

STEVENS INSTITUTE OF TECHNOLOGY

DEPARTMENT OF ELECTRICAL ENGINEERING

EE628: DATA ACQUISITION/PROC II

Homework Assignment 6

Submitted by:
Hadia HAMEED
CWID: 10440803

Submitted to:
Prof. Rensheng WANG

March 28, 2019

3 PROBLEM 3:

1 Problem 1:

Use the posted Python Code file to test MNIST image data. Test if you can obtain the decoded images and show them properly.

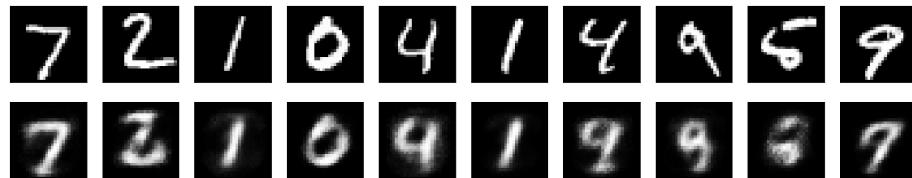


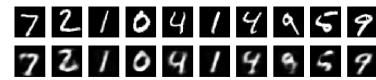
Figure 1: Output of auto-encoder for one layer and $epochs = 10$

2 Problem 2:

Use different epoch size from 5, 10, 20, 30, 40, 50, 100 and test the same code.



(a) $epochs = 5$



(b) $epochs = 20$



(c) $epochs = 30$



(d) $epochs = 40$



(e) $epochs = 50$



(f) $epochs = 100$

Figure 2: Results for digit recognition using single-layer auto-encoder for different values of epochs

3 Problem 3:

Use different number of layers of the deep networks (2, 3, 4, 5) and compare the performances.

3 PROBLEM 3:

Layer (type)	Output Shape	Param #
<hr/>		
dense_1 (Dense)	(None, 128)	100480
dense_2 (Dense)	(None, 64)	8256
dense_3 (Dense)	(None, 32)	2080
dense_4 (Dense)	(None, 64)	2112
dense_5 (Dense)	(None, 128)	8320
dense_6 (Dense)	(None, 784)	101136
<hr/>		
Total params: 222,384		
Trainable params: 222,384		
Non-trainable params: 0		

Figure 3: Auto-encoder with 3 layers

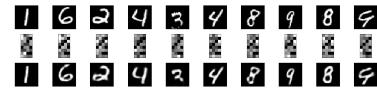
Layer (type)	Output Shape	Param #
<hr/>		
dense_5 (Dense)	(None, 192)	150720
dense_6 (Dense)	(None, 128)	24704
dense_7 (Dense)	(None, 64)	8256
dense_8 (Dense)	(None, 32)	2080
dense_9 (Dense)	(None, 64)	2112
dense_10 (Dense)	(None, 128)	8320
dense_11 (Dense)	(None, 192)	24768
dense_12 (Dense)	(None, 784)	151312
<hr/>		
Total params: 372,272		
Trainable params: 372,272		
Non-trainable params: 0		

Figure 4: Auto-encoder with 4 layers

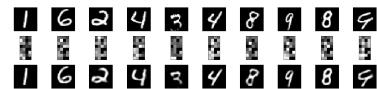
4 PROBLEM 4: USE AUTO ENCODER TO FIND ANOMALY IMAGES:



(a) *layers* = 2



(b) *layers* = 3



(c) *layers* = 4



(d) *layers* = 5

Figure 5: Results for digit recognition using multi-layer auto-encoder for different number of layers with *epochs* = 50

4 Problem 4: Use auto encoder to find anomaly images:

- 4.1 You randomly download a few images other than the MNIST image dataset. For example, animals, furnitures, automobiles, etc.**



Figure 6: Chosen anomalous images

4 PROBLEM 4: USE AUTO ENCODER TO FIND ANOMALY IMAGES:

4.2 Reform these images to a grayscale images without color channels (similar to the minist dataset).

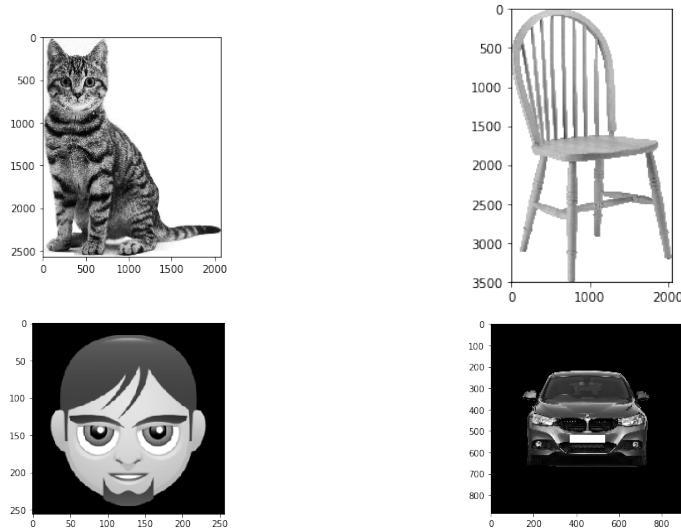


Figure 7: Reformed images

4 PROBLEM 4: USE AUTO ENCODER TO FIND ANOMALY IMAGES:

- 4.3** Use the above auto encoder to predict these download and reformed grayscale images. Show how much differences between the input images and the reconstructed after auto-encoder images.



Figure 8: Reconstruction by the auto-encoder. Detected as anomalies.

4.4 Code:

```
from PIL import Image
from resizeimage import resizeimage

x=Image.open('face.png','r')
x=x.convert('L') #makes it greyscale
x = resizeimage.resize_cover(x, [28, 28])
```

4 PROBLEM 4: USE AUTO ENCODER TO FIND ANOMALY IMAGES:

```
y=np.asarray(x.getdata(),dtype=np.float64).reshape((x.size[1],x.size[0]))  
  
yy = y.reshape(1, 784)  
encoded_imgs = encoder.predict(yy)  
decoded_imgs = decoder.predict(encoded_imgs)  
  
# display original  
ax = plt.subplot(2, 1, 1)  
plt.imshow(yy.reshape(28, 28))  
plt.gray()  
ax.get_xaxis().set_visible(False)  
ax.get_yaxis().set_visible(False)  
  
# display reconstruction  
ax = plt.subplot(2, 1, 2)  
plt.imshow(decoded_imgs.reshape(28, 28))  
plt.gray()  
ax.get_xaxis().set_visible(False)  
ax.get_yaxis().set_visible(False)  
plt.show()
```