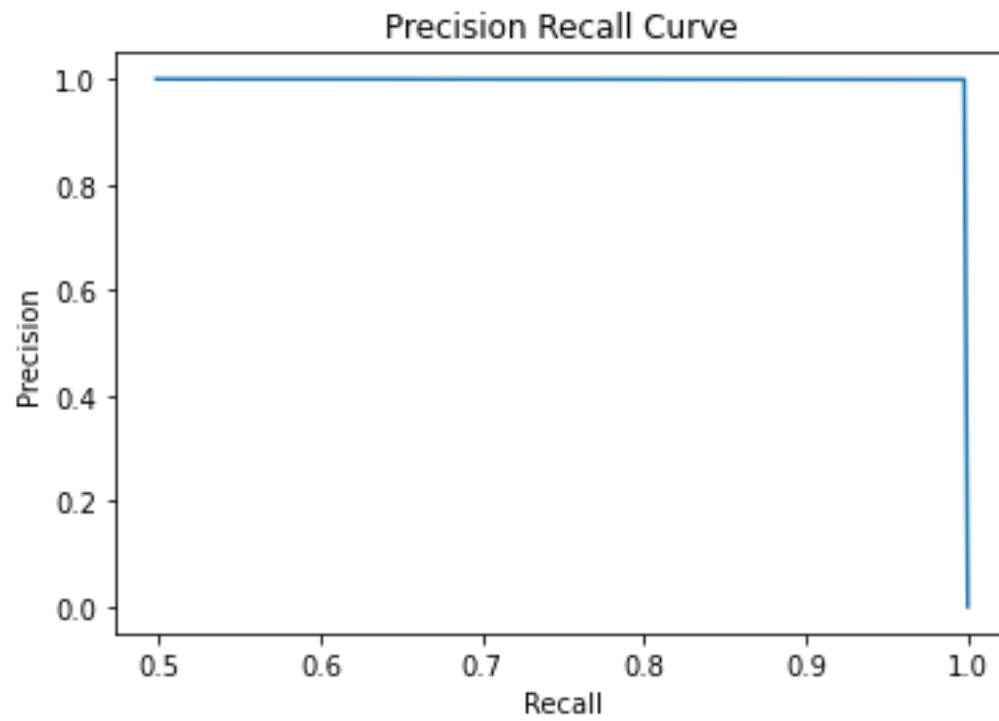
```
Recall: 0.9992170203574707
```

```
F1-Score: 0.9985295506360705
```

```
AUC score: 0.9985345116823332
```

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Normal       | 1.00      | 1.00   | 1.00     | 37244   |
| Fraud        | 1.00      | 1.00   | 1.00     | 37038   |
| accuracy     |           |        | 1.00     | 74282   |
| macro avg    | 1.00      | 1.00   | 1.00     | 74282   |
| weighted avg | 1.00      | 1.00   | 1.00     | 74282   |





In [ ]: