autoencoder

April 19, 2020

```
Video 13.1 https://www.youtube.com/watch?v=kIGHE7Cfe1s
   Video 13.2 https://www.youtube.com/watch?v=Rm9bJcDd1KU
   Video 13.3 https://youtu.be/6HjZk-3LsjE
In [33]: from keras.callbacks import TensorBoard
         from keras.layers import Input, Dense
         from keras.models import Model
         from keras.datasets import mnist
         import numpy as np
         import keras
         (xtrain, ytrain), (xtest, ytest) = mnist.load_data()
         xtrain = xtrain.astype('float32') / 255.
         xtest = xtest.astype('float32') / 255.
         xtrain = xtrain.reshape((len(xtrain), np.prod(xtrain.shape[1:])))
         xtest = xtest.reshape((len(xtest), np.prod(xtest.shape[1:])))
         xtrain.shape, xtest.shape
Out [33]: ((60000, 784), (10000, 784))
In [13]: import matplotlib.pyplot as plt
         %matplotlib inline
In [6]: # this is the size of our encoded representations
        encoding_dim = 4 # 32 floats -> compression of factor 24.5, assuming the input is 784
        # this is our input placeholder
        x = input_img = Input(shape=(784,))
        # "encoded" is the encoded representation of the input
        x = Dense(256, activation='relu')(x)
        x = Dense(128, activation='relu')(x)
        encoded = Dense(encoding_dim, activation='relu')(x)
        # "decoded" is the lossy reconstruction of the input
        x = Dense(128, activation='relu')(encoded)
        x = Dense(256, activation='relu')(x)
```

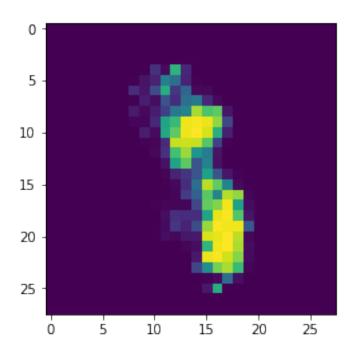
```
decoded = Dense(784, activation='sigmoid')(x)
    # this model maps an input to its reconstruction
    autoencoder = Model(input_img, decoded)
    encoder = Model(input_img, encoded)
    # create a placeholder for an encoded (32-dimensional) input
    encoded_input = Input(shape=(encoding_dim,))
    # retrieve the last layer of the autoencoder model
    dcd1 = autoencoder.layers[-1]
    dcd2 = autoencoder.layers[-2]
    dcd3 = autoencoder.layers[-3]
    # create the decoder model
    decoder = Model(encoded_input, dcd1(dcd2(dcd3(encoded_input))))
In [7]: autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')
In [8]: autoencoder.fit(xtrain, xtrain,
             epochs=100,
             batch_size=256,
             shuffle=True,
             validation_data=(xtest, xtest))
             #callbacks=[TensorBoard(log_dir='/tmp/autoencoder')])
WARNING:tensorflow:From /Users/Broth/anaconda3/lib/python3.7/site-packages/tensorflow/python/or
Instructions for updating:
Use tf.cast instead.
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
Epoch 2/100
Epoch 3/100
Epoch 4/100
Epoch 5/100
Epoch 6/100
Epoch 7/100
Epoch 8/100
Epoch 9/100
```

```
Epoch 10/100
Epoch 11/100
Epoch 12/100
Epoch 13/100
Epoch 14/100
Epoch 15/100
60000/60000 [============== ] - 3s 55us/step - loss: 0.214 - val_loss: 0.2198
Epoch 16/100
Epoch 17/100
Epoch 18/100
60000/60000 [============== ] - 3s 57us/step - loss: 0.2187 - val_loss: 0.2178
Epoch 19/100
Epoch 20/100
Epoch 21/100
Epoch 22/100
60000/60000 [============== ] - 3s 57us/step - loss: 0.2159 - val_loss: 0.2150
Epoch 23/100
Epoch 24/100
Epoch 25/100
Epoch 26/100
Epoch 27/100
Epoch 28/100
Epoch 29/100
Epoch 30/100
Epoch 31/100
Epoch 32/100
Epoch 33/100
60000/60000 [============== ] - 3s 56us/step - loss: 0.2100 - val_loss: 0.2097
```

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Epoch 34/100
Epoch 35/100
Epoch 36/100
Epoch 37/100
Epoch 38/100
Epoch 39/100
Epoch 40/100
Epoch 41/100
Epoch 42/100
Epoch 43/100
Epoch 44/100
Epoch 45/100
60000/60000 [=============== ] - 3s 57us/step - loss: 0.2049 - val_loss: 0.2064
Epoch 46/100
60000/60000 [============== ] - 3s 56us/step - loss: 0.2045 - val_loss: 0.2047
Epoch 47/100
Epoch 48/100
Epoch 49/100
60000/60000 [=============== ] - 3s 57us/step - loss: 0.2034 - val_loss: 0.2037
Epoch 50/100
60000/60000 [=============== ] - 3s 57us/step - loss: 0.2030 - val_loss: 0.2034
Epoch 51/100
Epoch 52/100
Epoch 53/100
Epoch 54/100
Epoch 55/100
Epoch 56/100
Epoch 57/100
60000/60000 [============== ] - 3s 57us/step - loss: 0.2005 - val_loss: 0.2009
```

```
Epoch 58/100
Epoch 59/100
60000/60000 [=============== ] - 3s 57us/step - loss: 0.1997 - val_loss: 0.1999
Epoch 60/100
Epoch 61/100
Epoch 62/100
60000/60000 [=============== ] - 3s 57us/step - loss: 0.1988 - val_loss: 0.1987
Epoch 63/100
60000/60000 [============== ] - 3s 57us/step - loss: 0.1985 - val_loss: 0.1983
Epoch 64/100
Epoch 65/100
Epoch 66/100
60000/60000 [============== ] - 3s 57us/step - loss: 0.1975 - val_loss: 0.1975
Epoch 67/100
60000/60000 [============== ] - 3s 57us/step - loss: 0.1972 - val loss: 0.1971
Epoch 68/100
Epoch 69/100
Epoch 70/100
60000/60000 [============== ] - 3s 57us/step - loss: 0.1963 - val_loss: 0.1977
Epoch 71/100
Epoch 72/100
Epoch 73/100
Epoch 74/100
Epoch 75/100
Epoch 76/100
Epoch 77/100
60000/60000 [=============== ] - 3s 58us/step - loss: 0.1944 - val_loss: 0.1960
Epoch 78/100
Epoch 79/100
Epoch 80/100
Epoch 81/100
60000/60000 [============== ] - 3s 58us/step - loss: 0.1929 - val_loss: 0.1937
```

```
Epoch 82/100
Epoch 83/100
Epoch 84/100
60000/60000 [=============== ] - 3s 58us/step - loss: 0.1898 - val loss: 0.1909
Epoch 85/100
Epoch 86/100
Epoch 87/100
Epoch 88/100
Epoch 89/100
Epoch 90/100
Epoch 91/100
Epoch 92/100
Epoch 93/100
Epoch 94/100
Epoch 95/100
Epoch 96/100
Epoch 97/100
Epoch 98/100
Epoch 99/100
Epoch 100/100
Out[8]: <keras.callbacks.dallbacks.History at Oxb37a3dfd0>
In [10]: noise = np.random.normal(20,4, (4,4))
  noise_preds = decoder.predict(noise)
In [14]: plt.imshow(noise_preds[1].reshape(28,28))
Out[14]: <matplotlib.image.AxesImage at Oxb26d6f6d8>
```

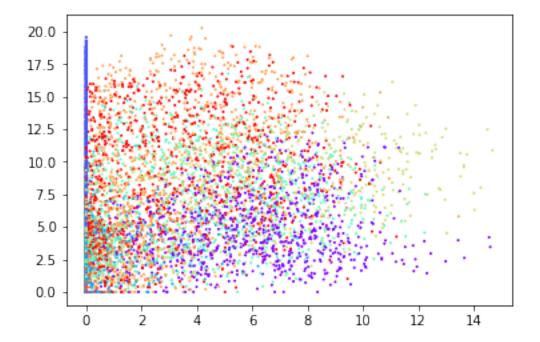


```
In [16]: encoded_imgs = encoder.predict(xtest)
         np.max(encoded_imgs)
Out[16]: 50.756348
In [17]: encoded_imgs = encoder.predict(xtest)
         decoded_imgs = decoder.predict(encoded_imgs)
         import matplotlib.pyplot as plt
         n = 20 # how many digits we will display
         plt.figure(figsize=(40, 4))
         for i in range(n):
             # display original
             ax = plt.subplot(2, n, i + 1)
             plt.imshow(xtest[i].reshape(28, 28))
             plt.gray()
             ax.get_xaxis().set_visible(False)
             ax.get_yaxis().set_visible(False)
             # display reconstruction
             ax = plt.subplot(2, n, i + 1 + n)
             plt.imshow(decoded_imgs[i].reshape(28, 28))
             plt.gray()
             ax.get_xaxis().set_visible(False)
             ax.get_yaxis().set_visible(False)
         plt.show()
```

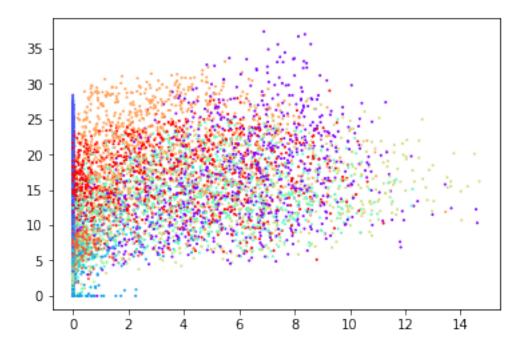
72104149590690159734

```
In [18]: encoded_imgs
```

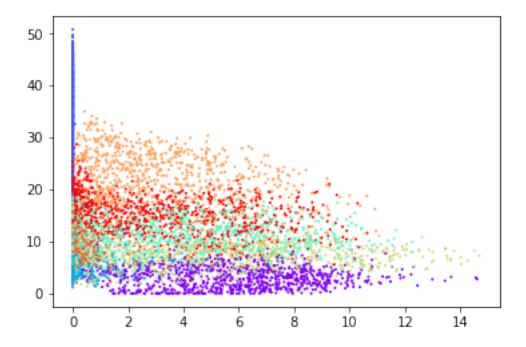
Out[19]: <matplotlib.collections.PathCollection at 0xb282f84a8>

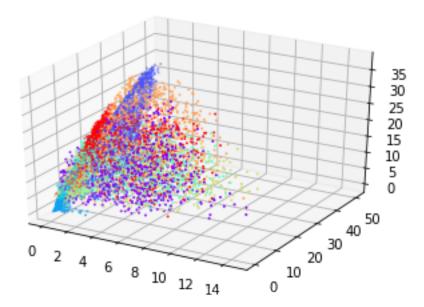


Out[20]: <matplotlib.collections.PathCollection at 0xb28623128>



Out[21]: <matplotlib.collections.PathCollection at 0xb286d1f98>





In []:

1 Assignment

1.0.1 1. Change the encoding_dim through various values (range(2,18,2) and store or keep track of the best loss you can get. Plot the 8 pairs of dimensions vs loss on a scatter plot

```
In [50]: dims = list(range(2,18,2))

losses = []
for dim in dims:
    encoding_dim = dim # 32 floats -> compression of factor 24.5, assuming the input

# this is our input placeholder
    x = input_img = Input(shape=(784,))
    # "encoded" is the encoded representation of the input
    x = Dense(256, activation='relu')(x)
    x = Dense(128, activation='relu')(x)
    encoded = Dense(encoding_dim, activation='relu')(x)
```

```
x = Dense(256, activation='relu')(x)
         decoded = Dense(784, activation='sigmoid')(x)
         # this model maps an input to its reconstruction
         autoencoder = Model(input_img, decoded)
         encoder = Model(input_img, encoded)
         # create a placeholder for an encoded (32-dimensional) input
         encoded_input = Input(shape=(encoding_dim,))
         # retrieve the last layer of the autoencoder model
         dcd1 = autoencoder.layers[-1]
         dcd2 = autoencoder.layers[-2]
         dcd3 = autoencoder.layers[-3]
         # create the decoder model
         decoder = Model(encoded_input, dcd1(dcd2(dcd3(encoded_input))))
         autoencoder.compile(optimizer='adadelta', loss='binary crossentropy')
        history = autoencoder.fit(xtrain, xtrain,
                 epochs=100,
                 batch_size=256,
                 shuffle=True,
                 validation_data=(xtest, xtest))
                 #callbacks=[TensorBoard(log_dir='/tmp/autoencoder')])
         losses.append(history.history['val_loss'][-1])
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
60000/60000 [=============== ] - 5s 84us/step - loss: 0.3540 - val_loss: 0.2644
Epoch 2/100
60000/60000 [============= ] - 4s 59us/step - loss: 0.2595 - val loss: 0.2560
Epoch 3/100
Epoch 4/100
Epoch 5/100
Epoch 6/100
Epoch 7/100
```

"decoded" is the lossy reconstruction of the input

x = Dense(128, activation='relu')(encoded)

```
Epoch 8/100
Epoch 9/100
Epoch 10/100
60000/60000 [=============== ] - 4s 62us/step - loss: 0.2477 - val_loss: 0.2475
Epoch 11/100
Epoch 12/100
60000/60000 [=============== ] - 4s 63us/step - loss: 0.2455 - val_loss: 0.2453
Epoch 13/100
60000/60000 [=============== ] - 4s 63us/step - loss: 0.2446 - val_loss: 0.2443
Epoch 14/100
Epoch 15/100
Epoch 16/100
60000/60000 [============== ] - 4s 65us/step - loss: 0.2425 - val_loss: 0.2427
Epoch 17/100
Epoch 18/100
Epoch 19/100
Epoch 20/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.2318 - val_loss: 0.2292
Epoch 21/100
Epoch 22/100
Epoch 23/100
Epoch 24/100
Epoch 25/100
Epoch 26/100
Epoch 27/100
Epoch 28/100
Epoch 29/100
Epoch 30/100
Epoch 31/100
60000/60000 [=============== ] - 4s 69us/step - loss: 0.2160 - val_loss: 0.2152
```

```
Epoch 32/100
Epoch 33/100
Epoch 34/100
Epoch 35/100
Epoch 36/100
Epoch 37/100
Epoch 38/100
Epoch 39/100
60000/60000 [=============== ] - 4s 70us/step - loss: 0.2094 - val_loss: 0.2094
Epoch 40/100
Epoch 41/100
Epoch 42/100
Epoch 43/100
60000/60000 [=============== ] - 4s 74us/step - loss: 0.2072 - val_loss: 0.2070
Epoch 44/100
60000/60000 [============== ] - 4s 70us/step - loss: 0.2067 - val_loss: 0.2067
Epoch 45/100
Epoch 46/100
Epoch 47/100
Epoch 48/100
Epoch 49/100
Epoch 50/100
Epoch 51/100
Epoch 52/100
Epoch 53/100
Epoch 54/100
Epoch 55/100
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Epoch 56/100
Epoch 57/100
Epoch 58/100
Epoch 59/100
Epoch 60/100
Epoch 61/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1998 - val_loss: 0.2004
Epoch 62/100
Epoch 63/100
Epoch 64/100
60000/60000 [============== ] - 4s 69us/step - loss: 0.1988 - val_loss: 0.1990
Epoch 65/100
Epoch 66/100
Epoch 67/100
60000/60000 [=============== ] - 4s 68us/step - loss: 0.1979 - val_loss: 0.1984
Epoch 68/100
60000/60000 [============== ] - 4s 68us/step - loss: 0.1977 - val_loss: 0.1975
Epoch 69/100
Epoch 70/100
Epoch 71/100
Epoch 72/100
Epoch 73/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1962 - val_loss: 0.1974
Epoch 74/100
Epoch 75/100
Epoch 76/100
Epoch 77/100
Epoch 78/100
Epoch 79/100
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```
Epoch 80/100
Epoch 81/100
Epoch 82/100
Epoch 83/100
Epoch 84/100
Epoch 85/100
Epoch 86/100
60000/60000 [=============== ] - 4s 65us/step - loss: 0.1928 - val_loss: 0.1937
Epoch 87/100
Epoch 88/100
Epoch 89/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1922 - val loss: 0.1925
Epoch 90/100
Epoch 91/100
Epoch 92/100
60000/60000 [============== ] - 4s 65us/step - loss: 0.1915 - val_loss: 0.1932
Epoch 93/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1914 - val_loss: 0.1923
Epoch 94/100
Epoch 95/100
Epoch 96/100
Epoch 97/100
Epoch 98/100
Epoch 99/100
Epoch 100/100
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
Epoch 2/100
Epoch 3/100
```

```
Epoch 4/100
60000/60000 [============== ] - 4s 65us/step - loss: 0.2484 - val_loss: 0.2441
Epoch 5/100
Epoch 6/100
Epoch 7/100
Epoch 8/100
Epoch 9/100
Epoch 10/100
Epoch 11/100
Epoch 12/100
Epoch 13/100
Epoch 14/100
Epoch 15/100
Epoch 16/100
Epoch 17/100
Epoch 18/100
Epoch 19/100
Epoch 20/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.2000 - val loss: 0.2005
Epoch 21/100
Epoch 22/100
Epoch 23/100
Epoch 24/100
Epoch 25/100
Epoch 26/100
Epoch 27/100
```

```
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1930 - val_loss: 0.1924
Epoch 28/100
Epoch 29/100
Epoch 30/100
Epoch 31/100
Epoch 32/100
Epoch 33/100
Epoch 34/100
Epoch 35/100
Epoch 36/100
Epoch 37/100
Epoch 38/100
Epoch 39/100
Epoch 40/100
Epoch 41/100
Epoch 42/100
Epoch 43/100
60000/60000 [============== ] - 4s 65us/step - loss: 0.1817 - val_loss: 0.1805
Epoch 44/100
60000/60000 [============== ] - 4s 65us/step - loss: 0.1803 - val loss: 0.1792
Epoch 45/100
Epoch 46/100
Epoch 47/100
Epoch 48/100
Epoch 49/100
Epoch 50/100
Epoch 51/100
```

```
60000/60000 [=============== ] - 4s 65us/step - loss: 0.1712 - val_loss: 0.1705
Epoch 52/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1704 - val_loss: 0.1701
Epoch 53/100
Epoch 54/100
Epoch 55/100
Epoch 56/100
Epoch 57/100
Epoch 58/100
Epoch 59/100
Epoch 60/100
Epoch 61/100
Epoch 62/100
Epoch 63/100
Epoch 64/100
Epoch 65/100
Epoch 66/100
Epoch 67/100
Epoch 68/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1622 - val loss: 0.1625
Epoch 69/100
Epoch 70/100
Epoch 71/100
Epoch 72/100
Epoch 73/100
Epoch 74/100
Epoch 75/100
```

```
Epoch 76/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1595 - val_loss: 0.1601
Epoch 77/100
Epoch 78/100
Epoch 79/100
Epoch 80/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1584 - val_loss: 0.1600
Epoch 81/100
Epoch 82/100
Epoch 83/100
Epoch 84/100
Epoch 85/100
Epoch 86/100
Epoch 87/100
Epoch 88/100
Epoch 89/100
Epoch 90/100
Epoch 91/100
Epoch 92/100
60000/60000 [============== ] - 4s 65us/step - loss: 0.1559 - val loss: 0.1560
Epoch 93/100
Epoch 94/100
60000/60000 [=============== ] - 4s 68us/step - loss: 0.1556 - val_loss: 0.1557
Epoch 95/100
Epoch 96/100
Epoch 97/100
Epoch 98/100
Epoch 99/100
```

```
Epoch 100/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1546 - val_loss: 0.1547
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
Epoch 2/100
Epoch 3/100
Epoch 4/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.2297 - val_loss: 0.2244
Epoch 5/100
Epoch 6/100
Epoch 7/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.2074 - val_loss: 0.2041
Epoch 8/100
Epoch 9/100
Epoch 10/100
Epoch 11/100
Epoch 12/100
Epoch 13/100
Epoch 14/100
Epoch 15/100
Epoch 16/100
Epoch 17/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1722 - val_loss: 0.1715
Epoch 18/100
Epoch 19/100
Epoch 20/100
Epoch 21/100
Epoch 22/100
```

```
Epoch 23/100
Epoch 24/100
Epoch 25/100
Epoch 26/100
Epoch 27/100
Epoch 28/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1615 - val_loss: 0.1606
Epoch 29/100
Epoch 30/100
Epoch 31/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1597 - val_loss: 0.1585
Epoch 32/100
Epoch 33/100
Epoch 34/100
Epoch 35/100
60000/60000 [=============== ] - 4s 65us/step - loss: 0.1576 - val_loss: 0.1574
Epoch 36/100
Epoch 37/100
Epoch 38/100
Epoch 39/100
Epoch 40/100
Epoch 41/100
Epoch 42/100
Epoch 43/100
Epoch 44/100
Epoch 45/100
Epoch 46/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1530 - val_loss: 0.1527
```

```
Epoch 47/100
Epoch 48/100
Epoch 49/100
Epoch 50/100
Epoch 51/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1513 - val_loss: 0.1515
Epoch 52/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1510 - val_loss: 0.1517
Epoch 53/100
Epoch 54/100
60000/60000 [=============== ] - 4s 65us/step - loss: 0.1505 - val_loss: 0.1505
Epoch 55/100
Epoch 56/100
Epoch 57/100
Epoch 58/100
Epoch 59/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1493 - val_loss: 0.1497
Epoch 60/100
Epoch 61/100
Epoch 62/100
Epoch 63/100
Epoch 64/100
Epoch 65/100
Epoch 66/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1469 - val_loss: 0.1472
Epoch 67/100
Epoch 68/100
Epoch 69/100
Epoch 70/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1450 - val_loss: 0.1452
```

```
Epoch 71/100
Epoch 72/100
Epoch 73/100
Epoch 74/100
Epoch 75/100
Epoch 76/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1426 - val_loss: 0.1435
Epoch 77/100
Epoch 78/100
Epoch 79/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1415 - val_loss: 0.1404
Epoch 80/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1413 - val loss: 0.1408
Epoch 81/100
Epoch 82/100
Epoch 83/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1403 - val_loss: 0.1408
Epoch 84/100
Epoch 85/100
Epoch 86/100
Epoch 87/100
Epoch 88/100
Epoch 89/100
Epoch 90/100
Epoch 91/100
Epoch 92/100
Epoch 93/100
Epoch 94/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1378 - val_loss: 0.1375
```

```
Epoch 95/100
Epoch 96/100
Epoch 97/100
Epoch 98/100
Epoch 99/100
Epoch 100/100
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
Epoch 2/100
Epoch 3/100
Epoch 4/100
Epoch 5/100
Epoch 6/100
Epoch 7/100
Epoch 8/100
Epoch 9/100
Epoch 10/100
Epoch 11/100
60000/60000 [============== ] - 4s 64us/step - loss: 0.1833 - val loss: 0.1809
Epoch 12/100
60000/60000 [============== ] - 4s 65us/step - loss: 0.1800 - val loss: 0.1777
Epoch 13/100
Epoch 14/100
Epoch 15/100
Epoch 16/100
Epoch 17/100
Epoch 18/100
```

```
Epoch 19/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1638 - val_loss: 0.1629
Epoch 20/100
Epoch 21/100
Epoch 22/100
Epoch 23/100
Epoch 24/100
Epoch 25/100
Epoch 26/100
Epoch 27/100
Epoch 28/100
Epoch 29/100
Epoch 30/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1479 - val_loss: 0.1460
Epoch 31/100
Epoch 32/100
Epoch 33/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1454 - val_loss: 0.1443
Epoch 34/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1446 - val_loss: 0.1426
Epoch 35/100
60000/60000 [============= ] - 4s 66us/step - loss: 0.1439 - val loss: 0.1430
Epoch 36/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1433 - val loss: 0.1424
Epoch 37/100
Epoch 38/100
Epoch 39/100
Epoch 40/100
Epoch 41/100
Epoch 42/100
```

```
60000/60000 [=============== ] - 4s 65us/step - loss: 0.1402 - val_loss: 0.1403
Epoch 43/100
60000/60000 [=============== ] - 4s 68us/step - loss: 0.1398 - val_loss: 0.1394
Epoch 44/100
Epoch 45/100
Epoch 46/100
Epoch 47/100
Epoch 48/100
Epoch 49/100
Epoch 50/100
Epoch 51/100
Epoch 52/100
Epoch 53/100
Epoch 54/100
Epoch 55/100
Epoch 56/100
Epoch 57/100
Epoch 58/100
Epoch 59/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1345 - val loss: 0.1339
Epoch 60/100
Epoch 61/100
Epoch 62/100
Epoch 63/100
Epoch 64/100
Epoch 65/100
Epoch 66/100
```

```
Epoch 67/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1328 - val_loss: 0.1331
Epoch 68/100
Epoch 69/100
Epoch 70/100
Epoch 71/100
Epoch 72/100
Epoch 73/100
Epoch 74/100
Epoch 75/100
Epoch 76/100
Epoch 77/100
Epoch 78/100
Epoch 79/100
Epoch 80/100
Epoch 81/100
Epoch 82/100
Epoch 83/100
60000/60000 [============== ] - 4s 65us/step - loss: 0.1297 - val loss: 0.1293
Epoch 84/100
Epoch 85/100
Epoch 86/100
Epoch 87/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1291 - val_loss: 0.1290
Epoch 88/100
Epoch 89/100
Epoch 90/100
```

```
Epoch 91/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1287 - val_loss: 0.1285
Epoch 92/100
Epoch 93/100
Epoch 94/100
Epoch 95/100
Epoch 96/100
Epoch 97/100
Epoch 98/100
Epoch 99/100
Epoch 100/100
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
Epoch 2/100
Epoch 3/100
Epoch 4/100
Epoch 5/100
Epoch 6/100
Epoch 7/100
Epoch 8/100
Epoch 9/100
Epoch 10/100
Epoch 11/100
Epoch 12/100
Epoch 13/100
```

```
Epoch 14/100
Epoch 15/100
Epoch 16/100
Epoch 17/100
Epoch 18/100
Epoch 19/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1457 - val_loss: 0.1422
Epoch 20/100
Epoch 21/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1422 - val_loss: 0.1394
Epoch 22/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1407 - val_loss: 0.1395
Epoch 23/100
Epoch 24/100
Epoch 25/100
Epoch 26/100
Epoch 27/100
Epoch 28/100
Epoch 29/100
Epoch 30/100
Epoch 31/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1316 - val_loss: 0.1298
Epoch 32/100
Epoch 33/100
Epoch 34/100
Epoch 35/100
Epoch 36/100
Epoch 37/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1279 - val_loss: 0.1280
```

```
Epoch 38/100
Epoch 39/100
Epoch 40/100
Epoch 41/100
Epoch 42/100
Epoch 43/100
Epoch 44/100
Epoch 45/100
Epoch 46/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1238 - val_loss: 0.1222
Epoch 47/100
Epoch 48/100
Epoch 49/100
Epoch 50/100
Epoch 51/100
Epoch 52/100
Epoch 53/100
Epoch 54/100
Epoch 55/100
Epoch 56/100
Epoch 57/100
Epoch 58/100
Epoch 59/100
Epoch 60/100
Epoch 61/100
60000/60000 [=============== ] - 4s 65us/step - loss: 0.1191 - val_loss: 0.1178
```

```
Epoch 62/100
Epoch 63/100
Epoch 64/100
Epoch 65/100
Epoch 66/100
Epoch 67/100
Epoch 68/100
Epoch 69/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1172 - val_loss: 0.1164
Epoch 70/100
60000/60000 [============== ] - 4s 65us/step - loss: 0.1171 - val_loss: 0.1164
Epoch 71/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1168 - val loss: 0.1155
Epoch 72/100
Epoch 73/100
60000/60000 [=============== ] - 4s 65us/step - loss: 0.1164 - val_loss: 0.1149
Epoch 74/100
Epoch 75/100
Epoch 76/100
Epoch 77/100
Epoch 78/100
Epoch 79/100
Epoch 80/100
Epoch 81/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1151 - val_loss: 0.1145
Epoch 82/100
Epoch 83/100
Epoch 84/100
Epoch 85/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1145 - val_loss: 0.1145
```

```
Epoch 86/100
Epoch 87/100
Epoch 88/100
Epoch 89/100
Epoch 90/100
Epoch 91/100
Epoch 92/100
Epoch 93/100
Epoch 94/100
60000/60000 [============== ] - 4s 70us/step - loss: 0.1133 - val_loss: 0.1127
Epoch 95/100
60000/60000 [=============== ] - 4s 65us/step - loss: 0.1131 - val loss: 0.1149
Epoch 96/100
Epoch 97/100
Epoch 98/100
Epoch 99/100
Epoch 100/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1125 - val_loss: 0.1122
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
60000/60000 [============== ] - 5s 85us/step - loss: 0.3342 - val_loss: 0.2626
Epoch 2/100
Epoch 3/100
Epoch 4/100
Epoch 5/100
Epoch 6/100
Epoch 7/100
Epoch 8/100
Epoch 9/100
```

```
Epoch 10/100
Epoch 11/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1584 - val loss: 0.1541
Epoch 12/100
Epoch 13/100
Epoch 14/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1497 - val_loss: 0.1472
Epoch 15/100
Epoch 16/100
Epoch 17/100
Epoch 18/100
Epoch 19/100
Epoch 20/100
Epoch 21/100
Epoch 22/100
Epoch 23/100
Epoch 24/100
Epoch 25/100
Epoch 26/100
60000/60000 [============= ] - 4s 67us/step - loss: 0.1293 - val loss: 0.1275
Epoch 27/100
Epoch 28/100
Epoch 29/100
Epoch 30/100
Epoch 31/100
Epoch 32/100
Epoch 33/100
```

```
Epoch 34/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1231 - val_loss: 0.1224
Epoch 35/100
Epoch 36/100
Epoch 37/100
Epoch 38/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1210 - val_loss: 0.1199
Epoch 39/100
Epoch 40/100
Epoch 41/100
Epoch 42/100
Epoch 43/100
Epoch 44/100
Epoch 45/100
Epoch 46/100
Epoch 47/100
Epoch 48/100
Epoch 49/100
Epoch 50/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1162 - val loss: 0.1158
Epoch 51/100
Epoch 52/100
Epoch 53/100
Epoch 54/100
Epoch 55/100
Epoch 56/100
Epoch 57/100
```

```
Epoch 58/100
Epoch 59/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1137 - val loss: 0.1136
Epoch 60/100
Epoch 61/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1133 - val loss: 0.1124
Epoch 62/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1130 - val_loss: 0.1122
Epoch 63/100
Epoch 64/100
Epoch 65/100
Epoch 66/100
Epoch 67/100
Epoch 68/100
Epoch 69/100
Epoch 70/100
Epoch 71/100
Epoch 72/100
Epoch 73/100
Epoch 74/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1107 - val loss: 0.1100
Epoch 75/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1105 - val loss: 0.1104
Epoch 76/100
Epoch 77/100
Epoch 78/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1100 - val_loss: 0.1099
Epoch 79/100
Epoch 80/100
Epoch 81/100
```

```
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1095 - val_loss: 0.1093
Epoch 82/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1093 - val_loss: 0.1098
Epoch 83/100
Epoch 84/100
Epoch 85/100
Epoch 86/100
Epoch 87/100
Epoch 88/100
Epoch 89/100
Epoch 90/100
Epoch 91/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1080 - val_loss: 0.1075
Epoch 92/100
Epoch 93/100
Epoch 94/100
Epoch 95/100
Epoch 96/100
Epoch 97/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1074 - val_loss: 0.1073
Epoch 98/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1072 - val loss: 0.1070
Epoch 99/100
Epoch 100/100
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
Epoch 2/100
Epoch 3/100
Epoch 4/100
```

```
Epoch 5/100
Epoch 6/100
Epoch 7/100
Epoch 8/100
Epoch 9/100
Epoch 10/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1678 - val_loss: 0.1634
Epoch 11/100
Epoch 12/100
Epoch 13/100
Epoch 14/100
60000/60000 [============== ] - 4s 65us/step - loss: 0.1544 - val loss: 0.1525
Epoch 15/100
Epoch 16/100
Epoch 17/100
Epoch 18/100
Epoch 19/100
Epoch 20/100
Epoch 21/100
Epoch 22/100
Epoch 23/100
Epoch 24/100
Epoch 25/100
Epoch 26/100
Epoch 27/100
Epoch 28/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1337 - val_loss: 0.1333
```

```
Epoch 29/100
Epoch 30/100
Epoch 31/100
Epoch 32/100
Epoch 33/100
Epoch 34/100
Epoch 35/100
Epoch 36/100
Epoch 37/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1280 - val_loss: 0.1263
Epoch 38/100
Epoch 39/100
Epoch 40/100
Epoch 41/100
Epoch 42/100
Epoch 43/100
Epoch 44/100
Epoch 45/100
Epoch 46/100
Epoch 47/100
Epoch 48/100
Epoch 49/100
Epoch 50/100
Epoch 51/100
Epoch 52/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1218 - val_loss: 0.1204
```

```
Epoch 53/100
Epoch 54/100
Epoch 55/100
Epoch 56/100
Epoch 57/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1204 - val_loss: 0.1195
Epoch 58/100
Epoch 59/100
Epoch 60/100
Epoch 61/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1193 - val_loss: 0.1186
Epoch 62/100
Epoch 63/100
Epoch 64/100
Epoch 65/100
60000/60000 [=============== ] - 4s 66us/step - loss: 0.1183 - val_loss: 0.1167
Epoch 66/100
Epoch 67/100
Epoch 68/100
Epoch 69/100
Epoch 70/100
Epoch 71/100
Epoch 72/100
Epoch 73/100
Epoch 74/100
Epoch 75/100
Epoch 76/100
```

```
Epoch 77/100
Epoch 78/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1159 - val_loss: 0.1147
Epoch 79/100
Epoch 80/100
Epoch 81/100
Epoch 82/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1152 - val_loss: 0.1147
Epoch 83/100
Epoch 84/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1149 - val_loss: 0.1144
Epoch 85/100
Epoch 86/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1146 - val loss: 0.1151
Epoch 87/100
Epoch 88/100
Epoch 89/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1143 - val_loss: 0.1136
Epoch 90/100
Epoch 91/100
Epoch 92/100
Epoch 93/100
Epoch 94/100
Epoch 95/100
Epoch 96/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1133 - val_loss: 0.1124
Epoch 97/100
Epoch 98/100
Epoch 99/100
Epoch 100/100
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
60000/60000 [=============== ] - 5s 88us/step - loss: 0.3690 - val_loss: 0.2641
Epoch 2/100
Epoch 3/100
Epoch 4/100
Epoch 5/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.2050 - val_loss: 0.1977
Epoch 6/100
Epoch 7/100
Epoch 8/100
Epoch 9/100
Epoch 10/100
Epoch 11/100
Epoch 12/100
Epoch 13/100
Epoch 14/100
Epoch 15/100
Epoch 16/100
Epoch 17/100
60000/60000 [============= ] - 4s 73us/step - loss: 0.1394 - val loss: 0.1380
Epoch 18/100
60000/60000 [=============== ] - 4s 70us/step - loss: 0.1375 - val loss: 0.1346
Epoch 19/100
Epoch 20/100
Epoch 21/100
Epoch 22/100
Epoch 23/100
Epoch 24/100
```

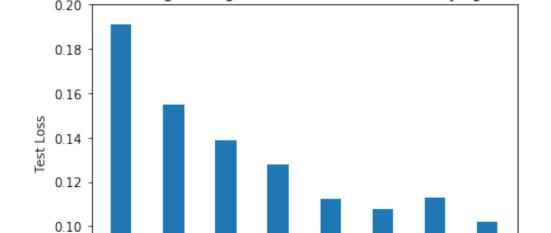
```
Epoch 25/100
Epoch 26/100
Epoch 27/100
Epoch 28/100
Epoch 29/100
60000/60000 [============== ] - 4s 68us/step - loss: 0.1229 - val_loss: 0.1207
Epoch 30/100
60000/60000 [============== ] - 4s 69us/step - loss: 0.1220 - val_loss: 0.1200
Epoch 31/100
Epoch 32/100
Epoch 33/100
Epoch 34/100
Epoch 35/100
Epoch 36/100
Epoch 37/100
Epoch 38/100
Epoch 39/100
60000/60000 [=============== ] - 4s 69us/step - loss: 0.1159 - val_loss: 0.1154
Epoch 40/100
60000/60000 [============== ] - 4s 69us/step - loss: 0.1153 - val_loss: 0.1131
Epoch 41/100
60000/60000 [============== ] - 4s 68us/step - loss: 0.1150 - val loss: 0.1129
Epoch 42/100
Epoch 43/100
Epoch 44/100
Epoch 45/100
60000/60000 [============== ] - 4s 69us/step - loss: 0.1130 - val_loss: 0.1122
Epoch 46/100
Epoch 47/100
Epoch 48/100
```

```
Epoch 49/100
60000/60000 [=============== ] - 4s 68us/step - loss: 0.1116 - val_loss: 0.1106
Epoch 50/100
Epoch 51/100
Epoch 52/100
Epoch 53/100
60000/60000 [=============== ] - 4s 68us/step - loss: 0.1103 - val_loss: 0.1104
Epoch 54/100
Epoch 55/100
Epoch 56/100
Epoch 57/100
Epoch 58/100
Epoch 59/100
Epoch 60/100
Epoch 61/100
Epoch 62/100
Epoch 63/100
Epoch 64/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1074 - val_loss: 0.1066
Epoch 65/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1072 - val loss: 0.1071
Epoch 66/100
Epoch 67/100
Epoch 68/100
Epoch 69/100
Epoch 70/100
Epoch 71/100
Epoch 72/100
```

```
Epoch 73/100
Epoch 74/100
Epoch 75/100
Epoch 76/100
Epoch 77/100
60000/60000 [=============== ] - 4s 68us/step - loss: 0.1050 - val_loss: 0.1039
Epoch 78/100
60000/60000 [============== ] - 4s 66us/step - loss: 0.1048 - val_loss: 0.1043
Epoch 79/100
Epoch 80/100
Epoch 81/100
Epoch 82/100
Epoch 83/100
Epoch 84/100
Epoch 85/100
Epoch 86/100
Epoch 87/100
Epoch 88/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1032 - val_loss: 0.1045
Epoch 89/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1031 - val loss: 0.1034
Epoch 90/100
Epoch 91/100
Epoch 92/100
Epoch 93/100
Epoch 94/100
Epoch 95/100
Epoch 96/100
```

```
In [52]: plt.bar(dims, losses)
        plt.title('Test Loss for Image Recognition AutoEncoder with Varying Dimensions')
        plt.xlabel('Number of Dimensions')
        plt.xticks(dims)
        plt.ylabel('Test Loss')
        plt.ylim(0.075, 0.2)
        plt.show()
```

Test Loss for Image Recognition AutoEncoder with Varying Dimensions



Judging by the graph, 16 dimensions appears to yield the lowest loss score

1.0.2 2. Using the previous assignment's model of detecting images, how does the accuracy change when you run the digit-prediction model on these 'decoded' values?

Number of Dimensions

10

14

0.08

```
xtrain = xtrain.astype('float32') / 255.
         xtest = xtest.astype('float32') / 255.
         xtrain = xtrain.reshape((len(xtrain), np.prod(xtrain.shape[1:])))
         xtest = xtest.reshape((len(xtest), np.prod(xtest.shape[1:])))
         xtrain.shape, xtest.shape, ytrain.shape, ytest.shape
Out [65]: ((60000, 784), (10000, 784), (60000,), (10000,))
In [67]: #run best model, then decode images
         dim = 16
         encoding_dim = dim # 32 floats -> compression of factor 24.5, assuming the input is
         loss = []
         # this is our input placeholder
         x = input_img = Input(shape=(784,))
         # "encoded" is the encoded representation of the input
         x = Dense(256, activation='relu')(x)
         x = Dense(128, activation='relu')(x)
         encoded = Dense(encoding_dim, activation='relu')(x)
         # "decoded" is the lossy reconstruction of the input
         x = Dense(128, activation='relu')(encoded)
         x = Dense(256, activation='relu')(x)
         decoded = Dense(784, activation='sigmoid')(x)
         # this model maps an input to its reconstruction
         autoencoder = Model(input_img, decoded)
         encoder = Model(input_img, encoded)
         # create a placeholder for an encoded (32-dimensional) input
         encoded_input = Input(shape=(encoding_dim,))
         # retrieve the last layer of the autoencoder model
         dcd1 = autoencoder.layers[-1]
         dcd2 = autoencoder.layers[-2]
         dcd3 = autoencoder.layers[-3]
         # create the decoder model.
         decoder = Model(encoded_input, dcd1(dcd2(dcd3(encoded_input))))
         autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')
         history = autoencoder.fit(xtrain, xtrain,
                         epochs=100,
                         batch_size=256,
```

```
shuffle=True,
validation_data=(xtest, xtest))
#callbacks=[TensorBoard(log_dir='/tmp/autoencoder')])
```

loss.append(history.history['val_loss'][-1])

```
encoded_imgs = encoder.predict(xtest)
   decoded_imgs = decoder.predict(encoded_imgs)
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
Epoch 2/100
60000/60000 [============== ] - 4s 64us/step - loss: 0.2536 - val_loss: 0.2430
Epoch 3/100
60000/60000 [============== ] - 4s 62us/step - loss: 0.2328 - val_loss: 0.2227
Epoch 4/100
Epoch 5/100
Epoch 6/100
Epoch 7/100
Epoch 8/100
60000/60000 [=============== ] - 4s 64us/step - loss: 0.1703 - val loss: 0.1667
Epoch 9/100
Epoch 10/100
Epoch 11/100
Epoch 12/100
Epoch 13/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1484 - val_loss: 0.1452
Epoch 14/100
Epoch 15/100
Epoch 16/100
Epoch 17/100
60000/60000 [=============== ] - 4s 70us/step - loss: 0.1391 - val_loss: 0.1366
Epoch 18/100
Epoch 19/100
```

```
Epoch 20/100
60000/60000 [============== ] - 4s 72us/step - loss: 0.1342 - val_loss: 0.1317
Epoch 21/100
Epoch 22/100
Epoch 23/100
60000/60000 [============== ] - 4s 74us/step - loss: 0.1300 - val loss: 0.1289
Epoch 24/100
60000/60000 [============== ] - 4s 71us/step - loss: 0.1287 - val_loss: 0.1263
Epoch 25/100
Epoch 26/100
Epoch 27/100
Epoch 28/100
Epoch 29/100
Epoch 30/100
Epoch 31/100
60000/60000 [=============== ] - 4s 65us/step - loss: 0.1218 - val_loss: 0.1197
Epoch 32/100
Epoch 33/100
Epoch 34/100
Epoch 35/100
Epoch 36/100
60000/60000 [============== ] - 4s 68us/step - loss: 0.1184 - val loss: 0.1159
Epoch 37/100
Epoch 38/100
Epoch 39/100
Epoch 40/100
Epoch 41/100
Epoch 42/100
Epoch 43/100
```

```
60000/60000 [=============== ] - 4s 70us/step - loss: 0.1143 - val_loss: 0.1140
Epoch 44/100
60000/60000 [============== ] - 4s 70us/step - loss: 0.1139 - val_loss: 0.1122
Epoch 45/100
60000/60000 [============== ] - 4s 71us/step - loss: 0.1135 - val loss: 0.1123
Epoch 46/100
Epoch 47/100
Epoch 48/100
60000/60000 [=============== ] - 4s 69us/step - loss: 0.1122 - val_loss: 0.1121
Epoch 49/100
Epoch 50/100
Epoch 51/100
Epoch 52/100
Epoch 53/100
Epoch 54/100
Epoch 55/100
Epoch 56/100
Epoch 57/100
Epoch 58/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1086 - val_loss: 0.1074
Epoch 59/100
Epoch 60/100
60000/60000 [============== ] - 4s 68us/step - loss: 0.1081 - val loss: 0.1070
Epoch 61/100
Epoch 62/100
Epoch 63/100
Epoch 64/100
Epoch 65/100
Epoch 66/100
Epoch 67/100
```

```
60000/60000 [=============== ] - 4s 69us/step - loss: 0.1060 - val_loss: 0.1057
Epoch 68/100
60000/60000 [=============== ] - 5s 75us/step - loss: 0.1059 - val_loss: 0.1057
Epoch 69/100
60000/60000 [============== ] - 4s 72us/step - loss: 0.1057 - val loss: 0.1053
Epoch 70/100
Epoch 71/100
Epoch 72/100
Epoch 73/100
60000/60000 [=============== ] - 4s 69us/step - loss: 0.1047 - val_loss: 0.1043
Epoch 74/100
Epoch 75/100
Epoch 76/100
Epoch 77/100
Epoch 78/100
Epoch 79/100
Epoch 80/100
Epoch 81/100
Epoch 82/100
Epoch 83/100
Epoch 84/100
60000/60000 [============== ] - 4s 67us/step - loss: 0.1026 - val loss: 0.1015
Epoch 85/100
Epoch 86/100
Epoch 87/100
Epoch 88/100
Epoch 89/100
Epoch 90/100
Epoch 91/100
```

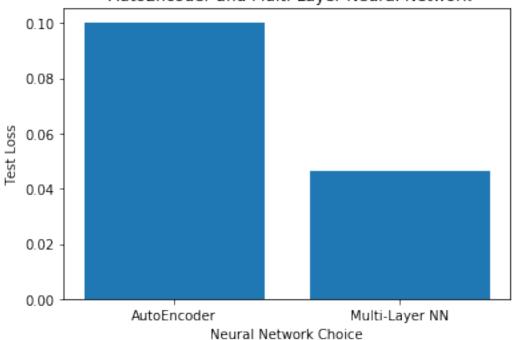
```
Epoch 92/100
Epoch 93/100
Epoch 94/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1011 - val loss: 0.1014
Epoch 95/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1011 - val loss: 0.0998
Epoch 96/100
Epoch 97/100
60000/60000 [=============== ] - 4s 67us/step - loss: 0.1007 - val_loss: 0.1014
Epoch 98/100
Epoch 99/100
60000/60000 [=============== ] - 4s 68us/step - loss: 0.1004 - val_loss: 0.1006
Epoch 100/100
In [71]: from keras.models import Sequential
     from keras.layers import Dropout
     from keras.optimizers import RMSprop
     #run best model from last week's assignment
     batch size = 128
     num_classes = 10
     epochs = 20
     # convert class vectors to binary class matrices
     y_train = keras.utils.to_categorical(ytrain, num_classes)
     y_test = keras.utils.to_categorical(ytest, num_classes)
     model = Sequential()
     model.add(Dense(512, activation='relu', input_shape=(784,)))
     model.add(Dropout(0.2))
     model.add(Dense(512, activation='relu'))
     model.add(Dropout(0.2))
     model.add(Dense(10, activation='softmax'))
     model.summary()
     model.compile(loss='categorical_crossentropy',
              optimizer=RMSprop(),
              metrics=['accuracy'])
```

```
batch_size=batch_size,
         epochs=epochs,
         verbose=1,
         validation_data=(x_test, y_test))
  loss.append(model.evaluate(x_test, y_test, verbose=0)[0])
Model: "sequential_6"
Layer (type) Output Shape
                 Param #
______
         (None, 512)
dense 236 (Dense)
_____
dropout_9 (Dropout)
        (None, 512)
-----
dense_237 (Dense) (None, 512)
                 262656
dropout_10 (Dropout) (None, 512)
dense_238 (Dense) (None, 10)
                 5130
Total params: 669,706
Trainable params: 669,706
Non-trainable params: 0
Train on 10000 samples, validate on 10000 samples
Epoch 1/20
Epoch 2/20
Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
Epoch 7/20
Epoch 8/20
Epoch 9/20
Epoch 10/20
Epoch 11/20
```

model.fit(decoded_imgs, y_test,

```
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
In [72]: models = ['AutoEncoder', 'Multi-Layer NN']
  plt.bar(models, loss)
  plt.xlabel('Neural Network Choice')
  plt.title('Comparing Image Recognition Loss of an\n AutoEncoder and Multi-Layer Neural
  #plt.xticks(dims)
  plt.ylabel('Test Loss')
  #plt.ylim(0.075, 0.2)
  plt.show()
```





Judging the above graph, the MLNN actually appears to perform better than the AutoEncoder.

1.0.3 3. Apply noise to only the input of the autoencoder (not the output). demonstrate that your autoencoder can strip out noise.

```
In [76]: #import random noise packages
    from skimage.util import random_noise

    xtrain_noise = random_noise(xtrain, seed = 1234, var = 0.25)
    xtest_noise = random_noise(xtest, seed = 1234, var = 0.25)

#rerun encoder with noise

loss = []

encoding_dim = dim  # 32 floats -> compression of factor 24.5, assuming the input is

# this is our input placeholder
    x = input_img = Input(shape=(784,))
    # "encoded" is the encoded representation of the input
    x = Dense(256, activation='relu')(x)
    x = Dense(128, activation='relu')(x)
    encoded = Dense(encoding_dim, activation='relu')(x)
```

```
x = Dense(128, activation='relu')(encoded)
      x = Dense(256, activation='relu')(x)
      decoded = Dense(784, activation='sigmoid')(x)
      # this model maps an input to its reconstruction
     autoencoder = Model(input_img, decoded)
      encoder = Model(input_img, encoded)
      # create a placeholder for an encoded (32-dimensional) input
      encoded_input = Input(shape=(encoding_dim,))
      # retrieve the last layer of the autoencoder model
     dcd1 = autoencoder.layers[-1]
      dcd2 = autoencoder.layers[-2]
      dcd3 = autoencoder.layers[-3]
      # create the decoder model
     decoder = Model(encoded_input, dcd1(dcd2(dcd3(encoded_input))))
      autoencoder.compile(optimizer='adadelta', loss='binary crossentropy')
     autoencoder.fit(xtrain_noise, xtrain_noise,
                epochs=100,
                batch_size=256,
                shuffle=True,
                validation_data=(xtest_noise, xtest_noise))
                #callbacks=[TensorBoard(log_dir='/tmp/autoencoder')])
Train on 60000 samples, validate on 10000 samples
Epoch 1/100
Epoch 2/100
Epoch 3/100
Epoch 4/100
Epoch 5/100
Epoch 6/100
Epoch 7/100
60000/60000 [=============== ] - 4s 71us/step - loss: 0.5563 - val_loss: 0.5552
Epoch 8/100
60000/60000 [============== ] - 4s 75us/step - loss: 0.5540 - val_loss: 0.5529
Epoch 9/100
```

"decoded" is the lossy reconstruction of the input

```
Epoch 10/100
60000/60000 [============== ] - 5s 76us/step - loss: 0.5509 - val_loss: 0.5501
Epoch 11/100
60000/60000 [============= ] - 5s 78us/step - loss: 0.5496 - val loss: 0.5488
Epoch 12/100
60000/60000 [=============== ] - 5s 79us/step - loss: 0.5483 - val_loss: 0.5475
Epoch 13/100
Epoch 14/100
60000/60000 [============== ] - 5s 77us/step - loss: 0.5464 - val_loss: 0.5456
Epoch 15/100
Epoch 16/100
Epoch 17/100
Epoch 18/100
Epoch 19/100
Epoch 20/100
Epoch 21/100
Epoch 22/100
Epoch 23/100
Epoch 24/100
Epoch 25/100
Epoch 26/100
60000/60000 [============== ] - 4s 73us/step - loss: 0.5365 - val loss: 0.5361
Epoch 27/100
Epoch 28/100
Epoch 29/100
Epoch 30/100
Epoch 31/100
Epoch 32/100
Epoch 33/100
```

```
60000/60000 [=============== ] - 4s 74us/step - loss: 0.5338 - val_loss: 0.5334
Epoch 34/100
60000/60000 [============== ] - 4s 75us/step - loss: 0.5336 - val_loss: 0.5329
Epoch 35/100
Epoch 36/100
60000/60000 [=============== ] - 5s 76us/step - loss: 0.5331 - val_loss: 0.5328
Epoch 37/100
Epoch 38/100
60000/60000 [============== ] - 4s 74us/step - loss: 0.5327 - val_loss: 0.5329
Epoch 39/100
Epoch 40/100
Epoch 41/100
Epoch 42/100
Epoch 43/100
Epoch 44/100
Epoch 45/100
Epoch 46/100
Epoch 47/100
Epoch 48/100
60000/60000 [=============== ] - 4s 74us/step - loss: 0.5310 - val_loss: 0.5305
Epoch 49/100
Epoch 50/100
60000/60000 [============== ] - 4s 75us/step - loss: 0.5309 - val loss: 0.5308
Epoch 51/100
Epoch 52/100
60000/60000 [=============== ] - 4s 74us/step - loss: 0.5306 - val_loss: 0.5304
Epoch 53/100
Epoch 54/100
Epoch 55/100
Epoch 56/100
Epoch 57/100
```

```
Epoch 58/100
60000/60000 [============== ] - 5s 76us/step - loss: 0.5301 - val_loss: 0.5297
Epoch 59/100
Epoch 60/100
60000/60000 [=============== ] - 4s 74us/step - loss: 0.5300 - val_loss: 0.5296
Epoch 61/100
60000/60000 [=============== ] - 4s 74us/step - loss: 0.5299 - val loss: 0.5298
Epoch 62/100
60000/60000 [============== ] - 5s 75us/step - loss: 0.5299 - val_loss: 0.5296
Epoch 63/100
Epoch 64/100
Epoch 65/100
Epoch 66/100
Epoch 67/100
Epoch 68/100
Epoch 69/100
60000/60000 [=============== ] - 4s 74us/step - loss: 0.5295 - val_loss: 0.5289
Epoch 70/100
Epoch 71/100
Epoch 72/100
Epoch 73/100
60000/60000 [============== ] - 5s 76us/step - loss: 0.5292 - val_loss: 0.5294
Epoch 74/100
60000/60000 [============== ] - 5s 75us/step - loss: 0.5292 - val loss: 0.5290
Epoch 75/100
Epoch 76/100
Epoch 77/100
Epoch 78/100
Epoch 79/100
Epoch 80/100
Epoch 81/100
```

```
60000/60000 [=============== ] - 5s 75us/step - loss: 0.5288 - val_loss: 0.5292
Epoch 82/100
60000/60000 [============== ] - 4s 75us/step - loss: 0.5288 - val_loss: 0.5282
Epoch 83/100
60000/60000 [============== ] - 4s 75us/step - loss: 0.5287 - val loss: 0.5284
Epoch 84/100
60000/60000 [=============== ] - 4s 75us/step - loss: 0.5287 - val_loss: 0.5281
Epoch 85/100
Epoch 86/100
60000/60000 [============== ] - 5s 76us/step - loss: 0.5286 - val_loss: 0.5282
Epoch 87/100
Epoch 88/100
Epoch 89/100
Epoch 90/100
Epoch 91/100
60000/60000 [=============== ] - 5s 75us/step - loss: 0.5284 - val_loss: 0.5283
Epoch 92/100
Epoch 93/100
Epoch 94/100
Epoch 95/100
Epoch 96/100
Epoch 97/100
60000/60000 [============== ] - 5s 76us/step - loss: 0.5281 - val_loss: 0.5280
Epoch 98/100
60000/60000 [============= ] - 5s 76us/step - loss: 0.5279 - val loss: 0.5277
Epoch 99/100
60000/60000 [============== ] - 5s 76us/step - loss: 0.5280 - val loss: 0.5277
Epoch 100/100
Out [76]: <keras.callbacks.dallbacks.History at 0xb684645f8>
In [77]: encoded_imgs = encoder.predict(xtest_noise)
    decoded_imgs = decoder.predict(encoded_imgs)
```

n = 20 # how many digits we will display

import matplotlib.pyplot as plt

```
plt.figure(figsize=(40, 4))
   for i in range(n):
       # display original
       ax = plt.subplot(2, n, i + 1)
       plt.imshow(xtest_noise[i].reshape(28, 28))
       plt.gray()
       ax.get_xaxis().set_visible(False)
       ax.get_yaxis().set_visible(False)
       # display reconstruction
       ax = plt.subplot(2, n, i + 1 + n)
       plt.imshow(decoded_imgs[i].reshape(28, 28))
       plt.gray()
       ax.get_xaxis().set_visible(False)
       ax.get_yaxis().set_visible(False)
   plt.show()
7 3 4 0 9 1 4 5 6 9 0 6 9 0 1 3 9 7 3 4
```

Looking at the above image comparisons, you can tell that, for the most part, the auto-encoder can strip out most of the input noise. It does not do a perfect job with noise at 0.25 variance, but I think that at least $\sim 60\%$ of the above images are correct and discernable.