Deep Learning Course (980)

Assignment Four

Assignment Goals:

- Implementing Fully Connected AutoEncoders
- Implementing Convolutional AutoEncoders
- · Understand Variational Autoncoder intuition

In this assignment, you will be asked to design a Fully Connected and a CNN AutoEncoder. With a simple change in your Fully Connected AutoEncoder, you will become more familiar with Variational AutoEncoder.

DataSet: In this Assignment, you will use the MNIST handwritten digit database. You can use (xtrain,), (xtest,) = tensorflow.keras.datasets.mnist.load data() to load the dataset.

- 1. (30 points) Implement a Fully Connected AutoEncoder in TensorFlow (cf. Chapter 7). Your AutoEncoder should have a bottleneck with two neurons and Mean Squared Error (MSE) as the objective function. In an AutoEncoder, the layer with the least number of neurons is referred to as a bottleneck. Train your model on MNIST. Plot the train and test loss. Randomly select 10 images from the test set, encode them and visualize the decoded images.
- 2. (35 points) Implement a convolutional AutoEncoder (CAE) that uses only the following types of layers: convolution, pooling, upsampling and transpose. You are limited to use MSE. The encoder and decoder should include one or more layers, with the size and number of filters chosen by you. Start with a bottleneck of size 2, train your model on MNIST and plot the train and test loss. Randomly select 10 images from the test set, encode them and visualize the decoded images. Are the reconstructed images readable for humans? If not, try to find a CAE architecture, including a larger bottleneck, that is powerful enough to generate readable images. The bottleneck should be as small as possible for readability, this is part of the grading criteria.
- 3. (35 points) This question is about using an AutoEncoder to generate similar but not identical hand digits. We use a naive approach: Try to see if a trained decoder can map randomly generated inputs (random numbers) to a recognizable hand-written digit.
 - A. Start with your Fully Connected and trained AutoEncoder from part 1. Try to generate new images by inputting some random numbers to the decoder (i.e. the bottleneck layer) and report your results. Hint: This is not easy. You probably want to input at least 10 random numbers.
 - B. Now restrict the AutoEncoder hidden bottleneck layer(s) to have a standard multi-variate normal distribution with mean zeroes and the identity matrix as variance (i.e. no correlations). Retrain the Fully Connected AutoEncoder with the normalized bottleneck. Now randomly generate inputs to the bottleneck layer that are drawn from the multi-variate standard normal distribution, and use the random inputs to generate new images. Report your result.
 - C. Are the output images different between 1) and 2)? If so, why do you think this difference occurs?
- 4. (20 points) Optional: change the AutoEncoder which you developed in the last part of section 3 so that it becomes a Variational AutoEncoder (Introduced by Kingma 2014; see Chapter 7.1). Does the VAE produce a different quality of output image?

Submission Notes:

Please use Jupyter Notebook. The notebook should include the final code, results, and answers. You should submit your Notebook in .pdf and .ipynb format. (penalty 10 points). Your AutoEncoders should have only one bottleneck.

Instructions:

The university policy on academic dishonesty and plagiarism (cheating) will be taken very seriously in this course. Everything submitted should be your writing or coding. You must not let other students copy your work.

```
In [2]: import tensorflow as tf
    from tensorflow import keras
    from keras.models import Model, Sequential, load_model
    from keras.layers import Dense, Input, Conv2D, Conv2DTranspose, MaxPooling2D,
    UpSampling2D, Lambda
    from keras import backend as K
    from keras.callbacks import ModelCheckpoint
    import numpy as np
    from tensorflow.python.client import device_lib
    from matplotlib import pyplot as plt

    (x_train, _), (x_test, _) = keras.datasets.mnist.load_data()

# normalize the data
    x_train = x_train.astype('float32') / 255.
    x_test = x_test.astype('float32') / 255.
```

Layer (type)	Output Shape	Param #
dense_22 (Dense)	(None, 512)	401920
dense_23 (Dense)	(None, 2)	1026
dense_24 (Dense)	(None, 512)	1536
dense_25 (Dense)	(None, 784)	402192

Total params: 806,674 Trainable params: 806,674 Non-trainable params: 0

file:///C:/Users/songyih/Downloads/Assignment Four.html

```
In [73]: # train model
         print(device_lib.list_local_devices())
         autoencoder_fc.compile(optimizer='adam', loss='mean_squared_error', metrics=[
          'accuracy'])
         best_model_checkpoint = ModelCheckpoint(
              './best_model_fc.pth',
             monitor="val_acc",
             save_best_only=True,
             save_weights_only=False
         )
         autoencoder_fc_history = autoencoder_fc.fit(
             x_train_flatten,
             x_train_flatten,
             epochs=100,
             batch_size=128,
             shuffle=True,
             validation_data=(x_test_flatten, x_test_flatten),
             callbacks=[best model checkpoint]
```

)

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```
[name: "/device:CPU:0"
device_type: "CPU"
memory limit: 268435456
locality {
}
incarnation: 12452917752891272547
, name: "/device:GPU:0"
device type: "GPU"
memory_limit: 6700198133
locality {
 bus id: 1
 links {
 }
incarnation: 14822082337168630399
physical device desc: "device: 0, name: GeForce GTX 1070, pci bus id: 0000:0
1:00.0, compute capability: 6.1"
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
acc: 0.0107 - val loss: 0.0539 - val acc: 0.0112
Epoch 2/100
acc: 0.0124 - val_loss: 0.0501 - val_acc: 0.0103
Epoch 3/100
acc: 0.0120 - val_loss: 0.0477 - val_acc: 0.0107
Epoch 4/100
acc: 0.0101 - val_loss: 0.0465 - val_acc: 0.0096
acc: 0.0103 - val loss: 0.0455 - val acc: 0.0092
Epoch 6/100
acc: 0.0122 - val loss: 0.0446 - val acc: 0.0105
Epoch 7/100
acc: 0.0125 - val loss: 0.0438 - val acc: 0.0096
Epoch 8/100
acc: 0.0119 - val_loss: 0.0433 - val_acc: 0.0110
Epoch 9/100
acc: 0.0111 - val loss: 0.0429 - val acc: 0.0062
Epoch 10/100
acc: 0.0106 - val_loss: 0.0427 - val_acc: 0.0080
Epoch 11/100
acc: 0.0097 - val loss: 0.0425 - val acc: 0.0081
Epoch 12/100
acc: 0.0096 - val loss: 0.0421 - val acc: 0.0081
Epoch 13/100
```

```
acc: 0.0097 - val loss: 0.0418 - val acc: 0.0106
Epoch 14/100
acc: 0.0101 - val loss: 0.0418 - val acc: 0.0085
Epoch 15/100
60000/60000 [============== ] - 2s 27us/step - loss: 0.0411 -
acc: 0.0094 - val loss: 0.0416 - val acc: 0.0105
Epoch 16/100
acc: 0.0091 - val loss: 0.0415 - val acc: 0.0101
Epoch 17/100
60000/60000 [============== ] - 2s 27us/step - loss: 0.0407 -
acc: 0.0101 - val loss: 0.0415 - val acc: 0.0072
Epoch 18/100
acc: 0.0101 - val loss: 0.0412 - val acc: 0.0105
Epoch 19/100
acc: 0.0105 - val loss: 0.0411 - val acc: 0.0093
Epoch 20/100
60000/60000 [============= ] - 2s 27us/step - loss: 0.0402 -
acc: 0.0100 - val loss: 0.0411 - val acc: 0.0126
Epoch 21/100
acc: 0.0110 - val_loss: 0.0409 - val_acc: 0.0109
Epoch 22/100
acc: 0.0099 - val_loss: 0.0409 - val_acc: 0.0095
Epoch 23/100
acc: 0.0106 - val_loss: 0.0407 - val_acc: 0.0104
Epoch 24/100
acc: 0.0106 - val loss: 0.0407 - val acc: 0.0096
Epoch 25/100
acc: 0.0108 - val_loss: 0.0406 - val_acc: 0.0115
Epoch 26/100
acc: 0.0108 - val_loss: 0.0405 - val_acc: 0.0093
Epoch 27/100
acc: 0.0104 - val_loss: 0.0406 - val_acc: 0.0102
acc: 0.0110 - val loss: 0.0404 - val acc: 0.0110
Epoch 29/100
acc: 0.0111 - val loss: 0.0403 - val acc: 0.0110
Epoch 30/100
acc: 0.0114 - val loss: 0.0403 - val acc: 0.0119
Epoch 31/100
acc: 0.0109 - val_loss: 0.0403 - val_acc: 0.0123
Epoch 32/100
```

```
acc: 0.0108 - val loss: 0.0403 - val acc: 0.0101
Epoch 33/100
acc: 0.0107 - val loss: 0.0402 - val acc: 0.0108
Epoch 34/100
60000/60000 [=============== ] - 2s 28us/step - loss: 0.0386 -
acc: 0.0118 - val loss: 0.0401 - val acc: 0.0128
Epoch 35/100
acc: 0.0109 - val loss: 0.0401 - val acc: 0.0131
Epoch 36/100
60000/60000 [============== ] - 2s 28us/step - loss: 0.0384 -
acc: 0.0109 - val loss: 0.0401 - val acc: 0.0105
Epoch 37/100
acc: 0.0111 - val loss: 0.0400 - val acc: 0.0085
Epoch 38/100
acc: 0.0111 - val loss: 0.0400 - val acc: 0.0118
Epoch 39/100
acc: 0.0112 - val loss: 0.0399 - val acc: 0.0107
Epoch 40/100
acc: 0.0109 - val_loss: 0.0399 - val_acc: 0.0108
Epoch 41/100
acc: 0.0113 - val_loss: 0.0399 - val_acc: 0.0134
Epoch 42/100
acc: 0.0114 - val_loss: 0.0398 - val_acc: 0.0132
Epoch 43/100
60000/60000 [=========== ] - 2s 28us/step - loss: 0.0379 -
acc: 0.0113 - val loss: 0.0399 - val acc: 0.0135
Epoch 44/100
acc: 0.0114 - val_loss: 0.0398 - val_acc: 0.0106
Epoch 45/100
acc: 0.0109 - val_loss: 0.0397 - val_acc: 0.0101
Epoch 46/100
acc: 0.0115 - val_loss: 0.0398 - val_acc: 0.0113
Epoch 47/100
acc: 0.0114 - val loss: 0.0398 - val acc: 0.0115
Epoch 48/100
acc: 0.0116 - val loss: 0.0397 - val acc: 0.0100
Epoch 49/100
acc: 0.0114 - val loss: 0.0398 - val acc: 0.0107
Epoch 50/100
acc: 0.0112 - val_loss: 0.0398 - val_acc: 0.0114
Epoch 51/100
60000/60000 [============ ] - 2s 28us/step - loss: 0.0374 -
```

```
acc: 0.0114 - val loss: 0.0397 - val acc: 0.0122
Epoch 52/100
acc: 0.0118 - val loss: 0.0399 - val acc: 0.0109
Epoch 53/100
60000/60000 [============== ] - 2s 28us/step - loss: 0.0373 -
acc: 0.0117 - val loss: 0.0397 - val acc: 0.0093
Epoch 54/100
acc: 0.0109 - val loss: 0.0398 - val acc: 0.0138
Epoch 55/100
60000/60000 [============== ] - 2s 27us/step - loss: 0.0372 -
acc: 0.0119 - val loss: 0.0396 - val acc: 0.0105
Epoch 56/100
acc: 0.0112 - val_loss: 0.0397 - val_acc: 0.0121
Epoch 57/100
acc: 0.0126 - val loss: 0.0395 - val acc: 0.0126
Epoch 58/100
60000/60000 [============== ] - 2s 26us/step - loss: 0.0371 -
acc: 0.0115 - val loss: 0.0397 - val acc: 0.0115
Epoch 59/100
acc: 0.0116 - val_loss: 0.0396 - val_acc: 0.0103
Epoch 60/100
acc: 0.0114 - val_loss: 0.0396 - val_acc: 0.0110
Epoch 61/100
acc: 0.0117 - val_loss: 0.0396 - val_acc: 0.0110
Epoch 62/100
60000/60000 [=========== ] - 2s 26us/step - loss: 0.0369 -
acc: 0.0118 - val loss: 0.0396 - val acc: 0.0117
Epoch 63/100
acc: 0.0116 - val_loss: 0.0395 - val_acc: 0.0103
Epoch 64/100
acc: 0.0116 - val_loss: 0.0396 - val_acc: 0.0127
Epoch 65/100
acc: 0.0118 - val_loss: 0.0396 - val_acc: 0.0130
acc: 0.0115 - val loss: 0.0396 - val acc: 0.0109
Epoch 67/100
acc: 0.0117 - val loss: 0.0396 - val acc: 0.0123
Epoch 68/100
acc: 0.0116 - val loss: 0.0398 - val acc: 0.0105
Epoch 69/100
acc: 0.0119 - val_loss: 0.0396 - val_acc: 0.0154
Epoch 70/100
```

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acc: 0.0121 - val loss: 0.0395 - val acc: 0.0138
Epoch 71/100
acc: 0.0119 - val loss: 0.0395 - val acc: 0.0105
Epoch 72/100
60000/60000 [=============== ] - 2s 27us/step - loss: 0.0366 -
acc: 0.0117 - val loss: 0.0396 - val acc: 0.0137
Epoch 73/100
acc: 0.0117 - val loss: 0.0397 - val acc: 0.0127
Epoch 74/100
acc: 0.0121 - val loss: 0.0397 - val acc: 0.0141
Epoch 75/100
acc: 0.0122 - val_loss: 0.0397 - val_acc: 0.0100
Epoch 76/100
acc: 0.0119 - val loss: 0.0395 - val acc: 0.0129
Epoch 77/100
acc: 0.0121 - val loss: 0.0398 - val acc: 0.0111
Epoch 78/100
acc: 0.0121 - val_loss: 0.0395 - val_acc: 0.0119
Epoch 79/100
acc: 0.0118 - val_loss: 0.0395 - val_acc: 0.0104
Epoch 80/100
acc: 0.0118 - val_loss: 0.0396 - val_acc: 0.0117
Epoch 81/100
60000/60000 [=========== ] - 2s 27us/step - loss: 0.0363 -
acc: 0.0123 - val loss: 0.0395 - val acc: 0.0101
Epoch 82/100
acc: 0.0125 - val_loss: 0.0396 - val_acc: 0.0119
Epoch 83/100
acc: 0.0124 - val_loss: 0.0397 - val_acc: 0.0111
Epoch 84/100
acc: 0.0113 - val_loss: 0.0395 - val_acc: 0.0101
Epoch 85/100
acc: 0.0123 - val loss: 0.0397 - val acc: 0.0118
Epoch 86/100
acc: 0.0124 - val loss: 0.0397 - val acc: 0.0105
Epoch 87/100
acc: 0.0120 - val loss: 0.0395 - val acc: 0.0124
Epoch 88/100
acc: 0.0116 - val_loss: 0.0396 - val_acc: 0.0136
Epoch 89/100
60000/60000 [=========== ] - 2s 32us/step - loss: 0.0361 -
```

```
acc: 0.0120 - val loss: 0.0395 - val acc: 0.0110
Epoch 90/100
60000/60000 [============== ] - 2s 29us/step - loss: 0.0361 -
acc: 0.0123 - val_loss: 0.0397 - val_acc: 0.0110
Epoch 91/100
60000/60000 [============== ] - 2s 27us/step - loss: 0.0361 -
acc: 0.0115 - val loss: 0.0397 - val acc: 0.0107
Epoch 92/100
60000/60000 [============== ] - 2s 27us/step - loss: 0.0361 -
acc: 0.0122 - val loss: 0.0395 - val acc: 0.0130
Epoch 93/100
60000/60000 [============== ] - 2s 27us/step - loss: 0.0360 -
acc: 0.0121 - val loss: 0.0396 - val acc: 0.0108
Epoch 94/100
acc: 0.0121 - val loss: 0.0396 - val acc: 0.0118
Epoch 95/100
acc: 0.0128 - val loss: 0.0395 - val acc: 0.0114
Epoch 96/100
60000/60000 [============== ] - 2s 29us/step - loss: 0.0360 -
acc: 0.0120 - val loss: 0.0396 - val acc: 0.0122
Epoch 97/100
acc: 0.0124 - val_loss: 0.0396 - val acc: 0.0129
Epoch 98/100
acc: 0.0124 - val_loss: 0.0395 - val_acc: 0.0101
Epoch 99/100
acc: 0.0122 - val_loss: 0.0396 - val_acc: 0.0115
Epoch 100/100
acc: 0.0116 - val loss: 0.0396 - val acc: 0.0100
```

```
In [74]: # plot the train and test loss
plt.plot(autoencoder_fc_history.history['loss'])
plt.plot(autoencoder_fc_history.history['val_loss'])
plt.title('Train and test loss for fully connected AE')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```

Train and test loss for fully connected AE 0.065 Train Test 0.065 0.055 0.045 0.040 0.045 Epoch

```
In [75]:
         # visualization
         img num = 10
         autoencoder_fc_best = load_model('./best_model_fc.pth')
         plt.figure(figsize=(18, 4))
         plt.gray()
         for i in range(img num):
             # randomly pick an image from test dataset
             chosen test img = x test flatten[np.random.randint(x test flatten.shape[0
         ])]
             img_decoded = autoencoder_fc_best.predict(chosen_test_img.reshape(1, 784))
             ax = plt.subplot(2, img_num, i+1)
             plt.imshow(chosen test img.reshape(28, 28))
             ax.axis('off')
             ax = plt.subplot(2, img_num, img_num+i+1)
             plt.imshow(img_decoded.reshape(28, 28))
             ax.axis('off')
         plt.show()
```

''' Part 2: Implement a convolutional AutoEncoder (CAE) In [47]: x train = x train.reshape((len(x train), 28, 28, 1)) $x_{\text{test}} = x_{\text{test.reshape}}((\text{len}(x_{\text{test}}), 28, 28, 1))$ # build the network with a bottleneck of two neurons autoencoder conv = Sequential() # encoder network autoencoder_conv.add(Conv2D(32, (3, 3), activation='relu', padding='same', inp ut shape=x train.shape[1:])) autoencoder_conv.add(MaxPooling2D(pool_size=(2, 2))) autoencoder_conv.add(Conv2D(64, (3, 3), activation='relu', padding='same')) autoencoder conv.add(MaxPooling2D(pool size=(2, 2))) autoencoder conv.add(Conv2D(128, (3, 3), activation='relu', padding='same')) autoencoder_conv.add(MaxPooling2D(pool_size=(2, 2))) autoencoder conv.add(Conv2D(2, (3, 3), activation='relu', padding='same')) autoencoder conv.add(MaxPooling2D(pool size=(2, 2))) # decoder network autoencoder conv.add(Conv2DTranspose(64, (7, 7), activation='relu', padding='v alid')) autoencoder_conv.add(UpSampling2D((2, 2))) autoencoder_conv.add(Conv2DTranspose(32, (3, 3), activation='relu', padding='s ame')) autoencoder conv.add(UpSampling2D((2, 2))) autoencoder conv.add(Conv2D(1, (3, 3), activation='sigmoid', padding='same')) autoencoder_conv.summary()

Layer (type)	Output	Shape	Param #
conv2d_1 (Conv2D)		28, 28, 32)	320
max_pooling2d_1 (MaxPooling2	(None,	14, 14, 32)	0
conv2d_2 (Conv2D)	(None,	14, 14, 64)	18496
max_pooling2d_2 (MaxPooling2	(None,	7, 7, 64)	0
conv2d_3 (Conv2D)	(None,	7, 7, 128)	73856
max_pooling2d_3 (MaxPooling2	(None,	3, 3, 128)	0
conv2d_4 (Conv2D)	(None,	3, 3, 2)	2306
max_pooling2d_4 (MaxPooling2	(None,	1, 1, 2)	0
conv2d_transpose_1 (Conv2DTr	(None,	7, 7, 64)	6336
up_sampling2d_1 (UpSampling2	(None,	14, 14, 64)	0
conv2d_transpose_2 (Conv2DTr	(None,	14, 14, 32)	18464
up_sampling2d_2 (UpSampling2	(None,	28, 28, 32)	0
conv2d_5 (Conv2D)	(None,	28, 28, 1)	289

Total params: 120,067 Trainable params: 120,067 Non-trainable params: 0 4/1/2020

```
In [48]: # train model
         print(device_lib.list_local_devices())
         autoencoder_conv.compile(optimizer='adam', loss='mean_squared_error', metrics=
          ['accuracy'])
         best_model_checkpoint = ModelCheckpoint(
              './best_model_conv.pth',
             monitor="val_acc",
              save_best_only=True,
              save_weights_only=False
          )
         autoencoder_conv_history = autoencoder_conv.fit(
             x_train,
             x_train,
              epochs=100,
             batch_size=256,
             shuffle=True,
             validation_data=(x_test, x_test),
              callbacks=[best model checkpoint]
          )
```

```
[name: "/device:CPU:0"
device_type: "CPU"
memory limit: 268435456
locality {
}
incarnation: 15526130026912515061
, name: "/device:GPU:0"
device type: "GPU"
memory_limit: 6700198133
locality {
 bus id: 1
 links {
 }
incarnation: 2915467488262415717
physical device desc: "device: 0, name: GeForce GTX 1070, pci bus id: 0000:0
1:00.0, compute capability: 6.1"
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
60000/60000 [================ ] - 6s 100us/step - loss: 0.0733 -
acc: 0.7987 - val loss: 0.0582 - val acc: 0.7959
Epoch 2/100
acc: 0.7955 - val_loss: 0.0525 - val_acc: 0.7943
Epoch 3/100
acc: 0.7951 - val loss: 0.0499 - val acc: 0.7942
Epoch 4/100
acc: 0.7950 - val_loss: 0.0480 - val_acc: 0.7939
Epoch 5/100
acc: 0.7954 - val loss: 0.0465 - val acc: 0.7977
Epoch 6/100
acc: 0.7960 - val loss: 0.0458 - val acc: 0.7931
Epoch 7/100
acc: 0.7964 - val loss: 0.0451 - val acc: 0.7935
Epoch 8/100
acc: 0.7967 - val_loss: 0.0445 - val_acc: 0.7971
Epoch 9/100
acc: 0.7970 - val loss: 0.0441 - val acc: 0.7939
Epoch 10/100
60000/60000 [============== ] - 4s 69us/step - loss: 0.0439 -
acc: 0.7972 - val_loss: 0.0438 - val_acc: 0.7965
Epoch 11/100
acc: 0.7974 - val loss: 0.0434 - val acc: 0.7955
Epoch 12/100
60000/60000 [============== ] - 4s 68us/step - loss: 0.0433 -
acc: 0.7975 - val loss: 0.0439 - val acc: 0.7931
Epoch 13/100
```

```
acc: 0.7976 - val loss: 0.0437 - val acc: 0.7995
Epoch 14/100
60000/60000 [============== ] - 4s 69us/step - loss: 0.0427 -
acc: 0.7978 - val loss: 0.0430 - val acc: 0.7988
Epoch 15/100
60000/60000 [============== ] - 4s 70us/step - loss: 0.0425 -
acc: 0.7979 - val loss: 0.0431 - val acc: 0.7927
Epoch 16/100
60000/60000 [============ ] - 4s 68us/step - loss: 0.0423 -
acc: 0.7980 - val loss: 0.0423 - val acc: 0.7987
Epoch 17/100
60000/60000 [============== ] - 4s 69us/step - loss: 0.0421 -
acc: 0.7981 - val loss: 0.0422 - val acc: 0.7969
Epoch 18/100
acc: 0.7982 - val loss: 0.0422 - val acc: 0.7992
Epoch 19/100
acc: 0.7983 - val loss: 0.0418 - val acc: 0.7960
Epoch 20/100
60000/60000 [============= ] - 4s 69us/step - loss: 0.0416 -
acc: 0.7983 - val loss: 0.0416 - val acc: 0.7965
Epoch 21/100
acc: 0.7984 - val_loss: 0.0414 - val_acc: 0.7968
Epoch 22/100
acc: 0.7985 - val_loss: 0.0417 - val_acc: 0.7985
Epoch 23/100
acc: 0.7985 - val_loss: 0.0414 - val_acc: 0.7952
Epoch 24/100
acc: 0.7985 - val loss: 0.0413 - val acc: 0.7956
Epoch 25/100
acc: 0.7986 - val_loss: 0.0413 - val_acc: 0.7946
Epoch 26/100
acc: 0.7987 - val_loss: 0.0412 - val_acc: 0.7988
Epoch 27/100
acc: 0.7987 - val_loss: 0.0410 - val_acc: 0.7986
acc: 0.7988 - val loss: 0.0407 - val acc: 0.7971
Epoch 29/100
acc: 0.7988 - val loss: 0.0412 - val acc: 0.7988
Epoch 30/100
acc: 0.7988 - val loss: 0.0411 - val acc: 0.7975
Epoch 31/100
60000/60000 [=========== ] - 4s 69us/step - loss: 0.0402 -
acc: 0.7990 - val_loss: 0.0410 - val_acc: 0.7994
Epoch 32/100
```

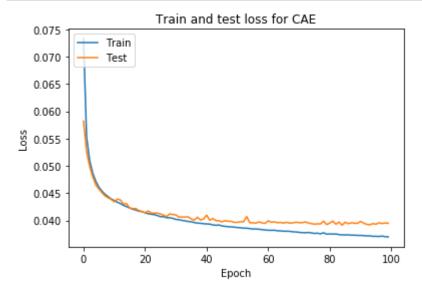
```
acc: 0.7990 - val loss: 0.0406 - val acc: 0.7987
Epoch 33/100
acc: 0.7990 - val loss: 0.0406 - val acc: 0.7956
Epoch 34/100
60000/60000 [============== ] - 4s 71us/step - loss: 0.0399 -
acc: 0.7990 - val loss: 0.0406 - val acc: 0.7983
Epoch 35/100
acc: 0.7991 - val loss: 0.0407 - val acc: 0.7986
Epoch 36/100
acc: 0.7991 - val loss: 0.0403 - val acc: 0.7974
Epoch 37/100
acc: 0.7992 - val loss: 0.0401 - val acc: 0.7978
Epoch 38/100
acc: 0.7992 - val loss: 0.0406 - val acc: 0.7963
Epoch 39/100
60000/60000 [============= ] - 4s 72us/step - loss: 0.0395 -
acc: 0.7993 - val loss: 0.0401 - val acc: 0.7958
Epoch 40/100
acc: 0.7993 - val_loss: 0.0403 - val_acc: 0.7980
Epoch 41/100
acc: 0.7993 - val_loss: 0.0410 - val_acc: 0.7992
Epoch 42/100
acc: 0.7993 - val_loss: 0.0400 - val_acc: 0.7971
Epoch 43/100
60000/60000 [=========== ] - 4s 71us/step - loss: 0.0392 -
acc: 0.7994 - val loss: 0.0403 - val acc: 0.7961
Epoch 44/100
acc: 0.7994 - val_loss: 0.0400 - val_acc: 0.7973
Epoch 45/100
acc: 0.7994 - val_loss: 0.0399 - val_acc: 0.7971
Epoch 46/100
acc: 0.7995 - val_loss: 0.0397 - val_acc: 0.7985
Epoch 47/100
60000/60000 [============ ] - 4s 69us/step - loss: 0.0389 -
acc: 0.7996 - val loss: 0.0399 - val acc: 0.7961
Epoch 48/100
acc: 0.7996 - val loss: 0.0398 - val acc: 0.7996
Epoch 49/100
acc: 0.7996 - val loss: 0.0398 - val acc: 0.7980
Epoch 50/100
acc: 0.7996 - val_loss: 0.0396 - val_acc: 0.7969
Epoch 51/100
```

```
acc: 0.7996 - val loss: 0.0397 - val acc: 0.7986
Epoch 52/100
acc: 0.7996 - val loss: 0.0398 - val acc: 0.7987
Epoch 53/100
60000/60000 [============== ] - 4s 71us/step - loss: 0.0386 -
acc: 0.7997 - val loss: 0.0397 - val acc: 0.7965
Epoch 54/100
acc: 0.7997 - val loss: 0.0407 - val acc: 0.8007
Epoch 55/100
60000/60000 [=============== ] - 4s 69us/step - loss: 0.0385 -
acc: 0.7998 - val loss: 0.0396 - val acc: 0.7983
Epoch 56/100
acc: 0.7997 - val loss: 0.0396 - val acc: 0.7982
Epoch 57/100
acc: 0.7998 - val loss: 0.0395 - val acc: 0.7966
Epoch 58/100
60000/60000 [============== ] - 4s 70us/step - loss: 0.0384 -
acc: 0.7998 - val loss: 0.0397 - val acc: 0.7951
Epoch 59/100
acc: 0.7998 - val_loss: 0.0395 - val_acc: 0.7969
Epoch 60/100
acc: 0.7999 - val_loss: 0.0395 - val_acc: 0.7977
Epoch 61/100
acc: 0.7999 - val_loss: 0.0399 - val_acc: 0.7979
Epoch 62/100
60000/60000 [=========== ] - 4s 70us/step - loss: 0.0382 -
acc: 0.7999 - val loss: 0.0397 - val acc: 0.7977
Epoch 63/100
acc: 0.7999 - val_loss: 0.0397 - val_acc: 0.7980
Epoch 64/100
acc: 0.8000 - val_loss: 0.0396 - val_acc: 0.7954
Epoch 65/100
acc: 0.8000 - val_loss: 0.0396 - val_acc: 0.7952
Epoch 66/100
60000/60000 [============ ] - 4s 70us/step - loss: 0.0380 -
acc: 0.8000 - val loss: 0.0395 - val acc: 0.7958
Epoch 67/100
acc: 0.8000 - val loss: 0.0397 - val acc: 0.7977
Epoch 68/100
acc: 0.8000 - val loss: 0.0395 - val acc: 0.7987
Epoch 69/100
acc: 0.8001 - val_loss: 0.0395 - val_acc: 0.7991
Epoch 70/100
```

```
acc: 0.8001 - val loss: 0.0397 - val acc: 0.7984
Epoch 71/100
acc: 0.8001 - val loss: 0.0396 - val acc: 0.7976
Epoch 72/100
60000/60000 [============== ] - 4s 69us/step - loss: 0.0378 -
acc: 0.8001 - val loss: 0.0396 - val acc: 0.7960
Epoch 73/100
acc: 0.8001 - val loss: 0.0397 - val acc: 0.7965
Epoch 74/100
acc: 0.8001 - val loss: 0.0395 - val acc: 0.7962
Epoch 75/100
acc: 0.8001 - val loss: 0.0394 - val acc: 0.7975
Epoch 76/100
acc: 0.8002 - val loss: 0.0393 - val acc: 0.7980
Epoch 77/100
60000/60000 [============== ] - 4s 70us/step - loss: 0.0377 -
acc: 0.8002 - val loss: 0.0394 - val acc: 0.7976
Epoch 78/100
acc: 0.8003 - val_loss: 0.0394 - val_acc: 0.7975
Epoch 79/100
acc: 0.8001 - val_loss: 0.0399 - val_acc: 0.7998
Epoch 80/100
acc: 0.8003 - val_loss: 0.0392 - val_acc: 0.7981
Epoch 81/100
60000/60000 [=========== ] - 4s 71us/step - loss: 0.0375 -
acc: 0.8003 - val loss: 0.0395 - val acc: 0.7986
Epoch 82/100
acc: 0.8003 - val_loss: 0.0399 - val_acc: 0.8001
Epoch 83/100
acc: 0.8002 - val_loss: 0.0393 - val_acc: 0.7984
Epoch 84/100
acc: 0.8003 - val_loss: 0.0397 - val_acc: 0.7990
Epoch 85/100
60000/60000 [============ ] - 4s 72us/step - loss: 0.0373 -
acc: 0.8004 - val loss: 0.0391 - val acc: 0.7980
Epoch 86/100
acc: 0.8004 - val loss: 0.0397 - val acc: 0.7959
Epoch 87/100
acc: 0.8004 - val loss: 0.0394 - val acc: 0.7993
Epoch 88/100
acc: 0.8004 - val_loss: 0.0396 - val_acc: 0.7990
Epoch 89/100
```

```
acc: 0.8004 - val loss: 0.0395 - val acc: 0.7959
Epoch 90/100
60000/60000 [============== ] - 4s 69us/step - loss: 0.0372 -
acc: 0.8004 - val loss: 0.0395 - val acc: 0.7966
Epoch 91/100
60000/60000 [============== ] - 4s 69us/step - loss: 0.0372 -
acc: 0.8004 - val loss: 0.0398 - val acc: 0.7948
Epoch 92/100
60000/60000 [============ ] - 4s 70us/step - loss: 0.0372 -
acc: 0.8005 - val loss: 0.0395 - val acc: 0.8001
Epoch 93/100
60000/60000 [============== ] - 4s 69us/step - loss: 0.0372 -
acc: 0.8005 - val loss: 0.0393 - val acc: 0.7966
Epoch 94/100
acc: 0.8005 - val loss: 0.0392 - val acc: 0.7978
Epoch 95/100
acc: 0.8005 - val loss: 0.0394 - val acc: 0.7954
Epoch 96/100
60000/60000 [============== ] - 4s 70us/step - loss: 0.0371 -
acc: 0.8005 - val loss: 0.0393 - val acc: 0.7983
Epoch 97/100
acc: 0.8006 - val_loss: 0.0396 - val acc: 0.7964
Epoch 98/100
acc: 0.8005 - val_loss: 0.0394 - val_acc: 0.7966
Epoch 99/100
acc: 0.8006 - val_loss: 0.0395 - val_acc: 0.7973
Epoch 100/100
acc: 0.8006 - val loss: 0.0395 - val acc: 0.7962
```

```
In [57]: # plot the train and test loss
plt.plot(autoencoder_conv_history.history['loss'])
plt.plot(autoencoder_conv_history.history['val_loss'])
plt.title('Train and test loss for CAE')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



```
In [56]:
         # visualization
         img num = 10
         autoencoder_conv_best = load_model('./best_model_conv.pth')
         plt.figure(figsize=(18, 4))
         plt.gray()
         for i in range(img num):
             # randomly pick an image from test dataset
             chosen test img = x test[np.random.randint(x test.shape[0])]
             img_decoded = autoencoder_conv_best.predict(chosen_test_img.reshape(1, 28,
         28, 1))
             ax = plt.subplot(2, img_num, i+1)
             plt.imshow(chosen test img.reshape(28, 28))
             ax.axis('off')
             ax = plt.subplot(2, img_num, img_num+i+1)
             plt.imshow(img_decoded.reshape(28, 28))
             ax.axis('off')
         plt.show()
```

The some of the reconstructed images are not readable for human. To solve the problem, I build another model and enlarged the bottleneck to 12.

In [51]: # find a CAE architecture that is powerful enough to generate readable images # build the network with larger bottleneck autoencoder conv refine = Sequential() # encoder network autoencoder_conv_refine.add(Conv2D(32, (3, 3), activation='relu', padding='sam e', input_shape=x_train.shape[1:])) autoencoder conv refine.add(MaxPooling2D(pool size=(2, 2))) autoencoder_conv_refine.add(Conv2D(64, (3, 3), activation='relu', padding='sam e')) autoencoder conv refine.add(MaxPooling2D(pool size=(2, 2))) autoencoder conv refine.add(Conv2D(128, (3, 3), activation='relu', padding='sa me')) autoencoder conv refine.add(MaxPooling2D(pool size=(2, 2))) autoencoder conv refine.add(Conv2D(12, (3, 3), activation='relu', padding='sam e')) autoencoder conv refine.add(MaxPooling2D(pool size=(2, 2))) # decoder network autoencoder_conv_refine.add(Conv2DTranspose(128, (7, 7), activation='relu', pa dding='valid')) autoencoder conv refine.add(UpSampling2D((2, 2))) autoencoder_conv_refine.add(Conv2DTranspose(64, (3, 3), activation='relu', pad ding='same')) autoencoder conv refine.add(UpSampling2D((2, 2))) autoencoder conv refine.add(Conv2D(1, (3, 3), activation='sigmoid', padding='s ame')) autoencoder_conv_refine.summary()

Layer (type)	Output	Shape	Param #
conv2d_6 (Conv2D)	(None,	28, 28, 32)	320
max_pooling2d_5 (MaxPooling2	(None,	14, 14, 32)	0
conv2d_7 (Conv2D)	(None,	14, 14, 64)	18496
max_pooling2d_6 (MaxPooling2	(None,	7, 7, 64)	0
conv2d_8 (Conv2D)	(None,	7, 7, 128)	73856
<pre>max_pooling2d_7 (MaxPooling2</pre>	(None,	3, 3, 128)	0
conv2d_9 (Conv2D)	(None,	3, 3, 12)	13836
max_pooling2d_8 (MaxPooling2	(None,	1, 1, 12)	0
conv2d_transpose_3 (Conv2DTr	(None,	7, 7, 128)	75392
up_sampling2d_3 (UpSampling2	(None,	14, 14, 128)	0
<pre>conv2d_transpose_4 (Conv2DTr</pre>	(None,	14, 14, 64)	73792
up_sampling2d_4 (UpSampling2	(None,	28, 28, 64)	0
conv2d_10 (Conv2D)	(None,	28, 28, 1)	577
			=

Total params: 256,269 Trainable params: 256,269 Non-trainable params: 0

```
In [52]: # train model
         print(device_lib.list_local_devices())
         autoencoder_conv_refine.compile(optimizer='adam', loss='mean_squared_error', m
         etrics=['accuracy'])
         best_model_checkpoint = ModelCheckpoint(
              './best_model_conv_refine.pth',
             monitor="val_acc",
             save_best_only=True,
             save_weights_only=False
         )
         autoencoder_conv_refine_history = autoencoder_conv_refine.fit(
             x_train,
             x_train,
             epochs=20,
             batch_size=256,
             shuffle=True,
             validation_data=(x_test, x_test),
             callbacks=[best model checkpoint]
         )
```

```
[name: "/device:CPU:0"
device_type: "CPU"
memory limit: 268435456
locality {
}
incarnation: 14877197587185339757
, name: "/device:GPU:0"
device type: "GPU"
memory_limit: 6700198133
locality {
 bus id: 1
 links {
 }
incarnation: 13845019592877475944
physical device desc: "device: 0, name: GeForce GTX 1070, pci bus id: 0000:0
1:00.0, compute capability: 6.1"
Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [================ ] - 7s 109us/step - loss: 0.0562 -
acc: 0.7976 - val loss: 0.0296 - val acc: 0.8050
Epoch 2/20
acc: 0.8061 - val_loss: 0.0214 - val_acc: 0.8072
Epoch 3/20
60000/60000 [================ ] - 6s 101us/step - loss: 0.0208 -
acc: 0.8085 - val_loss: 0.0195 - val_acc: 0.8072
Epoch 4/20
acc: 0.8095 - val_loss: 0.0180 - val_acc: 0.8084
acc: 0.8100 - val loss: 0.0174 - val acc: 0.8089
Epoch 6/20
acc: 0.8104 - val loss: 0.0165 - val acc: 0.8094
Epoch 7/20
acc: 0.8107 - val loss: 0.0163 - val acc: 0.8090
Epoch 8/20
acc: 0.8110 - val_loss: 0.0157 - val_acc: 0.8095
Epoch 9/20
acc: 0.8112 - val loss: 0.0151 - val acc: 0.8104
Epoch 10/20
60000/60000 [============== ] - 6s 98us/step - loss: 0.0151 -
acc: 0.8114 - val_loss: 0.0148 - val_acc: 0.8102
Epoch 11/20
acc: 0.8116 - val loss: 0.0146 - val acc: 0.8112
Epoch 12/20
acc: 0.8117 - val loss: 0.0143 - val acc: 0.8110
Epoch 13/20
```

```
acc: 0.8118 - val loss: 0.0141 - val acc: 0.8109
      Epoch 14/20
      acc: 0.8119 - val loss: 0.0140 - val acc: 0.8113
      Epoch 15/20
      acc: 0.8120 - val loss: 0.0137 - val acc: 0.8111
      Epoch 16/20
      60000/60000 [========================= ] - 6s 97us/step - loss: 0.0136 -
      acc: 0.8121 - val loss: 0.0140 - val acc: 0.8116
      Epoch 17/20
      acc: 0.8122 - val loss: 0.0135 - val acc: 0.8114
      Epoch 18/20
      acc: 0.8123 - val loss: 0.0133 - val acc: 0.8113
      Epoch 19/20
      acc: 0.8124 - val loss: 0.0132 - val acc: 0.8111
      Epoch 20/20
      acc: 0.8124 - val loss: 0.0130 - val acc: 0.8112
In [54]: # visualization
      img num = 10
      autoencoder_conv_refine_best = load_model('./best_model_conv_refine.pth')
      plt.figure(figsize=(18, 4))
      plt.gray()
      for i in range(img num):
         # randomly pick an image from test dataset
         chosen test img = x test[np.random.randint(x test.shape[0])]
         img_decoded = autoencoder_conv_refine_best.predict(chosen_test_img.reshape
      (1, 28, 28, 1))
         ax = plt.subplot(2, img num, i+1)
         plt.imshow(chosen test img.reshape(28, 28))
         ax.axis('off')
         ax = plt.subplot(2, img_num, img_num+i+1)
         plt.imshow(img_decoded.reshape(28, 28))
         ax.axis('off')
      plt.show()
       6380698931
       638069893
```

try to find a CAE architecture, including a larger bottleneck, that is powerful enough to generate readable images.

After enlarge the bottleneck from 2 to 12, the CAE is able to generate readable images as shown above

Layer (type)	Output Shape	Param #
dense_22 (Dense)	(None, 512)	401920
dense_23 (Dense)	(None, 2)	1026
dense_24 (Dense)	(None, 512)	1536
dense_25 (Dense)	(None, 784)	402192

Total params: 806,674 Trainable params: 806,674 Non-trainable params: 0

```
In [77]: # extract the decoder network from the original model
    decoder_fc_layer1 = autoencoder_fc_best.layers[2]
    decoder_fc_layer2 = autoencoder_fc_best.layers[3]
    decoder_input = Input(shape=(2,))
    decoder_fc = Model(decoder_input, decoder_fc_layer2(decoder_fc_layer1(decoder_input)))
    decoder_fc.summary()
```

Layer (type)	Output Shape	Param #
input_5 (InputLayer)	(None, 2)	0
dense_24 (Dense)	(None, 512)	1536
dense_25 (Dense)	(None, 784)	402192
=======================================		

Total params: 403,728 Trainable params: 403,728 Non-trainable params: 0

```
In [101]: | img num = 10
          plt.figure(figsize=(18, 4))
          plt.gray()
          # randomly generate some numbers as the input of decoder
          generated_input = (np.random.rand(img_num, 2, )) * 20
          print(generated input)
          generated_imgs = decoder_fc.predict(generated_input)
          for i in range(img_num):
              img_decoded = generated_imgs[i]
              ax = plt.subplot(1, img_num, i+1)
              plt.imshow(img_decoded.reshape(28, 28))
              ax.axis('off')
          plt.show()
          [[ 0.7087463 13.67673812]
           [14.86996982 16.08176403]
           [ 6.35220493 13.33000247]
           [15.78123443 19.65897981]
           [17.11051112 10.38312941]
           [18.26681465 17.23007229]
           [ 0.07462502 15.54017014]
           [ 1.59308199 18.56136937]
           [19.18960768 2.40478631]]
```

2 5 6 8 5 9 9 2 2 6

```
In [200]: # Part 3.2:
          # restrict the AutoEncoder hidden bottleneck layer(s)
          # to have a standard multi-variate normal distribution
          # with mean zeroes and the identity matrix as variance
          def normalize bottleneck(args):
              norm_mean, norm_var = args
              eps = K.random normal(shape=(K.shape(norm mean)[0], K.int shape(norm mean)
          [1]))
              norm = norm mean + K.exp(0.5 * norm var) * eps
              return norm
          # flatten the input image data
          input size = 784
          x train flatten = x train.reshape(-1, input size)
          x test flatten = x test.reshape(-1, input size)
          # construct the encoder part
          autoencoder_fc_norm_input = Input(shape=(input_size, ))
          intermediate_output1 = Dense(512, activation='relu')(autoencoder_fc_norm_input
          norm mean = Dense(2)(intermediate output1)
          norm_var = Dense(2)(intermediate_output1)
          encoder output = Lambda(normalize bottleneck, output shape=(2, ))([norm mean,
          norm var])
          # construct the decoder part
          intermediate output2 = Dense(512, activation='relu')(encoder output)
          decoder output = Dense(input size, activation='sigmoid')(intermediate output2)
          autoencoder fc norm = Model(autoencoder fc norm input, decoder output)
          autoencoder fc norm.summary()
```

Layer (type)		Output	Shape ======	Param #	Connected to
======== input_19 (Inp		(None,	784)	0	
dense_43 (Der	ise)	(None,	512)	401920	input_19[0]
dense_44 (Der	nse)	(None,	2)	1026	dense_43[0]
dense_45 (Der [0]	nse)	(None,	2)	1026	dense_43[0]
lambda_8 (Lam [0]	nbda)	(None,	2)	0	dense_44[0] dense_45[0]
dense_46 (Der [0]	nse)	(None,	512)	1536	lambda_8[0]
dense_47 (Der [0]	ise)	(None,	·	402192	dense_46[0]
Total params: Trainable par Non-trainable	807,700 cams: 807				

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```
In [201]: # train model
          print(device_lib.list_local_devices())
          autoencoder_fc_norm.compile(optimizer='adam', loss='mean_squared_error', metri
          cs=['accuracy'])
          best_model_checkpoint = ModelCheckpoint(
               './best_model_fc_norm.pth',
              monitor="val_acc",
              save_best_only=True,
              save_weights_only=False
          )
          autoencoder_fc_history = autoencoder_fc_norm.fit(
              x_train_flatten,
              x_train_flatten,
              epochs=50,
              batch_size=256,
              shuffle=True,
              validation_data=(x_test_flatten, x_test_flatten),
              callbacks=[best model checkpoint]
```

```
[name: "/device:CPU:0"
device_type: "CPU"
memory limit: 268435456
locality {
}
incarnation: 5998046289788614467
, name: "/device:GPU:0"
device type: "GPU"
memory_limit: 6700198133
locality {
 bus id: 1
 links {
 }
incarnation: 14375085748194495944
physical device desc: "device: 0, name: GeForce GTX 1070, pci bus id: 0000:0
1:00.0, compute capability: 6.1"
Train on 60000 samples, validate on 10000 samples
Epoch 1/50
acc: 0.0129 - val loss: 0.0562 - val acc: 0.0099
Epoch 2/50
acc: 0.0148 - val_loss: 0.0520 - val_acc: 0.0128
Epoch 3/50
acc: 0.0146 - val_loss: 0.0501 - val_acc: 0.0126
Epoch 4/50
acc: 0.0111 - val_loss: 0.0489 - val_acc: 0.0084
acc: 0.0101 - val loss: 0.0476 - val acc: 0.0075
Epoch 6/50
acc: 0.0090 - val loss: 0.0468 - val acc: 0.0085
Epoch 7/50
acc: 0.0090 - val loss: 0.0459 - val acc: 0.0093
Epoch 8/50
acc: 0.0086 - val_loss: 0.0454 - val_acc: 0.0068
Epoch 9/50
acc: 0.0084 - val loss: 0.0448 - val acc: 0.0057
Epoch 10/50
acc: 0.0091 - val loss: 0.0443 - val acc: 0.0059
Epoch 11/50
acc: 0.0087 - val loss: 0.0442 - val acc: 0.0067
Epoch 12/50
acc: 0.0087 - val_loss: 0.0437 - val_acc: 0.0092
Epoch 13/50
```

```
acc: 0.0092 - val loss: 0.0434 - val acc: 0.0094
Epoch 14/50
acc: 0.0089 - val loss: 0.0432 - val acc: 0.0099
Epoch 15/50
60000/60000 [============== ] - 1s 24us/step - loss: 0.0425 -
acc: 0.0086 - val loss: 0.0429 - val acc: 0.0068
Epoch 16/50
acc: 0.0094 - val loss: 0.0426 - val acc: 0.0092
Epoch 17/50
acc: 0.0092 - val loss: 0.0425 - val acc: 0.0088
Epoch 18/50
acc: 0.0102 - val loss: 0.0423 - val acc: 0.0082
Epoch 19/50
acc: 0.0096 - val loss: 0.0421 - val acc: 0.0104
Epoch 20/50
60000/60000 [============= ] - 2s 26us/step - loss: 0.0414 -
acc: 0.0102 - val loss: 0.0420 - val acc: 0.0066
Epoch 21/50
acc: 0.0100 - val_loss: 0.0418 - val_acc: 0.0100
Epoch 22/50
acc: 0.0104 - val_loss: 0.0419 - val_acc: 0.0071
Epoch 23/50
acc: 0.0106 - val_loss: 0.0416 - val_acc: 0.0109
Epoch 24/50
60000/60000 [=========== ] - 1s 25us/step - loss: 0.0407 -
acc: 0.0100 - val loss: 0.0414 - val acc: 0.0137
Epoch 25/50
acc: 0.0101 - val_loss: 0.0415 - val_acc: 0.0137
Epoch 26/50
acc: 0.0103 - val_loss: 0.0413 - val_acc: 0.0137
Epoch 27/50
acc: 0.0112 - val_loss: 0.0412 - val_acc: 0.0116
acc: 0.0109 - val loss: 0.0411 - val acc: 0.0088
Epoch 29/50
acc: 0.0114 - val loss: 0.0411 - val acc: 0.0109
Epoch 30/50
acc: 0.0109 - val loss: 0.0411 - val acc: 0.0068
Epoch 31/50
acc: 0.0113 - val_loss: 0.0410 - val_acc: 0.0129
Epoch 32/50
60000/60000 [============ ] - 1s 25us/step - loss: 0.0397 -
```

```
acc: 0.0116 - val loss: 0.0410 - val acc: 0.0075
Epoch 33/50
acc: 0.0112 - val loss: 0.0409 - val acc: 0.0111
Epoch 34/50
60000/60000 [============== ] - 1s 25us/step - loss: 0.0395 -
acc: 0.0117 - val loss: 0.0409 - val acc: 0.0097
Epoch 35/50
acc: 0.0123 - val loss: 0.0408 - val acc: 0.0082
Epoch 36/50
60000/60000 [============== ] - 2s 25us/step - loss: 0.0393 -
acc: 0.0115 - val loss: 0.0408 - val acc: 0.0078
Epoch 37/50
acc: 0.0125 - val loss: 0.0407 - val acc: 0.0118
Epoch 38/50
acc: 0.0124 - val loss: 0.0407 - val acc: 0.0104
Epoch 39/50
60000/60000 [============== ] - 2s 26us/step - loss: 0.0390 -
acc: 0.0127 - val loss: 0.0406 - val acc: 0.0127
Epoch 40/50
acc: 0.0126 - val_loss: 0.0405 - val_acc: 0.0096
Epoch 41/50
acc: 0.0120 - val_loss: 0.0405 - val_acc: 0.0124
Epoch 42/50
acc: 0.0129 - val_loss: 0.0405 - val_acc: 0.0065
Epoch 43/50
acc: 0.0132 - val loss: 0.0406 - val acc: 0.0121
Epoch 44/50
acc: 0.0134 - val_loss: 0.0404 - val_acc: 0.0133
Epoch 45/50
acc: 0.0132 - val loss: 0.0404 - val acc: 0.0131
Epoch 46/50
acc: 0.0130 - val_loss: 0.0404 - val_acc: 0.0088
Epoch 47/50
acc: 0.0134 - val loss: 0.0404 - val acc: 0.0127
Epoch 48/50
acc: 0.0131 - val loss: 0.0403 - val acc: 0.0138
Epoch 49/50
acc: 0.0134 - val loss: 0.0403 - val acc: 0.0140
Epoch 50/50
acc: 0.0134 - val loss: 0.0402 - val acc: 0.0137
```

```
In [3]: # load the best model with normalized bottleneck
   autoencoder_fc_norm_best = load_model('./best_model_fc_norm.pth')

# extract the decoder network from the original model
   decoder_fc_norm_layer1 = autoencoder_fc_norm_best.layers[5]
   decoder_fc_norm_layer2 = autoencoder_fc_norm_best.layers[6]
   decoder_norm_input = Input(shape=(2,))
   decoder_fc_norm = Model(decoder_norm_input, decoder_fc_norm_layer2(decoder_fc_norm_layer1(decoder_norm_input)))
   decoder_fc_norm.summary()
```

WARNING:tensorflow:From C:\Users\songyih\AppData\Roaming\Python\Python37\site -packages\tensorflow\python\framework\op_def_library.py:263: colocate_with (f rom tensorflow.python.framework.ops) is deprecated and will be removed in a f uture version.

Instructions for updating:

Colocations handled automatically by placer.

WARNING:tensorflow:From C:\Users\songyih\AppData\Roaming\Python\Python37\site -packages\tensorflow\python\ops\math_ops.py:3066: to_int32 (from tensorflow.p ython.ops.math_ops) is deprecated and will be removed in a future version. Instructions for updating:

Use tf.cast instead.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 2)	0
dense_46 (Dense)	(None, 512)	1536
dense_47 (Dense)	(None, 784)	402192

Total params: 403,728 Trainable params: 403,728 Non-trainable params: 0

```
In [102]: # generate images by inputing random number to decoder
    print("Generate images by inputing different var values draw from the distribu
    tion")
    img_num = 10
    plt.figure(figsize=(18, 18))
    plt.gray()

random_vars = np.linspace(-4, 4, img_num)[::-1]

for i in range(len(random_vars)):
    z_sample = np.array([[0, random_vars[i]]])
    img_decoded = decoder_fc_norm.predict(z_sample)
    ax = plt.subplot(1, img_num, i+1)
    plt.imshow(img_decoded.reshape(28, 28))
    ax.axis('off')
    plt.show()
```

Generate images by inputing different var values draw from the distribution



```
In [105]: # generate images by inputing random number to decoder
    print("Generate images by inputing different mean values draw from the distrib
    ution")
    random_means = np.linspace(-3, 3, img_num)
    plt.figure(figsize=(18, 18))
    plt.gray()
    for i in range(len(random_means)):
        z_sample = np.array([[random_means[i], 1]])
        img_decoded = decoder_fc_norm.predict(z_sample)
        ax = plt.subplot(1, img_num, i+1)
        plt.imshow(img_decoded.reshape(28, 28))
        ax.axis('off')
    plt.show()
```

Generate images by inputing different mean values draw from the distribution



Part 3.3: Are the output images different between 1) and 2)? If so, why do you think this difference occurs?

The output images are different between 1) and 2). In the output image from part 3.2 we can clearly see how the generated digits gradually shifting from one to another, and the reconstructed images is not simplying imitating the original dataset, but creating new styles. I think this is because the encoder we build in part 3.2 is not just generating encoding information for a single image embedding, but an embedding that is shifted from original embedding.

''' Part 4: Optional: change the AutoEncoder which you developed in the In [30]: last part of section 3 so that it becomes a Variational AutoEncoder # the network structure is a copy of part 3.3, the different part is at the lo ss function def normalize bottleneck(args): norm mean, norm var = args eps = K.random_normal(shape=(K.shape(norm_mean)[0], K.int_shape(norm_mean) [1])) $norm = norm_mean + K.exp(0.5 * norm_var) * eps$ return norm # flatten the input image data $input_size = 784$ x train flatten = x train.reshape(-1, input size) x_test_flatten = x_test.reshape(-1, input_size) # the network is the same as in section 3 # construct the encoder part vae_input = Input(shape=(input_size,)) intermediate output1 = Dense(512, activation='relu')(vae input) norm mean = Dense(2)(intermediate output1) norm var = Dense(2)(intermediate output1) encoder output = Lambda(normalize bottleneck, output shape=(2,))([norm mean, norm var]) # construct the decoder part intermediate output2 = Dense(512, activation='relu')(encoder output) decoder_output = Dense(input_size, activation='sigmoid')(intermediate_output2) variational_autoencoder = Model(vae_input, decoder_output) variational autoencoder.summary()

Layer (type)	· · · · · · · · · · · · · · · · · · ·	Param #	Connected to
input_2 (InputLayer)	(None, 784)	0	
dense_1 (Dense) [0]	(None, 512)	401920	input_2[0]
dense_2 (Dense) [0]	(None, 2)	1026	dense_1[0]
dense_3 (Dense) [0]	(None, 2)	1026	dense_1[0]
lambda_1 (Lambda) [0]	(None, 2)	0	dense_2[0]
[0]			delise_5[0]
dense_4 (Dense) [0]	(None, 512)	1536	lambda_1[0]
dense_5 (Dense) [0]	(None, 784)	402192	dense_4[0]
Trainable params: 807,700 Non-trainable params: 0			

```
In [31]:
         # make the losses for VAE
         from keras.losses import mse
         # reconstruction loss
         mse_loss = mse(vae_input, decoder_output) * input_size
         # variational loss
         variational_loss = -1 * K.sum((1 + norm_var - K.square(norm_mean) - K.exp(norm
         _var)) / 2, axis=-1)
         # combine the reconstruction loss and variational loss to make the total loss
         variational_autoencoder.add_loss(K.mean(mse_loss + variational_loss))
```

```
In [33]: # train model
         print(device_lib.list_local_devices())
         variational_autoencoder.compile(optimizer='adam')
         best_model_checkpoint = ModelCheckpoint(
              './best_model_vae_weights.pth',
             monitor="val_loss",
             save_best_only=True,
             save_weights_only=True
         vae_history = variational_autoencoder.fit(
             x_train_flatten,
             None,
             epochs=200,
             batch_size=256,
             shuffle=True,
             validation_data=(x_test_flatten, None),
             callbacks=[best_model_checkpoint]
         )
```

```
[name: "/device:CPU:0"
device_type: "CPU"
memory_limit: 268435456
locality {
}
incarnation: 601061563355615771
, name: "/device:GPU:0"
device type: "GPU"
memory_limit: 6700198133
locality {
 bus id: 1
 links {
 }
incarnation: 10085529536070215849
physical device desc: "device: 0, name: GeForce GTX 1070, pci bus id: 0000:0
1:00.0, compute capability: 6.1"
Train on 60000 samples, validate on 10000 samples
Epoch 1/200
60000/60000 [=========== ] - 1s 20us/step - loss: 36.9952 -
val loss: 37.8383
Epoch 2/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.9169 -
val loss: 37.6753
Epoch 3/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.8884 -
val loss: 37.6780
Epoch 4/200
60000/60000 [=============== ] - 1s 14us/step - loss: 36.8542 -
val_loss: 37.6410
Epoch 5/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.8374 -
val loss: 37.6742
Epoch 6/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.8007 -
val loss: 37.6107
Epoch 7/200
60000/60000 [============== ] - 1s 14us/step - loss: 36.7830 -
val loss: 37.6381
Epoch 8/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.7391 -
val loss: 37.6143
Epoch 9/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.7035 -
val loss: 37.6207
Epoch 10/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.6921 -
val loss: 37.5911
Epoch 11/200
60000/60000 [============== ] - 1s 13us/step - loss: 36.6466 -
val loss: 37.5805
Epoch 12/200
60000/60000 [============== ] - 1s 13us/step - loss: 36.6287 -
val loss: 37.6085
Epoch 13/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.6082 -
```

```
val loss: 37.4984
Epoch 14/200
60000/60000 [=============== ] - 1s 14us/step - loss: 36.5781 -
val loss: 37.5257
Epoch 15/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.5691 -
val loss: 37.5432
Epoch 16/200
60000/60000 [============== ] - 1s 13us/step - loss: 36.5426 -
val loss: 37.6034
Epoch 17/200
60000/60000 [============= ] - 1s 13us/step - loss: 36.5053 -
val loss: 37.6021
Epoch 18/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.4748 -
val loss: 37.5333
Epoch 19/200
60000/60000 [============== ] - 1s 13us/step - loss: 36.4801 -
val loss: 37.4724
Epoch 20/200
60000/60000 [============= ] - 1s 13us/step - loss: 36.4459 -
val loss: 37.5506
Epoch 21/200
60000/60000 [=============== ] - 1s 14us/step - loss: 36.4246 -
val loss: 37.4551
Epoch 22/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.3860 -
val loss: 37.4665
Epoch 23/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.3644 -
val loss: 37.4245
Epoch 24/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.3708 -
val loss: 37.4610
Epoch 25/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.3357 -
val loss: 37.4702
Epoch 26/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.3282 -
val loss: 37.4650
Epoch 27/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.2967 -
val loss: 37.5081
Epoch 28/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.2638 -
val loss: 37.5185
Epoch 29/200
60000/60000 [============ ] - 1s 13us/step - loss: 36.2556 -
val loss: 37.4402
Epoch 30/200
60000/60000 [============== ] - 1s 14us/step - loss: 36.2393 -
val loss: 37.4399
Epoch 31/200
60000/60000 [=============== ] - 1s 14us/step - loss: 36.2189 -
val loss: 37.4493
Epoch 32/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.2089 -
```

```
val loss: 37.4030
Epoch 33/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.2029 -
val loss: 37.4180
Epoch 34/200
60000/60000 [============== ] - 1s 13us/step - loss: 36.1933 -
val loss: 37.4648
Epoch 35/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.1450 -
val loss: 37.3682
Epoch 36/200
60000/60000 [============= ] - 1s 13us/step - loss: 36.1310 -
val loss: 37.3750
Epoch 37/200
60000/60000 [============== ] - 1s 13us/step - loss: 36.1170 -
val loss: 37.3665
Epoch 38/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.1044 -
val loss: 37.4114
Epoch 39/200
60000/60000 [============= ] - 1s 13us/step - loss: 36.0741 -
val loss: 37.3864
Epoch 40/200
60000/60000 [============== ] - 1s 13us/step - loss: 36.0625 -
val loss: 37.3510
Epoch 41/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.0420 -
val loss: 37.2938
Epoch 42/200
60000/60000 [=============== ] - 1s 13us/step - loss: 36.0579 -
val loss: 37.3987
Epoch 43/200
60000/60000 [============== ] - 1s 13us/step - loss: 36.0229 -
val loss: 37.3851
Epoch 44/200
60000/60000 [============== ] - 1s 13us/step - loss: 36.0207 -
val loss: 37.3757
Epoch 45/200
60000/60000 [================ ] - 1s 13us/step - loss: 35.9887 -
val loss: 37.3486
Epoch 46/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.9710 -
val loss: 37.3606
Epoch 47/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.9669 -
val loss: 37.3607
Epoch 48/200
60000/60000 [============ ] - 1s 13us/step - loss: 35.9458 -
val loss: 37.4169
Epoch 49/200
60000/60000 [============== ] - 1s 13us/step - loss: 35.9243 -
val loss: 37.3572
Epoch 50/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.9402 -
val loss: 37.4062
Epoch 51/200
60000/60000 [================ ] - 1s 13us/step - loss: 35.9274 -
```

```
val loss: 37.4800
Epoch 52/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.9028 -
val loss: 37.2688
Epoch 53/200
60000/60000 [======================= ] - 1s 13us/step - loss: 35.8827 -
val loss: 37.3620
Epoch 54/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.8693 -
val loss: 37.3269
Epoch 55/200
60000/60000 [============= ] - 1s 13us/step - loss: 35.8654 -
val loss: 37.4246
Epoch 56/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.8555 -
val loss: 37.3315
Epoch 57/200
60000/60000 [============= ] - 1s 13us/step - loss: 35.8347 -
val loss: 37.3694
Epoch 58/200
60000/60000 [================ ] - 1s 13us/step - loss: 35.8240 -
val loss: 37.3218
Epoch 59/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.8015 -
val loss: 37.3415
Epoch 60/200
60000/60000 [================ ] - 1s 13us/step - loss: 35.8064 -
val loss: 37.3676
Epoch 61/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.7843 -
val loss: 37.3181
Epoch 62/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.7646 -
val loss: 37.2809
Epoch 63/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.7812 -
val loss: 37.3449
Epoch 64/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.7490 -
val loss: 37.2400
Epoch 65/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.7331 -
val loss: 37.3666
Epoch 66/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.7238 -
val loss: 37.3437
Epoch 67/200
60000/60000 [============ ] - 1s 13us/step - loss: 35.7316 -
val loss: 37.3185
Epoch 68/200
60000/60000 [============== ] - 1s 14us/step - loss: 35.6913 -
val loss: 37.2665
Epoch 69/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.6897 -
val loss: 37.3279
Epoch 70/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.6802 -
```

```
val loss: 37.3781
Epoch 71/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.6535 -
val loss: 37.2465
Epoch 72/200
60000/60000 [======================== ] - 1s 13us/step - loss: 35.6538 -
val loss: 37.1988
Epoch 73/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.6569 -
val loss: 37.3542
Epoch 74/200
60000/60000 [============= ] - 1s 13us/step - loss: 35.6145 -
val loss: 37.1547
Epoch 75/200
60000/60000 [================ ] - 1s 13us/step - loss: 35.6286 -
val loss: 37.2323
Epoch 76/200
60000/60000 [============= ] - 1s 13us/step - loss: 35.6195 -
val loss: 37.2157
Epoch 77/200
60000/60000 [================ ] - 1s 13us/step - loss: 35.5989 -
val loss: 37.3590
Epoch 78/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.5941 -
val loss: 37.2881
Epoch 79/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.5663 -
val loss: 37.2350
Epoch 80/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.5701 -
val loss: 37.1743
Epoch 81/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.5463 -
val loss: 37.2264
Epoch 82/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.5518 -
val loss: 37.3206
Epoch 83/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.5258 -
val loss: 37.2497
Epoch 84/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.5249 -
val loss: 37.3483
Epoch 85/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.5361 -
val loss: 37.3037
Epoch 86/200
60000/60000 [============ ] - 1s 13us/step - loss: 35.5092 -
val loss: 37.3865
Epoch 87/200
60000/60000 [============== ] - 1s 14us/step - loss: 35.5036 -
val loss: 37.2918
Epoch 88/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.4845 -
val loss: 37.1966
Epoch 89/200
60000/60000 [================= ] - 1s 14us/step - loss: 35.4678 -
```

```
val loss: 37.2311
Epoch 90/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.4398 -
val loss: 37.2437
Epoch 91/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.4643 -
val loss: 37.1710
Epoch 92/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.4633 -
val loss: 37.2677
Epoch 93/200
60000/60000 [============= ] - 1s 13us/step - loss: 35.4379 -
val loss: 37.1997
Epoch 94/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.4168 -
val loss: 37.1976
Epoch 95/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.4283 -
val loss: 37.2507
Epoch 96/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.4167 -
val loss: 37.1987
Epoch 97/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.4113 -
val loss: 37.3720
Epoch 98/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.3899 -
val loss: 37.2006
Epoch 99/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.3808 -
val loss: 37.2104
Epoch 100/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.3844 -
val loss: 37.2518
Epoch 101/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.3649 -
val loss: 37.2221
Epoch 102/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.3489 -
val loss: 37.2647
Epoch 103/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.3582 -
val loss: 37.1926
Epoch 104/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.3356 -
val loss: 37.3029
Epoch 105/200
60000/60000 [============ ] - 1s 13us/step - loss: 35.3275 -
val loss: 37.1519
Epoch 106/200
60000/60000 [============== ] - 1s 14us/step - loss: 35.3371 -
val loss: 37.2554
Epoch 107/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.3193 -
val loss: 37.2947
Epoch 108/200
60000/60000 [================ ] - 1s 14us/step - loss: 35.2957 -
```

```
val loss: 37.1770
Epoch 109/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.2929 -
val loss: 37.1822
Epoch 110/200
60000/60000 [============= ] - 1s 13us/step - loss: 35.2917 -
val loss: 37.2941
Epoch 111/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.2995 -
val loss: 37.2422
Epoch 112/200
60000/60000 [============= ] - 1s 14us/step - loss: 35.2918 -
val loss: 37.3082
Epoch 113/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.2819 -
val loss: 37.2484
Epoch 114/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.2685 -
val loss: 37.3603
Epoch 115/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.2827 -
val loss: 37.2066
Epoch 116/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.2381 -
val loss: 37.1642
Epoch 117/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.2449 -
val loss: 37.1738
Epoch 118/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.2319 -
val loss: 37.2021
Epoch 119/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.2098 -
val loss: 37.2116
Epoch 120/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.2094 -
val loss: 37.1892
Epoch 121/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.2295 -
val loss: 37.2024
Epoch 122/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.2040 -
val_loss: 37.2288
Epoch 123/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.2009 -
val loss: 37.2448
Epoch 124/200
60000/60000 [============ ] - 1s 14us/step - loss: 35.1904 -
val loss: 37.2295
Epoch 125/200
60000/60000 [============== ] - 1s 14us/step - loss: 35.1797 -
val loss: 37.1070
Epoch 126/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.1598 -
val loss: 37.2343
Epoch 127/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.1530 -
```

```
val loss: 37.2558
Epoch 128/200
60000/60000 [=============== ] - 1s 14us/step - loss: 35.1626 -
val loss: 37.1623
Epoch 129/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.1526 -
val loss: 37.1796
Epoch 130/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.1585 -
val loss: 37.1577
Epoch 131/200
60000/60000 [============= ] - 1s 13us/step - loss: 35.1409 -
val loss: 37.1362
Epoch 132/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.1416 -
val loss: 37.2200
Epoch 133/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.1342 -
val loss: 37.1798
Epoch 134/200
60000/60000 [================ ] - 1s 13us/step - loss: 35.1424 -
val loss: 37.1684
Epoch 135/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.1064 -
val loss: 37.1960
Epoch 136/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.1127 -
val loss: 37.1992
Epoch 137/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.0893 -
val loss: 37.1657
Epoch 138/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.0891 -
val loss: 37.1862
Epoch 139/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.0820 -
val loss: 37.1704
Epoch 140/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.0716 -
val loss: 37.1153
Epoch 141/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.0770 -
val_loss: 37.2717
Epoch 142/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.0770 -
val loss: 37.1966
Epoch 143/200
60000/60000 [============ ] - 1s 13us/step - loss: 35.0731 -
val loss: 37.1733
Epoch 144/200
60000/60000 [============== ] - 1s 13us/step - loss: 35.0455 -
val loss: 37.1020
Epoch 145/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.0365 -
val loss: 37.1848
Epoch 146/200
60000/60000 [================ ] - 1s 14us/step - loss: 35.0548 -
```

```
val loss: 37.2207
Epoch 147/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.0496 -
val loss: 37.1514
Epoch 148/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.0224 -
val loss: 37.1320
Epoch 149/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.0139 -
val loss: 37.2379
Epoch 150/200
60000/60000 [============= ] - 1s 13us/step - loss: 35.0092 -
val loss: 37.1663
Epoch 151/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.0133 -
val loss: 37.1807
Epoch 152/200
60000/60000 [=============== ] - 1s 13us/step - loss: 35.0004 -
val loss: 37.2297
Epoch 153/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.9995 -
val loss: 37.1857
Epoch 154/200
60000/60000 [============== ] - 1s 13us/step - loss: 34.9926 -
val loss: 37.2727
Epoch 155/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.9701 -
val loss: 37.1845
Epoch 156/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.9944 -
val loss: 37.1764
Epoch 157/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.9690 -
val loss: 37.1127
Epoch 158/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.9538 -
val loss: 37.2683
Epoch 159/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.9541 -
val loss: 37.1843
Epoch 160/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.9441 -
val_loss: 37.1824
Epoch 161/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.9647 -
val loss: 37.1457
Epoch 162/200
60000/60000 [============ ] - 1s 13us/step - loss: 34.9670 -
val loss: 37.1996
Epoch 163/200
60000/60000 [============== ] - 1s 13us/step - loss: 34.9269 -
val loss: 37.2346
Epoch 164/200
60000/60000 [============== ] - 1s 13us/step - loss: 34.9673 -
val loss: 37.2294
Epoch 165/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.9083 -
```

```
val loss: 37.2393
Epoch 166/200
60000/60000 [============== ] - 1s 13us/step - loss: 34.9223 -
val loss: 37.1361
Epoch 167/200
60000/60000 [============= ] - 1s 13us/step - loss: 34.8989 -
val loss: 37.1900
Epoch 168/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.9037 -
val loss: 37.0476
Epoch 169/200
60000/60000 [============= ] - 1s 13us/step - loss: 34.9042 -
val loss: 37.2811
Epoch 170/200
60000/60000 [================ ] - 1s 13us/step - loss: 34.9087 -
val loss: 37.3212
Epoch 171/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.9001 -
val loss: 37.2154
Epoch 172/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.8903 -
val loss: 37.1862
Epoch 173/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.8856 -
val loss: 37.2628
Epoch 174/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.8861 -
val loss: 37.1823
Epoch 175/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.8772 -
val loss: 37.1817
Epoch 176/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.8907 -
val loss: 37.1231
Epoch 177/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.8745 -
val loss: 37.1837
Epoch 178/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.8564 -
val loss: 37.2309
Epoch 179/200
60000/60000 [=============== ] - 1s 14us/step - loss: 34.8661 -
val_loss: 37.2312
Epoch 180/200
60000/60000 [=============== ] - 1s 14us/step - loss: 34.8648 -
val loss: 37.2136
Epoch 181/200
60000/60000 [============ ] - 1s 13us/step - loss: 34.8437 -
val loss: 37.1749
Epoch 182/200
60000/60000 [============== ] - 1s 13us/step - loss: 34.8588 -
val loss: 37.1522
Epoch 183/200
60000/60000 [============== ] - 1s 13us/step - loss: 34.8223 -
val loss: 37.2122
Epoch 184/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.8189 -
```

```
val loss: 37.1229
Epoch 185/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.8331 -
val loss: 37.2309
Epoch 186/200
60000/60000 [============= ] - 1s 13us/step - loss: 34.8326 -
val loss: 37.1323
Epoch 187/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.8076 -
val loss: 37.1670
Epoch 188/200
60000/60000 [============= ] - 1s 13us/step - loss: 34.8295 -
val loss: 37.2170
Epoch 189/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.8040 -
val loss: 37.2571
Epoch 190/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.7864 -
val loss: 37.2005
Epoch 191/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.7864 -
val loss: 37.2764
Epoch 192/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.7937 -
val loss: 37.1294
Epoch 193/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.7991 -
val loss: 37.2520
Epoch 194/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.7950 -
val loss: 37.2566
Epoch 195/200
60000/60000 [============ ] - 1s 13us/step - loss: 34.7870 -
val loss: 37.2069
Epoch 196/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.7706 -
val loss: 37.1804
Epoch 197/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.7662 -
val loss: 37.1843
Epoch 198/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.7473 -
val loss: 37.1853
Epoch 199/200
60000/60000 [=============== ] - 1s 13us/step - loss: 34.7520 -
val loss: 37.1706
Epoch 200/200
60000/60000 [============ ] - 1s 13us/step - loss: 34.7438 -
val loss: 37.2497
```

```
In [35]: # Load the best varational auto-encoder model
   variational_autoencoder.load_weights('./best_model_vae_weights.pth')

# extract the decoder network from the original model
   decoder_vae_layer1 = variational_autoencoder.layers[5]
   decoder_vae_layer2 = variational_autoencoder.layers[6]
   vae_input = Input(shape=(2,))
   decoder_vae = Model(vae_input, decoder_vae_layer2(decoder_vae_layer1(vae_input)))
   decoder_vae.summary()
```

Layer (type)	Output Shape	Param #
input_4 (InputLayer)	(None, 2)	0
dense_4 (Dense)	(None, 512)	1536
dense_5 (Dense)	(None, 784)	402192

Total params: 403,728 Trainable params: 403,728 Non-trainable params: 0

```
In [43]: # generate images by inputing random number to decoder
    print("Generate images by inputing different var values draw from the distribu
    tion")
    img_num = 10
    plt.figure(figsize=(18, 18))
    plt.gray()

random_vars = np.linspace(-3, 3, img_num)[::-1]

for i in range(len(random_vars)):
    z_sample = np.array([[2, random_vars[i]]])
    img_decoded = decoder_vae.predict(z_sample)
    ax = plt.subplot(1, img_num, i+1)
    plt.imshow(img_decoded.reshape(28, 28))
    ax.axis('off')
    plt.show()
```

Generate images by inputing different var values draw from the distribution



```
In [44]: # generate images by inputing random number to decoder
    print("Generate images by inputing different mean values draw from the distrib
    ution")
    random_means = np.linspace(-2, 2, img_num)
    plt.figure(figsize=(18, 18))
    plt.gray()
    for i in range(len(random_means)):
        z_sample = np.array([[random_means[i], 1]])
        img_decoded = decoder_vae.predict(z_sample)
        ax = plt.subplot(1, img_num, i+1)
        plt.imshow(img_decoded.reshape(28, 28))
        ax.axis('off')
    plt.show()
```

Generate images by inputing different mean values draw from the distribution



Does the VAE produce a different quality of output image?

The VAE do produce different quality of output image. We can see the images produces by VAE have more randomness.

```
In [ ]:
```