Reference: Keras tutorial : https://www.tensorflow.org/tutorials/generative/autoencoder . Chapter 17 of Geron's book.

This file trains an autoencoder with the instances of the normal digit in the training data.

Then, it measures the reconstruction loss for the digits in the test data.

The reconstruction loss for the instances of the abnormal digit in the test data is higher.

A threshold is determined based on the distribution of the reconstruction losses of the normal training data (threshold = mean + 2.5*std of this distribution).

Then, if the reconstruction loss of a digit in the test data is higher than this threshold, it is classified as abnormal.

By comparing with the known labels of test data (with T for normal digit(s) and F for abnormal digit(s)), the confusion matrix and the accuracy is calculated.

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras

from sklearn.metrics import accuracy_score, precision_score, recall_score, confusion_matrix
from sklearn.model_selection import train_test_split
from keras import layers, losses
from keras.datasets import mnist
from keras.models import Model
# import cv2
```

Loading the MNIST data and forming arrays of the normal training data, validation data (normal and abnormal, and the test data (normal and abnormal)

```
#Labels
# 0 T-shirt/top
# 1 Trouser
# 2 Pullover
# 3 Dress
# 4 Coat
# 5 Sandal
# 6 Shirt
# 7 Sneaker
# 8 Bag
```

```
# 9 Ankle boot

nl1 = 0
nl2 = 2
nl3 = 6
abn = 7

(x_train_0, y_train_0), (x_test, y_test) = keras.datasets.fashion_mnist.load_data()

x_train_0 = x_train_0.astype(np.float32) / 255
x_test = x_test.astype(np.float32) / 255

train_size = x_train_0.shape[0] * 9 // 10

x_train, x_valid, y_train, y_valid = train_test_split(x_train_0, y_train_0, train_size = trai

normal_data = x_train[(y_train == nl1) | (y_train == nl2) | (y_train == nl3)]    # Normal tra
normal_labels = y_train[(y_train == nl1) | (y_train == nl2) | (y_train == nl3)]

valid_data = x_valid[(y_valid == abn) | (y_valid == nl1) | (y_valid == nl2) |  (y_valid == nl
valid_labels = y_valid[(y_valid == abn) | (y_valid == nl1) | (y_valid == nl2) |  (y_valid ==

test_data = x_test[(y_test == abn) | (y_test == nl1) | (y_test == nl2) |(y_test == nl3)]   #
test_labels = y_test[(y_test == abn) | (y_test == nl1) | (y_test == nl2) | (y_test == nl3)]

test_labels_T_F = np.where((test_labels == nl1) | (test_labels == nl2) | (test_labels == nl3)
# Array of T and F, T where test digits are normal and F where test digits are abnormal

valid_labels_T_F = np.where((valid_labels == nl1) | (valid_labels == nl2) |(valid_labels == n
# Array of T and F, T where test digits are normal and F where test digits are abnormal

normal_data.shape, normal_labels.shape, valid_data.shape, valid_labels.shape, test_data.shape

     ((16161, 28, 28), (16161,), (2416, 28, 28), (2416,), (4000, 28, 28), (4000,))


normal_test_data = test_data[(test_labels == nl1) | (test_labels == nl2) | (test_labels == nl
abnormal_test_data = test_data[test_labels == abn]                          # The abnormal di
normal_test_labels = test_labels[(test_labels == nl1) | (test_labels == nl2) | (test_labels =
abnormal_test_labels = test_labels[test_labels == abn]                          # Their label


normal_test_data.shape, abnormal_test_data.shape

     ((3000, 28, 28), (1000, 28, 28))


normal_valid_data = valid_data[(valid_labels == nl1) | (valid_labels == nl2) | (valid_labels
abnormal_valid_data = valid_data[valid_labels == abn]                          # The abnorma
normal_valid_labels = valid_labels[(valid_labels == nl1) | (valid_labels == nl2) | (valid_lab
abnormal_valid_labels = valid_labels[valid_labels == abn]                          # Their l
```

```
normal_valid_data.shape, abnormal_valid_data.shape
```

```
((1839, 28, 28), (577, 28, 28))
```

Building and training the network

```
class AnomalyDetector(Model):
  def __init__(self):
    super(AnomalyDetector, self).__init__()
    self.encoder = tf.keras.Sequential([
      layers.Flatten(),
      layers.Dense(256, activation="selu"),
      layers.Dense(128, activation="selu"),
      layers.Dense(64, activation="selu"),
      layers.Dense(16, activation="selu")])

    self.decoder = tf.keras.Sequential([
      layers.Dense(64, activation="selu"),
      layers.Dense(128, activation="selu"),
      layers.Dense(256, activation="selu"),
      layers.Dense(28*28, activation="sigmoid"),
      layers.Reshape((28, 28))])

  def call(self, x):
    encoded = self.encoder(x)
    decoded = self.decoder(encoded)
    return decoded

autoencoder = AnomalyDetector()
```

```
# autoencoder.compile(optimizer='adam', loss='mae')
autoencoder.compile(optimizer='rmsprop', loss='binary_crossentropy')
```

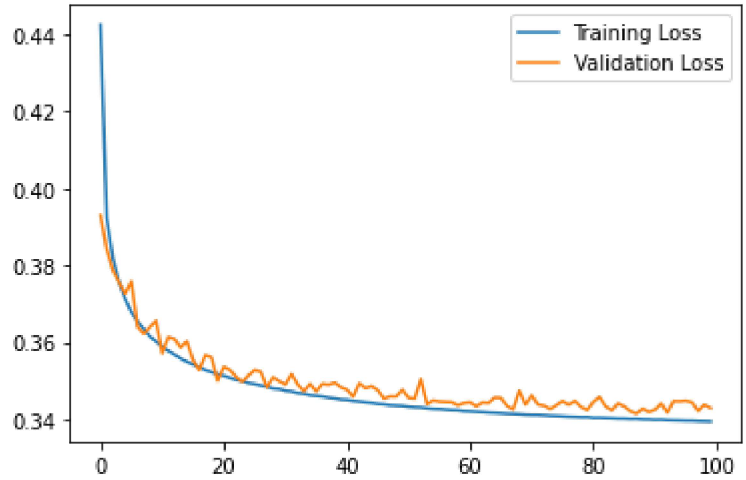
```
checkpoint_cb = keras.callbacks.ModelCheckpoint("AE_model", monitor="val_loss", save_best_onl

history = autoencoder.fit(normal_data, normal_data,
          epochs=100,
          batch_size=128,
          validation_data=(normal_valid_data, normal_valid_data),
          callbacks=[checkpoint_cb],
          shuffle=True)
```

```
127/127 [==============================] - 1s 7ms/step - loss: 0.3411 - val_loss: 0.34
Epoch 74/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3410 - val_loss: 0.34
Epoch 75/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3409 - val_loss: 0.34
Epoch 76/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3408 - val_loss: 0.34
Epoch 77/100
```

```
Epoch 77/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3407 - val_loss: 0.34
Epoch 78/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3407 - val_loss: 0.34
Epoch 79/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3406 - val_loss: 0.34
Epoch 80/100
125/127 [============================>.] - ETA: 0s - loss: 0.3406INFO:tensorflow:Asse
127/127 [==============================] - 3s 21ms/step - loss: 0.3406 - val_loss: 0.
Epoch 81/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3404 - val_loss: 0.34
Epoch 82/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3404 - val_loss: 0.34
Epoch 83/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3404 - val_loss: 0.34
Epoch 84/100
122/127 [===========================>..] - ETA: 0s - loss: 0.3403INFO:tensorflow:Asse
127/127 [==============================] - 3s 21ms/step - loss: 0.3403 - val_loss: 0.
Epoch 85/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3402 - val_loss: 0.34
Epoch 86/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3402 - val_loss: 0.34
Epoch 87/100
121/127 [===========================>..] - ETA: 0s - loss: 0.3402INFO:tensorflow:Asse
127/127 [==============================] - 3s 23ms/step - loss: 0.3401 - val_loss: 0.
Epoch 88/100
122/127 [===========================>..] - ETA: 0s - loss: 0.3399INFO:tensorflow:Asse
127/127 [==============================] - 3s 21ms/step - loss: 0.3402 - val_loss: 0.
Epoch 89/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3400 - val_loss: 0.34
Epoch 90/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3400 - val_loss: 0.34
Epoch 91/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3399 - val_loss: 0.34
Epoch 92/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3399 - val_loss: 0.34
Epoch 93/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3398 - val_loss: 0.34
Epoch 94/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3398 - val_loss: 0.34
Epoch 95/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3398 - val_loss: 0.34
Epoch 96/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3397 - val_loss: 0.34
Epoch 97/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3397 - val_loss: 0.34
Epoch 98/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3396 - val_loss: 0.34
Epoch 99/100
127/127 [==============================] - 1s 7ms/step - loss: 0.3396 - val_loss: 0.34
Epoch 100/100
```

```
plt.plot(history.history["loss"], label="Training Loss")
plt.plot(history.history["val_loss"], label="Validation Loss")
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f5bce1e3490>
```




```
model = autoencoder
model.summary(expand_nested=True, show_trainable=True)
```

```
Model: "anomaly_detector_5"
_________________________________________________________________________________
 Layer (type)                 Output Shape              Param #   Trainable
=================================================================================
 sequential_10 (Sequential)  (None, 16)                243152     Y
|-------------------------------------------------------------------------------|
| flatten_5 (Flatten)       (None, 784)               0          Y              |
|                                                                               |
| dense_40 (Dense)          (None, 256)               200960     Y              |
|                                                                               |
| dense_41 (Dense)          (None, 128)               32896      Y              |
|                                                                               |
| dense_42 (Dense)          (None, 64)                8256       Y              |
|                                                                               |
| dense_43 (Dense)          (None, 16)                1040       Y              |
---------------------------------------------------------------------------------
 sequential_11 (Sequential)  (None, 28, 28)            243920     Y
|-------------------------------------------------------------------------------|
| dense_44 (Dense)          (None, 64)                1088       Y              |
|                                                                               |
| dense_45 (Dense)          (None, 128)               8320       Y              |
|                                                                               |
| dense_46 (Dense)          (None, 256)               33024      Y              |
|                                                                               |
| dense_47 (Dense)          (None, 784)               201488     Y              |
|                                                                               |
| reshape_5 (Reshape)       (None, 28, 28)            0          Y              |
---------------------------------------------------------------------------------

=================================================================================
Total params: 487,072
Trainable params: 487,072
Non-trainable params: 0
_________________________________________________________________________________
```

```
model_encoder = autoencoder.encoder
# model_encoder.summary(expand_nested=True, show_trainable=True)

model_decoder = autoencoder.decoder
# model_decoder.summary(expand_nested=True, show_trainable=True)


model_layers = np.array(model.layers)
n_layers = model_layers.shape[0]
# np.concatenate((np.arange(n_layers).reshape(n_layers,1), model_layers.reshape(n_layers,1)),
```

The original and reconstructed images for the first 30 instances of the normal training data, validation data, normal validation data, abnormal validation data, test data, normal test data, and abnormal test data

```
def plot_image(image):
    plt.imshow(image, cmap="binary")
    plt.axis("off")


def show_reconstructions(autoencoder, images, n_images=5):
    encoded_data = autoencoder.encoder(images[:n_images]).numpy()
    decoded_data = autoencoder.decoder(encoded_data).numpy()
    reconstructions = decoded_data
    fig = plt.figure(figsize=(n_images * 1.5, 3))
    for image_index in range(n_images):
        plt.subplot(2, n_images, 1 + image_index)
        plot_image(images[image_index])
        plt.subplot(2, n_images, 1 + n_images + image_index)
        plot_image(reconstructions[image_index])
```

```
show_reconstructions(autoencoder, normal_data, 30)
plt.show()
```

```
show_reconstructions(autoencoder, valid_data, 30)
plt.show()
```

```
show_reconstructions(autoencoder, normal_valid_data, 30)
```

```
plt.show()
```

```
show_reconstructions(autoencoder, abnormal_valid_data, 30)
plt.show()
```

```
show_reconstructions(autoencoder, test_data, 30)
plt.show()
```

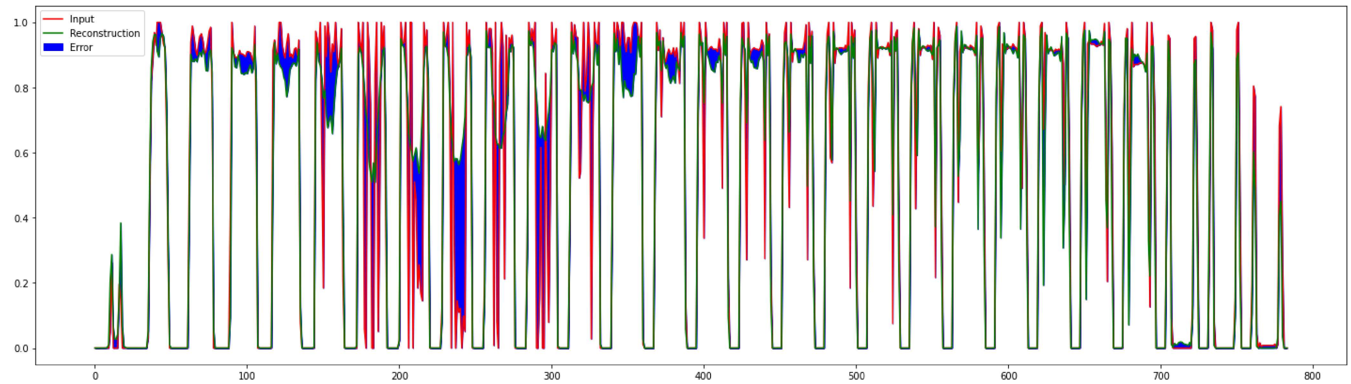
```
show_reconstructions(autoencoder, normal_test_data, 30)
plt.show()
```

```
show_reconstructions(autoencoder, abnormal_test_data, 30)
plt.show()
```

```
encoded_data = autoencoder.encoder(normal_test_data).numpy()
decoded_data = autoencoder.decoder(encoded_data).numpy()
```

1-Dim plot of pixels of the first normal test data

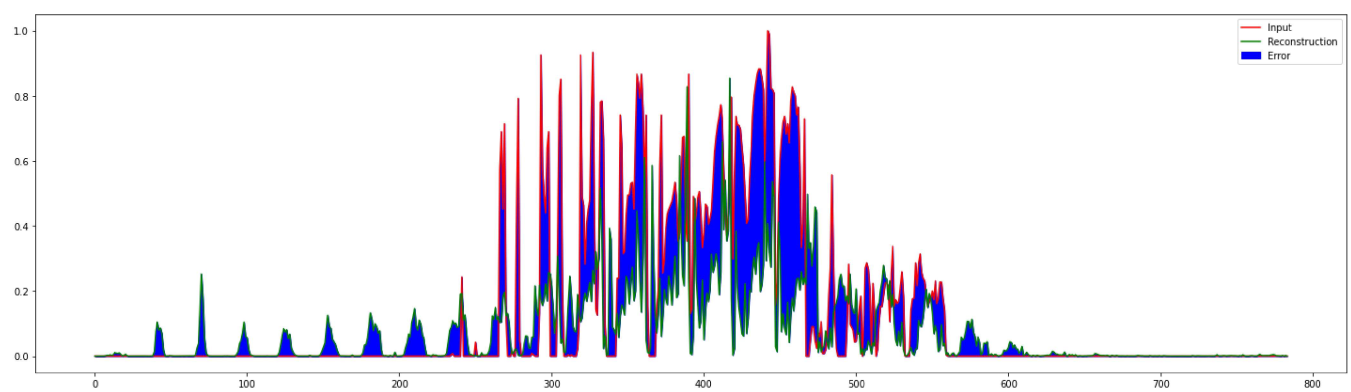
```
plt.figure(figsize=(25,7))
plt.plot(normal_test_data[0].ravel(), 'r')
plt.plot(decoded_data[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), decoded_data[0].ravel(), normal_test_data[0].ravel(), colo
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```




```
encoded_abn_data = autoencoder.encoder(abnormal_test_data).numpy()
decoded_abn_data = autoencoder.decoder(encoded_abn_data).numpy()
```

1-Dim plot of pixels of the first abnormal test data

```
plt.figure(figsize=(25,7))
plt.plot(abnormal_test_data[0].ravel(), 'r')
plt.plot(decoded_abn_data[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), decoded_abn_data[0].ravel(), abnormal_test_data[0].ravel()
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```

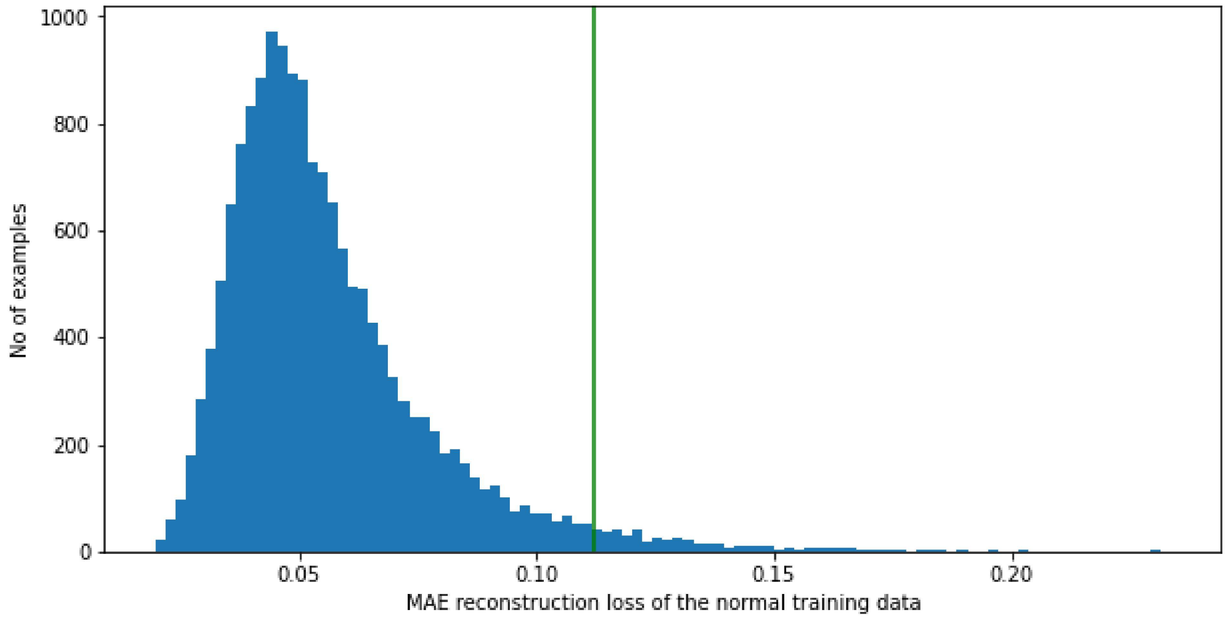


Distributions of the reconstruction losses and the calculation of the threshold.

Distribution of the reconstruction losses of the normal training data

```
reconstructions = autoencoder.predict(normal_data)
train_loss = tf.keras.losses.mae(reconstructions.reshape(-1, 784), normal_data.reshape(-1, 78
plt.figure(figsize=(10,5))
plt.hist(train_loss[None,:], bins=100)
```

```
threshold1 = np.mean(train_loss) + 2.5*np.std(train_loss)
plt.axvline(threshold1,c='g')
plt.xlabel("MAE reconstruction loss of the normal training data")
plt.ylabel("No of examples")
plt.show()
```




```
mean1 = np.mean(train_loss)
std1 = np.std(train_loss)
print("Mean: ", mean1)
print("Std: ", std1)
```

```
Mean:  0.056416955
Std:  0.022316255
```

```
threshold_train_mean_2_5_std = np.mean(train_loss) + 2.5*np.std(train_loss)
print("Threshold based on the mean of the training data MAE reconstruction losses + 2.5 std:
```

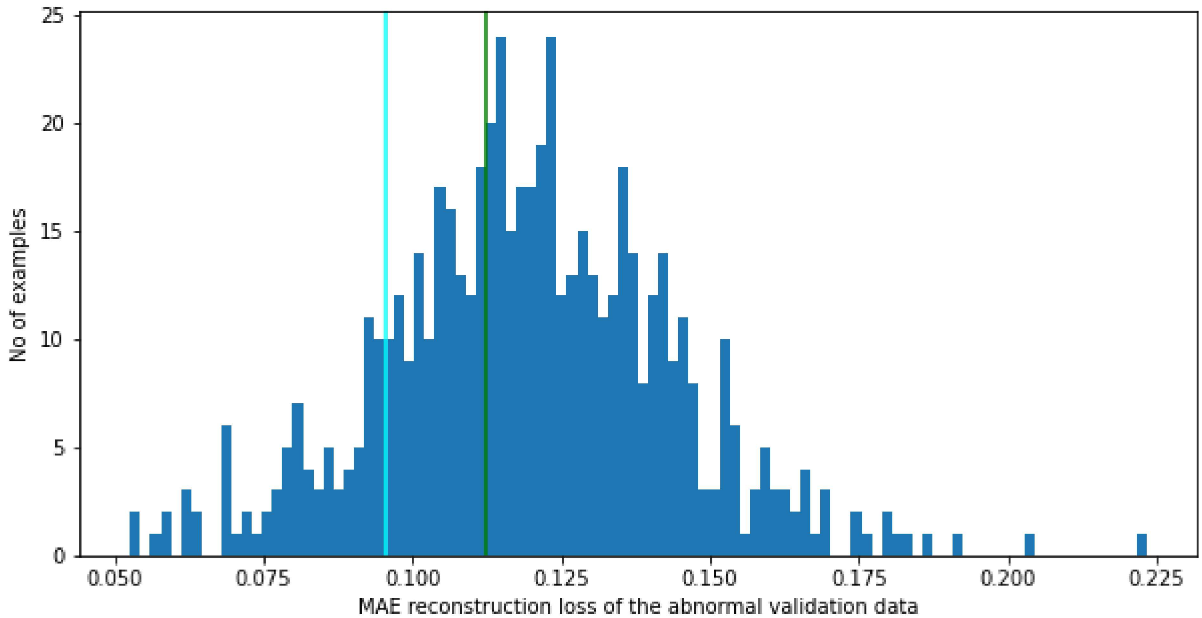
```
Threshold based on the mean of the training data MAE reconstruction losses + 2.5 std:  (
```

```
threshold1 = threshold_train_mean_2_5_std
```

Distribution of the reconstruction losses of the abnormal validation data

```
reconstructions = autoencoder.predict(abnormal_valid_data)
abn_valid_loss = tf.keras.losses.mae(reconstructions.reshape(-1,784), abnormal_valid_data.res
plt.figure(figsize=(10,5))
plt.hist(abn_valid_loss[None, :], bins=100)
threshold2 = np.mean(abn_valid_loss) - np.std(abn_valid_loss)
plt.axvline(threshold2,c='cyan')
```

```
plt.axvline(threshold1,c='g')
plt.xlabel("MAE reconstruction loss of the abnormal validation data")
plt.ylabel("No of examples")
plt.show()
```




```
abnormal_valid_mean_loss = np.mean(abn_valid_loss)
```

```
abnormal_valid_mean_loss , np.std(abn_valid_loss)
```

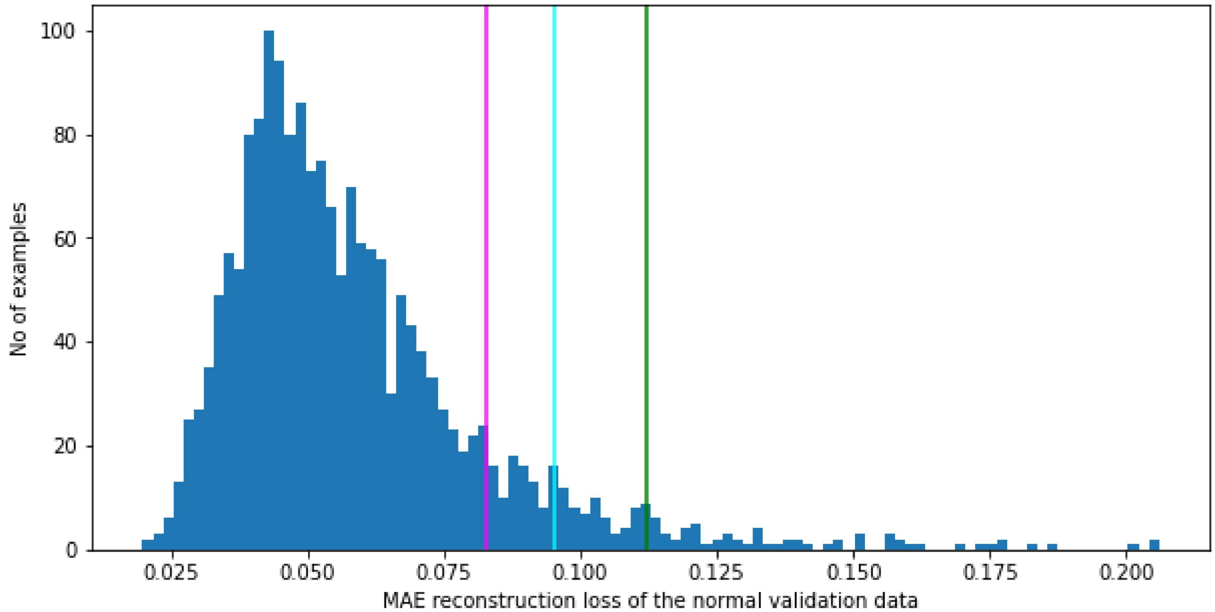
```
(0.11948547, 0.024155084)
```

```
threshold2 = abnormal_valid_mean_loss - np.std(abn_valid_loss)
print("Threshold2: ", threshold2)
```

```
Threshold2:  0.09533039
```

Distribution of the reconstruction losses of the normal validation data

```
reconstructions = autoencoder.predict(normal_valid_data)
nl_valid_loss = tf.keras.losses.mae(reconstructions.reshape(-1,784), normal_valid_data.reshap
plt.figure(figsize=(10,5))
plt.hist(nl_valid_loss[None, :], bins=100)
threshold3 = np.mean(nl_valid_loss) + np.std(nl_valid_loss)
plt.axvline(threshold3, c='magenta')
plt.axvline(threshold2, c='cyan')
plt.axvline(threshold1, c='g')
plt.xlabel("MAE reconstruction loss of the normal validation data")
plt.ylabel("No of examples")
plt.show()
```




```
normal_valid_mean_loss = np.mean(nl_valid_loss)
```

```
normal_valid_mean_loss , np.std(nl_valid_loss)
```

```
(0.058521885, 0.024120117)
```

```
threshold3 = normal_valid_mean_loss + np.std(nl_valid_loss)
print("Threshold3: ", threshold3)
```

```
Threshold3:  0.082642004
```

Calculation of a preliminary threshold based on (threshold2 + threshold3) / 2 = Average of (mean + std of the distribution of the reconstruction losses of the normal validation data) and (mean - std of the distribution of the reconstruction losses of the abnormal validation data)

```
Avg_of_threshold_2_3 = (threshold2 + threshold3)/2
print("Average of threshold 2 and 3: ", Avg_of_threshold_2_3)
```

```
Average of threshold 2 and 3:  0.08898619562387466
```

```
threshold4 = Avg_of_threshold_2_3
```

Calculation of the threshold that gives the best accuracy on the validation data and set this as the threshold.

```
def predict(model, data, threshold):
```

```
  reconstructions = model.predict(data)
  loss = tf.keras.losses.mae(reconstructions.reshape(-1, 784), data.reshape(-1, 784))
  return tf.math.less(loss, threshold)
```

```
increment = (abnormal_valid_mean_loss- normal_valid_mean_loss)/100
thresholds = np.arange(normal_valid_mean_loss, abnormal_valid_mean_loss, increment)
thrs_size = thresholds.shape[0]
accuracies = np.zeros(thrs_size)
for i in range(thrs_size):
  preds = predict(autoencoder, valid_data, thresholds[i])
  accuracies[i] = accuracy_score(preds, valid_labels_T_F)
argmax = np.argmax(accuracies)
valid_data_best_threshold = thresholds[argmax]
print("The best threshold based on validation data: ", valid_data_best_threshold)
```

```
The best threshold based on validation data:  0.09510003477334958
```

```
thr_acc = np.zeros((thrs_size, 2))
thr_acc[:, 0] = thresholds
thr_acc[:, 1] = accuracies
thr_acc[argmax-2:argmax+3]
```

```
array([[0.09388076, 0.90852649],
       [0.0944904 , 0.9093543 ],
       [0.09510003, 0.91100993],
       [0.09570967, 0.91100993],
       [0.09631931, 0.91018212]])
```

```
threshold5 = valid_data_best_threshold
```

```
threshold = threshold5
```

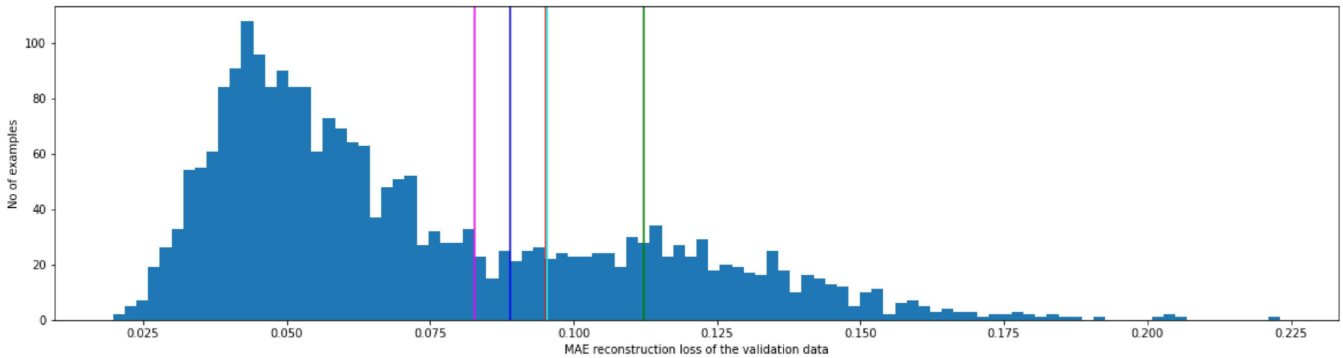
Distribution of the reconstruction losses of all the validation data (normal and abnormal)

The blue line is threshold4 (= the average of threshold3 [magenta] and threshold2 [cyan]).

The red line is the threshold that gives the best accuracy for the validation data.

```
reconstructions = autoencoder.predict(valid_data)
valid_loss = tf.keras.losses.mae(reconstructions.reshape(-1,784), valid_data.reshape(-1,784))
plt.figure(figsize=(20,5))
plt.hist(valid_loss[None, :], bins=100)
plt.axvline(threshold, c='r')
plt.axvline(threshold4, c='b')
```

```
plt.axvline(threshold2, c='cyan')
plt.axvline(threshold3, c='magenta')
plt.axvline(threshold1, c='green')
plt.xlabel("MAE reconstruction loss of the validation data")
plt.ylabel("No of examples")
plt.show()
```



Distribution of the reconstruction losses of the test data (normal and abnormal)

The blue line is threshold4 (= the average of threshold3 [magenta] and threshold2 [cyan]).

The red line is the threshold that gives the best accuracy for the validation data.

```
reconstructions = autoencoder.predict(test_data)
test_loss = tf.keras.losses.mae(reconstructions.reshape(-1,784), test_data.reshape(-1,784))
plt.figure(figsize=(20,5))
plt.hist(test_loss[None, :], bins=100)
plt.axvline(threshold, c='r')
plt.axvline(threshold4, c='b')
plt.axvline(threshold2, c='cyan')
plt.axvline(threshold3, c='magenta')
plt.axvline(threshold1, c='green')
plt.xlabel("MAE reconstruction loss of the test data")
plt.ylabel("No of examples")
plt.show()
```


```
reconstructions = autoencoder.predict(normal_test_data)
nl_test_loss = tf.keras.losses.mae(reconstructions.reshape(-1,784), normal_test_data.reshape(
np.mean(nl_test_loss) , np.std(nl_test_loss)
```

```
(0.058738858, 0.02368334)
```


```
reconstructions = autoencoder.predict(abnormal_test_data)
abn_test_loss = tf.keras.losses.mae(reconstructions.reshape(-1,784), abnormal_test_data.resha
np.mean(abn_test_loss) , np.std(abn_test_loss)
```

```
(0.11910072, 0.021687808)
```

Calculation of the accuracy and the confusion matrix on the test data with threshold set based on the best threshold from the validation data

```
# def predict(model, data, threshold):
#  reconstructions = model.predict(data)
#  loss = tf.keras.losses.mae(reconstructions.reshape(-1, 784), data.reshape(-1, 784))
#  return tf.math.less(loss, threshold)

mean_nl_test_loss = np.mean(nl_test_loss)
std_nl_test_loss = np.std(nl_test_loss)

mean_abn_test_loss = np.mean(abn_test_loss)
std_abn_test_loss = np.std(abn_test_loss)

def print_stats(predictions, labels):
  cf = confusion_matrix(labels, predictions)

  print("mean_nl_test_loss: {}".format(mean_nl_test_loss))
  print("std_nl_test_loss: {}".format(std_nl_test_loss))
  print("mean_abn_test_loss: {}".format(mean_abn_test_loss))
  print("std_abn_test_loss: {}".format(std_abn_test_loss))

  print("Confusion Matrix: \n prediction: F      T ")
  print("             {}   {}".format(preds[preds == False].shape[0], preds[preds == True].sh
  print(" label: F   [[{}   {}]    {}".format(cf[0,0], cf[0,1], test_labels_T_F[test_labels_T
  print("        T    [{}   {}]]   {}".format(cf[1,0], cf[1,1], test_labels_T_F[test_labels_T
  print("Accuracy = {}".format(accuracy_score(labels, predictions)))
  print("Precision = {}".format(precision_score(labels, predictions)))
  print("Recall = {}".format(recall_score(labels, predictions)))
```

```
preds = predict(autoencoder, test_data, valid_data_best_threshold)
```

```
preds = predict(autoencoder, test_data, valid_data_best_threshold)
print_stats(preds, test_labels_T_F)
```

```
mean_nl_test_loss: 0.05873885750770569
std_nl_test_loss: 0.0236833393573761
mean_abn_test_loss: 0.11910071969032288
std_abn_test_loss: 0.021687807515263557
Confusion Matrix:
 prediction: F      T
             1089   2911
 label: F   [[865   135]    1000
       T    [224   2776]]   3000
Accuracy = 0.91025
Precision = 0.9536241841291653
Recall = 0.9253333333333333
```

```
print(confusion_matrix(test_labels_T_F, preds))
```

```
[[ 865  135]
 [ 224 2776]]
```

Extra accuracy info

Just informative. Please record the above accuracy.

Accuracy on the test data with threshold set based on (threshold2 + threshold3) / 2 = Average of (mean + std of the distribution of the reconstruction losses of the normal validation data) and (mean - std of the distribution of the reconstruction losses of the abnormal validation data)

```
preds = predict(autoencoder, test_data, Avg_of_threshold_2_3)
print_stats(preds, test_labels_T_F)
```

```
mean_nl_test_loss: 0.05873885750770569
std_nl_test_loss: 0.0236833393573761
mean_abn_test_loss: 0.11910071969032288
std_abn_test_loss: 0.021687807515263557
Confusion Matrix:
 prediction: F      T
             1210   2790
 label: F   [[913   87]    1000
       T    [297   2703]]   3000
Accuracy = 0.904
Precision = 0.9688172043010753
Recall = 0.901
```

Accuracy on the test data with threshold set based on the mean of the training data MAE

```
preds = predict(autoencoder, test_data, threshold_train_mean_2_5_std)
print_stats(preds, test_labels_T_F)
```

```
mean_nl_test_loss: 0.05873885750770569
std_nl_test_loss: 0.0236833393573761
mean_abn_test_loss: 0.11910071969032288
std_abn_test_loss: 0.021687807515263557
Confusion Matrix:
 prediction: F      T
             745   3255
 label: F   [[643   357]    1000
        T    [102   2898]]   3000
Accuracy = 0.88525
Precision = 0.8903225806451613
Recall = 0.966
```

✓ 0s completed at 11:32 AM