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
# 7 Sneaker
# 8 Bag
# 9 Ankle boot

nl1 = 9
```

```
nl2 = 9
abn1 = 3
abn2 = 3
(x_train_0, y_train_0), (x_test, y_test) = keras.datasets.fashion_mnist.load_data()

x_train_0 = x_train_0.astype(np.float32) / 255
x_test = x_test.astype(np.float32) / 255

train_size = x_train_0.shape[0] * 9 // 10

x_train, x_valid, y_train, y_valid = train_test_split(x_train_0, y_train_0, train_size = train_size)

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

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

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

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

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


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

```
((5408, 28, 28), (5408,), (1180, 28, 28), (1180,), (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
```

```
((592, 28, 28), (588, 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.random_nor


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

# 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, codings_p])
variational_encoder = keras.models.Model(
    inputs=[inputs], outputs=[codings_mean_1, codings_log_var_1, codings_mean_2, codings_log_var_2, cod

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)) # *  codi
sum1 = K.sum(1 + array1, axis=-1)
sum2 = K.sum(1 + array2, axis=-1)

# latent_loss = -0.5 * tf.math.maximum(sum1, sum2)

latent_loss = -0.5 * (sum1 + sum2)

latent_loss = latent_loss * 0.5

# 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_half_model", monitor="val_loss", s

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)
```

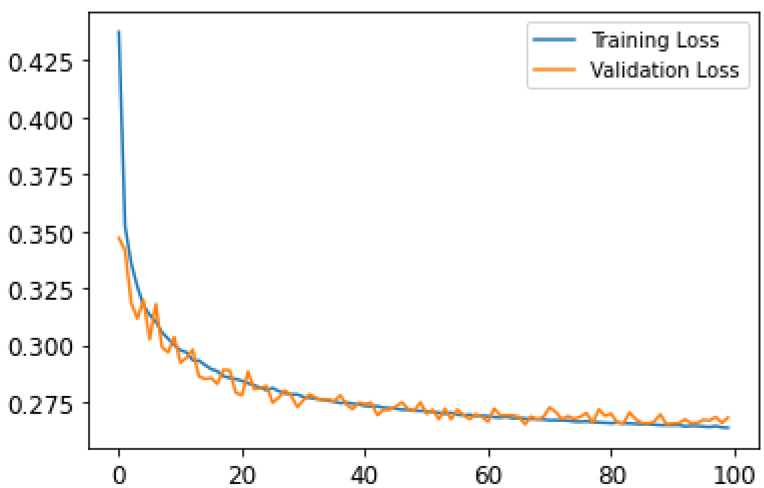
```
Epoch 71/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2670 - val_loss: 0.2727
Epoch 72/100
43/43 [==============================] - 1s 12ms/step - loss: 0.2671 - val_loss: 0.2706
Epoch 73/100
43/43 [==============================] - 1s 12ms/step - loss: 0.2669 - val_loss: 0.2675
Epoch 74/100
43/43 [==============================] - 1s 12ms/step - loss: 0.2669 - val_loss: 0.2688
Epoch 75/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2665 - val_loss: 0.2676
Epoch 76/100
43/43 [==============================] - 1s 12ms/step - loss: 0.2664 - val_loss: 0.2685
Epoch 77/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2666 - val_loss: 0.2702
Epoch 78/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2662 - val_loss: 0.2658
Epoch 79/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2660 - val_loss: 0.2718
Epoch 80/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2659 - val_loss: 0.2689
Epoch 81/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2657 - val_loss: 0.2699
Epoch 82/100
43/43 [==============================] - 1s 12ms/step - loss: 0.2660 - val_loss: 0.2660
Epoch 83/100
43/43 [==============================] - 1s 12ms/step - loss: 0.2657 - val_loss: 0.2656
Epoch 84/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2656 - val_loss: 0.2705
Epoch 85/100
43/43 [==============================] - 1s 14ms/step - loss: 0.2654 - val_loss: 0.2674
```

```
Epoch 86/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2652 - val_loss: 0.2658
Epoch 87/100
43/43 [==============================] - 1s 14ms/step - loss: 0.2653 - val_loss: 0.2656
Epoch 88/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2651 - val_loss: 0.2664
Epoch 89/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2649 - val_loss: 0.2696
Epoch 90/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2649 - val_loss: 0.2653
Epoch 91/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2648 - val_loss: 0.2656
Epoch 92/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2649 - val_loss: 0.2657
Epoch 93/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2643 - val_loss: 0.2674
Epoch 94/100
43/43 [==============================] - 1s 12ms/step - loss: 0.2645 - val_loss: 0.2658

Epoch 95/100
43/43 [==============================] - 1s 13ms/step - loss: 0.2645 - val_loss: 0.2658
Epoch 96/100
43/43 [==============================] - 1s 12ms/step - loss: 0.2642 - val_loss: 0.2672
Epoch 97/100
43/43 [==============================] - 1s 12ms/step - loss: 0.2640 - val_loss: 0.2669
Epoch 98/100
43/43 [==============================] - 1s 12ms/step - loss: 0.2644 - val_loss: 0.2684
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 0x7fe2ea6e8d10>
```




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

```
bda)

 tf.math.subtract_5 (TFOpLambda  (None, 16)          0           ['dense_16[0][0]',
 )                                                                 '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[0][0]',
 )                                                                'tf.math.square_2[0][0]']

 tf.math.subtract_7 (TFOpLambda  ()                  0           ['tf.math.reduce_mean_2[0][0]'
 )

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

 tf.math.multiply_4 (TFOpLambda  (None, 16)          0           ['tf.math.reduce_mean_2[0][0]'
 )                                                                'tf.math.subtract_6[0][0]']

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

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

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

 tf.math.reduce_sum_2 (TFOpLamb  (None,)             0           ['tf.__operators__.add_3[0][0]
 da)                                                             ]

 tf.math.reduce_sum_3 (TFOpLamb  (None,)             0           ['tf.__operators__.add_4[0][0]
 da)                                                             ]

 tf.__operators__.add_5 (TFOpLa  (None,)             0           ['tf.math.reduce_sum_2[0][0]',
 mbda)                                                            'tf.math.reduce_sum_3[0][0]']

 tf.math.multiply_6 (TFOpLambda  (None,)             0           ['tf.__operators__.add_5[0][0]
 )                                                               ]

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

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

 tf.math.truediv_1 (TFOpLambda)  ()                  0           ['tf.math.reduce_mean_3[0][0]'

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

==============================================================================================
Total params: 490,257
```

```
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=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()
```

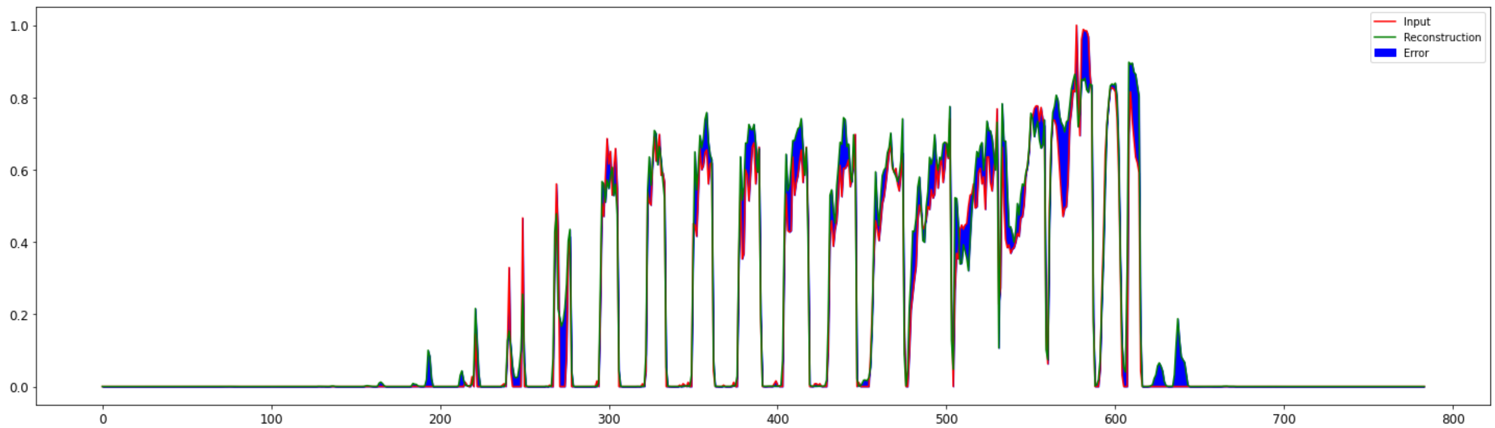
```
show_reconstructions(variational_ae, normal_test_data, 30)
plt.show()
```

```
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)
```

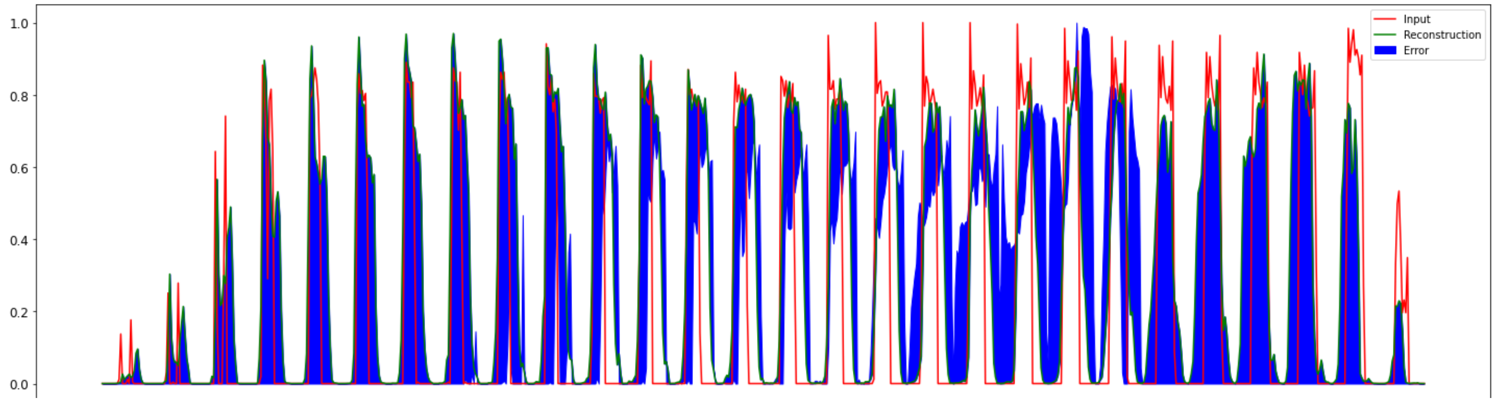
```
plt.figure(figsize=(25,7))
plt.plot(normal_test_data[0].ravel(), 'r')
plt.plot(reconstructions_nl_test[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), reconstructions_nl_test[0].ravel(), normal_test_data[0].ravel(), col
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```



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

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

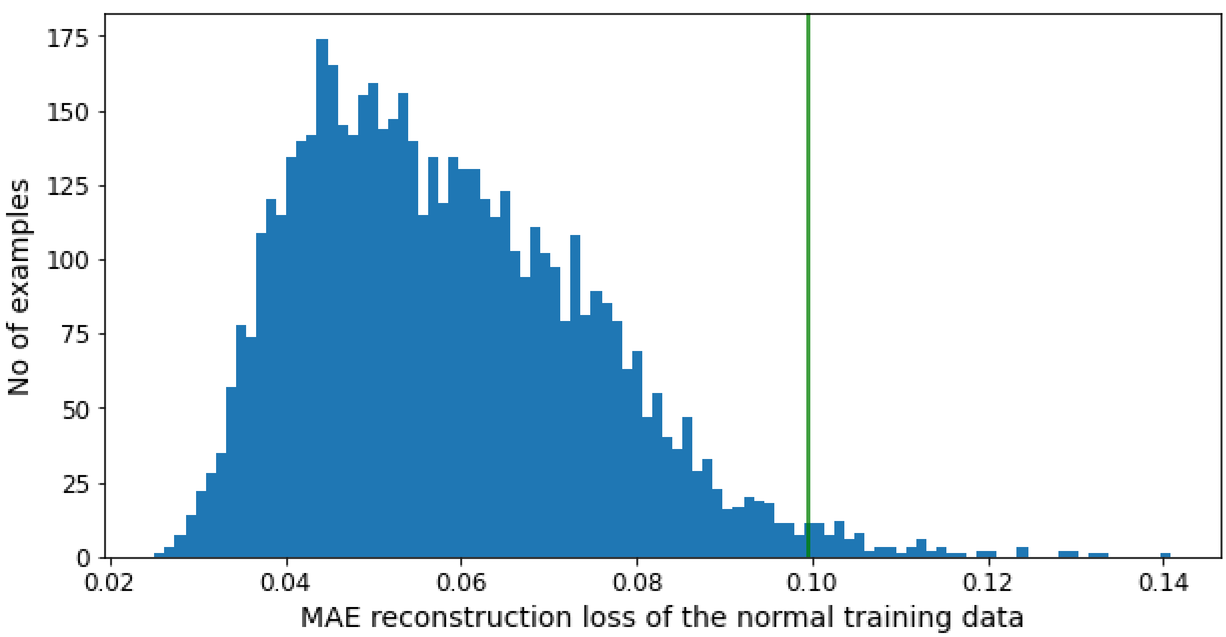
```
plt.figure(figsize=(25,7))
plt.plot(abnormal_test_data[0].ravel(), 'r')
plt.plot(reconstructions_abn_test[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), reconstructions_abn_test[0].ravel(), normal_test_data[0].ravel(), co
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```



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:  0.058422666
Std:  0.01648219
```

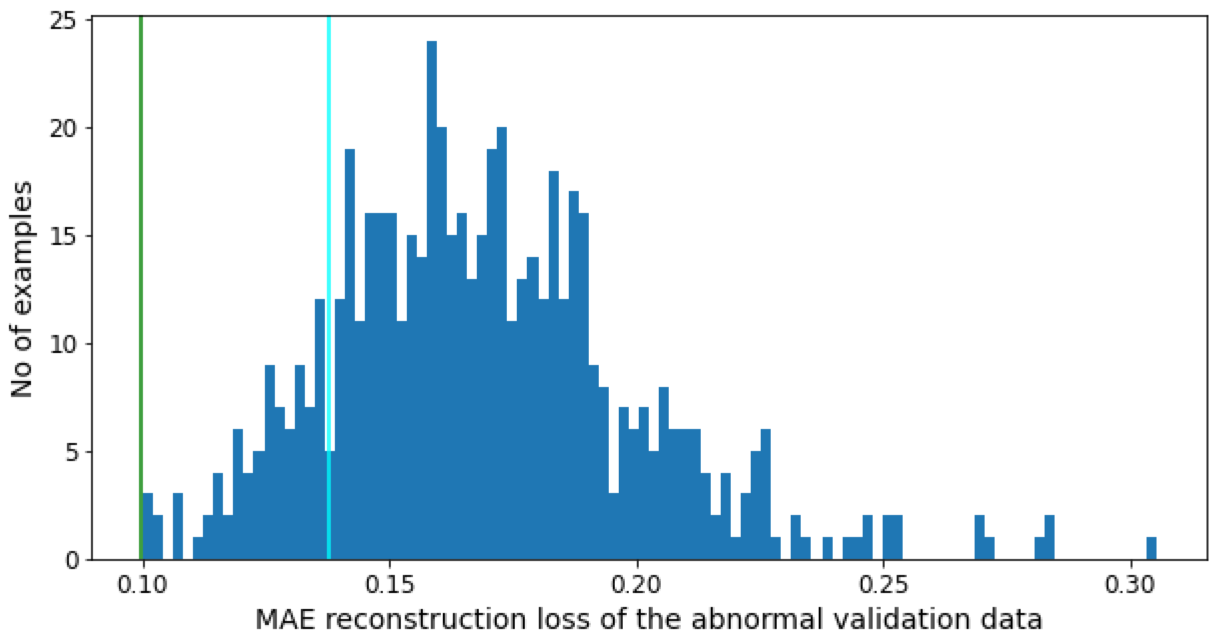
```
threshold_train_mean_2_5_std = np.mean(train_loss) + 2.5*np.std(train_loss)
print("Threshold based on the mean of the training data MAE reconstruction losses + 2.5 std: ", thresho
```

```
Threshold based on the mean of the training data MAE reconstruction losses + 2.5 std:  0.09962813
```

```
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)
```

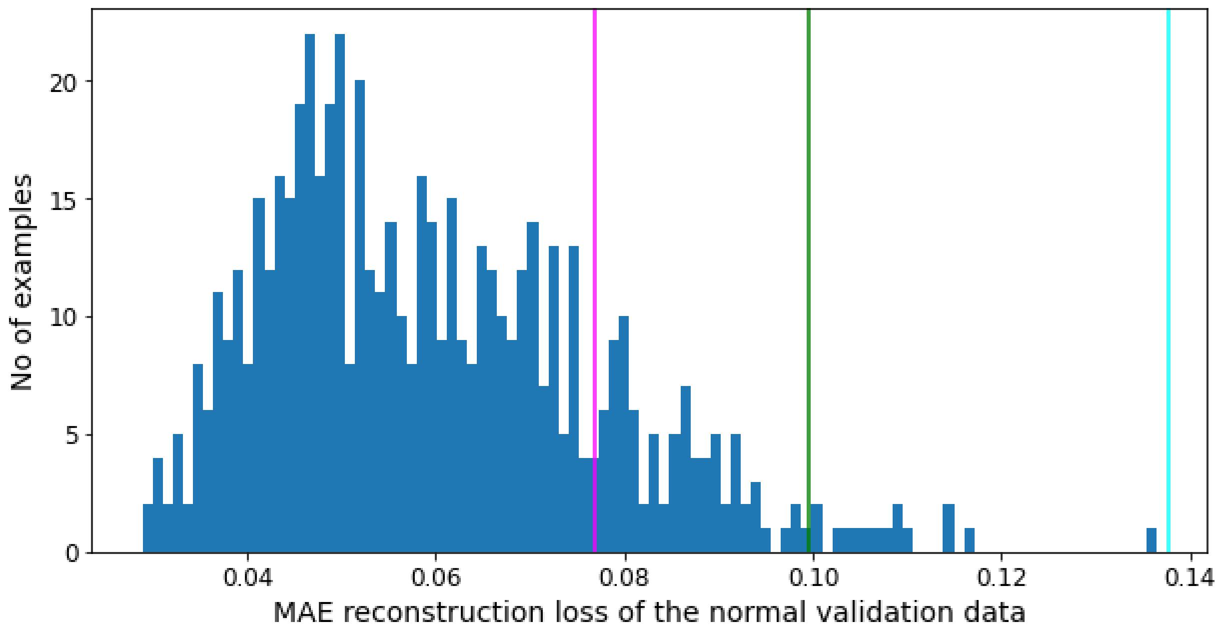
```
(0.1687943, 0.031025061)
```

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

```
Threshold2:  0.13776924
```

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)
```

```
(0.05950849, 0.017469853)
```

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

```
Threshold3:  0.07697834
```

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:  0.10737378895282745
```

```
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:  0.10977996692061438
```

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

```
array([[0.10759425, 0.98983051],
       [0.10868711, 0.98898305],
       [0.10977997, 0.99067797],
       [0.11087283, 0.98983051],
       [0.11196568, 0.98898305]])
```

```
threshold5 = valid_data_best_threshold
```

```
threshold = threshold5
```

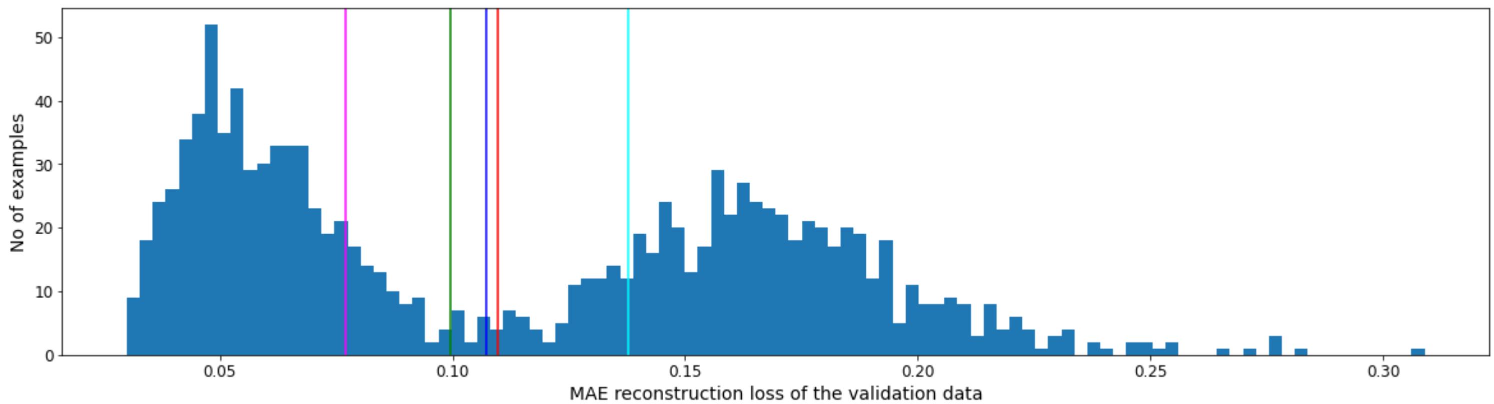
Distribution of the reconstruction losses of all the validation data (normal and abnormal)

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()
```

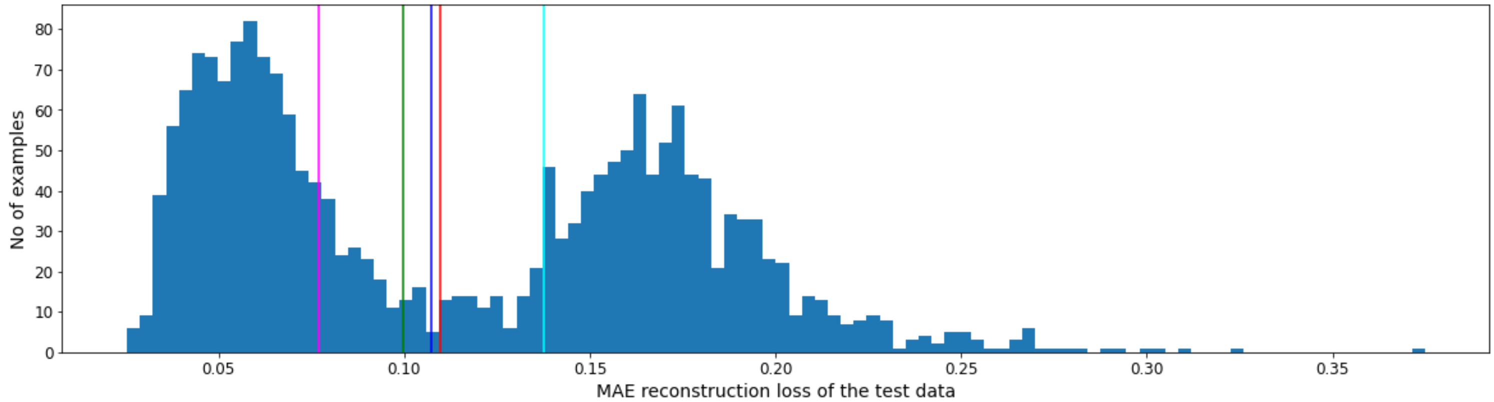


Distribution of the reconstruction losses of the test data (normal and abnormal)

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)
```

```
(0.060542334, 0.020380896)
```

```
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)
```

```
(0.17031997, 0.033426944)
```

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
            981   1019
 label: F   [[971   29]    1000
        T    [10   990]]   1000
Accuracy = 0.9805
Normal Test Data Mean = 0.060542333871126175
Normal Test Data Standard Deviation = 0.0203808955848217
Abnormal Test Data Mean = 0.17031997442245483
Abnormal Test Data Standard Deviation = 0.03342694416642189
Precision = 0.971540726202159
Recall = 0.99
0.9805
0.060542334
0.020380896
0.17031997
0.033426944
0.971540726202159
0.99
0.9805 0.060542334 0.020380896 0.17031997 0.033426944 0.971540726202159 0.99
```

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

```
Threshold = 0.10977996692061438
```

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

```
[[971  29]
 [ 10 990]]
```

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
            998   1002
 label: F   [[979   21]    1000
        T    [19   981]]   1000
Accuracy = 0.98
Normal Test Data Mean = 0.060542333871126175
Normal Test Data Standard Deviation = 0.0203808955848217
Abnormal Test Data Mean = 0.17031997442245483
Abnormal Test Data Standard Deviation = 0.03342694416642189
Precision = 0.9790419161676647
Recall = 0.981
0.98
0.060542334
0.020380896
0.17031997
0.033426944
0.9790419161676647
0.981
0.98 0.060542334 0.020380896 0.17031997 0.033426944 0.9790419161676647 0.981
```

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
            1019   981
 label: F   [[990   10]    1000
        T    [29   971]]   1000
Accuracy = 0.9805
Normal Test Data Mean = 0.060542333871126175
Normal Test Data Standard Deviation = 0.0203808955848217
Abnormal Test Data Mean = 0.17031997442245483
Abnormal Test Data Standard Deviation = 0.03342694416642189
Precision = 0.9898063200815495
Recall = 0.971
0.9805
0.060542334
0.020380896
0.17031997
0.033426944
0.9898063200815495
0.971
0.9805 0.060542334 0.020380896 0.17031997 0.033426944 0.9898063200815495 0.971
```

Extra Info

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

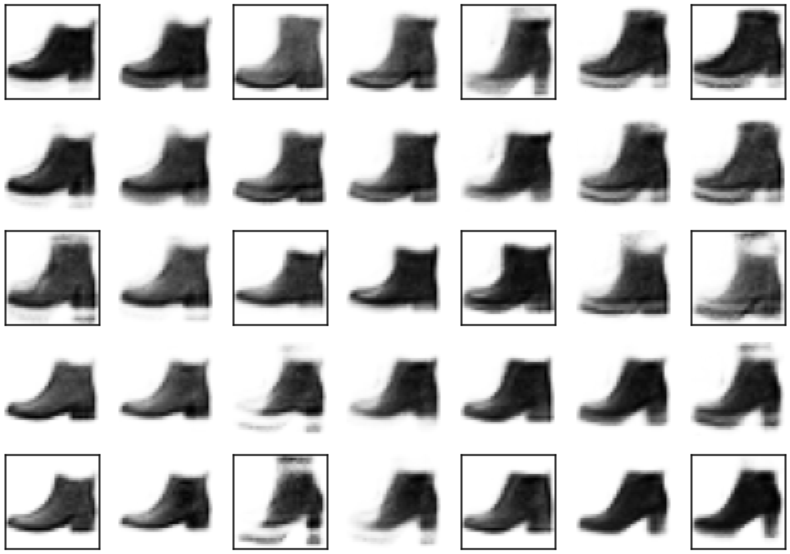
```
def plot_multiple_images(images, n_cols=None):
    n_cols = n_cols or len(images)
```

```python
    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)
```

```python
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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