

References: Chapter 17 of Geron's book. For 1-Dim plots, Keras tutorial :

<https://www.tensorflow.org/tutorials/generative/autoencoder>

This file trains a VAE with the instances of the normal digits in the training data.

Then, it measures the reconstruction loss for the digits in the test data.

The reconstruction loss for the instances of the abnormal digits in the test data is higher.

A threshold is determined based on the distribution of the reconstruction losses of the normal training data (threshold = mean + 2.5*std of this distribution).

Then, if the reconstruction loss of a digit in the test data is higher than this threshold, it is classified as abnormal.

By comparing with the known labels of test data (with T for normal digit(s) and F for abnormal digit(s)), the confusion matrix and the accuracy is calculated.

```
import sklearn
import tensorflow as tf
from tensorflow import keras
import numpy as np

import matplotlib as mpl
import matplotlib.pyplot as plt
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)

from sklearn.metrics import accuracy_score, precision_score, recall_score, confusion_matrix
from sklearn.model_selection import train_test_split
```

Loading the MNIST data and forming arrays of the normal training data, the

- ▼ validation data (normal and abnormal) and the test data (normal and abnormal)

```
#Labels
# 0 T-shirt/top
# 1 Trouser
# 2 Pullover
# 3 Dress
# 4 Coat
# 5 Sandal
# 6 Shirt
```

```

# 7 Sneaker
# 8 Bag
# 9 Ankle boot

nl1 = 5
nl2 = 7
nl3 = 9
abn1 = 4
abn2 = 4

(x_train_0, y_train_0), (x_test, y_test) = keras.datasets.fashion_mnist.load_data()

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

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

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

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 == 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_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 == nl3))
# 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

((16171, 28, 28), (16171,), (2444, 28, 28), (2444,), (4000, 28, 28), (4000,))

normal_test_data = test_data[(test_labels == nl1) | (test_labels == nl2) | (test_labels == nl3)]
abnormal_test_data = test_data[(test_labels == abn1) | (test_labels == abn2)]           # The abnormal digits
normal_test_labels = test_labels[(test_labels == nl1) | (test_labels == nl2) | (test_labels == nl3)]
abnormal_test_labels = test_labels[(test_labels == abn1) | (test_labels == abn2)]       # Their labels

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 == nl3)]
abnormal_valid_data = valid_data[(valid_labels == abn1) | (valid_labels == abn2)]         # The abnormal digits

```

```

normal_valid_labels = valid_labels[(valid_labels == nl1) | (valid_labels == nl2) | (valid_labels == nl3)]
abnormal_valid_labels = valid_labels[(valid_labels == abn1) | (valid_labels == abn2) | (valid_labels == abn3)] # Th

normal_valid_data.shape, abnormal_valid_data.shape

((1829, 28, 28), (615, 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

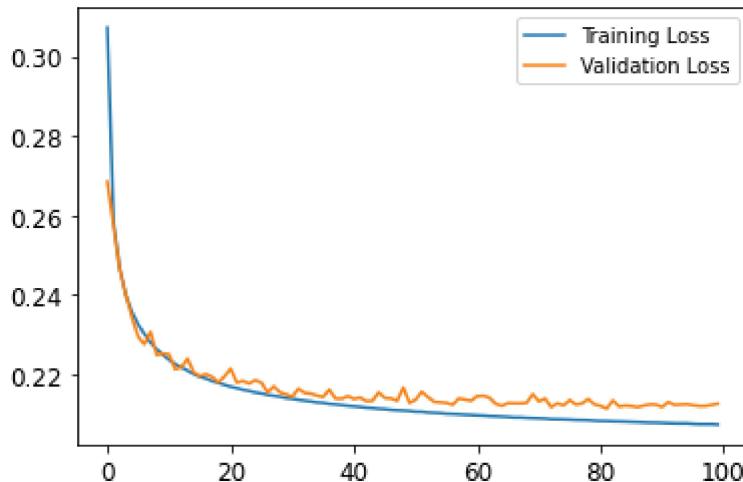
history = variational_ae.fit(normal_data, normal_data, epochs=100, batch_size=128, callbacks=
    validation_data=(normal_valid_data, normal_valid_data), shuffle=True)

Epoch 73/100
123/127 [=====>..] - ETA: 0s - loss: 0.2088INFO:tensorflow:Asse
127/127 [=====] - 2s 18ms/step - loss: 0.2089 - val_loss: 0.
Epoch 74/100
127/127 [=====] - 1s 5ms/step - loss: 0.2088 - val_loss: 0.2
Epoch 75/100
127/127 [=====] - 1s 5ms/step - loss: 0.2088 - val_loss: 0.2
Epoch 76/100
127/127 [=====] - 1s 6ms/step - loss: 0.2087 - val_loss: 0.2
Epoch 77/100
127/127 [=====] - 1s 5ms/step - loss: 0.2087 - val_loss: 0.2
Epoch 78/100
127/127 [=====] - 1s 5ms/step - loss: 0.2086 - val_loss: 0.2
Epoch 79/100
127/127 [=====] - 1s 5ms/step - loss: 0.2086 - val_loss: 0.2
Epoch 80/100
127/127 [=====] - 1s 6ms/step - loss: 0.2085 - val_loss: 0.2
Epoch 81/100
127/127 [=====] - 1s 5ms/step - loss: 0.2084 - val_loss: 0.2
Epoch 82/100
120/127 [=====>..] - ETA: 0s - loss: 0.2086INFO:tensorflow:Asse
127/127 [=====] - 2s 18ms/step - loss: 0.2084 - val_loss: 0.
Epoch 83/100
127/127 [=====] - 1s 6ms/step - loss: 0.2083 - val_loss: 0.2
Epoch 84/100
127/127 [=====] - 1s 6ms/step - loss: 0.2083 - val_loss: 0.2
Epoch 85/100
127/127 [=====] - 1s 5ms/step - loss: 0.2082 - val_loss: 0.2
Epoch 86/100
127/127 [=====] - 1s 5ms/step - loss: 0.2082 - val_loss: 0.2
Epoch 87/100
```

```
127/127 [=====] - 1s 6ms/step - loss: 0.2081 - val_loss: 0.2
Epoch 88/100
127/127 [=====] - 1s 6ms/step - loss: 0.2081 - val_loss: 0.2
Epoch 89/100
127/127 [=====] - 1s 5ms/step - loss: 0.2080 - val_loss: 0.2
Epoch 90/100
127/127 [=====] - 1s 5ms/step - loss: 0.2080 - val_loss: 0.2
Epoch 91/100
127/127 [=====] - 1s 6ms/step - loss: 0.2079 - val_loss: 0.2
Epoch 92/100
127/127 [=====] - 1s 5ms/step - loss: 0.2079 - val_loss: 0.2
Epoch 93/100
127/127 [=====] - 1s 5ms/step - loss: 0.2078 - val_loss: 0.2
Epoch 94/100
127/127 [=====] - 1s 6ms/step - loss: 0.2078 - val_loss: 0.2
Epoch 95/100
127/127 [=====] - 1s 6ms/step - loss: 0.2078 - val_loss: 0.2
Epoch 96/100
127/127 [=====] - 1s 6ms/step - loss: 0.2077 - val_loss: 0.2
Epoch 97/100
127/127 [=====] - 1s 6ms/step - loss: 0.2076 - val_loss: 0.2
Epoch 98/100
127/127 [=====] - 1s 6ms/step - loss: 0.2076 - val_loss: 0.2
Epoch 99/100
127/127 [=====] - 1s 5ms/step - loss: 0.2076 - val_loss: 0.2
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 0x7f0682058e50>



```
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), (None, 16), (None, 16)]	244192	Y	
=====				
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

```
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()
```



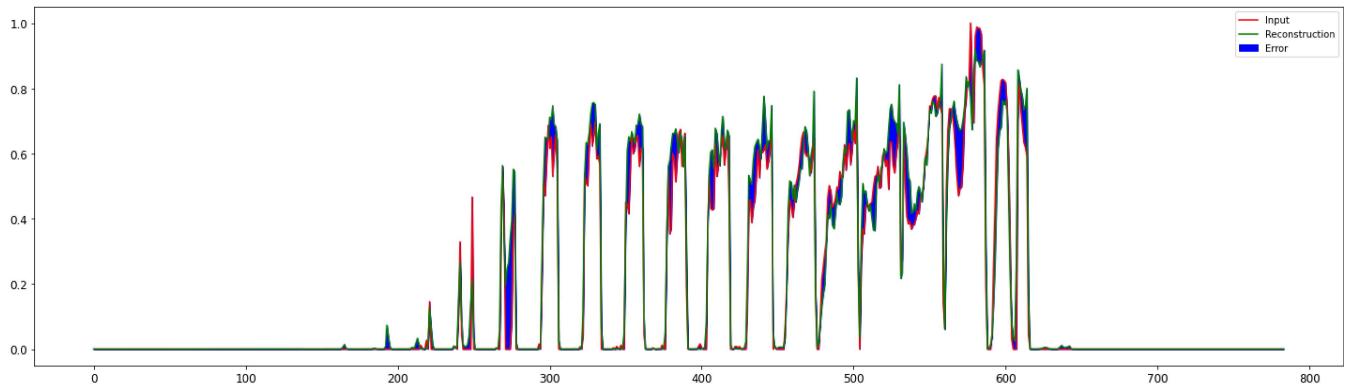
```
show_reconstructions(variational_ae, abnormal_test_data, 30)
plt.show()
```



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

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

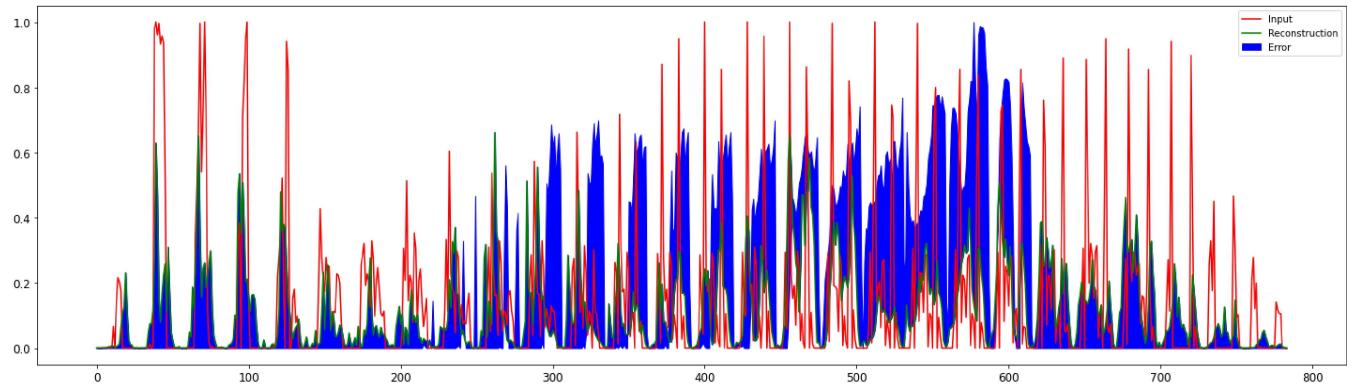
```
plt.figure(figsize=(25,7))
plt.plot(normal_test_data[0].ravel(), 'r')
plt.plot(reconstructions_nl_test[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), reconstructions_nl_test[0].ravel(), normal_test_data[0].ravel(), color='blue')
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()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



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

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

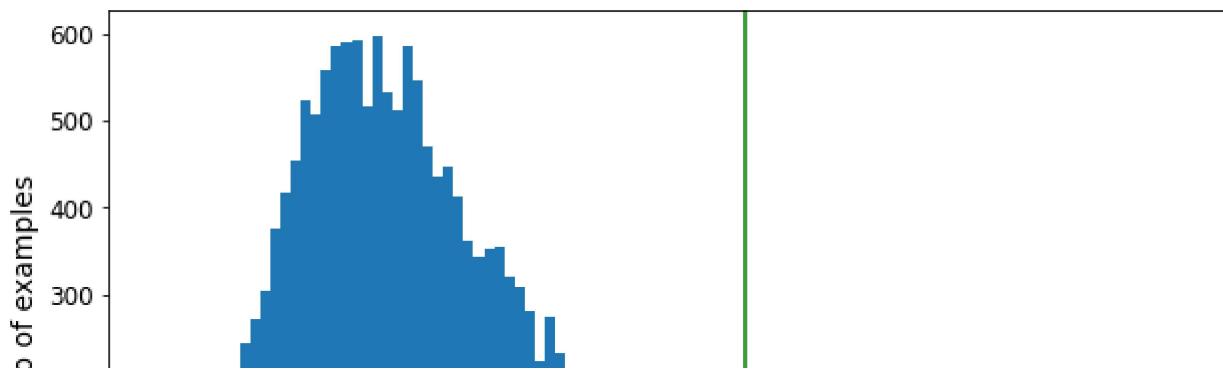
```
plt.figure(figsize=(25,7))
plt.plot(abnormal_test_data[0].ravel(), 'r')
plt.plot(reconstructions_abn_test[0].ravel(), 'g')
plt.fill_between(np.arange(28*28), reconstructions_abn_test[0].ravel(), normal_test_data[0].ravel(), 'b')
plt.legend(labels=["Input", "Reconstruction", "Error"])
plt.show()
```



▼ 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()
```



```
mean1 = np.mean(train_loss)
std1 = np.std(train_loss)
print("Mean: ", mean1)
print("Std: ", std1)
```

```
Mean:  0.04677902
Std:  0.018296575
```

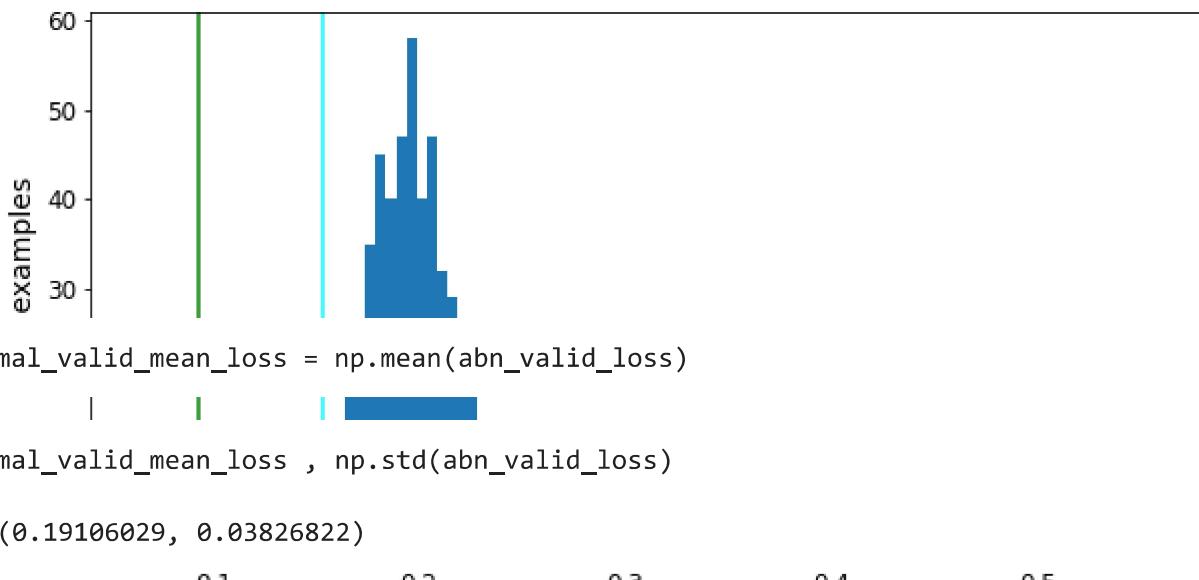
```
threshold_train_mean_2_5_std = np.mean(train_loss) + 2.5*np.std(train_loss)
print("Threshold based on the mean of the training data MAE reconstruction losses + 2.5 std:
```

```
Threshold based on the mean of the training data MAE reconstruction losses + 2.5 std:  6.25
```

```
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(-1,784))
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()
```

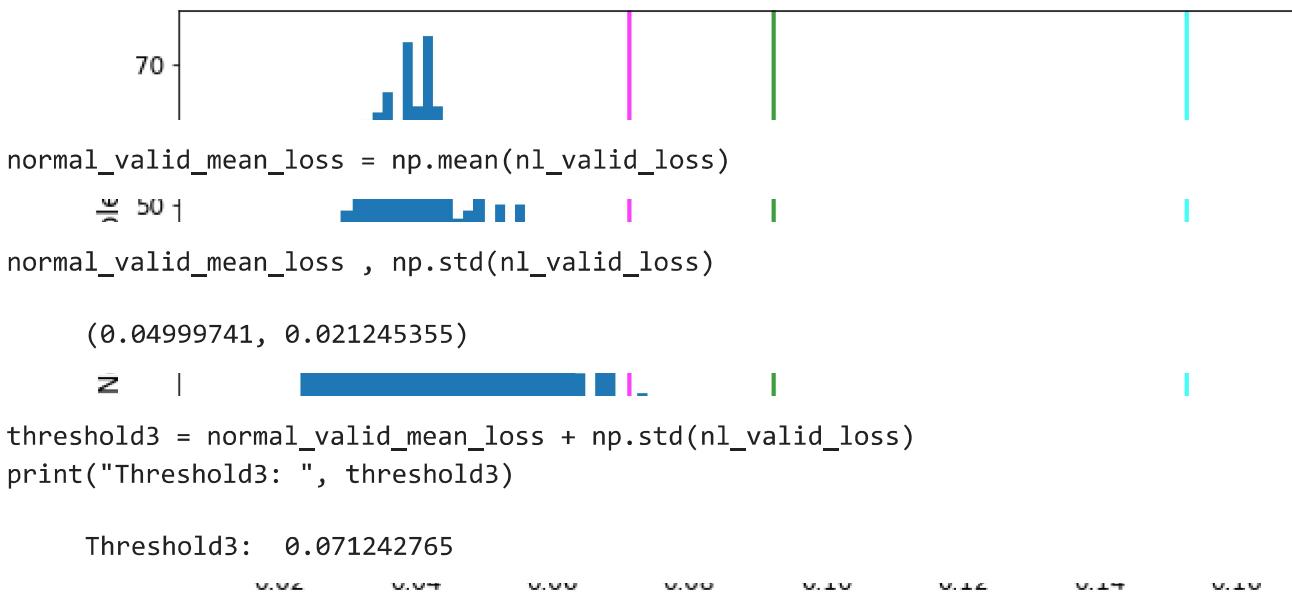


```
threshold2 = abnormal_valid_mean_loss - np.std(abn_valid_loss)
print("Threshold2: ", threshold2)
```

Threshold2: 0.15279207

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()
```



Calculation of a preliminary threshold based on $(\text{threshold2} + \text{threshold3}) / 2 = \text{Average of } (\text{mean} + \text{std of the distribution of the reconstruction losses of the normal validation data}) \text{ and } (\text{mean} - \text{std of the distribution of the reconstruction losses of the abnormal validation data})$

```
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: 0.11201741546392441

`threshold4 = Avg_of_threshold_2_3`

Calculation of the threshold that gives the best accuracy on the validation data and set this as the threshold.

```
def predict(model, data, threshold):
    reconstructions = model.predict(data)
    loss = tf.keras.losses.mae(reconstructions.reshape(-1, 784), data.reshape(-1, 784))
    return tf.math.less(loss, threshold)

increment = (abnormal_valid_mean_loss - normal_valid_mean_loss)/100
thresholds = np.arange(normal_valid_mean_loss, abnormal_valid_mean_loss, increment)
thrs_size = thresholds.shape[0]
accuracies = np.zeros(thrs_size)
for i in range(thrs_size):
    preds = predict(variational_ae, valid_data, thresholds[i])
    accuracies[i] = accuracy_score(preds, valid_labels_T_F)
argmax = np.argmax(accuracies)
```

```

valid_data_best_threshold = thresholds[argmax]
print("The best threshold based on validation data: ", valid_data_best_threshold)

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

array([[0.11911823, 0.97913257],
       [0.12052885, 0.9799509 ],
       [0.12193948, 0.98036007],
       [0.12335011, 0.98036007],
       [0.12476074, 0.9799509 ]])

```

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()

```



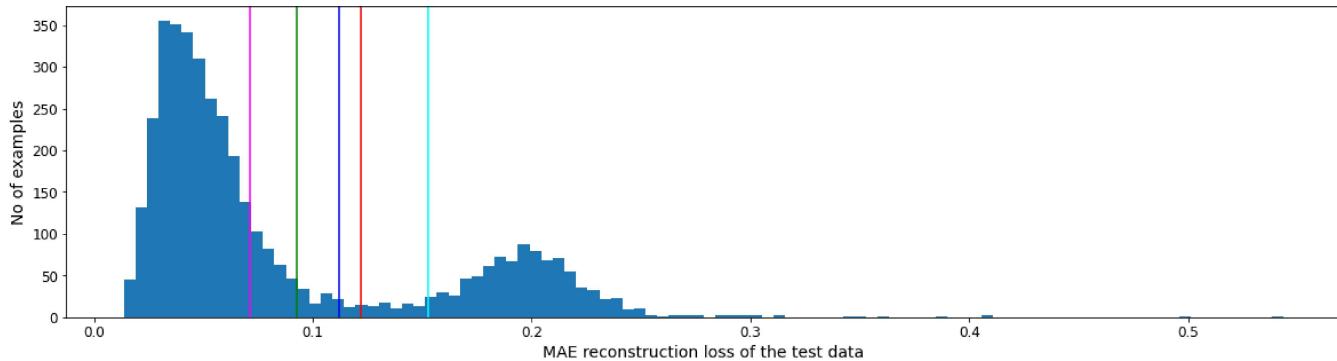
▼ Distribution of the reconstruction losses of the test data (normal and abnormal)

Legend: [magenta] [green] [blue] [red] [cyan]

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))

(0.049792383, 0.021399984)
```

```

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)

(0.19309796, 0.04034483)

```

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].shape[0]))
    print(" label: F  [[{}  {}]]  {}".format(cf[0,0], cf[0,1], test_labels_T_F[test_labels_T_F == 0]))
    print("          T  [[{}  {}]]  {}".format(cf[1,0], cf[1,1], test_labels_T_F[test_labels_T_F == 1]))
    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: 0.04979238286614418
    std_nl_test_loss: 0.021399984136223793
    mean_abn_test_loss: 0.19309796392917633
    std_abn_test_loss: 0.040344830602407455
    Confusion Matrix:
        prediction: F      T
                    984  3016
    label: F  [[958  42]  1000
                T  [26  2974]]  3000
    Accuracy = 0.983

```

```
Precision = 0.9860742705570292
Recall = 0.9913333333333333
```

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

```
[[ 958   42]
 [ 26 2974]]
```

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: 0.04979238286614418
std_nl_test_loss: 0.021399984136223793
mean_abn_test_loss: 0.19309796392917633
std_abn_test_loss: 0.040344830602407455
Confusion Matrix:
 prediction: F      T
               1010   2990
label: F      [[966   34]    1000
               T      [44   2956]]   3000
Accuracy = 0.9805
Precision = 0.988628762541806
Recall = 0.9853333333333333
```

Accuracy on the test data with threshold set based on the mean of the training data MAE reconstruction losses + 2.5 std

```
preds = predict(variational_ae, test_data, threshold_train_mean_2_5_std)
print_stats(preds, test_labels_T_F)
```

```
mean_nl_test_loss: 0.04979238286614418
std_nl_test_loss: 0.021399984136223793
mean_abn_test_loss: 0.19309796392917633
std_abn_test_loss: 0.040344830602407455
Confusion Matrix:
 prediction: F      T
               1103   2897
```

```

label: F   [[981    19]    1000
           T   [122   2878]]   3000
Accuracy = 0.96475
Precision = 0.9934414911977908
Recall = 0.9593333333333334

```

Extra Info

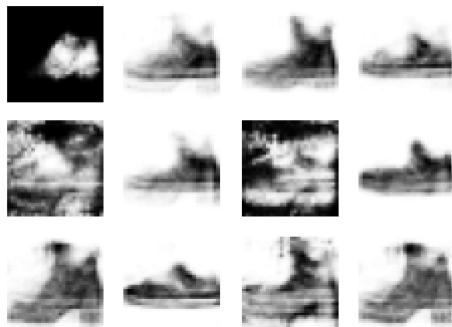
Giving the VAE codings (please see book) (Just informative, not the goal here)

```

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)

```



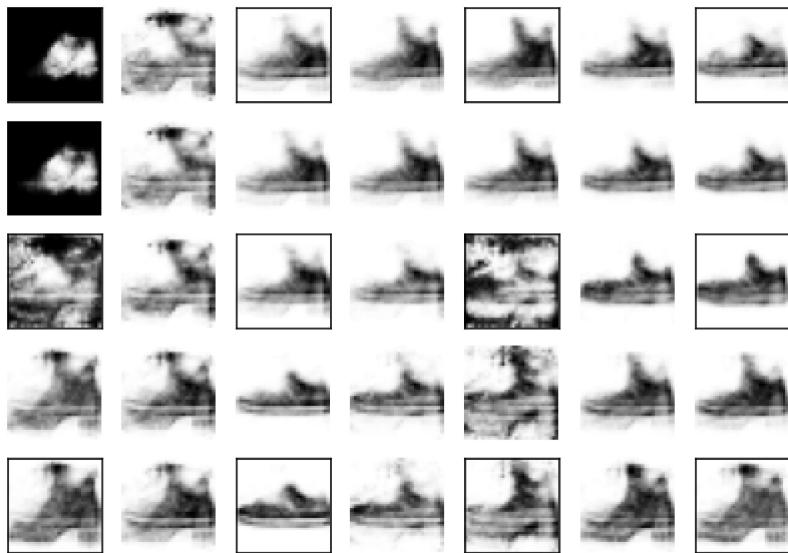
```

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)
```



✓ 1s completed at 3:15 PM

● ✕