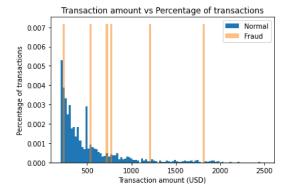
```
import pandas as pd
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model selection import train test split
!pip install tensorflow --user
!pip install keras
!pip install daytime
!pip install torch
     Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.2.0)
     Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.57.0)
     Requirement already satisfied: h5py>=2.9.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.9.0)
     Requirement already satisfied: keras<2.14,>=2.13.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.13.1)
     Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (16.0.6)
     Requirement already satisfied: numpy<=1.24.3,>=1.22 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.23.5)
     Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.3.0)
     Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from tensorflow) (23.1)
     Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3 in /usr/local/lib/pyt
     Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from tensorflow) (67.7.2)
     Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.16.0)
     Requirement already satisfied: tensorboard<2.14,>=2.13 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.13.0)
     Requirement already satisfied: tensorflow-estimator<2.14,>=2.13.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.13.
     Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.3.0)
     Requirement already satisfied: typing-extensions<4.6.0,>=3.6.6 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (4.5.0)
     Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.15.0)
     Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.3
     Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.10/dist-packages (from astunparse>=1.6.0->tensorflow) (0.
     Requirement already satisfied: google-auth<3,>=1.6.3 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.14,>=2.13->tensor
     Requirement already satisfied: google-auth-oauthlib<1.1,>=0.5 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.14,>=2.1
     Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.14,>=2.13->tensorflow)
     Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.14,>=2.13->tensorfl
     Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.1
     Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from tensorboard<2.14,>=2.13->tensorflow)
     Requirement already satisfied: cachetools<6.0,>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from google-auth<3,>=1.6.3->tensorb
     Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.10/dist-packages (from google-auth<3,>=1.6.3->tensorbo
     Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.10/dist-packages (from google-auth<3,>=1.6.3->tensorboard<2.14
     Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python3.10/dist-packages (from google-auth-oauthlib<1.1,>=0
     Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorb
     Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorboard<2.14,>=
     Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorboard<2
     Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorboard<2
     Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.10/dist-packages (from werkzeug>=1.0.1->tensorboard<2.14,>
     Requirement already satisfied: pyasn1<0.6.0,>=0.4.6 in /usr/local/lib/python3.10/dist-packages (from pyasn1-modules>=0.2.1->google-au
     Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.10/dist-packages (from requests-oauthlib>=0.7.0->google-auth
     Requirement already satisfied: keras in /usr/local/lib/python3.10/dist-packages (2.13.1)
     Collecting daytime
      Downloading daytime-0.4.tar.gz (2.4 kB)
      Preparing metadata (setup.py) ... done
     Building wheels for collected packages: daytime
       Building wheel for daytime (setup.py) ... done
      Created wheel for daytime: filename=daytime-0.4-py3-none-any.whl size=2401 sha256=d69b05a4940166d0408ab50f9126eeadebef8d9d4761edce6
      Stored in directory: /root/.cache/pip/wheels/cd/40/c7/fc109bc6716d31e4d5fdc0cd72891253fa46032e71d9aa1b93
     Successfully built daytime
     Installing collected packages: daytime
     Successfully installed daytime-0.4
     Requirement already satisfied: torch in /usr/local/lib/python3.10/dist-packages (2.0.1+cu118)
     Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from torch) (3.12.2)
     Requirement already satisfied: typing-extensions in /usr/local/lib/python3.10/dist-packages (from torch) (4.5.0)
     Requirement already satisfied: sympy in /usr/local/lib/python3.10/dist-packages (from torch) (1.12)
     Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-packages (from torch) (3.1)
     Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from torch) (3.1.2)
     Requirement already satisfied: triton==2.0.0 in /usr/local/lib/python3.10/dist-packages (from torch) (2.0.0)
     Requirement already satisfied: cmake in /usr/local/lib/python3.10/dist-packages (from triton==2.0.0->torch) (3.27.4.1)
     Requirement already satisfied: lit in /usr/local/lib/python3.10/dist-packages (from triton==2.0.0->torch) (16.0.6)
     Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2->torch) (2.1.3)
     Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.10/dist-packages (from sympy->torch) (1.3.0)
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, recall_score, accuracy_score, precision_score
RANDOM SEED = 2021
TEST_PCT = 0.3
LABELS = ["Normal", "Fraud"]
#dataset = pd.read_csv("E:\Teachning material\Deep learning BE IT 2019 course\creditcard.csv")
dataset = pd.read csv("creditcard.csv")
#dataset.head
print(list(dataset.columns))
dataset.describe()
    FileNotFoundError
                                       Traceback (most recent call last)
    <ipython-input-5-b461edf64e98> in <cell line: 2>()
         1 #dataset = pd.read_csv("E:\Teachning material\Deep learning BE IT 2019
    course\creditcard.csv")
    ---> 2 dataset = pd.read_csv("creditcard.csv")
         3 #dataset.head
         4 print(list(dataset.columns))
         5 dataset.describe()
                              - 💲 6 frames
    /usr/local/lib/python3.10/dist-packages/pandas/io/common.py in get_handle(path_or_buf,
    mode, encoding, compression, memory_map, is_text, errors, storage_options)
854 if ioargs.encoding and "b" not in ioargs.mode:
       855
                     # Encoding
    --> 856
                     handle = open(
                        handle,
       858
                        ioargs.mode,
    FileNotFoundError: [Errno 2] No such file or directory: 'creditcard.csv'
    #check for any nullvalues
print("Any nulls in the dataset ",dataset.isnull().values.any() )
print('----')
print("No. of unique labels ", len(dataset['Class'].unique()))
print("Label values ",dataset.Class.unique())
#0 is for normal credit card transaction
#1 is for fraudulent credit card transaction
print('----')
print("Break down of the Normal and Fraud Transactions")
print(pd.value_counts(dataset['Class'], sort = True) )
    Any nulls in the dataset True
    No. of unique labels 3
    Label values [ 0. 1. nan]
    Break down of the Normal and Fraud Transactions
        17836
    0.0
           81
    Name: Class, dtype: int64
#Visualizing the imbalanced dataset
count classes = pd.value counts(dataset['Class'], sort = True)
count_classes.plot(kind = 'bar', rot=0)
plt.xticks(range(len(dataset['Class'].unique())), dataset.Class.unique())
plt.title("Frequency by observation number")
plt.xlabel("Class")
plt.ylabel("Number of Observations");
```

```
17500 - 15000 - 12500 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 100000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000 - 10000
```

```
# Save the normal and fradulent transactions in separate dataframe
normal_dataset = dataset[dataset.Class == 0]
fraud_dataset = dataset[dataset.Class == 1]
#Visualize transactionamounts for normal and fraudulent transactions
bins = np.linspace(200, 2500, 100)
plt.hist(normal_dataset.Amount, bins=bins, alpha=1, density=True, label='Normal')
plt.hist(fraud_dataset.Amount, bins=bins, alpha=0.5, density=True, label='Fraud')
plt.legend(loc='upper right')
plt.title("Transaction amount vs Percentage of transactions")
plt.xlabel("Transaction amount (USD)")
plt.ylabel("Percentage of transactions");
plt.show()
```



'''Time and Amount are the columns that are not scaled, so applying StandardScaler to only Amount and T Normalizing the values between 0 and 1 did not work great for the dataset.'''

```
'Time and Amount are the columns that are not scaled, so applying StandardScaler to only y Amount and Time columns. \nNormalizing the values between 0 and 1 did not work great for the datacet'

sc=StandardScaler()

dataset['Time'] = sc.fit_transform(dataset['Time'].values.reshape(-1, 1))

dataset['Amount'] = sc.fit_transform(dataset['Amount'].values.reshape(-1, 1))

'''The last column in the dataset is our target variable.'''

raw_data = dataset.values

# The last element contains if the transaction is normal which is represented by a 0 and if fraud then labels = raw_data[:, -1]

# The other data points are the electrocadriogram data data = raw_data[:, 0:-1]

train_data, test_data, train_labels, test_labels = train_test_split(
    data, labels, test_size=0.2, random_state=2021
)
```

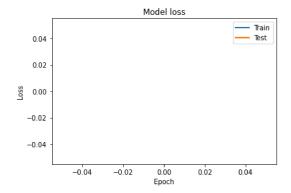
```
'''Normalize the data to have a value between 0 and 1'''
min val = tf.reduce min(train data)
max_val = tf.reduce_max(train_data)
train_data = (train_data - min_val) / (max_val - min_val)
test_data = (test_data - min_val) / (max_val - min_val)
train_data = tf.cast(train_data, tf.float32)
test_data = tf.cast(test_data, tf.float32)
'''Use only normal transactions to train the Autoencoder.
Normal data has a value of 0 in the target variable. Using the target variable to create a normal and f
train_labels = train_labels.astype(bool)
test_labels = test_labels.astype(bool)
#creating normal and fraud datasets
normal_train_data = train_data[~train_labels]
normal test data = test data[~test labels]
fraud_train_data = train_data[train_labels]
fraud_test_data = test_data[test_labels]
print(" No. of records in Fraud Train Data=",len(fraud_train_data))
print(" No. of records in Normal Train data=",len(normal_train_data))
print(" No. of records in Fraud Test Data=",len(fraud test data))
print(" No. of records in Normal Test data=",len(normal_test_data))
    No. of records in Fraud Train Data= 70
    No. of records in Normal Train data= 14264
    No. of records in Fraud Test Data= 12
    No. of records in Normal Test data= 3572
nb epoch = 50
batch size = 64
input_dim = normal_train_data.shape[1] #num of columns, 30
encoding dim = 14
hidden dim 1 = int(encoding dim / 2) #
hidden_dim 2=4
learning rate = 1e-7
#input Layer
input_layer = tf.keras.layers.Input(shape=(input_dim, ))
#Encoder
encoder = tf.keras.layers.Dense(encoding_dim, activation="tanh",
                         activity_regularizer=tf.keras.regularizers.12(learning_rate))(input_layer)
encoder=tf.keras.layers.Dropout(0.2)(encoder)
encoder = tf.keras.layers.Dense(hidden_dim_1, activation='relu')(encoder)
encoder = tf.keras.layers.Dense(hidden_dim_2, activation=tf.nn.leaky_relu)(encoder)
# Decoder
decoder = tf.keras.layers.Dense(hidden_dim_1, activation='relu')(encoder)
decoder=tf.keras.layers.Dropout(0.2)(decoder)
decoder = tf.keras.layers.Dense(encoding_dim, activation='relu')(decoder)
decoder = tf.keras.layers.Dense(input dim, activation='tanh')(decoder)
#Autoencoder
autoencoder = tf.keras.Model(inputs=input_layer, outputs=decoder)
autoencoder.summary()
    Model: "model"
```

```
Output Shape
                                Param #
   Laver (type)
  ______
   input_1 (InputLayer)
                  [(None, 30)]
                                0
   dense (Dense)
                  (None, 14)
                                434
   dropout (Dropout)
                  (None, 14)
                                0
   dense_1 (Dense)
                  (None, 7)
                                105
   dense 2 (Dense)
                  (None, 4)
                                32
   dense_3 (Dense)
                  (None, 7)
                                35
   dropout_1 (Dropout)
                  (None, 7)
                                0
   dense_4 (Dense)
                  (None, 14)
                                112
   dense_5 (Dense)
                  (None, 30)
                                450
  ______
  Total params: 1,168
  Trainable params: 1,168
  Non-trainable params: 0
"""Define the callbacks for checkpoints and early stopping"""
cp = tf.keras.callbacks.ModelCheckpoint(filepath="autoencoder_fraud.h5",
                       mode='min', monitor='val_loss', verbose=2, save_best_only=True)
# define our early stopping
early stop = tf.keras.callbacks.EarlyStopping(
  monitor='val_loss',
  min delta=0.0001,
  patience=10,
  verbose=1,
  mode='min',
  restore best weights=True)
#Compile the Autoencoder
autoencoder.compile(metrics=['accuracy'],
              loss='mean squared error',
               optimizer='adam')
#Train the Autoencoder
history = autoencoder.fit(normal train data, normal train data,
               epochs=nb_epoch,
              batch size=batch size,
               shuffle=True,
              validation data=(test data, test data),
               verbose=1,
               callbacks=[cp, early_stop]
               ).history
Epoch 1/50
  Epoch 1: val_loss did not improve from inf
  Epoch 2/50
  Epoch 2: val loss did not improve from inf
  Epoch 3: val_loss did not improve from inf
```

```
Epoch 4: val loss did not improve from inf
Epoch 5/50
Epoch 5: val loss did not improve from inf
Epoch 6: val loss did not improve from inf
Epoch 7: val_loss did not improve from inf
223/223 [================================ ] - 1s 3ms/step - loss: nan - accuracy: 1.0000 - val_loss: nan - val_accuracy: 1.0000
Epoch 8/50
Epoch 8: val_loss did not improve from inf
Epoch 9/50
Epoch 9: val_loss did not improve from inf
Epoch 10/50
Epoch 10: val loss did not improve from inf
Restoring model weights from the end of the best epoch: 1.
Epoch 10: early stopping
```

#Plot training and test loss

```
plt.plot(history['loss'], linewidth=2, label='Train')
plt.plot(history['val_loss'], linewidth=2, label='Test')
plt.legend(loc='upper right')
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
#plt.ylim(ymin=0.70,ymax=1)
plt.show()
```

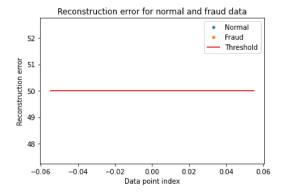


"""Detect Anomalies on test data

Anomalies are data points where the reconstruction loss is higher

To calculate the reconstruction loss on test data, predict the test data and calculate the mean square error between the test data and the reconstructed t

#Plotting the test data points and their respective reconstruction error sets a threshold value to visu #if the threshold value needs to be adjusted.



'''Detect anomalies as points where the reconstruction loss is greater than a fixed threshold. Here we see that a value of 52 for the threshold will be good.

Evaluating the performance of the anomaly detection'''

```
threshold_fixed =52
pred_y = [1 if e > threshold_fixed else 0 for e in error_df.Reconstruction_error.values]
error_df['pred'] =pred_y
conf_matrix = confusion_matrix(error_df.True_class, pred_y)
plt.figure(figsize=(4, 4))
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.xlabel('Predicted class')
plt.show()
# print Accuracy, precision and recall
print(" Accuracy: ",accuracy_score(error_df['True_class'], error_df['pred']))
print(" Recall: ",recall_score(error_df['True_class'], error_df['pred']))
print(" Precision: ",precision_score(error_df['True_class'], error_df['pred']))
```



'''As our dataset is highly imbalanced, we see a high accuracy but a low recall and precision.

Things to further improve precision and recall would add more relevant features, different architecture for autoencoder, different hyperparameters, or a different algorithm.'''

'As our dataset is highly imbalanced, we see a high accuracy but a low recall and precision.\n\nThings to further improve precision and recall would add more relevant features, \ndifferent architecture for autoencoder, different hyperparameters, or a different algorith

M Predicted class

history