```python
import keras
from keras.layers import Dense, Conv2D, Conv2DTranspose, Lambda,
Input, Flatten, Reshape, MaxPooling2D, UpSampling2D
from keras.models import Sequential, Model
from keras.losses import binary_crossentropy, kl_divergence
import tensorflow as tf
from tensorflow.keras import backend as K
from tensorflow.data import AUTOTUNE
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from keras.preprocessing.image import array_to_img
from keras.callbacks import TensorBoard
import cv2
```

```
/opt/conda/lib/python3.10/site-packages/scipy/__init__.py:146:
UserWarning: A NumPy version >=1.16.5 and <1.23.0 is required for this
version of SciPy (detected version 1.24.3
  warnings.warn(f"A NumPy version >={np_minversion} and
<{np_maxversion}"
```

```python
tf.config.list_physical_devices('GPU')
```

```
[PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
```

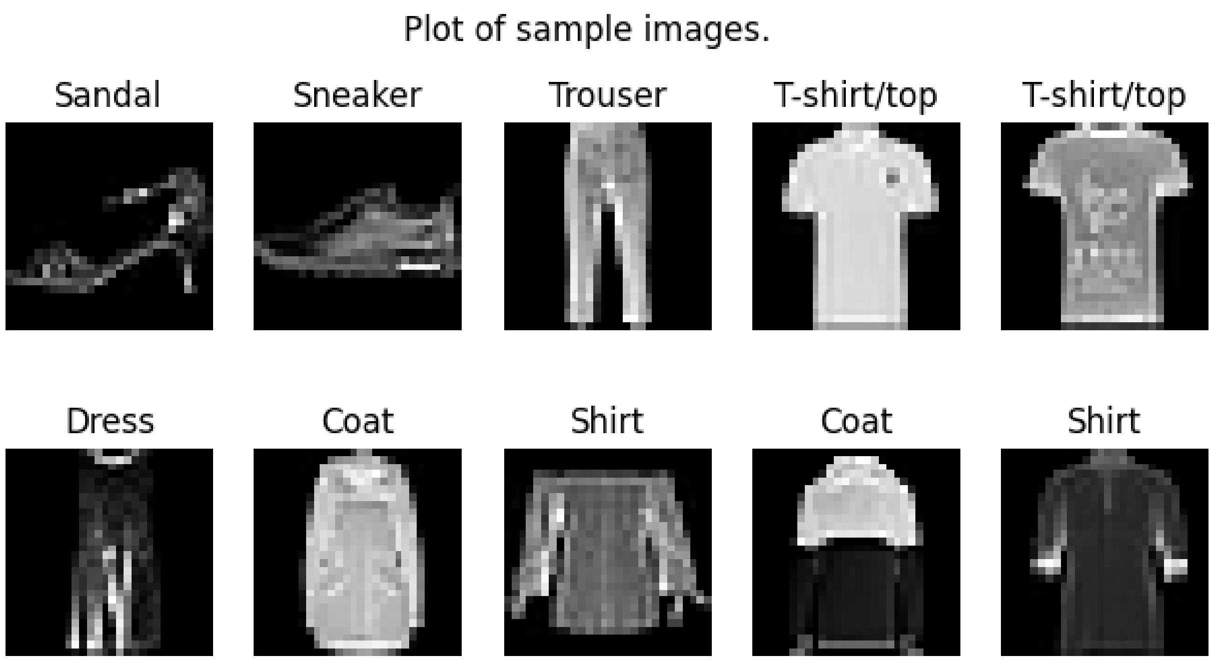
```python
(X_train, y_train), (X_test, y_test) =
keras.datasets.fashion_mnist.load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-
keras-datasets/train-labels-idx1-ubyte.gz
29515/29515 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-
keras-datasets/train-images-idx3-ubyte.gz
26421880/26421880 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-
keras-datasets/t10k-labels-idx1-ubyte.gz
5148/5148 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-
keras-datasets/t10k-images-idx3-ubyte.gz
4422102/4422102 [==============================] - 0s 0us/step
```

Plotting sample images

```python
def plot_sample():
    indexes = np.random.randint(0, len(X_train), size=10)
    fig, axes = plt.subplots(2, 5, sharex=True, sharey=True,
figsize=(8, 4))
    axes = axes.flatten()
```

```
    for i, index in enumerate(indexes):
        axes[i].imshow(X_train[index], cmap="gray")
        axes[i].set(title=f"{labels[y_train[index]]}")
        # axes[i].tick_params(axis='both', which='both', bottom=False,
left=False)
        axes[i].axis("off")
    fig.suptitle("Plot of sample images.")
    plt.show()

labels = {0: "T-shirt/top",
        1: "Trouser",
        2: "Pullover",
        3: "Dress",
        4: "Coat",
        5: "Sandal",
        6: "Shirt",
        7: "Sneaker",
        8: "Bag",
        9: "Ankle boot"
}

plot_sample()
```




```
train_data = np.concatenate((X_train, X_test))
target = np.concatenate((y_train, y_test))

train_data = train_data.reshape((-1, 28, 28, 1))

train_ds = tf.data.Dataset.from_tensor_slices(train_data)
```

```
batch_size = 128
train_ds = train_ds.map(lambda x:
x/255).batch(batch_size).prefetch(AUTOTUNE)
train_ds
```

```
<_PrefetchDataset element_spec=TensorSpec(shape=(None, 28, 28, 1),
dtype=tf.float32, name=None)>
```

Sampling

```
@tf.function
def sampling(inputs):
    mean, log_var = inputs
    eps = K.random_normal(shape=tf.shape(mean))
    z = mean + K.exp(0.5*log_var) * eps
    return z
```

Building the Encoder

```
latent_dim = 2

encoder_input = Input(shape=(28, 28, 1), dtype=tf.float32,
batch_size=batch_size)
x = Conv2D(64, kernel_size=(3, 3), strides=2, padding="same",
activation="relu")(encoder_input)
x = Conv2D(128, kernel_size=(2, 2), strides=2, padding="same",
activation="relu")(x)
x = Flatten()(x)
x = Dense(64)(x)
mean = Dense(latent_dim, name="mean")(x)
log_var = Dense(latent_dim, name="log_var")(x)
z = Lambda(function=sampling, name="z")([mean, log_var])

encoder = Model(inputs=encoder_input, outputs=[mean, log_var, z],
name="encoder")
encoder.summary()
```

```
Model: "encoder"
_______________________________________________________________________
____________________________
 Layer (type)                 Output Shape                    Param #
Connected to
=======================================================================
============================
 input_1 (InputLayer)         [(128, 28, 28, 1)]              0          []
```

```
 conv2d (Conv2D)              (128, 14, 14, 64)          640
['input_1[0][0]']


 conv2d_1 (Conv2D)            (128, 7, 7, 128)           32896
['conv2d[0][0]']


 flatten (Flatten)            (128, 6272)                0
['conv2d_1[0][0]']


 dense (Dense)                (128, 64)                  401472
['flatten[0][0]']


 mean (Dense)                 (128, 2)                   130
['dense[0][0]']


 log_var (Dense)              (128, 2)                   130
['dense[0][0]']


 z (Lambda)                   (128, 2)                   0
['mean[0][0]',

'log_var[0][0]']


======================================================================
============================
Total params: 435268 (1.66 MB)
Trainable params: 435268 (1.66 MB)
Non-trainable params: 0 (0.00 Byte)
______________________________________________________________________
____________________________
```

Building the Decoder

```
decoder_input = Input(shape=(latent_dim, ), dtype=tf.float32,
name="decoder_input", batch_size=batch_size)
x = Dense(7*7*128, activation="relu")(decoder_input)
x = Reshape((7, 7, 128))(x)
x = Conv2DTranspose(128, kernel_size=(3, 3), strides=2,
activation="relu", padding="same")(x)
```

```
x = Conv2DTranspose(64, kernel_size=(3, 3), strides=2,
activation="relu", padding="same")(x)
decoder_output = Conv2DTranspose(1, kernel_size=(3, 3),
activation="sigmoid", padding="same")(x)

decoder = Model(inputs=decoder_input, outputs=decoder_output,
name="decoder")
decoder.summary()
```

```
Model: "decoder"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 decoder_input (InputLayer)  [(128, 2)]                0

 dense_1 (Dense)             (128, 6272)               18816

 reshape (Reshape)           (128, 7, 7, 128)          0

 conv2d_transpose (Conv2DTr  (128, 14, 14, 128)        147584
 anspose)

 conv2d_transpose_1 (Conv2D  (128, 28, 28, 64)         73792
 Transpose)

 conv2d_transpose_2 (Conv2D  (128, 28, 28, 1)          577
 Transpose)

=================================================================
Total params: 240769 (940.50 KB)
Trainable params: 240769 (940.50 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Putting all of them together.

```
class VariationalAutoEncoder(Model):
    def __init__(self, encoder, decoder, **kwargs):
        super().__init__(**kwargs)
        self.encoder = encoder
        self.decoder = decoder
        self.total_loss_tracker = keras.metrics.Mean("total_loss")
        self.reconstruction_loss_tracker =
keras.metrics.Mean("reconstruction_loss")
        self.kl_loss_tracker = keras.metrics.Mean("kl_loss")

    @property
    def metric(self):
```

```python
        return [
            self.total_loss_tracker,
            self.reconstruction_loss_tracker,
            self.kl_loss_tracker,
        ]

    def call(self, inputs):
        mean, log_var, z = self.encoder(inputs)
        output = self.decoder(z)
        return output

    def train_step(self, data):
        with tf.GradientTape() as tape:
            mean, log_var, z = self.encoder(data)
            reconstruction = self.decoder(z)
            reconstruction_loss =
tf.reduce_mean(tf.reduce_sum(binary_crossentropy(data,
reconstruction), axis=(1, 2)))
            kl_loss = -0.5 * (1 + log_var - tf.square(mean) -
tf.exp(log_var))
            kl_loss = tf.reduce_mean(tf.reduce_sum(kl_loss, axis=1))
            total_loss = reconstruction_loss + kl_loss
        grads = tape.gradient(total_loss, self.trainable_weights)
        self.optimizer.apply_gradients(zip(grads,
self.trainable_weights))
        self.total_loss_tracker.update_state(total_loss)

self.reconstruction_loss_tracker.update_state(reconstruction_loss)
        self.kl_loss_tracker.update_state(kl_loss)
        return {
            "loss": self.total_loss_tracker.result(),
            "reconstruction_loss":
self.reconstruction_loss_tracker.result(),
            "kl_loss": self.kl_loss_tracker.result(),
        }

vae_model = VariationalAutoEncoder(encoder, decoder)
vae_model.build(input_shape=(None, 28, 28, 1))
vae_model.summary()
```

```
Model: "variational_auto_encoder"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 encoder (Functional)        [(128, 2),                435268    
                              (128, 2),                          
                              (128, 2)]                          
                                                                 
 decoder (Functional)        (128, 28, 28, 1)          240769    
```

```
=================================================================
Total params: 676043 (2.58 MB)
Trainable params: 676037 (2.58 MB)
Non-trainable params: 6 (24.00 Byte)
_________________________________________________________________
```

```
optimizer = keras.optimizers.Adam()
vae_model.compile(optimizer=optimizer)
vae_model.fit(train_ds, epochs=30)
```

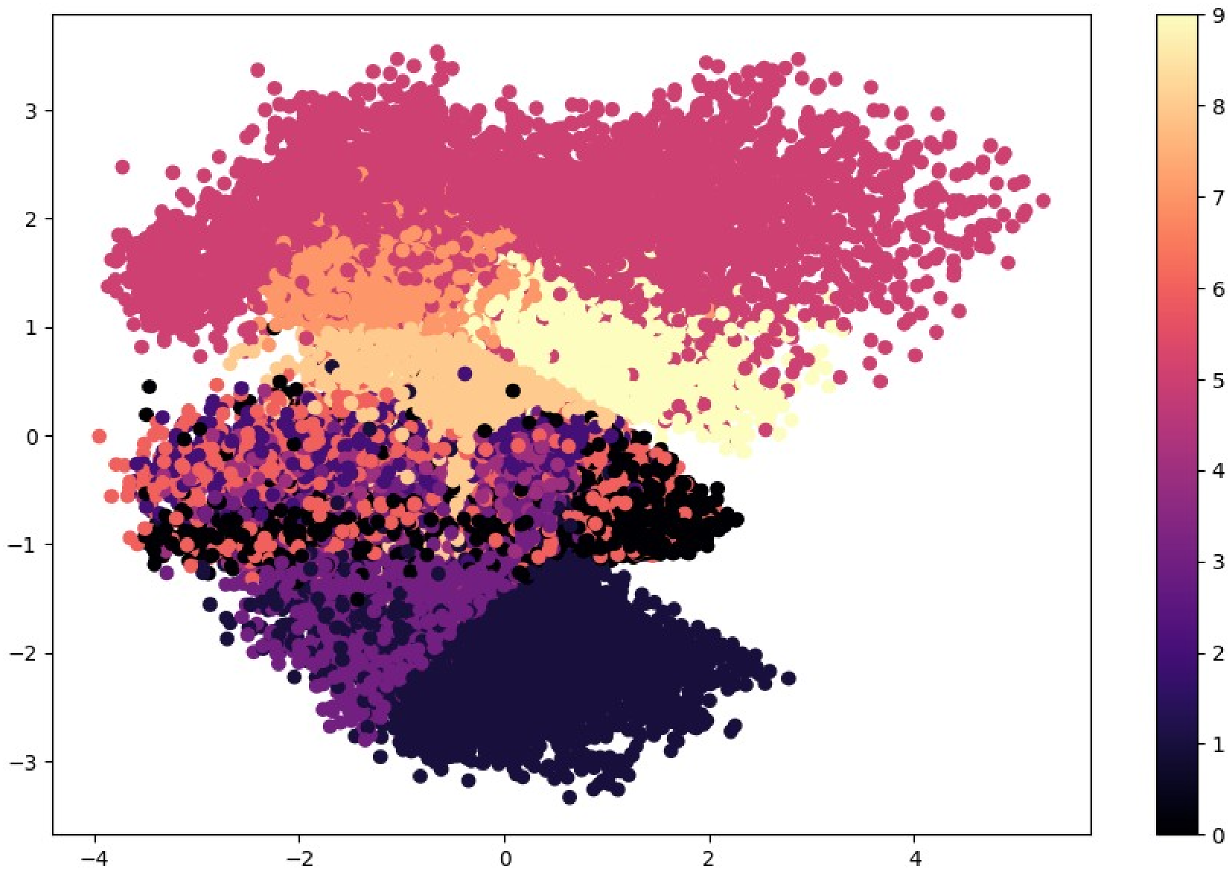
```
Epoch 1/30
547/547 [==============================] - 11s 11ms/step - loss:
338.8705 - reconstruction_loss: 294.1093 - kl_loss: 5.4137
Epoch 2/30
547/547 [==============================] - 6s 11ms/step - loss:
271.2779 - reconstruction_loss: 264.7787 - kl_loss: 5.9228
Epoch 3/30
547/547 [==============================] - 6s 11ms/step - loss:
267.7236 - reconstruction_loss: 261.9473 - kl_loss: 5.9957
Epoch 4/30
547/547 [==============================] - 6s 11ms/step - loss:
266.0434 - reconstruction_loss: 260.2846 - kl_loss: 6.0594
Epoch 5/30
547/547 [==============================] - 6s 11ms/step - loss:
264.7780 - reconstruction_loss: 259.1953 - kl_loss: 6.0915
Epoch 6/30
547/547 [==============================] - 6s 11ms/step - loss:
264.0908 - reconstruction_loss: 258.3819 - kl_loss: 6.1366
Epoch 7/30
547/547 [==============================] - 6s 11ms/step - loss:
263.4052 - reconstruction_loss: 257.6855 - kl_loss: 6.1484
Epoch 8/30
547/547 [==============================] - 6s 11ms/step - loss:
262.8427 - reconstruction_loss: 257.1904 - kl_loss: 6.1831
Epoch 9/30
547/547 [==============================] - 6s 11ms/step - loss:
262.3690 - reconstruction_loss: 256.6744 - kl_loss: 6.2058
Epoch 10/30
547/547 [==============================] - 6s 11ms/step - loss:
261.9220 - reconstruction_loss: 256.2764 - kl_loss: 6.2420
Epoch 11/30
547/547 [==============================] - 6s 11ms/step - loss:
261.6667 - reconstruction_loss: 255.9937 - kl_loss: 6.2545
Epoch 12/30
547/547 [==============================] - 6s 11ms/step - loss:
261.3044 - reconstruction_loss: 255.5917 - kl_loss: 6.2861
Epoch 13/30
547/547 [==============================] - 6s 11ms/step - loss:
261.0711 - reconstruction_loss: 255.4165 - kl_loss: 6.2840
Epoch 14/30
```

```
547/547 [==============================] - 6s 11ms/step - loss:
260.7332 - reconstruction_loss: 255.0385 - kl_loss: 6.3109
Epoch 15/30
547/547 [==============================] - 6s 11ms/step - loss:
260.4450 - reconstruction_loss: 254.8237 - kl_loss: 6.3157
Epoch 16/30
547/547 [==============================] - 6s 11ms/step - loss:
260.2678 - reconstruction_loss: 254.5655 - kl_loss: 6.3357
Epoch 17/30
547/547 [==============================] - 6s 11ms/step - loss:
260.0703 - reconstruction_loss: 254.4158 - kl_loss: 6.3477
Epoch 18/30
547/547 [==============================] - 6s 11ms/step - loss:
259.8221 - reconstruction_loss: 254.1930 - kl_loss: 6.3504
Epoch 19/30
547/547 [==============================] - 6s 11ms/step - loss:
259.6532 - reconstruction_loss: 253.9686 - kl_loss: 6.3628
Epoch 20/30
547/547 [==============================] - 6s 11ms/step - loss:
259.4709 - reconstruction_loss: 253.8060 - kl_loss: 6.3844
Epoch 21/30
547/547 [==============================] - 6s 11ms/step - loss:
259.4213 - reconstruction_loss: 253.7628 - kl_loss: 6.3915
Epoch 22/30
547/547 [==============================] - 6s 11ms/step - loss:
259.2568 - reconstruction_loss: 253.5398 - kl_loss: 6.4044
Epoch 23/30
547/547 [==============================] - 6s 11ms/step - loss:
259.1452 - reconstruction_loss: 253.3590 - kl_loss: 6.4186
Epoch 24/30
547/547 [==============================] - 6s 11ms/step - loss:
258.8579 - reconstruction_loss: 253.1680 - kl_loss: 6.3890
Epoch 25/30
547/547 [==============================] - 6s 11ms/step - loss:
258.7797 - reconstruction_loss: 253.0986 - kl_loss: 6.4268
Epoch 26/30
547/547 [==============================] - 6s 11ms/step - loss:
258.5958 - reconstruction_loss: 252.8883 - kl_loss: 6.4230
Epoch 27/30
547/547 [==============================] - 6s 11ms/step - loss:
258.5024 - reconstruction_loss: 252.7816 - kl_loss: 6.4350
Epoch 28/30
547/547 [==============================] - 6s 11ms/step - loss:
258.4366 - reconstruction_loss: 252.6566 - kl_loss: 6.4569
Epoch 29/30
547/547 [==============================] - 6s 11ms/step - loss:
258.4442 - reconstruction_loss: 252.5764 - kl_loss: 6.4636
Epoch 30/30
```

```
547/547 [==============================] - 6s 11ms/step - loss:
258.2846 - reconstruction_loss: 252.4638 - kl_loss: 6.4863

<keras.src.callbacks.History at 0x7e9338047c40>
```

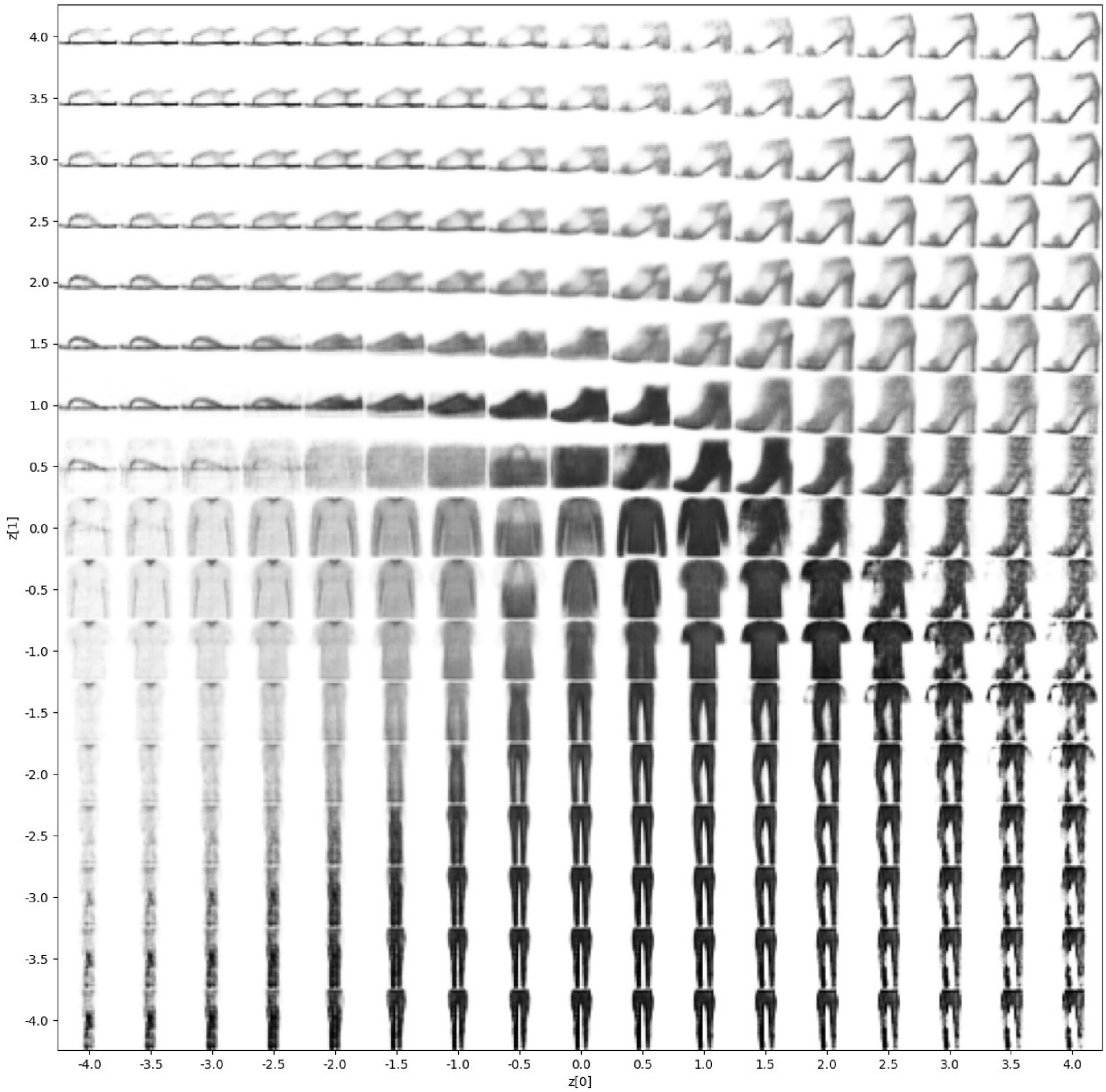
Visualizing the latent space

```
mean, *_ = vae_model.encoder.predict(train_ds)

547/547 [==============================] - 1s 2ms/step

fig = plt.figure(figsize=(11, 7))
plt.scatter(mean[:, 0], mean[:, 1], c=target, cmap="magma")
plt.colorbar()
plt.show()
```




```
def plot_latent_space(vae, n=17, figsize=15):

    image_size = 28
    scale = 4.0
    figure = np.zeros((image_size * n, image_size * n))
```

```python
    # linearly spaced coordinates corresponding to the 2D plot
    # of digit classes in the latent space
    grid_x = np.linspace(-scale, scale, n)
    grid_y = np.linspace(-scale, scale, n)[::-1]

    for i, yi in enumerate(grid_y):
        for j, xi in enumerate(grid_x):
            z_sample = np.array([[xi, yi]])
            x_decoded = vae.decoder.predict(z_sample, verbose=0)
            digit = x_decoded[0].reshape(image_size, image_size)
            figure[
                i * image_size : (i + 1) * image_size,
                j * image_size : (j + 1) * image_size,
            ] = digit

    plt.figure(figsize=(figsize, figsize))
    start_range = image_size // 2
    end_range = n * image_size + start_range
    pixel_range = np.arange(start_range, end_range, image_size)
    sample_range_x = np.round(grid_x, 1)
    sample_range_y = np.round(grid_y, 1)
    plt.xticks(pixel_range, sample_range_x)
    plt.yticks(pixel_range, sample_range_y)
    plt.xlabel("z[0]")
    plt.ylabel("z[1]")
    plt.imshow(figure, cmap="gray_r")
    plt.show()


plot_latent_space(vae_model)
```



Generating sample images

```
def generate_images(vector):
    decoded = vae_model.decoder.predict(vector)
    decoded = np.squeeze(decoded, axis=0)

    fig = plt.figure(figsize=(3,2))
    plt.imshow(decoded, cmap="gray")
    plt.axis("off")
```

```
vector = np.array([[-3.5, -0.5]])
generate_images(vector)
```

```
1/1 [==============================] - 0s 17ms/step
```