# assignment12\_KingRamsey

### March 4, 2022

This is a companion notebook for the book Deep Learning with Python, Second Edition. For readability, it only contains runnable code blocks and section titles, and omits everything else in the book: text paragraphs, figures, and pseudocode.

If you want to be able to follow what's going on, I recommend reading the notebook side by side with your copy of the book.

This notebook was generated for TensorFlow 2.6.

- 0.1 Generating images with variational autoencoders
- 0.1.1 Sampling from latent spaces of images
- 0.1.2 Concept vectors for image editing
- 0.1.3 Variational autoencoders
- 0.1.4 Implementing a VAE with Keras

VAE encoder network

[3]: encoder.summary()

```
[(None, 28, 28, 1)] 0
input_1 (InputLayer)
conv2d (Conv2D)
               (None, 14, 14, 32) 320
                              input_1[0][0]
______
               (None, 7, 7, 64) 18496
conv2d_1 (Conv2D)
                              conv2d[0][0]
______
flatten (Flatten)
               (None, 3136) 0
                              conv2d_1[0][0]
_____
               (None, 16) 50192 flatten[0][0]
dense (Dense)
----
               (None, 2)
z_mean (Dense)
                        34 dense[0][0]
______
z log var (Dense)
              (None, 2)
                        34
                            dense[0][0]
_____
Total params: 69,076
Trainable params: 69,076
Non-trainable params: 0
```

# Latent-space-sampling layer

```
[4]: import tensorflow as tf

class Sampler(layers.Layer):
    def call(self, z_mean, z_log_var):
        batch_size = tf.shape(z_mean)[0]
        z_size = tf.shape(z_mean)[1]
        epsilon = tf.random.normal(shape=(batch_size, z_size))
        return z_mean + tf.exp(0.5 * z_log_var) * epsilon
```

# VAE decoder network, mapping latent space points to images

```
[5]: 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, □
→padding="same")(x)
```

# [6]: decoder.summary()

#### Model: "decoder"

	0
	9408
54)	0
, 64)	36928
, 32)	18464
, 1)	289
	=======
_	, . ======

# VAE model with custom train\_step()

```
[7]: class VAE(keras.Model):
         def __init__(self, encoder, decoder, **kwargs):
             super().__init__(**kwargs)
             self.encoder = encoder
             self.decoder = decoder
             self.sampler = Sampler()
             self.total_loss_tracker = keras.metrics.Mean(name="total_loss")
             self.reconstruction_loss_tracker = keras.metrics.Mean(
                 name="reconstruction_loss")
             self.kl_loss_tracker = keras.metrics.Mean(name="kl_loss")
         @property
         def metrics(self):
             return [self.total_loss_tracker,
                     self.reconstruction_loss_tracker,
                     self.kl_loss_tracker]
         def train_step(self, data):
```

```
with tf.GradientTape() as tape:
           z_mean, z_log_var = self.encoder(data)
           z = self.sampler(z_mean, z_log_var)
           reconstruction = decoder(z)
           reconstruction_loss = tf.reduce_mean(
               tf.reduce_sum(
                   keras.losses.binary_crossentropy(data, reconstruction),
                   axis=(1, 2)
               )
           )
           kl_loss = -0.5 * (1 + z_log_var - tf.square(z_mean) - tf.
\rightarrowexp(z_log_var))
           total_loss = reconstruction_loss + tf.reduce_mean(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 {
           "total_loss": self.total_loss_tracker.result(),
           "reconstruction loss": self.reconstruction loss tracker.result(),
           "kl_loss": self.kl_loss_tracker.result(),
       }
```

### Training the VAE

```
[8]: import numpy as np
   (x_train, _), (x_test, _) = keras.datasets.mnist.load_data()
   mnist_digits = np.concatenate([x_train, x_test], axis=0)
   mnist_digits = np.expand_dims(mnist_digits, -1).astype("float32") / 255
   vae = VAE(encoder, decoder)
   vae.compile(optimizer=keras.optimizers.Adam(), run_eagerly=True)
   vae.fit(mnist_digits, epochs=30, batch_size=128)
  Epoch 1/30
  - reconstruction_loss: 936.2541 - kl_loss: 7.0439
  - reconstruction_loss: 805.0542 - kl_loss: 9.1214
  - reconstruction_loss: 757.4304 - kl_loss: 8.1818
  - reconstruction_loss: 720.3558 - kl_loss: 7.5751
```

```
Epoch 5/30
- reconstruction_loss: 704.2355 - kl_loss: 7.1491
- reconstruction_loss: 694.5892 - kl_loss: 6.9016
Epoch 7/30
- reconstruction_loss: 687.5301 - kl_loss: 6.6583
Epoch 8/30
- reconstruction_loss: 682.8683 - kl_loss: 6.5641
Epoch 9/30
- reconstruction_loss: 678.5387 - kl_loss: 6.3807
Epoch 10/30
547/547 [============] - 70s 129ms/step - total_loss: 680.9442
- reconstruction_loss: 674.7290 - kl_loss: 6.2152
Epoch 11/30
- reconstruction_loss: 672.1674 - kl_loss: 6.0560
Epoch 12/30
- reconstruction_loss: 670.0017 - kl_loss: 5.9564
Epoch 13/30
- reconstruction_loss: 667.1535 - kl_loss: 5.8684
Epoch 14/30
- reconstruction_loss: 665.1780 - kl_loss: 5.8028
Epoch 15/30
- reconstruction_loss: 663.8165 - kl_loss: 5.7104
Epoch 16/30
- reconstruction_loss: 662.0244 - kl_loss: 5.6704
Epoch 17/30
- reconstruction_loss: 660.4729 - kl_loss: 5.6120
Epoch 18/30
- reconstruction_loss: 658.9274 - kl_loss: 5.5732
- reconstruction_loss: 658.2141 - kl_loss: 5.5604
Epoch 20/30
- reconstruction_loss: 656.6661 - kl_loss: 5.5501
```

```
Epoch 21/30
- reconstruction_loss: 655.5096 - kl_loss: 5.4772
Epoch 22/30
- reconstruction_loss: 654.7386 - kl_loss: 5.4837
Epoch 23/30
- reconstruction_loss: 653.7598 - kl_loss: 5.4893
Epoch 24/30
- reconstruction_loss: 652.4306 - kl_loss: 5.4453
Epoch 25/30
- reconstruction_loss: 652.0070 - kl_loss: 5.4008
Epoch 26/30
- reconstruction_loss: 651.0792 - kl_loss: 5.4177
Epoch 27/30
- reconstruction_loss: 650.0897 - kl_loss: 5.3817
Epoch 28/30
- reconstruction_loss: 649.7756 - kl_loss: 5.3753
Epoch 29/30
- reconstruction_loss: 648.6729 - kl_loss: 5.3647
Epoch 30/30
- reconstruction_loss: 647.8334 - kl_loss: 5.3494
```

[8]: <tensorflow.python.keras.callbacks.History at 0x7fbca8393190>

# Sampling a grid of images from the 2D latent space

```
[9]: import matplotlib.pyplot as plt

n = 30
digit_size = 28
figure = np.zeros((digit_size * n, digit_size * n))

grid_x = np.linspace(-1, 1, n)
grid_y = np.linspace(-1, 1, 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)
```

```
digit = x_decoded[0].reshape(digit_size, digit_size)
        figure[
            i * digit_size : (i + 1) * digit_size,
            j * digit_size : (j + 1) * digit_size,
        ] = digit
plt.figure(figsize=(15, 15))
start_range = digit_size // 2
end_range = n * digit_size + start_range
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.axis("off")
plt.imshow(figure, cmap="Greys_r")
```

```
*************
444444888882222222222
44444888888882222222
 888888883333333
 555555533333333
   888
  5 5 5 5 5 5
   3
   335
  5555
  8
  8
  8
  8
   8
   8
  88888
```

```
[12]: import os
  from pathlib import Path

results_dir = Path('results').joinpath('vae')
  results_dir.mkdir(parents=True,exist_ok=True)
  results_dir.joinpath('figure.png')
```

# [12]: PosixPath('results/vae/figure.png')

# 0.1.5 Wrapping up