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 = 0
nl2 = 2
nl3 = 6
abn1 = 7
abn2 = 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
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
```

    ((16223, 28, 28), (16223,), (2387, 28, 28), (2387,), (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
```

```
((1777, 28, 28), (610, 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)
```

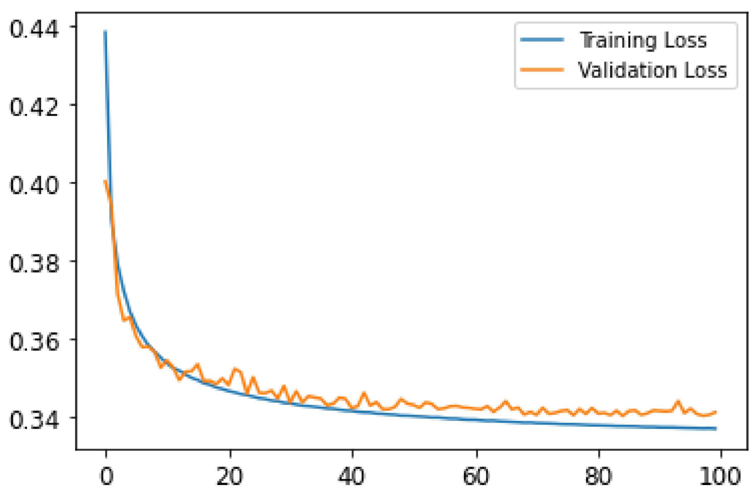
```
variational_decoder = keras.models.Model(inputs=[decoder_inputs], outputs=[outputs])

_, _, 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 73/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3383 - val_loss: 0.34
Epoch 74/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3383 - val_loss: 0.34
Epoch 75/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3381 - val_loss: 0.34
Epoch 76/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3381 - val_loss: 0.34
Epoch 77/100
126/127 [============================>.] - ETA: 0s - loss: 0.3381INFO:tensorflow:Asse
127/127 [==============================] - 3s 26ms/step - loss: 0.3381 - val_loss: 0.
Epoch 78/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3380 - val_loss: 0.34
Epoch 79/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3379 - val_loss: 0.34
Epoch 80/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3378 - val_loss: 0.34
Epoch 81/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3378 - val_loss: 0.34
Epoch 82/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3378 - val_loss: 0.34
Epoch 83/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3377 - val_loss: 0.34
Epoch 84/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3376 - val_loss: 0.34
Epoch 85/100
124/127 [===========================>..] - ETA: 0s - loss: 0.3377INFO:tensorflow:Asse
127/127 [==============================] - 3s 26ms/step - loss: 0.3376 - val_loss: 0.
Epoch 86/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3376 - val_loss: 0.34
Epoch 87/100
```

```
127/127 [==============================] - 1s 8ms/step - loss: 0.3376 - val_loss: 0.34
Epoch 88/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3375 - val_loss: 0.34
Epoch 89/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3374 - val_loss: 0.34
Epoch 90/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3374 - val_loss: 0.34
Epoch 91/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3373 - val_loss: 0.34
Epoch 92/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3373 - val_loss: 0.34
Epoch 93/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3373 - val_loss: 0.34
Epoch 94/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3372 - val_loss: 0.34
Epoch 95/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3372 - val_loss: 0.34
Epoch 96/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3371 - val_loss: 0.34
Epoch 97/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3371 - val_loss: 0.34
Epoch 98/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3370 - val_loss: 0.34
Epoch 99/100
127/127 [==============================] - 1s 8ms/step - loss: 0.3371 - 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 0x7fed2f902f10>
```




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

```
Model: "model_5"
____________________________________________________________________________
 Layer (type)                Output Shape              Param #   Trainable
```

```
==============================================================================
 input_3 (InputLayer)        [(None, 28, 28)]          0         Y

 model_3 (Functional)        [(None, 16),              244192    Y
                              (None, 16),
                              (None, 16)]
|---------------------------------------------------------------------------|
| input_3 (InputLayer)      [(None, 28, 28)]          0         Y          |
|                                                                           |
| flatten_1 (Flatten)       (None, 784)               0         Y          |
|                                                                           |
| dense_9 (Dense)           (None, 256)               200960    Y          |
|                                                                           |
| dense_10 (Dense)          (None, 128)               32896     Y          |
|                                                                           |
| dense_11 (Dense)          (None, 64)                8256      Y          |
|                                                                           |
| dense_12 (Dense)          (None, 16)                1040      Y          |
|                                                                           |
| dense_13 (Dense)          (None, 16)                1040      Y          |
|                                                                           |
| sampling_1 (Sampling)     (None, 16)                0         Y          |
-----------------------------------------------------------------------------
 model_4 (Functional)        (None, 28, 28)            243920    Y
|---------------------------------------------------------------------------|
| input_4 (InputLayer)      [(None, 16)]              0         Y          |
|                                                                           |
| dense_14 (Dense)          (None, 64)                1088      Y          |
|                                                                           |
| dense_15 (Dense)          (None, 128)               8320      Y          |
|                                                                           |
| dense_16 (Dense)          (None, 256)               33024     Y          |
|                                                                           |
| dense_17 (Dense)          (None, 784)               201488    Y          |
|                                                                           |
| reshape_1 (Reshape)       (None, 28, 28)            0         Y          |
-----------------------------------------------------------------------------

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

```python
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()
```

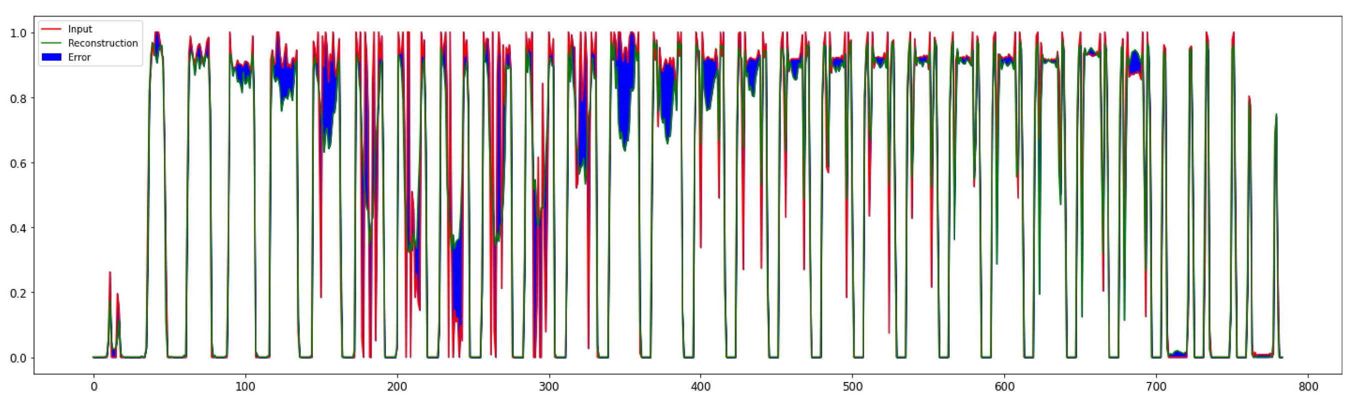
```
show_reconstructions(variational_ae, normal_test_data, 30)
plt.show()
```

```
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)
```

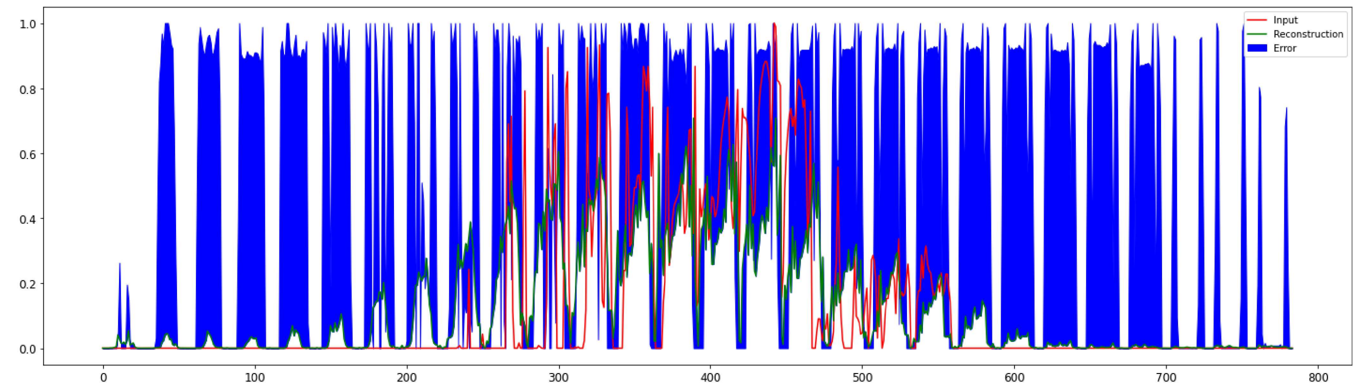
```
plt.figure(figsize=(25,7))
plt.plot(normal_test_data[0].ravel(), 'r')
plt.plot(reconstructions_nl_test[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), reconstructions_nl_test[0].ravel(), normal_test_data[0].ra
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```



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

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

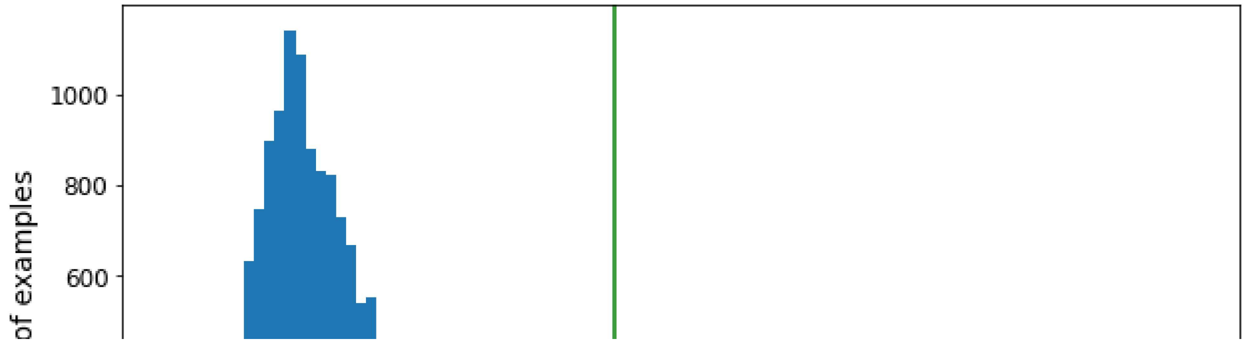
```
plt.figure(figsize=(25,7))
plt.plot(abnormal_test_data[0].ravel(), 'r')
plt.plot(reconstructions_abn_test[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), reconstructions_abn_test[0].ravel(), normal_test_data[0].r
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```



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:  0.052356128
Std:  0.022197621
```

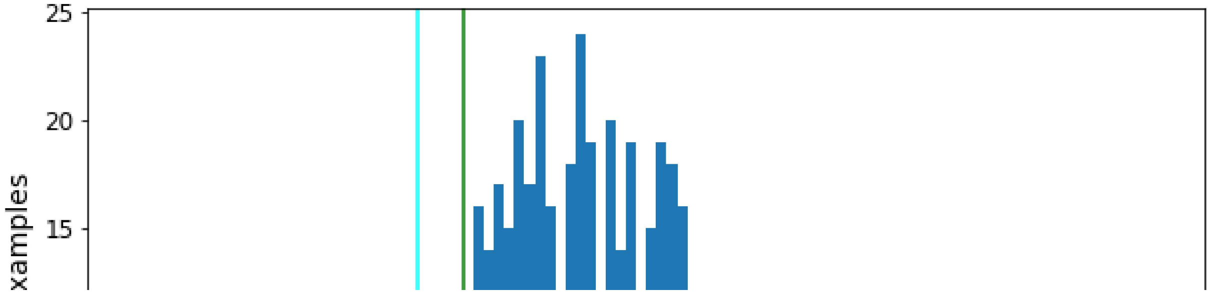
```
threshold_train_mean_2_5_std = np.mean(train_loss) + 2.5*np.std(train_loss)
print("Threshold based on the mean of the training data MAE reconstruction losses + 2.5 std:
```

```
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)
```

```
(0.122946754, 0.021634983)
```

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

```
Threshold2:  0.10131177
```

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)
```

```
(0.055079177, 0.0244427)
```

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

```
Threshold3:  0.07952188
```

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:  0.09041682630777359
```

```
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:  0.09783575057983412
```

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

```
array([[0.0964784 , 0.92626728],
       [0.09715707, 0.92794302],
       [0.09783575, 0.9287809 ],
       [0.09851443, 0.92752409],
       [0.0991931 , 0.9287809 ]])
```

```
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.

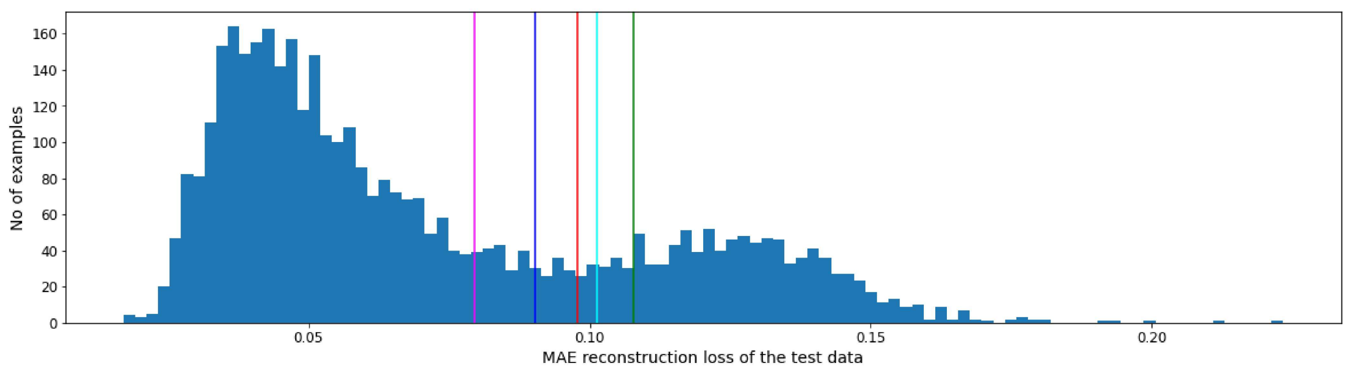
```
reconstructions = variational_ae.predict(valid_data)
valid_loss = tf.keras.losses.mae(reconstructions.reshape(-1,784), valid_data.reshape(-1,784))
plt.figure(figsize=(20,5))
plt.hist(valid_loss[None, :], bins=100)
plt.axvline(threshold, c='r')
plt.axvline(threshold4, c='b')
plt.axvline(threshold2, 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)
```

```
(0.054992806, 0.023722362)
```

```
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)
```

```
(0.12214983, 0.020931581)
```

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: 0.054992806166410446
std_nl_test_loss: 0.023722361773252487
mean_abn_test_loss: 0.12214983254671097
std_abn_test_loss: 0.020931581035256386
Confusion Matrix:
 prediction: F      T
            1040   2960
 label: F   [[870   130]    1000
       T    [170   2830]]   3000
Accuracy = 0.925
```

```
Precision = 0.956081081081081
Recall = 0.9433333333333334
```

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

```
[[ 870  130]
 [ 170 2830]]
```

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: 0.054992806166410446
std_nl_test_loss: 0.023722361773252487
mean_abn_test_loss: 0.12214983254671097
std_abn_test_loss: 0.020931581035256386
Confusion Matrix:
 prediction: F      T
            1149   2851
 label: F   [[923   77]    1000
        T    [226   2774]]   3000
Accuracy = 0.92425
Precision = 0.9729919326552087
Recall = 0.9246666666666666
```

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: 0.054992806166410446
std_nl_test_loss: 0.023722361773252487
mean_abn_test_loss: 0.12214983254671097
std_abn_test_loss: 0.020931581035256386
Confusion Matrix:
 prediction: F      T
            889   3111
 label: F   [[770   230]    1000
```

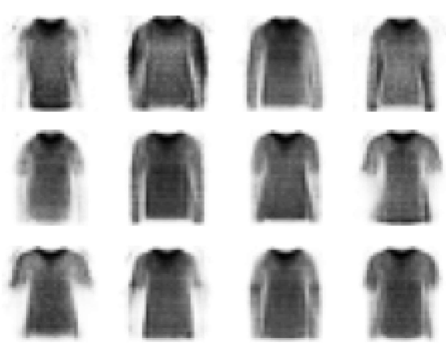
```
        T    [119   2881]]   3000
 Accuracy = 0.91275
 Precision = 0.9260687881710061
 Recall = 0.9603333333333334
```

Extra Info

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

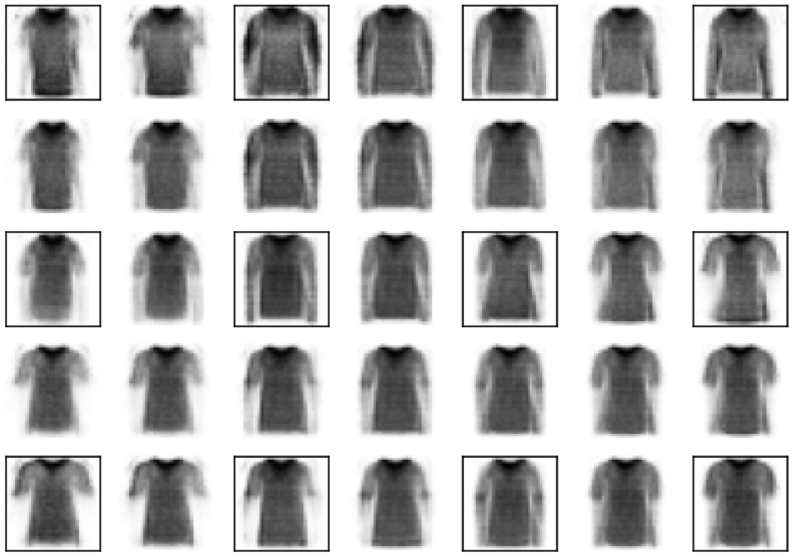
```
def plot_multiple_images(images, n_cols=None):
    n_cols = n_cols or len(images)
    n_rows = (len(images) - 1) // n_cols + 1
    if images.shape[-1] == 1:
        images = np.squeeze(images, axis=-1)
    plt.figure(figsize=(n_cols, n_rows))
    for index, image in enumerate(images):
        plt.subplot(n_rows,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



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