Data Science Bootcamp

Capstone Project 2

FindDefault: Prediction of Credit Card fraud

1. Problem Statement

A credit card is one of the most used financial products to make online purchases and payments. Though the Credit cards can be a convenient way to manage your finances, they can also be risky. Credit card fraud is the unauthorized use of someone else's credit card or credit card information to make purchases or withdraw cash.

It is important that credit card companies are able to recognize fraudulent credit card transactions so that customers are not charged for items that they did not purchase.

Let us begin by importing the required libraries

In [1]:

```
# Import libraries
import pandas as pd
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
import seaborn as sns
import pickle

from scipy import stats

from sklearn.model_selection import train_test_split
from keras.models import Model, load_model
from keras.layers import Input, Dense
from keras.callbacks import ModelCheckpoint, TensorBoard
from keras import regularizers

from pylab import rcParams

%matplotlib inline

sns.set(style='whitegrid', palette='muted', font_scale=1)

rcParams['figure.figsize'] = 10, 5

RANDOM_SEED = 42
LABELS = ["Legit", "Fraud"]
```

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

2. The Dataset

This provided credit_card.csv dataset contains 492 frauds out of 284,807 transactions.

The dataset is highly unbalanced, the positive class (frauds) account for 0.172% of all transactions.

- Data has 31 features from V1-V28 & Time, Amount and Class
- Input features: V1-V28, Time and Amount
- Target variable: Class

In [2]:

```
# Read Data
df = pd.read_csv('/Users/shashi/Documents/Capstone project2/creditcard.csv')
df
```

Out[2]:

284807 rows × 31 columns

3. Data Exploration

- The Data does not have any missing values which is evident from the above result and hence, need not be handled.
- The Data has only Target Variable Class as the categorical variable.
- Remaining Features are numerical and need to be only standardized for comparison after balancing the dataset.
- The Time is distributed throughout the data equitably and hence, serves as an independent feature.

We now label the class feature as below

- Class:1 = fraud
- Class:2 = legit

In [3]:

```
# Label the class
fraud = df[df.Class == 1]
legit = df[df.Class == 0]
```

In [4]:

```
# Describe Data
df.describe()
```

Out[4]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Class
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	...	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	284807.000000	284807.000000
mean	94813.859575	1.759061e-12	-8.251130e-13	-9.654937e-13	8.321385e-13	1.649999e-13	4.248366e-13	-3.054600e-13	8.777971e-14	-1.179749e-12	...	-3.405756e-13	-5.723197e-13	-9.725856e-13	1.464150e-12	-6.987102e-13	-5.617874e-13	3.332082e-12	-3.518874e-12	88.349619	0.001727
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+00	1.098632e+00	...	7.345240e-01	7.257016e-01	6.244603e-01	6.056471e-01	5.212781e-01	4.822270e-01	4.036325e-01	3.300833e-01	250.120109	0.041527

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Class
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+01	-1.343407e+01	...	-3.483038e+01	-1.093314e+01	-4.480774e+01	-2.836627e+00	-1.029540e+01	-2.604551e+00	-2.256568e+01	-1.543008e+01	0.000000	0.000000
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-01	-6.430976e-01	...	-2.283949e-01	-5.423504e-01	-1.618463e-01	-3.545861e-01	-3.171451e-01	-3.269839e-01	-7.083953e-02	-5.295979e-02	5.600000	0.000000
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-02	-5.142873e-02	...	-2.945017e-02	6.781943e-03	-1.119293e-02	4.097606e-02	1.659350e-02	-5.213911e-02	1.342146e-03	1.124383e-02	22.000000	0.000000

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Class
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-01	5.971390e-01	...	1.863772e-01	5.285536e-01	1.476421e-01	4.395266e-01	3.507156e-01	2.409522e-01	9.104512e-02	7.827995e-02	77.165000	0.000000
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+01	1.559499e+01	...	2.720284e+01	1.050309e+01	2.252841e+01	4.584549e+00	7.519589e+00	3.517346e+00	3.161220e+01	3.384781e+01	25691.160000	1.000000

8 rows × 31 columns

In [5]:

```
# Print data columns
df.columns
```

Out[5]:

```
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 [6]:

```
# Check missing data values
df.isnull().values.any()
```

Out[6]:

```
False
```

In [7]:

```
# Display a countplot
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("Transactions");
```

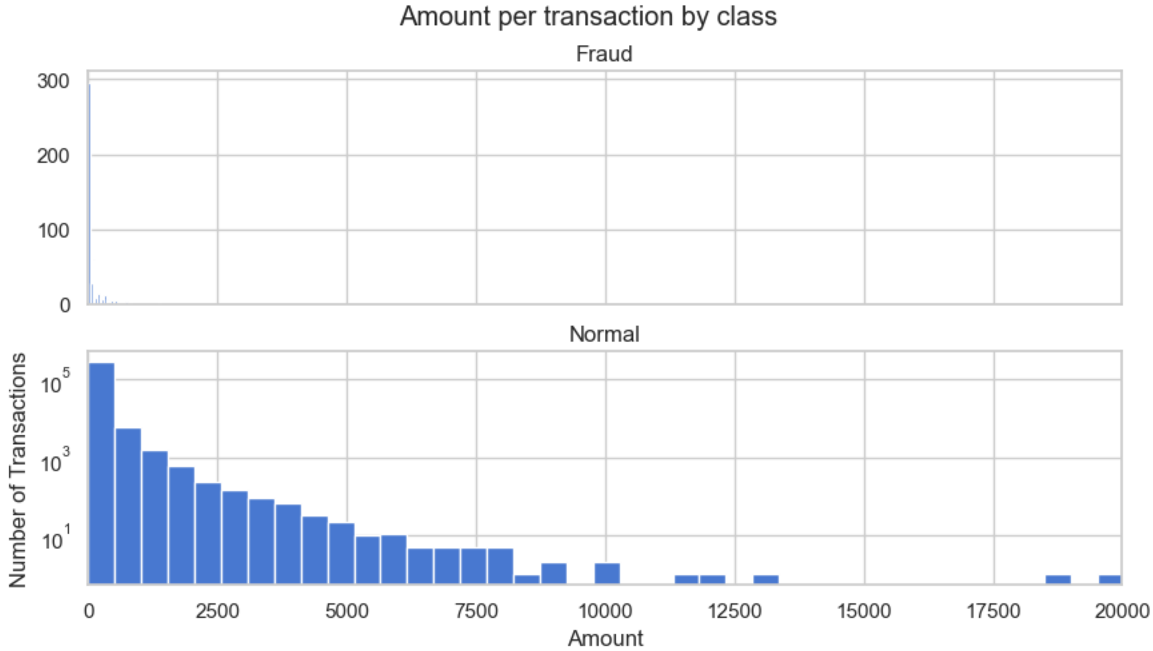
- The Dataset is highly imbalanced as evident from the countplot with majoritarian class label 'Legit' and minority class label 'Fraud'
- Thus, if we run the model on such imbalanced data we may end up highly overfitting it on the data and resulting in non-deployable model
- Hence, we will perform Synthetic Minority Oversampling on the data to balance it out as shown later after exploring other features.

Let us try to determine the nature of transactions which are fraud and obtain a relevant set of the same with respect to their amount.

In [8]:

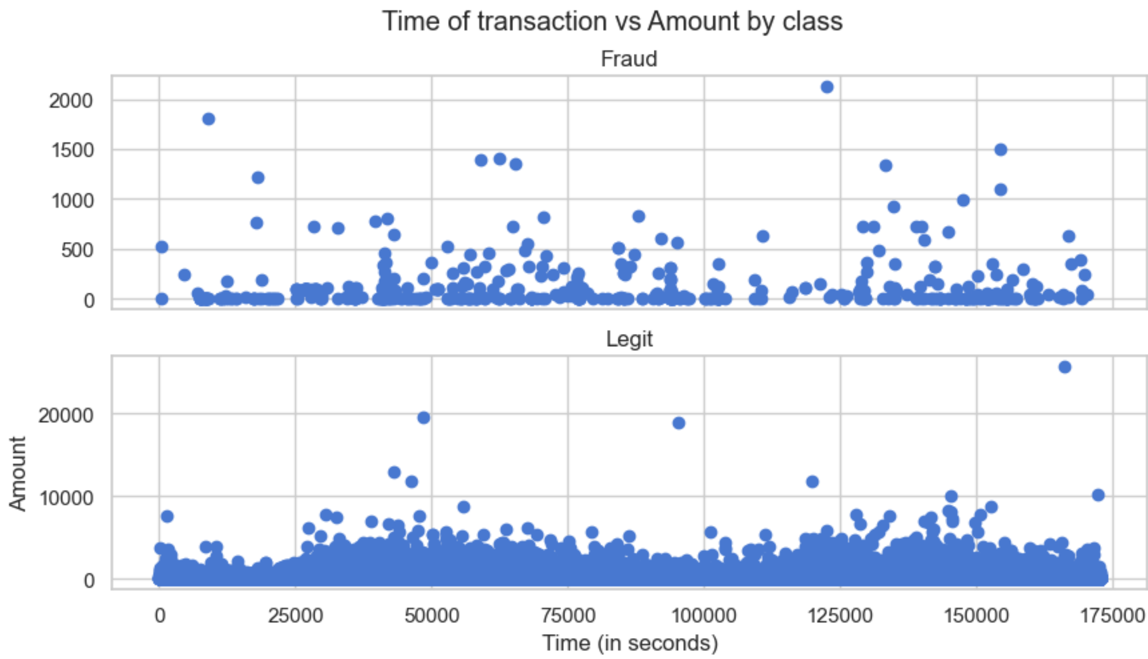
```
# Display a histogram
f, (ax1, ax2) = plt.subplots(2, 1, sharex=True)
f.suptitle('Amount per transaction by class')
bins = 50

ax1.hist(fraud.Amount, bins = bins)
ax1.set_title('Fraud')

ax2.hist(legit.Amount, bins = bins)
ax2.set_title('Normal')

plt.xlabel('Amount')
plt.ylabel('Number of Transactions')
plt.xlim((0, 20000))
```

```
plt.yscale('log')
plt.show();
```



In [9]:

```
# Display a scatter plot
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(legit.Time, legit.Amount)
ax2.set_title('Legit')

plt.xlabel('Time (in seconds)')
plt.ylabel('Amount')
plt.show()
```



It can also be observed that the fraud transactions are evenly distributed about time. Also the fraud transactions amounts seems to be not more than 2500.

Let us try to prove the above insights related to fraud transactions amount & time.

In [10]:

```
# Transactions count on amount
amount_more = 0
amount_less = 0

for i in range(df.shape[0]):
    if(df.iloc[i]["Amount"] < 2500):
        amount_less += 1
    else:
        amount_more += 1

print(amount_more)
print(amount_less)
```

```
449
284358
```

In [11]:

```
percentage_less = (amount_less/df.shape[0])*100
percentage_less
```

Out[11]:

```
99.84234938045763
```

Hence, we observe that the 99.85% of transactions amount to less than 2500.

Let us see how many of these are fraud and others legitimate.

In [12]:

```
# Classified transactions
frd = 0
lgt = 1

for i in range(df.shape[0]):
```

```
    if(df.iloc[i]["Amount"]<2500):
        if(df.iloc[i]["Class"] == 0):
            lgt += 1
        else:
            frd+=1

print(frd)
print(lgt)
```

Out[12]:

```
492
283867
```

In [13]:

```
df.Class.value_counts()
```

Out[13]:

```
0    284315
1       492
Name: Class, dtype: int64
```

Thus, we can conclude that since the number of fraud transaction below the amount of 2500 is same as the number of total fraud transactions. Hence, all fraud transactions are less than 2500.

4. Data Preparation

From the above distribution plot, it is clear that the fraudulent transactions are spread throughout the time period

Let’s drop the Time column (not going to use it) and use the scikit’s StandardScaler on the Amount. The scaler removes the mean and scales the values to unit variance.

In [14]:

```
# Remove time column
from sklearn.preprocessing import StandardScaler

data = df.drop(['Time'], axis=1)

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

Let's train our Autoencoder to detect any anomaly on new transactions that are normal and legit. Reserving the correct class on the test set will give us a way to evaluate the performance of our model. We will reserve 20% of our data for testing.

In [15]:

```
# Train auto encoder
X_train, X_test = train_test_split(data, test_size=0.2,
random_state=RANDOM_SEED)
X_train = X_train[X_train.Class == 0]
X_train = X_train.drop(['Class'], axis=1)

y_test = X_test['Class']
X_test = X_test.drop(['Class'], axis=1)

X_train = X_train.values
X_test = X_test.values
```

In [16]:

```
X_train.shape
```

Out[16]:

```
(227451, 29)
```

5. Data Modelling

- Study the Feature Correlations of the given data
- Plot a Heatmap
- Run GridSearch on the Data
- Fine Tune the Classifiers
- Create Pipelines for evaluation

Our Autoencoder uses 4 fully connected layers with 14, 7, 7 and 29 neurons respectively. The first two layers are used for our encoder, the last two go for the decoder. Additionally, L1 regularization will be used during training:

In [17]:

```
input_dim = X_train.shape[1]
encoding_dim = 14
```

In [18]:

```
input_layer = Input(shape=(input_dim, ))

encoder = Dense(encoding_dim, activation="tanh",
                activity_regularizer=regularizers.l1(10e-5))(input_layer)
encoder = Dense(int(encoding_dim / 2), activation="relu")(encoder)

decoder = Dense(int(encoding_dim / 2), activation='tanh')(encoder)
decoder = Dense(input_dim, activation='relu')(decoder)

autoencoder = Model(inputs=input_layer, outputs=decoder)
```

Let's train our model for 100 epochs with a batch size of 32 samples and save the best performing model to a file. The ModelCheckpoint provided by Keras is really handy for such tasks. Additionally, the training progress will be exported in a format that TensorBoard understands.

In [19]:

```
nb_epoch = 100
batch_size = 32

autoencoder.compile(optimizer='adam',
                    loss='mean_squared_error',
                    metrics=['accuracy'])

checkpointer = ModelCheckpoint(filepath="trained_model_h5.keras",
                               verbose=0,
                               save_best_only=True)
```

```python
tensorboard = TensorBoard(log_dir='./logs',
                          histogram_freq=0,
                          write_graph=True,
                          write_images=True)

history = autoencoder.fit(X_train, X_train,
                    epochs=nb_epoch,
                    batch_size=batch_size,
                    shuffle=True,
                    validation_data=(X_test, X_test),
                    verbose=1,
                    callbacks=[checkpointer, tensorboard]).history
```

Epoch 1/100

```
7108/7108 [==============================] - 8s 1ms/step - loss: 0.8116 - a
ccuracy: 0.5798 - val_loss: 0.7857 - val_accuracy: 0.6587
Epoch 2/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7462 - a
ccuracy: 0.6695 - val_loss: 0.7687 - val_accuracy: 0.6814
Epoch 3/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7343 - a
ccuracy: 0.6894 - val_loss: 0.7604 - val_accuracy: 0.6999
Epoch 4/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7283 - a
ccuracy: 0.6975 - val_loss: 0.7563 - val_accuracy: 0.7042
Epoch 5/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7252 - a
ccuracy: 0.7033 - val_loss: 0.7538 - val_accuracy: 0.7077
Epoch 6/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7223 - a
ccuracy: 0.7082 - val_loss: 0.7518 - val_accuracy: 0.7135
Epoch 7/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7204 - a
ccuracy: 0.7145 - val_loss: 0.7512 - val_accuracy: 0.7172
Epoch 8/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7186 - a
ccuracy: 0.7191 - val_loss: 0.7493 - val_accuracy: 0.7297
Epoch 9/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7173 - a
ccuracy: 0.7243 - val_loss: 0.7479 - val_accuracy: 0.7306
Epoch 10/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7164 - a
ccuracy: 0.7265 - val_loss: 0.7463 - val_accuracy: 0.7341
Epoch 11/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7153 - a
ccuracy: 0.7289 - val_loss: 0.7464 - val_accuracy: 0.7281
Epoch 12/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7150 - a
ccuracy: 0.7297 - val_loss: 0.7459 - val_accuracy: 0.7338
Epoch 13/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7148 - a
ccuracy: 0.7303 - val_loss: 0.7453 - val_accuracy: 0.7380
Epoch 14/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7141 - a
ccuracy: 0.7313 - val_loss: 0.7447 - val_accuracy: 0.7327
```

```
Epoch 15/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7138 - a
ccuracy: 0.7318 - val_loss: 0.7439 - val_accuracy: 0.7358
Epoch 16/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7134 - a
ccuracy: 0.7330 - val_loss: 0.7428 - val_accuracy: 0.7437
Epoch 17/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7133 - a
ccuracy: 0.7335 - val_loss: 0.7436 - val_accuracy: 0.7376
Epoch 18/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7129 - a
ccuracy: 0.7341 - val_loss: 0.7443 - val_accuracy: 0.7374
Epoch 19/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7126 - a
ccuracy: 0.7344 - val_loss: 0.7425 - val_accuracy: 0.7392
Epoch 20/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7133 - a
ccuracy: 0.7343 - val_loss: 0.7436 - val_accuracy: 0.7346
Epoch 21/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7123 - a
ccuracy: 0.7359 - val_loss: 0.7419 - val_accuracy: 0.7395
Epoch 22/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7121 - a
ccuracy: 0.7357 - val_loss: 0.7419 - val_accuracy: 0.7409
Epoch 23/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7124 - a
ccuracy: 0.7346 - val_loss: 0.7419 - val_accuracy: 0.7398
Epoch 24/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7107 - a
ccuracy: 0.7343 - val_loss: 0.7428 - val_accuracy: 0.7253
Epoch 25/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7046 - a
ccuracy: 0.7324 - val_loss: 0.7397 - val_accuracy: 0.7350
Epoch 26/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7032 - a
ccuracy: 0.7347 - val_loss: 0.7370 - val_accuracy: 0.7293
Epoch 27/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7034 - a
ccuracy: 0.7361 - val_loss: 0.7331 - val_accuracy: 0.7421
Epoch 28/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7027 - a
ccuracy: 0.7375 - val_loss: 0.7342 - val_accuracy: 0.7412
Epoch 29/100
7108/7108 [==============================] - 7s 1000us/step - loss: 0.7027
- accuracy: 0.7360 - val_loss: 0.7345 - val_accuracy: 0.7293
Epoch 30/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7022 - a
ccuracy: 0.7370 - val_loss: 0.7334 - val_accuracy: 0.7388
Epoch 31/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7025 - a
ccuracy: 0.7369 - val_loss: 0.7366 - val_accuracy: 0.7259
Epoch 32/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7021 - a
ccuracy: 0.7367 - val_loss: 0.7329 - val_accuracy: 0.7440
Epoch 33/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7017 - a
ccuracy: 0.7375 - val_loss: 0.7325 - val_accuracy: 0.7400
```

```
Epoch 34/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7016 - a
ccuracy: 0.7375 - val_loss: 0.7380 - val_accuracy: 0.7235
Epoch 35/100
7108/7108 [==============================] - 7s 1000us/step - loss: 0.7019
- accuracy: 0.7369 - val_loss: 0.7319 - val_accuracy: 0.7383
Epoch 36/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7016 - a
ccuracy: 0.7369 - val_loss: 0.7320 - val_accuracy: 0.7428
Epoch 37/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7019 - a
ccuracy: 0.7366 - val_loss: 0.7324 - val_accuracy: 0.7427
Epoch 38/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7018 - a
ccuracy: 0.7375 - val_loss: 0.7315 - val_accuracy: 0.7421
Epoch 39/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7018 - a
ccuracy: 0.7367 - val_loss: 0.7322 - val_accuracy: 0.7433
Epoch 40/100
7108/7108 [==============================] - 7s 995us/step - loss: 0.7017 -
accuracy: 0.7360 - val_loss: 0.7336 - val_accuracy: 0.7340
Epoch 41/100
7108/7108 [==============================] - 7s 994us/step - loss: 0.7016 -
accuracy: 0.7369 - val_loss: 0.7321 - val_accuracy: 0.7453
Epoch 42/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7016 - a
ccuracy: 0.7367 - val_loss: 0.7371 - val_accuracy: 0.7309
Epoch 43/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7014 - a
ccuracy: 0.7371 - val_loss: 0.7325 - val_accuracy: 0.7451
Epoch 44/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7017 - a
ccuracy: 0.7375 - val_loss: 0.7347 - val_accuracy: 0.7360
Epoch 45/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7020 - a
ccuracy: 0.7362 - val_loss: 0.7317 - val_accuracy: 0.7455
Epoch 46/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7011 - a
ccuracy: 0.7370 - val_loss: 0.7321 - val_accuracy: 0.7422
Epoch 47/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7017 - a
ccuracy: 0.7357 - val_loss: 0.7312 - val_accuracy: 0.7441
Epoch 48/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7014 - a
ccuracy: 0.7364 - val_loss: 0.7314 - val_accuracy: 0.7389
Epoch 49/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7015 - a
ccuracy: 0.7363 - val_loss: 0.7310 - val_accuracy: 0.7458
Epoch 50/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7013 - a
ccuracy: 0.7375 - val_loss: 0.7322 - val_accuracy: 0.7341
Epoch 51/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7019 - a
ccuracy: 0.7372 - val_loss: 0.7338 - val_accuracy: 0.7308
Epoch 52/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7015 - a
ccuracy: 0.7372 - val_loss: 0.7318 - val_accuracy: 0.7396
```

```
Epoch 53/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7015 - a
ccuracy: 0.7365 - val_loss: 0.7340 - val_accuracy: 0.7300
Epoch 54/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7010 - a
ccuracy: 0.7375 - val_loss: 0.7334 - val_accuracy: 0.7323
Epoch 55/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7011 - a
ccuracy: 0.7367 - val_loss: 0.7426 - val_accuracy: 0.7129
Epoch 56/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7014 - a
ccuracy: 0.7375 - val_loss: 0.7319 - val_accuracy: 0.7479
Epoch 57/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7014 - a
ccuracy: 0.7372 - val_loss: 0.7323 - val_accuracy: 0.7428
Epoch 58/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7011 - a
ccuracy: 0.7376 - val_loss: 0.7329 - val_accuracy: 0.7397
Epoch 59/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7012 - a
ccuracy: 0.7374 - val_loss: 0.7327 - val_accuracy: 0.7340
Epoch 60/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7010 - a
ccuracy: 0.7385 - val_loss: 0.7347 - val_accuracy: 0.7414
Epoch 61/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7008 - a
ccuracy: 0.7376 - val_loss: 0.7310 - val_accuracy: 0.7451
Epoch 62/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7011 - a
ccuracy: 0.7373 - val_loss: 0.7316 - val_accuracy: 0.7454
Epoch 63/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7012 - a
ccuracy: 0.7384 - val_loss: 0.7360 - val_accuracy: 0.7220
Epoch 64/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7008 - a
ccuracy: 0.7378 - val_loss: 0.7317 - val_accuracy: 0.7451
Epoch 65/100
7108/7108 [==============================] - 7s 994us/step - loss: 0.7007 -
accuracy: 0.7384 - val_loss: 0.7329 - val_accuracy: 0.7411
Epoch 66/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7008 - a
ccuracy: 0.7383 - val_loss: 0.7330 - val_accuracy: 0.7367
Epoch 67/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7014 - a
ccuracy: 0.7373 - val_loss: 0.7339 - val_accuracy: 0.7326
Epoch 68/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7010 - a
ccuracy: 0.7372 - val_loss: 0.7318 - val_accuracy: 0.7450
Epoch 69/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7011 - a
ccuracy: 0.7378 - val_loss: 0.7315 - val_accuracy: 0.7472
Epoch 70/100
7108/7108 [==============================] - 7s 993us/step - loss: 0.7008 -
accuracy: 0.7393 - val_loss: 0.7420 - val_accuracy: 0.7242
Epoch 71/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7024 - a
ccuracy: 0.7378 - val_loss: 0.7323 - val_accuracy: 0.7339
```

```
Epoch 72/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7005 - a
ccuracy: 0.7387 - val_loss: 0.7314 - val_accuracy: 0.7412
Epoch 73/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7007 - a
ccuracy: 0.7382 - val_loss: 0.7319 - val_accuracy: 0.7378
Epoch 74/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7010 - a
ccuracy: 0.7391 - val_loss: 0.7317 - val_accuracy: 0.7415
Epoch 75/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7006 - a
ccuracy: 0.7388 - val_loss: 0.7326 - val_accuracy: 0.7453
Epoch 76/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7006 - a
ccuracy: 0.7384 - val_loss: 0.7334 - val_accuracy: 0.7361
Epoch 77/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7006 - a
ccuracy: 0.7393 - val_loss: 0.7320 - val_accuracy: 0.7460
Epoch 78/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7008 - a
ccuracy: 0.7382 - val_loss: 0.7314 - val_accuracy: 0.7445
Epoch 79/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7006 - a
ccuracy: 0.7389 - val_loss: 0.7314 - val_accuracy: 0.7479
Epoch 80/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7012 - a
ccuracy: 0.7388 - val_loss: 0.7334 - val_accuracy: 0.7435
Epoch 81/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7004 - a
ccuracy: 0.7389 - val_loss: 0.7307 - val_accuracy: 0.7459
Epoch 82/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7009 - a
ccuracy: 0.7378 - val_loss: 0.7320 - val_accuracy: 0.7460
Epoch 83/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7004 - a
ccuracy: 0.7390 - val_loss: 0.7319 - val_accuracy: 0.7385
Epoch 84/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7009 - a
ccuracy: 0.7382 - val_loss: 0.7323 - val_accuracy: 0.7428
Epoch 85/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7005 - a
ccuracy: 0.7384 - val_loss: 0.7303 - val_accuracy: 0.7452
Epoch 86/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7006 - a
ccuracy: 0.7388 - val_loss: 0.7336 - val_accuracy: 0.7323
Epoch 87/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7004 - a
ccuracy: 0.7391 - val_loss: 0.7303 - val_accuracy: 0.7522
Epoch 88/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7007 - a
ccuracy: 0.7386 - val_loss: 0.7345 - val_accuracy: 0.7292
Epoch 89/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7006 - a
ccuracy: 0.7390 - val_loss: 0.7333 - val_accuracy: 0.7321
Epoch 90/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7006 - a
ccuracy: 0.7392 - val_loss: 0.7319 - val_accuracy: 0.7463
```

```
Epoch 91/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7009 - a
ccuracy: 0.7381 - val_loss: 0.7345 - val_accuracy: 0.7420
Epoch 92/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7005 - a
ccuracy: 0.7390 - val_loss: 0.7330 - val_accuracy: 0.7376
Epoch 93/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7005 - a
ccuracy: 0.7390 - val_loss: 0.7335 - val_accuracy: 0.7349
Epoch 94/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7004 - a
ccuracy: 0.7382 - val_loss: 0.7315 - val_accuracy: 0.7494
Epoch 95/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7003 - a
ccuracy: 0.7380 - val_loss: 0.7333 - val_accuracy: 0.7408
Epoch 96/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7006 - a
ccuracy: 0.7387 - val_loss: 0.7332 - val_accuracy: 0.7461
Epoch 97/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7002 - a
ccuracy: 0.7389 - val_loss: 0.7330 - val_accuracy: 0.7387
Epoch 98/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7006 - a
ccuracy: 0.7385 - val_loss: 0.7321 - val_accuracy: 0.7420
Epoch 99/100
7108/7108 [==============================] - 7s 1ms/step - loss: 0.7002 - a
ccuracy: 0.7398 - val_loss: 0.7322 - val_accuracy: 0.7404
Epoch 100/100
7108/7108 [==============================] - 8s 1ms/step - loss: 0.7004 - a
ccuracy: 0.7394 - val_loss: 0.7341 - val_accuracy: 0.7273
```

In [20]:

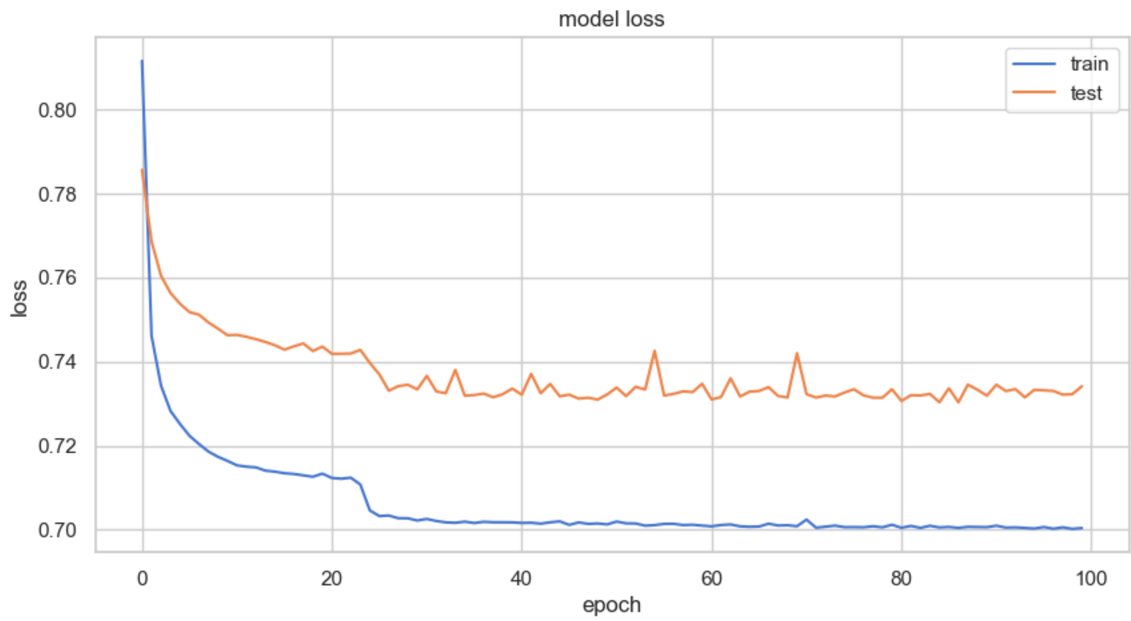
```
# Load the model to autoencoder
autoencoder = load_model('trained_model_h5.keras')
```

6. Model Evaluation

The best performing trained model has been loaded to the auto encoder. Now we can evaluate the effectiveness of the model by conducting various tests finding errors/loss.

In [21]:

```
# Display a line chart
plt.plot(history['loss'])
plt.plot(history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right');
```



Let's have a look at how the error is distributed.

In [22]:

```
# Predict the autoencoder error
predictions = autoencoder.predict(X_test)
```

```
1781/1781 [==============================] - 1s 604us/step
```

Out[22]

In [23]:

```
# Classify as the reconstruction error
mse = np.mean(np.power(X_test - predictions, 2), axis=1)
error_df = pd.DataFrame({'reconstruction_error': mse,
                        'true_class': y_test})
```

In [24]:

```
# Describe the error data
error_df.describe()
```

Out[24]:

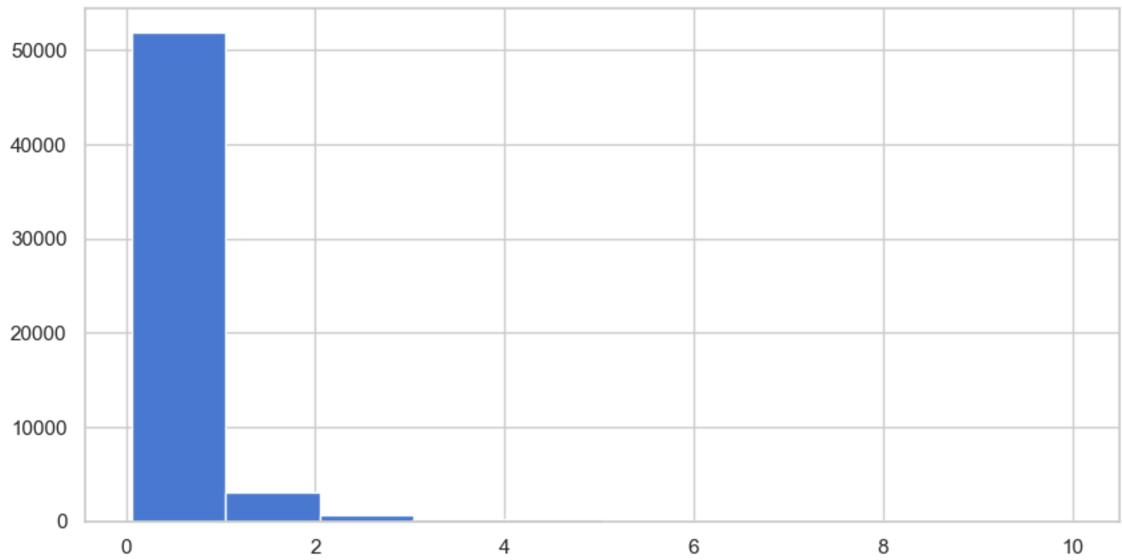
	reconstruction_error	true_class
count	56962.000000	56962.000000
mean	0.729377	0.001720
std	3.377687	0.041443
min	0.059653	0.000000
25%	0.236277	0.000000

	reconstruction_error	true_class
50%	0.384439	0.000000
75%	0.604821	0.000000
max	250.607221	1.000000

6(a). Reconstruction error without fraud

In [25]:

```
# Display a bar chart
fig = plt.figure()
ax = fig.add_subplot(111)
normal_error_df = error_df[(error_df['true_class']== 0) &
(error_df['reconstruction_error'] < 10)]
_ = ax.hist(normal_error_df.reconstruction_error.values, bins=10)
```



In [26]:

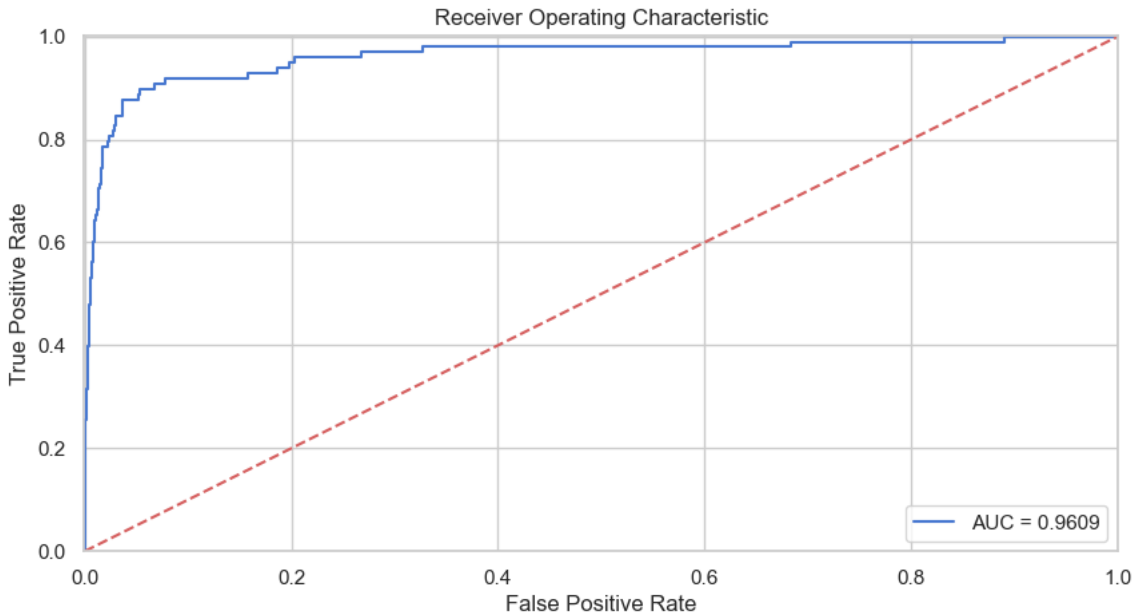
```
from sklearn.metrics import (confusion_matrix, precision_recall_curve, auc,
                             roc_curve, recall_score,
classification_report, f1_score,
                             precision_recall_fscore_support)
```

Let us make use of ROC curves, a very useful tool for understanding the performance of binary classifiers.

In [27]:

```
# Generate an ROC curve
fpr, tpr, thresholds = roc_curve(error_df.true_class,
error_df.reconstruction_error)
roc_auc = auc(fpr, tpr)
```

```
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, label='AUC = %0.4f'% roc_auc)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([-0.001, 1])
plt.ylim([0, 1.001])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show();
```



The ROC curve plots the true positive rate versus the false positive rate, over different threshold values. Basically, we want the blue line to be as close as possible to the upper left corner. While our results look pretty good, we have to keep in mind of the nature of our dataset.

In [28]:

```
# Create Train and Test Data in ratio 70:30
X = df.drop(labels='Class', axis=1) # Features
y = df.loc[:,'Class']               # Target Variable
```

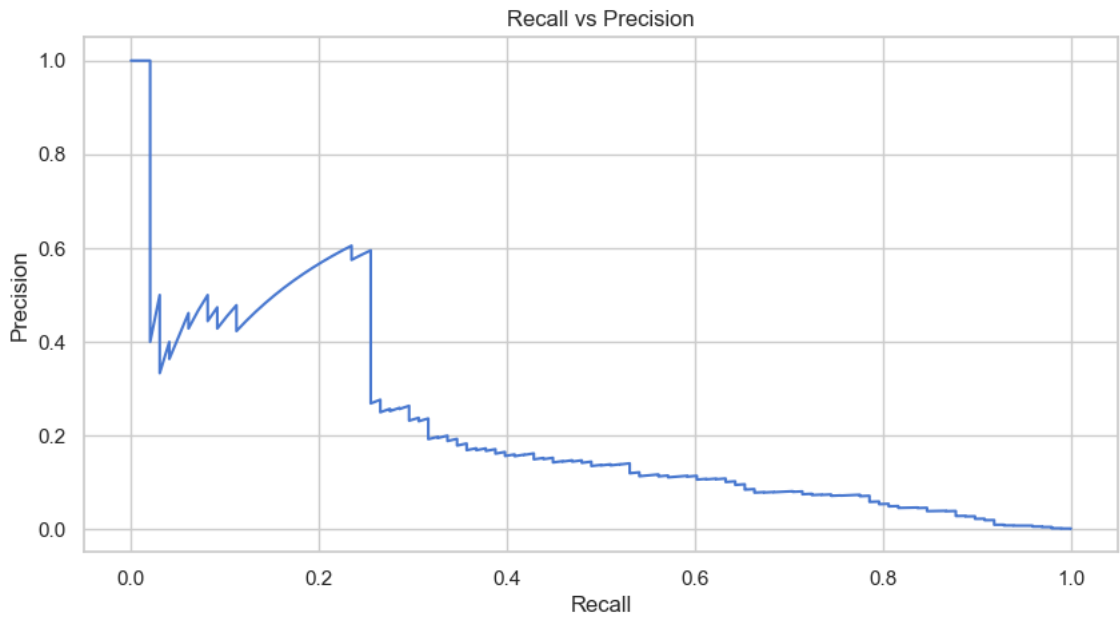
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=1, stratify=y)
```

6(b). Precision vs Recall

High recall but low precision means many results, most of which has low or no relevancy. When precision is high but recall is low we have the opposite - few returned results with very high relevancy. Ideally, you would want high precision and high recall - many results with that are highly relevant.

In [29]:

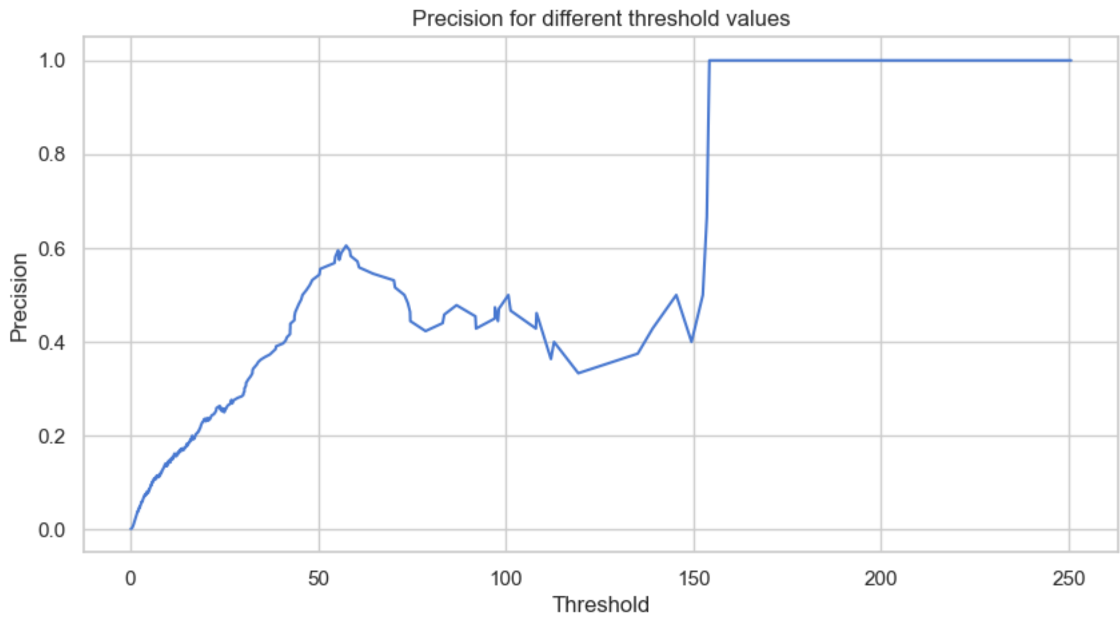
```
# Display Line plot - recall vs precision
precision, recall, th = precision_recall_curve(error_df.true_class,
error_df.reconstruction_error)
plt.plot(recall, precision, 'b', label='Precision-Recall curve')
plt.title('Recall vs Precision')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.show()
```



A high area under the curve represents both high recall and high precision, where high precision relates to a low false positive rate, and high recall relates to a low false negative rate. High scores for both show that the classifier is returning accurate results (high precision), as well as returning a majority of all positive results (high recall).

In [30]:

```
# Display line plot - precision
plt.plot(th, precision[1:], 'b', label='Threshold-Precision curve')
plt.title('Precision for different threshold values')
plt.xlabel('Threshold')
plt.ylabel('Precision')
plt.show()
```



You can see that as the reconstruction error increases our precision rises as well. Let's have a look at the recall:

In [31]:

```
# Display line plot - recall
plt.plot(th, recall[1:], 'b', label='Threshold-Recall curve')
plt.title('Recall for different threshold values')
```

```
plt.xlabel('Reconstruction error')
plt.ylabel('Recall')
plt.show()
```

Here, we have the exact opposite situation. As the reconstruction error increases the recall decreases.

7. Prediction

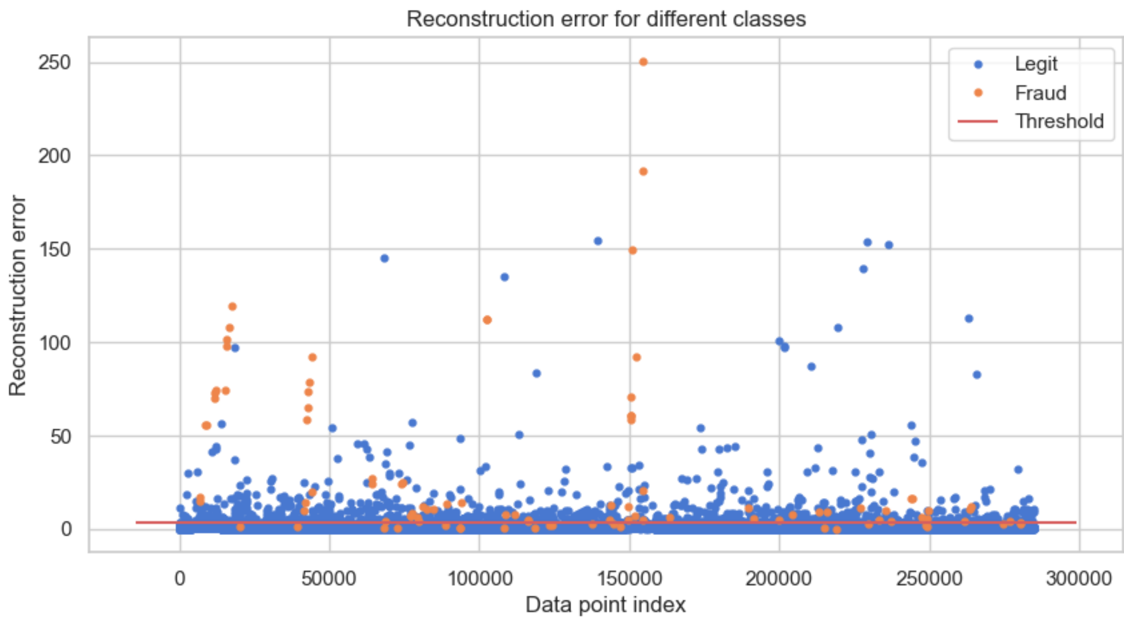
Our model is a bit different this time. It doesn't know how to predict new values. But we don't need that. In order to predict whether or not a new/unseen transaction is normal or fraudulent, we'll calculate the reconstruction error from the transaction data itself. If the error is larger than a predefined threshold, we'll mark it as a fraud (since our model should have a low error on normal transactions). Let's pick that value:

In [32]:

```
# Set threshold
threshold = 3.1
```

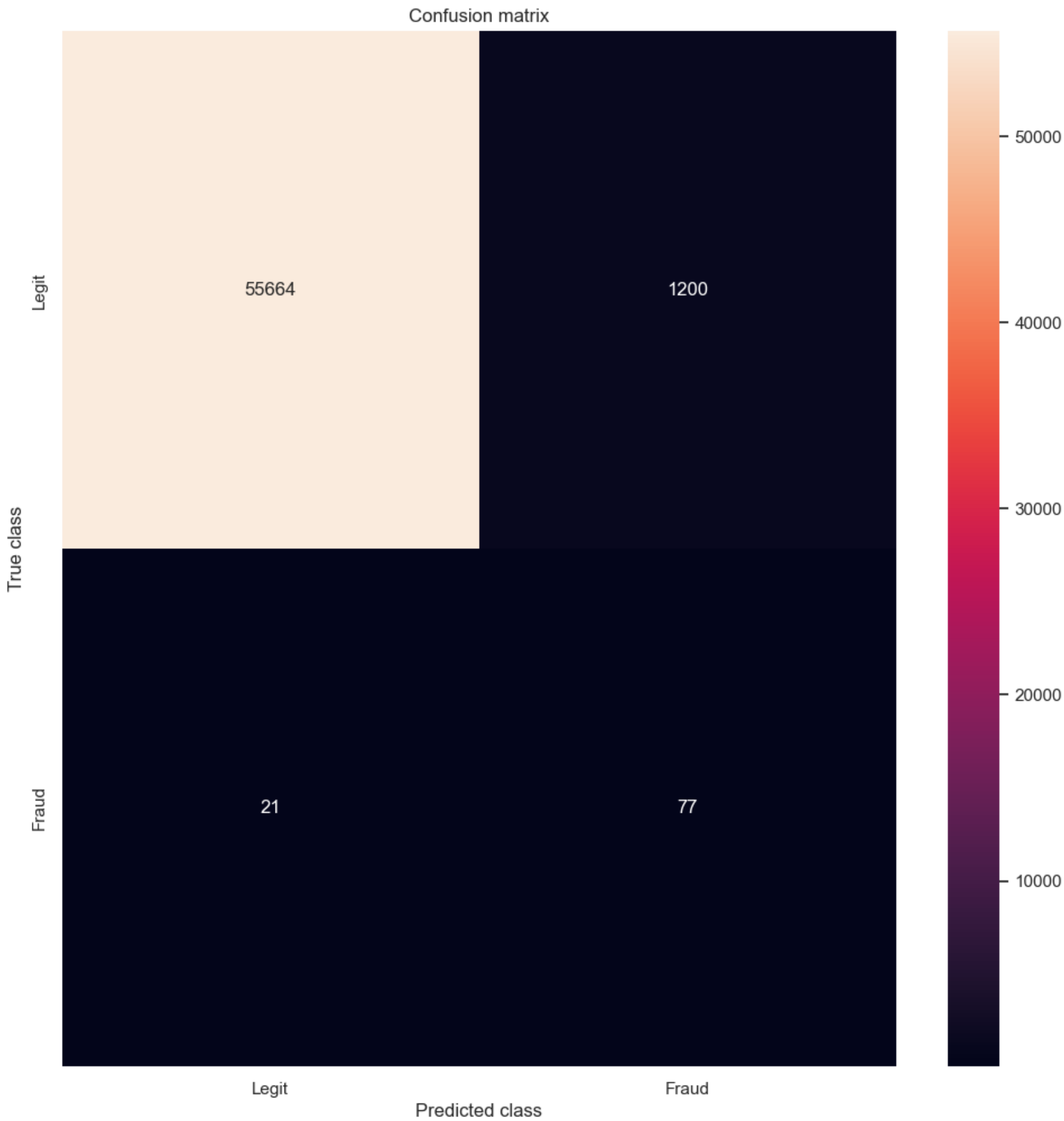
In [33]:

```
# Display scatter plot - error reconstruction
groups = error_df.groupby('true_class')
fig, ax = plt.subplots()

for name, group in groups:
    ax.plot(group.index, group.reconstruction_error, marker='o', ms=3.5,
linestyle='',
            label= "Fraud" if name == 1 else "Legit")
ax.hlines(threshold, ax.get_xlim()[0], ax.get_xlim()[1], colors="r",
zorder=100, label='Threshold')
ax.legend()
plt.title("Reconstruction error for different classes")
plt.ylabel("Reconstruction error")
plt.xlabel("Data point index")
plt.show();
```



In [34]:

```
# Display heat map - confusion matrix
y_pred = [1 if e > threshold else 0 for e in
error_df.reconstruction_error.values]
conf_matrix = confusion_matrix(error_df.true_class, y_pred)

plt.figure(figsize=(12, 12))
sns.heatmap(conf_matrix, xticklabels=LABELS, yticklabels=LABELS,
annot=True, fmt="d");
plt.title("Confusion matrix")
plt.ylabel('True class')
plt.xlabel('Predicted class')
plt.show()
```



Our model seems to catch a lot of the fraudulent cases, but there is a catch. The number of legitimate transactions classified as frauds is really high. This might be a problem (probably not). You might want to increase or decrease the value of the threshold, depending on the problem. Current value has been tested from 3.1 to 10 for getting better accuracy.

Conclusion

We have created a simple Deep Autoencoder in Keras that can reconstruct what a legitimate transaction can look like. Our dataset was in such a state that we really don't know what the original features look like.

Keras gave us very clean and easy to use API to build a non-trivial Deep Autoencoder.