EE5179: Deep Learning for Imaging

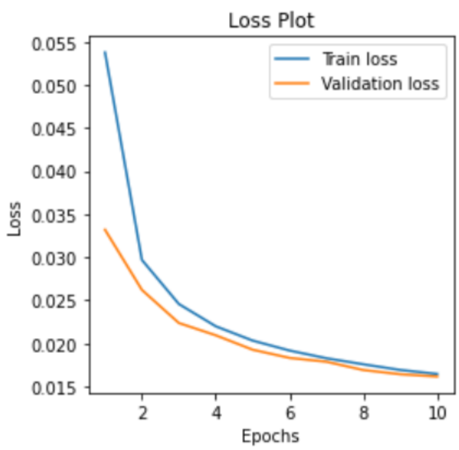
Programming Assignment 4: Auto-encoders

1. Comparing PCA and Autoencoders

Autoencoder design:

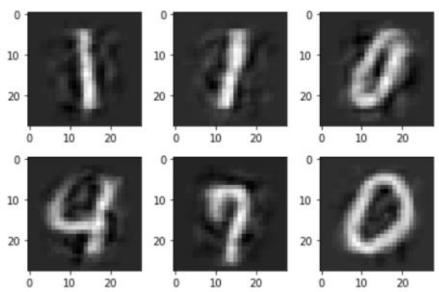
Encoder	Decoder
– input (784)	– fc (128)
– fc (512)	– fc (256)
– fc (256)	– fc (784)
– fc (128)	
– fc (30)	

Training plot for the autoencoder:

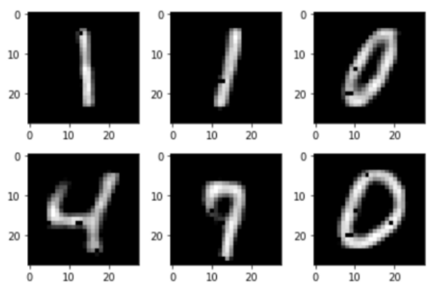


Test loss: 0.017%

Visual Comparison of reconstruction using AE and PCA (number of components = 30):



Reconstruction using PCA



Reconstruction using AE

Observations:

- Using a greater number of components in PCA leads to better reconstruction
- Using an autoencoder has a much better reconstruction in contrast to PCA

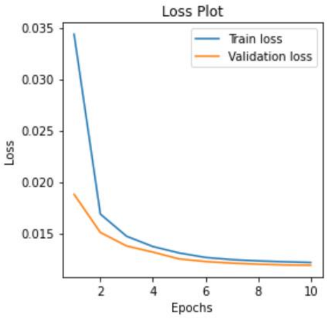
2. Experimenting with hidden units of varying sizes

Autoencoder design:

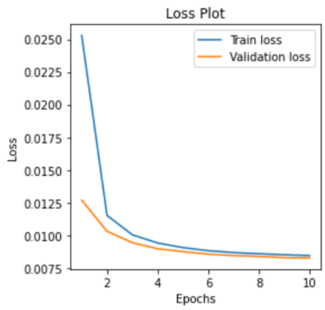
The architecture consists of only a hidden layer and the output layer: fc(x)-fc(784)

X is varied from 64, 128, 256 to perform this experiment.

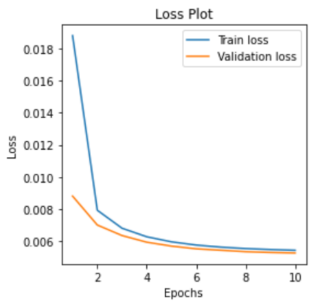
Training loss plots:



Hidden size = 64



Hidden size = 128

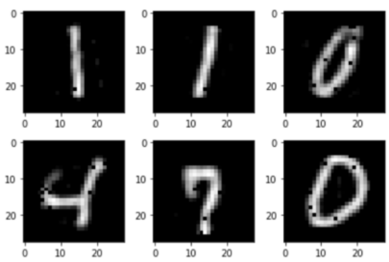


Hidden size = 256

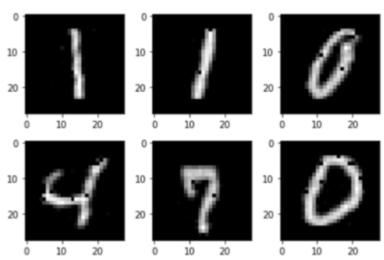
Test losses:

Hidden size	Test loss
64	0.013%
128	0.009%
256	0.006%

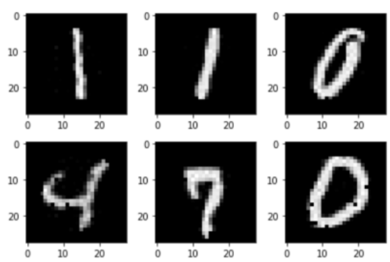
Visual comparison of reconstruction:



Hidden size = 64

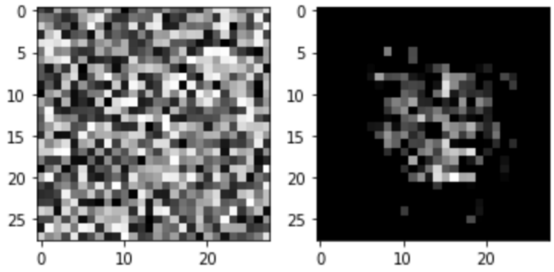


Hidden size = 128



Hidden size = 256

Reconstruction of noise image:



Input: noise image Output: reconstructed image (hidden layer size = 256)

Observations:

- Increasing the hidden layer size improves the reconstruction
- There are a few black pixels noticeable in the reconstruction. The number of these reduce with increase in hidden layer size.
- Reconstruction of a noise image outputs an image that has a lot of the pixels towards the corners removed. This shows that the encoder learns the digits and removes the background pixels.

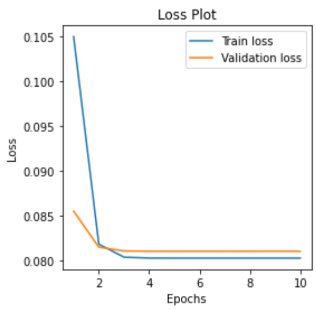
3. Sparse Autoencoders

Autoencoder design:

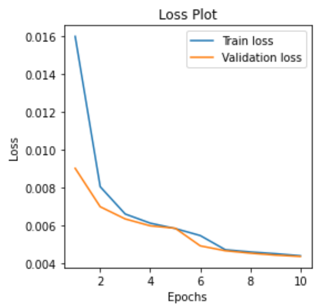
Very similar to the autoencoder in the previous case, we have an AE with a single hidden layer. This will be an autoencoder that is overcomplete. We take hidden layer size = 1225. fc(1225)-fc(784)

Training loss plots:

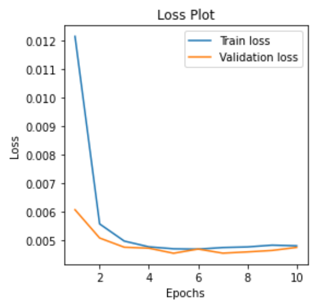
Sparse autoencoders are regularised autoencoders. They use L1 penalty. We increase sparsity by increasing the penalty on the regularisation term, L_{L1}.



L_{L1} = 1e-4



L_{L1} = 1e-7

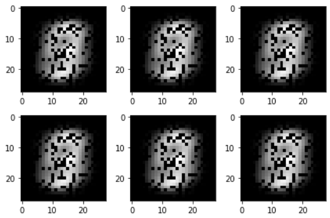


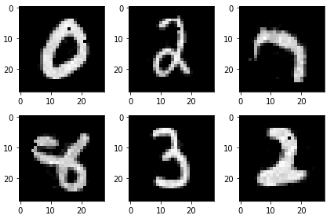
L_{L1} = 1e-10

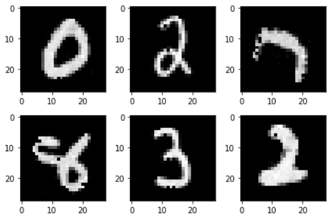
Test losses:

L_{L1}	Test loss
1e-4	0.080%
1e-7	0.004%
1e-10	0.005%

Visual comparison of reconstruction:


L_{L1} = 1e-4


L_{L1} = 1e-7

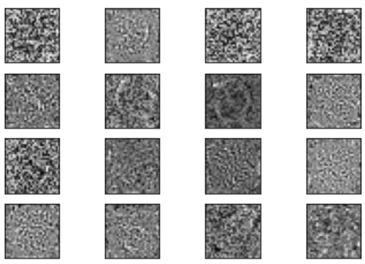

L_{L1} = 1e-10

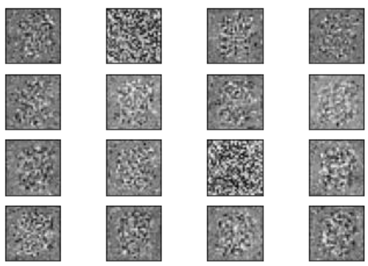
Average activation:

Average activations compared between sparse autoencoder with different activations and the standard AE (hidden layer size = 256).

AE	Average activation
SAE, L_{L1} = 1e-4	≈ 0
SAE, L_{L1} = 1e-7	0.222
SAE, L_{L1} = 1e-10	1.556
AE	0.940

Decoder weights:


SAE (L_{L1} = 1e-7)


Standard AE

Observations:

- Very high sparsity results in very poor reconstruction.
- Higher the sparsity, lower the average activation.
- At L_{L1} = 1e-7, the SAE performs the best. We compare this model with a standard AE of hidden layer size 256.

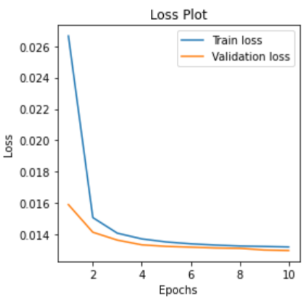
- In comparison to 1225 hidden layer size in SAE, and Standard AE of hidden layer size 256, the two have comparable total activation per neuron.
- The compared decoder weights show that the SAE learns the structure of the outline of the digits better. The AE on the other hand has learned weights that resemble noise.

4. Denoising Autoencoders

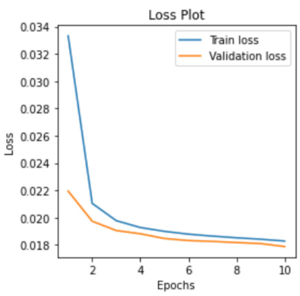
Autoencoder design:

This DAE has a single hidden layer of size 256. Regularisation done by varying the noise factors 0.3, 0.5, 0.8, 0.9.

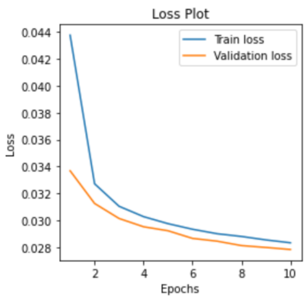
Training loss plots:



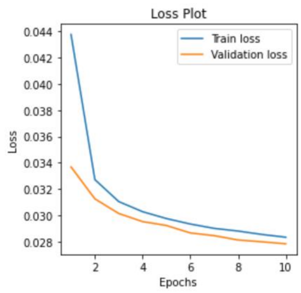
Noise factor = 0.3



Noise factor = 0.5



Noise factor = 0.8

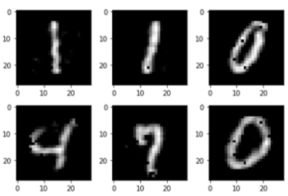


Noise factor = 0.9

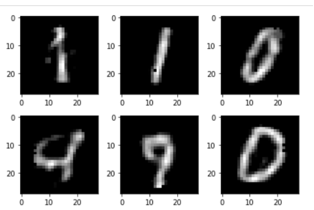
Test losses:

Noise factor	Test loss
0.3	0.014%
0.5	0.019%
0.8	0.029%
0.9	0.032%

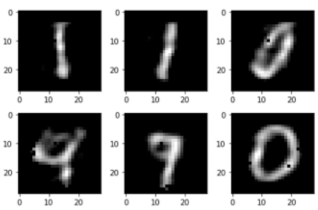
Visual comparison of reconstruction:



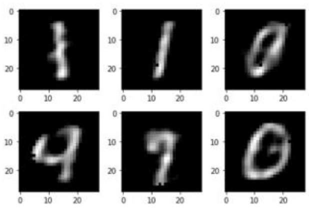
NF = 0.3



NF = 0.5

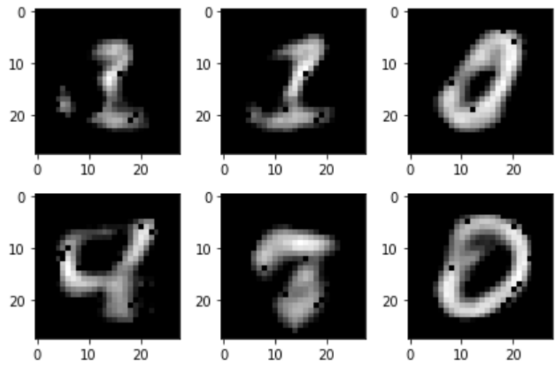


NF = 0.8

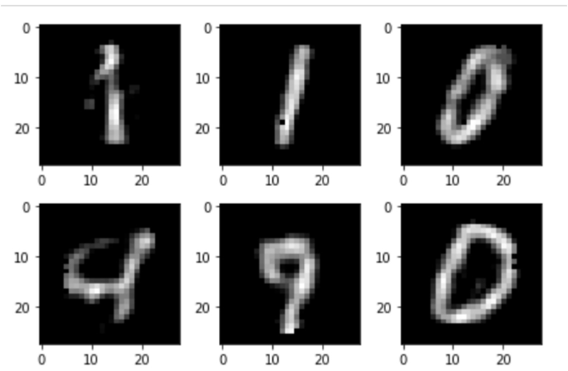


NF = 0.9

Passing noisy images to Standard AE and DAE: Comparison:

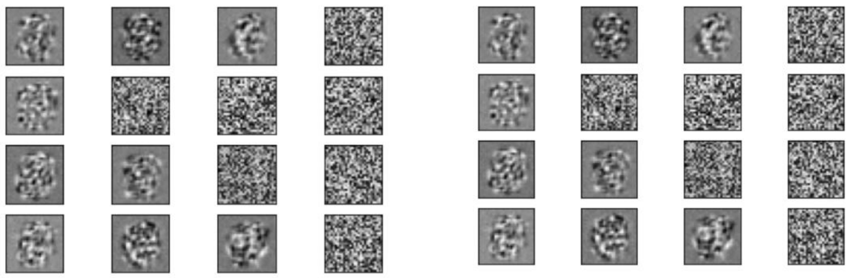


Output from Standard AE
when noisy input is passed

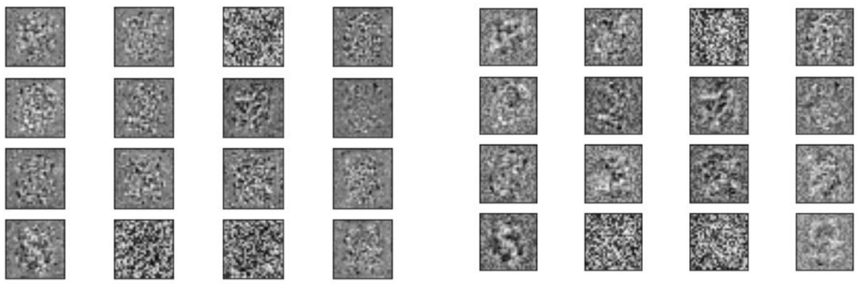


Output from DAE

Learned filters:



Learned encoder and decoder weights of DAE



Learned encoder and decoder weights of standard AE

Observations:

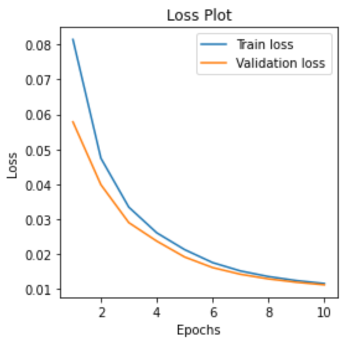
- Passing noise corrupted images through a standard AE, results in poor reconstruction. We see how DAE effectively learns the underlying distribution of the image data independent of the noise.
- Increasing the noise factor results in poorer test accuracy. However, visually we see that the model reconstructs better when the noise factor is increased to about 0.8.
- Upon observing the learned weights of DAE and standard AE, we see how the DAE weights better capture the variations.

5. Convolutional Autoencoders

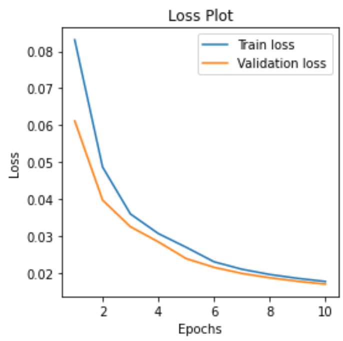
Autoencoder design:

Encoder	Decoder: Unpool	Decoder: Deconvolve	Decoder: Unpool + deconvolve
Input-Conv1(8 3x3 filters with stride 1)	Unpool (7x7x16 to 14x14x16)	Conv1 (7x7x16 to 9x9x16)	Unpool
2x2 Maxpooling	Conv2 (14x14x16 to 14x14x8)	Conv2 (10x10x16 to 14x14x8)	Conv1
Conv2(16 3x3 filters with stride 1)	Unpool (14x14x8 to 28x28x8)	Conv3 (14x14x8 to 28x28x1)	Unpool
2x2 Maxpooling	Conv3 (28x28x8 to 28x28x1)		Conv2
Conv3(16 3x3 filters with stride 1)			Unpool
2x2 Maxpooling			Conv3

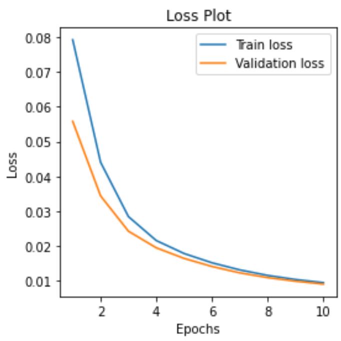
Training loss plots:



Unpool



Deconv

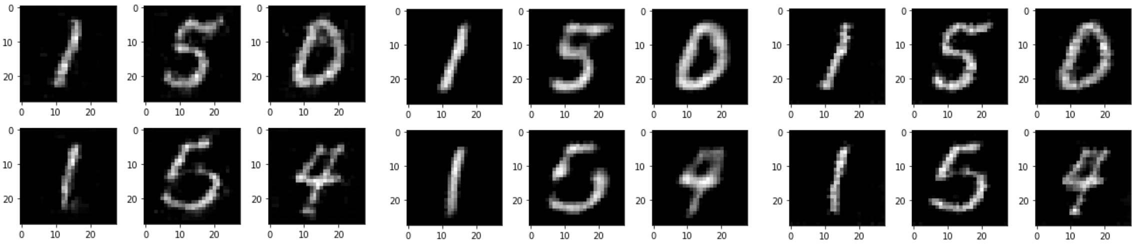


Unpool+Deconv

Test losses:

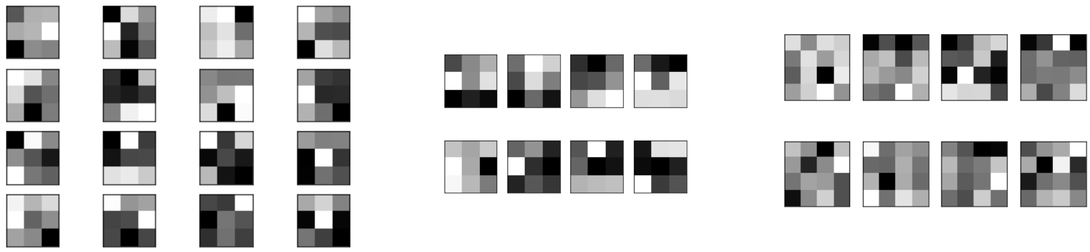
Decoder model	Test loss
Unpool	0.012%
Deconv	0.017%
Unpool+Deconv	0.009%

Reconstruction visualisation:



Unpool Deconv Unpool+Deconv

Decoder weights:



Unpool Deconv Unpool+Deconv

Observations:

- The model is trained at a lower learning rate (=0.0001)
- The reconstruction is better with unpooling. The decoder weights also show the learning of the edges
- Upsampling using unpool+deconv has kernel weights that don't learn edges or weights very well