ECE 637 Deep Learning Lab Exercises

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Section 1

Exercise 1.1

1. Create two lists, `A` and `B`: `A` contains 3 arbitrary numbers and `B` contains 3 arbitrary strings.
2. Concatenate two lists into a bigger list and name that list `C`.
3. Print the first element in `C`.
4. Print the second last element in `C` via negative indexing.
5. Remove the second element of `A` from `C`.
6. Print `C` again.

```
# ----------- YOUR CODE -----------
A = [1, 3, 5]
B = ['test', 'dummy', 'data']
C = A + B
print('C: ', C)
print('The first element in C = ', C[0])
print('the second to last element in C = ', C[-2])
del C[1]
print('C: ', C)
```

```
C:  [1, 3, 5, 'test', 'dummy', 'data']
The first element in C =  1
the second to last element in C =  dummy
C:  [1, 5, 'test', 'dummy', 'data']
```

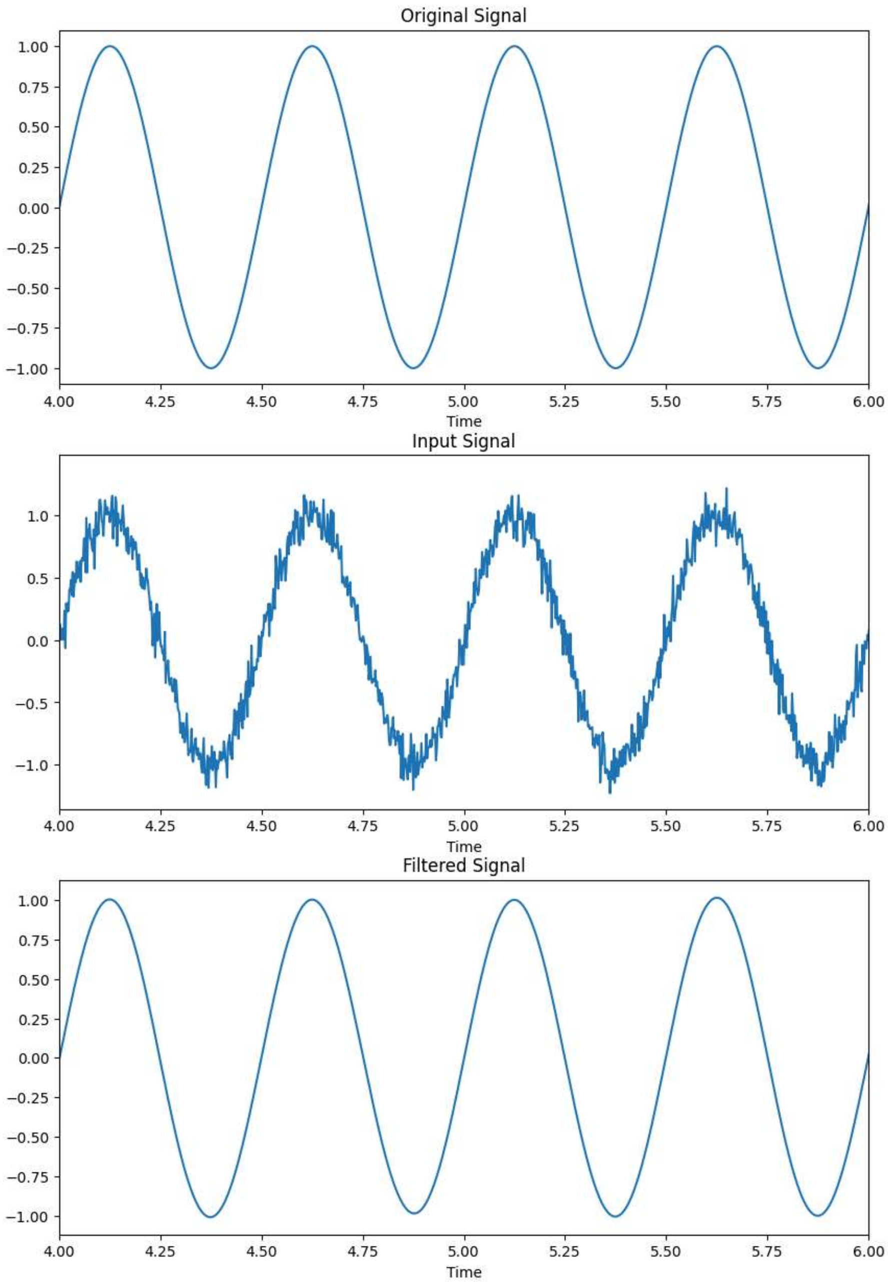
Exercise 1.2

In this exercise, you will use a low-pass IIR filter to remove noise from a sine-wave signal.

You should organize your plots in a 3x1 subplot format.

1. Generate a discrete-time signal, `x`, by sampling a 2Hz continuous time sine wave signal with peak amplitude 1 from time 0s to 10s and at a sampling frequency of 500 Hz. Display the signal, `x`, from time 4s to 6s in the first row of a 3x1 subplot with the title "original signal".
2. Add Gaussian white random noise with 0 mean and standard deviation 0.1 to `x` and call it `x_n`. Display `x_n` from 4s to 6s on the second row of the subplot with the title "input signal".
3. Design a low-pass butterworth IIR filter of order 5 with a cut-off frequency of 4Hz, designed to filter out the noise. Hint: Use the signal.butter function and note that the frequencies are relative to the Nyquist frequency. Apply the IIR filter to `x_n`, and name the output `y`. Hint: Use signal.filtfilt function. Plot `y` from 4s to 6s on the third row of the subplot with the title "filtered signal".

```
import numpy as np                                  # import the numpy packages and use a shorter alising name
import matplotlib.pyplot as plt              # again import the matplotlib's pyplot packages
from scipy import signal                              # import a minor package signal from scipy
plt.figure(figsize=(10, 15))                       # fix the plot size

#   ----------- YOUR CODE -----------
# Part 1
f = 2
f_sample = 500
T_sample = 1 / f_sample
t_start = 0
t_finish = 10
n = f_sample * (t_finish - t_start)
t = np.linspace(t_start, t_finish, n)
x = np.sin(2 * np.pi * f * t)
plt.subplot(3, 1, 1)
plt.plot(t, x)
plt.xlim([4, 6])
plt.title('Original Signal')
plt.xlabel('Time')

# Part 2
mean = 0
std = 0.1
noise = np.random.normal(mean, std, n)
x_n = np.zeros((1, np.size(t)))
for i in range(np.size(t)):
    x_n[0, i] = x[i] + noise[i]
plt.subplot(3, 1, 2)
plt.plot(t, x_n[0, :])
plt.xlim([4, 6])
plt.title('Input Signal')
plt.xlabel('Time')

# Part 3
f_cutoff = 4
b, a = signal.butter(5, f_cutoff, btype='low', fs=f_sample)
y = signal.filtfilt(b, a, x_n[0, :], padlen=3)
plt.subplot(3, 1, 3)
plt.plot(t, y)
plt.xlim([4, 6])
plt.title('Filtered Signal')
plt.xlabel('Time')

plt.show()
```



Section 2

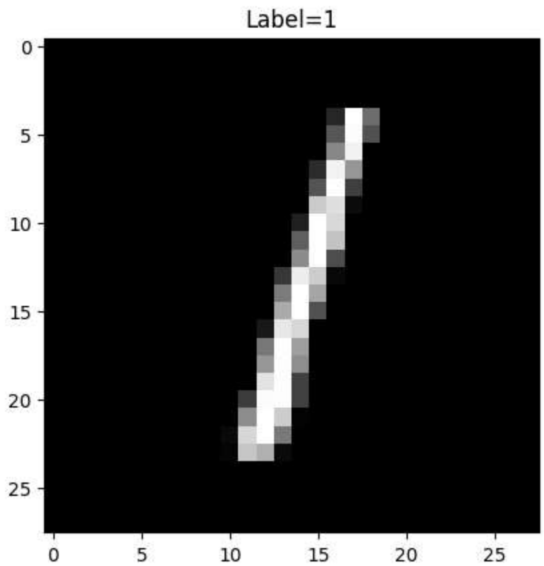
Exercise 2.1

- Plot the third image in the test data set

- Find the correspoding label for the this image and make it the title of the figure

```
import keras
from keras.datasets import mnist
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()

train_images = train_images.reshape((60000, 28, 28, 1))
test_images = test_images.reshape((10000, 28, 28, 1))

# ----------- YOUR CODE -----------
test_im = test_images[2, :, :, 0]
plt.imshow(test_im, cmap='gray')
test_im_label = test_labels[2]
plt.title('Label=' + str(test_im_label))
```

```
Text(0.5, 1.0, 'Label=1')
```



Exercise 2.2

It is usually helpful to have an accuracy plot as well as a loss value plot to get an intuitive sense of how effectively the model is being trained.

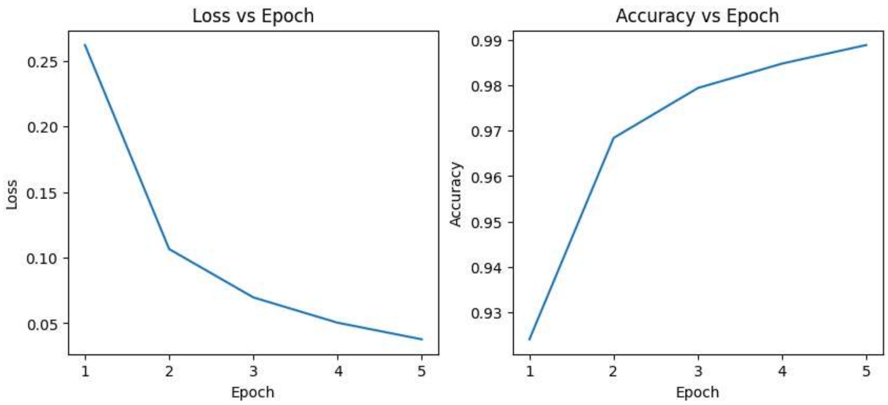
- Add code to this example for plotting two graphs with the following requirements:
  - Use a 1x2 subplot with the left subplot showing the loss function and right subplot showing the accuracy.
  - For each graph, plot the value with respect to epochs. Clearly label the x-axis, y-axis and the title.

(Hint: The value of of loss and accuracy are stored in the `hist` variable. Try to print out `hist.history` and `his.history.keys()` .)

```
import keras
from keras.datasets import mnist
from keras import models
from keras import layers
from keras.utils import to_categorical

(train_images, train_labels), (test_images, test_labels) = mnist.load_data()

train_images = train_images.reshape((60000, 28, 28, 1))
test_images = test_images.reshape((10000, 28, 28, 1))

network = models.Sequential()
network.add(layers.Flatten(input_shape=(28, 28, 1)))
network.add(layers.Dense(512, activation='relu'))
network.add(layers.Dense(10, activation='softmax'))

network.summary()

network.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])

train_images_nor = train_images.astype('float32') / 255
test_images_nor = test_images.astype('float32') / 255

train_labels_cat = to_categorical(train_labels)
test_labels_cat = to_categorical(test_labels)

hist = network.fit(train_images_nor, train_labels_cat, epochs=5, batch_size=128)
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 784)               0

 dense (Dense)               (None, 512)               401920

 dense_1 (Dense)             (None, 10)                5130

=================================================================
Total params: 407050 (1.55 MB)
Trainable params: 407050 (1.55 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
Epoch 1/5
469/469 [==============================] - 5s 6ms/step - loss: 0.2621 - accuracy: 0.9241
Epoch 2/5
469/469 [==============================] - 3s 7ms/step - loss: 0.1065 - accuracy: 0.9684
Epoch 3/5
469/469 [==============================] - 3s 7ms/step - loss: 0.0697 - accuracy: 0.9794
Epoch 4/5
469/469 [==============================] - 3s 6ms/step - loss: 0.0504 - accuracy: 0.9847
Epoch 5/5
469/469 [==============================] - 3s 6ms/step - loss: 0.0377 - accuracy: 0.9888
```

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 4))

#   ----------- YOUR CODE -----------
epoch = [1, 2, 3, 4, 5]
plt.subplot(1, 2, 1)
plt.plot(epoch, hist.history['loss'])
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Loss vs Epoch')

plt.subplot(1, 2, 2)
plt.plot(epoch, hist.history['accuracy'])
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Accuracy vs Epoch')
plt.show()
```



Exercise 2.3

Use the dense network from Section 2 as the basis to construct of a deeper network with

- 5 dense hidden layers with dimensions [512, 256, 128, 64, 32] each of which uses a ReLU non-linearity

Question: Will the accuracy on the testing data always get better if we keep making the neural network larger?

No, the accuracy on the testing data will not always get better if the neural network is made larger. As the neural network gets larger, it will reach great accuracy on the training data. However, this will cause overfitting issue, which means the model is not general enough to predict data that are not part of the training dataset.

```
import keras
from keras import models
from keras import layers

#   -----------  YOUR CODE  -----------
network = models.Sequential()
network.add(layers.Flatten(input_shape=(28, 28, 1)))
network.add(layers.Dense(512, activation='relu'))
network.add(layers.Dense(256, activation='relu'))
network.add(layers.Dense(128, activation='relu'))
network.add(layers.Dense(64, activation='relu'))
network.add(layers.Dense(32, activation='relu'))
network.add(layers.Dense(10, activation='softmax'))

network.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten_1 (Flatten)         (None, 784)               0

 dense_2 (Dense)             (None, 512)               401920

 dense_3 (Dense)             (None, 256)               131328

 dense_4 (Dense)             (None, 128)               32896

 dense_5 (Dense)             (None, 64)                8256

 dense_6 (Dense)             (None, 32)                2080

 dense_7 (Dense)             (None, 10)                330

=================================================================
Total params: 576810 (2.20 MB)
Trainable params: 576810 (2.20 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
import keras
```

```
from keras.datasets import mnist
from keras.utils import to_categorical

(train_images, train_labels), (test_images, test_labels) = mnist.load_data()

train_images = train_images.reshape((60000, 28, 28, 1))
test_images = test_images.reshape((10000, 28, 28, 1))


network.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])

train_images_nor = train_images.astype('float32') / 255
test_images_nor = test_images.astype('float32') / 255

train_labels_cat = to_categorical(train_labels)
test_labels_cat = to_categorical(test_labels)

hist = network.fit(train_images_nor, train_labels_cat, epochs=5, batch_size=128)

test_loss, test_acc = network.evaluate(test_images_nor, test_labels_cat)
print('test_accuracy:', test_acc)
```

```
Epoch 1/5
469/469 [==============================] - 4s 5ms/step - loss: 0.3057 - accuracy: 0.9060
Epoch 2/5
469/469 [==============================] - 2s 4ms/step - loss: 0.1038 - accuracy: 0.9689
Epoch 3/5
469/469 [==============================] - 2s 4ms/step - loss: 0.0684 - accuracy: 0.9790
Epoch 4/5
469/469 [==============================] - 2s 4ms/step - loss: 0.0510 - accuracy: 0.9845
Epoch 5/5
469/469 [==============================] - 2s 4ms/step - loss: 0.0373 - accuracy: 0.9887
313/313 [==============================] - 1s 3ms/step - loss: 0.0878 - accuracy: 0.9765
test_accuracy: 0.9764999747276306
```

Section 3

Exercise 3.1

In this exercise, you will access the relationship between the feature extraction layer and classification layer. The example above uses two sets of convolutional layers and pooling layers in the feature extraction layer and two dense layers in the classification layers. The overall performance is around 98% for both training and test dataset. In this exercise, try to create a similar CNN network with the following requirements:

- Achieve the overall accuracy higher than 99% for training and testing dataset.
- Keep the total number of parameters used in the network lower than 100,000.

```
import keras
from keras import models
from keras import layers

network = models.Sequential()

#  ----------- YOUR CODE -----------
network.add(layers.Conv2D(16, (3, 3), activation='relu', padding = 'same', input_shape=(28, 28, 1)))
network.add(layers.MaxPooling2D((2, 2)))
network.add(layers.Conv2D(32, (3, 3), activation='relu', padding = 'same'))
network.add(layers.MaxPooling2D((2, 2)))

network.add(layers.Flatten())
network.add(layers.Dense(16, activation='relu'))
network.add(layers.Dense(10, activation='softmax'))

network.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 28, 28, 16)        160

 max_pooling2d (MaxPooling2  (None, 14, 14, 16)        0
```

```
 D)

 conv2d_1 (Conv2D)           (None, 14, 14, 32)        4640

 max_pooling2d_1 (MaxPoolin  (None, 7, 7, 32)          0
 g2D)

 flatten_2 (Flatten)         (None, 1568)              0

 dense_8 (Dense)             (None, 16)                25104

 dense_9 (Dense)             (None, 10)                170

=================================================================
Total params: 30074 (117.48 KB)
Trainable params: 30074 (117.48 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
from keras.datasets import mnist
from keras.utils import to_categorical

(train_images, train_labels), (test_images, test_labels) = mnist.load_data()

train_images = train_images.reshape((60000, 28, 28, 1))
train_images_nor = train_images.astype('float32') / 255
test_images = test_images.reshape((10000, 28, 28, 1))
test_images_nor = test_images.astype('float32') / 255

train_labels_cat = to_categorical(train_labels)
test_labels_cat = to_categorical(test_labels)

network.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])
network.fit(train_images_nor, train_labels_cat, epochs=5, batch_size=128)

test_loss, test_acc = network.evaluate(test_images_nor, test_labels_cat)
print('test_accuracy:', test_acc)
```

```
Epoch 1/5
469/469 [==============================] - 5s 5ms/step - loss: 0.3856 - accuracy: 0.8804
Epoch 2/5
469/469 [==============================] - 2s 4ms/step - loss: 0.0998 - accuracy: 0.9689
Epoch 3/5
469/469 [==============================] - 2s 4ms/step - loss: 0.0686 - accuracy: 0.9792
Epoch 4/5
469/469 [==============================] - 2s 4ms/step - loss: 0.0539 - accuracy: 0.9832
Epoch 5/5
469/469 [==============================] - 2s 5ms/step - loss: 0.0442 - accuracy: 0.9866
313/313 [==============================] - 1s 3ms/step - loss: 0.0375 - accuracy: 0.9869
test_accuracy: 0.9868999719619751
```

Section 4

Exercise 4.1

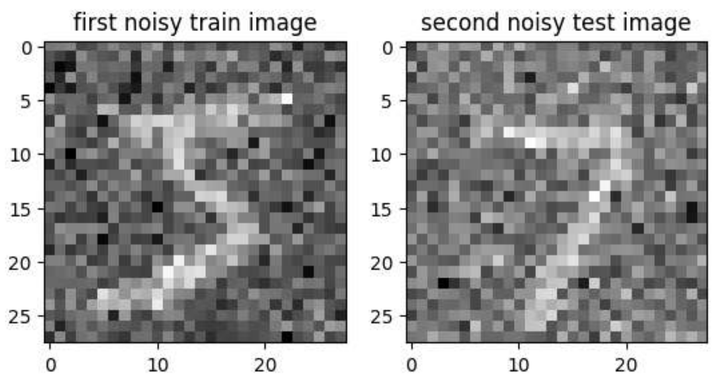
In this exercise you will need to create the entire neural network that does image denoising tasks. Try to mimic the code provided above and follow the structure as provided in the instructions below.

Task 1: Create the datasets

1. Import necessary packages
2. Load the MNIST data from Keras, and save the training dataset images as `train_images`, save the test dataset images as `test_images`
3. Add additive white gaussian noise to the train images as well as the test images and save the noisy images to `train_images_noisy` and `test_images_noisy` respectivly. The noise should have mean value 0, and standard deviation 0.4. (Hint: Use np.random.normal)
4. Show the first image in the training dataset as well as the test dataset (plot the images in 1 x 2 subplot form)

```
#    -----------  YOUR  CODE  -----------
from  keras.datasets  import  mnist
from  keras.utils  import  to_categorical

(train_images,  train_labels),  (test_images,  test_labels)  =  mnist.load_data()

train_images  =  train_images.reshape((60000,  28,  28,  1))

train_images_nor  =  train_images.astype('float32')  /  255
test_images  =  test_images.reshape((10000,  28,  28,  1))
test_images_nor  =  test_images.astype('float32')  /  255

train_noise  =  np.random.normal(0,  0.4,  train_images.shape)
test_noise  =  np.random.normal(0,  0.4,  test_images.shape)
train_images_noisy  =  train_images_nor  +  train_noise
test_images_noisy  =  test_images_nor  +  test_noise

plt.subplot(1,2,1)
plt.imshow(train_images_noisy[0],  cmap='gray')
plt.title('first  noisy  train  image')

plt.subplot(1,2,2)
plt.imshow(test_images_noisy[0],  cmap='gray')
plt.title('second  noisy  test  image')
```

```
Text(0.5, 1.0, 'second noisy test image')
```



Task 2: Create the neural network model

1. Create a sequential model called `encoder` with the following layers sequentially:
    - convolutional layer with `32` output channels, `3x3` kernel size, and the padding convention `'same'` with `'relu'` activition function.
    - max pooling layer with `2x2` kernel size
    - convolutional layer with `16` output channels, `3x3` kernel size, and the padding convention `'same'` with `'relu'` activition function.
    - max pooling layer with `2x2` kernel size
    - convolutional layer with `8` output channels, `3x3` kernel size, and the padding convention `'same'` with `'relu'` activition function and name the layer as `'convOutput'`.
    - flatten layer
    - dense layer with output dimension as `encoding_dim` with `'relu'` activition function.
2. Create a sequential model called `decoder` with the following layers sequentially:
    - dense layer with the input dimension as `encoding_dim` and the output dimension as the product of the output dimenstions of the `'convOutput'` layer.
    - reshape layer that convert the tensor into the same shape as `'convOutput'`
    - convolutional layer with `8` output channels, `3x3` kernel size, and the padding convention `'same'` with `'relu'` activition function.
    - upsampling layer with `2x2` kernel size
    - convolutional layer with `16` output channels, `3x3` kernel size, and the padding convention `'same'` with `'relu'` activition function.
    - upsampling layer with `2x2` kernel size
    - convolutional layer with `32` output channels, `3x3` kernel size, and the padding convention `'same'` with `'relu'` activition function
    - convolutional layer with `1` output channels, `3x3` kernel size, and the padding convention `'same'` with `'sigmoid'` activition function
3. Create a sequential model called `autoencoder` with the following layers sequentially:
    - `encoder` model
    - `decoder` model

```
#   -----------  YOUR  CODE  -----------
encoding_dim  =  32

encoder  =  models.Sequential()
encoder.add(layers.Conv2D(32,  (3,  3),  activation='relu',  padding='same',  input_shape=(28,  28,  1)))
encoder.add(layers.MaxPooling2D((2,  2)))
encoder.add(layers.Conv2D(16,  (3,  3),  activation='relu',  padding='same'))
encoder.add(layers.MaxPooling2D((2,  2)))
encoder.add(layers.Conv2D(8,  (3,  3),  activation='relu',  padding='same',  name='convOutput'))
encoder.add(layers.Flatten())
encoder.add(layers.Dense(encoding_dim,  activation='relu'))

convShape  =  encoder.get_layer('convOutput').output_shape[1:]
denseShape  =  convShape[0]*convShape[1]*convShape[2]

decoder  =  models.Sequential()
decoder.add(layers.Dense(denseShape,  input_shape=(encoding_dim,)))
decoder.add(layers.Reshape(convShape))
decoder.add(layers.Conv2D(8,  (3,  3),  activation='relu',  padding  =  'same'))
decoder.add(layers.UpSampling2D((2,  2)))
decoder.add(layers.Conv2D(16,  (3,  3),  activation='relu',  padding  =  'same'))
decoder.add(layers.UpSampling2D((2,  2)))
decoder.add(layers.Conv2D(32,  (3,  3),  activation='relu',  padding  =  'same'))
decoder.add(layers.Conv2D(1,  (3,  3),  activation='sigmoid',  padding  =  'same'))

#  3
autoencoder  =  models.Sequential()
autoencoder.add(encoder)
autoencoder.add(decoder)


encoder.summary()
decoder.summary()
autoencoder.summary()
```

```
 g2D)

 conv2d_3 (Conv2D)           (None, 14, 14, 16)        4624

 max_pooling2d_3 (MaxPoolin  (None, 7, 7, 16)          0
 g2D)

 convOutput (Conv2D)         (None, 7, 7, 8)           1160

 flatten_3 (Flatten)         (None, 392)               0

 dense_10 (Dense)            (None, 32)                12576

=================================================================
Total params: 18680 (72.97 KB)
Trainable params: 18680 (72.97 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_11 (Dense)            (None, 392)               12936

 reshape (Reshape)           (None, 7, 7, 8)           0

 conv2d_4 (Conv2D)           (None, 7, 7, 8)           584

 up_sampling2d (UpSampling2  (None, 14, 14, 8)         0
 D)

 conv2d_5 (Conv2D)           (None, 14, 14, 16)        1168

 up_sampling2d_1 (UpSamplin  (None, 28, 28, 16)        0
 g2D)

 conv2d_6 (Conv2D)           (None, 28, 28, 32)        4640
```

```
Model: sequential_5
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential_3 (Sequential)   (None, 32)                18680

 sequential_4 (Sequential)   (None, 28, 28, 1)         19617

=================================================================
Total params: 38297 (149.60 KB)
Trainable params: 38297 (149.60 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Task 3: Create the neural network model

Fit the model to the training data using the following hyper-parameters:

- `adam` optimizer
- `binary_crossentropy` loss function
- `20` training epochs
- batch size as `256`
- set `shuffle` as `True`

Compile the model and fit ...

```
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
history = autoencoder.fit(train_images_noisy, train_images_nor,
                          epochs=20,
                          batch_size=256,
                          shuffle=True)
```

```
Epoch 1/20
235/235 [==============================] - 8s 13ms/step - loss: 0.2592
Epoch 2/20
235/235 [==============================] - 3s 11ms/step - loss: 0.1508
Epoch 3/20
235/235 [==============================] - 3s 11ms/step - loss: 0.1305
Epoch 4/20
235/235 [==============================] - 2s 11ms/step - loss: 0.1227
Epoch 5/20
235/235 [==============================] - 2s 11ms/step - loss: 0.1183
Epoch 6/20
235/235 [==============================] - 3s 11ms/step - loss: 0.1155
Epoch 7/20
235/235 [==============================] - 3s 12ms/step - loss: 0.1133
Epoch 8/20
235/235 [==============================] - 3s 11ms/step - loss: 0.1117
Epoch 9/20
235/235 [==============================] - 3s 11ms/step - loss: 0.1101
Epoch 10/20
235/235 [==============================] - 3s 11ms/step - loss: 0.1085
Epoch 11/20
235/235 [==============================] - 3s 11ms/step - loss: 0.1075
Epoch 12/20
235/235 [==============================] - 3s 12ms/step - loss: 0.1063
Epoch 13/20
235/235 [==============================] - 3s 13ms/step - loss: 0.1056
Epoch 14/20
235/235 [==============================] - 3s 12ms/step - loss: 0.1049
Epoch 15/20
235/235 [==============================] - 3s 11ms/step - loss: 0.1043
Epoch 16/20
235/235 [==============================] - 3s 11ms/step - loss: 0.1037
Epoch 17/20
235/235 [==============================] - 3s 12ms/step - loss: 0.1033
Epoch 18/20
235/235 [==============================] - 3s 11ms/step - loss: 0.1027
Epoch 19/20
235/235 [==============================] - 2s 11ms/step - loss: 0.1024
Epoch 20/20
235/235 [==============================] - 2s 11ms/step - loss: 0.1021
```

Task 4: Create the neural network model (No need to write code, just run the following commands)

```
def showImages(input_imgs, encoded_imgs, output_imgs, size=1.5, groundTruth=None):

    numCols = 3 if groundTruth is None else 4

    num_images = input_imgs.shape[0]

    encoded_imgs = encoded_imgs.reshape((num_images, 1, -1))


    plt.figure(figsize=((numCols+encoded_imgs.shape[2]/input_imgs.shape[2])*size, num_images*size))

    pltIdx = 0
    col = 0
    for i in range(0, num_images):

        col += 1
        # plot input image
        pltIdx += 1
        ax = plt.subplot(num_images, numCols, pltIdx)
        plt.imshow(input_imgs[i].reshape(28, 28))
        plt.gray()
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)
        if col == 1:
            plt.title('Input Image')

        # plot encoding
        pltIdx += 1
        ax = plt.subplot(num_images, numCols, pltIdx)
        plt.imshow(encoded_imgs[i])
        plt.gray()
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)
        if col == 1:
            plt.title('Encoded Image')

        # plot reconstructed image
        pltIdx += 1
        ax = plt.subplot(num_images, numCols, pltIdx)
        plt.imshow(output_imgs[i].reshape(28, 28))
        plt.gray()
        ax.get_xaxis().set_visible(False)
        ax.get_yaxis().set_visible(False)
        if col == 1:
            plt.title('Reconstructed Image')

        if numCols == 4:
            # plot ground truth image
            pltIdx += 1
            ax = plt.subplot(num_images, numCols, pltIdx)
            plt.imshow(groundTruth[i].reshape(28, 28))
            plt.gray()
            ax.get_xaxis().set_visible(False)
            ax.get_yaxis().set_visible(False)

            if col == 1:
                plt.title('Ground Truth')

    plt.show()


num_images = 10

input_labels = test_labels[0:num_images]
I = np.argsort(input_labels)

input_imgs = test_images_noisy[I]

encoded_imgs = encoder.predict(test_images_noisy[I])
output_imgs = decoder.predict(encoded_imgs)

showImages(input_imgs, encoded_imgs, output_imgs, size=2, groundTruth=test_images_nor[I])
```