References: Chapter 17 of Geron's book. For 1-Dim plots, Keras tutorial : https://www.tensorflow.org/tutorials/generative/autoencoder

This file trains a VAE with the instances of the normal digits 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 digits 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 sklearn
import tensorflow as tf
from tensorflow import keras
import numpy as np

import matplotlib as mpl
import matplotlib.pyplot as plt
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)


from sklearn.metrics import accuracy_score, precision_score, recall_score, confusion_matrix
from sklearn.model_selection import train_test_split
```

Loading the MNIST data and forming arrays of the normal training data, the 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 = 9
nl2 = 9
abn1 = 3
```

```
abn1 = 5
abn2 = 3

(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 = train_size)

normal_data = x_train[(y_train == nl1) | (y_train == nl2)]        # Normal training data (Normal digits
normal_labels = y_train[(y_train == nl1) | (y_train == nl2)]

valid_data = x_valid[(y_valid == abn1) | (y_valid == abn2) | (y_valid == nl1) | (y_valid == nl2)]    #
valid_labels = y_valid[(y_valid == abn1) | (y_valid == abn2) | (y_valid == nl1) | (y_valid == nl2)]

test_data = x_test[(y_test == abn1) | (y_test == abn2) | (y_test == nl1) | (y_test == nl2)]    # Test d
test_labels = y_test[(y_test == abn1) | (y_test == abn2) | (y_test == nl1) | (y_test == nl2)]

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

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-id
32768/29515 [=================================] - 0s 0us/step
40960/29515 [=========================================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-id
26427392/26421880 [==============================] - 0s 0us/step
26435584/26421880 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-labels-idx
16384/5148 [================================================================================
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-idx
4423680/4422102 [==============================] - 0s 0us/step
4431872/4422102 [==============================] - 0s 0us/step
```

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

```
((5370, 28, 28), (5370,), (1214, 28, 28), (1214,), (2000, 28, 28), (2000,))
```

```
normal_test_data = test_data[(test_labels == nl1) | (test_labels == nl2)]          # The normal digit
abnormal_test_data = test_data[(test_labels == abn1) | (test_labels == abn2)]      # The abnormal dig
normal_test_labels = test_labels[(test_labels == nl1) | (test_labels == nl2)]      # Their labels
abnormal_test_labels = test_labels[(test_labels == abn1) | (test_labels == abn2)]  # Their labels
```

```
normal_test_data.shape, abnormal_test_data.shape
```

```
((1000, 28, 28), (1000, 28, 28))
```

```
normal_valid_data = valid_data[(valid_labels == nl1) | (valid_labels == nl2)]          # The normal d
```

```
abnormal_valid_data = valid_data[(valid_labels == abn1) | (valid_labels == abn2)]        # The abnormal
normal_valid_labels = valid_labels[(valid_labels == nl1) | (valid_labels == nl2)]        # Their labels
abnormal_valid_labels = valid_labels[(valid_labels == abn1) | (valid_labels == abn1)]    # Their labels
```

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

```
((630, 28, 28), (584, 28, 28))
```

Building and training the network

```
K = keras.backend
# def rounded_accuracy(y_true, y_pred):
  #  return keras.metrics.binary_accuracy(tf.round(y_true), tf.round(y_pred))


# For details please see Geron's book. Uses the reparametrization trick to do stochastic
# sampling from the MVN distribution, while allowing the 2 parallel layers containing the
# means and stds of the MVN distribution for each dimension to be trained via
# backpropogation of the error signal.
class Sampling(keras.layers.Layer):
    def call(self, inputs):
        mean, log_var = inputs
        return K.random_normal(tf.shape(log_var)) * K.exp(log_var / 2) + mean


# For details please see Geron's book.
codings_size = 16   # The number of dimensions of the MVN distribution in the sampling layer

inputs = keras.layers.Input(shape=[28, 28])
z = keras.layers.Flatten()(inputs)
z = keras.layers.Dense(256, activation="selu")(z)
z = keras.layers.Dense(128, activation="selu")(z)
z = keras.layers.Dense(64, activation="selu")(z)

# Parallel layers at the end of the encoder for means
# and standard deviations of the Multivariate Normal (MVN) distribution
# in the dimensions of the coding size (here 32).
codings_mean = keras.layers.Dense(codings_size)(z)
codings_log_var = keras.layers.Dense(codings_size)(z)

# Sampling layer at the end of the encoder
codings = Sampling()([codings_mean, codings_log_var])
variational_encoder = keras.models.Model(
    inputs=[inputs], outputs=[codings_mean, codings_log_var, codings])

decoder_inputs = keras.layers.Input(shape=[codings_size])
x = keras.layers.Dense(64, activation="selu")(decoder_inputs)
x = keras.layers.Dense(128, activation="selu")(x)
x = keras.layers.Dense(256, activation="selu")(x)
x = keras.layers.Dense(28 * 28, activation="sigmoid")(x)
outputs = keras.layers.Reshape([28, 28])(x)
variational_decoder = keras.models.Model(inputs=[decoder_inputs], outputs=[outputs])
```

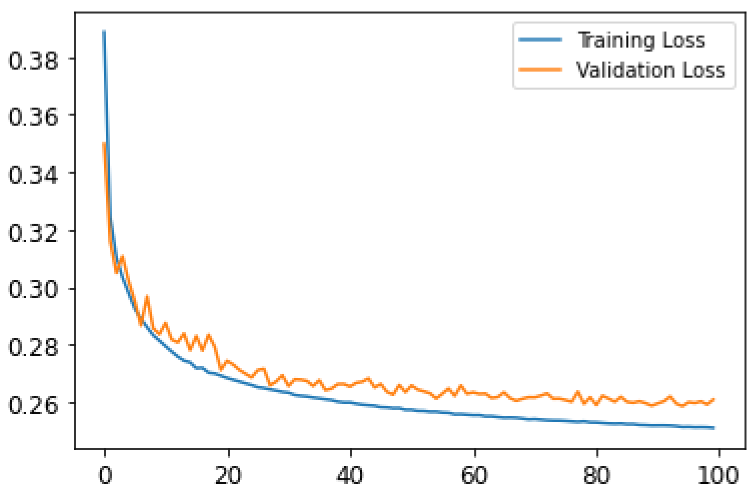
```
_, _, codings = variational_encoder(inputs)
reconstructions = variational_decoder(codings)
variational_ae = keras.models.Model(inputs=[inputs], outputs=[reconstructions])

# The latent loss function
# latent_loss = -0.5 * K.sum(
#     1 + codings_log_var - K.exp(codings_log_var) - K.square(codings_mean),
#     axis=-1)

# Add the latent loss to the reconstruction loss
# variational_ae.add_loss(K.mean(latent_loss) / 784.)

# For the reconstruction loss binary cross-entropy loss is used.
# For details please see Chapter 17 of Geron's book (Stacked AE and VAE sections)
variational_ae.compile(loss="binary_crossentropy", optimizer="rmsprop")

checkpoint_cb = keras.callbacks.ModelCheckpoint("wo_latent_VAE_model", monitor="val_loss", save_best_on

history = variational_ae.fit(normal_data, normal_data, epochs=100, batch_size=128, callbacks=[checkpoin
                             validation_data=(normal_valid_data, normal_valid_data), shuffle=True)
```

```
42/42 [==============================] - 0s 6ms/step - loss: 0.2537 - val_loss: 0.2630
Epoch 74/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2536 - val_loss: 0.2612
Epoch 75/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2536 - val_loss: 0.2613
Epoch 76/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2535 - val_loss: 0.2607
Epoch 77/100
42/42 [==============================] - ETA: 0s - loss: 0.2533INFO:tensorflow:Assets written t
42/42 [==============================] - 2s 42ms/step - loss: 0.2533 - val_loss: 0.2601
Epoch 78/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2531 - val_loss: 0.2637
Epoch 79/100
42/42 [==============================] - ETA: 0s - loss: 0.2533INFO:tensorflow:Assets written t
42/42 [==============================] - 2s 48ms/step - loss: 0.2533 - val_loss: 0.2594
Epoch 80/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2530 - val_loss: 0.2617
Epoch 81/100
33/42 [======================>.......] - ETA: 0s - loss: 0.2529INFO:tensorflow:Assets written t
42/42 [==============================] - 2s 43ms/step - loss: 0.2529 - val_loss: 0.2590
Epoch 82/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2528 - val_loss: 0.2622
Epoch 83/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2526 - val_loss: 0.2612
Epoch 84/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2525 - val_loss: 0.2601
Epoch 85/100
42/42 [==============================] - 0s 5ms/step - loss: 0.2526 - val_loss: 0.2619
Epoch 86/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2523 - val_loss: 0.2601
Epoch 87/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2524 - val_loss: 0.2598
Epoch 88/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2521 - val_loss: 0.2603
Epoch 89/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2520 - val_loss: 0.2597
```

```
Epoch 90/100
42/42 [==============================] - ETA: 0s - loss: 0.2519INFO:tensorflow:Assets written t
42/42 [==============================] - 2s 43ms/step - loss: 0.2519 - val_loss: 0.2588
Epoch 91/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2519 - val_loss: 0.2596
Epoch 92/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2519 - val_loss: 0.2603
Epoch 93/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2518 - val_loss: 0.2620
Epoch 94/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2517 - val_loss: 0.2595
Epoch 95/100

38/42 [==========================>...] - ETA: 0s - loss: 0.2513INFO:tensorflow:Assets written t
42/42 [==============================] - 2s 49ms/step - loss: 0.2514 - val_loss: 0.2586
Epoch 96/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2514 - val_loss: 0.2600
Epoch 97/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2513 - val_loss: 0.2597
Epoch 98/100
42/42 [==============================] - 0s 6ms/step - loss: 0.2513 - val_loss: 0.2603
```

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

```
<matplotlib.legend.Legend at 0x7f60d1402f10>
```




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

```
Model: "model_2"
_________________________________________________________________________________
 Layer (type)                Output Shape              Param #    Trainable
=================================================================================
 input_1 (InputLayer)        [(None, 28, 28)]          0          Y

 model (Functional)          [(None, 16),              244192     Y
                              (None, 16),
                              (None, 16)]
|-------------------------------------------------------------------------------|
| input_1 (InputLayer)      [(None, 28, 28)]          0          Y             |
|                                                                               |
```

```
| flatten (Flatten)          (None, 784)               0          Y            |
|                                                                              |
| dense (Dense)              (None, 256)               200960     Y            |
|                                                                              |
| dense_1 (Dense)            (None, 128)               32896      Y            |
|                                                                              |
| dense_2 (Dense)            (None, 64)                8256       Y            |
|                                                                              |
| dense_3 (Dense)            (None, 16)                1040       Y            |
|                                                                              |
| dense_4 (Dense)            (None, 16)                1040       Y            |
|                                                                              |
| sampling (Sampling)        (None, 16)                0          Y            |
---------------------------------------------------------------------------------
 model_1 (Functional)        (None, 28, 28)            243920     Y
|-------------------------------------------------------------------------------|
| input_2 (InputLayer)       [(None, 16)]              0          Y            |
|                                                                              |
| dense_5 (Dense)            (None, 64)                1088       Y            |
|                                                                              |
| dense_6 (Dense)            (None, 128)               8320       Y            |
|                                                                              |
| dense_7 (Dense)            (None, 256)               33024      Y            |
|                                                                              |
| dense_8 (Dense)            (None, 784)               201488     Y            |
|                                                                              |
| reshape (Reshape)          (None, 28, 28)            0          Y            |
---------------------------------------------------------------------------------

=================================================================================
Total params: 488,112
Trainable params: 488,112
Non-trainable params: 0
_________________________________________________________________________________
```

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

```
model_decoder = variational_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)), axis = 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(model, images, n_images=5):
    reconstructions = model.predict(images[:n_images])
    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(variational_ae, normal_data, 30)
plt.show()
```

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

```
show_reconstructions(variational_ae, normal_valid_data, 30)
plt.show()
```

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

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

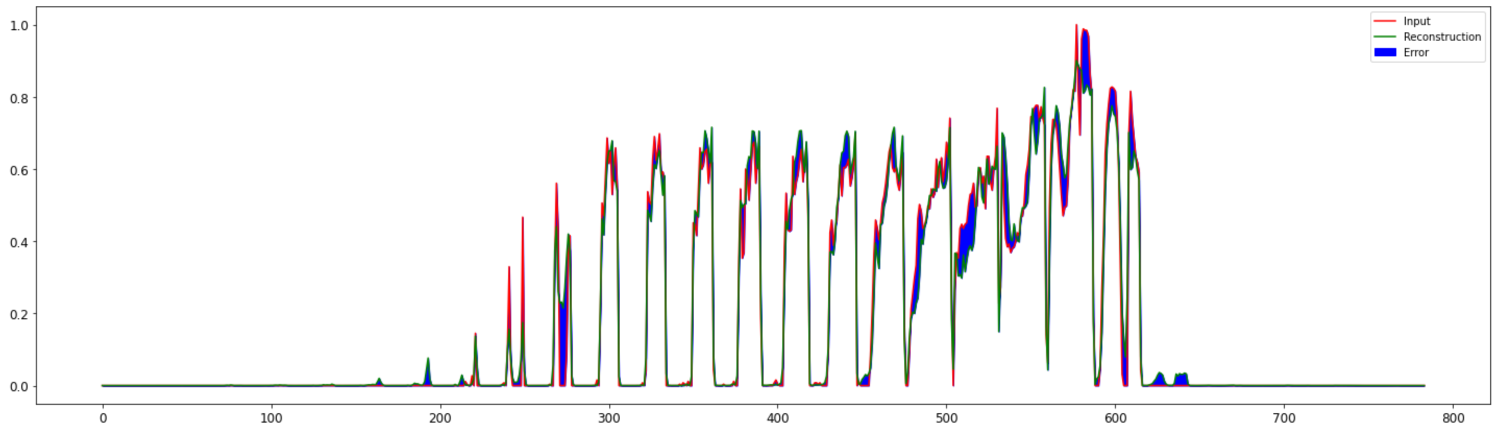
```
show_reconstructions(variational_ae, normal_test_data, 30)
plt.show()
```

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

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

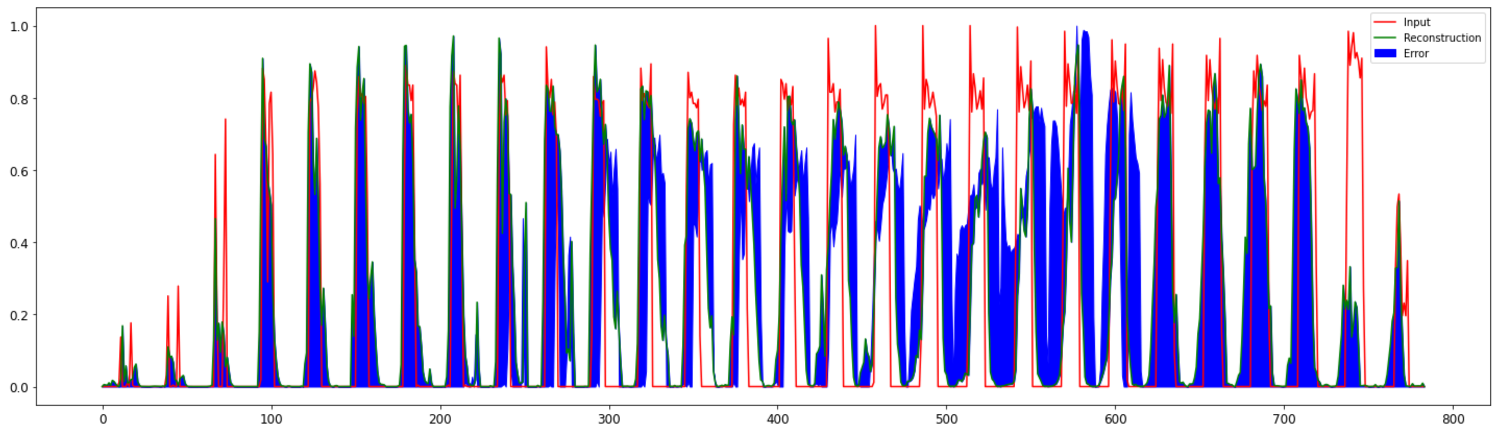
```
reconstructions_nl_test = variational_ae.predict(normal_test_data)
```

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



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

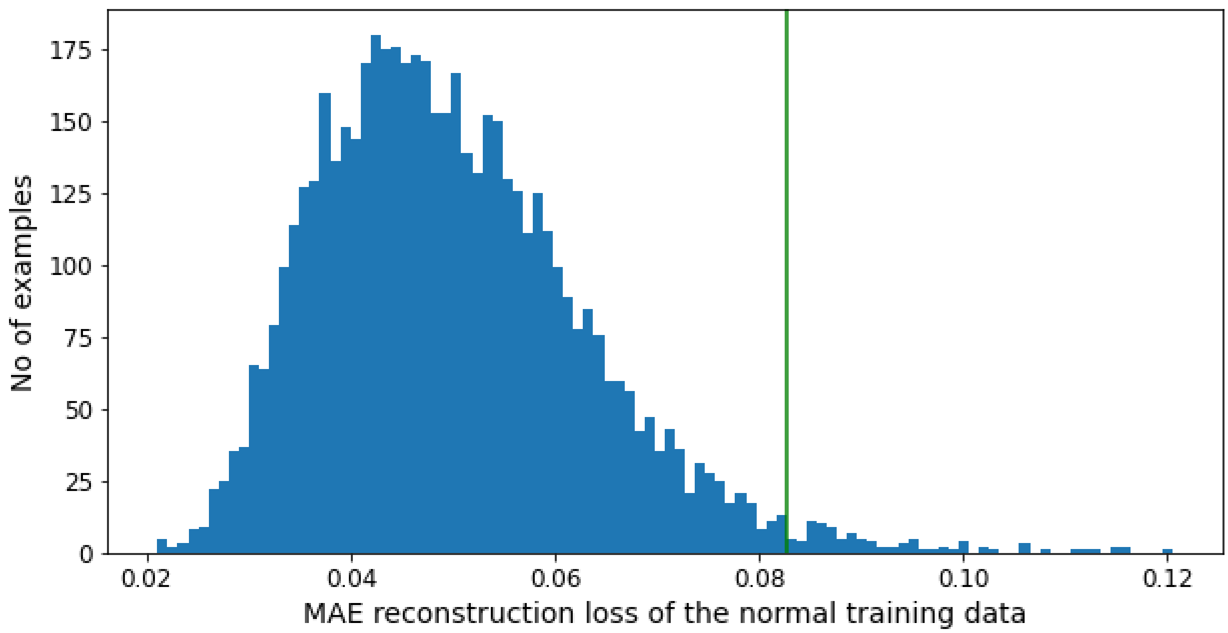
```
reconstructions_abn_test = variational_ae.predict(abnormal_test_data)


plt.figure(figsize=(25,7))
plt.plot(abnormal_test_data[0].ravel(), 'r')
plt.plot(reconstructions_abn_test[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), reconstructions_abn_test[0].ravel(), normal_test_data[0].ravel(), co
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 = variational_ae.predict(normal_data)
train_loss = tf.keras.losses.mae(reconstructions.reshape(-1, 784), normal_data.reshape(-1, 784))
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()
```




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

```
Mean:  0.049961545
Std:  0.013086356
```

```
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: ", thresho
```

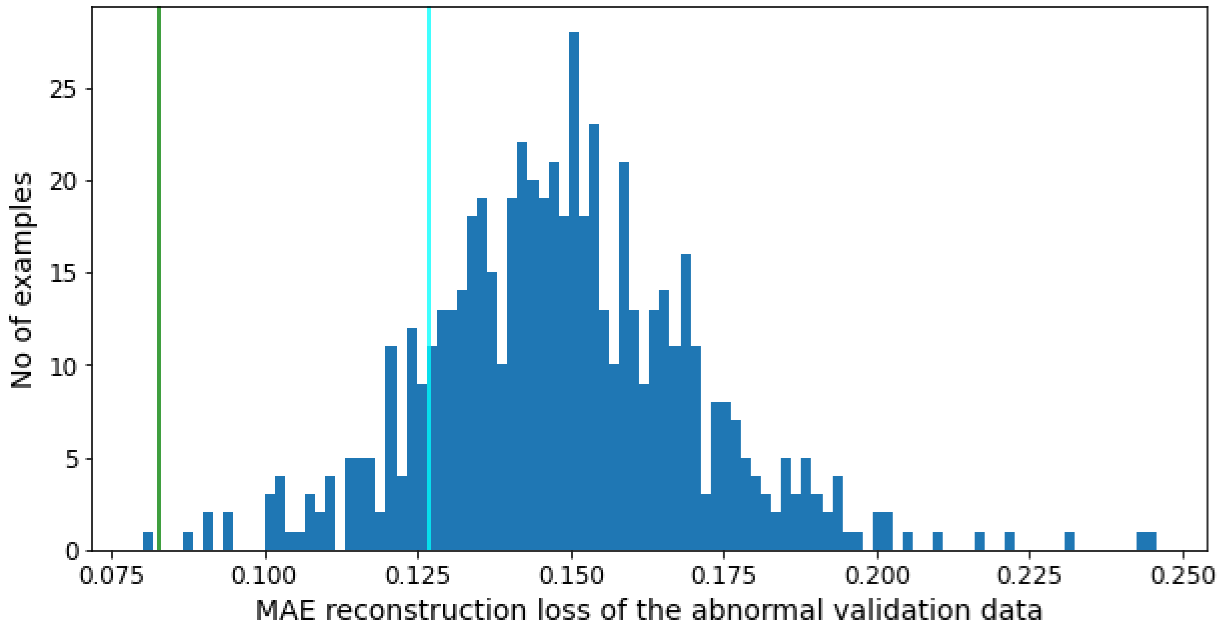
```
Threshold based on the mean of the training data MAE reconstruction losses + 2.5 std:  0.08267743!
```

```
threshold1 = threshold_train_mean_2_5_std
```

Distribution of the reconstruction losses of the abnormal validation data

```
reconstructions = variational_ae.predict(abnormal_valid_data)
abn_valid_loss = tf.keras.losses.mae(reconstructions.reshape(-1,784), abnormal_valid_data.reshape(-1,78
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)
```

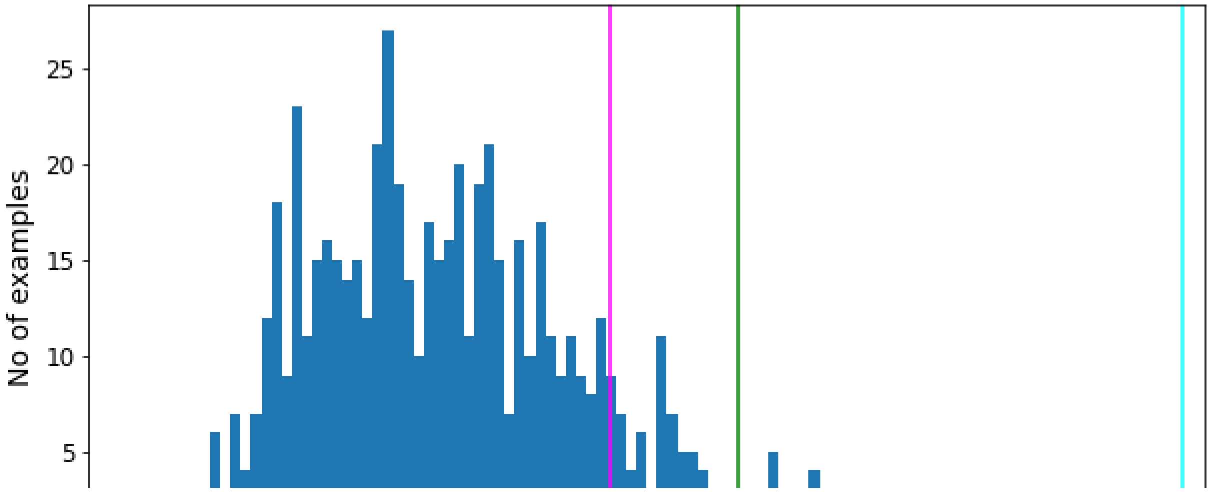
```
(0.14888944, 0.022019867)
```

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

```
Threshold2:  0.12686957
```

Distribution of the reconstruction losses of the normal validation data

```
reconstructions = variational_ae.predict(normal_valid_data)
nl_valid_loss = tf.keras.losses.mae(reconstructions.reshape(-1,784), normal_valid_data.reshape(-1,784))
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)
```

```
(0.054820165, 0.015171096)
```

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

```
Threshold3:  0.06999126
```

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:  0.09843041747808456
```

```
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(variational_ae, 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:  0.09338856667280188
```

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

```
array([[0.09150718, 0.9892916 ],
       [0.09244787, 0.99011532],
       [0.09338857, 0.99093904],
       [0.09432926, 0.9892916 ],
       [0.09526995, 0.9892916 ]])
```

```
threshold5 = valid_data_best_threshold
```

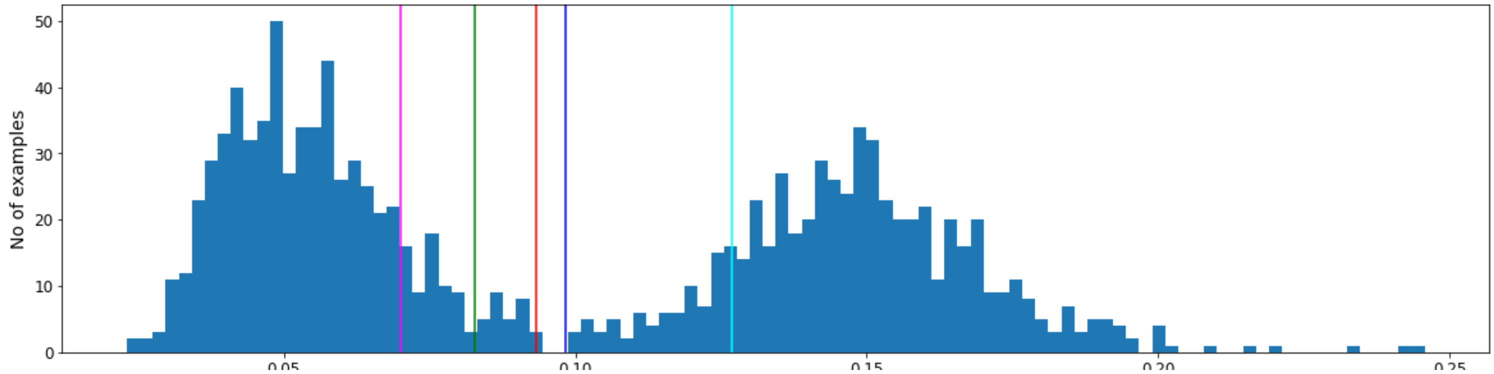
```
threshold = threshold5
```

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 = variational_ae.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()
```

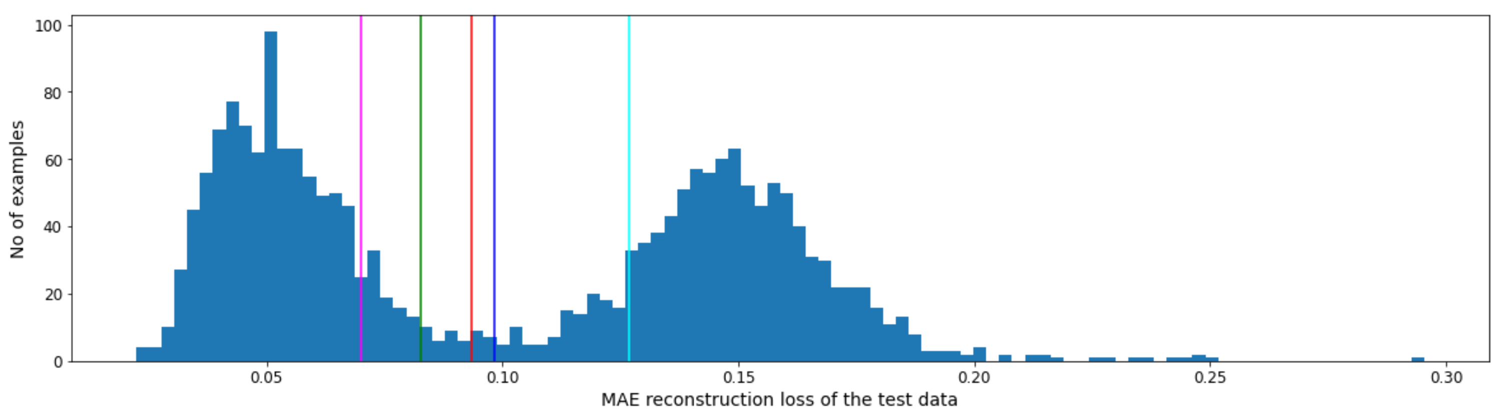


Distribution of the reconstruction losses of the test data (normal and abnormal)

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 = variational_ae.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()
```



Mean and standard deviation of reconstruction losses for normal and abnormal test data

```
reconstructions = variational_ae.predict(normal_test_data)
```

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

```
(0.054254945, 0.017188106)
```

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

```
(0.14916016, 0.022140818)
```

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)

def print_stats(predictions, labels):
  cf = confusion_matrix(labels, predictions)
  print("Confusion Matrix: \n prediction: F      T ")
  print("             {}   {}".format(preds[preds == False].shape[0], preds[preds == True].shape[0]))
  print(" label: F   [[{}   {}]    {}".format(cf[0,0], cf[0,1], test_labels_T_F[test_labels_T_F == Fals
  print("        T    [{}   {}]]   {}".format(cf[1,0], cf[1,1], test_labels_T_F[test_labels_T_F == True
  print("Accuracy = {}".format(accuracy_score(labels, predictions)))
  print("Normal Test Data Mean = {}".format(np.mean(nl_test_loss)))
  print("Normal Test Data Standard Deviation = {}".format(np.std(nl_test_loss)))
  print("Abnormal Test Data Mean = {}".format(np.mean(abn_test_loss)))
  print("Abnormal Test Data Standard Deviation = {}".format(np.std(abn_test_loss)))
  print("Precision = {}".format(precision_score(labels, predictions)))
  print("Recall = {}".format(recall_score(labels, predictions)))
  print(accuracy_score(labels, predictions))
  print(np.mean(nl_test_loss))
  print(np.std(nl_test_loss))
  print(np.mean(abn_test_loss))
  print(np.std(abn_test_loss))
  print(precision_score(labels, predictions))
  print(recall_score(labels, predictions))
  print(accuracy_score(labels, predictions), np.mean(nl_test_loss), np.std(nl_test_loss), np.mean(abn_t
        precision_score(labels, predictions), recall_score(labels, predictions))


preds = predict(variational_ae, test_data, threshold)
print_stats(preds, test_labels_T_F)
```

```
Confusion Matrix:
 prediction: F      T
             1015   985
 label: F   [[991    9]    1000
        T    [24   976]]   1000
Accuracy = 0.9835
Normal Test Data Mean = 0.05425494536757469
Normal Test Data Standard Deviation = 0.01718810573220253
```

```
Abnormal Test Data Mean = 0.14916016161441803
Abnormal Test Data Standard Deviation = 0.02214081771671772
Precision = 0.9908629441624366
Recall = 0.976
0.9835
0.054254945
0.017188106
0.14916016
0.022140818
0.9908629441624366
0.976
0.9835 0.054254945 0.017188106 0.14916016 0.022140818 0.9908629441624366 0.976
```

```
print("Threshold =", valid_data_best_threshold)
```

```
Threshold = 0.09338856667280188
```

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

```
[[991   9]
 [ 24 976]]
```

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(variational_ae, test_data, Avg_of_threshold_2_3)
print_stats(preds, test_labels_T_F)
```

```
Confusion Matrix:
 prediction: F      T
             999   1001
 label: F   [[986   14]    1000
        T    [13   987]]   1000
Accuracy = 0.9865
Normal Test Data Mean = 0.05425494536757469
Normal Test Data Standard Deviation = 0.01718810573220253
Abnormal Test Data Mean = 0.14916016161441803
Abnormal Test Data Standard Deviation = 0.02214081771671772
Precision = 0.986013986013986
Recall = 0.987
0.9865
0.054254945
0.017188106
0.14916016
0.022140818
0.986013986013986
0.987
0.9865 0.054254945 0.017188106 0.14916016 0.022140818 0.986013986013986 0.987
```

Accuracy on the test data with threshold set based on the mean of the training data MAE reconstruction losses + 2.5 std

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

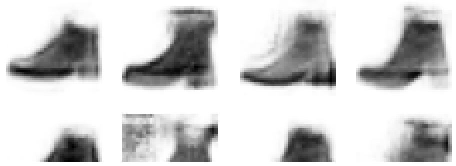
```
Confusion Matrix:
 prediction: F      T
            1046   954
 label: F   [[1000   0]    1000
        T    [46   954]]   1000
Accuracy = 0.977
Normal Test Data Mean = 0.05425494536757469
Normal Test Data Standard Deviation = 0.01718810573220253
Abnormal Test Data Mean = 0.14916016161441803
Abnormal Test Data Standard Deviation = 0.02214081771671772
Precision = 1.0
Recall = 0.954
0.977
0.054254945
0.017188106
0.14916016
0.022140818
1.0
0.954
0.977 0.054254945 0.017188106 0.14916016 0.022140818 1.0 0.954
```

Extra Info

Giving the VAE codings (please see book) (Just informative, not the goal here)

```
def plot_multiple_images(images, n_cols=None):
    n_cols = n_cols or len(images)
    n_rows = (len(images) - 1) // n_cols + 1
    if images.shape[-1] == 1:
        images = np.squeeze(images, axis=-1)
    plt.figure(figsize=(n_cols, n_rows))
    for index, image in enumerate(images):
        plt.subplot(n_rows, n_cols, index + 1)
        plt.imshow(image, cmap="binary")
        plt.axis("off")
```

```
codings = tf.random.normal(shape=[12, codings_size])
images = variational_decoder(codings).numpy()
plot_multiple_images(images, 4)
# save_fig("vae_generated_images_plot", tight_layout=False)
```



```
codings_grid = tf.reshape(codings, [1, 3, 4, codings_size])
larger_grid = tf.image.resize(codings_grid, size=[5, 7])
interpolated_codings = tf.reshape(larger_grid, [-1, codings_size])
images = variational_decoder(interpolated_codings).numpy()

plt.figure(figsize=(7, 5))
for index, image in enumerate(images):
    plt.subplot(5, 7, index + 1)
    if index%7%2==0 and index//7%2==0:
        plt.gca().get_xaxis().set_visible(False)
        plt.gca().get_yaxis().set_visible(False)
    else:
        plt.axis("off")
    plt.imshow(image, cmap="binary")
# save_fig("semantic_interpolation_plot", tight_layout=False)
```