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 = 5
nl2 = 7
nl3 = 9
abn1 = 4
abn2 = 4

(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
normal_labels = y_train[(y_train == nl1) | (y_train == nl2) | (y_train == nl3)]

valid_data = x_valid[(y_valid == abn1) | (y_valid == abn2) | (y_valid == nl1) | (y_valid == n
valid_labels = y_valid[(y_valid == abn1) | (y_valid == abn2) | (y_valid == nl1) | (y_valid ==

test_data = x_test[(y_test == abn1) | (y_test == abn2) | (y_test == nl1) | (y_test == nl2) |
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) | (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 ==
# 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
```

```
((16159, 28, 28), (16159,), (2449, 28, 28), (2449,), (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 == abn1) | (test_labels == abn2)]        # The ab
normal_test_labels = test_labels[(test_labels == nl1) | (test_labels == nl2) | (test_labels =
abnormal_test_labels = test_labels[(test_labels == abn1) | (test_labels == abn2)]    # Their


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 == abn1) | (valid_labels == abn2)]        # Th
```

```
normal_valid_labels = valid_labels[(valid_labels == nl1) | (valid_labels == nl2) | (valid_lab
abnormal_valid_labels = valid_labels[(valid_labels == abn1) | (valid_labels == abn1)]    # Th

normal_valid_data.shape, abnormal_valid_data.shape
```

```
((1841, 28, 28), (608, 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)
```

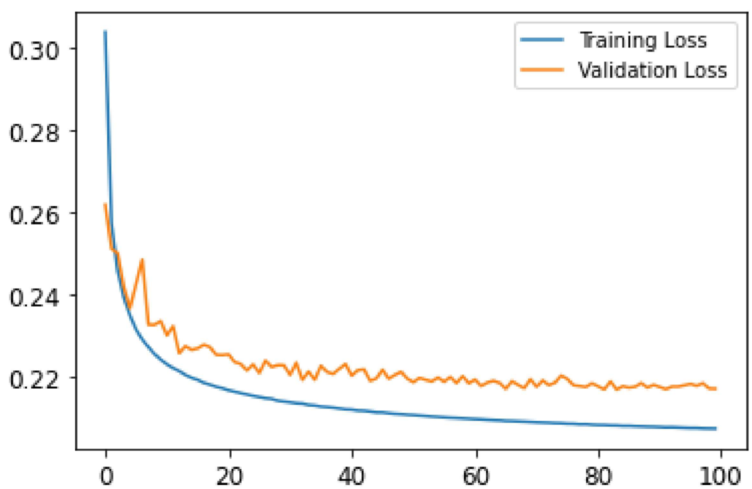
```
variational_decoder = keras.models.Model(inputs=[decoder_inputs], outputs=[outputs])

_, _, 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", sa

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

```
Epoch 1/100
120/127 [===========================>..] - ETA: 0s - loss: 0.3059INFO:tensorflow:Asse
127/127 [==============================] - 4s 21ms/step - loss: 0.3036 - val_loss: 0.
Epoch 2/100
117/127 [==========================>...] - ETA: 0s - loss: 0.2575INFO:tensorflow:Asse
127/127 [==============================] - 2s 18ms/step - loss: 0.2573 - val_loss: 0.
Epoch 3/100
126/127 [============================>.] - ETA: 0s - loss: 0.2456INFO:tensorflow:Asse
127/127 [==============================] - 2s 17ms/step - loss: 0.2456 - val_loss: 0.
Epoch 4/100
123/127 [============================>.] - ETA: 0s - loss: 0.2392INFO:tensorflow:Asse
127/127 [==============================] - 3s 20ms/step - loss: 0.2391 - val_loss: 0.
Epoch 5/100
121/127 [===========================>..] - ETA: 0s - loss: 0.2347INFO:tensorflow:Asse
127/127 [==============================] - 2s 18ms/step - loss: 0.2348 - val_loss: 0.
Epoch 6/100
127/127 [==============================] - 1s 5ms/step - loss: 0.2313 - val_loss: 0.2
Epoch 7/100
127/127 [==============================] - 1s 5ms/step - loss: 0.2289 - val_loss: 0.2
Epoch 8/100
118/127 [==========================>...] - ETA: 0s - loss: 0.2272INFO:tensorflow:Asse
127/127 [==============================] - 2s 18ms/step - loss: 0.2270 - val_loss: 0.
Epoch 9/100
122/127 [===========================>..] - ETA: 0s - loss: 0.2254INFO:tensorflow:Asse
127/127 [==============================] - 2s 19ms/step - loss: 0.2253 - val_loss: 0.
Epoch 10/100
127/127 [==============================] - 1s 5ms/step - loss: 0.2240 - val_loss: 0.2
Epoch 11/100
122/127 [===========================>..] - ETA: 0s - loss: 0.2229INFO:tensorflow:Asse
127/127 [==============================] - 2s 18ms/step - loss: 0.2228 - val_loss: 0.
Epoch 12/100
```

```
127/127 [==============================] - 1s 5ms/step - loss: 0.2219 - val_loss: 0.2
Epoch 13/100
121/127 [===========================>..] - ETA: 0s - loss: 0.2214INFO:tensorflow:Asse
127/127 [==============================] - 2s 18ms/step - loss: 0.2212 - val_loss: 0.
Epoch 14/100
127/127 [==============================] - 1s 5ms/step - loss: 0.2203 - val_loss: 0.2
Epoch 15/100
127/127 [==============================] - 1s 5ms/step - loss: 0.2196 - val_loss: 0.2
Epoch 16/100
127/127 [==============================] - 1s 5ms/step - loss: 0.2191 - val_loss: 0.2
Epoch 17/100
127/127 [==============================] - 1s 5ms/step - loss: 0.2183 - val_loss: 0.2
Epoch 18/100
127/127 [==============================] - 1s 5ms/step - loss: 0.2179 - val_loss: 0.2
Epoch 19/100
119/127 [===========================>..] - ETA: 0s - loss: 0.2173INFO:tensorflow:Asse
127/127 [==============================] - 3s 20ms/step - loss: 0.2174 - val_loss: 0.
Epoch 20/100
121/127 [===========================>..] - ETA: 0s - loss: 0.2171INFO:tensorflow:Asse
127/127 [==============================] - 2s 18ms/step - loss: 0.2170 - val_loss: 0.
Epoch 21/100
127/127 [==============================] - 1s 5ms/step - loss: 0.2165 - val_loss: 0.2
Epoch 22/100
127/127 [==============================] - ETA: 0s - loss: 0.2162INFO:tensorflow:Asse
127/127 [==============================] - 2s 18ms/step - loss: 0.2162 - val_loss: 0.
Epoch 23/100
```

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

```
<matplotlib.legend.Legend at 0x7f068c1a4b90>
```




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

```
Model: "model_8"
_________________________________________________________________________
 Layer (type)                Output Shape              Param #   Trainable
```

```
=============================================================================
 input_5 (InputLayer)        [(None, 28, 28)]          0         Y

 model_6 (Functional)        [(None, 16),              244192    Y
                              (None, 16),
                              (None, 16)]
|---------------------------------------------------------------------------|
| input_5 (InputLayer)      [(None, 28, 28)]          0         Y          |
|                                                                           |
| flatten_2 (Flatten)       (None, 784)               0         Y          |
|                                                                           |
| dense_18 (Dense)          (None, 256)               200960    Y          |
|                                                                           |
| dense_19 (Dense)          (None, 128)               32896     Y          |
|                                                                           |
| dense_20 (Dense)          (None, 64)                8256      Y          |
|                                                                           |
| dense_21 (Dense)          (None, 16)                1040      Y          |
|                                                                           |
| dense_22 (Dense)          (None, 16)                1040      Y          |
|                                                                           |
| sampling_2 (Sampling)     (None, 16)                0         Y          |
-----------------------------------------------------------------------------
 model_7 (Functional)        (None, 28, 28)            243920    Y
|---------------------------------------------------------------------------|
| input_6 (InputLayer)      [(None, 16)]              0         Y          |
|                                                                           |
| dense_23 (Dense)          (None, 64)                1088      Y          |
|                                                                           |
| dense_24 (Dense)          (None, 128)               8320      Y          |
|                                                                           |
| dense_25 (Dense)          (None, 256)               33024     Y          |
|                                                                           |
| dense_26 (Dense)          (None, 784)               201488    Y          |
|                                                                           |
| reshape_2 (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)),
```

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()
```

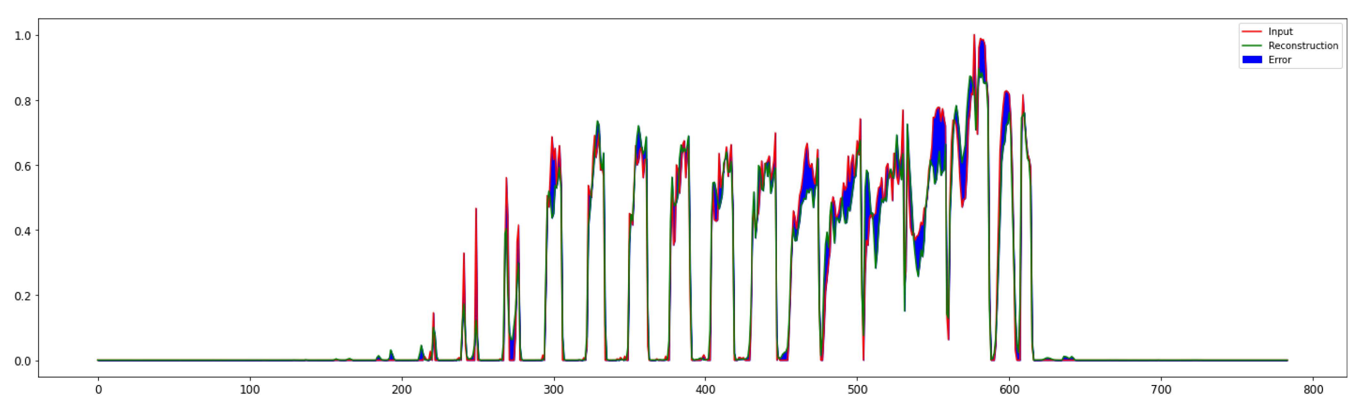
```
show_reconstructions(variational_ae, normal_test_data, 30)
plt.show()
```

```
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)
```

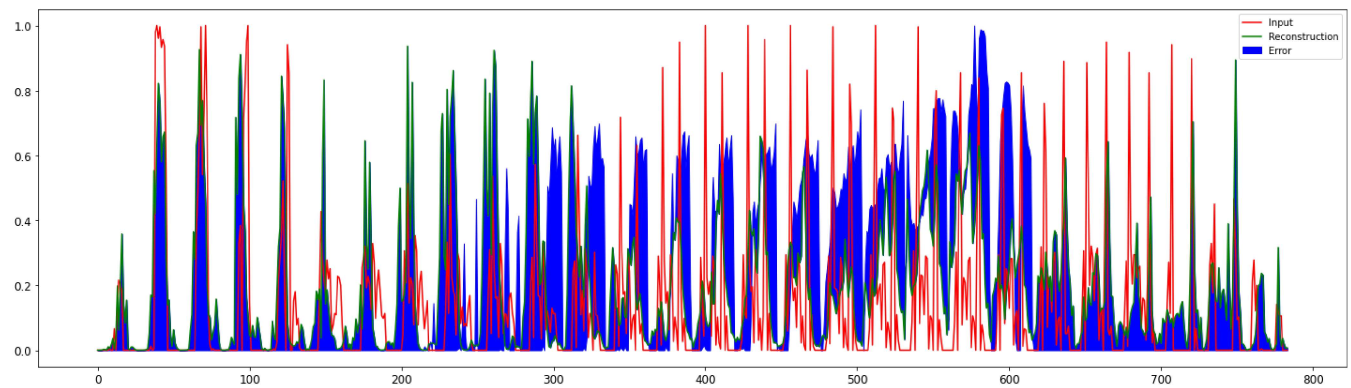
```
plt.figure(figsize=(25,7))
plt.plot(normal_test_data[0].ravel(), 'r')
plt.plot(reconstructions_nl_test[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), reconstructions_nl_test[0].ravel(), normal_test_data[0].ra
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```



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

```
reconstructions_abn_test = variational_ae.predict(abnormal_test_data)
```

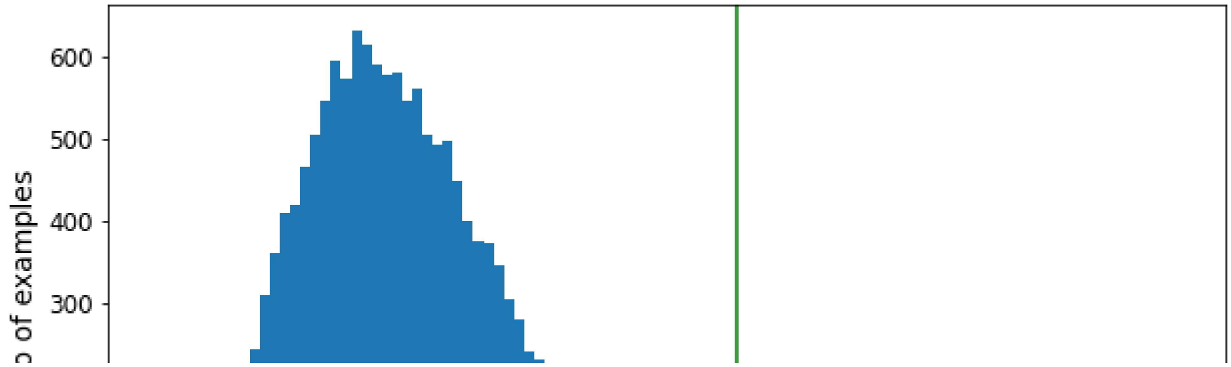
```
plt.figure(figsize=(25,7))
plt.plot(abnormal_test_data[0].ravel(), 'r')
plt.plot(reconstructions_abn_test[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), reconstructions_abn_test[0].ravel(), normal_test_data[0].r
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```



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, 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:  0.04641446
Std:  0.01709281
```

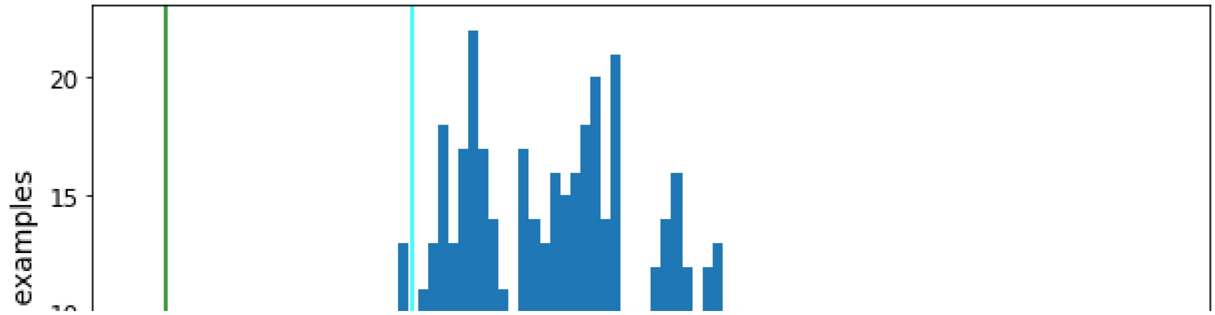
```
threshold_train_mean_2_5_std = np.mean(train_loss) + 2.5*np.std(train_loss)
print("Threshold based on the mean of the training data MAE reconstruction losses + 2.5 std:
```

```
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 = variational_ae.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)
```

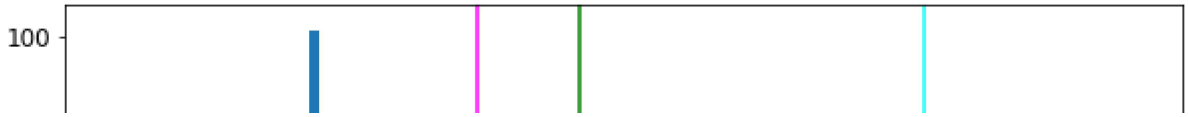
    (0.18210389, 0.03633168)


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

    Threshold2: 0.1457722

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.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)
```

```
(0.050850566, 0.021381473)
```

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

```
Threshold3:  0.07223204
```

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:  0.10900212079286575
```

```
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)
```

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

```
array([[0.11778976, 0.98080849],
       [0.11910229, 0.98203348],
       [0.12041482, 0.98285014],
       [0.12172736, 0.98121682],
       [0.12303989, 0.98040016]])
```

```
threshold5 = valid_data_best_threshold
```

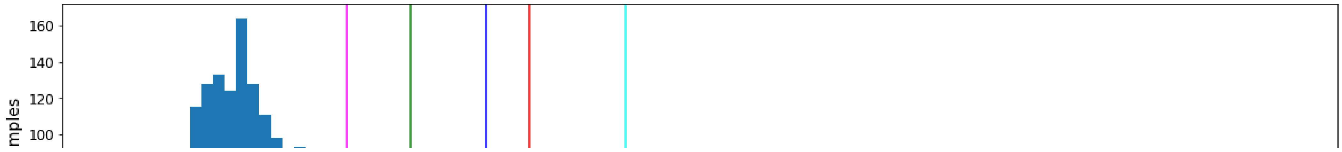
```
threshold = threshold5
```

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()
```

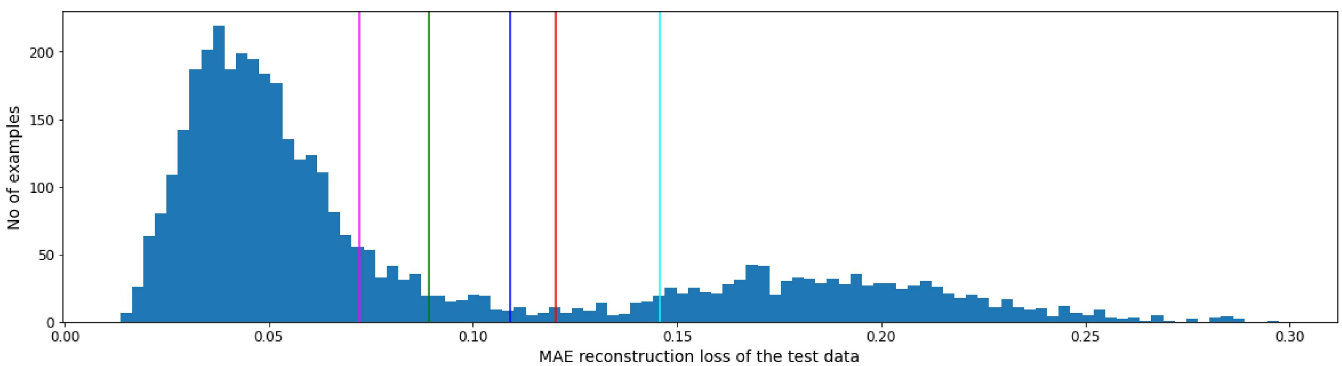


Distribution of the reconstruction losses of the test data (normal and abnormal)

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(
np.mean(nl_test_loss) , np.std(nl_test_loss)
```

```
(0.049619813, 0.020535689)
```

```
reconstructions = variational_ae.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)
```

```
(0.1857742, 0.03608678)
```

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

```
mean_nl_test_loss: 0.04961981251835823
std_nl_test_loss: 0.02053568884730339
mean_abn_test_loss: 0.18577420711517334
std_abn_test_loss: 0.036086779087781906
Confusion Matrix:
 prediction: F      T
             987   3013
 label: F   [[963   37]    1000
        T    [24   2976]]   3000
Accuracy = 0.98475
```

```
Precision = 0.9877198805177564
Recall = 0.992
```

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

```
[[ 963   37]
 [  24 2976]]
```

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)
```

```
mean_nl_test_loss: 0.04961981251835823
std_nl_test_loss: 0.02053568884730339
mean_abn_test_loss: 0.18577420711517334
std_abn_test_loss: 0.036086779087781906
Confusion Matrix:
 prediction: F      T
             1020   2980
 label: F   [[976   24]    1000
        T    [44   2956]]   3000
Accuracy = 0.983
Precision = 0.9919463087248322
Recall = 0.9853333333333333
```

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)
```

```
mean_nl_test_loss: 0.04961981251835823
std_nl_test_loss: 0.02053568884730339
mean_abn_test_loss: 0.18577420711517334
std_abn_test_loss: 0.036086779087781906
Confusion Matrix:
 prediction: F      T
             1133   2867
```

```
  label: F   [[993   7]    1000
             T    [140   2860]]   3000
 Accuracy = 0.96325
 Precision = 0.997558423439135
 Recall = 0.9533333333333334
```

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)
```