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

This file trains a modified VAE (with a different sampling layer and a different loss function) 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
```

```
# 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
```

```
((16219, 28, 28), (16219,), (2392, 28, 28), (2392,), (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
```

```
((1781, 28, 28), (611, 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))
```

```
# Modified sampling layer with the addition of mean_2, log_var_2, and fraction p, with
# the appropriate change in the reparametrization trick to do stochastic
# sampling from the superposition of the two MVN distributions, while allowing
# the 5 parallel layers containing the means and stds of the two MVNs and the fractions p's
# for each dimension to be trained via backpropogation of the error signal.
class Sampling(keras.layers.Layer):
    def call(self, inputs):
        mean_1, log_var_1, mean_2, log_var_2, p = inputs
        return (K.random_normal(tf.shape(log_var_1)) * K.exp(log_var_1 / 2) + mean_1)*p + (K.
```

```
# For details please see Geron's book.
codings_size = 16  # The number of dimensions of the two MVN distributions in the sampling la

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)

# Adding output nodes (parallel layers) at the end of the encoder for means
# and standard deviations of a second Multivariate Normal (MVN) distribution
# in the dimensions of the coding size (here 32). In each of the dimensions,
# this first MVN is multiplied by a fraction p and added to the second MVN
# multiplied by 1 - p in each dimension.
# final distribution = p * first MVN + (1 - p) * second MVN
# Another parallel layer (set of nodes) is added to keep and train the fractions p's
# in each dimension
codings_mean_1 = keras.layers.Dense(codings_size)(z)
codings_log_var_1 = keras.layers.Dense(codings_size)(z)
codings_mean_2 = keras.layers.Dense(codings_size)(z)
codings_log_var_2 = keras.layers.Dense(codings_size)(z)
codings_p = keras.layers.Dense(1, activation='sigmoid')(z)
```

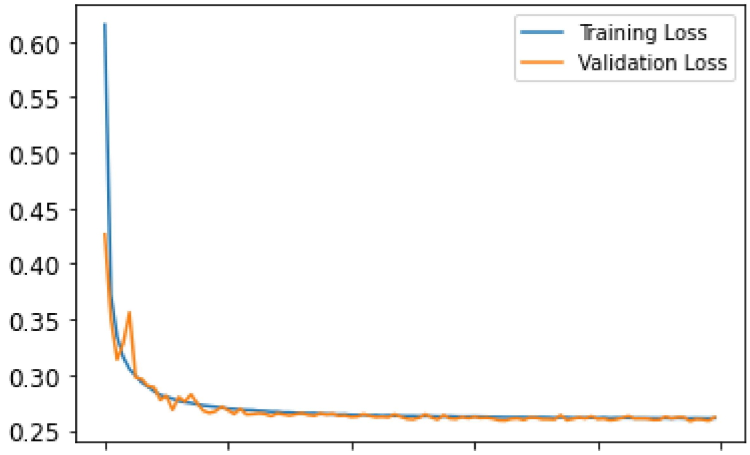
```
# Modified sampling layer at the end of the encoder
codings = Sampling()([codings_mean_1, codings_log_var_1, codings_mean_2, codings_log_var_2, c
variational_encoder = keras.models.Model(
    inputs=[inputs], outputs=[codings_mean_1, codings_log_var_1, codings_mean_2, codings_log_

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])

# New latent loss function that will be added to the reconstruction binary cross-entropy loss
# The whole network (Encoder, sampling layer, and decoder) will train to minimize this loss
p_mean = K.mean(codings_p)
array1 = p_mean*(codings_log_var_1 - K.exp(codings_log_var_1) - K.square(codings_mean_1))
array2 = (1-p_mean)*(codings_log_var_2 - K.exp(codings_log_var_2) - K.square(codings_mean_2))
sum1 = K.sum(1 + array1, axis=-1)
sum2 = K.sum(1 + array2, axis=-1)

latent_loss = -0.5 * (sum1 + sum2)

latent_loss = latent_loss * 16

# 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 (same as regular VAE).
# 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("modVAE_latent_times_16_model", monitor="val_

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

```
Epoch 72/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2619 - val_loss: 0.
Epoch 73/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2618 - val_loss: 0.
Epoch 74/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2615 - val_loss: 0.
Epoch 75/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2618 - val_loss: 0.
Epoch 76/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2619 - val_loss: 0.
Epoch 77/100
```

```
Epoch 77/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2615 - val_loss: 0.
Epoch 78/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2615 - val_loss: 0.
Epoch 79/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2615 - val_loss: 0.
Epoch 80/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2614 - val_loss: 0.
Epoch 81/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2613 - val_loss: 0.
Epoch 82/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2617 - val_loss: 0.
Epoch 83/100
127/127 [==============================] - 1s 12ms/step - loss: 0.2613 - val_loss: 0.
Epoch 84/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2616 - val_loss: 0.
Epoch 85/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2613 - val_loss: 0.
Epoch 86/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2613 - val_loss: 0.
Epoch 87/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2612 - val_loss: 0.
Epoch 88/100
127/127 [==============================] - 1s 12ms/step - loss: 0.2612 - val_loss: 0.
Epoch 89/100
127/127 [==============================] - 1s 12ms/step - loss: 0.2611 - val_loss: 0.
Epoch 90/100
127/127 [==============================] - 1s 12ms/step - loss: 0.2611 - val_loss: 0.
Epoch 91/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2611 - val_loss: 0.
Epoch 92/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2611 - val_loss: 0.
Epoch 93/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2609 - val_loss: 0.
Epoch 94/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2612 - val_loss: 0.
Epoch 95/100
127/127 [==============================] - 1s 12ms/step - loss: 0.2610 - val_loss: 0.
Epoch 96/100
125/127 [============================>.] - ETA: 0s - loss: 0.2610INFO:tensorflow:Asse
127/127 [==============================] - 5s 40ms/step - loss: 0.2610 - val_loss: 0.
Epoch 97/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2611 - val_loss: 0.
Epoch 98/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2610 - val_loss: 0.
Epoch 99/100
127/127 [==============================] - 1s 11ms/step - loss: 0.2609 - val_loss: 0.
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 0x7fc656aca150>
```




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

```
 )                                                        'tf.math.exp_2[0][0

 tf.math.square_2 (TFOpLambda)  (None, 16)         0     ['dense_15[0][0]']

 tf.math.subtract_8 (TFOpLambda  (None, 16)        0     ['dense_18[0][0]',
 )                                                        'tf.math.exp_3[0][0

 tf.math.square_3 (TFOpLambda)  (None, 16)         0     ['dense_17[0][0]']

 tf.math.subtract_6 (TFOpLambda  (None, 16)        0     ['tf.math.subtract_5
 )                                                        'tf.math.square_2[0

 tf.math.subtract_7 (TFOpLambda  ()                0     ['tf.math.reduce_mea
 )

 tf.math.subtract_9 (TFOpLambda  (None, 16)        0     ['tf.math.subtract_8
 )                                                        'tf.math.square_3[0

 tf.math.multiply_4 (TFOpLambda  (None, 16)        0     ['tf.math.reduce_mea
 )                                                        'tf.math.subtract_6

 tf.math.multiply_5 (TFOpLambda  (None, 16)        0     ['tf.math.subtract_7
 )                                                        'tf.math.subtract_9

 tf.__operators__.add_3 (TFOpLa  (None, 16)        0     ['tf.math.multiply_4
 mbda)

 tf.__operators__.add_4 (TFOpLa  (None, 16)        0     ['tf.math.multiply_5
 mbda)

 tf.math.reduce_sum_2 (TFOpLamb  (None,)           0     ['tf.__operators__.a
 da)                                                     ]

 tf.math.reduce_sum_3 (TFOpLamb  (None,)           0     ['tf.__operators__.a
 da)                                                     ]

 tf.__operators__.add_5 (TFOpLa  (None,)           0     ['tf.math.reduce_sum_
 mbda)                                                    'tf.math.reduce_sum_
```

```
 tf.math.multiply_6 (TFOpLambda  (None,)              0           ['tf.__operators__.a
 )                                                                ]

 tf.math.multiply_7 (TFOpLambda  (None,)              0           ['tf.math.multiply_6
 )

 tf.math.reduce_mean_3 (TFOpLam  ()                   0           ['tf.math.multiply_7
 bda)

 tf.math.truediv_1 (TFOpLambda)  ()                   0           ['tf.math.reduce_mea

 add_loss_1 (AddLoss)          ()                     0           ['tf.math.truediv_1[(

==================================================================================
Total params: 490,257
Trainable params: 490,257
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=test_data, 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()
```

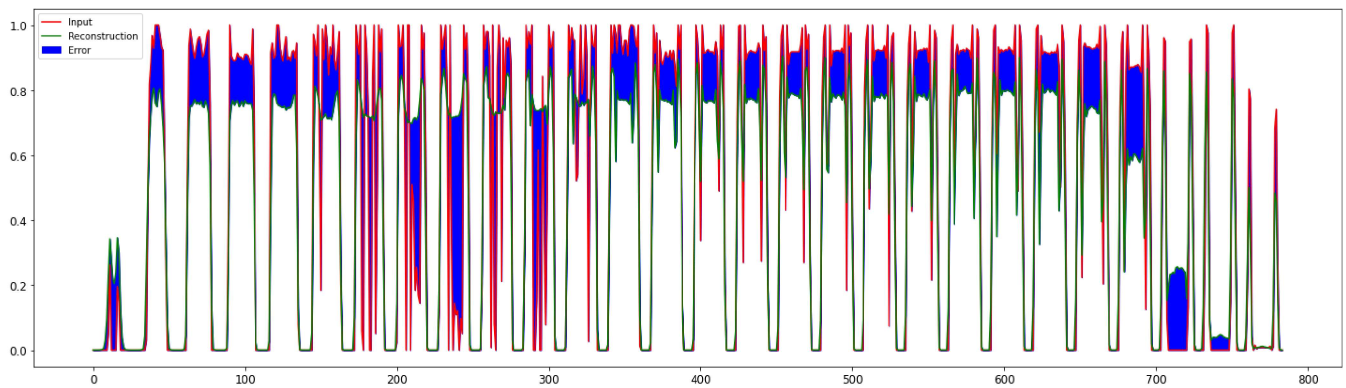
```
show_reconstructions(variational_ae, normal_test_data, 30)
plt.show()
```

```
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)
```

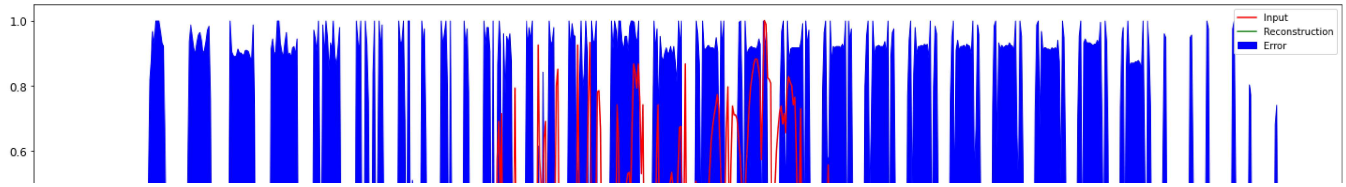
```
plt.figure(figsize=(25,7))
plt.plot(normal_test_data[0].ravel(), 'r')
plt.plot(reconstructions_nl_test[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), reconstructions_nl_test[0].ravel(), normal_test_data[0].ra
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```



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

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

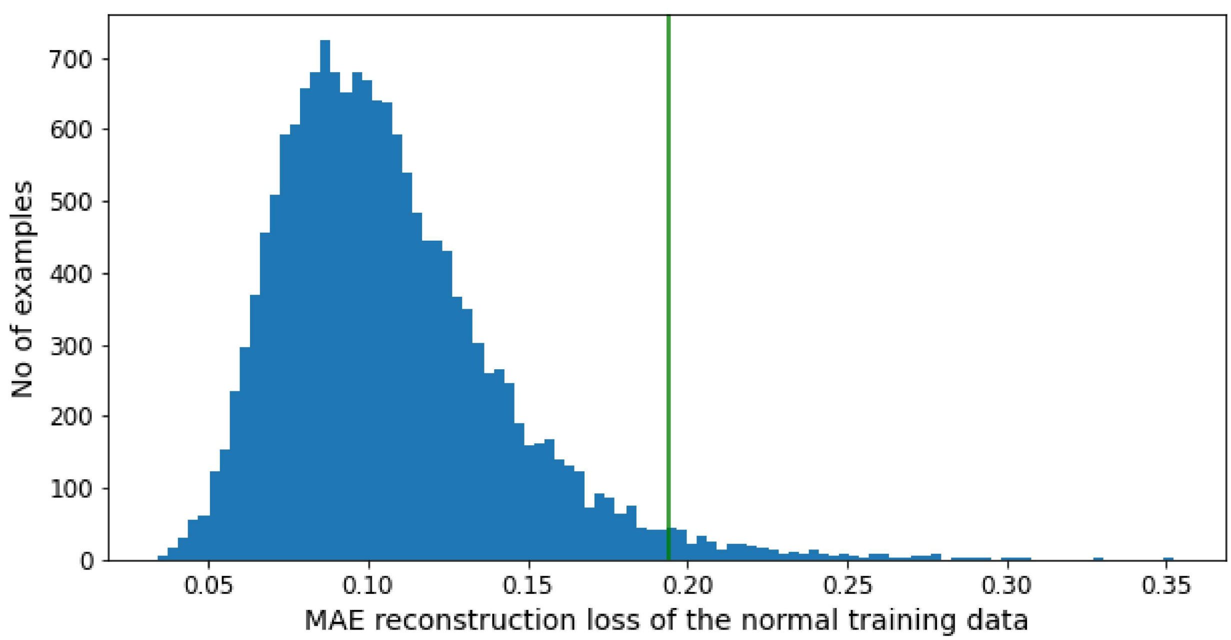
```
plt.figure(figsize=(25,7))
plt.plot(abnormal_test_data[0].ravel(), 'r')
plt.plot(reconstructions_abn_test[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), reconstructions_abn_test[0].ravel(), normal_test_data[0].r
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```



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:  0.10631974
Std:  0.035087824
```

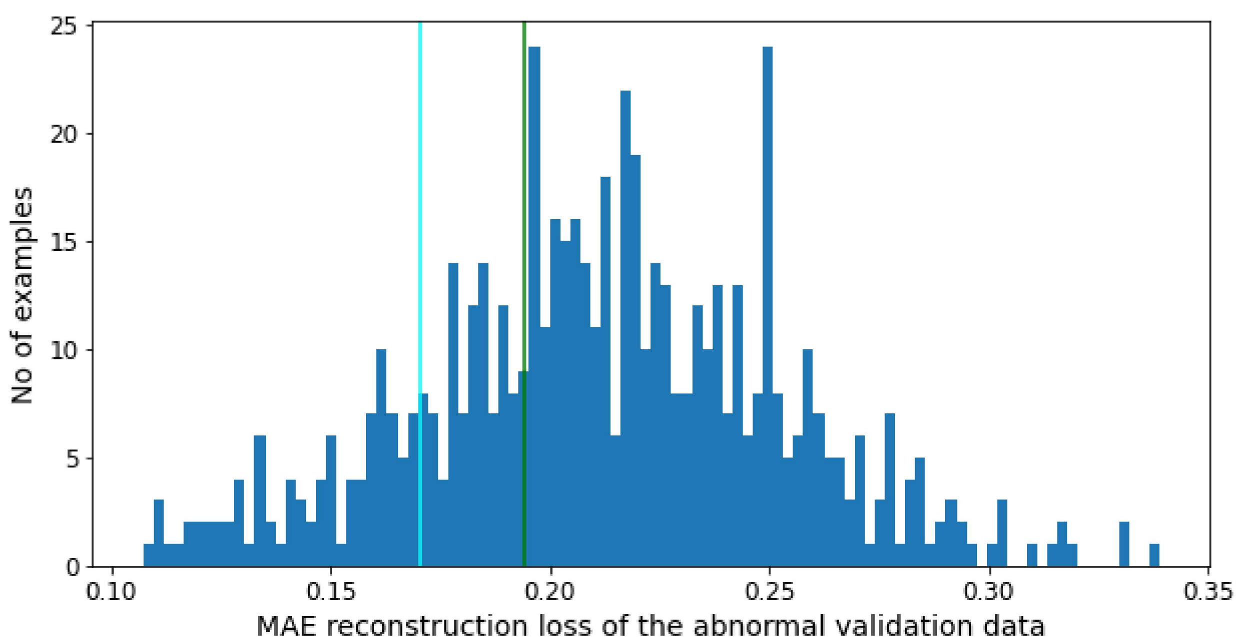
```
threshold_train_mean_2_5_std = np.mean(train_loss) + 2.5*np.std(train_loss)
print("Threshold based on the mean of the training data MAE reconstruction losses + 2.5 std:
```

```
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)
```

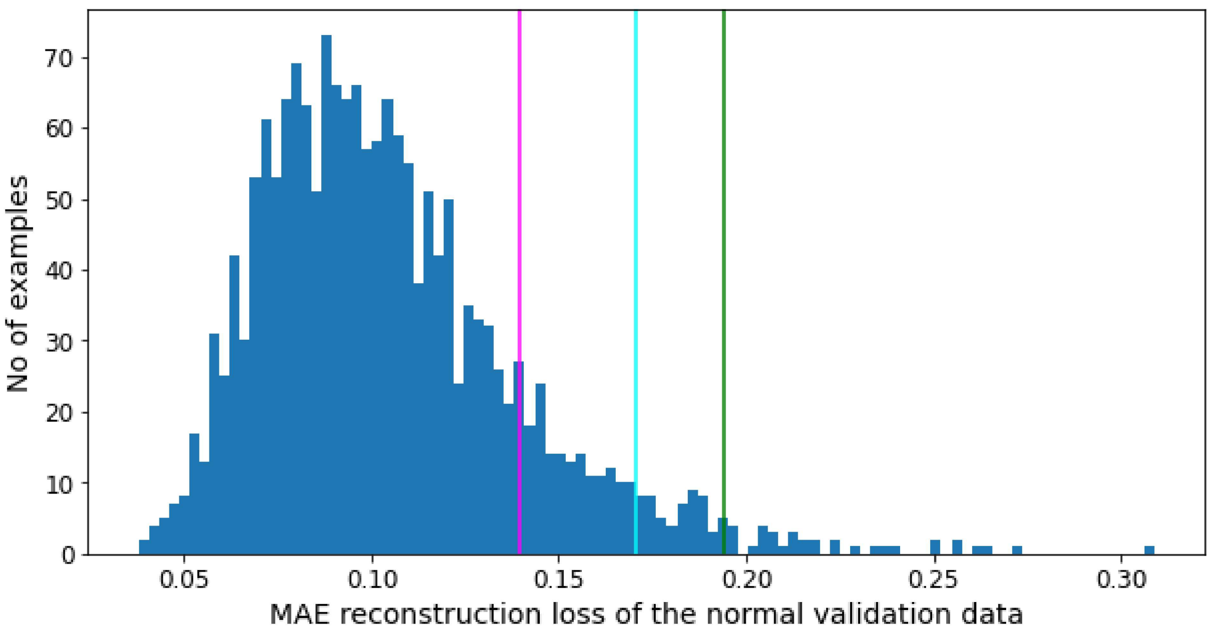
```
(0.21181376, 0.041259747)
```

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

```
Threshold2:  0.17055401
```

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)
```

```
(0.10467548, 0.03498847)
```

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

```
Threshold3:  0.13966395
```

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:  0.1551089882850647
```

```
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:  0.17217259787023081
```

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

```
array([[0.17002983, 0.92516722],
       [0.17110122, 0.92976589],
       [0.1721726 , 0.93018395],
       [0.17324398, 0.92683946],
       [0.17431536, 0.92140468]])
```

```
threshold5 = valid_data_best_threshold
```

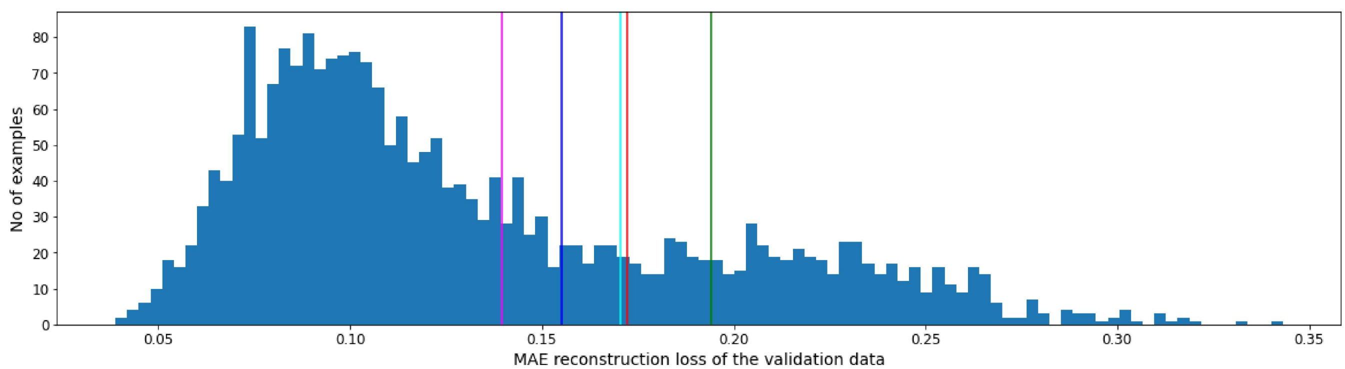
```
threshold = threshold5
```

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()
```



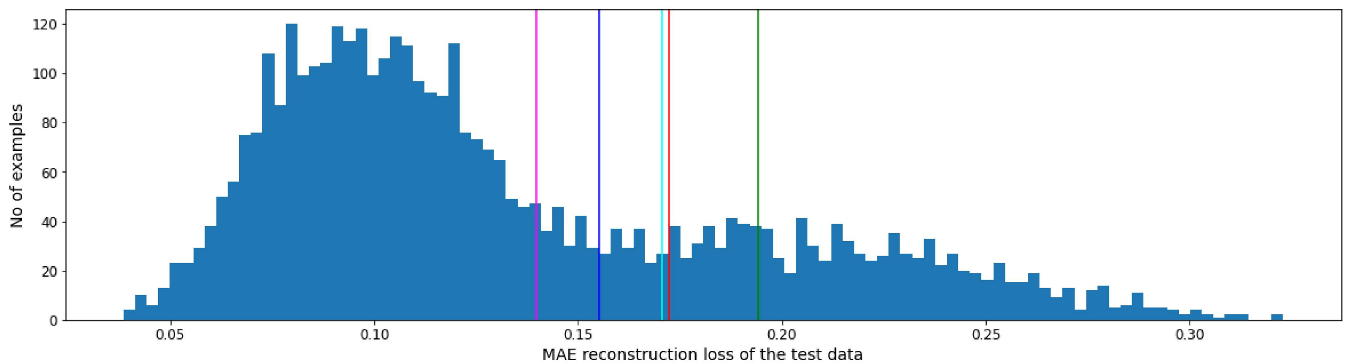
Distribution of the reconstruction losses of the test data (normal and abnormal)

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)
```

```
(0.10660073, 0.03554992)
```

```
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)
```

```
(0.21350326, 0.04092715)
```

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: 0.10660073161125183
std_nl_test_loss: 0.03554992005228996
mean_abn_test_loss: 0.21350325644016266
std_abn_test_loss: 0.04092714935541153
Confusion Matrix:
 prediction: F      T
            1001   2999
 label: F   [[831   169]    1000
        T    [170   2830]]   3000
Accuracy = 0.91525
Precision = 0.9436478826275425
Recall = 0.9433333333333334
```

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

```
[[ 831  169]
 [ 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: 0.10660073161125183
std_nl_test_loss: 0.03554992005228996
mean_abn_test_loss: 0.21350325644016266
std_abn_test_loss: 0.04092714935541153
Confusion Matrix:
 prediction: F      T
             1181   2819
 label: F   [[920   80]    1000
        T    [261   2739]]   3000
Accuracy = 0.91475
Precision = 0.9716211422490245
Recall = 0.913
```

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: 0.10660073161125183
std_nl_test_loss: 0.03554992005228996
mean_abn_test_loss: 0.21350325644016266
std_abn_test_loss: 0.04092714935541153
Confusion Matrix:
 prediction: F      T
             776   3224
 label: F   [[690   310]    1000
        T    [86   2914]]   3000
Accuracy = 0.901
Precision = 0.9038461538461539
Recall = 0.9713333333333334
```

Extra Info

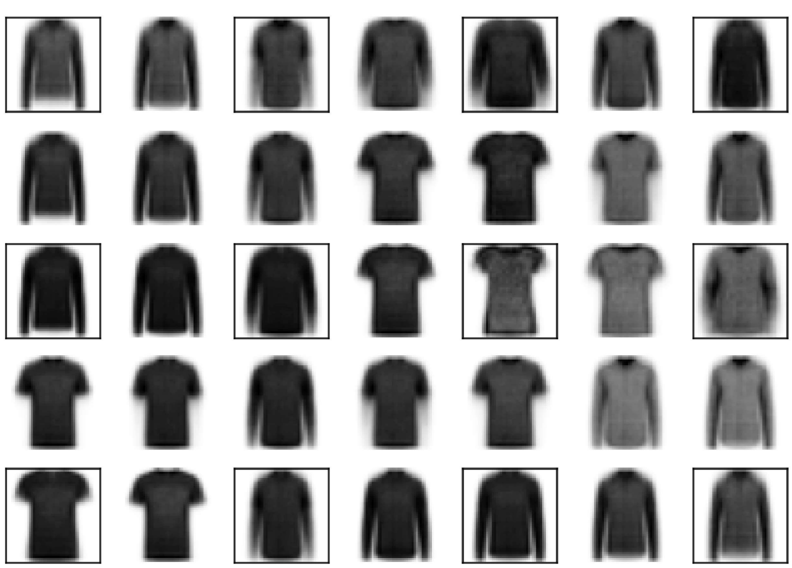
Giving the VAE codings (please see book) (Just informative, not the goal here)

```
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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