Deep Learning Assignment 1

Yun-shao Sung* and Chung-Ling Yao†

Abstract. This is the report for deep learning assignment 1

1. Warmup. Write $\frac{\partial E}{\partial X_{in}}$ in terms of $\frac{\partial E}{\partial X_{out}}$

$$\frac{\partial E}{\partial X_{in}} = \frac{\partial E}{\partial X_{out}} \frac{\partial F(X_{in}, W_i)}{\partial X_{in}} = \frac{\partial E}{\partial X_{out}} \frac{e^{X_{in}}}{(1+e^{X_{in}})^2} = \frac{\partial E}{\partial X_{out}} X_{out}(1 - X_{out}) \tag{1.1}$$

2. Multinomial logistic regression. Write the expression of $\frac{\partial (X_{out})_i}{\partial (X_{in})_j}$
if $i = j$, , and let $C = \sum_k e^{(X_I)_k} - e^{(X_I)_i}$

$$(X_o)_i = \frac{e^{(X_I)_i}}{\sum_k e^{(X_I)_k}} = \frac{e^{(X_I)_i}}{e^{(X_I)_0} + e^{(X_I)_i} + \ldots e^{(X_I)_i} + \ldots + e^{(X_I)_k}} = \frac{e^{(X_I)_i}}{C + e^{(X_I)_i}} \tag{2.1}$$

$$\frac{\partial (X_o)_i}{\partial (X_I)_i} = \frac{\partial}{\partial (X_I)_i} \left(\frac{e^{(X_I)_i}}{C + e^{(X_I)_i}} \right) = \frac{-\beta e^{-\beta (X_I)_i}}{C + e^{(X_I)_i}} + \frac{\beta e^{-2\beta (X_I)_i}}{(C + e^{(X_I)_i})^2} = \beta X_o(-1 + X_o) \tag{2.2}$$

if $i \neq j$, and let $K = \sum_k e^{(X_I)_k} - e^{(X_I)_j}$

$$\frac{\partial (X_o)_i}{\partial (X_I)_j} = \frac{\partial}{\partial (X_I)_j} \left(\frac{e^{(X_I)_i}}{K + e^{(X_I)_j}} \right) = \frac{\beta e^{-\beta (X_I)_i} e^{-\beta (X_I)_j}}{(K + e^{(X_I)_i})^2} = \beta (X_o)_i (X_o)_j \tag{2.3}$$

3. Torch (MNIST Handwritten Digit Recognition).

3.1. Original Model. The training and test accuracy of the original model. In the following experiments, we will compare the outcome of different configure with the original model. The training accuracy achieve 100% in epoch 30. The test accuracy increased slowly in the first several epochs. After that, the test accuracy stopped increasing. It never exceeded 99.56% and changed up and down slightly in each epoch.

*yss265@nyu.edu
†cly264@nyu.edu

Epoch	Training Accuracy (%)	Test Accuracy (%)
1	96.71	99.04
2	99.04	99.41
3	99.34	99.40
4	99.53	99.47
5	99.62	99.48
6	99.77	99.54
7	99.81	99.48
8	99.86	99.43
9	99.89	99.49
10	99.92	99.51

Table 3.1

The training and test accuracy of the original model

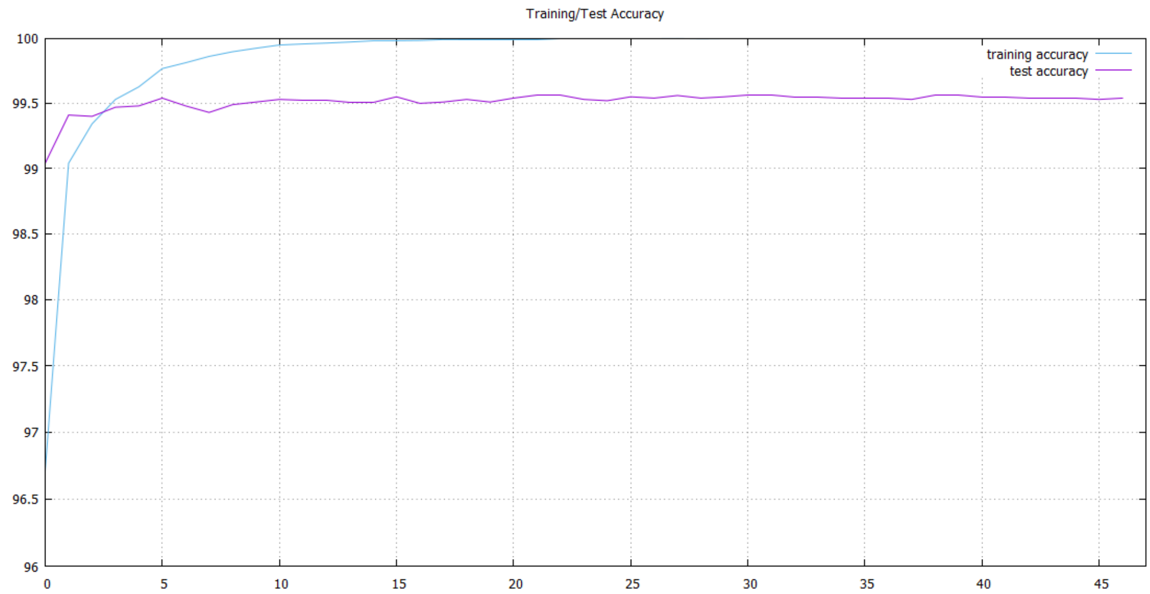


Figure 3.1. *The training and test accuracy with epochs*

3.2. Different normalization methods. Use different normalization methods, such as different Gaussian 1D normalization array size or without normalization. Virtualize it to see how the normalization changed the images, and compare the training/test accuracy in the first three epochs. We can find the performance of default settings (Gaussian1D(7)) is better than Gaussian1D(15) and no-normalization.

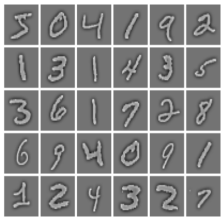
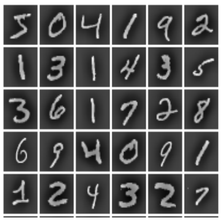
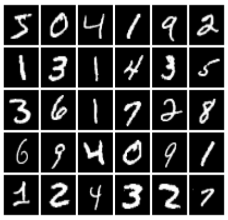
Normalization	Gaussian1D(7)		Gaussian1D(15)		no normalization	
Vitualization						
Accuracy in each epoch	training	test	training	test	training	test
1	96.71	99.04	96.72	98.88	96.66	98.79
2	99.04	99.41	99.00	99.11	98.99	99.14
3	99.34	99.40	99.32	99.28	99.27	99.31

Table 3.2

The training and test accuracy of different normalization methods

3.3. Different activation function. The original activation function is tanh. We tried reLU and compare them. We found the original tanh function works better in both training and test accuracy.

Loss Function	Tanh(default)		reLU	
Accuracy in each epoch	training	test	training	test
1	96.71	99.04	96.52	98.73
2	99.04	99.41	98.86	99.02
3	99.34	99.40	99.13	99.08

Table 3.3

The training and test accuracy of different activation function

3.4. Different loss function. The original loss function is NLL. We changed it to multi-margin and MSE. We found the multi-margin generate the same result with NLL. The MSE looks slightly better in training accuracy, but not in test accuracy.

Loss Function	NLL(default)		Multi-margin		MSE	
Accuracy in each epoch	training	test	training	test	training	test
1	96.71	99.04	96.71	99.04	96.74	99.04
2	99.04	99.41	99.04	99.41	99.07	99.30
3	99.34	99.40	99.34	99.40	99.35	–

Table 3.4

The training and test accuracy of different loss function

3.5. 3-layer model structure. With the original process pipline: SpatialConvolutionMM, Tanh, SpatialLPPooling, SpatialSubtractiveNormalization, and NLL as loss function, we construct additional layer, and the dimension is from (64,64,128) to (32,64,128,256). So now it is 3-layer structure, followed by standard 2-layer neural network. For training set, there is a noticeable faster convergent rate in 3-layer than in 2-layer model, that 3-layer model can reach 100% accuracy when at epoch 21 compare to epoch 29 in 2-layer model. However, this phenomenon seems differ not much when running on test set. Potentional explaination is the 3-layer model may have better way to fit the training data so converged faster, but might be a bit over-fitted when run on general test set.

Loss Function	3-layer Model		2-layer Model	
Accuracy in each epoch	training	test	training	test
20	99.99	99.51	99.98	99.53
21	100.00	99.51	99.98	99.51
22	99.99	99.53	99.99	99.54
23	100.00	99.53	99.99	99.56
24	100.00	99.57	99.99	99.56
25	100.00	99.52	99.99	99.53
26	100.00	99.52	99.99	99.52
27	100.00	99.56	99.99	99.55
28	100.00	99.52	99.99	99.54
29	100.00	99.52	100.00	99.56
30	100.00	99.53	99.99	99.54
31	100.00	99.52	100.00	99.55

Table 3.5

The training and test accuracy of 3-layer versus 2-layer model

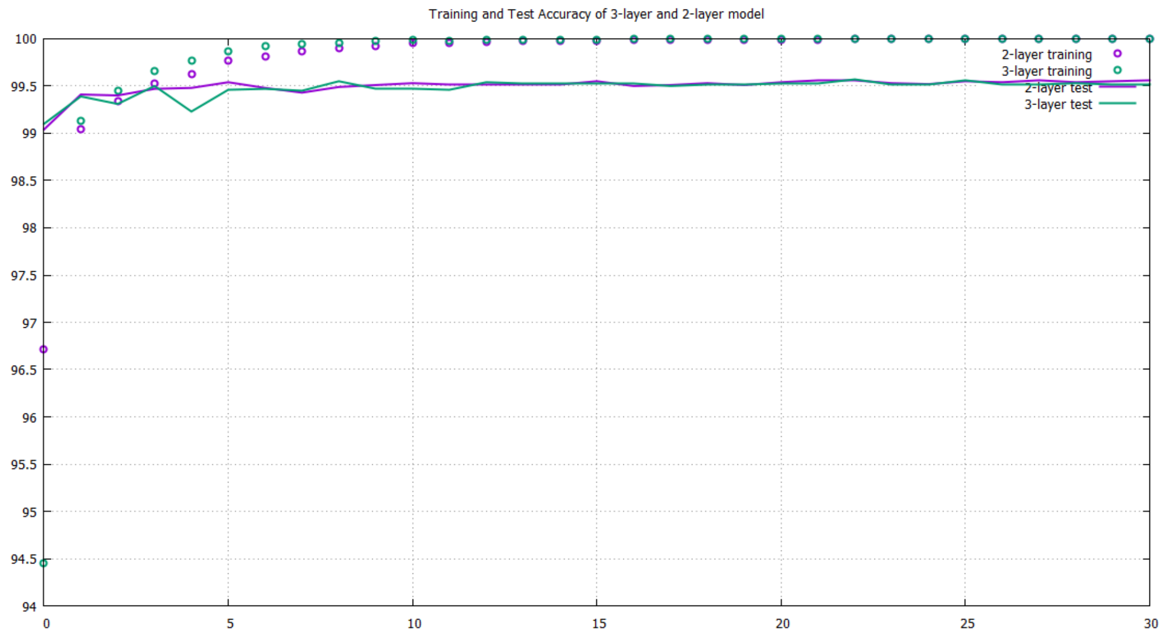


Figure 3.2. *The training and test accuracy of 3-layer versus 2-layer model*