EE6132: Deep Learning for Image Processing

Assignment 2: Convolutional Neural Networks

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Contents

1	Que	estion 1: MNIST classification using CNN 3
	1.1	Baseline Model
		1.1.1 Overall architecture
		1.1.2 Results
		1.1.3 Sample predictions
	1.2	2 convolutional layers
		1.2.1 Overall architecture
		1.2.2 Results
		1.2.3 Sample predictions
	1.3	2 convolutional layers + 1 hidden fully connected layer
		1.3.1 Overall architecture
		1.3.2 Results
		1.3.3 Sample predictions
2	Con	nerating Adversarial Examples 9
_	2.1	Adversarial Examples for label 0
	$\frac{2.1}{2.2}$	Adversarial Examples for label 1
	2.3	Adversarial Examples for label 2
	$\frac{2.5}{2.4}$	Adversarial Examples for label 3
	2.5	Adversarial Examples for label 4
	2.6	Adversarial Examples for label 5
	$\frac{2.0}{2.7}$	Adversarial Examples for label 6
	2.8	Adversarial Examples for label 7
	2.9	Adversarial Examples for label 8
	2.10	
_		
3		ualizing Convolutional Neural Networks 19
	3.1	Final layer neurons as cost
	32	Max pooling centre neurons as cost

1 Question 1: MNIST classification using CNN

1.1 Baseline Model

1.1.1 Overall architecture

Input --→ Conv (32 3x3 filters, Stride of 1, Zero padding of 1) --→ 2x2 Maxpool (Stride of 2) --→ Fully connected (10 outputs) --→ Softmax classifier

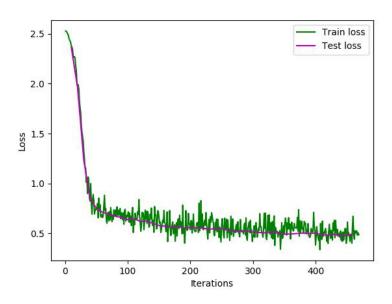
Batch size	128
Regularization	L2 (for weights only)
Regularization parameter (λ)	0.01
No. of training epochs	5
Update algorithm	SGD with Momentum acceleration

1.1.2 Results

The final test accuracy obtained for the model is 92.65%.

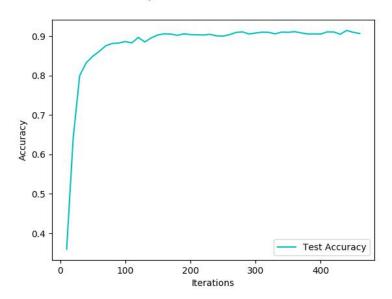
Following is the plot showing training and validation loss evolution over iterations:

Loss evolution for Baseline Model

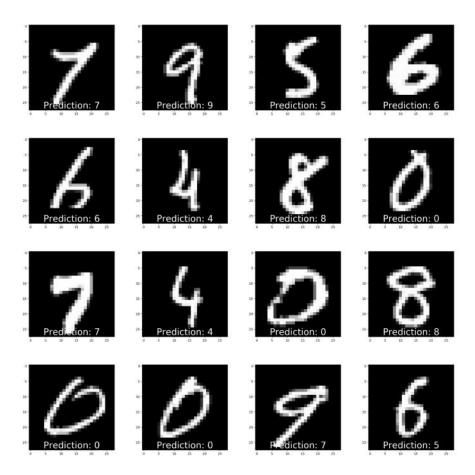


Following is the plot showing validation accuracy evolution over iterations:

Accuracy evolution for Baseline Model



1.1.3 Sample predictions



As can be seen from the above predictions, baseline model could predict ${\bf 14}$ out of ${\bf 16}$ images correctly.

1.2 2 convolutional layers

1.2.1 Overall architecture

Input $-\rightarrow$ Conv1 (32 3x3 filters, Stride of 1, Zero padding of 1) $-\rightarrow$ 2x2 Maxpool (Stride of 2) $-\rightarrow$ Conv2 (32 3x3 filters, Stride of 1, Zero padding of 1) $-\rightarrow$ 2x2 Maxpool (Stride of 2) $-\rightarrow$ Fully connected (10 outputs) $-\rightarrow$ Softmax classifier

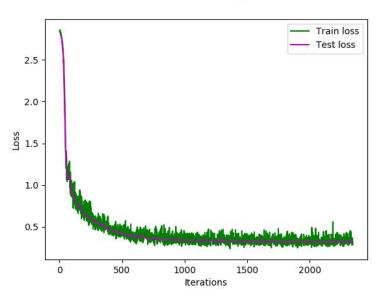
Batch size	128
Regularization	L2 (for weights only)
Regularization parameter (λ)	0.01
No. of training epochs	5
Update algorithm	SGD with Momentum acceleration

1.2.2 Results

The final test accuracy obtained for the model is 96.38%.

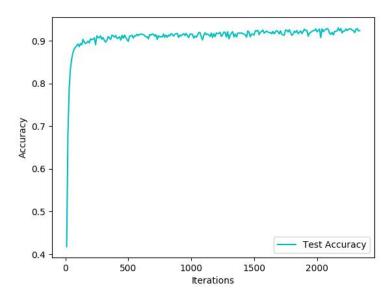
Following is the plot showing training and validation loss evolution over iterations:

Loss evolution for 2 conv layered Model

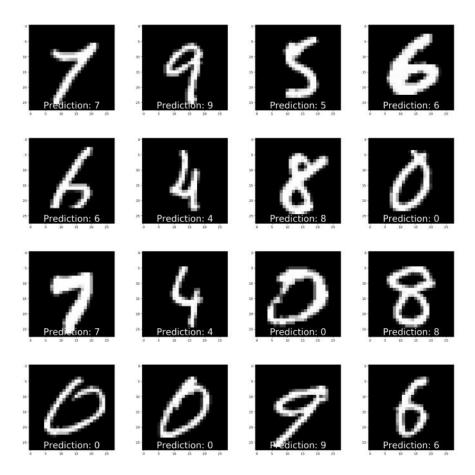


Following is the plot showing validation accuracy evolution over iterations:

Accuracy evolution for 2 conv layered Model



1.2.3 Sample predictions



As can be seen from the above predictions, baseline model could predict ${f 16}$ out of ${f 16}$ images correctly.

1.3 2 convolutional layers + 1 hidden fully connected layer

1.3.1 Overall architecture

Input $-\to$ Conv1 (32 3x3 filters, Stride of 1, Zero padding of 1) $-\to$ 2x2 Maxpool (Stride of 2) $-\to$ Conv2 (32 3x3 filters, Stride of 1, Zero padding of 1) $-\to$ 2x2 Maxpool (Stride of 2) $-\to$ Fully connected (500 outputs) $-\to$ Fully connected (10 outputs) $-\to$ Softmax classifier

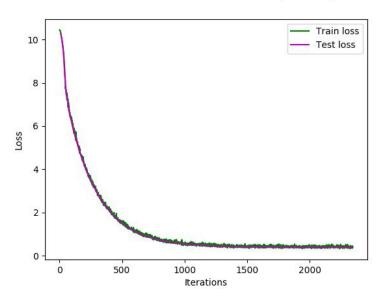
Batch size	128
Regularization	L2 (for weights only)
Regularization parameter (λ)	0.01
No. of training epochs	5
Update algorithm	SGD with Momentum acceleration

1.3.2 Results

The final test accuracy obtained for the model is 96.65%.

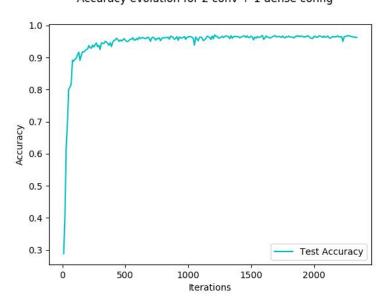
Following is the plot showing training and validation loss evolution over iterations:

Loss evolution for 2 Conv + 1 Dense layer config

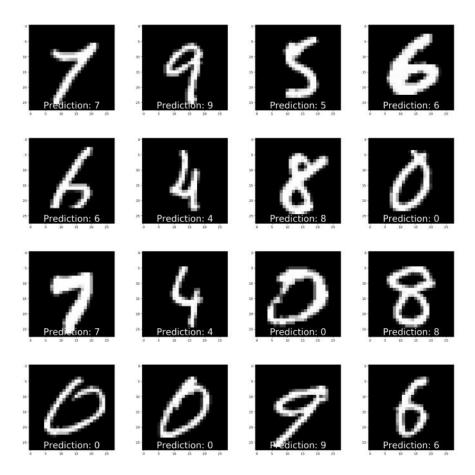


Following is the plot showing validation accuracy evolution over iterations:

Accuracy evolution for 2 conv + 1 dense config



1.3.3 Sample predictions



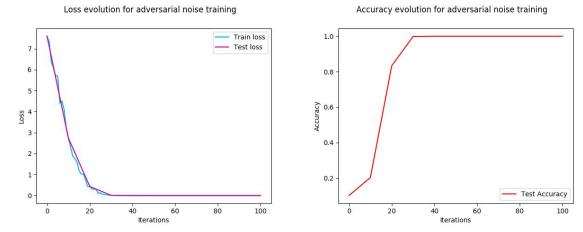
As can be seen from the above predictions, baseline model could predict ${f 16}$ out of ${f 16}$ images correctly.

2 Generating Adversarial Examples

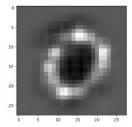
The best model obtained from the above examples is the model with 2 convolutional + 1 hidden dense configuration. Hence we use a trained model of that particular configuration for the following experiments. For training the noise, we carry out 100 batch iterations because the loss seems to converge within 100 iterations itself. And in each of the 10 cases, prediction accuracy reaches $\sim 100\%$.

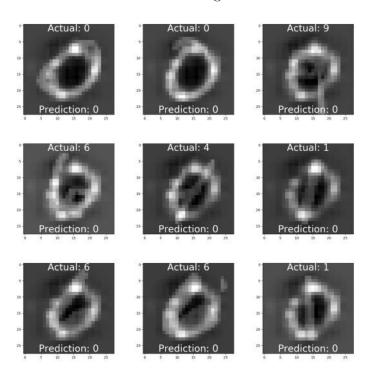
2.1 Adversarial Examples for label 0

Following are plots of loss evolution and accuracy evolution for adversarial noise training.



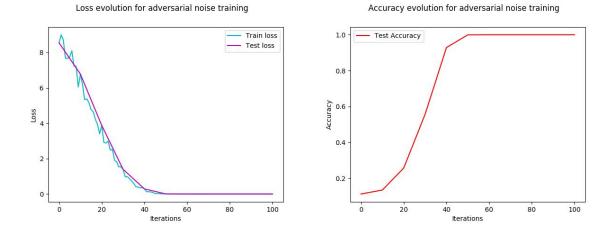
Following is the generated adversarial noise for 0:



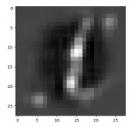


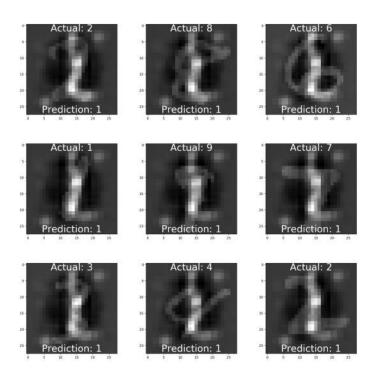
2.2 Adversarial Examples for label 1

Following are plots of loss evolution and accuracy evolution for adversarial noise training.



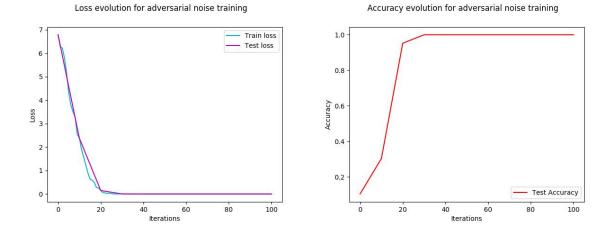
Following is the generated adversarial noise for 1:



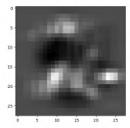


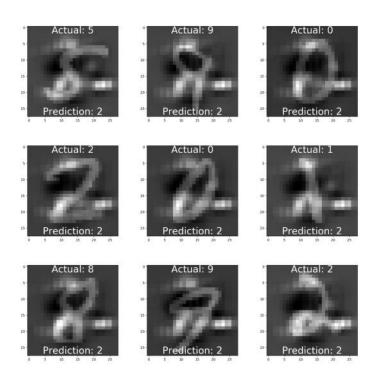
2.3 Adversarial Examples for label 2

Following are plots of loss evolution and accuracy evolution for adversarial noise training.



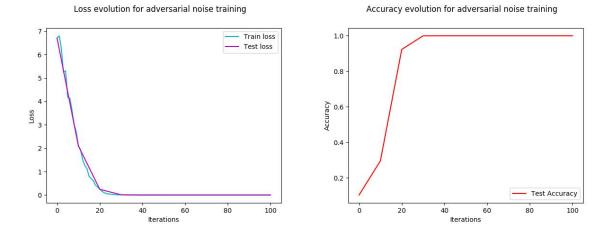
Following is the generated adversarial noise for 2:



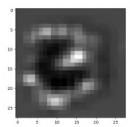


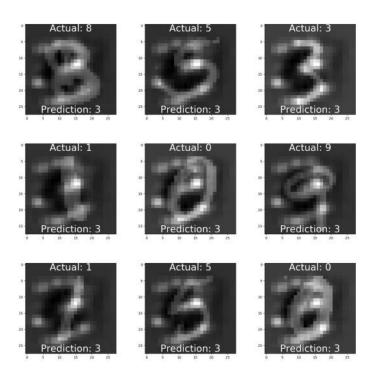
2.4 Adversarial Examples for label 3

Following are plots of loss evolution and accuracy evolution for adversarial noise training.



Following is the generated adversarial noise for 2:





2.5 Adversarial Examples for label 4

Following are plots of loss evolution and accuracy evolution for adversarial noise training.

Loss evolution for adversarial noise training

Accuracy evolution for adversarial noise training

1.0

0.8

0.8

0.4

0.2

0.2

0.2

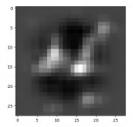
1.0

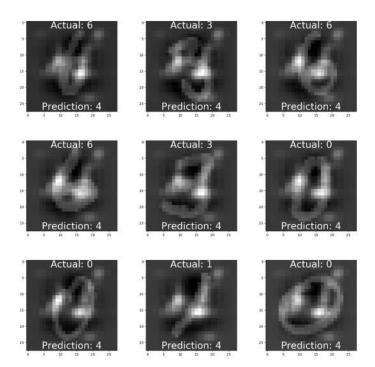
Test Accuracy

Test Accuracy

Iterations

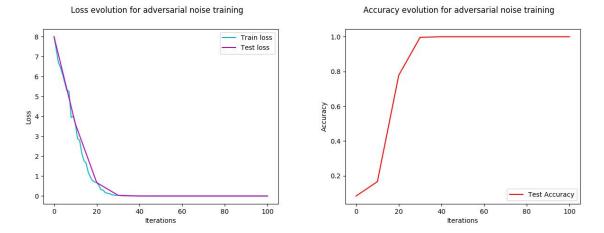
Following is the generated adversarial noise for 4:



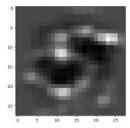


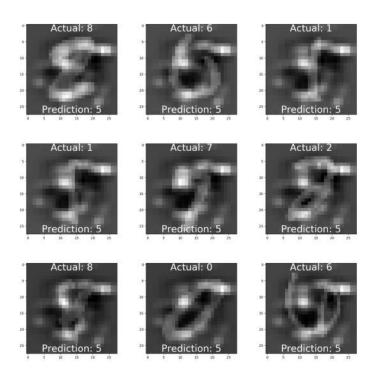
2.6 Adversarial Examples for label 5

Following are plots of loss evolution and accuracy evolution for adversarial noise training.



Following is the generated adversarial noise for 5:





2.7 Adversarial Examples for label 6

Following are plots of loss evolution and accuracy evolution for adversarial noise training.

Loss evolution for adversarial noise training

Accuracy evolution for adversarial noise training

1.0

0.8

0.8

0.4

0.2

0.2

0.2

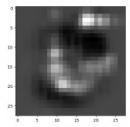
1.0

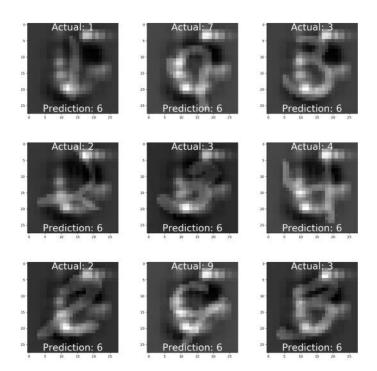
Test Accuracy

Test Accuracy

Iterations

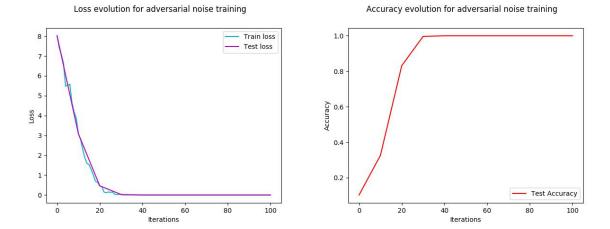
Following is the generated adversarial noise for 6:



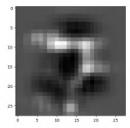


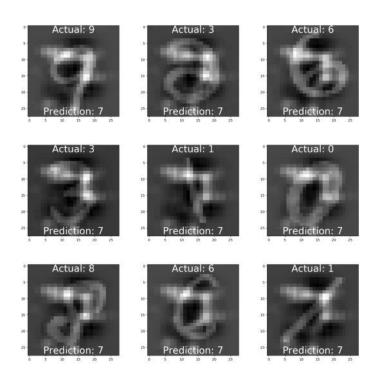
2.8 Adversarial Examples for label 7

Following are plots of loss evolution and accuracy evolution for adversarial noise training.



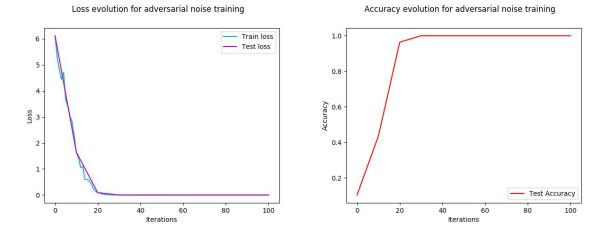
Following is the generated adversarial noise for 7:



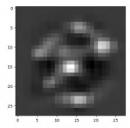


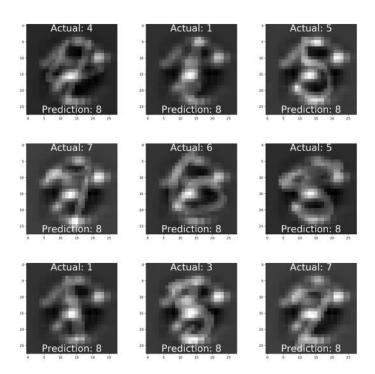
2.9 Adversarial Examples for label 8

Following are plots of loss evolution and accuracy evolution for adversarial noise training.



Following is the generated adversarial noise for 8:

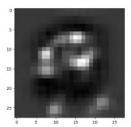


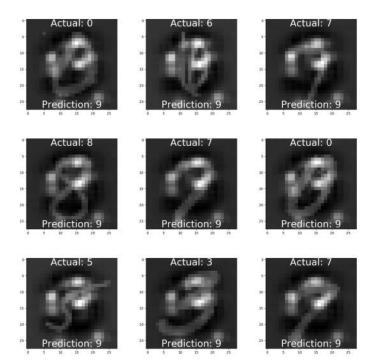


2.10 Adversarial Examples for label 9

Following are plots of loss evolution and accuracy evolution for adversarial noise training.

Following is the generated adversarial noise for 9:

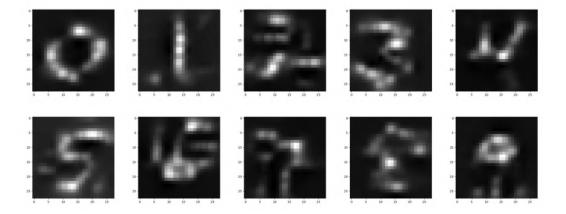




3 Visualizing Convolutional Neural Networks

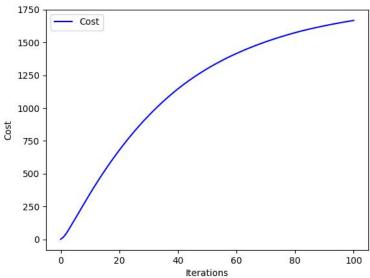
3.1 Final layer neurons as cost

The noise matrix visualizations for optimizing over final neurons are as follows:



There is a common trend observed in the increase in cost function over optimization iterations:

Cost evolution over optimization iterations



3.2 Max pooling centre neurons as cost

The noise matrix visualizations for optimizing over maxpool filter centre neurons are as follows:

