Assignment 12

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Using section 8.4 in Deep Learning with Python as a guide, implement a variational autoencoder using the MNIST data set and save a grid of 15 x 15 digits to the results/vae directory. If you would rather work on a more interesting dataset, you can use the CelebFaces Attributes Dataset instead.

```
In [8]: import numpy as np
   import tensorflow as tf
   from tensorflow import keras
   from tensorflow.keras import layers

In [2]: class Sampling(layers.Layer):
   """Uses (z mean, z log var) to sample z, the vector encoding a dig
```

```
In [2]: class Sampling(layers.Layer):
    """Uses (z_mean, z_log_var) to sample z, the vector encoding a dig
it."""

def call(self, inputs):
    z_mean, z_log_var = inputs
    batch = tf.shape(z_mean)[0]
    dim = tf.shape(z_mean)[1]
    epsilon = tf.keras.backend.random_normal(shape=(batch, dim))
    return z_mean + tf.exp(0.5 * z_log_var) * epsilon
```

```
In [3]: latent_dim = 2

encoder_inputs = keras.Input(shape=(28, 28, 1))
    x = layers.Conv2D(32, 3, activation="relu", strides=2, padding="same")
    (encoder_inputs)
    x = layers.Conv2D(64, 3, activation="relu", strides=2, padding="same")
    (x)
    x = layers.Flatten()(x)
    x = layers.Dense(16, activation="relu")(x)
    z_mean = layers.Dense(latent_dim, name="z_mean")(x)
    z_log_var = layers.Dense(latent_dim, name="z_log_var")(x)
    z = Sampling()([z_mean, z_log_var])
    encoder = keras.Model(encoder_inputs, [z_mean, z_log_var, z], name="encoder")
    encoder.summary()
```

Model: "encoder"

Layer (type) nected to	Output Shape	Param #	Con
		:=======	=====
<pre>input_1 (InputLayer)</pre>	[(None, 28, 28, 1)]	0	
conv2d (Conv2D) ut_1[0][0]	(None, 14, 14, 32)	320	inp
conv2d_1 (Conv2D) v2d[0][0]	(None, 7, 7, 64)	18496	con
flatten (Flatten) v2d_1[0][0]	(None, 3136)	0	con
dense (Dense) tten[0][0]	(None, 16)	50192	fla
z_mean (Dense) se[0][0]	(None, 2)	34	den
z_log_var (Dense) se[0][0]	(None, 2)	34	den
<pre>sampling (Sampling) ean[0][0]</pre>	(None, 2)	0	z_m
og_var[0][0]			z_1
Total params: 69,076 Trainable params: 69,076 Non-trainable params: 0			

In [4]: latent_inputs = keras.Input(shape=(latent_dim,))
 x = layers.Dense(7 * 7 * 64, activation="relu")(latent_inputs)
 x = layers.Reshape((7, 7, 64))(x)
 x = layers.Conv2DTranspose(64, 3, activation="relu", strides=2, paddin
 g="same")(x)
 x = layers.Conv2DTranspose(32, 3, activation="relu", strides=2, paddin
 g="same")(x)
 decoder_outputs = layers.Conv2DTranspose(1, 3, activation="sigmoid", p
 adding="same")(x)
 decoder = keras.Model(latent_inputs, decoder_outputs, name="decoder")
 decoder.summary()

Model: "decoder"

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 2)]	0
dense_1 (Dense)	(None, 3136)	9408
reshape (Reshape)	(None, 7, 7, 64)	0
conv2d_transpose (Conv2DTran	(None, 14, 14, 64)	36928
conv2d_transpose_1 (Conv2DTr	(None, 28, 28, 32)	18464
conv2d_transpose_2 (Conv2DTr	(None, 28, 28, 1)	289

Total params: 65,089
Trainable params: 65,089
Non-trainable params: 0

In [5]:

class VAE(keras.Model):

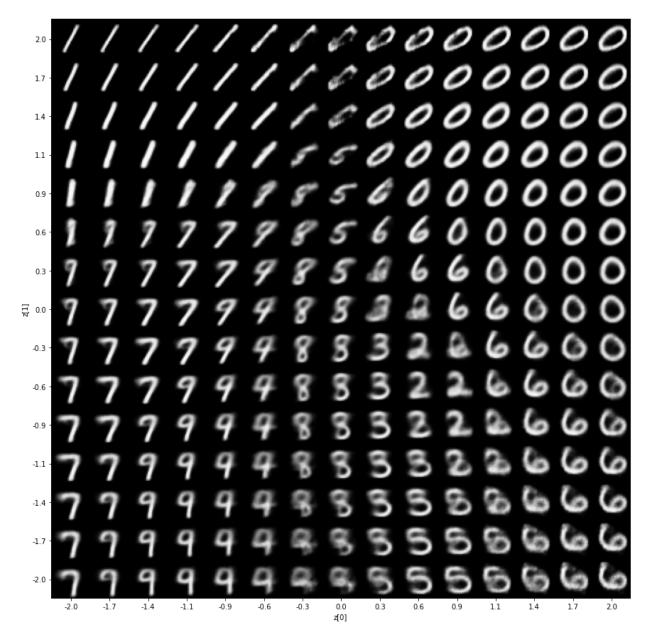
```
def init (self, encoder, decoder, **kwargs):
              super(VAE, self). init (**kwargs)
              self.encoder = encoder
              self.decoder = decoder
          def train step(self, data):
              if isinstance(data, tuple):
                  data = data[0]
              with tf.GradientTape() as tape:
                  z mean, z log var, z = encoder(data)
                  reconstruction = decoder(z)
                  reconstruction loss = tf.reduce mean(
                     keras.losses.binary crossentropy(data, reconstruction)
                  reconstruction loss *= 28 * 28
                 kl loss = 1 + z log var - tf.square(z mean) - tf.exp(z log
       var)
                 kl loss = tf.reduce mean(kl loss)
                 kl loss *= -0.5
                  total loss = reconstruction loss + kl loss
              grads = tape.gradient(total loss, self.trainable weights)
              self.optimizer.apply gradients(zip(grads, self.trainable weigh
       ts))
              return {
                  "loss": total loss,
                  "reconstruction loss": reconstruction loss,
                  "kl loss": kl loss,
              }
      (x_train, _), (x_test, _) = keras.datasets.mnist.load_data()
In [6]:
       mnist digits = np.concatenate([x train, x test], axis=0)
       mnist digits = np.expand dims(mnist digits, -1).astype("float32") / 25
       vae = VAE(encoder, decoder)
       vae.compile(optimizer=keras.optimizers.Adam())
       vae.fit(mnist digits, epochs=30, batch size=128)
       Downloading data from https://storage.googleapis.com/tensorflow/tf-k
       eras-datasets/mnist.npz
       Epoch 1/30
       682 - reconstruction loss: 199.4540 - kl loss: 2.9142
       Epoch 2/30
       128 - reconstruction loss: 159.4889 - kl loss: 3.0239
       Epoch 3/30
```

```
287 - reconstruction loss: 154.3713 - kl loss: 3.1575
Epoch 4/30
329 - reconstruction loss: 151.9954 - kl loss: 3.2376
Epoch 5/30
180 - reconstruction loss: 150.4177 - kl loss: 3.3003
Epoch 6/30
100 - reconstruction loss: 149.2735 - kl loss: 3.3365
Epoch 7/30
836 - reconstruction loss: 148.3357 - kl loss: 3.3480
Epoch 8/30
421 - reconstruction loss: 147.6427 - kl loss: 3.3994
Epoch 9/30
833 - reconstruction loss: 146.9797 - kl loss: 3.4037
Epoch 10/30
730 - reconstruction loss: 146.4460 - kl loss: 3.4270
Epoch 11/30
690 - reconstruction loss: 146.0347 - kl loss: 3.4342
Epoch 12/30
961 - reconstruction loss: 145.5439 - kl loss: 3.4522
Epoch 13/30
019 - reconstruction loss: 145.1272 - kl loss: 3.4746
Epoch 14/30
547 - reconstruction loss: 144.8601 - kl loss: 3.4946
Epoch 15/30
077 - reconstruction loss: 144.6002 - kl loss: 3.5075
Epoch 16/30
308 - reconstruction loss: 144.2117 - kl loss: 3.5191
Epoch 17/30
377 - reconstruction loss: 144.0077 - kl loss: 3.5300
Epoch 18/30
641 - reconstruction loss: 143.8094 - kl loss: 3.5546
Epoch 19/30
738 - reconstruction loss: 143.5065 - kl loss: 3.5673
```

```
Epoch 20/30
453 - reconstruction loss: 143.2773 - kl loss: 3.5680
Epoch 21/30
664 - reconstruction loss: 143.2013 - kl loss: 3.5651
Epoch 22/30
439 - reconstruction loss: 142.9481 - kl loss: 3.5958
Epoch 23/30
700 - reconstruction loss: 142.7789 - kl loss: 3.5911
Epoch 24/30
900 - reconstruction loss: 142.6831 - kl loss: 3.6070
Epoch 25/30
991 - reconstruction loss: 142.3880 - kl loss: 3.6111
Epoch 26/30
081 - reconstruction loss: 142.2842 - kl loss: 3.6240
Epoch 27/30
139 - reconstruction loss: 142.1850 - kl loss: 3.6290
Epoch 28/30
528 - reconstruction loss: 142.0203 - kl loss: 3.6326
Epoch 29/30
576 - reconstruction loss: 141.9096 - kl loss: 3.6480
Epoch 30/30
119 - reconstruction loss: 141.7675 - kl loss: 3.6444
```

Out[6]: <tensorflow.python.keras.callbacks.History at 0x7f945e2b3780>

In [7]: import matplotlib.pyplot as plt def plot latent(encoder, decoder): # display a n*n 2D manifold of digits n = 15digit size = 28 scale = 2.0figsize = 15figure = np.zeros((digit_size * n, digit_size * n)) # 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 = decoder.predict(z sample) digit = x decoded[0].reshape(digit size, digit size) figure i * digit_size : (i + 1) * digit_size, j * digit size : (j + 1) * digit size, 1 = digit plt.figure(figsize=(figsize, figsize)) start range = digit size // 2 end range = n * digit size + start range + 1 pixel range = np.arange(start range, end range, digit 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="Greys r") plt.savefig("mnist vae.png") plt.show() plot latent(encoder, decoder)



In [7]: