Trabalho 2 - Redes

Criar um detector de anomalias usando pytorch. Faça um experimento com um dataset. Neste experimento você deve gerar o gráfico com curvas de erro de treino e de validação. Você deve escolher o melhor modelo de acordo com este gráfico e aplicar num conjunto de teste separado este modelo. Você deve ao final saber a taxa de acerto de anomalias vc não anomalias. Utilize métricas como f1 por classe e mcc (mathews correlation coeficient).

Importante. Para a detecção de anomalias, é necessário a escolha (tanto devios padrão da média) ou calibração (conjunto de validação) de um limiar para o erro de reconstrução.

Imports

Primeiro é preciso importar as bibliotecas e funções a serem utilizadas.

In [1]:
```
import torch
from torchvision import datasets
from torchvision.transforms import ToTensor
from torch.utils.data import DataLoader
from torch import nn
import matplotlib.pyplot as plt
import pandas as pd
import torch.utils.data as data_utils
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classifica
```

Pegando e Tratando o Dataset

"creditcard.csv" é um dataset sobre transações de cartão de crédito que possui uma label diferenciando transações normais de transações fraudulentas. O trabalho a seguir mostra como usar o detector de anomalias de um autoencoder para detectar transações com fraude.

[Link para o dataset]

In [2]:
```
df = pd.read_csv("data/creditcard.csv")
print("Shape of the dataset: ", df.shape)
df
```

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

Out[2]:

	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
...	...	...	...	...	...	...	...	...
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

284807 rows × 31 columns

É necessário primeiro treinar o autoencoder apenas com transações não fraudulentas, então basta separar e depois dividir o dataset em treino, teste e validação.

In [3]:

```
# Normalizando a coluna "Amount" e removendo a coluna "Time"
df['log10_amount'] = np.log10(df.Amount + 0.00001)
df = df.drop(['Time', 'Amount'], axis=1)

# Separando as transações com fraude e sem fraude
clean = df[df['Class'] == 0]
fraud = df[df['Class'] == 1]

print("Número de transações normais: ", len(clean))
print("Número de transações fraudulentas: ", len(fraud))
```

```
Número de transações normais:  284315
Número de transações fraudulentas:  492
```

A partição de teste continua com a coluna da classe para rotularmos no futuro.

In [4]:

```
# Dividindo o dataset em treino e teste
X_train, X_test = train_test_split(clean, test_size=0.2, random_state=42)

# Tirando a classe do treino
X_train = X_train.drop('Class', axis=1)

# Adicionando as anomalias no teste
X_test = pd.concat([X_test, fraud]).sample(frac=1)

# Criando um dataset de validação a partir do treino
X_train, X_validate = train_test_split(X_train, test_size=0.2, random_state=42)

print("Shape do treino: ", X_train.shape)
print("Shape do teste: ", X_test.shape)
print("Shape da validação: ", X_validate.shape)
```

```
Shape do treino:  (181961, 29)
Shape do teste:  (57355, 30)
Shape da validação:  (45491, 29)
```

Transformando os dados em tensores e data_loaders.

In [5]:
```
train = torch.tensor(X_train.values.astype(np.float32))
train_target = torch.tensor(X_train.values.astype(np.float32))
train_tensor = data_utils.TensorDataset(train, train_target)
train_loader = data_utils.DataLoader(dataset = train_tensor, batch_size = 64, sh
```

In [6]:
```
test_target = torch.tensor(X_validate.values.astype(np.float32))
test = torch.tensor(X_validate.values.astype(np.float32))
test_tensor = data_utils.TensorDataset(test, test_target)
test_loader = data_utils.DataLoader(dataset = test_tensor, batch_size = 64, shuf
```

Definindo o device

Como minha placa de vídeo é AMD não possuo Cuda.

In [7]:
```
device = 'cuda' if torch.cuda.is_available() else 'cpu'
print('Using {} device'.format(device))
```

```
Using cpu device
```

Definindo a Rede Neural

Basta criar uma classe que herda nn.Module e definir as camadas da rede aqui. Reduzi os dados até ficarem com dimensão 2 para depois reconstrui-los novamente.

In [8]:
```
class NeuralNetwork(nn.Module):

    def __init__(self):
        super(NeuralNetwork, self).__init__()
        self.flatten = nn.Flatten()
        self.autoencoder = nn.Sequential(
            torch.nn.Linear(29, 16),
            torch.nn.ReLU(),
            torch.nn.Linear(16, 8),
            torch.nn.ReLU(),
            torch.nn.Linear(8, 4),
            torch.nn.ReLU(),
            torch.nn.Linear(4, 2),
            torch.nn.ReLU(),
            torch.nn.Linear(2, 4),
            torch.nn.ReLU(),
            torch.nn.Linear(4, 8),
            torch.nn.ReLU(),
            torch.nn.Linear(8, 16),
            torch.nn.ReLU(),
            torch.nn.Linear(16, 29)
        )

    def forward(self, x):
```

```
        logits = self.autoencoder(x)
        return logits
```

Jogando a Rede para a CPU

In [9]:
```
model = NeuralNetwork().to(device)
print(model)
```

```
NeuralNetwork(
  (flatten): Flatten(start_dim=1, end_dim=-1)
  (autoencoder): Sequential(
    (0): Linear(in_features=29, out_features=16, bias=True)
    (1): ReLU()
    (2): Linear(in_features=16, out_features=8, bias=True)
    (3): ReLU()
    (4): Linear(in_features=8, out_features=4, bias=True)
    (5): ReLU()
    (6): Linear(in_features=4, out_features=2, bias=True)
    (7): ReLU()
    (8): Linear(in_features=2, out_features=4, bias=True)
    (9): ReLU()
    (10): Linear(in_features=4, out_features=8, bias=True)
    (11): ReLU()
    (12): Linear(in_features=8, out_features=16, bias=True)
    (13): ReLU()
    (14): Linear(in_features=16, out_features=29, bias=True)
  )
)
```

Definindo a loss function e o otimizador

Learning rate final foi de 0.01 pois foi a com o melhor desempenho.

In [10]:
```
loss_fn = nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
```

Realizando o treinamento do Autoencoder

Funções para implementar o treino e o teste

Realizam os ajustes de pesos das redes e calculam a perda e acurácia do algoritmo

In [11]:
```
def train_loop(dataloader, model, loss_fn, optimizer):
    size = len(dataloader.dataset)
    loss_history = []
    batch_history = []

    for batch, (X, y) in enumerate(dataloader):
        pred = model(X)
        loss = loss_fn(pred, y)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

```python
        if batch % 100 == 0:
            loss, current = loss.item(), batch * len(X)
            print(f"loss: {loss:>7f} [{current:>5d}/{size:>5d}]")

            loss_history.append(loss)
            batch_history.append(current)

    return loss_history, batch_history
```

In [12]:
```python
def test_loop(dataloader, model, loss_fn):
    size = len(dataloader.dataset)
    test_loss, correct = 0, 0

    with torch.no_grad():
      for X, y in dataloader:
          pred = model(X)
          test_loss += loss_fn(pred, y).item()

    test_loss /= size
    correct   /= size
    print(f"Test Error: \n Accuracy: {100*correct:>0.1f}%, Avg loss: {test_loss:

    return test_loss, correct
```

Loop do Treino

Utilizei 10 epochs pois o desempenho não melhorava muito depois disso.

In [13]:
```python
epochs = 10
loss_test_history = []
acc_history = []
for t in range(epochs):
    print(f"Epoch {t+1}\n-------------------------------")
    loss_train_history, batch_history = train_loop(train_loader, model, loss_fn,
    loss, accuracy = test_loop(test_loader, model, loss_fn)
    loss_test_history.append(loss)
    acc_history.append(accuracy)
```

```
Epoch 1
-------------------------------
loss: 3.528685 [    0/181961]
loss: 1.380466 [ 6400/181961]
loss: 1.032883 [12800/181961]
loss: 1.056855 [19200/181961]
loss: 0.799937 [25600/181961]
loss: 0.792368 [32000/181961]
loss: 2.094324 [38400/181961]
loss: 0.800465 [44800/181961]
loss: 0.635147 [51200/181961]
loss: 0.704072 [57600/181961]
loss: 0.629619 [64000/181961]
loss: 0.575047 [70400/181961]
loss: 0.542762 [76800/181961]
loss: 0.756183 [83200/181961]
loss: 0.692511 [89600/181961]
loss: 0.852411 [96000/181961]
loss: 0.570929 [102400/181961]
loss: 0.653631 [108800/181961]
loss: 0.531707 [115200/181961]
loss: 0.549825 [121600/181961]
loss: 1.217990 [128000/181961]
loss: 0.635831 [134400/181961]
loss: 0.573344 [140800/181961]
loss: 0.792729 [147200/181961]
loss: 0.561708 [153600/181961]
loss: 0.698333 [160000/181961]
loss: 0.494113 [166400/181961]
loss: 0.705996 [172800/181961]
loss: 0.600648 [179200/181961]
Test Error: 
 Accuracy: 0.0%, Avg loss: 0.011093 

Epoch 2
-------------------------------
loss: 0.778258 [    0/181961]
loss: 0.703080 [ 6400/181961]
loss: 0.525705 [12800/181961]
loss: 0.536498 [19200/181961]
loss: 0.511154 [25600/181961]
loss: 0.967652 [32000/181961]
loss: 0.520271 [38400/181961]
loss: 0.612574 [44800/181961]
loss: 0.594822 [51200/181961]
loss: 0.738945 [57600/181961]
loss: 0.565620 [64000/181961]
loss: 0.542819 [70400/181961]
loss: 0.510231 [76800/181961]
loss: 0.798831 [83200/181961]
loss: 0.541807 [89600/181961]
loss: 0.514355 [96000/181961]
loss: 0.720332 [102400/181961]
loss: 0.577271 [108800/181961]
loss: 0.626209 [115200/181961]
loss: 0.732453 [121600/181961]
loss: 0.610666 [128000/181961]
loss: 0.598438 [134400/181961]
loss: 0.537533 [140800/181961]
loss: 0.606451 [147200/181961]
```

```
loss: 0.755120 [153600/181961]
loss: 0.629491 [160000/181961]
loss: 0.726301 [166400/181961]
loss: 0.834134 [172800/181961]
loss: 0.836606 [179200/181961]
Test Error: 
 Accuracy: 0.0%, Avg loss: 0.010937 

Epoch 3
-------------------------------
loss: 0.701882 [    0/181961]
loss: 0.589907 [ 6400/181961]
loss: 0.667777 [12800/181961]
loss: 0.567322 [19200/181961]
loss: 1.026934 [25600/181961]
loss: 0.583794 [32000/181961]
loss: 0.942902 [38400/181961]
loss: 0.941429 [44800/181961]
loss: 0.611844 [51200/181961]
loss: 0.722935 [57600/181961]
loss: 0.703335 [64000/181961]
loss: 0.871253 [70400/181961]
loss: 1.190430 [76800/181961]
loss: 0.569909 [83200/181961]
loss: 0.551666 [89600/181961]
loss: 0.538243 [96000/181961]
loss: 1.367089 [102400/181961]
loss: 0.537729 [108800/181961]
loss: 0.512404 [115200/181961]
loss: 0.735569 [121600/181961]
loss: 0.711763 [128000/181961]
loss: 0.820631 [134400/181961]
loss: 0.537278 [140800/181961]
loss: 1.016195 [147200/181961]
loss: 0.767331 [153600/181961]
loss: 0.444466 [160000/181961]
loss: 0.555755 [166400/181961]
loss: 1.051315 [172800/181961]
loss: 0.600103 [179200/181961]
Test Error: 
 Accuracy: 0.0%, Avg loss: 0.010544 

Epoch 4
-------------------------------
loss: 0.544423 [    0/181961]
loss: 0.597667 [ 6400/181961]
loss: 0.632707 [12800/181961]
loss: 0.575823 [19200/181961]
loss: 0.657778 [25600/181961]
loss: 0.580541 [32000/181961]
loss: 0.487790 [38400/181961]
loss: 0.794121 [44800/181961]
loss: 0.465966 [51200/181961]
loss: 0.647628 [57600/181961]
loss: 0.560103 [64000/181961]
loss: 0.517737 [70400/181961]
loss: 0.765939 [76800/181961]
loss: 0.575645 [83200/181961]
loss: 0.549299 [89600/181961]
loss: 0.519724 [96000/181961]
```

```
loss: 0.680858 [102400/181961]
loss: 0.872740 [108800/181961]
loss: 0.607081 [115200/181961]
loss: 0.664272 [121600/181961]
loss: 0.530803 [128000/181961]
loss: 0.791875 [134400/181961]
loss: 1.904207 [140800/181961]
loss: 1.103430 [147200/181961]
loss: 0.469237 [153600/181961]
loss: 0.516439 [160000/181961]
loss: 0.497359 [166400/181961]
loss: 0.512797 [172800/181961]
loss: 0.685729 [179200/181961]
Test Error:
 Accuracy: 0.0%, Avg loss: 0.010200

Epoch 5
-------------------------------
loss: 0.613069 [    0/181961]
loss: 0.602274 [ 6400/181961]
loss: 0.489798 [12800/181961]
loss: 0.490287 [19200/181961]
loss: 0.538656 [25600/181961]
loss: 0.703413 [32000/181961]
loss: 0.513204 [38400/181961]
loss: 0.521670 [44800/181961]
loss: 1.168654 [51200/181961]
loss: 0.528010 [57600/181961]
loss: 0.584087 [64000/181961]
loss: 0.833928 [70400/181961]
loss: 0.914606 [76800/181961]
loss: 0.606802 [83200/181961]
loss: 0.671045 [89600/181961]
loss: 0.658070 [96000/181961]
loss: 0.524119 [102400/181961]
loss: 0.610501 [108800/181961]
loss: 0.545487 [115200/181961]
loss: 0.575101 [121600/181961]
loss: 0.562703 [128000/181961]
loss: 0.522497 [134400/181961]
loss: 0.691455 [140800/181961]
loss: 0.567306 [147200/181961]
loss: 0.577691 [153600/181961]
loss: 0.559651 [160000/181961]
loss: 0.538438 [166400/181961]
loss: 0.502644 [172800/181961]
loss: 0.729654 [179200/181961]
Test Error:
 Accuracy: 0.0%, Avg loss: 0.009769

Epoch 6
-------------------------------
loss: 0.507863 [    0/181961]
loss: 0.759072 [ 6400/181961]
loss: 0.513212 [12800/181961]
loss: 0.998925 [19200/181961]
loss: 0.652682 [25600/181961]
loss: 1.102057 [32000/181961]
loss: 0.530971 [38400/181961]
loss: 0.637332 [44800/181961]
```

```
loss: 0.592625 [51200/181961]
loss: 0.603236 [57600/181961]
loss: 0.536175 [64000/181961]
loss: 0.629822 [70400/181961]
loss: 0.590862 [76800/181961]
loss: 0.792820 [83200/181961]
loss: 0.603729 [89600/181961]
loss: 0.708680 [96000/181961]
loss: 0.555912 [102400/181961]
loss: 0.519956 [108800/181961]
loss: 0.497622 [115200/181961]
loss: 0.587320 [121600/181961]
loss: 0.643164 [128000/181961]
loss: 0.506502 [134400/181961]
loss: 0.566225 [140800/181961]
loss: 0.530309 [147200/181961]
loss: 0.630318 [153600/181961]
loss: 0.473981 [160000/181961]
loss: 0.545809 [166400/181961]
loss: 0.518431 [172800/181961]
loss: 0.525965 [179200/181961]
Test Error:
 Accuracy: 0.0%, Avg loss: 0.009507

Epoch 7
-----------------------------------
loss: 0.465249 [    0/181961]
loss: 1.213933 [ 6400/181961]
loss: 0.533355 [12800/181961]
loss: 0.632338 [19200/181961]
loss: 0.511065 [25600/181961]
loss: 0.628418 [32000/181961]
loss: 0.484273 [38400/181961]
loss: 0.431977 [44800/181961]
loss: 0.487211 [51200/181961]
loss: 0.685117 [57600/181961]
loss: 0.569669 [64000/181961]
loss: 0.531131 [70400/181961]
loss: 0.544341 [76800/181961]
loss: 0.886092 [83200/181961]
loss: 0.617826 [89600/181961]
loss: 0.608811 [96000/181961]
loss: 0.566789 [102400/181961]
loss: 0.477063 [108800/181961]
loss: 0.544616 [115200/181961]
loss: 0.634755 [121600/181961]
loss: 0.483805 [128000/181961]
loss: 0.504919 [134400/181961]
loss: 0.548517 [140800/181961]
loss: 0.481495 [147200/181961]
loss: 0.744129 [153600/181961]
loss: 1.140593 [160000/181961]
loss: 0.519714 [166400/181961]
loss: 0.799968 [172800/181961]
loss: 0.566441 [179200/181961]
Test Error:
 Accuracy: 0.0%, Avg loss: 0.009448

Epoch 8
-----------------------------------
```

```
loss: 0.441633 [    0/181961]
loss: 0.588972 [ 6400/181961]
loss: 0.403638 [12800/181961]
loss: 0.630189 [19200/181961]
loss: 0.628326 [25600/181961]
loss: 0.556561 [32000/181961]
loss: 0.481409 [38400/181961]
loss: 0.555130 [44800/181961]
loss: 0.535113 [51200/181961]
loss: 0.441050 [57600/181961]
loss: 0.467233 [64000/181961]
loss: 0.466286 [70400/181961]
loss: 0.533763 [76800/181961]
loss: 0.499969 [83200/181961]
loss: 0.499983 [89600/181961]
loss: 0.492027 [96000/181961]
loss: 0.535834 [102400/181961]
loss: 0.477885 [108800/181961]
loss: 0.629171 [115200/181961]
loss: 0.458951 [121600/181961]
loss: 0.576767 [128000/181961]
loss: 0.533560 [134400/181961]
loss: 0.689163 [140800/181961]
loss: 0.435275 [147200/181961]
loss: 0.549445 [153600/181961]
loss: 0.479049 [160000/181961]
loss: 0.594021 [166400/181961]
loss: 0.765296 [172800/181961]
loss: 0.679397 [179200/181961]
Test Error: 
 Accuracy: 0.0%, Avg loss: 0.009225 

Epoch 9
-------------------------------
loss: 0.569665 [    0/181961]
loss: 0.606057 [ 6400/181961]
loss: 0.583664 [12800/181961]
loss: 0.475112 [19200/181961]
loss: 0.621621 [25600/181961]
loss: 0.588013 [32000/181961]
loss: 0.915815 [38400/181961]
loss: 0.464894 [44800/181961]
loss: 0.701686 [51200/181961]
loss: 0.628529 [57600/181961]
loss: 0.471361 [64000/181961]
loss: 0.444717 [70400/181961]
loss: 0.575736 [76800/181961]
loss: 0.463066 [83200/181961]
loss: 0.520210 [89600/181961]
loss: 0.467288 [96000/181961]
loss: 0.512837 [102400/181961]
loss: 0.591801 [108800/181961]
loss: 0.570880 [115200/181961]
loss: 0.520076 [121600/181961]
loss: 0.646615 [128000/181961]
loss: 0.674644 [134400/181961]
loss: 0.572018 [140800/181961]
loss: 0.798114 [147200/181961]
loss: 0.640432 [153600/181961]
loss: 0.476329 [160000/181961]
```

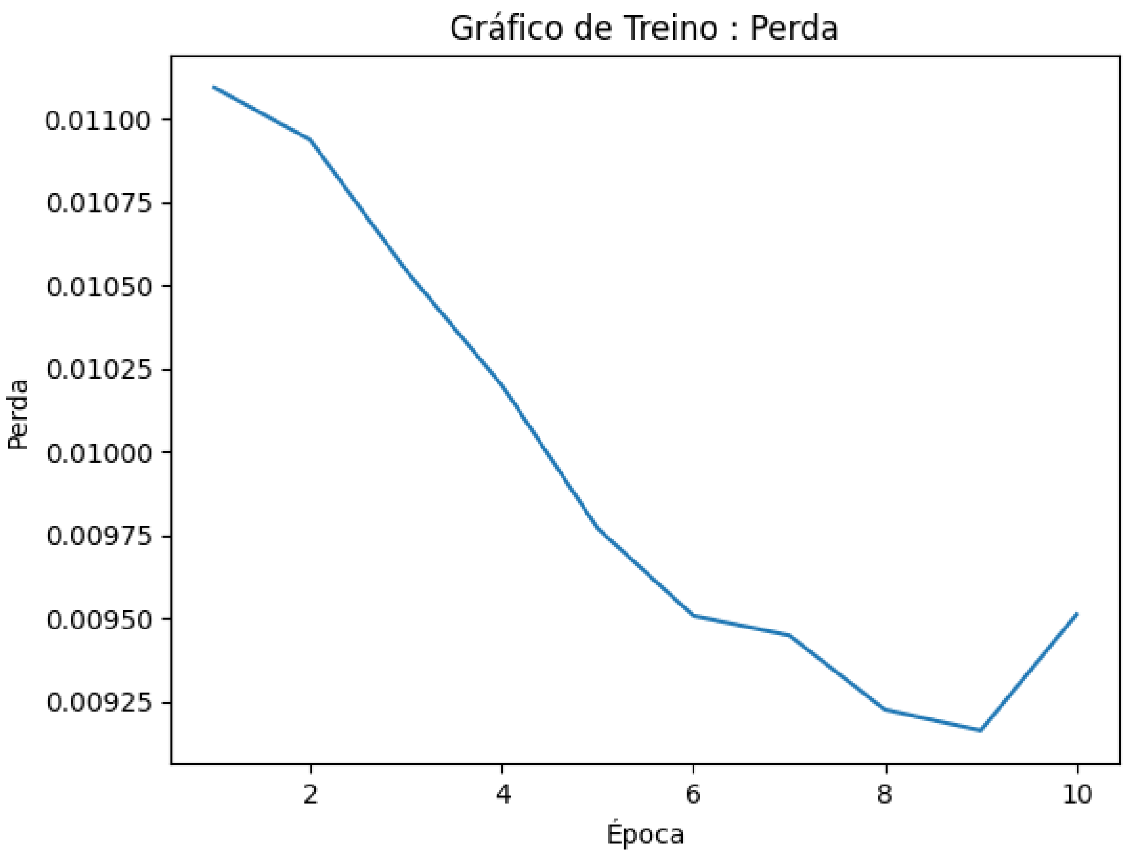
```
loss: 0.935829 [166400/181961]
loss: 0.410313 [172800/181961]
loss: 0.436116 [179200/181961]
Test Error:
 Accuracy: 0.0%, Avg loss: 0.009162

Epoch 10
-----------------------------------
loss: 0.538852 [    0/181961]
loss: 0.409875 [ 6400/181961]
loss: 0.478525 [12800/181961]
loss: 0.471718 [19200/181961]
loss: 0.503413 [25600/181961]
loss: 0.529588 [32000/181961]
loss: 0.416721 [38400/181961]
loss: 0.436523 [44800/181961]
loss: 0.608606 [51200/181961]
loss: 0.445065 [57600/181961]
loss: 0.448137 [64000/181961]
loss: 0.521934 [70400/181961]
loss: 0.510493 [76800/181961]
loss: 0.740662 [83200/181961]
loss: 0.709390 [89600/181961]
loss: 0.516749 [96000/181961]
loss: 0.557318 [102400/181961]
loss: 0.466853 [108800/181961]
loss: 0.484998 [115200/181961]
loss: 0.605989 [121600/181961]
loss: 1.699143 [128000/181961]
loss: 0.561844 [134400/181961]
loss: 0.541775 [140800/181961]
loss: 0.479112 [147200/181961]
loss: 0.426853 [153600/181961]
loss: 0.552864 [160000/181961]
loss: 0.485203 [166400/181961]
loss: 0.740411 [172800/181961]
loss: 0.377650 [179200/181961]
Test Error:
 Accuracy: 0.0%, Avg loss: 0.009511
```

Gráfico de Treino

Como foi o desempenho da rede durante o treino em relação ao avanço das épocas.

In [14]:

```
epoch = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
plt.title('Gráfico de Treino : Perda')
plt.plot(epoch, loss_test_history, label='loss')
plt.xlabel('Época')
plt.ylabel('Perda')
plt.show()
```



Criando o Detector de Anomalia

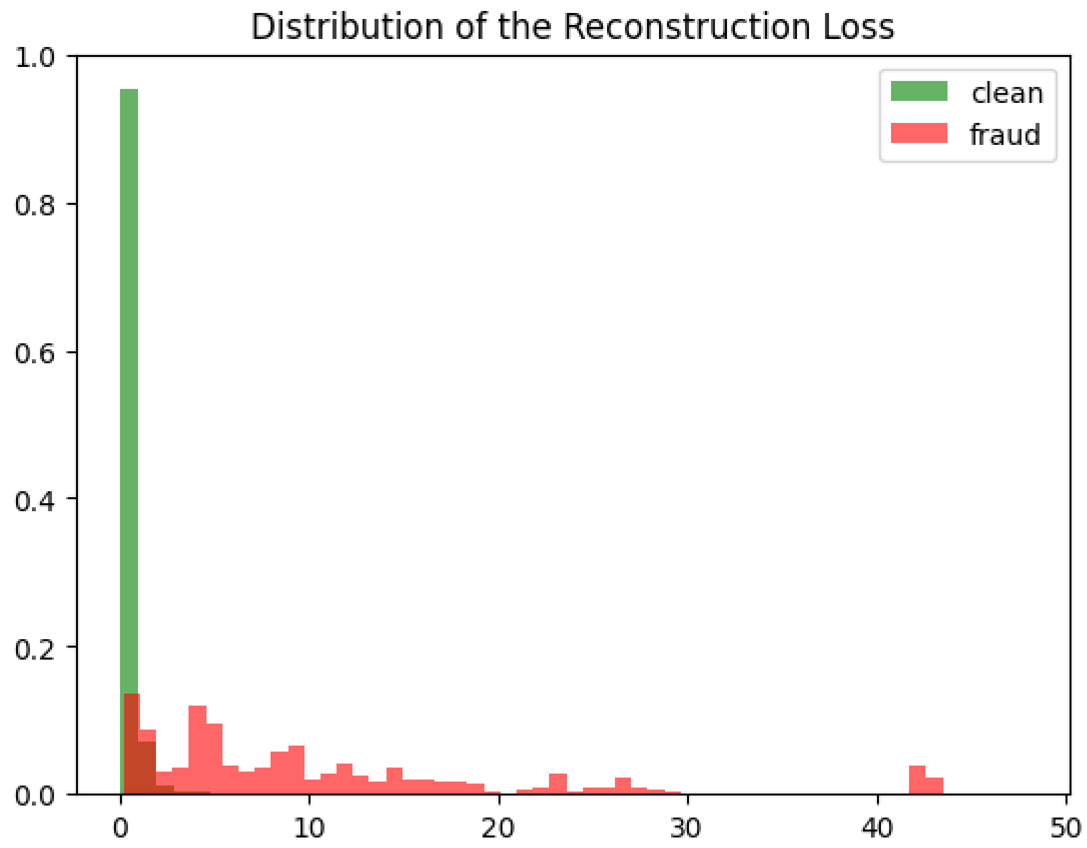
Com o autoencoder pronto é preciso estudar qual é a média de erro para as fraudes e não fraudes.

In [15]:
```
# Pegando o dataset de teste e removendo a classe
X_test = X_test.reset_index(drop=True)
test = X_test.drop('Class', axis=1)

# Transformando o dataset em tensor e passando no modelo
test = torch.tensor(test.values.astype(np.float32))
pred = model(test)

# Calculando a loss individual de cada exemplo
mse = np.mean(np.power(test.detach().numpy() - pred.detach().numpy(), 2), axis=1

print("Média da loss dos exemplos normais: " + str(np.mean(mse[X_test.index[X_te
print("Média da loss dos exemplos com fraude: " + str(np.mean(mse[X_test.index[X
```

```
Média da loss dos exemplos normais: 0.5962136
Média da loss dos exemplos com fraude: 22.535057
```

In [16]:
```
clean = mse[X_test.index[X_test['Class'] == 0]]
fraud = mse[X_test.index[X_test['Class'] == 1]]

# Removendo outliers para visualização do gráfico
clean = np.delete(clean, np.where(clean >= 50))
fraud = np.delete(fraud, np.where(fraud >= 50))

plt.hist(clean, bins=50, density=True, label="clean", alpha=.6, color="green")
plt.hist(fraud, bins=50, density=True, label="fraud", alpha=.6, color="red")
```

```
plt.title("Distribution of the Reconstruction Loss")
plt.legend()
plt.show()
```



Função para Prever Anomalia

Define se é fraude ou não.

In [17]:
```
def predict_anomaly(model, X, threshold):
    pred = model(X)
    mse = np.mean(np.power(X.detach().numpy() - pred.detach().numpy(), 2), axis=
    result = np.where(mse > threshold, 1, 0)
    return result
```

Resultados

Por fim, ao rodar algumas vezes com valores diferentes de threshold para o erro o valor 3 foi o que melhor balanceou as métricas definidas. Dependendo do contexto vale a pena abaixar ainda mais o threshold caso seja necessário encontrar todas as transações fraudulentas e não tenha problema obter muitos falsos positivos, pois quanto menor o threshold pior fica a precisão das fraudes.

OBS: No caso do contexto de cartões de crédito talvez seja melhor reduzir ainda mais o threshold para não passarem fraudes não detectadas

In [18]:
```
pred = predict_anomaly(model, test, 3)

cm = confusion_matrix(X_test['Class'], pred)
```

```python
ConfusionMatrixDisplay(cm, display_labels= ['Clean', 'Fraud']).plot()

report = classification_report(X_test['Class'], pred, output_dict=True)
print("Clean:\n\tPrecision: " + str(report['0']['precision']) + "\n\tRecall: " +
print("\nFraud:\n\tPrecision: " + str(report['1']['precision']) + "\n\tRecall: "
print("\nAcurácia: " + str(report['accuracy']))

mcc = matthews_corrcoef(X_test['Class'], pred)
print("\nMCC: " + str(mcc))
```

```
Clean:
	Precision: 0.9984007676315368
	Recall: 0.9881117774299633
	F1-Score: 0.993229627010783

Fraud:
	Precision: 0.37291280148423006
	Recall: 0.8170731707317073
	F1-Score: 0.5121019108280254

Acurácia: 0.9866445819893644

MCC: 0.5467870672393447
```