assignment12_FoxAndrea

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Date: May 29, 2021
Course: DSC650 - T301 Big Data
Assignment 12
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0.1 Assignment 12

```
Using section 8.4 in Deep Learning with Python as a guide, implement a variational autoencoder
```

[8]:
```
#load libraries
import keras
from keras import layers
import tensorflow.compat.v1.keras.backend as K
from tensorflow.keras.models import Model
import numpy as np
from tensorflow.keras.datasets import mnist
import tensorflow as tf
import os
from pathlib import Path
import matplotlib.pyplot as plt
from scipy.stats import norm
```

[16]:
```
#set directories and create results folder
current_dir = Path(os.getcwd()).absolute()
results_dir = current_dir.joinpath('results')
results_dir.mkdir(parents=True, exist_ok=True)
vae_dir = results_dir.joinpath('vae')

# Fixes version incompatibility errors between Keras and Tensorflow (saw this␣
↪from Robert on general chat)
tf.compat.v1.disable_eager_execution()
```

[10]:
```
#VAE encoder network
img_shape = (28, 28, 1)
batch_size = 16
latent_dim = 2  # Dimensionality of the latent space: a plane

input_img = keras.Input(shape=img_shape)
```

```
x = layers.Conv2D(32, 3,
                  padding='same', activation='relu')(input_img)
x = layers.Conv2D(64, 3,
                  padding='same', activation='relu',
                  strides=(2, 2))(x)
x = layers.Conv2D(64, 3,
                  padding='same', activation='relu')(x)
x = layers.Conv2D(64, 3,
                  padding='same', activation='relu')(x)
shape_before_flattening = K.int_shape(x)

x = layers.Flatten()(x)
x = layers.Dense(32, activation='relu')(x)

z_mean = layers.Dense(latent_dim)(x)
z_log_var = layers.Dense(latent_dim)(x)
```

[11]:
```
#latent-space-sampling function
def sampling(args):
    z_mean, z_log_var = args
    epsilon = K.random_normal(shape=(K.shape(z_mean)[0], latent_dim),
                              mean=0., stddev=1.)
    return z_mean + K.exp(z_log_var) * epsilon

z = layers.Lambda(sampling)([z_mean, z_log_var])
```

[12]:
```
#VAE encoder network, mapping latent space points to images
# This is the input where we will feed `z`.
decoder_input = layers.Input(K.int_shape(z)[1:])

# Upsample to the correct number of units
x = layers.Dense(np.prod(shape_before_flattening[1:]),
                 activation='relu')(decoder_input)

# Reshape into an image of the same shape as before our last `Flatten` layer
x = layers.Reshape(shape_before_flattening[1:])(x)

# We then apply then reverse operation to the initial
# stack of convolution layers: a `Conv2DTranspose` layers
# with corresponding parameters.
x = layers.Conv2DTranspose(32, 3,
                           padding='same', activation='relu',
                           strides=(2, 2))(x)
x = layers.Conv2D(1, 3,
                  padding='same', activation='sigmoid')(x)
# We end up with a feature map of the same size as the original input.
```

```python
# This is our decoder model.
decoder = Model(decoder_input, x)

# We then apply it to `z` to recover the decoded `z`.
z_decoded = decoder(z)
```

[13]:
```python
#Custom layer used to compute the VAE loss
class CustomVariationalLayer(keras.layers.Layer):

    def vae_loss(self, x, z_decoded):
        x = K.flatten(x)
        z_decoded = K.flatten(z_decoded)
        xent_loss = keras.metrics.binary_crossentropy(x, z_decoded)
        kl_loss = -5e-4 * K.mean(
            1 + z_log_var - K.square(z_mean) - K.exp(z_log_var), axis=-1)
        return K.mean(xent_loss + kl_loss)

    def call(self, inputs):
        x = inputs[0]
        z_decoded = inputs[1]
        loss = self.vae_loss(x, z_decoded)
        self.add_loss(loss, inputs=inputs)
        # We don't use this output.
        return x

# We call our custom layer on the input and the decoded output,
# to obtain the final model output.
y = CustomVariationalLayer()([input_img, z_decoded])
```

[14]:
```python
#training the VAE
vae = Model(input_img, y)
vae.compile(optimizer='rmsprop', loss=None)
vae.summary()

# Train the VAE on MNIST digits
(x_train, _), (x_test, y_test) = mnist.load_data()

x_train = x_train.astype('float32') / 255.
x_train = x_train.reshape(x_train.shape + (1,))
x_test = x_test.astype('float32') / 255.
x_test = x_test.reshape(x_test.shape + (1,))

vae.fit(x=x_train, y=None,
        shuffle=True,
        epochs=10,
        batch_size=batch_size,
        validation_data=(x_test, None))
```

```
WARNING:tensorflow:Output custom_variational_layer_1 missing from loss
dictionary. We assume this was done on purpose. The fit and evaluate APIs will
not be expecting any data to be passed to custom_variational_layer_1.
Model: "model_3"

--------------------------------------------------------------------------------
------------------
Layer (type)                    Output Shape         Param #     Connected to
================================================================================
==================
input_1 (InputLayer)            [(None, 28, 28, 1)]  0

--------------------------------------------------------------------------------
------------------
conv2d_5 (Conv2D)               (None, 28, 28, 32)   320         input_1[0][0]

--------------------------------------------------------------------------------
------------------
conv2d_6 (Conv2D)               (None, 14, 14, 64)   18496       conv2d_5[0][0]

--------------------------------------------------------------------------------
------------------
conv2d_7 (Conv2D)               (None, 14, 14, 64)   36928       conv2d_6[0][0]

--------------------------------------------------------------------------------
------------------
conv2d_8 (Conv2D)               (None, 14, 14, 64)   36928       conv2d_7[0][0]

--------------------------------------------------------------------------------
------------------
flatten_1 (Flatten)             (None, 12544)        0           conv2d_8[0][0]

--------------------------------------------------------------------------------
------------------
dense_4 (Dense)                 (None, 32)           401440      flatten_1[0][0]

--------------------------------------------------------------------------------
------------------
dense_5 (Dense)                 (None, 2)            66          dense_4[0][0]

--------------------------------------------------------------------------------
------------------
dense_6 (Dense)                 (None, 2)            66          dense_4[0][0]

--------------------------------------------------------------------------------
------------------
lambda_1 (Lambda)               (None, 2)            0           dense_5[0][0]
                                                                 dense_6[0][0]

--------------------------------------------------------------------------------
------------------
model_2 (Functional)            (None, 28, 28, 1)    56385       lambda_1[0][0]

--------------------------------------------------------------------------------
------------------
custom_variational_layer_1 (Cus (None, 28, 28, 1)    0           input_1[0][0]
                                                                 model_2[0][0]
================================================================================
==================
Total params: 550,629
```

```
Trainable params: 550,629
Non-trainable params: 0
---------------------------------------------------------------------------------
------------------
Train on 60000 samples, validate on 10000 samples
Epoch 1/10
59968/60000 [============================>.] - ETA: 0s - loss: 0.2334
```

```
/opt/conda/lib/python3.8/site-
packages/tensorflow/python/keras/engine/training.py:2325: UserWarning:
`Model.state_updates` will be removed in a future version. This property should
not be used in TensorFlow 2.0, as `updates` are applied automatically.
  warnings.warn('`Model.state_updates` will be removed in a future version. '
```

```
60000/60000 [==============================] - 85s 1ms/sample - loss: 0.2333 -
val_loss: 0.1987
Epoch 2/10
60000/60000 [==============================] - 84s 1ms/sample - loss: 0.1952 -
val_loss: 0.1920
Epoch 3/10
60000/60000 [==============================] - 83s 1ms/sample - loss: 0.1906 -
val_loss: 0.1880
Epoch 4/10
60000/60000 [==============================] - 83s 1ms/sample - loss: 0.1878 -
val_loss: 0.1869
Epoch 5/10
60000/60000 [==============================] - 83s 1ms/sample - loss: 0.1859 -
val_loss: 0.1846
Epoch 6/10
60000/60000 [==============================] - 82s 1ms/sample - loss: 0.1845 -
val_loss: 0.1835
Epoch 7/10
60000/60000 [==============================] - 83s 1ms/sample - loss: 0.1832 -
val_loss: 0.1880
Epoch 8/10
60000/60000 [==============================] - 83s 1ms/sample - loss: 0.1823 -
val_loss: 0.1815
Epoch 9/10
60000/60000 [==============================] - 83s 1ms/sample - loss: 0.1816 -
val_loss: 0.1825
Epoch 10/10
60000/60000 [==============================] - 83s 1ms/sample - loss: 0.1809 -
val_loss: 0.1824
```

[14]:
```
<tensorflow.python.keras.callbacks.History at 0x7f7738110fd0>
```

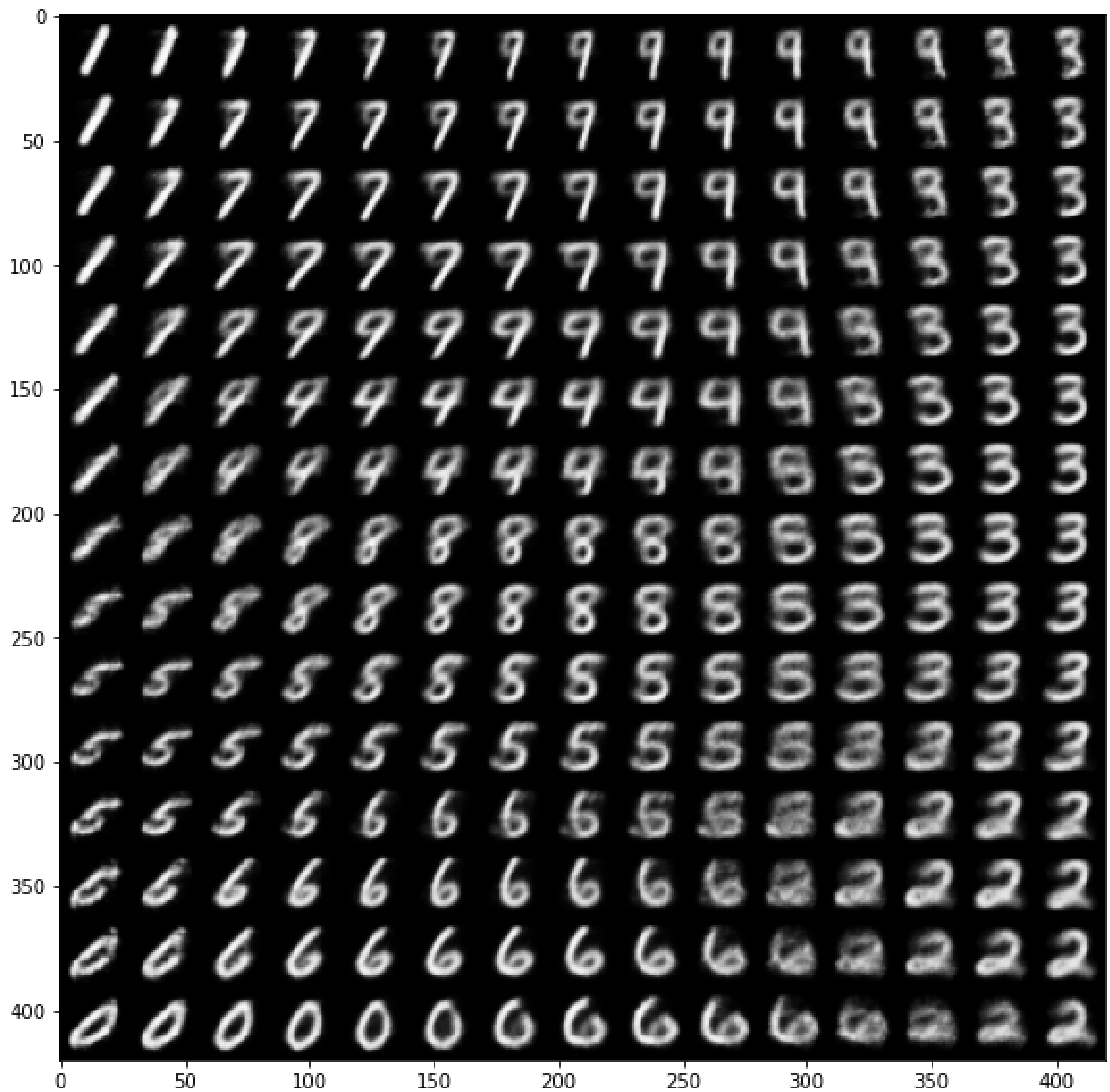
[17]:
```
#Sampling a grid of points from the 2D latent space and decoding them to images
# Display a 2D manifold of the digits
```

```
n = 15  # figure with 15x15 digits
digit_size = 28
figure = np.zeros((digit_size * n, digit_size * n))
# Linearly spaced coordinates on the unit square were transformed
# through the inverse CDF (ppf) of the Gaussian
# to produce values of the latent variables z,
# since the prior of the latent space is Gaussian
grid_x = norm.ppf(np.linspace(0.05, 0.95, n))
grid_y = norm.ppf(np.linspace(0.05, 0.95, n))

for i, yi in enumerate(grid_x):
    for j, xi in enumerate(grid_y):
        z_sample = np.array([[xi, yi]])
        z_sample = np.tile(z_sample, batch_size).reshape(batch_size, 2)
        x_decoded = decoder.predict(z_sample, batch_size=batch_size)
        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=(10, 10))
plt.imshow(figure, cmap='Greys_r')

#Robert mentioned this in general chat that he used so it saved it as well as␣
 ↪showed in output
plt.savefig(vae_dir.joinpath('15x15_Grid_of_Var_Encod_MNIST_Nums.png'),␣
 ↪bbox_inches='tight')
```


0
50
100
150
200
250
300
350
400
0
50
100
150
200
250
300
350
400