Assignment 1 Report

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This report is about the result from using my implementation of the multi-layers perceptron on Rust language to solve 2 problems given on 261456 - INTRO COMP INTEL FOR CPE class. If you are interested to know how I implement the multi-layers perceptron and trained a model to solve these problems , you can see the source code for all models that have been shown in this report on my Github repository.

1 Flood Dataset

Problem

We want to predict water level at 7 hours ahead given station 1 and station 2 data at present, 1 hour before, 2 hours before, and 3 hours before.

	A	B	C	D	E	F	G	H	I
1	s1_t3	s1_t2	s1_t1	s1_t0	s2_t3	s2_t2	s2_t1	s2_t0	t7
2	95	95	95	95	148	149	150	150	153
3	95	95	95	95	149	150	150	150	153
4	95	95	95	95	150	150	150	150	153
5	95	95	95	95	150	150	150	150	153
6	95	95	95	95	150	150	150	152	153
7	95	95	95	95	150	150	152	152	153
8	95	95	95	96	150	152	152	153	153
9	95	95	96	97	152	152	153	153	153
10	95	96	97	98	152	153	153	153	153
11	96	97	98	100	153	153	153	153	154
12	97	98	100	100	153	153	153	153	155
13	98	100	100	100	153	153	153	153	156
14	100	100	100	101	153	153	153	153	156

Figure 1: Examples of given data where s1_t3 is water level from 3 hours before at station 1, and so on. t7 is water level at 7 hours ahead.

Parameters Setting

- All nodes use *sigmoid* as an activation function except output node that use *linear* function.
- Weights are random number that is in range $[-1, 1]$
- Each layer's bias is 1
- Use MSE (Mean Squared Error) as a loss function.

Training

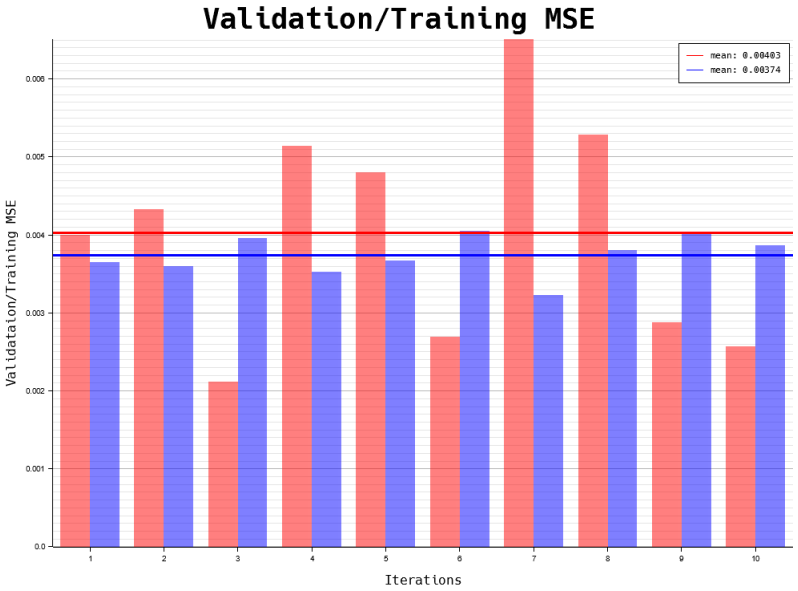
Use 10% cross-validation, and preprocess our data by using training set *mean* and *std* to standardize (For each data point x we calculate new $x' = \frac{x-mean}{std}$) both training set and validation set before training with SGD (Stochastic Gradient Descent) algorithm. Then, we train each cross-validation set for 1000 epochs.

We will create one base model that should perform good enough and create a variations base on that model, that is train with no *momentum*, train with smaller *learning rate*, and add more layers or hidden nodes to see that if we introduce those variations, will the model perform better, converge faster, or have no improvement at all?

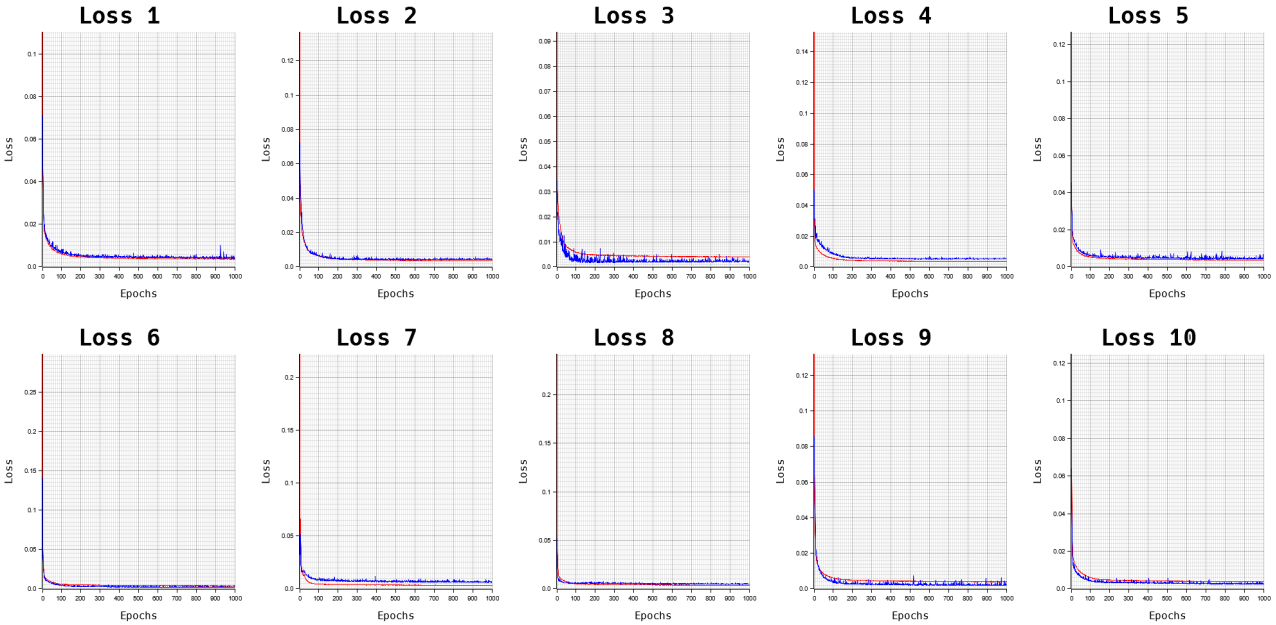
Training Result

Flood-8-4-1

Our base model that contains only 8 input nodes, 1 hidden layer with 4 nodes, and 1 output node train with $lr = 0.01$ and $momentum = 0.01$. The training process take about 60 seconds. Below is the graphs we get from training this model.



(a) Each iteration training (blue) and validation (red) MSE at last epoch

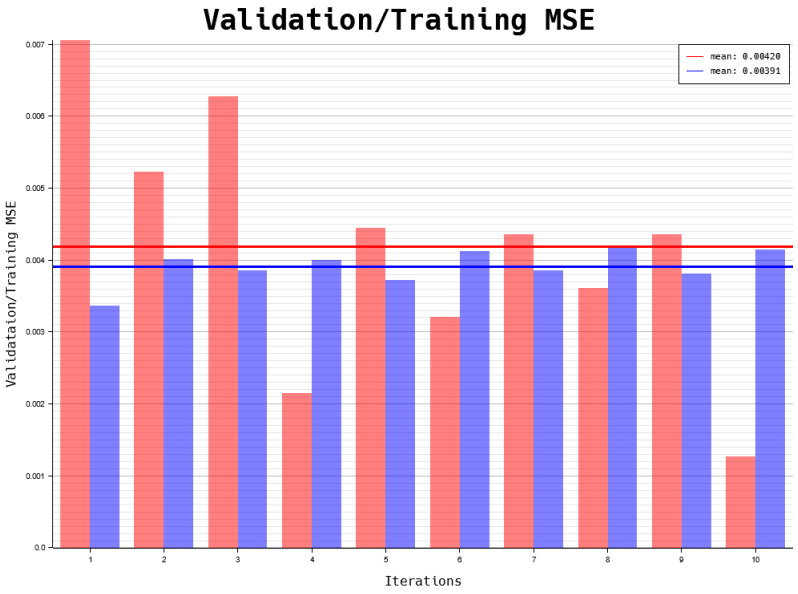


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

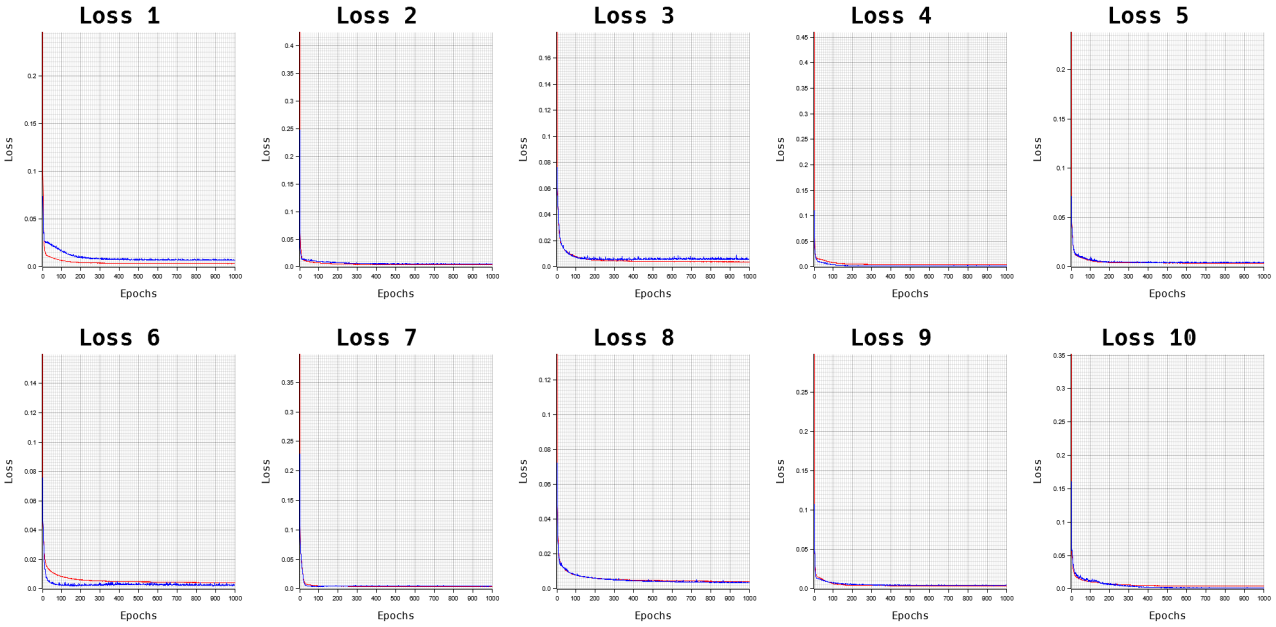
Figure 2: Training result of Flood-8-4-1.

Flood-8-4-1 with no momentum

Same base model but train with $lr = 0.01$ and $momentum = 0$. The training process take about 60 seconds. Below is the graphs we get from training this model.



(a) Each iteration training (blue) and validation (red) MSE at last epoch

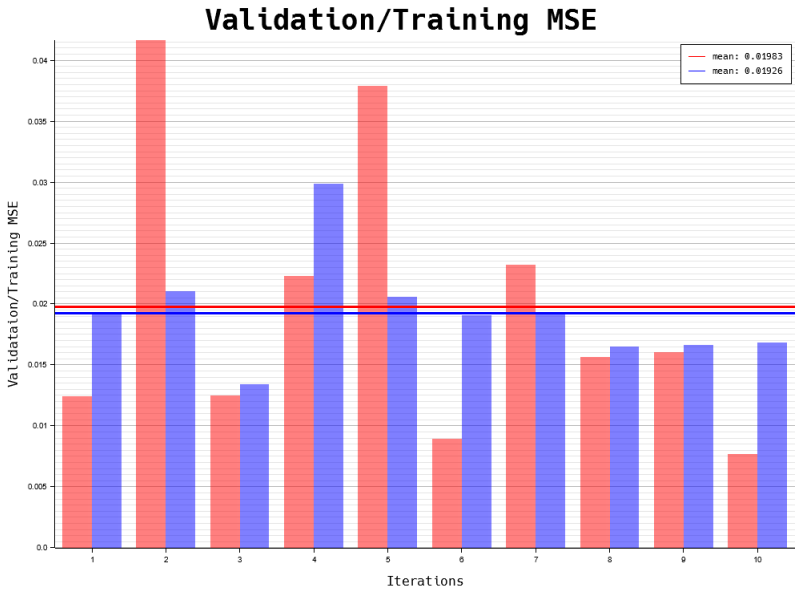


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

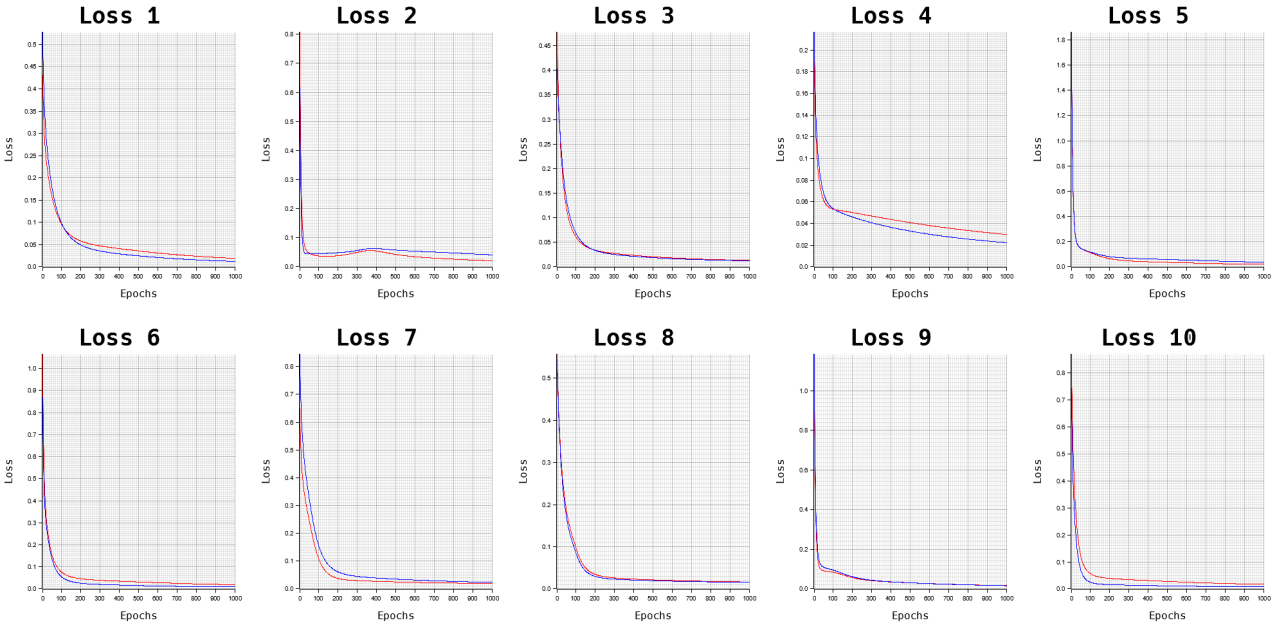
Figure 3: Training result of Flood-8-4-1 with no momentum.

Flood-8-4-1 with small learning rate

Same base model but train with $lr = 0.0001$ and $momentum = 0.01$. The training process take about 59 seconds. Below is the graphs we get from training this model.



(a) Each iteration training (blue) and validation (red) MSE at last epoch

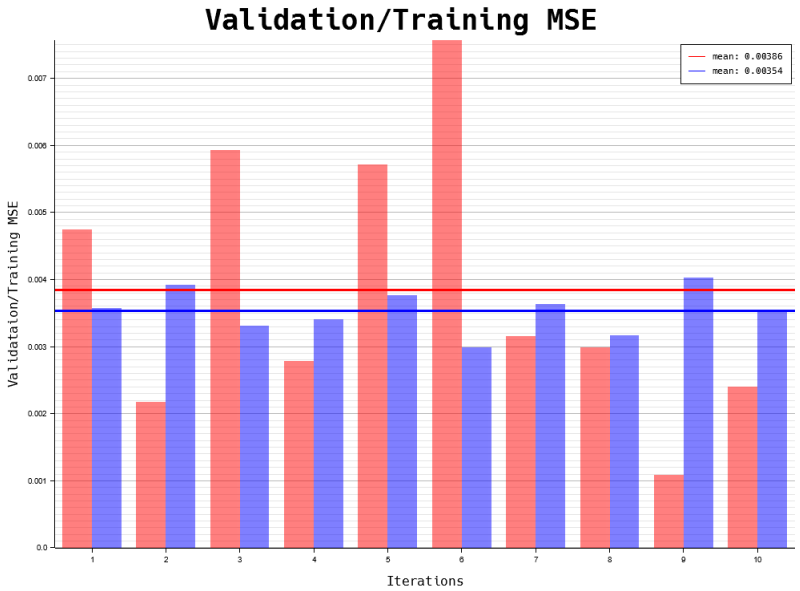


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

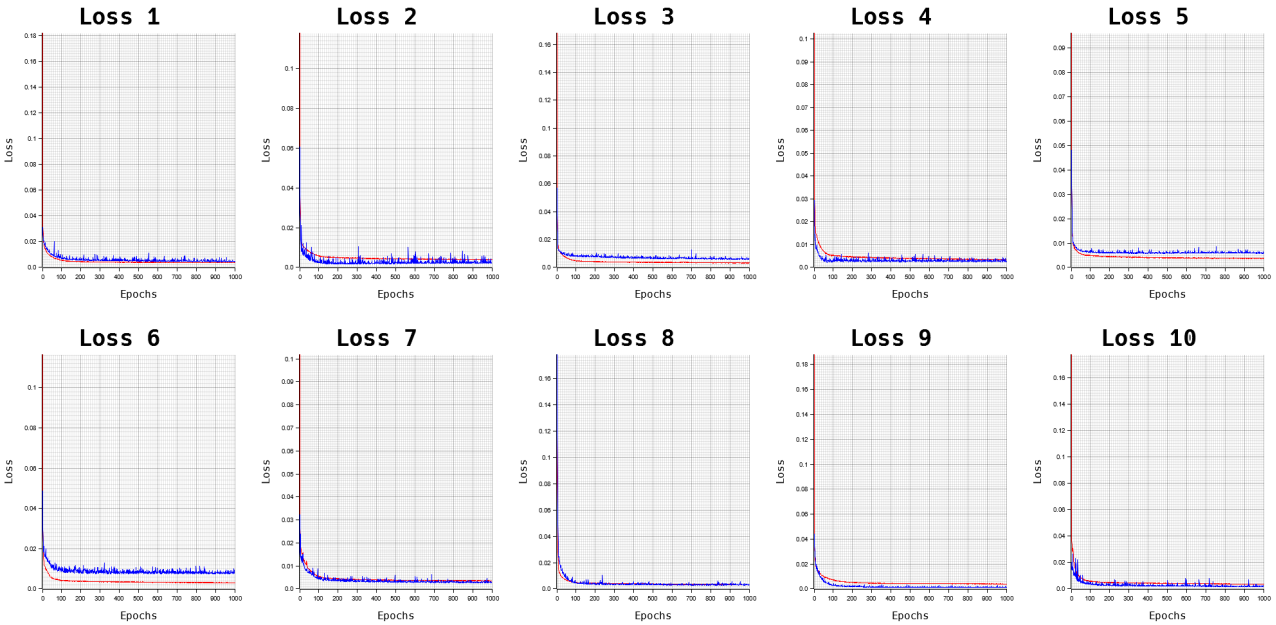
Figure 4: Training result of Flood-8-4-1 with smaller learning rate.

Flood-8-8-1

Bigger model that contains 8 input nodes, 1 hidden layer with 8 nodes, and 1 output node train with $lr = 0.01$ and $momentum = 0.01$. The training process take about 105 seconds. Below is the graphs we get from training this model.



(a) Each iteration training (blue) and validation (red) MSE at last epoch



(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

Figure 5: Training result of Flood-8-8-1.

Analysis

From table 1, we can see that model with the same size will use around the same amount of training time, but with the bigger model, the training time gets longer. We can also see that Flood-8-4-1 with small learning rate is the worst in terms of validation set mean MSE compare with other models, the model seems to be stuck at a certain gradient level (see fig. 4b the model is slowly converging but too slow). Lastly, we can also see that the best performing model in terms of validation set mean MSE is Flood-8-8-1 at 3.86×10^{-3}.

Model	Training Time (seconds)	Validation Set Mean MSE (10^{-3})
Flood-8-4-1	60	4.03
Flood-8-4-1 with no momentum	60	4.20
Flood-8-4-1 with small learniing rate	59	19.83
Flood-8-8-1	105	3.86

Table 1: Training time and validation set mean MSE (red line on fig. 2a, fig. 3a, fig. 4a, and fig. 5a) of each Flood model.

We can also see a similar pattern on all of our Flood models in fig. 2b, fig. 3b fig. 4b, and fig. 5b the MSE is decreasing very fast at the first 100 epochs and seems to be stuck at a certain level of MSE or very slow in reduce the MSE.

2 CrossPat Dataset

Problem

We want to predict the class (1 of possible 2 classes) that belongs to our inputs (or features).

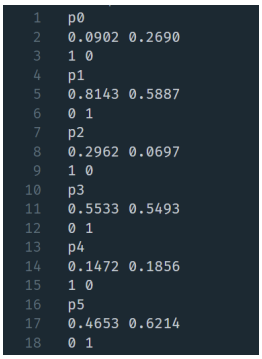


Figure 6: Examples of given data where px is an object and the first line after it is its features, the second line is its class

Parameters Setting

- All nodes use *sigmoid* as an activation function.
- Weights are random number that is in range $[-1, 1]$
- Each layer's bias is 1
- Use MSE (Mean Squared Error) as a loss function.

Training

Use 10% cross-validation with no data preprocessing, and train with SGD (Stochastic Gradient Descent) algorithm. Then, we train each cross-validation set for 5000 epochs.

We will create one base model that should perform good enough and create a variations base on that model, that is train with no *momentum*, train with smaller *learning rate*, and add more layers or hidden nodes to see that if we introduce those variations, will the model perform better, converge faster, or have no improvement?

Training Result

Accuracy is calculate using this equation $\frac{TP+TN}{TP+TN+FN+FP}$ where TP, TN, FN, FP comes from confustion matrix.

Cross-2-4-1

Our base model with 2 input nodes, 1 hidden layer with 4 nodes, and 1 output node train with $lr = 0.01$ and $momentum = 0.01$. We use only 1 output node because this is a binary classification task so we can just map a pair $(1, 0) \rightarrow 1$ and $(0, 1) \rightarrow 0$. The training process takes about 122 seconds..

Cross-2-4-1 with no momentum

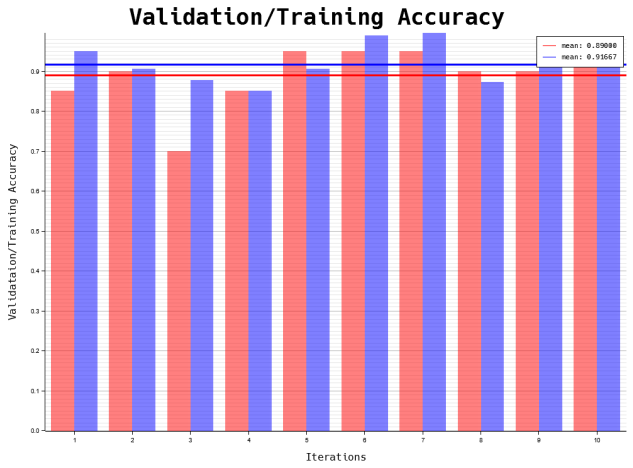
Same base model train with $lr = 0.01$ and $momentum = 0.0$. The training process takes about 122 seconds.

Cross-2-4-1 with smaller learning rate

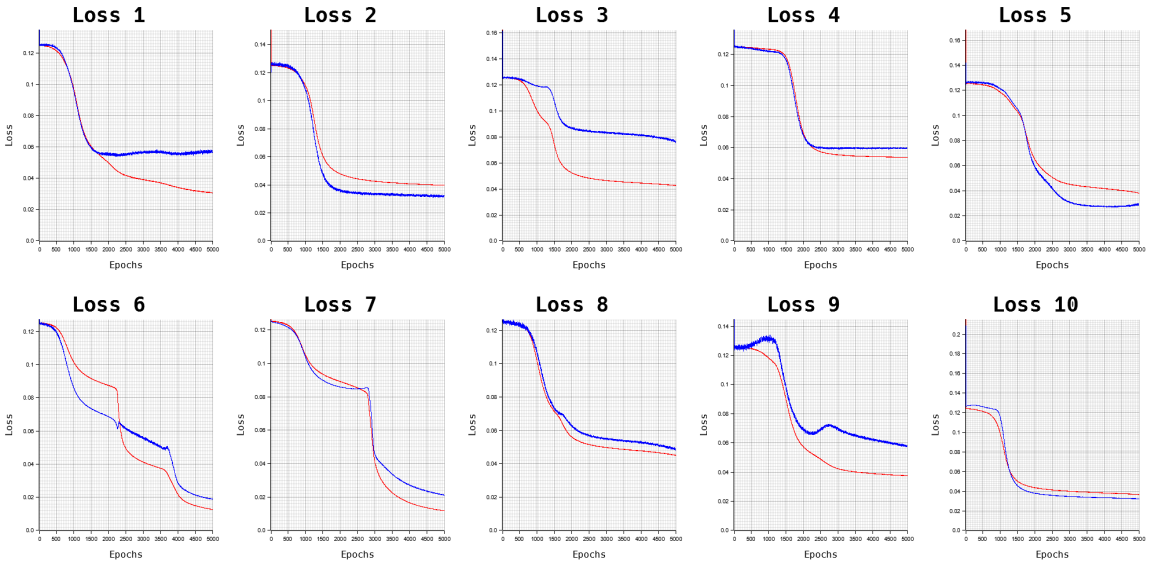
Same base model train with $lr = 0.0001$ and $momentum = 0.01$. The training process takes about 124 seconds.

Cross-2-8-1

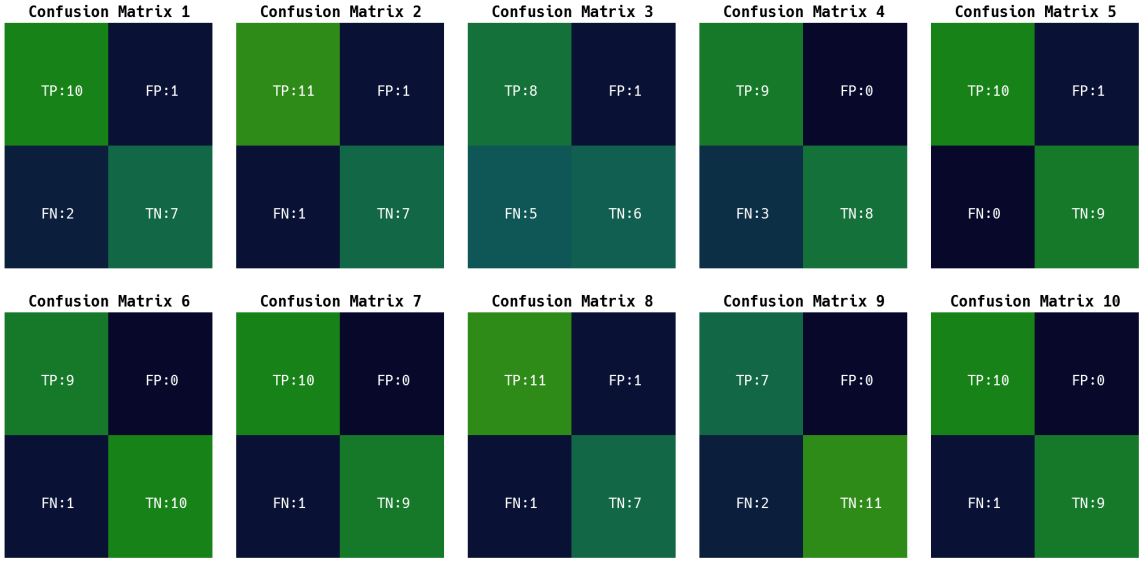
Bigger model that contains 2 input nodes, 1 hidden layer with 4 nodes, and 1 output node train with $lr = 0.01$ and $momentum = 0.01$. The training process takes about 230 seconds.



(a) Each iteration training (blue) and validation (red) set accuracy at last epoch

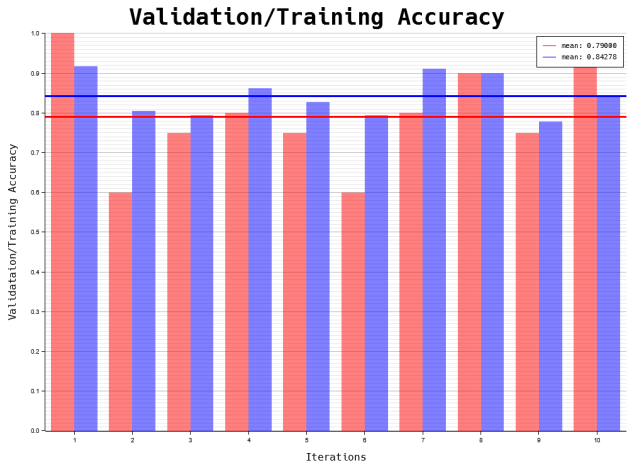


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

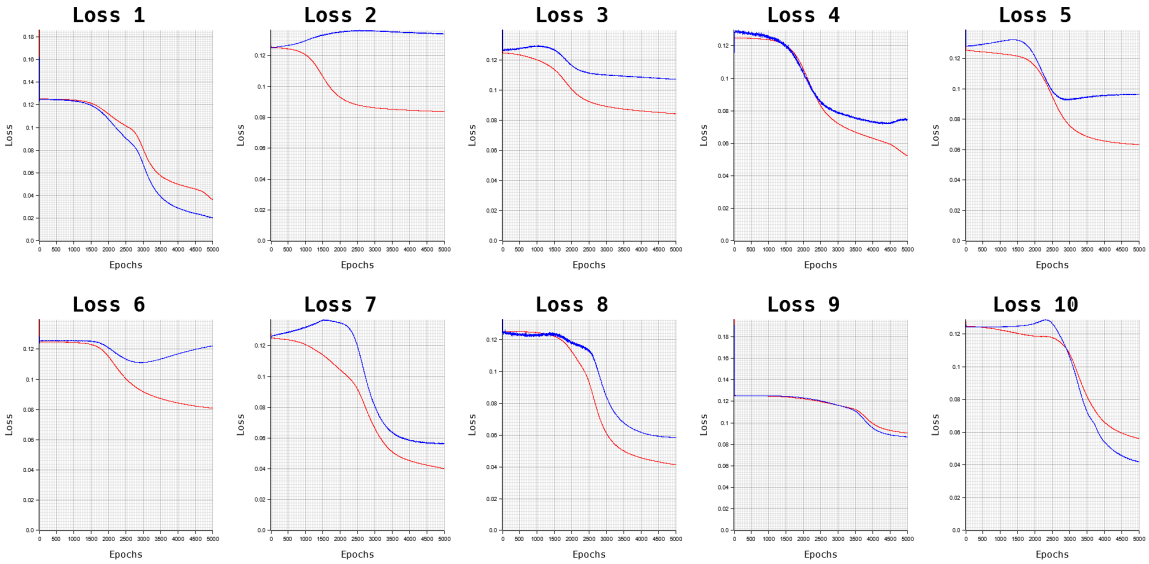


(c) Each iterations validation set confusion matrix where y-axis is an actual class $1, 0$ top to bottom and x-axis is predicted class $1, 0$ left to right.

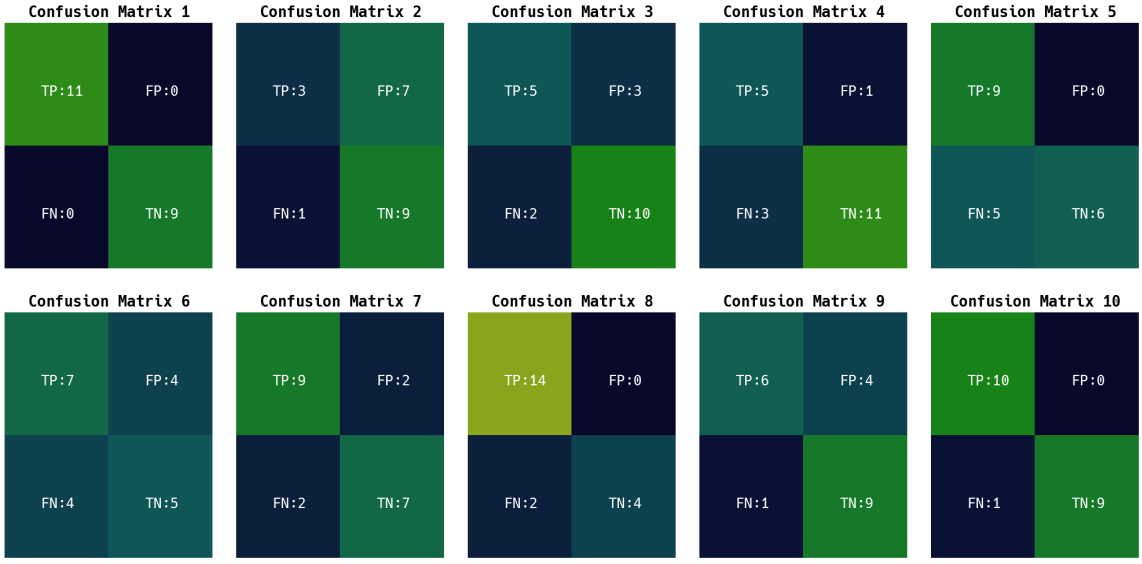
Figure 7: Training result of Cross-2-4-1.



(a) Each iteration training (blue) and validation (red) set accuracy at last epoch

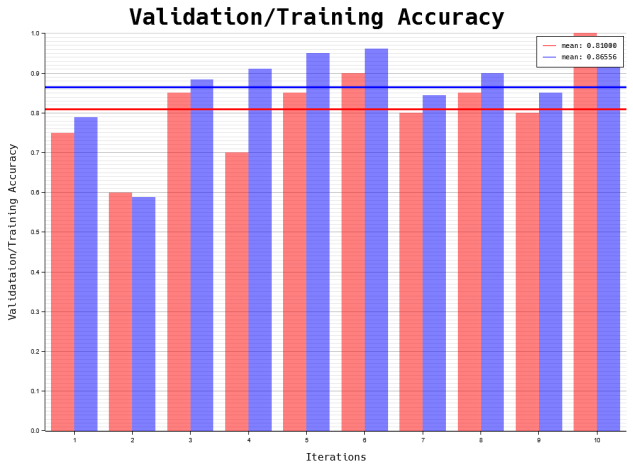


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

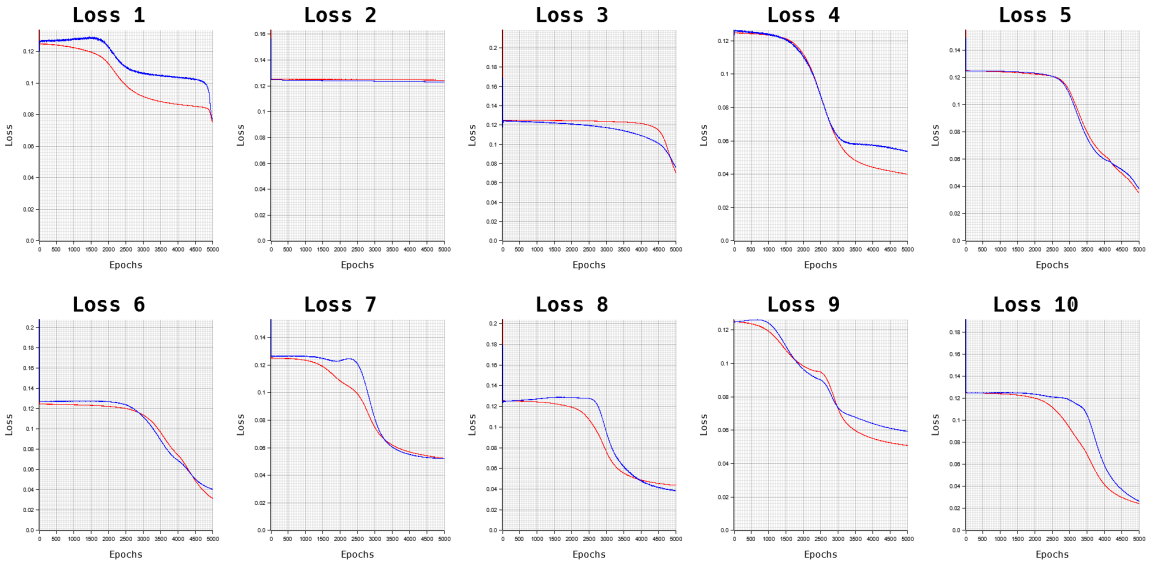


(c) Each iterations validation set confusion matrix where y-axis is an actual class $1, 0$ top to bottom and x-axis is predicted class $1, 0$ left to right.

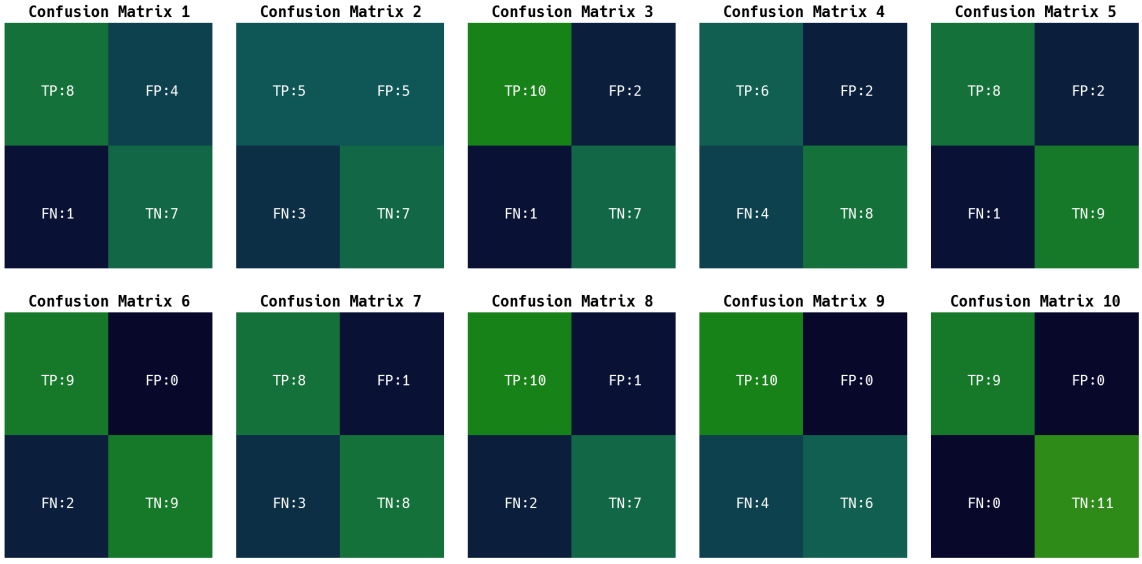
Figure 8: Training result of Cross-2-4-1 with no momentum.



(a) Each iteration training (blue) and validation (red) set accuracy at last epoch

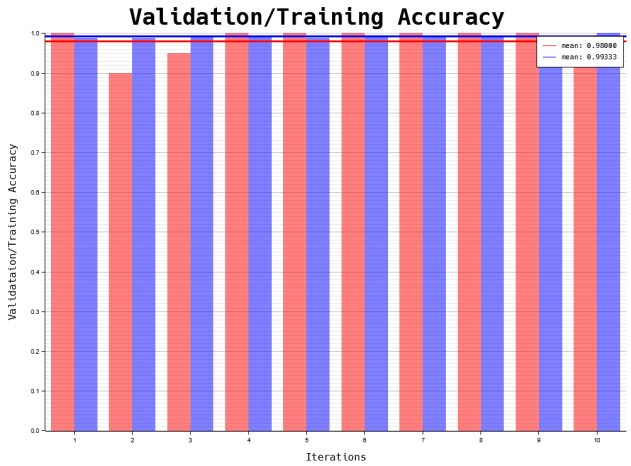


(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.

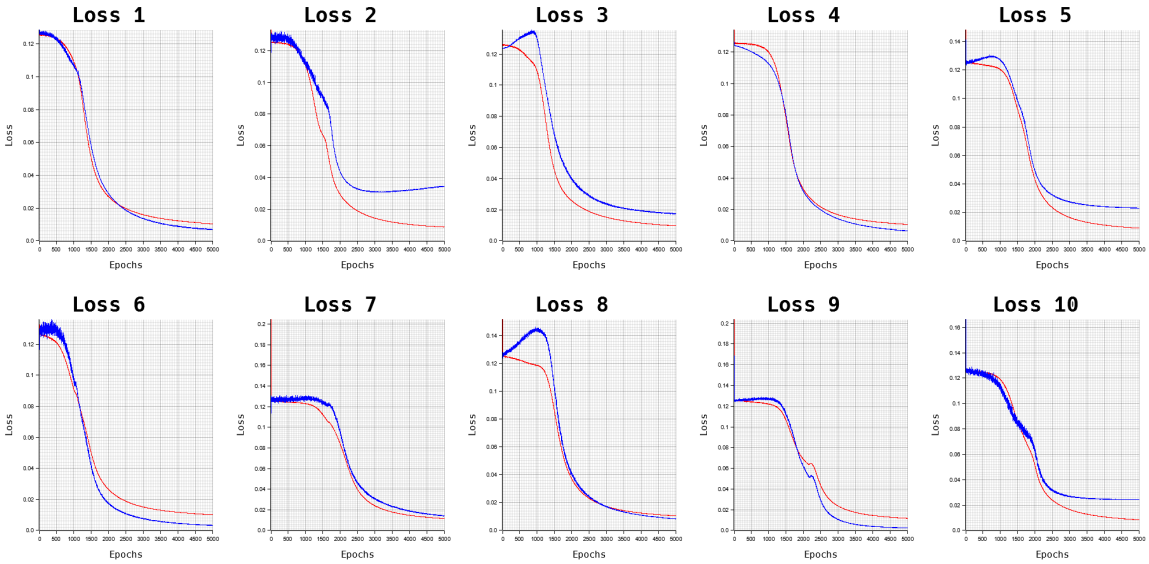


(c) Each iterations validation set confusion matrix where y-axis is an actual class $1, 0$ top to bottom and x-axis is predicted class $1, 0$ left to right.

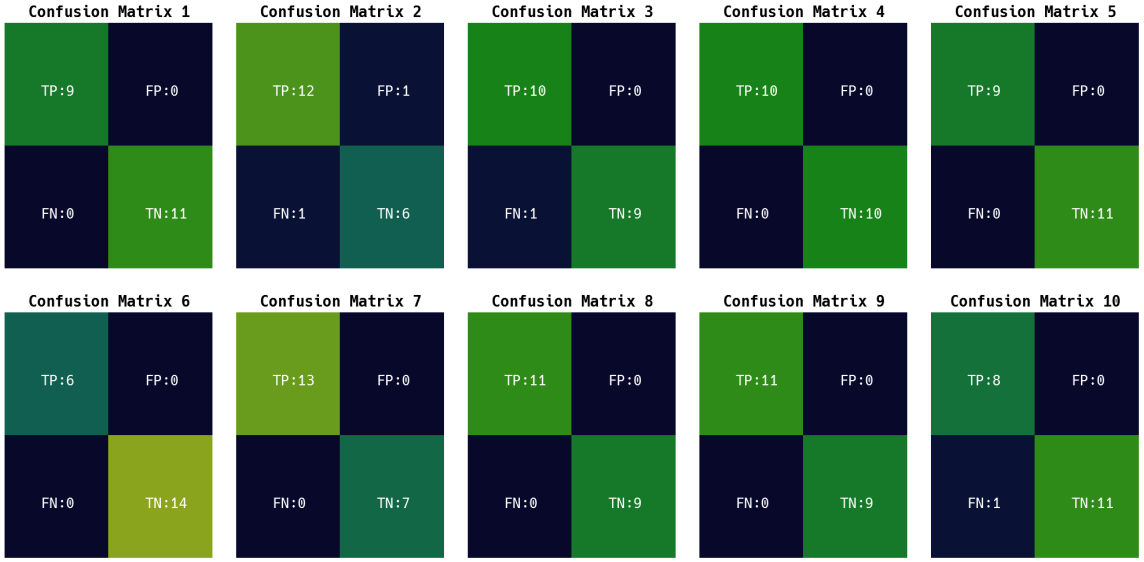
Figure 9: Training result of Cross-2-4-1 with smaller learning rate.



(a) Each iteration training (blue) and validation (red) set accuracy at last epoch



(b) Each iteration training MSE (blue) and validation MSE (red) at each epoch.



(c) Each iterations validation set confusion matrix where y-axis is an actual class $1, 0$ top to bottom and x-axis is predicted class $1, 0$ left to right.

Figure 10: Training result of Cross-2-8-1.

Analysis

From table 2, we can see that all Cross-2-4-1 models used around the same amount of training time but only the base model is performing okay in terms of validation set mean accuracy. And the biggest model Cross-2-8-1 is performing much better than others at 98% validation set mean accuracy but the training time used is also around 2 times other models training time.

Model	Training Time (seconds)	Validation Set Mean Accuracy (%)
Cross-2-4-1	122	89
Cross-2-4-1 with no momentum	122	79
Cross-2-4-1 with small learniing rate	124	81
Cross-2-8-1	230	98

Table 2: Training time and validation set mean accuracy (red line on fig. 7a, fig. 8a, fig. 9a, and fig. 10) of each Cross model.

From fig. 10b, we can also see that Cross-2-8-1 training is going smoother with a steady decrease in MSE compared with other models as we can see in fig. 7b, fig. 8b, and fig. 9b the graphs overall seem to go down and stop at a certain level indicating that the model stop learning. Confusion matrix of Cross-2-8-1 from fig. 10c also, show that the error is not biased to one specific class indicating that the model learned about the 2 classes equally. On the other hand, the confusion matrix of all Cross-2-4-1 models specifically in fig. 8c and fig. 9c we can see that there're a big number of FP and FN and in some iteration the error is biased to one of FP or FN.