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 (x*train,*), (x*test,*) = 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 [1]:
```
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, BatchNormalization
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.
```

```
C:\Users\songyih\AppData\Roaming\Python\Python37\site-packages\tensorflow\pyt
hon\framework\dtypes.py:526: FutureWarning: Passing (type, 1) or '1type' as a
synonym of type is deprecated; in a future version of numpy, it will be under
stood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\songyih\AppData\Roaming\Python\Python37\site-packages\tensorflow\pyt
hon\framework\dtypes.py:527: FutureWarning: Passing (type, 1) or '1type' as a
synonym of type is deprecated; in a future version of numpy, it will be under
stood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\songyih\AppData\Roaming\Python\Python37\site-packages\tensorflow\pyt
hon\framework\dtypes.py:528: FutureWarning: Passing (type, 1) or '1type' as a
synonym of type is deprecated; in a future version of numpy, it will be under
stood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\songyih\AppData\Roaming\Python\Python37\site-packages\tensorflow\pyt
hon\framework\dtypes.py:529: FutureWarning: Passing (type, 1) or '1type' as a
synonym of type is deprecated; in a future version of numpy, it will be under
stood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\songyih\AppData\Roaming\Python\Python37\site-packages\tensorflow\pyt
hon\framework\dtypes.py:530: FutureWarning: Passing (type, 1) or '1type' as a
synonym of type is deprecated; in a future version of numpy, it will be under
stood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\songyih\AppData\Roaming\Python\Python37\site-packages\tensorflow\pyt
hon\framework\dtypes.py:535: FutureWarning: Passing (type, 1) or '1type' as a
synonym of type is deprecated; in a future version of numpy, it will be under
stood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
Using TensorFlow backend.
```

In [72]:
```
''' Part 1: Implement a Fully Connected AutoEncoder in TensorFlow
'''

# 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)

# build the network with a bottleneck of two neurons
autoencoder_fc = Sequential()
autoencoder_fc.add(Dense(512, input_shape=(input_size,), activation='relu'))
autoencoder_fc.add(Dense(2, activation='relu'))
autoencoder_fc.add(Dense(512, input_shape=(input_size,), activation='relu'))
autoencoder_fc.add(Dense(input_size, activation='sigmoid'))

autoencoder_fc.summary()
```

```
_________________________________________________________________
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 [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]
)
```

```
[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
60000/60000 [==============================] - 3s 42us/step - loss: 0.0661 -
acc: 0.0107 - val_loss: 0.0539 - val_acc: 0.0112
Epoch 2/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0523 -
acc: 0.0124 - val_loss: 0.0501 - val_acc: 0.0103
Epoch 3/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0492 -
acc: 0.0120 - val_loss: 0.0477 - val_acc: 0.0107
Epoch 4/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0473 -
acc: 0.0101 - val_loss: 0.0465 - val_acc: 0.0096
Epoch 5/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0461 -
acc: 0.0103 - val_loss: 0.0455 - val_acc: 0.0092
Epoch 6/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0450 -
acc: 0.0122 - val_loss: 0.0446 - val_acc: 0.0105
Epoch 7/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0441 -
acc: 0.0125 - val_loss: 0.0438 - val_acc: 0.0096
Epoch 8/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0435 -
acc: 0.0119 - val_loss: 0.0433 - val_acc: 0.0110
Epoch 9/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0429 -
acc: 0.0111 - val_loss: 0.0429 - val_acc: 0.0062
Epoch 10/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0425 -
acc: 0.0106 - val_loss: 0.0427 - val_acc: 0.0080
Epoch 11/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0421 -
acc: 0.0097 - val_loss: 0.0425 - val_acc: 0.0081
Epoch 12/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0418 -
acc: 0.0096 - val_loss: 0.0421 - val_acc: 0.0081
Epoch 13/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0416 -
```

```
acc: 0.0097 - val_loss: 0.0418 - val_acc: 0.0106
Epoch 14/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0413 -
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
60000/60000 [==============================] - 2s 27us/step - loss: 0.0409 -
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
60000/60000 [==============================] - 2s 27us/step - loss: 0.0405 -
acc: 0.0101 - val_loss: 0.0412 - val_acc: 0.0105
Epoch 19/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0404 -
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
60000/60000 [==============================] - 2s 26us/step - loss: 0.0400 -
acc: 0.0110 - val_loss: 0.0409 - val_acc: 0.0109
Epoch 22/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0399 -
acc: 0.0099 - val_loss: 0.0409 - val_acc: 0.0095
Epoch 23/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0397 -
acc: 0.0106 - val_loss: 0.0407 - val_acc: 0.0104
Epoch 24/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0396 -
acc: 0.0106 - val_loss: 0.0407 - val_acc: 0.0096
Epoch 25/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0395 -
acc: 0.0108 - val_loss: 0.0406 - val_acc: 0.0115
Epoch 26/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0394 -
acc: 0.0108 - val_loss: 0.0405 - val_acc: 0.0093
Epoch 27/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0393 -
acc: 0.0104 - val_loss: 0.0406 - val_acc: 0.0102
Epoch 28/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0391 -
acc: 0.0110 - val_loss: 0.0404 - val_acc: 0.0110
Epoch 29/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0390 -
acc: 0.0111 - val_loss: 0.0403 - val_acc: 0.0110
Epoch 30/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0389 -
acc: 0.0114 - val_loss: 0.0403 - val_acc: 0.0119
Epoch 31/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0388 -
acc: 0.0109 - val_loss: 0.0403 - val_acc: 0.0123
Epoch 32/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0387 -
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acc: 0.0108 - val_loss: 0.0403 - val_acc: 0.0101
Epoch 33/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0387 -
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
60000/60000 [==============================] - 2s 28us/step - loss: 0.0385 -
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
60000/60000 [==============================] - 2s 27us/step - loss: 0.0383 -
acc: 0.0111 - val_loss: 0.0400 - val_acc: 0.0085
Epoch 38/100
60000/60000 [==============================] - 2s 29us/step - loss: 0.0383 -
acc: 0.0111 - val_loss: 0.0400 - val_acc: 0.0118
Epoch 39/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0381 -
acc: 0.0112 - val_loss: 0.0399 - val_acc: 0.0107
Epoch 40/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0381 -
acc: 0.0109 - val_loss: 0.0399 - val_acc: 0.0108
Epoch 41/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0380 -
acc: 0.0113 - val_loss: 0.0399 - val_acc: 0.0134
Epoch 42/100
60000/60000 [==============================] - 2s 29us/step - loss: 0.0379 -
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
60000/60000 [==============================] - 2s 28us/step - loss: 0.0378 -
acc: 0.0114 - val_loss: 0.0398 - val_acc: 0.0106
Epoch 45/100
60000/60000 [==============================] - 2s 29us/step - loss: 0.0378 -
acc: 0.0109 - val_loss: 0.0397 - val_acc: 0.0101
Epoch 46/100
60000/60000 [==============================] - 2s 29us/step - loss: 0.0377 -
acc: 0.0115 - val_loss: 0.0398 - val_acc: 0.0113
Epoch 47/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0376 -
acc: 0.0114 - val_loss: 0.0398 - val_acc: 0.0115
Epoch 48/100
60000/60000 [==============================] - 2s 29us/step - loss: 0.0376 -
acc: 0.0116 - val_loss: 0.0397 - val_acc: 0.0100
Epoch 49/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0375 -
acc: 0.0114 - val_loss: 0.0398 - val_acc: 0.0107
Epoch 50/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0375 -
acc: 0.0112 - val_loss: 0.0398 - val_acc: 0.0114
Epoch 51/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0374 -
```

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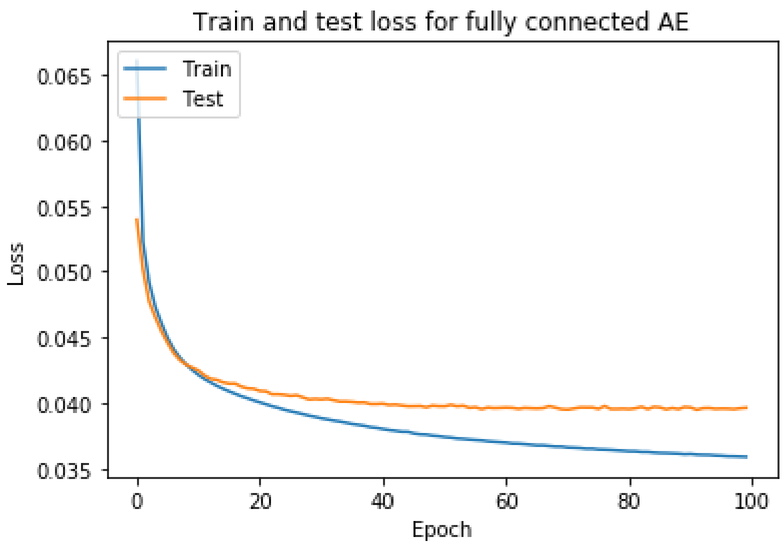
acc: 0.0114 - val_loss: 0.0397 - val_acc: 0.0122
Epoch 52/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0374 -
acc: 0.0118 - val_loss: 0.0399 - val_acc: 0.0109
Epoch 53/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0373 -
acc: 0.0117 - val_loss: 0.0397 - val_acc: 0.0093
Epoch 54/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0373 -
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
60000/60000 [==============================] - 2s 27us/step - loss: 0.0372 -
acc: 0.0112 - val_loss: 0.0397 - val_acc: 0.0121
Epoch 57/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0371 -
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
60000/60000 [==============================] - 2s 26us/step - loss: 0.0370 -
acc: 0.0116 - val_loss: 0.0396 - val_acc: 0.0103
Epoch 60/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0370 -
acc: 0.0114 - val_loss: 0.0396 - val_acc: 0.0110
Epoch 61/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0370 -
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
60000/60000 [==============================] - 2s 26us/step - loss: 0.0369 -
acc: 0.0116 - val_loss: 0.0395 - val_acc: 0.0103
Epoch 64/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0369 -
acc: 0.0116 - val_loss: 0.0396 - val_acc: 0.0127
Epoch 65/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0368 -
acc: 0.0118 - val_loss: 0.0396 - val_acc: 0.0130
Epoch 66/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0368 -
acc: 0.0115 - val_loss: 0.0396 - val_acc: 0.0109
Epoch 67/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0368 -
acc: 0.0117 - val_loss: 0.0396 - val_acc: 0.0123
Epoch 68/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0367 -
acc: 0.0116 - val_loss: 0.0398 - val_acc: 0.0105
Epoch 69/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0367 -
acc: 0.0119 - val_loss: 0.0396 - val_acc: 0.0154
Epoch 70/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0367 -
```

```
acc: 0.0121 - val_loss: 0.0395 - val_acc: 0.0138
Epoch 71/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0366 -
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
60000/60000 [==============================] - 2s 26us/step - loss: 0.0366 -
acc: 0.0117 - val_loss: 0.0397 - val_acc: 0.0127
Epoch 74/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0365 -
acc: 0.0121 - val_loss: 0.0397 - val_acc: 0.0141
Epoch 75/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0365 -
acc: 0.0122 - val_loss: 0.0397 - val_acc: 0.0100
Epoch 76/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0365 -
acc: 0.0119 - val_loss: 0.0395 - val_acc: 0.0129
Epoch 77/100
60000/60000 [==============================] - 2s 26us/step - loss: 0.0364 -
acc: 0.0121 - val_loss: 0.0398 - val_acc: 0.0111
Epoch 78/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0364 -
acc: 0.0121 - val_loss: 0.0395 - val_acc: 0.0119
Epoch 79/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0364 -
acc: 0.0118 - val_loss: 0.0395 - val_acc: 0.0104
Epoch 80/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0363 -
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
60000/60000 [==============================] - 2s 27us/step - loss: 0.0363 -
acc: 0.0125 - val_loss: 0.0396 - val_acc: 0.0119
Epoch 83/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0363 -
acc: 0.0124 - val_loss: 0.0397 - val_acc: 0.0111
Epoch 84/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0363 -
acc: 0.0113 - val_loss: 0.0395 - val_acc: 0.0101
Epoch 85/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0362 -
acc: 0.0123 - val_loss: 0.0397 - val_acc: 0.0118
Epoch 86/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0362 -
acc: 0.0124 - val_loss: 0.0397 - val_acc: 0.0105
Epoch 87/100
60000/60000 [==============================] - 2s 28us/step - loss: 0.0362 -
acc: 0.0120 - val_loss: 0.0395 - val_acc: 0.0124
Epoch 88/100
60000/60000 [==============================] - 2s 31us/step - loss: 0.0361 -
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
60000/60000 [==============================] - 2s 29us/step - loss: 0.0360 -
acc: 0.0121 - val_loss: 0.0396 - val_acc: 0.0118
Epoch 95/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0360 -
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
60000/60000 [==============================] - 2s 29us/step - loss: 0.0359 -
acc: 0.0124 - val_loss: 0.0396 - val_acc: 0.0129
Epoch 98/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0359 -
acc: 0.0124 - val_loss: 0.0395 - val_acc: 0.0101
Epoch 99/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0359 -
acc: 0.0122 - val_loss: 0.0396 - val_acc: 0.0115
Epoch 100/100
60000/60000 [==============================] - 2s 27us/step - loss: 0.0359 -
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()
```



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()
```

In [47]:
```
''' Part 2: Implement a convolutional AutoEncoder (CAE)
'''

x_train = x_train.reshape((len(x_train), 28, 28, 1))
x_test = x_test.reshape((len(x_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)            (None, 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
_________________________________________________________________
```

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
60000/60000 [==============================] - 4s 69us/step - loss: 0.0553 -
acc: 0.7955 - val_loss: 0.0525 - val_acc: 0.7943
Epoch 3/100
60000/60000 [==============================] - 4s 68us/step - loss: 0.0510 -
acc: 0.7951 - val_loss: 0.0499 - val_acc: 0.7942
Epoch 4/100
60000/60000 [==============================] - 4s 71us/step - loss: 0.0487 -
acc: 0.7950 - val_loss: 0.0480 - val_acc: 0.7939
Epoch 5/100
60000/60000 [==============================] - 4s 68us/step - loss: 0.0472 -
acc: 0.7954 - val_loss: 0.0465 - val_acc: 0.7977
Epoch 6/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0461 -
acc: 0.7960 - val_loss: 0.0458 - val_acc: 0.7931
Epoch 7/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0454 -
acc: 0.7964 - val_loss: 0.0451 - val_acc: 0.7935
Epoch 8/100
60000/60000 [==============================] - 4s 68us/step - loss: 0.0448 -
acc: 0.7967 - val_loss: 0.0445 - val_acc: 0.7971
Epoch 9/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0444 -
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
60000/60000 [==============================] - 4s 69us/step - loss: 0.0436 -
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
60000/60000 [==============================] - 4s 69us/step - loss: 0.0431 -
```

```
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
60000/60000 [==============================] - 4s 69us/step - loss: 0.0419 -
acc: 0.7982 - val_loss: 0.0422 - val_acc: 0.7992
Epoch 19/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0417 -
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
60000/60000 [==============================] - 4s 68us/step - loss: 0.0414 -
acc: 0.7984 - val_loss: 0.0414 - val_acc: 0.7968
Epoch 22/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0412 -
acc: 0.7985 - val_loss: 0.0417 - val_acc: 0.7985
Epoch 23/100
60000/60000 [==============================] - 4s 68us/step - loss: 0.0411 -
acc: 0.7985 - val_loss: 0.0414 - val_acc: 0.7952
Epoch 24/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0410 -
acc: 0.7985 - val_loss: 0.0413 - val_acc: 0.7956
Epoch 25/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0409 -
acc: 0.7986 - val_loss: 0.0413 - val_acc: 0.7946
Epoch 26/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0407 -
acc: 0.7987 - val_loss: 0.0412 - val_acc: 0.7988
Epoch 27/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0407 -
acc: 0.7987 - val_loss: 0.0410 - val_acc: 0.7986
Epoch 28/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0405 -
acc: 0.7988 - val_loss: 0.0407 - val_acc: 0.7971
Epoch 29/100
60000/60000 [==============================] - 4s 71us/step - loss: 0.0405 -
acc: 0.7988 - val_loss: 0.0412 - val_acc: 0.7988
Epoch 30/100
60000/60000 [==============================] - 4s 71us/step - loss: 0.0404 -
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
60000/60000 [==============================] - 4s 69us/step - loss: 0.0401 -
```

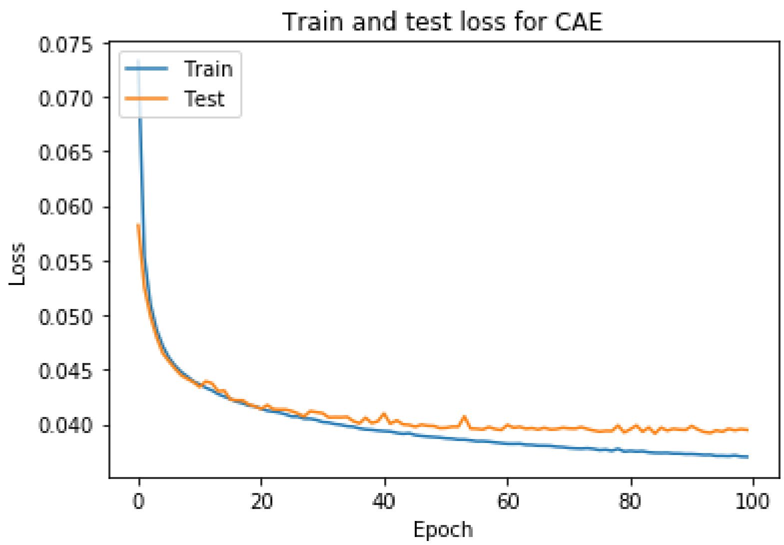
```
acc: 0.7990 - val_loss: 0.0406 - val_acc: 0.7987
Epoch 33/100
60000/60000 [==============================] - 4s 68us/step - loss: 0.0400 -
acc: 0.7990 - val_loss: 0.0406 - val_acc: 0.7956
Epoch 34/100
60000/60000 [==============================] - 4s 71us/step - loss: 0.0399 -
acc: 0.7990 - val_loss: 0.0406 - val_acc: 0.7983
Epoch 35/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0398 -
acc: 0.7991 - val_loss: 0.0407 - val_acc: 0.7986
Epoch 36/100
60000/60000 [==============================] - 4s 71us/step - loss: 0.0397 -
acc: 0.7991 - val_loss: 0.0403 - val_acc: 0.7974
Epoch 37/100
60000/60000 [==============================] - 4s 68us/step - loss: 0.0396 -
acc: 0.7992 - val_loss: 0.0401 - val_acc: 0.7978
Epoch 38/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0395 -
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
60000/60000 [==============================] - 4s 71us/step - loss: 0.0394 -
acc: 0.7993 - val_loss: 0.0403 - val_acc: 0.7980
Epoch 41/100
60000/60000 [==============================] - 4s 71us/step - loss: 0.0393 -
acc: 0.7993 - val_loss: 0.0410 - val_acc: 0.7992
Epoch 42/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0393 -
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
60000/60000 [==============================] - 4s 70us/step - loss: 0.0391 -
acc: 0.7994 - val_loss: 0.0400 - val_acc: 0.7973
Epoch 45/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0392 -
acc: 0.7994 - val_loss: 0.0399 - val_acc: 0.7971
Epoch 46/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0390 -
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
60000/60000 [==============================] - 4s 72us/step - loss: 0.0388 -
acc: 0.7996 - val_loss: 0.0398 - val_acc: 0.7996
Epoch 49/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0388 -
acc: 0.7996 - val_loss: 0.0398 - val_acc: 0.7980
Epoch 50/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0388 -
acc: 0.7996 - val_loss: 0.0396 - val_acc: 0.7969
Epoch 51/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0387 -
```

```
acc: 0.7996 - val_loss: 0.0397 - val_acc: 0.7986
Epoch 52/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0387 -
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
60000/60000 [==============================] - 4s 70us/step - loss: 0.0386 -
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
60000/60000 [==============================] - 4s 69us/step - loss: 0.0384 -
acc: 0.7997 - val_loss: 0.0396 - val_acc: 0.7982
Epoch 57/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0384 -
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
60000/60000 [==============================] - 4s 69us/step - loss: 0.0383 -
acc: 0.7998 - val_loss: 0.0395 - val_acc: 0.7969
Epoch 60/100
60000/60000 [==============================] - 4s 68us/step - loss: 0.0382 -
acc: 0.7999 - val_loss: 0.0395 - val_acc: 0.7977
Epoch 61/100
60000/60000 [==============================] - 4s 68us/step - loss: 0.0382 -
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
60000/60000 [==============================] - 4s 71us/step - loss: 0.0382 -
acc: 0.7999 - val_loss: 0.0397 - val_acc: 0.7980
Epoch 64/100
60000/60000 [==============================] - 4s 71us/step - loss: 0.0381 -
acc: 0.8000 - val_loss: 0.0396 - val_acc: 0.7954
Epoch 65/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0381 -
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
60000/60000 [==============================] - 4s 70us/step - loss: 0.0380 -
acc: 0.8000 - val_loss: 0.0397 - val_acc: 0.7977
Epoch 68/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0380 -
acc: 0.8000 - val_loss: 0.0395 - val_acc: 0.7987
Epoch 69/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0379 -
acc: 0.8001 - val_loss: 0.0395 - val_acc: 0.7991
Epoch 70/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0379 -
```

```
acc: 0.8001 - val_loss: 0.0397 - val_acc: 0.7984
Epoch 71/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0378 -
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
60000/60000 [==============================] - 4s 69us/step - loss: 0.0377 -
acc: 0.8001 - val_loss: 0.0397 - val_acc: 0.7965
Epoch 74/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0378 -
acc: 0.8001 - val_loss: 0.0395 - val_acc: 0.7962
Epoch 75/100
60000/60000 [==============================] - 4s 72us/step - loss: 0.0377 -
acc: 0.8001 - val_loss: 0.0394 - val_acc: 0.7975
Epoch 76/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0376 -
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
60000/60000 [==============================] - 4s 69us/step - loss: 0.0375 -
acc: 0.8003 - val_loss: 0.0394 - val_acc: 0.7975
Epoch 79/100
60000/60000 [==============================] - 4s 71us/step - loss: 0.0377 -
acc: 0.8001 - val_loss: 0.0399 - val_acc: 0.7998
Epoch 80/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0375 -
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
60000/60000 [==============================] - 4s 71us/step - loss: 0.0375 -
acc: 0.8003 - val_loss: 0.0399 - val_acc: 0.8001
Epoch 83/100
60000/60000 [==============================] - 4s 72us/step - loss: 0.0375 -
acc: 0.8002 - val_loss: 0.0393 - val_acc: 0.7984
Epoch 84/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0374 -
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
60000/60000 [==============================] - 4s 72us/step - loss: 0.0373 -
acc: 0.8004 - val_loss: 0.0397 - val_acc: 0.7959
Epoch 87/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0373 -
acc: 0.8004 - val_loss: 0.0394 - val_acc: 0.7993
Epoch 88/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0373 -
acc: 0.8004 - val_loss: 0.0396 - val_acc: 0.7990
Epoch 89/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0373 -
```

```
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
60000/60000 [==============================] - 4s 69us/step - loss: 0.0372 -
acc: 0.8005 - val_loss: 0.0392 - val_acc: 0.7978
Epoch 95/100
60000/60000 [==============================] - 4s 70us/step - loss: 0.0371 -
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
60000/60000 [==============================] - 4s 71us/step - loss: 0.0370 -
acc: 0.8006 - val_loss: 0.0396 - val_acc: 0.7964
Epoch 98/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0371 -
acc: 0.8005 - val_loss: 0.0394 - val_acc: 0.7966
Epoch 99/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0370 -
acc: 0.8006 - val_loss: 0.0395 - val_acc: 0.7973
Epoch 100/100
60000/60000 [==============================] - 4s 69us/step - loss: 0.0370 -
acc: 0.8006 - val_loss: 0.0395 - val_acc: 0.7962
```

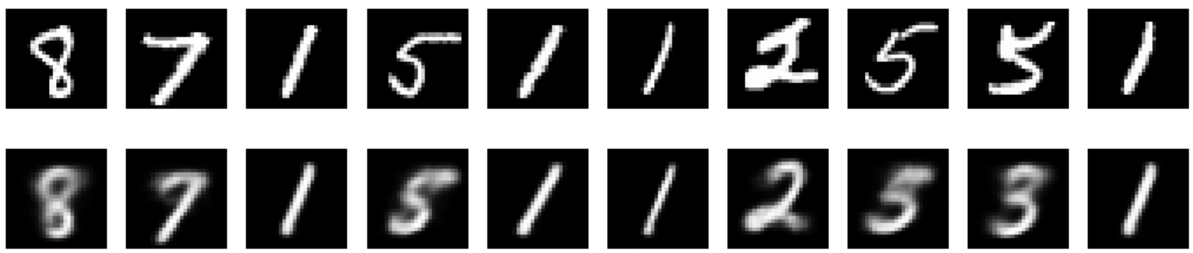
In [57]:
```
# plot the train and test loss
plt.plot(autoencoder_conv_history.history['loss'])
plt.plot(autoencoder_conv_history.history['val_loss'])
plt.title('Train and test loss for CAE')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



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='same', 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='same'))
autoencoder_conv_refine.add(MaxPooling2D(pool_size=(2, 2)))
autoencoder_conv_refine.add(Conv2D(128, (3, 3), activation='relu', padding='same'))
autoencoder_conv_refine.add(MaxPooling2D(pool_size=(2, 2)))
autoencoder_conv_refine.add(Conv2D(12, (3, 3), activation='relu', padding='same'))
autoencoder_conv_refine.add(MaxPooling2D(pool_size=(2, 2)))
# decoder network
autoencoder_conv_refine.add(Conv2DTranspose(128, (7, 7), activation='relu', padding='valid'))
autoencoder_conv_refine.add(UpSampling2D((2, 2)))
autoencoder_conv_refine.add(Conv2DTranspose(64, (3, 3), activation='relu', padding='same'))
autoencoder_conv_refine.add(UpSampling2D((2, 2)))
autoencoder_conv_refine.add(Conv2D(1, (3, 3), activation='sigmoid', padding='same'))

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     
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (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         
_________________________________________________________________
conv2d_transpose_4 (Conv2DTr (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
60000/60000 [==============================] - 6s 98us/step - loss: 0.0251 -
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
60000/60000 [==============================] - 6s 99us/step - loss: 0.0190 -
acc: 0.8095 - val_loss: 0.0180 - val_acc: 0.8084
Epoch 5/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0179 -
acc: 0.8100 - val_loss: 0.0174 - val_acc: 0.8089
Epoch 6/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0171 -
acc: 0.8104 - val_loss: 0.0165 - val_acc: 0.8094
Epoch 7/20
60000/60000 [==============================] - 6s 96us/step - loss: 0.0165 -
acc: 0.8107 - val_loss: 0.0163 - val_acc: 0.8090
Epoch 8/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0159 -
acc: 0.8110 - val_loss: 0.0157 - val_acc: 0.8095
Epoch 9/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0154 -
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
60000/60000 [==============================] - 6s 97us/step - loss: 0.0147 -
acc: 0.8116 - val_loss: 0.0146 - val_acc: 0.8112
Epoch 12/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0145 -
acc: 0.8117 - val_loss: 0.0143 - val_acc: 0.8110
Epoch 13/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0142 -
```

```
acc: 0.8118 - val_loss: 0.0141 - val_acc: 0.8109
Epoch 14/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0140 -
acc: 0.8119 - val_loss: 0.0140 - val_acc: 0.8113
Epoch 15/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0138 -
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
60000/60000 [==============================] - 6s 97us/step - loss: 0.0134 -
acc: 0.8122 - val_loss: 0.0135 - val_acc: 0.8114
Epoch 18/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0133 -
acc: 0.8123 - val_loss: 0.0133 - val_acc: 0.8113
Epoch 19/20
60000/60000 [==============================] - 6s 98us/step - loss: 0.0131 -
acc: 0.8124 - val_loss: 0.0132 - val_acc: 0.8111
Epoch 20/20
60000/60000 [==============================] - 6s 97us/step - loss: 0.0130 -
acc: 0.8124 - val_loss: 0.0130 - val_acc: 0.8112
```

In [54]:

```python
# 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()
```

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

In [76]:
```
''' Part 3: using an AutoEncoder to generate similar but not identical hand di
gits
'''

# Part 3.1:
# load the model trained in part 1
autoencoder_fc_best = load_model('./best_model_fc.pth')
autoencoder_fc_best.summary()
```

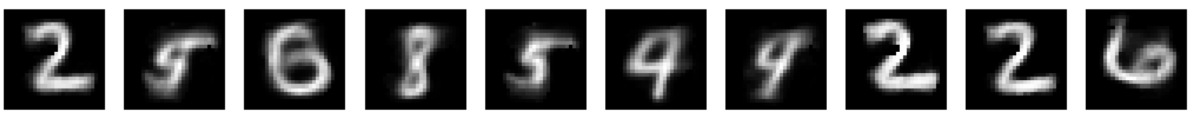
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_22 (Dense)             (None, 512)               401920    
_________________________________________________________________
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]
 [ 3.53354096  1.45952269]
 [ 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]]
```



In [7]:
```
# 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_mea
n, norm_var])
intermediate_output2 = Dense(2, activation='relu')(intermediate_output1)
encoder_output = BatchNormalization()(intermediate_output2)
# construct the decoder part
intermediate_output3 = Dense(512, activation='relu')(encoder_output)
decoder_output = Dense(input_size, activation='sigmoid')(intermediate_output3)

autoencoder_fc_norm = Model(autoencoder_fc_norm_input, decoder_output)
autoencoder_fc_norm.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_3 (InputLayer)         (None, 784)               0
_________________________________________________________________
dense_9 (Dense)              (None, 512)               401920
_________________________________________________________________
dense_10 (Dense)             (None, 2)                 1026
_________________________________________________________________
batch_normalization_3 (Batch (None, 2)                 8
_________________________________________________________________
dense_11 (Dense)             (None, 512)               1536
_________________________________________________________________
dense_12 (Dense)             (None, 784)               402192
=================================================================
Total params: 806,682
Trainable params: 806,678
Non-trainable params: 4
_________________________________________________________________
```

In [8]:
```
# 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: 616377031007688919
, name: "/device:GPU:0"
device_type: "GPU"
memory_limit: 6700198133
locality {
  bus_id: 1
  links {
  }
}
incarnation: 16757661795983644701
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
60000/60000 [==============================] - 2s 25us/step - loss: 0.0743 -
acc: 0.0097 - val_loss: 0.0538 - val_acc: 0.0126
Epoch 2/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0521 -
acc: 0.0130 - val_loss: 0.0510 - val_acc: 0.0123
Epoch 3/50
60000/60000 [==============================] - 1s 19us/step - loss: 0.0504 -
acc: 0.0098 - val_loss: 0.0502 - val_acc: 0.0094
Epoch 4/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0496 -
acc: 0.0086 - val_loss: 0.0490 - val_acc: 0.0083
Epoch 5/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0488 -
acc: 0.0082 - val_loss: 0.0481 - val_acc: 0.0084
Epoch 6/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0481 -
acc: 0.0089 - val_loss: 0.0474 - val_acc: 0.0082
Epoch 7/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0474 -
acc: 0.0099 - val_loss: 0.0475 - val_acc: 0.0076
Epoch 8/50
60000/60000 [==============================] - 1s 19us/step - loss: 0.0468 -
acc: 0.0098 - val_loss: 0.0463 - val_acc: 0.0075
Epoch 9/50
60000/60000 [==============================] - 1s 19us/step - loss: 0.0462 -
acc: 0.0096 - val_loss: 0.0458 - val_acc: 0.0066
Epoch 10/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0457 -
acc: 0.0090 - val_loss: 0.0451 - val_acc: 0.0095
Epoch 11/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0453 -
acc: 0.0095 - val_loss: 0.0450 - val_acc: 0.0091
Epoch 12/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0449 -
acc: 0.0088 - val_loss: 0.0446 - val_acc: 0.0107
Epoch 13/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0446 -
```

```
acc: 0.0088 - val_loss: 0.0443 - val_acc: 0.0084
Epoch 14/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0443 -
acc: 0.0089 - val_loss: 0.0441 - val_acc: 0.0091
Epoch 15/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0441 -
acc: 0.0088 - val_loss: 0.0438 - val_acc: 0.0075
Epoch 16/50
60000/60000 [==============================] - 1s 16us/step - loss: 0.0438 -
acc: 0.0085 - val_loss: 0.0437 - val_acc: 0.0081
Epoch 17/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0436 -
acc: 0.0083 - val_loss: 0.0433 - val_acc: 0.0078
Epoch 18/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0434 -
acc: 0.0088 - val_loss: 0.0436 - val_acc: 0.0069
Epoch 19/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0433 -
acc: 0.0083 - val_loss: 0.0432 - val_acc: 0.0083
Epoch 20/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0430 -
acc: 0.0080 - val_loss: 0.0431 - val_acc: 0.0082
Epoch 21/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0429 -
acc: 0.0081 - val_loss: 0.0429 - val_acc: 0.0084
Epoch 22/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0427 -
acc: 0.0080 - val_loss: 0.0430 - val_acc: 0.0118
Epoch 23/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0427 -
acc: 0.0079 - val_loss: 0.0426 - val_acc: 0.0074
Epoch 24/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0426 -
acc: 0.0082 - val_loss: 0.0427 - val_acc: 0.0074
Epoch 25/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0424 -
acc: 0.0082 - val_loss: 0.0425 - val_acc: 0.0104
Epoch 26/50
60000/60000 [==============================] - 1s 19us/step - loss: 0.0422 -
acc: 0.0080 - val_loss: 0.0431 - val_acc: 0.0078
Epoch 27/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0421 -
acc: 0.0084 - val_loss: 0.0423 - val_acc: 0.0085
Epoch 28/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0421 -
acc: 0.0091 - val_loss: 0.0423 - val_acc: 0.0077
Epoch 29/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0419 -
acc: 0.0083 - val_loss: 0.0422 - val_acc: 0.0071
Epoch 30/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0419 -
acc: 0.0086 - val_loss: 0.0423 - val_acc: 0.0081
Epoch 31/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0418 -
acc: 0.0095 - val_loss: 0.0419 - val_acc: 0.0100
Epoch 32/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0417 -
```

```
acc: 0.0092 - val_loss: 0.0419 - val_acc: 0.0068
Epoch 33/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0416 -
acc: 0.0097 - val_loss: 0.0423 - val_acc: 0.0063
Epoch 34/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0416 -
acc: 0.0088 - val_loss: 0.0417 - val_acc: 0.0104
Epoch 35/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0415 -
acc: 0.0095 - val_loss: 0.0416 - val_acc: 0.0131
Epoch 36/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0414 -
acc: 0.0100 - val_loss: 0.0418 - val_acc: 0.0128
Epoch 37/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0414 -
acc: 0.0096 - val_loss: 0.0420 - val_acc: 0.0114
Epoch 38/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0412 -
acc: 0.0105 - val_loss: 0.0420 - val_acc: 0.0109
Epoch 39/50
60000/60000 [==============================] - 1s 18us/step - loss: 0.0413 -
acc: 0.0102 - val_loss: 0.0418 - val_acc: 0.0135
Epoch 40/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0412 -
acc: 0.0105 - val_loss: 0.0416 - val_acc: 0.0114
Epoch 41/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0411 -
acc: 0.0096 - val_loss: 0.0418 - val_acc: 0.0130
Epoch 42/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0410 -
acc: 0.0108 - val_loss: 0.0415 - val_acc: 0.0081
Epoch 43/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0410 -
acc: 0.0105 - val_loss: 0.0414 - val_acc: 0.0125
Epoch 44/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0410 -
acc: 0.0103 - val_loss: 0.0415 - val_acc: 0.0112
Epoch 45/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0409 -
acc: 0.0104 - val_loss: 0.0415 - val_acc: 0.0099
Epoch 46/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0410 -
acc: 0.0100 - val_loss: 0.0417 - val_acc: 0.0127
Epoch 47/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0408 -
acc: 0.0102 - val_loss: 0.0415 - val_acc: 0.0091
Epoch 48/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0408 -
acc: 0.0101 - val_loss: 0.0427 - val_acc: 0.0104
Epoch 49/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0407 -
acc: 0.0104 - val_loss: 0.0416 - val_acc: 0.0118
Epoch 50/50
60000/60000 [==============================] - 1s 17us/step - loss: 0.0406 -
acc: 0.0097 - val_loss: 0.0414 - val_acc: 0.0075
```

In [9]:
```
# 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[4]
decoder_fc_norm_layer2 = autoencoder_fc_norm_best.layers[5]
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()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_4 (InputLayer)         (None, 2)                 0         
_________________________________________________________________
dense_11 (Dense)             (None, 512)               1536      
_________________________________________________________________
dense_12 (Dense)             (None, 784)               402192    
=================================================================
Total params: 403,728
Trainable params: 403,728
Non-trainable params: 0
_________________________________________________________________
```

In [34]:
```
# generate images by inputing random number to decoder
print("Generate images by inputing values draw from the distribution")
img_num = 10
plt.figure(figsize=(18, 18))
plt.gray()

random_input = np.linspace(-1.5, 1.5, img_num)[::-1]

for i in range(len(random_vars)):
    z_sample = np.array([[0, random_input[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 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 orignal embedding.

In [30]:
```
''' Part 4: Optional: change the AutoEncoder which you developed in the
last part of section 3 so that it becomes a Variational AutoEncoder
'''

# the batch normalization layer in the network structure
# is replaced by lambda layer
# and the loss function becomes the combination of
# variational_loss and mse_loss

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)                    Output Shape         Param #     Connected to
================================================================================
=====================
input_2 (InputLayer)            (None, 784)          0

________________________________________________________________________________
_____________________
dense_1 (Dense)                 (None, 512)          401920      input_2[0]
[0]
________________________________________________________________________________
_____________________
dense_2 (Dense)                 (None, 2)            1026        dense_1[0]
[0]
________________________________________________________________________________
_____________________
dense_3 (Dense)                 (None, 2)            1026        dense_1[0]
[0]
________________________________________________________________________________
_____________________
lambda_1 (Lambda)               (None, 2)            0           dense_2[0]
[0]
                                                                 dense_3[0]
[0]
________________________________________________________________________________
_____________________
dense_4 (Dense)                 (None, 512)          1536        lambda_1[0]
[0]
________________________________________________________________________________
_____________________
dense_5 (Dense)                 (None, 784)          402192      dense_4[0]
[0]
================================================================================
=====================
Total params: 807,700
Trainable params: 807,700
Non-trainable params: 0
________________________________________________________________________________
_____________________
```

In [31]:

```python
# 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()
```

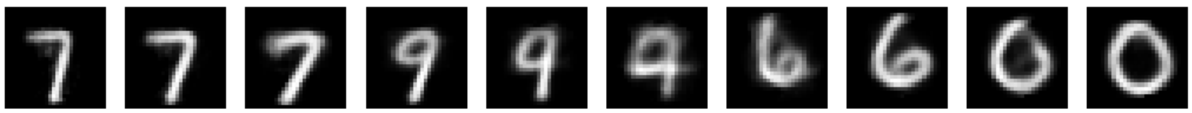
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_4 (InputLayer)         (None, 2)                 0         
_________________________________________________________________
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 [ ]: