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 = 6
nl2 = 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 = 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

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

```
((5399, 28, 28), (5399,), (1169, 28, 28), (1169,), (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
```

```
((601, 28, 28), (568, 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.)
```

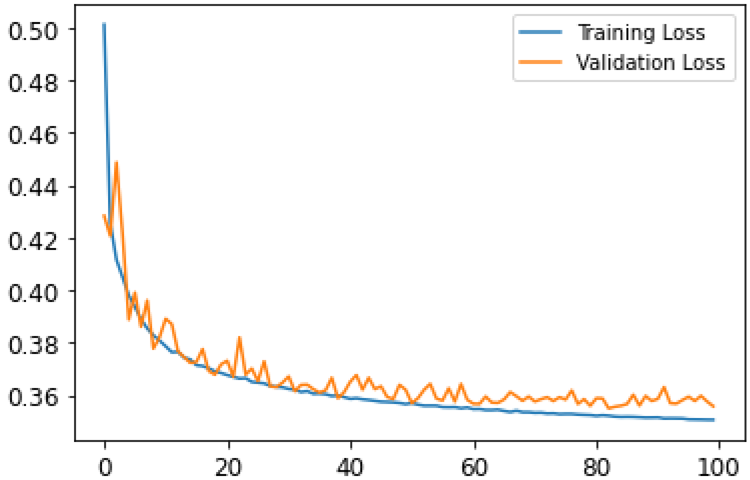
```
# For the reconstruction loss binary cross-entropy loss is used.
# For details please see Chapter 17 of Geron's book (Stacked AE and VAE sections)
variational_ae.compile(loss="binary_crossentropy", optimizer="rmsprop")

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)
```

```
43/43 [==============================] - 0s 8ms/step - loss: 0.3533 - val_loss: 0.3585
Epoch 73/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3530 - val_loss: 0.3592
Epoch 74/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3531 - val_loss: 0.3578

Epoch 75/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3528 - val_loss: 0.3592
Epoch 76/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3529 - val_loss: 0.3583
Epoch 77/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3529 - val_loss: 0.3618
Epoch 78/100
36/43 [========================>.....] - ETA: 0s - loss: 0.3530INFO:tensorflow:Assets written t
43/43 [==============================] - 3s 66ms/step - loss: 0.3526 - val_loss: 0.3566
Epoch 79/100
43/43 [==============================] - 0s 8ms/step - loss: 0.3525 - val_loss: 0.3585
Epoch 80/100
42/43 [============================>.] - ETA: 0s - loss: 0.3525INFO:tensorflow:Assets written t
43/43 [==============================] - 3s 66ms/step - loss: 0.3524 - val_loss: 0.3559
Epoch 81/100
43/43 [==============================] - 0s 8ms/step - loss: 0.3521 - val_loss: 0.3589
Epoch 82/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3524 - val_loss: 0.3588
Epoch 83/100
37/43 [========================>.....] - ETA: 0s - loss: 0.3516INFO:tensorflow:Assets written t
43/43 [==============================] - 3s 71ms/step - loss: 0.3522 - val_loss: 0.3550
Epoch 84/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3519 - val_loss: 0.3556
Epoch 85/100
43/43 [==============================] - 0s 8ms/step - loss: 0.3517 - val_loss: 0.3560
Epoch 86/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3518 - val_loss: 0.3567
Epoch 87/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3517 - val_loss: 0.3602
Epoch 88/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3516 - val_loss: 0.3560
Epoch 89/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3515 - val_loss: 0.3597
Epoch 90/100
43/43 [==============================] - 0s 8ms/step - loss: 0.3515 - val_loss: 0.3578
Epoch 91/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3515 - val_loss: 0.3586
Epoch 92/100
43/43 [==============================] - 0s 8ms/step - loss: 0.3511 - val_loss: 0.3631
Epoch 93/100
43/43 [==============================] - 0s 8ms/step - loss: 0.3512 - val_loss: 0.3570
Epoch 94/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3512 - val_loss: 0.3568
Epoch 95/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3511 - val_loss: 0.3581
```

```
Epoch 96/100
43/43 [==============================] - 0s 8ms/step - loss: 0.3508 - val_loss: 0.3594
Epoch 97/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3507 - val_loss: 0.3578
Epoch 98/100
43/43 [==============================] - 0s 9ms/step - loss: 0.3507 - val_loss: 0.3598
Epoch 99/100
```

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

```
<matplotlib.legend.Legend at 0x7f4e27933ad0>
```




```
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)), 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()
```

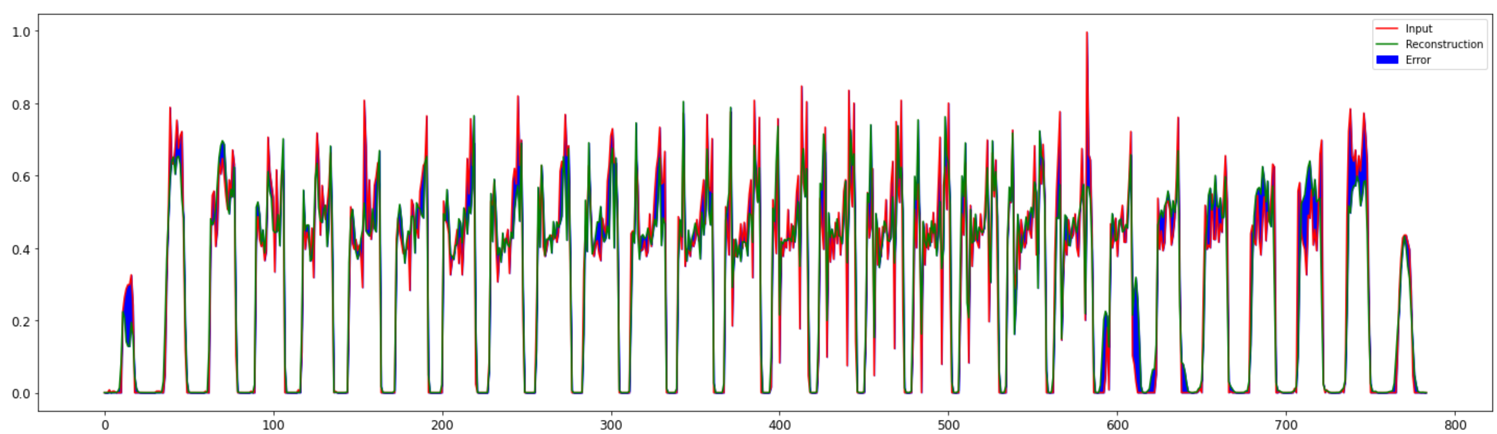
```
show_reconstructions(variational_ae, normal_test_data, 30)
plt.show()
```

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

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

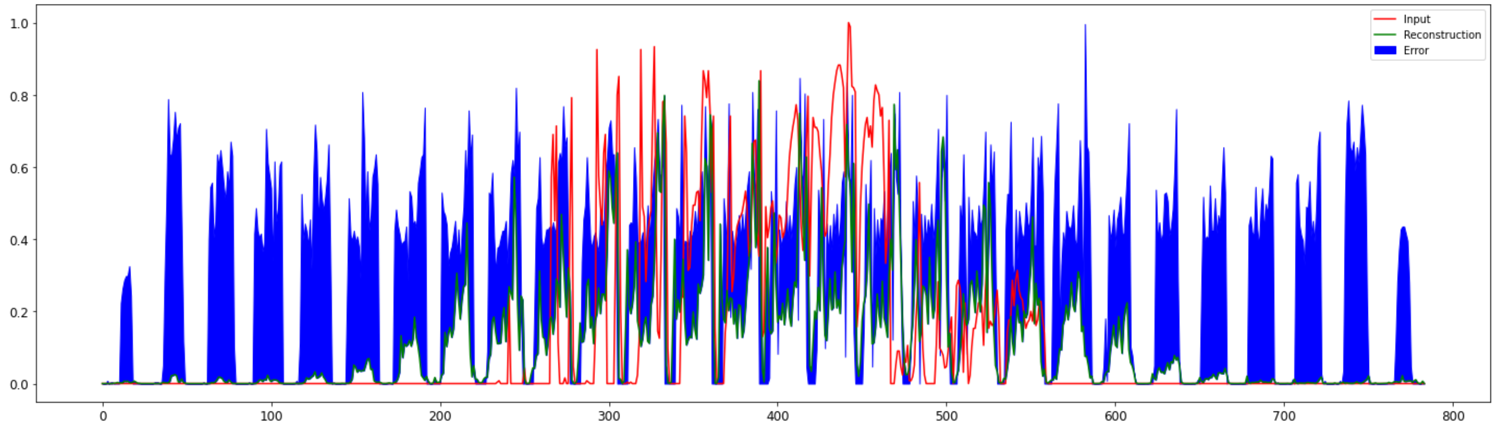
```
reconstructions_nl_test = variational_ae.predict(normal_test_data)
```

```
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

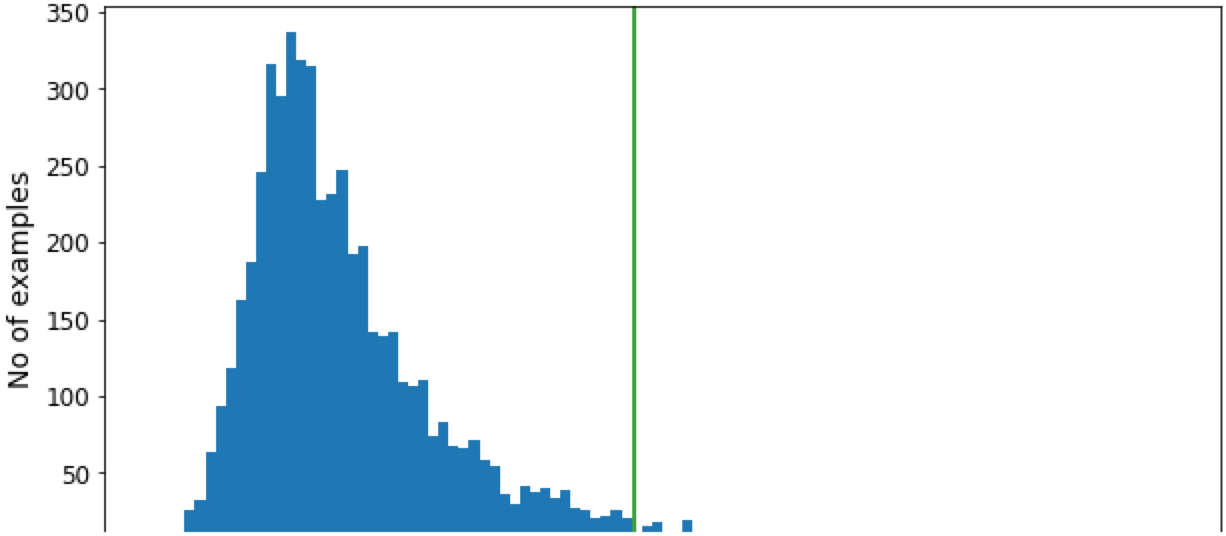
```
reconstructions_abn_test = variational_ae.predict(abnormal_test_data)


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:  0.05909251
Std:  0.023139345
```

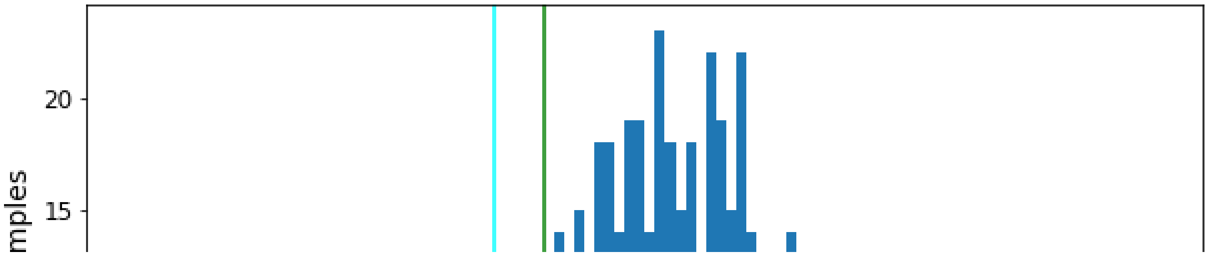
```
threshold_train_mean_2_5_std = np.mean(train_loss) + 2.5*np.std(train_loss)
print("Threshold based on the mean of the training data MAE reconstruction losses + 2.5 std: ", thresho
```

```
Threshold based on the mean of the training data MAE reconstruction losses + 2.5 std:  0.11694087
```

```
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)
```

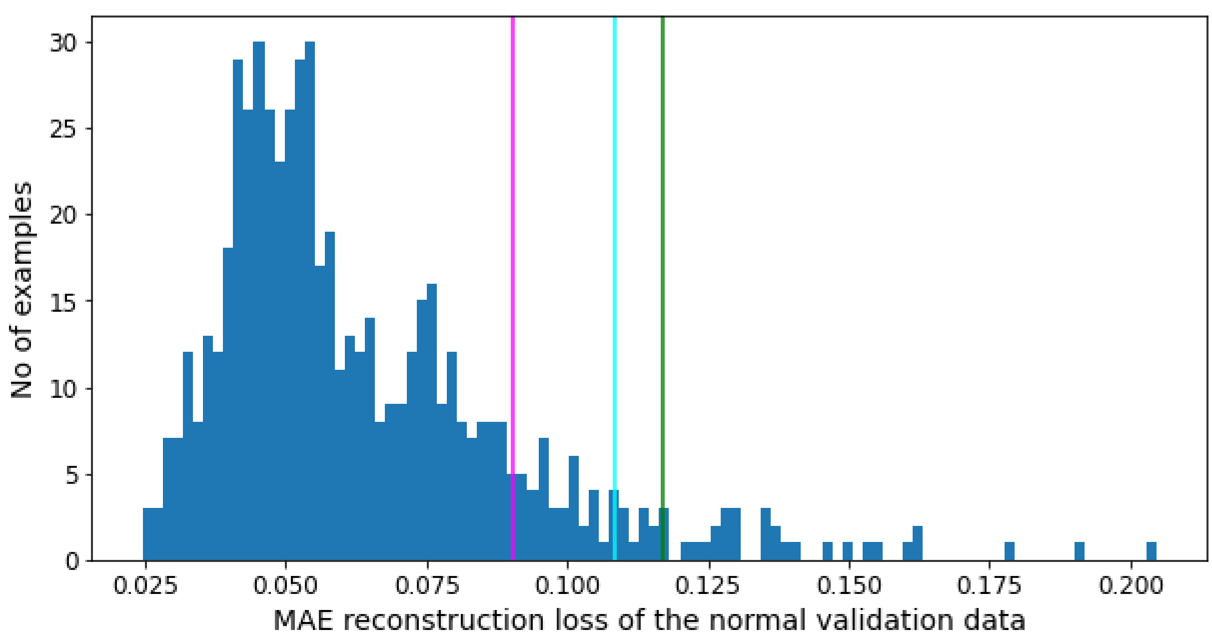
```
(0.13290054, 0.024282277)
```

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

```
Threshold2:  0.10861826
```

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)
```

```
(0.06357389, 0.026865857)
```

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

```
Threshold3:  0.090439744
```

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:  0.09952899813652039
```

```
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:  0.09546414688229574
```

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

```
array([[0.09407761, 0.90761334],
       [0.09477088, 0.90761334],
       [0.09546415, 0.90846878],
       [0.09615741, 0.90675791],
       [0.09685068, 0.90504705]])
```

```
threshold5 = valid_data_best_threshold
```

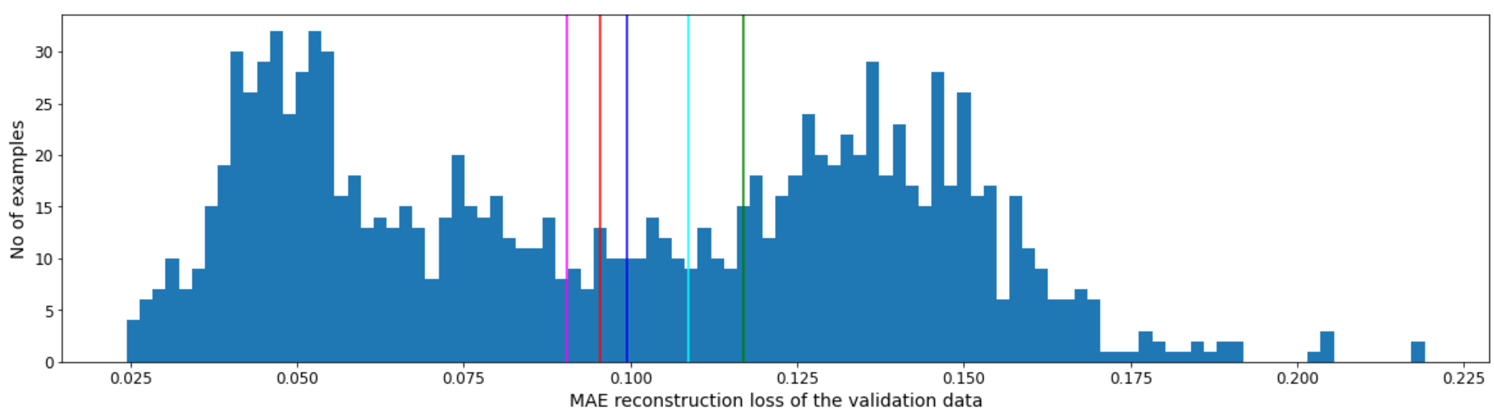
```
threshold = threshold5
```

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()
```

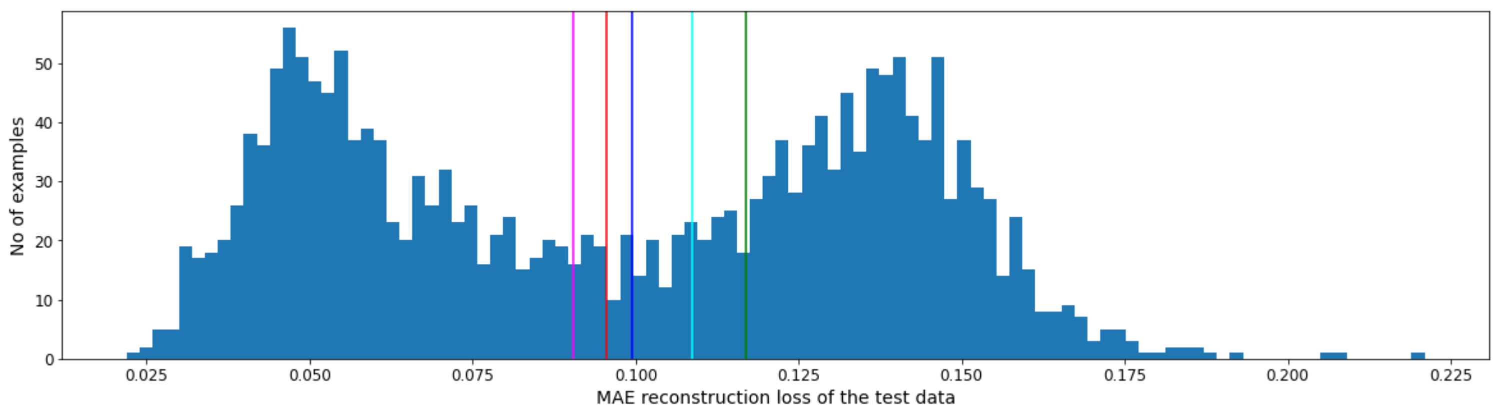


Distribution of the reconstruction losses of the test data (normal and abnormal)

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)
```

```
(0.06329051, 0.025211478)
```

```
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)
```

```
(0.13200705, 0.021519624)
```

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 
             1031   969
 label: F   [[937   63]    1000
        T    [94   906]]   1000
Accuracy = 0.9215
Normal Test Data Mean = 0.06329050660133362
Normal Test Data Standard Deviation = 0.025211477652192116
Abnormal Test Data Mean = 0.13200704753398895
Abnormal Test Data Standard Deviation = 0.021519623696804047
Precision = 0.934984520123839
Recall = 0.906
0.9215
0.06329051
0.025211478
0.13200705
0.021519624
0.934984520123839
0.906
0.9215 0.06329051 0.025211478 0.13200705 0.021519624 0.934984520123839 0.906
```

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

```
Threshold = 0.09546414688229574
```

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

```
[[937  63]
 [ 94 906]]
```

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
            1002   998
 label: F   [[920   80]    1000
        T    [82   918]]   1000
Accuracy = 0.919
Normal Test Data Mean = 0.06329050660133362
Normal Test Data Standard Deviation = 0.025211477652192116
Abnormal Test Data Mean = 0.13200704753398895
Abnormal Test Data Standard Deviation = 0.021519623696804047
Precision = 0.9198396793587175
Recall = 0.918
0.919
0.06329051
0.025211478
0.13200705
0.021519624
0.9198396793587175
0.918
0.919 0.06329051 0.025211478 0.13200705 0.021519624 0.9198396793587175 0.918
```

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
            827   1173
 label: F   [[783   217]    1000
        T    [44   956]]   1000
Accuracy = 0.8695
```

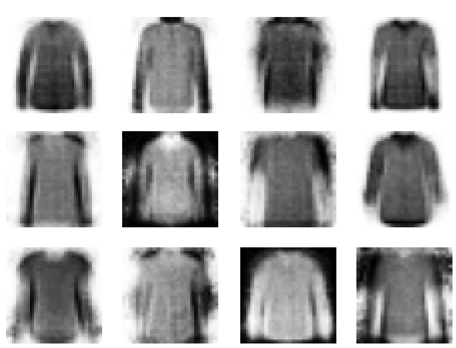
```
Normal Test Data Mean = 0.06329050660133362
Normal Test Data Standard Deviation = 0.025211477652192116
Abnormal Test Data Mean = 0.13200704753398895
Abnormal Test Data Standard Deviation = 0.021519623696804047
Precision = 0.815004262574595
Recall = 0.956
0.8695
0.06329051
0.025211478
0.13200705
0.021519624
0.815004262574595
0.956
0.8695 0.06329051 0.025211478 0.13200705 0.021519624 0.815004262574595 0.956
```

Extra Info

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

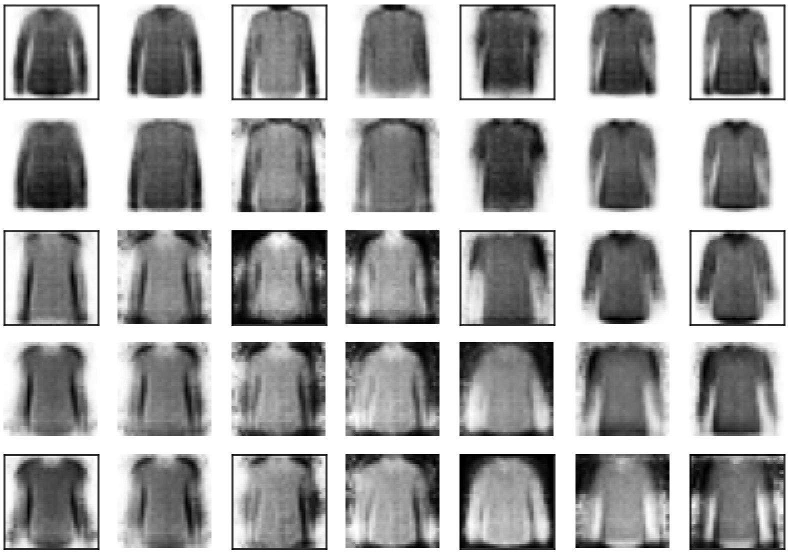
```
def plot_multiple_images(images, n_cols=None):
    n_cols = n_cols or len(images)
    n_rows = (len(images) - 1) // n_cols + 1
    if images.shape[-1] == 1:
        images = np.squeeze(images, axis=-1)
    plt.figure(figsize=(n_cols, n_rows))
    for index, image in enumerate(images):
        plt.subplot(n_rows,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