

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

SINGAPORE

**CZ4042 NEURAL NETWORKS
PROJECT 2 REPORT**

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Part A:

Deep Convolutional Neural Network

Introduction

The MNIST database of handwritten digits is a widely-used dataset to test image recognition algorithms. It contains a training set of 60000 digits and a test set of 10000 digits, each a centered image of size 28×28 .

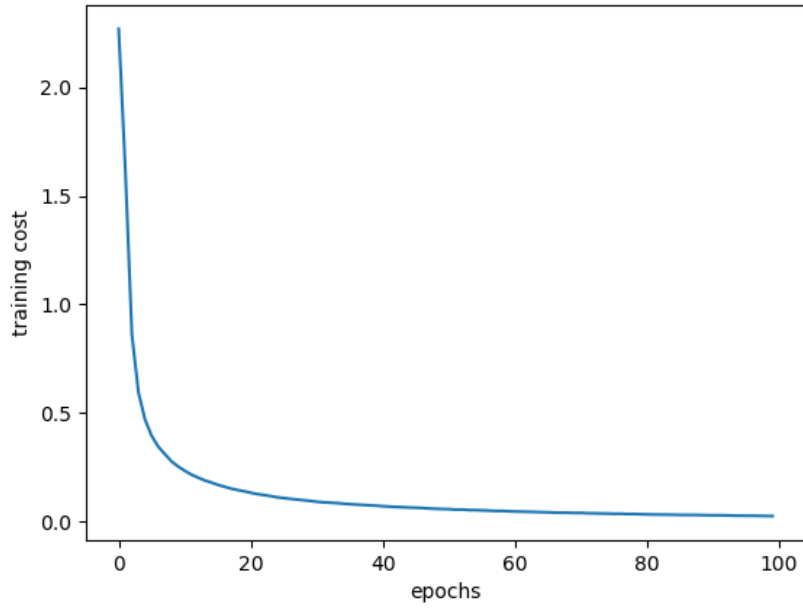
Deep Convolutional Neural Network (DCNN) is a class of deep feedforward neural networks that is considered a state-of-the-art approach in image recognition. In this project, we would design a DCNN with an input layer, two convolutional and maxpooling layers, a fully connected layer and an output softmax layer; training and testing would be done on a subset of the MNIST dataset.

Three algorithms to update the weights are explored:

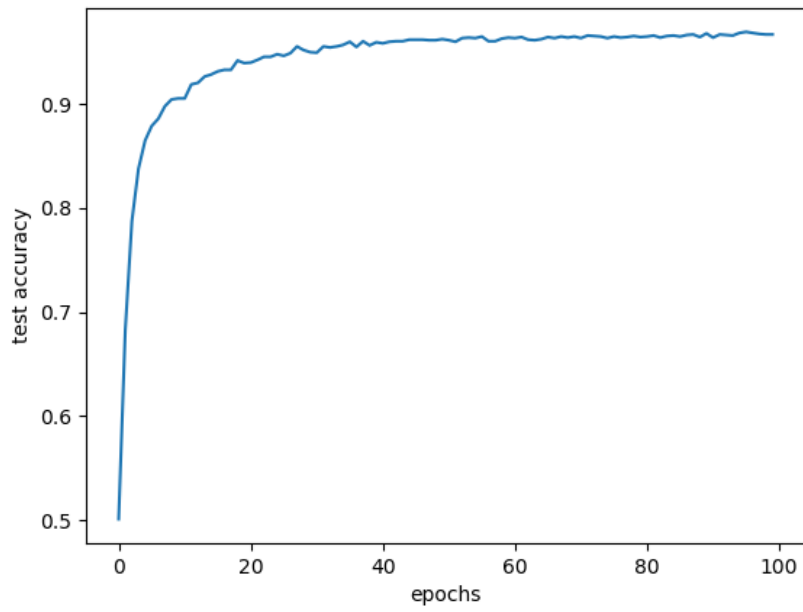
- Stochastic Gradient Descent
- Stochastic Gradient Descent with Momentum
- RMSProp

Stochastic Gradient Descent (SGD)

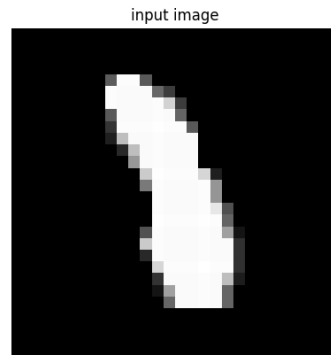
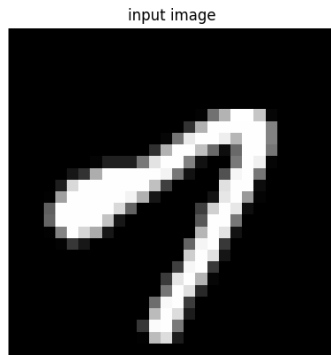
We have used up to 100 epochs; the following graph shows the training cost against the number of epochs.



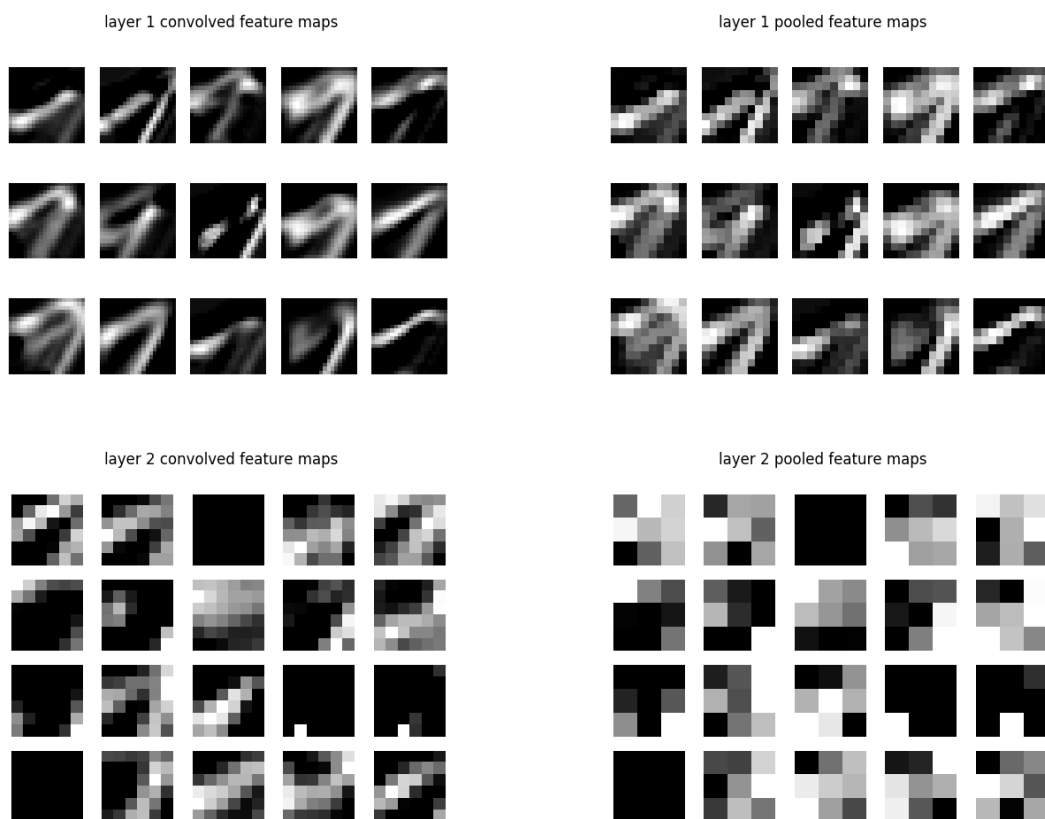
The following graph shows the test accuracy against the number of epochs.



Two images are chosen through setting different random seeds; the two seeds are 10 and 42.

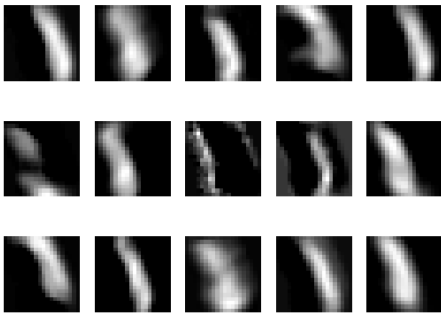


For image 1, the convolved and pooled feature maps are as follows:

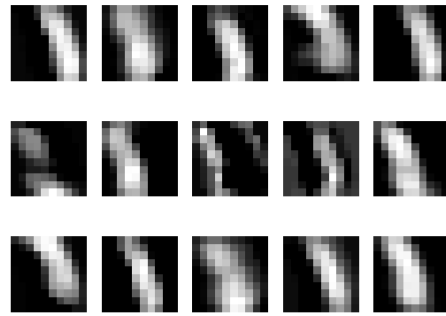


For image 2, the convolved and pooled feature maps are as follows:

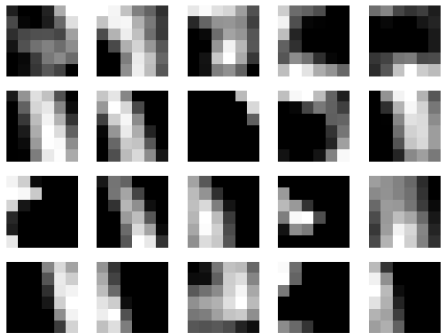
layer 1 convolved feature maps



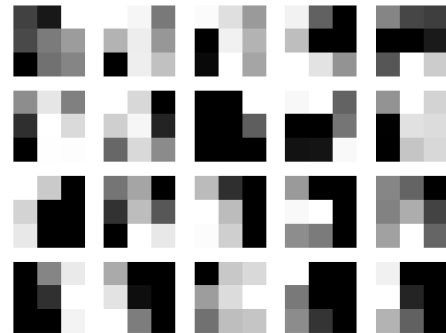
layer 1 pooled feature maps



layer 2 convolved feature maps



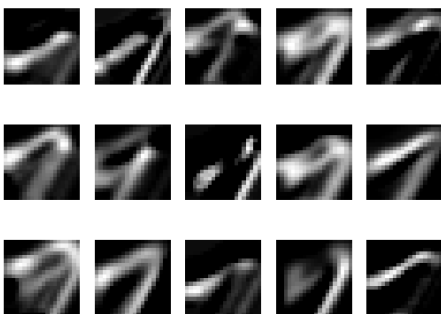
layer 2 pooled feature maps



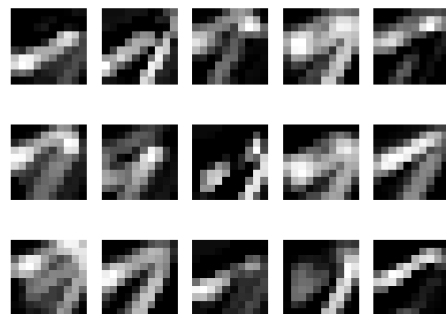
Stochastic Gradient Descent with Momentum

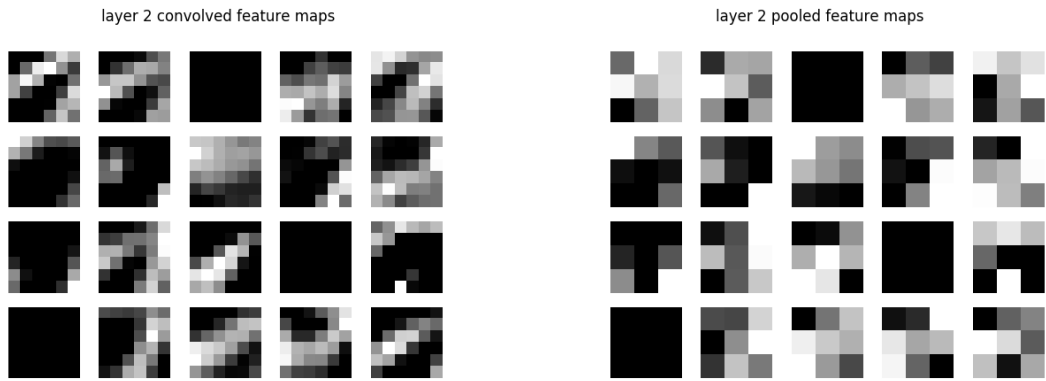
The same 2 images are chosen. For image 1, the convolved and pooled feature maps are as follows:

layer 1 convolved feature maps

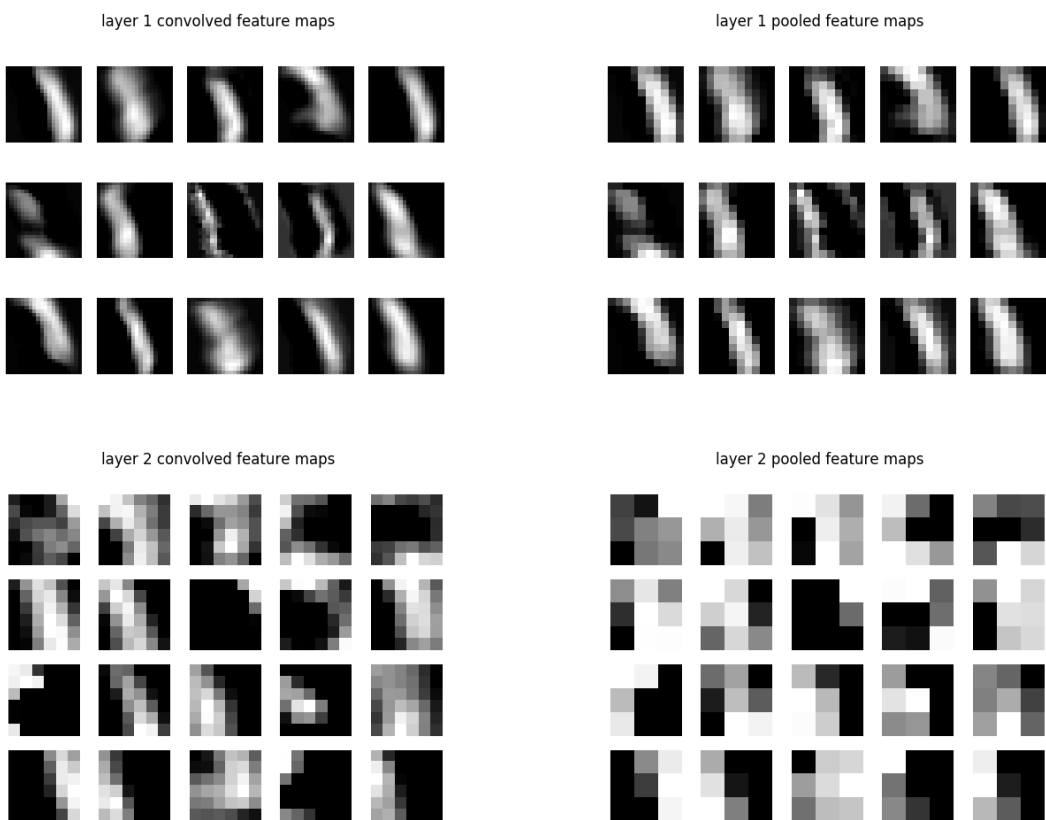


layer 1 pooled feature maps





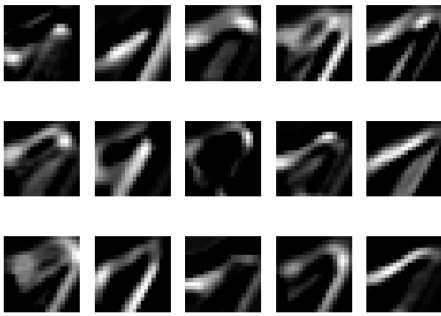
For image 2, the convolved and pooled feature maps are as follows:



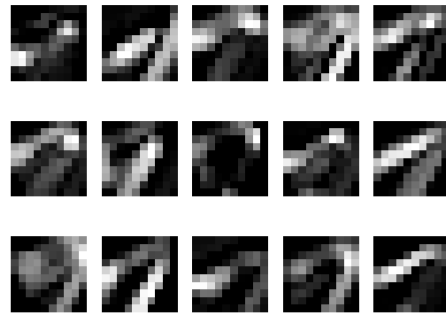
RMSProp

The same 2 images are chosen. For image 1, the convolved and pooled feature maps are as follows:

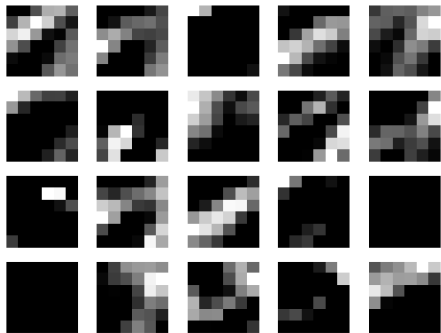
layer 1 convolved feature maps



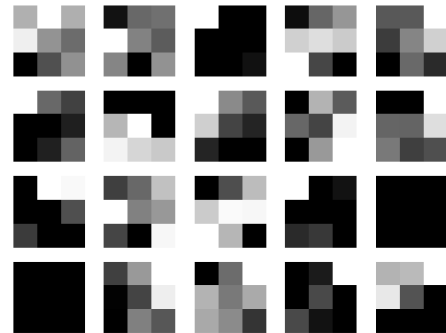
layer 1 pooled feature maps



layer 2 convolved feature maps

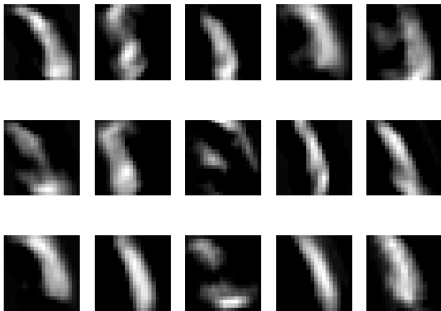


layer 2 pooled feature maps

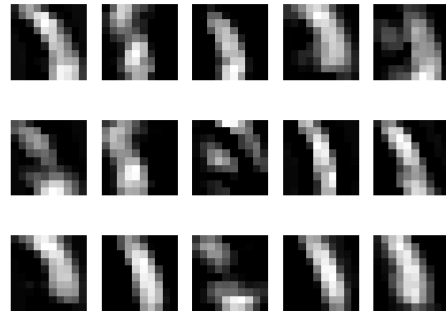


For image 2, the convolved and pooled feature maps are as follows:

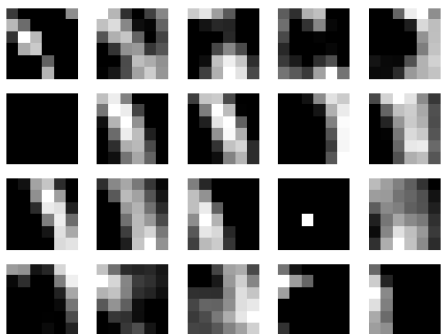
layer 1 convolved feature maps



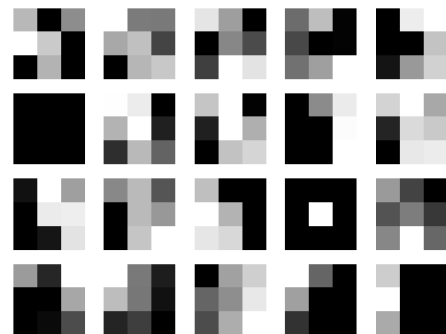
layer 1 pooled feature maps



layer 2 convolved feature maps

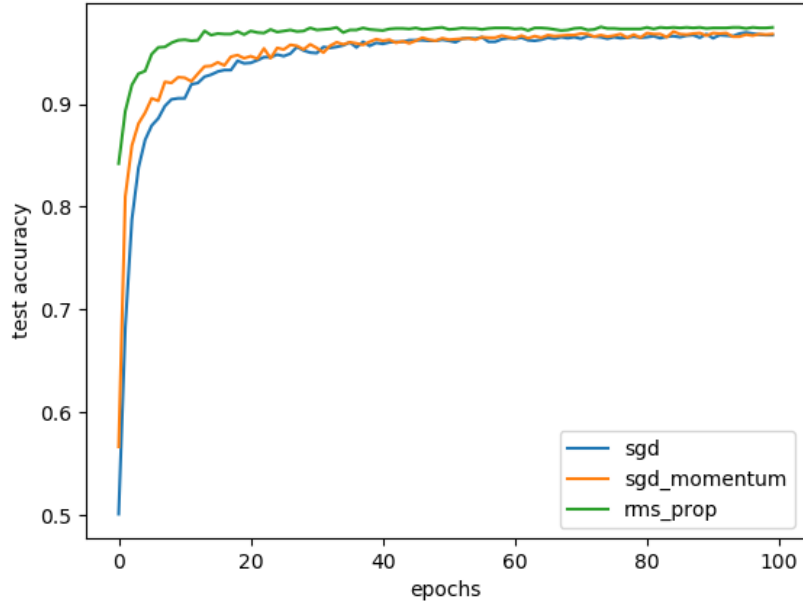


layer 2 pooled feature maps



Analysis

This graph shows the test accuracy against the number of epochs for all three algorithms.



The training time and training cost does not vary much between algorithms. Different algorithms however extracts slightly different features from the images, as evident from the feature maps, hence the difference in accuracy. For the same random seed of 10, SGD achieves an accuracy of 97%, SGD with Momentum achieves 97.2% and RMSProp achieves 98%; this shows that RMSProp gives the highest accuracy, and we could confidently conclude that RMSProp is the best algorithm to use in this context.

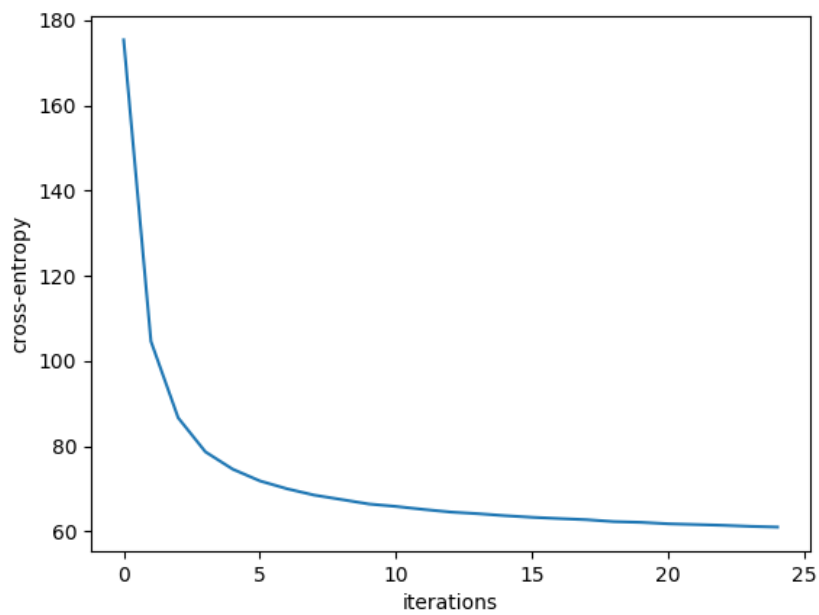
Part B: Autoencoders

Introduction

This part of the assignment aims to implement an autoencoder on the full MNIST dataset.

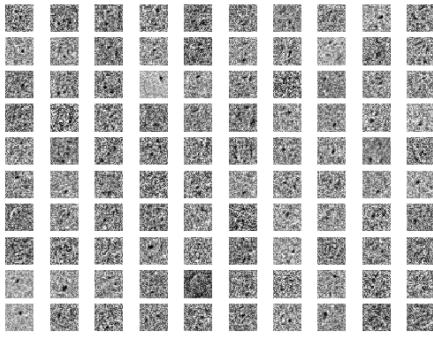
Stacked Denoising Autoencoder

The stacked denoising autoencoder consists of three hidden layers with 900, 625 and 400 neurons respectively. The following plot shows the training cost of the autoencoder.

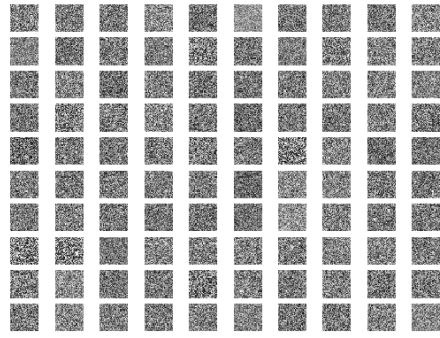


The following images show 100 samples of weights learned at each layer.

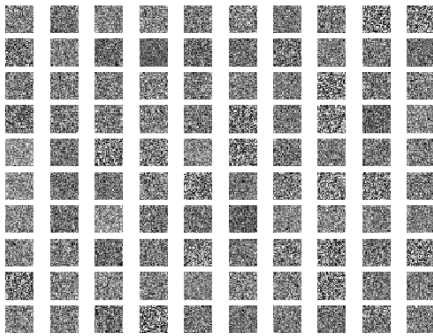
layer 1 weight samples



layer 2 weight samples

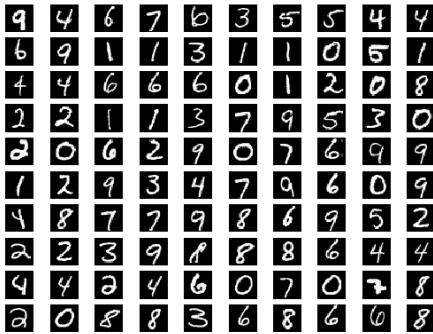


layer 3 weight samples

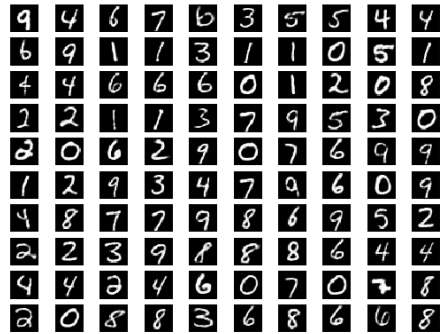


100 test images are chosen at random; the images and their reconstructions are shown below.

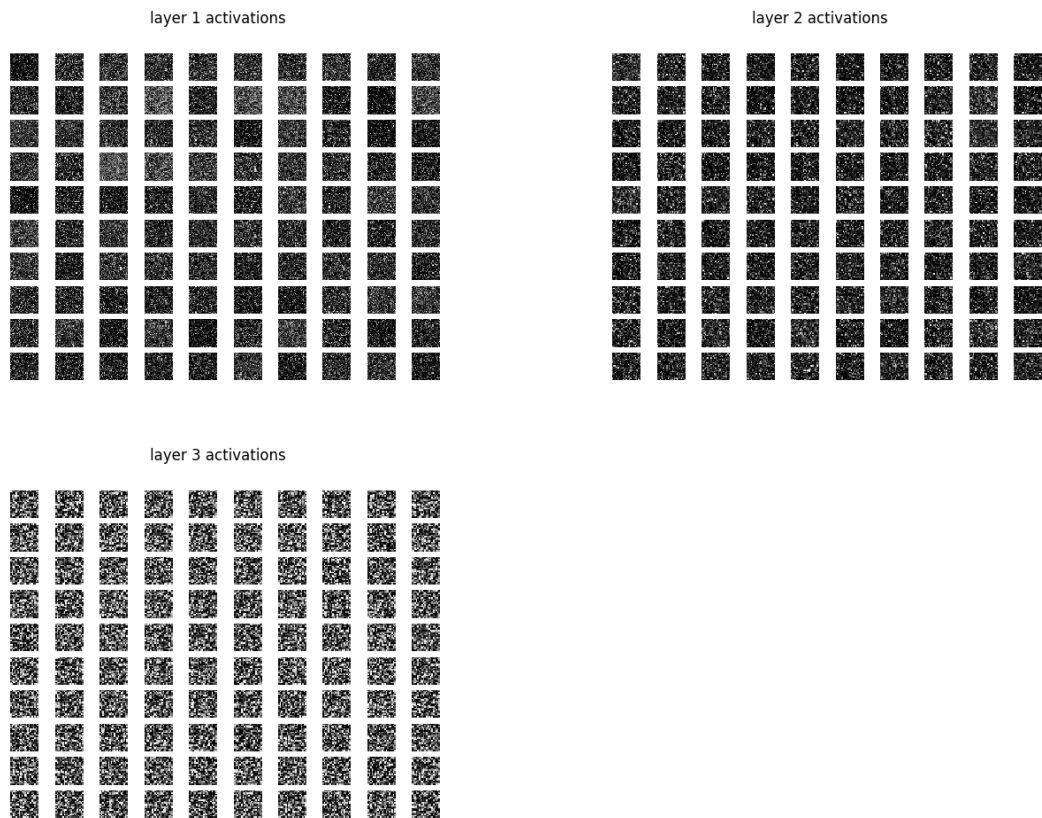
input images



reconstructed outputs

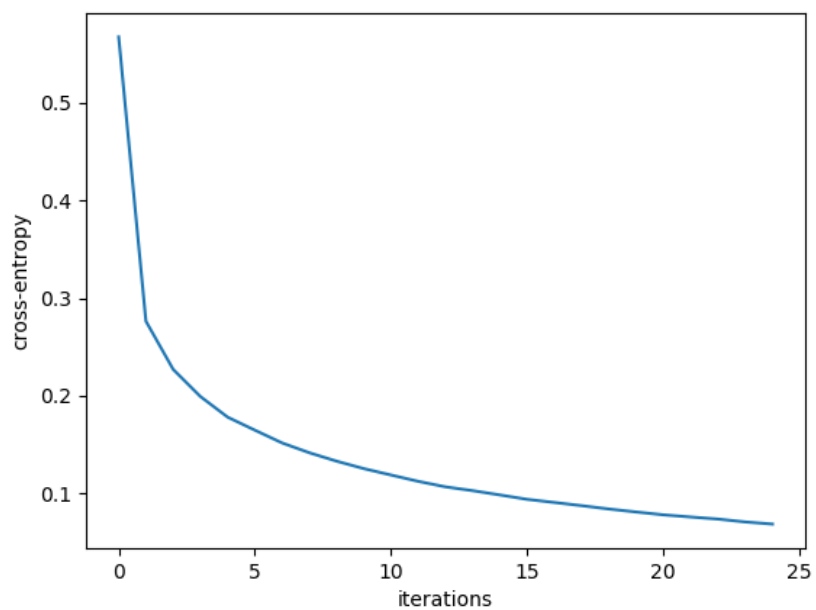


The hidden layer activations are shown below.

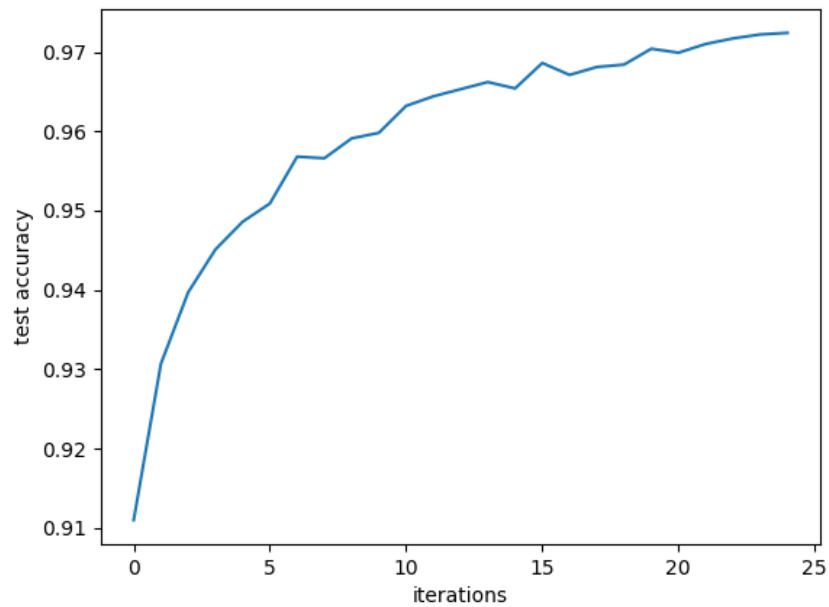


Feedforward Neural Network on Autoencoder

We added a softmax and an output layer to the stacked denoising autoencoder described above, to make a classifier on MNIST data. The training cost is shown below.

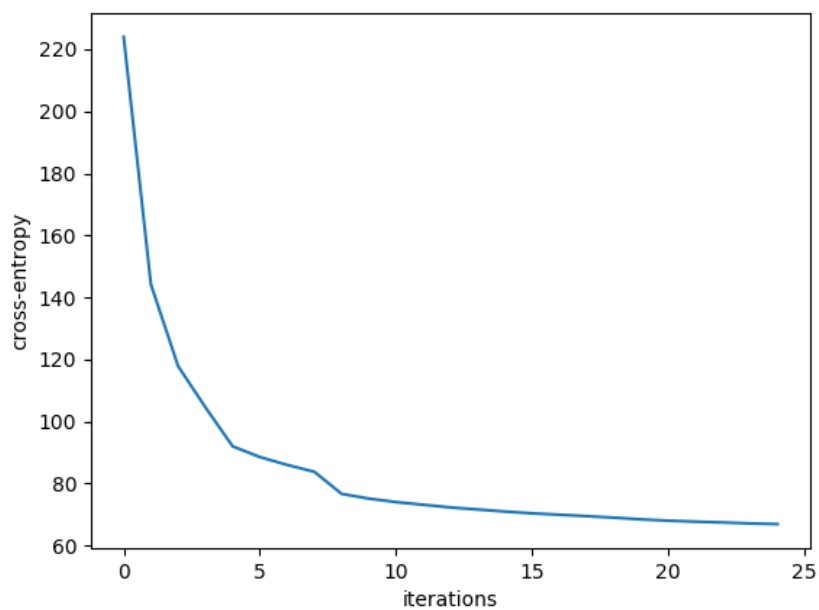


The test accuracy is shown below; the classifier achieves 97.2% accuracy after 25 epochs.

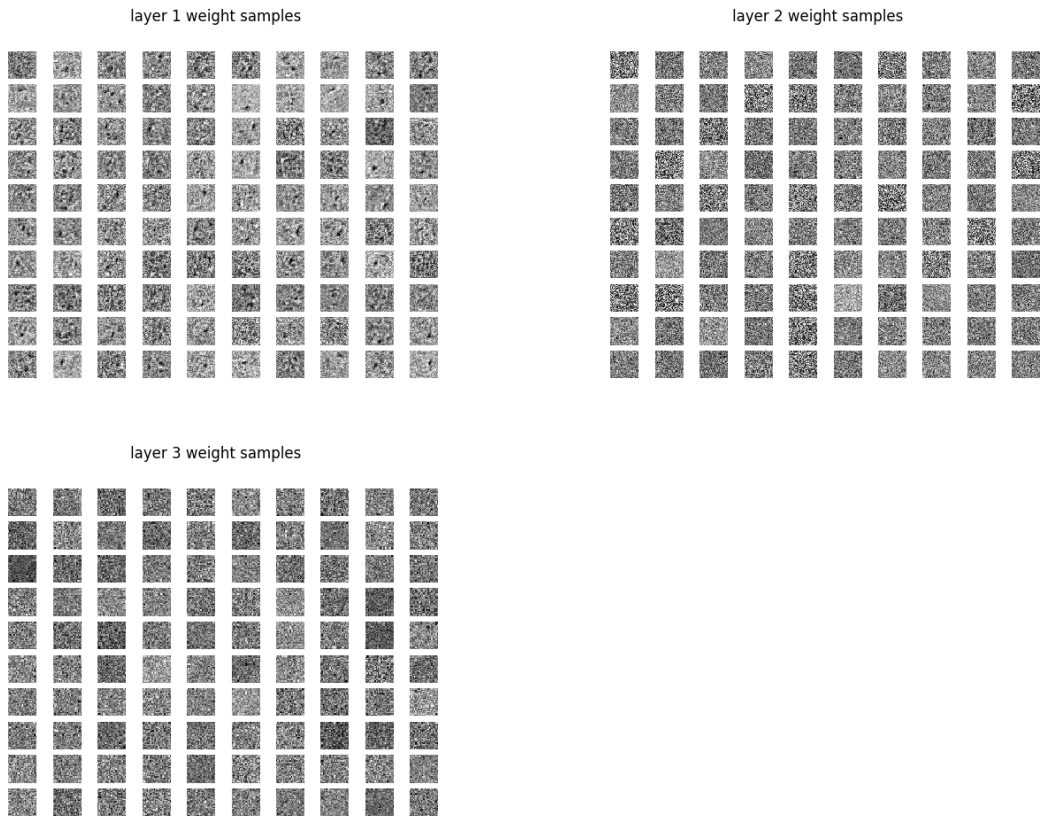


Autoencoder with Momentum and Sparsity

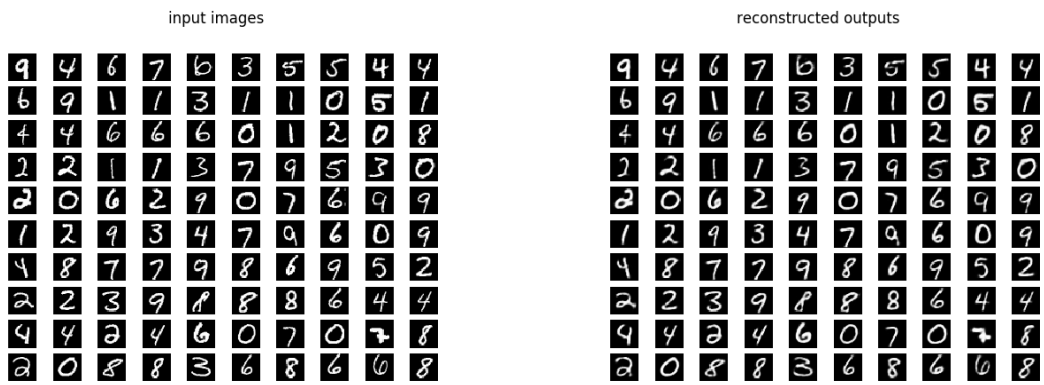
We added the momentum term and sparsity into the autoencoder. The following plot shows the training cost of the autoencoder.



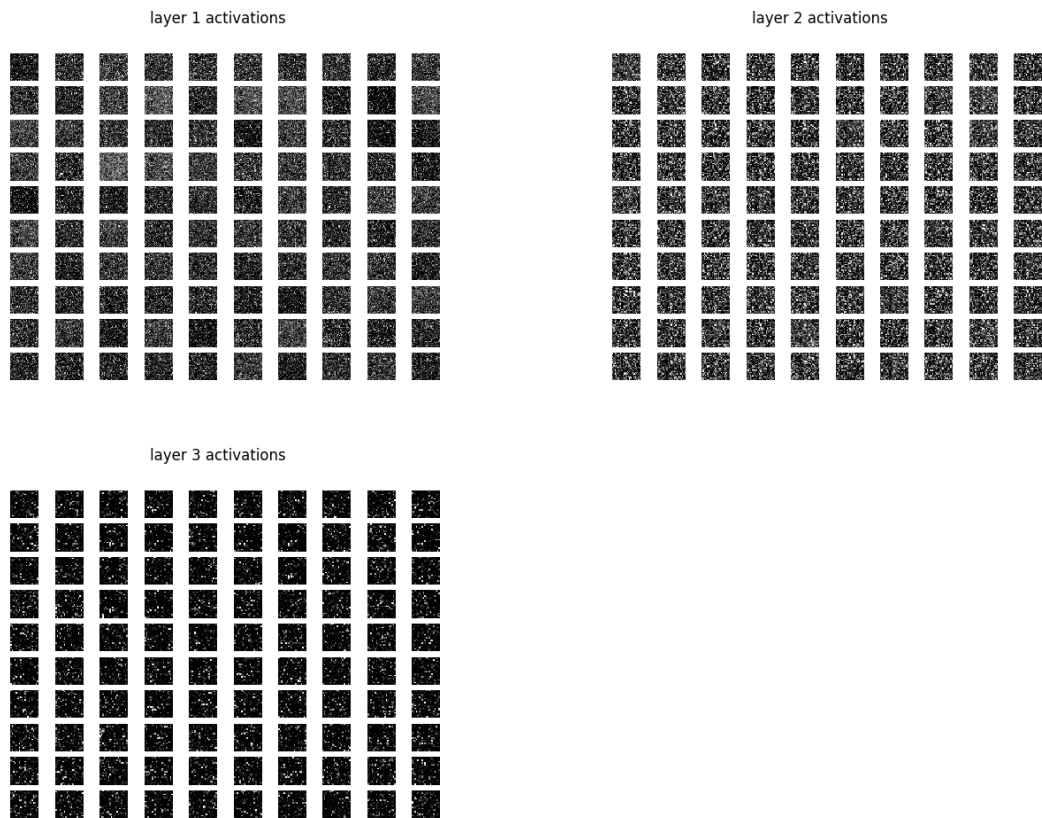
The following images show 100 samples of weights learned at each layer.



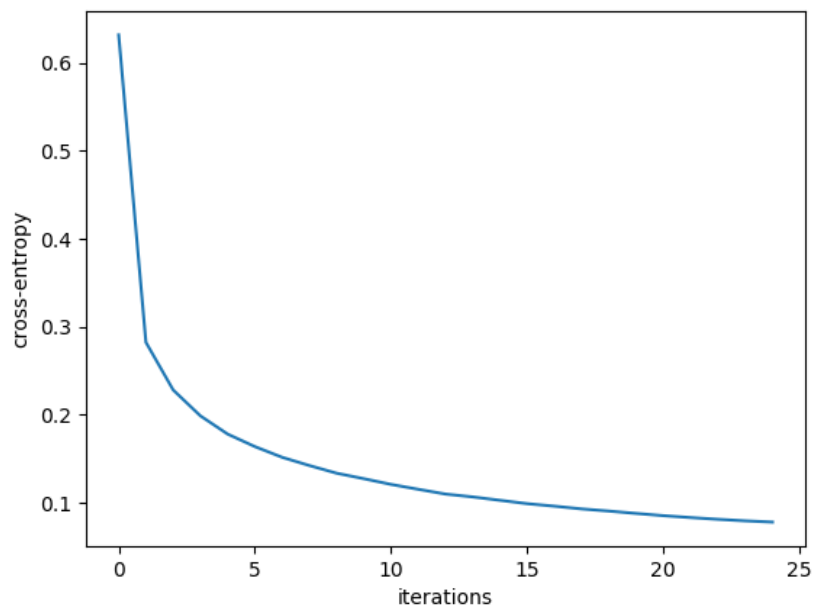
The same 100 images and their reconstructions are shown below.



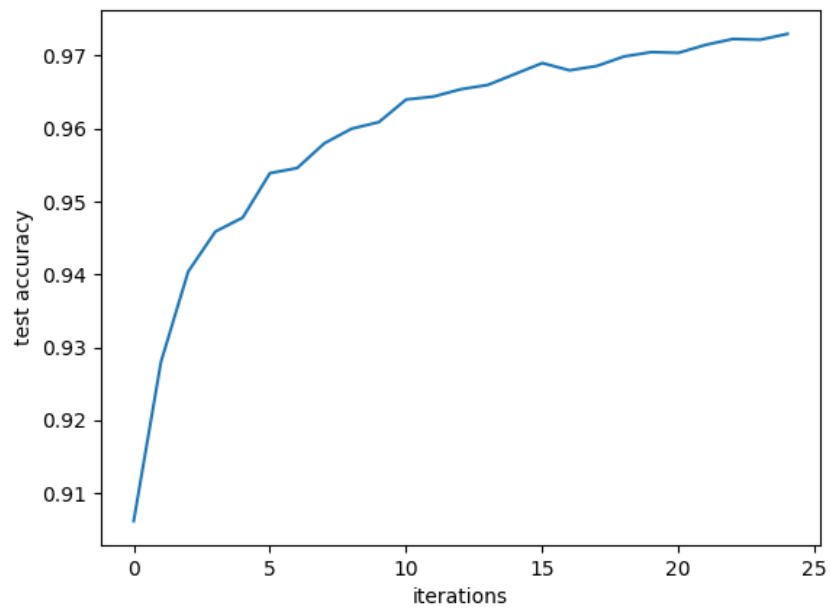
The hidden layer activations are shown below.



The training cost of the autoencoder classifier on MNIST data is shown below.

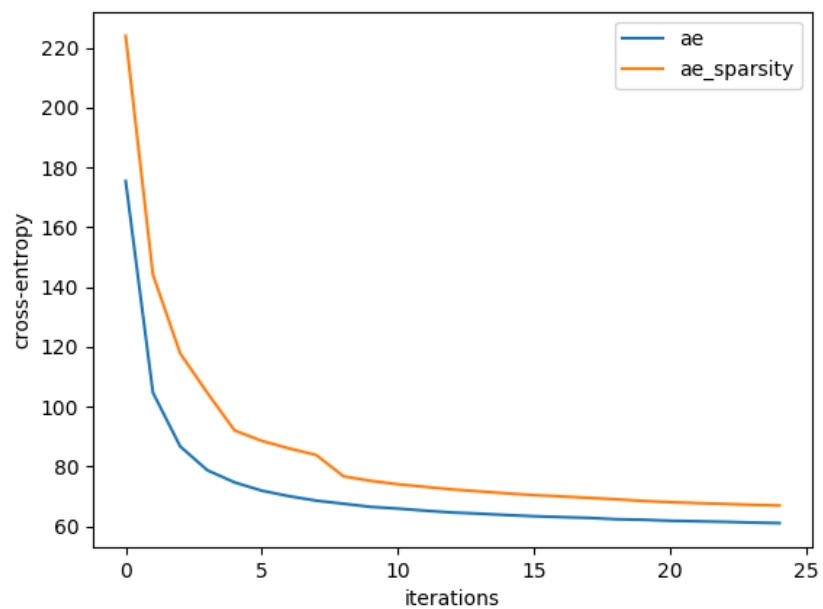


The test accuracy is shown below; the classifier achieves 97.3% accuracy after 25 epochs.

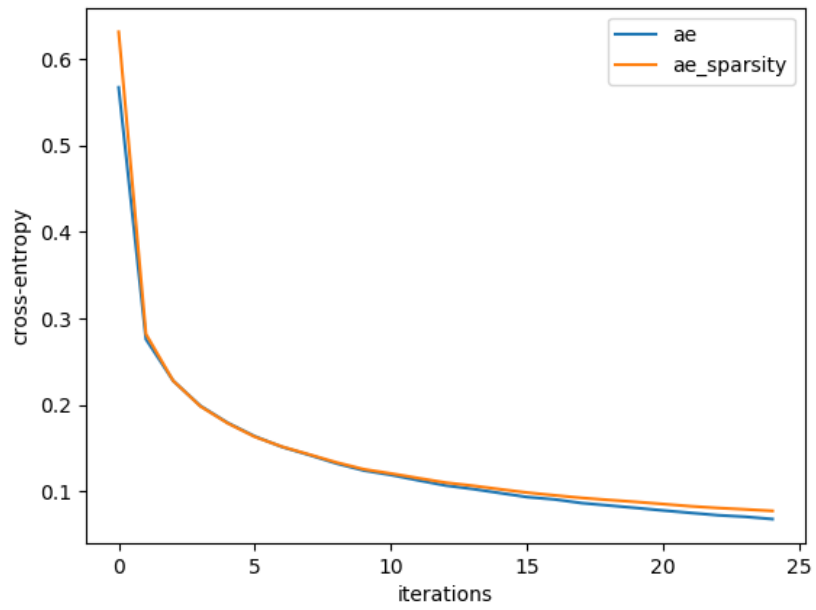


Analysis

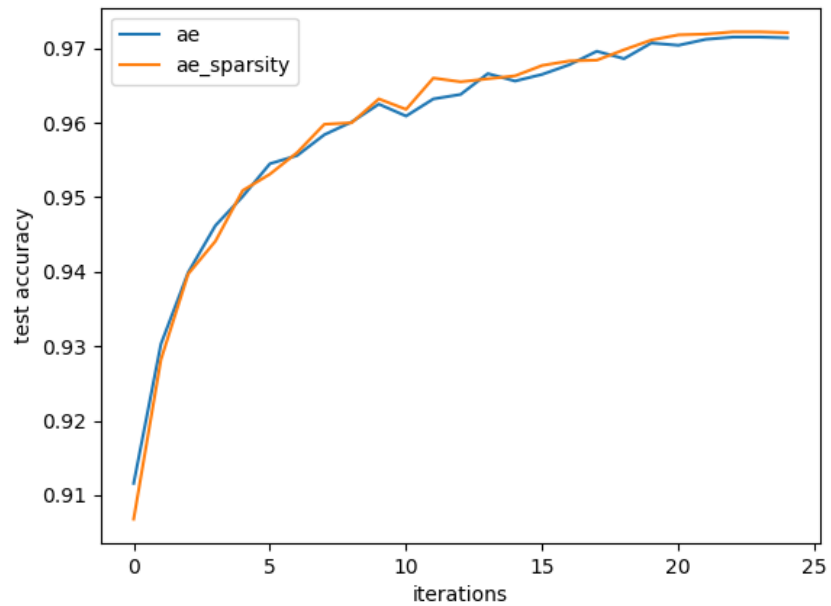
The following graph compares the training cost of the autoencoder on both approaches.



The following graph compares the training cost of the autoencoder classifier on both approaches.



The following graph compares the test accuracy of the autoencoder classifier on both approaches.



The addition of momentum and sparsity results in slightly higher training cost, in exchange for slightly better test accuracy.