

ELEC 576 / COMP 576 Fall 2020 : Assignment1

Mst Afroja Akter

October 2020

1 Backpropagation in a Simple Neural Network

(a). Dataset

We will use make-moon dataset from Scikit-learn. This dataset has two two classes (e.g. "male" and "female"). Figure 1 is the visualization of this dataset.

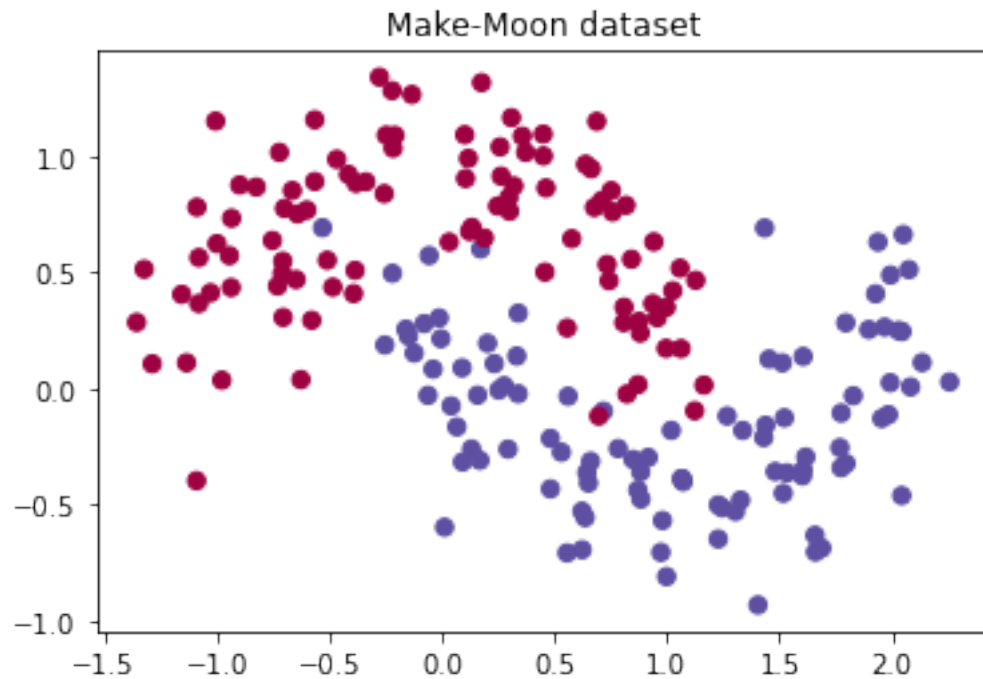


Figure 1: Make-Moon dataset

Activation Function

This part of the problem is in the code three-layer-neural-network.py We derived three activation functions 'Tanh', 'sigmoid' and 'ReLU' in the function actFun(self, z, type) and their derivative in the function diff-actFun.

(c) Build the Neural Network

The Neural Network has three layers: one input layer, one hidden layer and one output layer. The number of neurons per layer are 2, 4, 2 respectively. The input vector of the network is denoted by X and the output/target vector is denoted by y . The output layer has softmax activation function. For this network we used Entrophy loss function

$$L(y, \hat{y}) = -\frac{1}{N} \sum_{n \in N} \sum_{i \in C} y_{n,i} \log \hat{y}_{n,i}$$

Here, y are one-hot-encoded vectors and \hat{y} are vectors of probabilities.

(e)

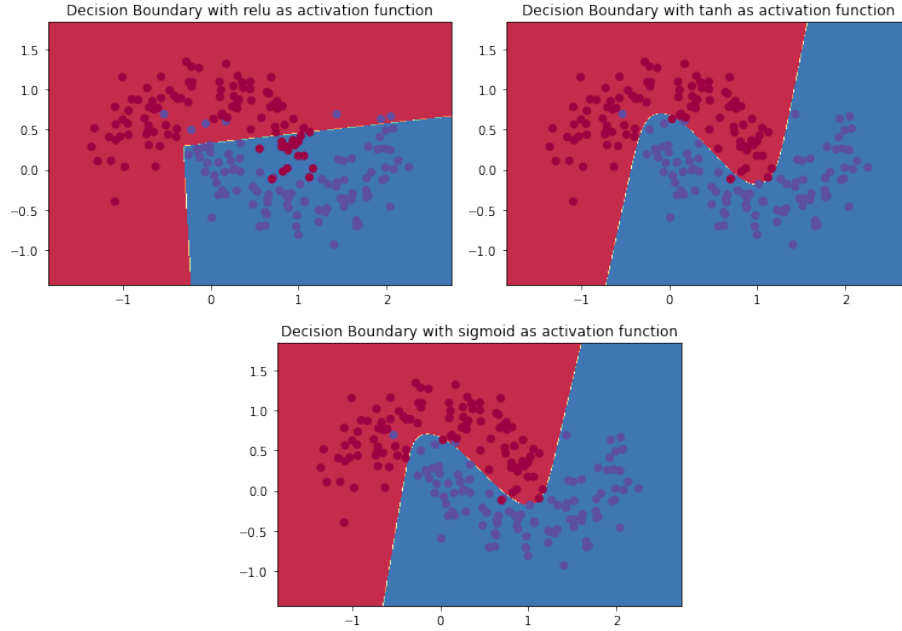


Figure 2: Decision Boundary with 'ReLU', 'tanh' and 'sigmoid' activation functions

The figure 2 shows the decision boundary plot with 'ReLU', 'tanh' and 'sigmoid' activation functions. Figure 3 shows the respective loss function keeping

the network architecture same. Here we see that decision boundary with 'tanh' and 'sigmoid' performs better than the decision boundary with 'ReLU' activation function. The loss function with relu activation function is unstable, which relates to the bad performance of decision boundary.

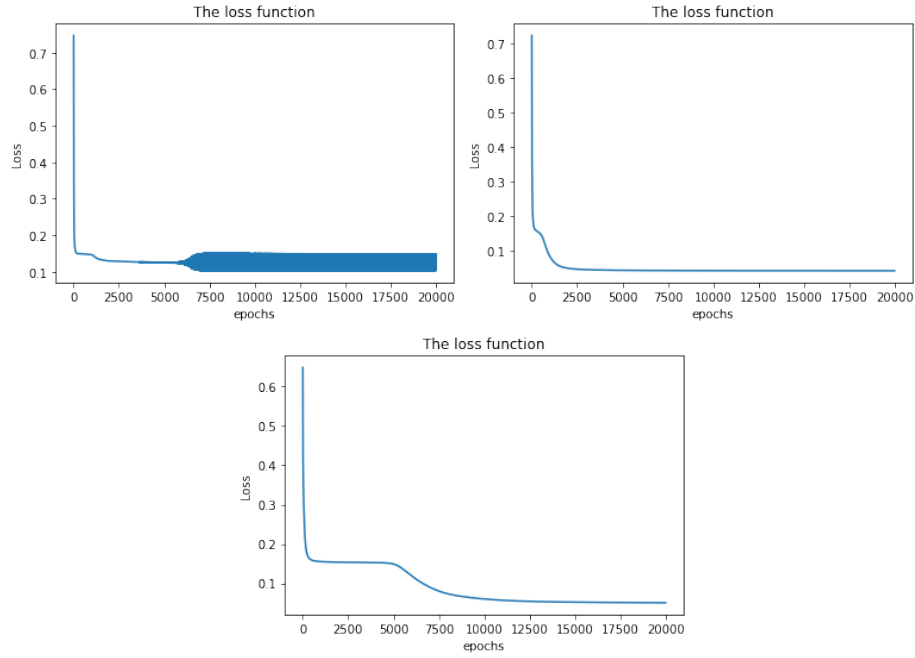


Figure 3: The Loss with 'ReLU', 'tanh' and 'sigmoid' activation functions

Figure 4 shows with higher number of neurons in the hidden layer leads to overfitting of the decision boundary. One obvious reason this overfitting could be due to the memorization of training data. In this situation neural network model performs better in training data and performs poorly in the test data.

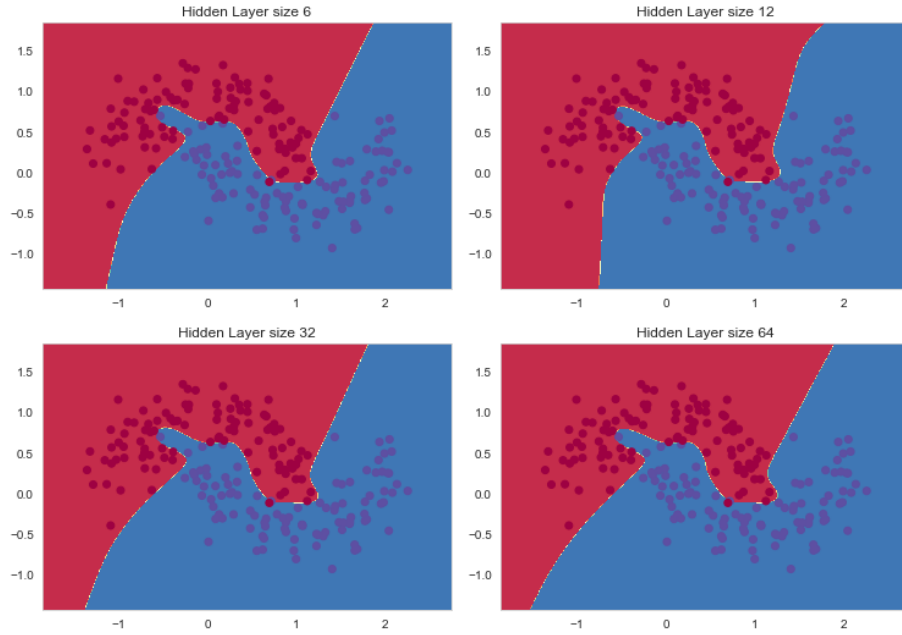


Figure 4: Decision Boundary with 6, 12, 32 and 64 hidden layers and 'tanh' activation function

(f)Deep Neural Network¹

Result in figure 5 generated with a deep neural network with two hidden layers and 3 neurons in each hidden layer. The input layer has two neuron and the output layer has two neuron. I used sigmoid activation function with learning rate 0.05 in 1000 iteration. I tried with higher iteration number but I couldn't get better result.

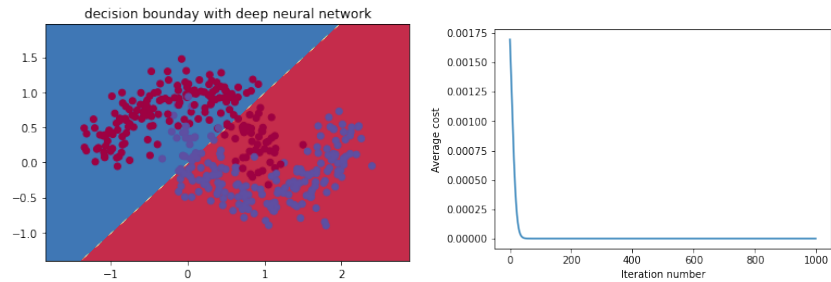


Figure 5: Decision boundary with deep neural network

¹I didn't use Class from the 'three layer neural network: I am not that comfortable yet with classes.

2 Training a Simple Deep Convolutional Network on MNIST

The simple deep convolutional network architecture:

conv1(5 - 5 - 1 - 32) - ReLU - maxpool(2 - 2) - conv2(5 - 5 - 32 - 64) - ReLU - maxpool(2 - 2) - fc(1024) - ReLU - DropOut(0.5) - Softmax(10)

(a)

Figure 6 and 7 shows the training loss and training accuracy of the simple deep convolutional network with the above mentioned architecture. The loss curves from figure 8 shows that the validation and test loss follows the training loss and the same for accuracy curves. This is a good indication of Network learning.

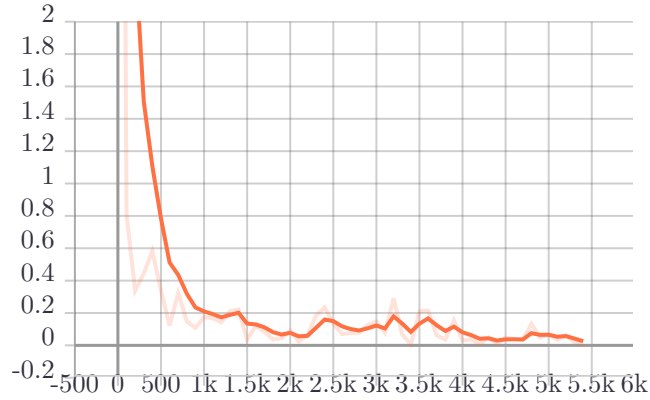


Figure 6: Train Loss

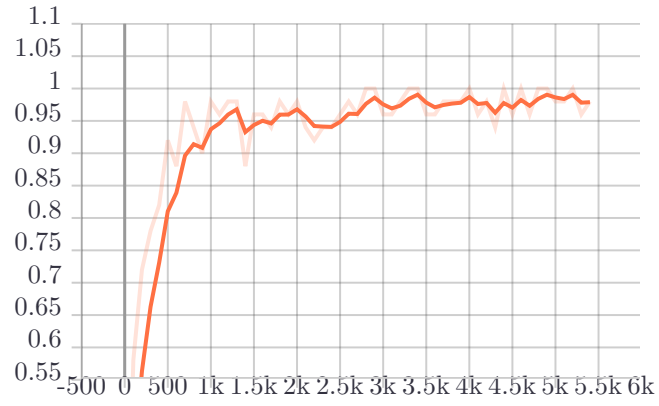


Figure 7: Train Accuracy

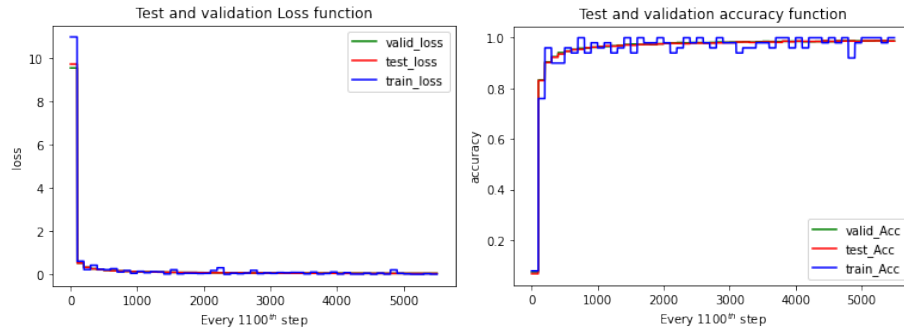
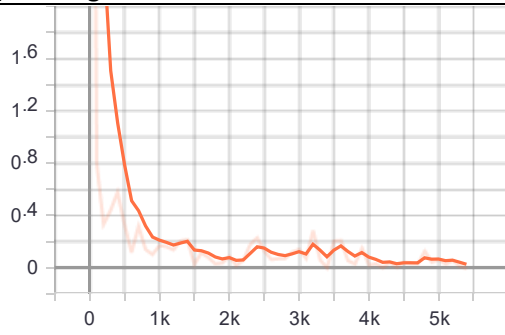
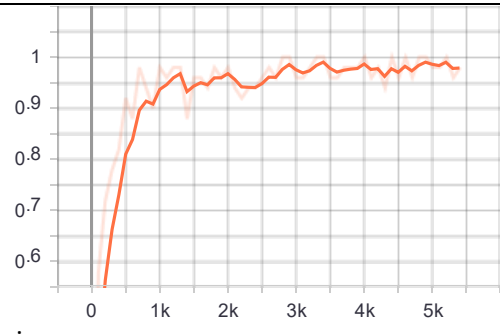


Figure 8: The loss and accuracy plots of training, validation and test

(b). The figures from Tensorboard:

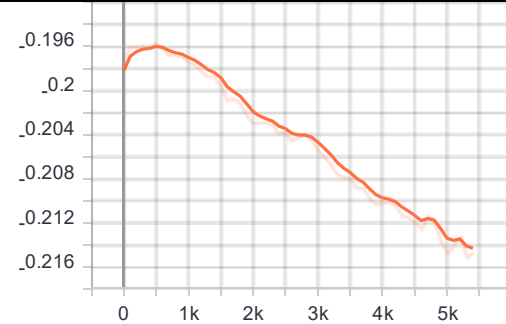
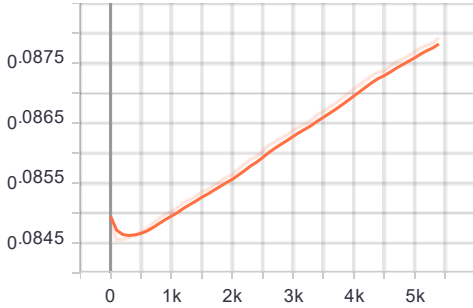


Train loss



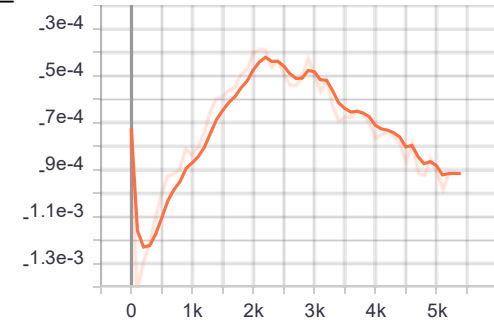
Train accuracy

W_conv1 std

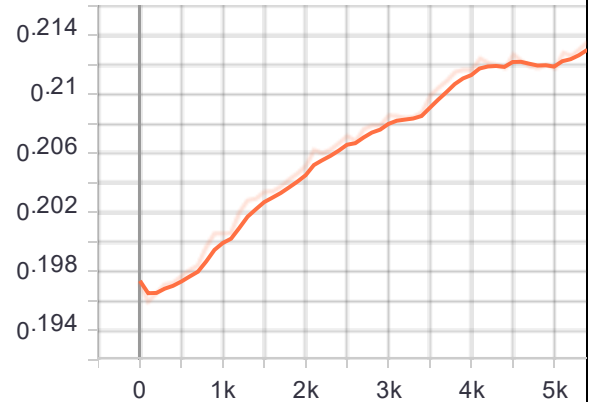


W_conv1 min

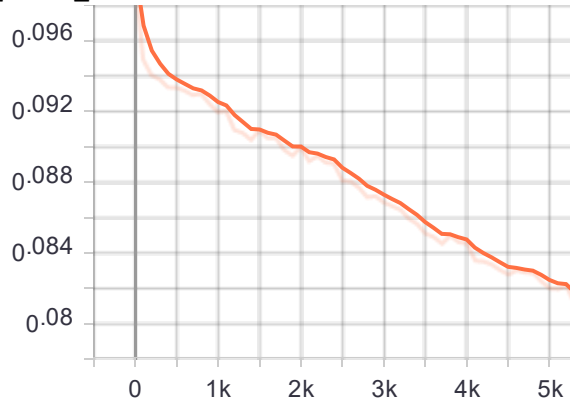
W_conv1 mean



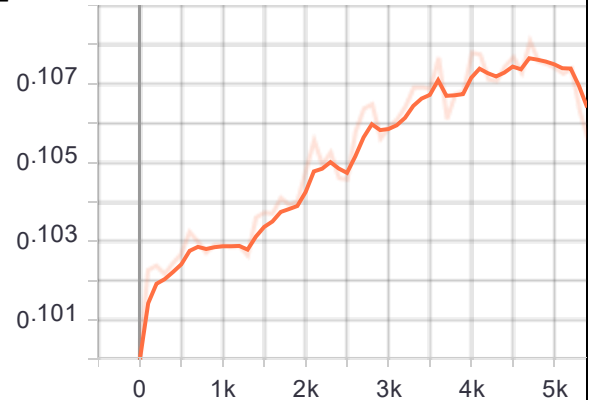
Conv1 W_conv1.max

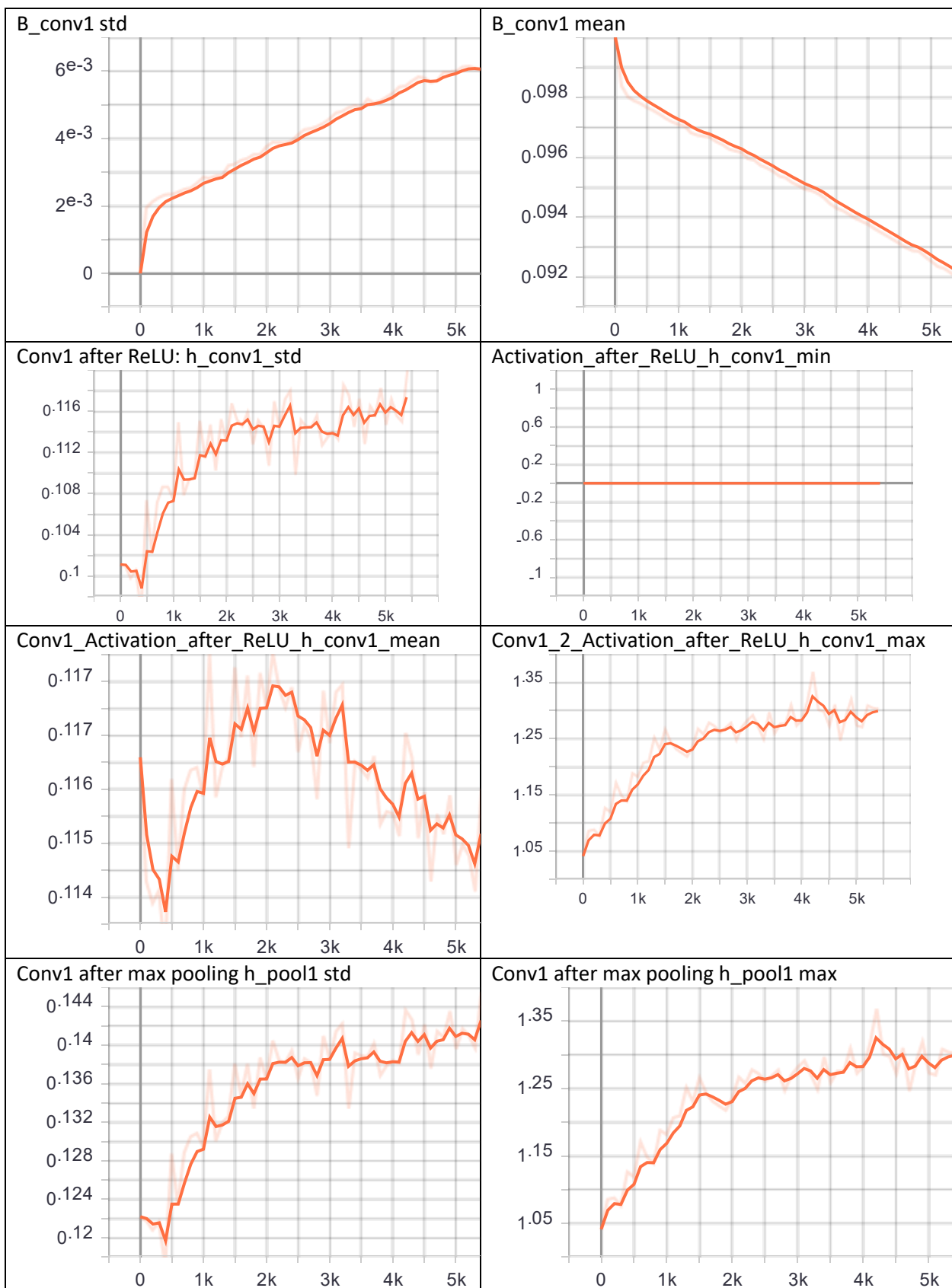


b_conv1_min

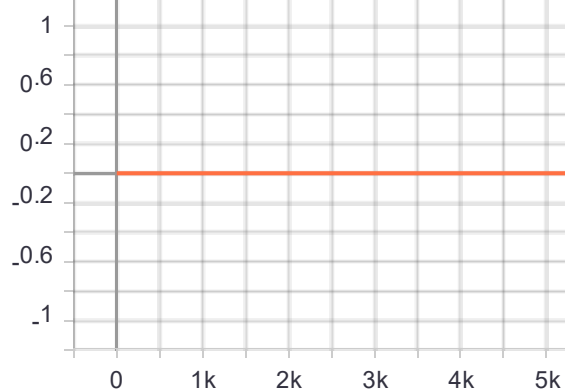


B_conv1 max





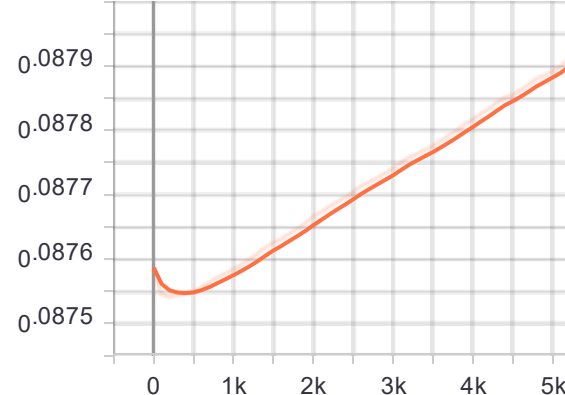
Conv1 after max pooling h_pool1 min



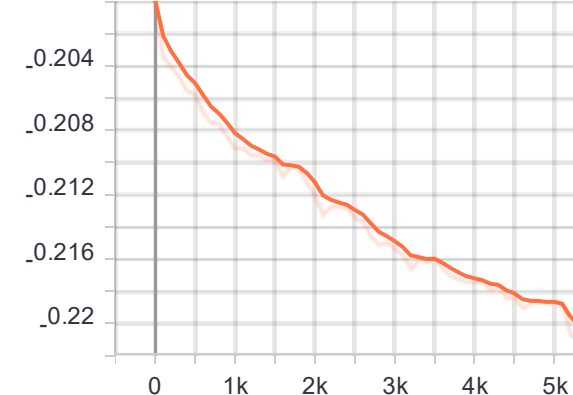
Conv1 after max pooling h_pool1 mean



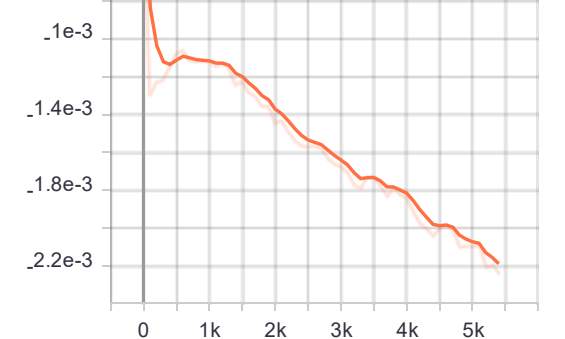
Conv2 w_conv2 std



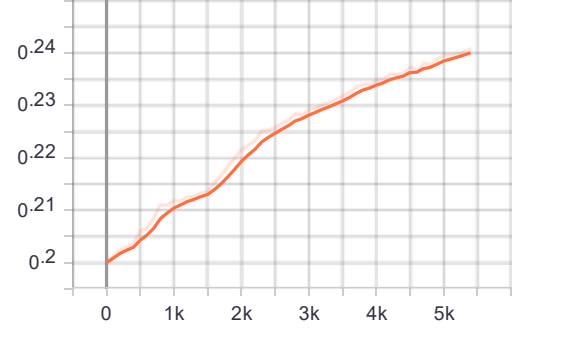
Conv2 w_conv2 min



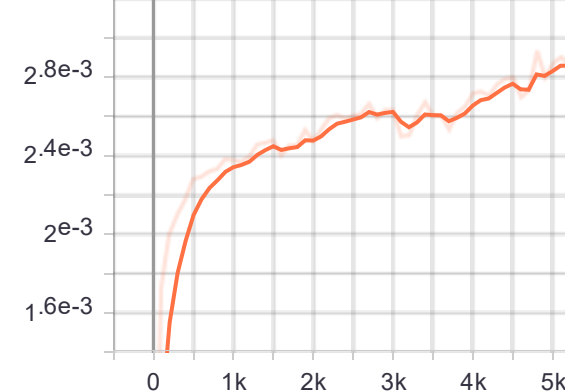
Conv2 w_conv2 mean



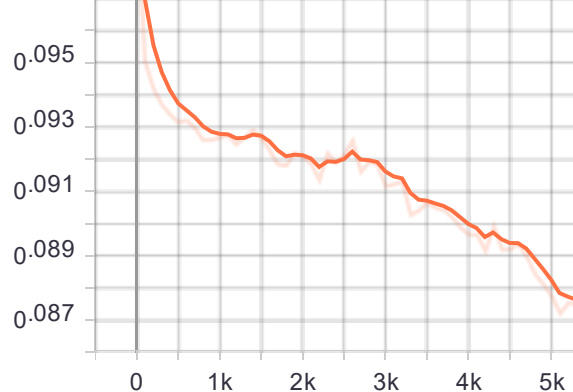
Conv2 w_conv2 max

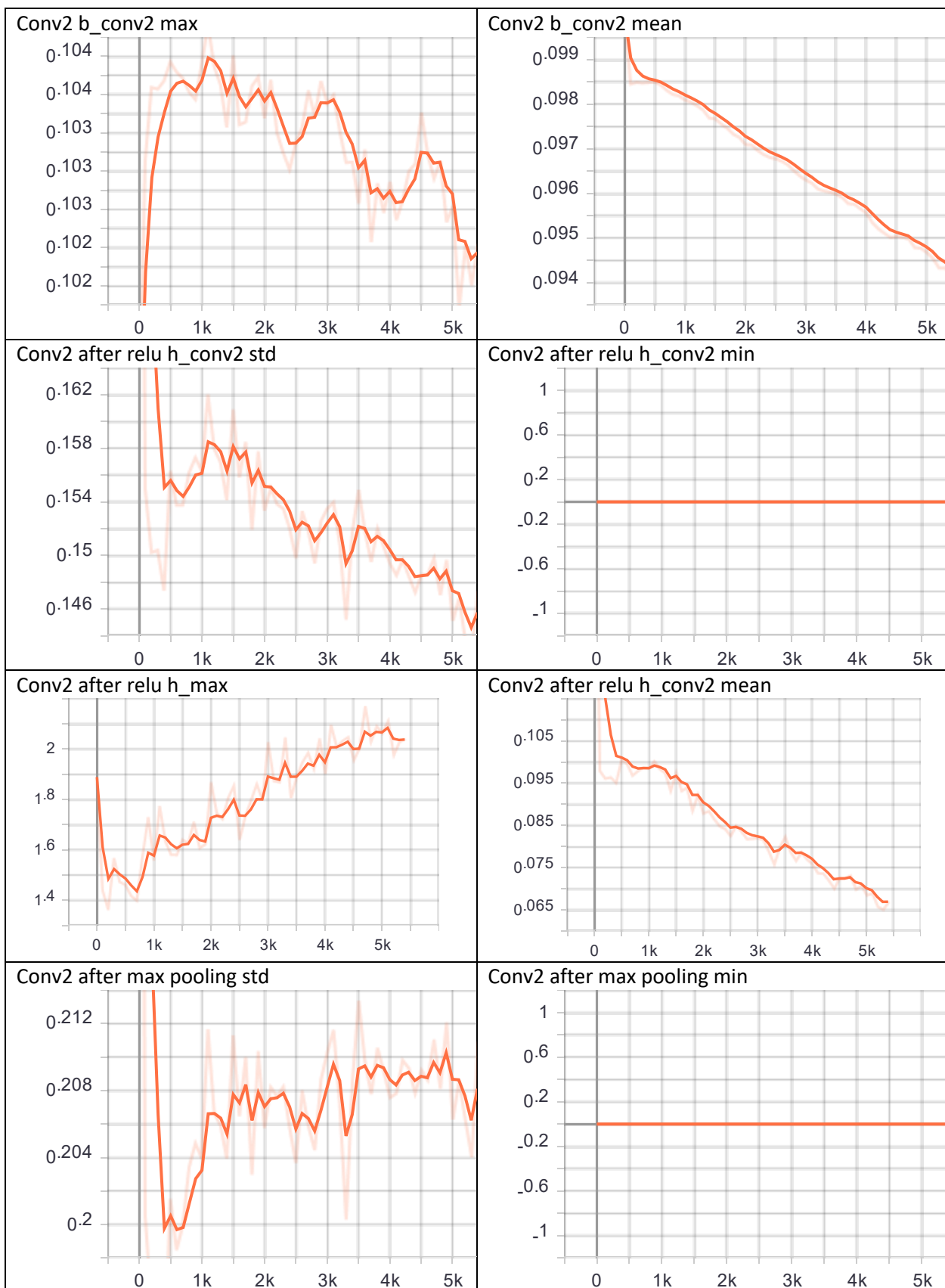


Conv2 b_conv2 std

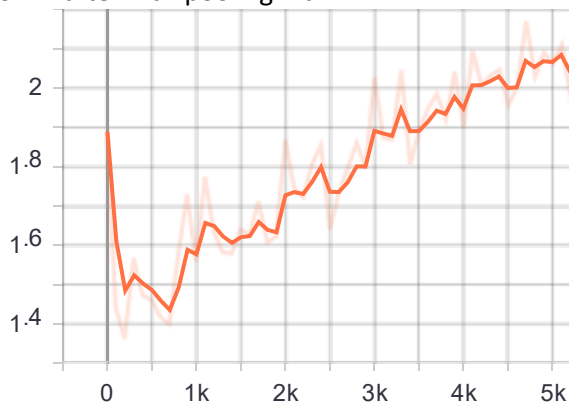


Conv2 b_conv2 min

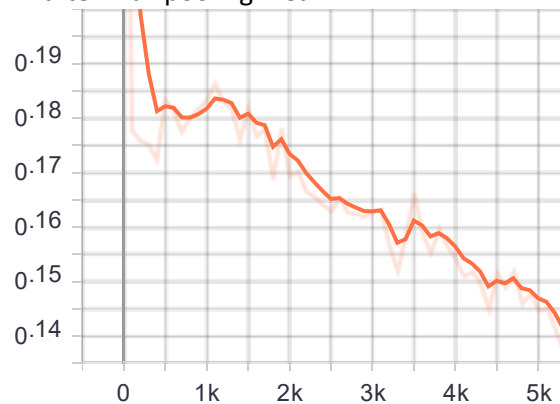




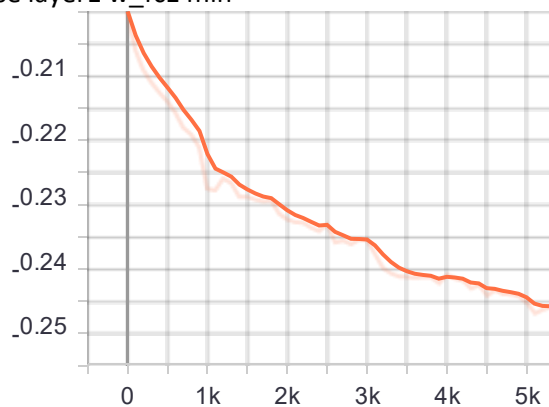
Conv2 after max pooling max



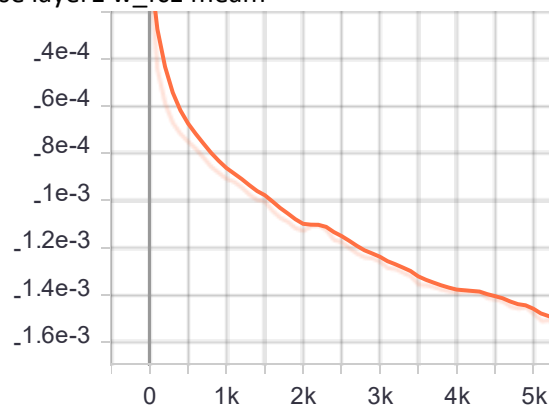
Conv2 after max pooling mean



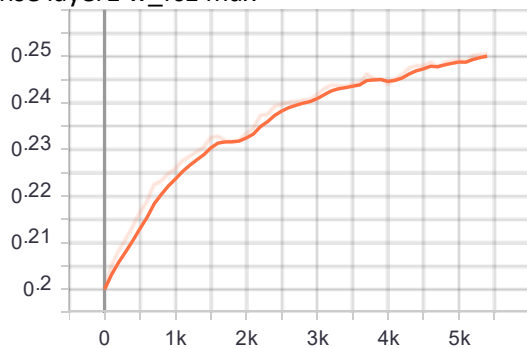
Dense layer1 w_fc1 min



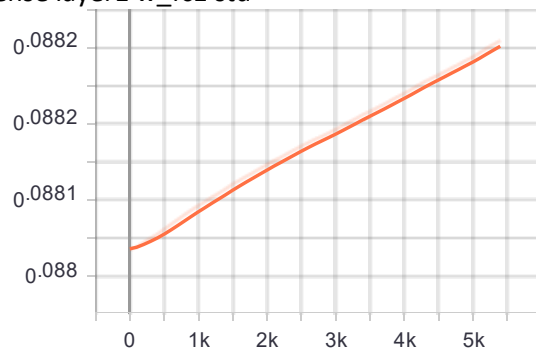
Dense layer1 w_fc1 meam



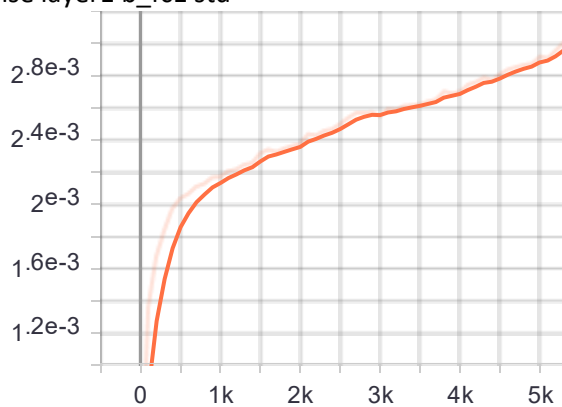
Dense layer1 w_fc1 max



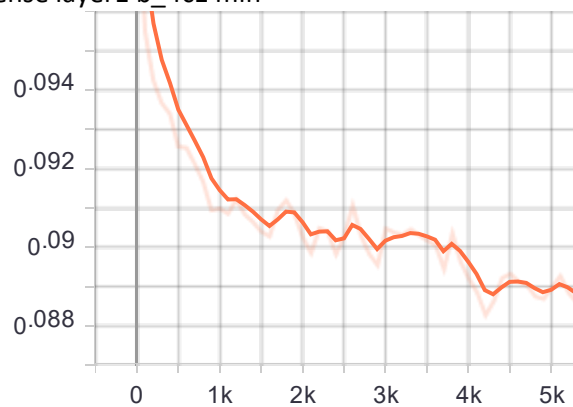
Dense layer1 w_fc1 std

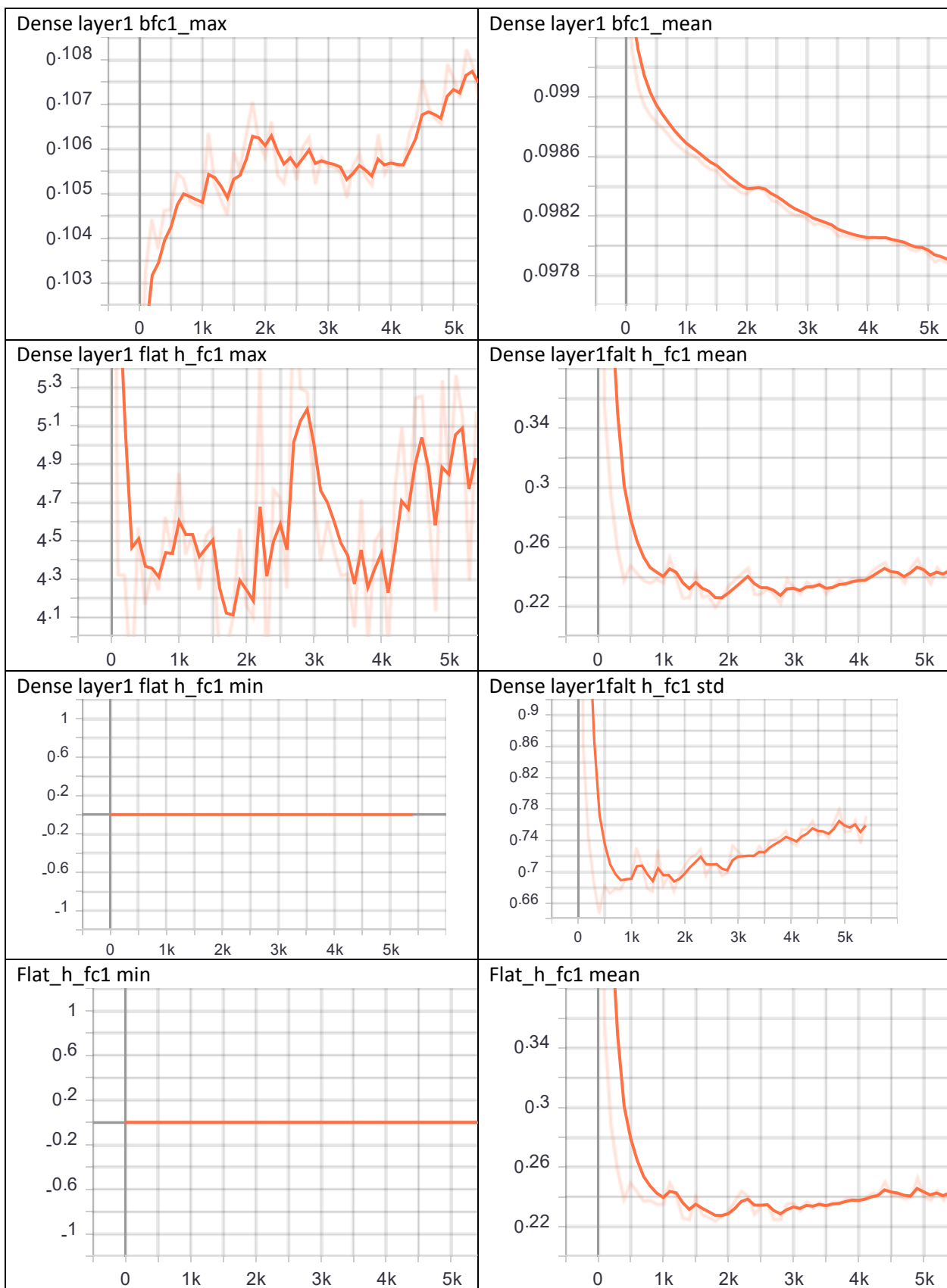


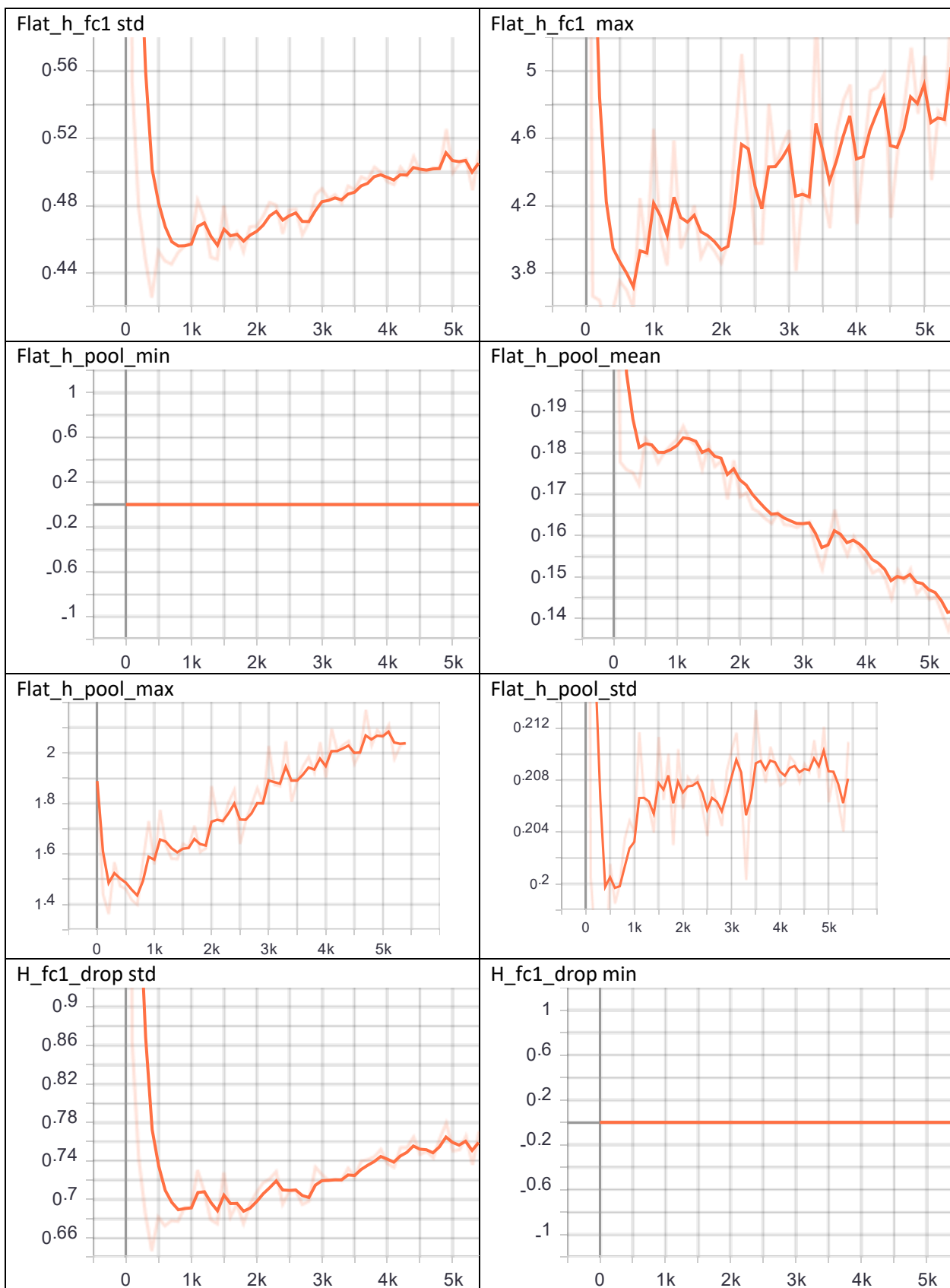
Dense layer1 b_fc1 std

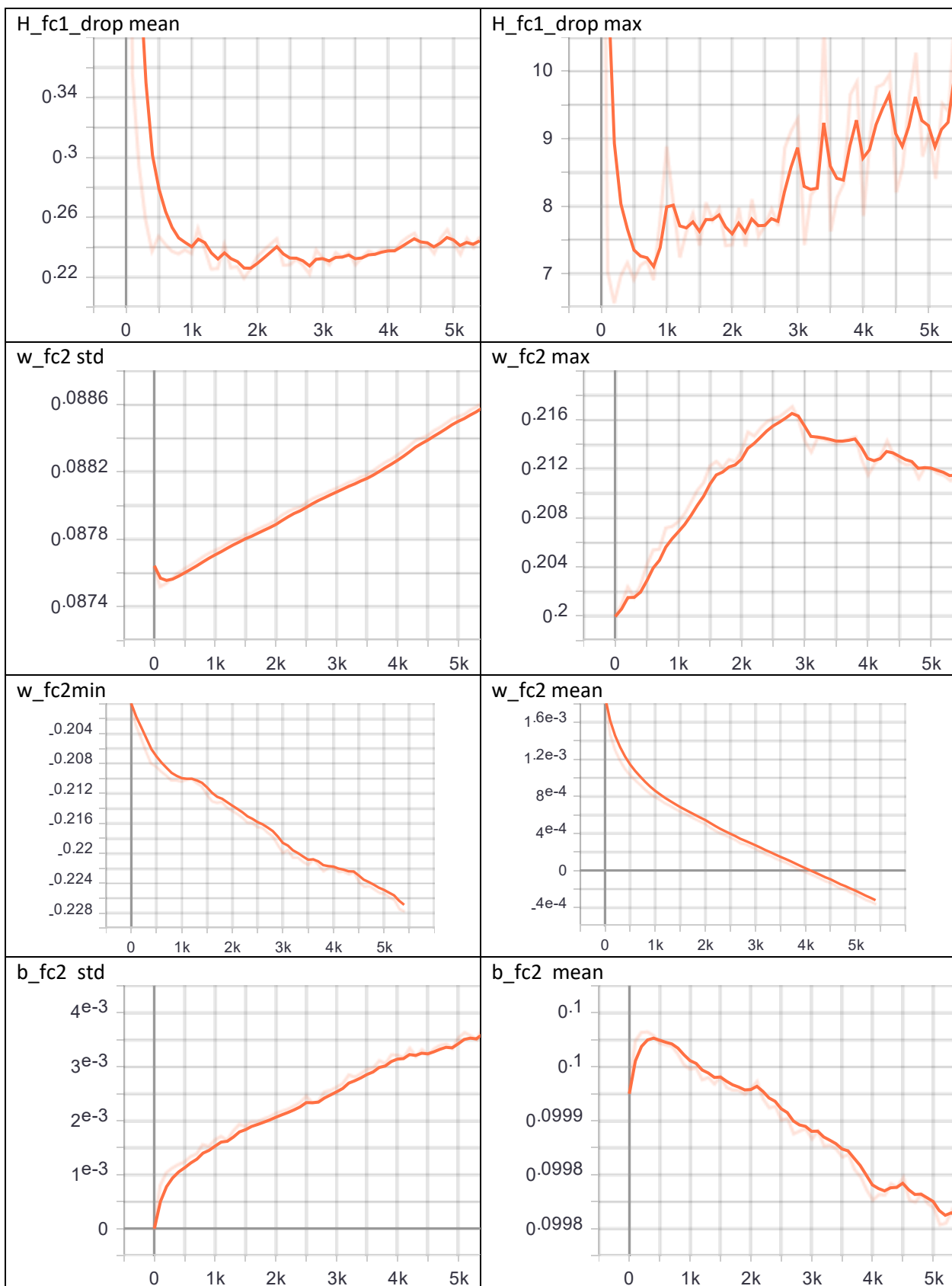


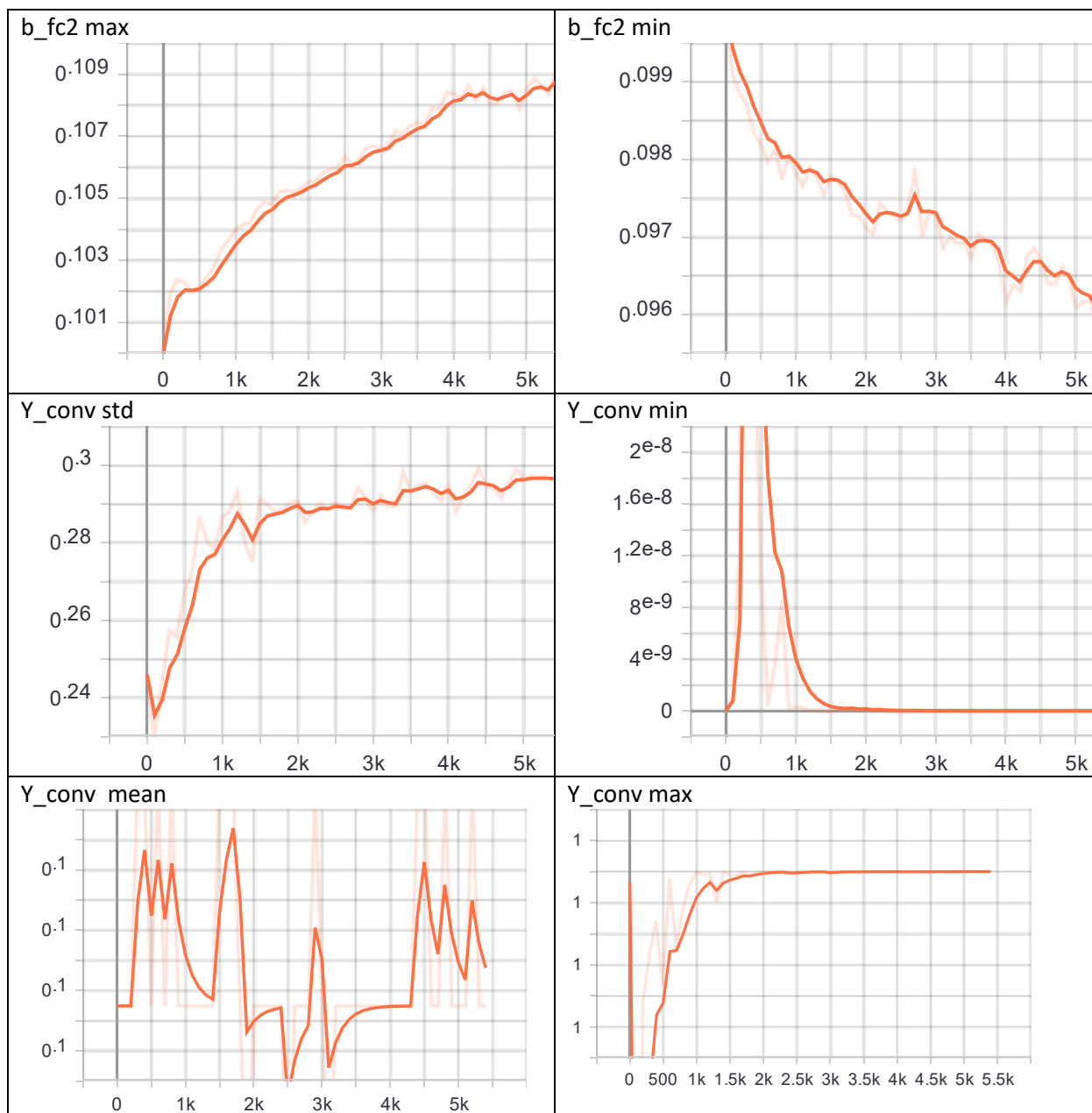
Dense layer1 b_fc1 min



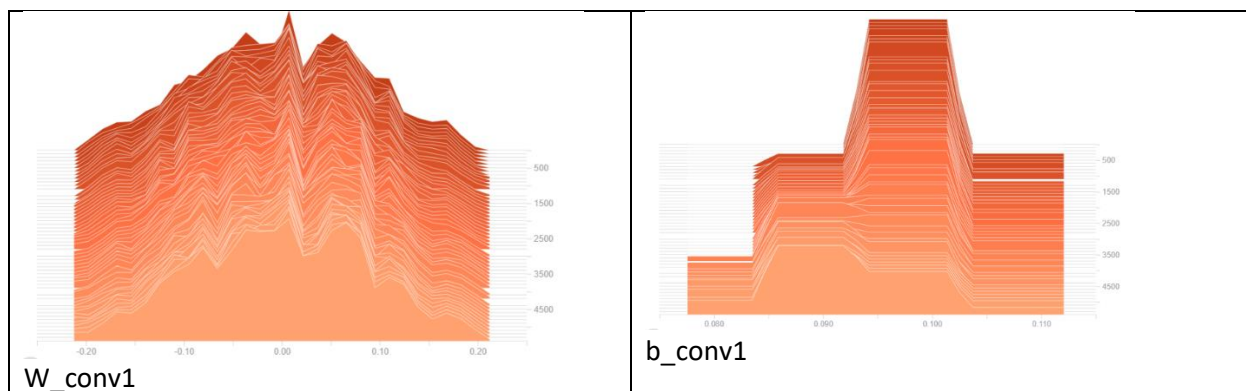


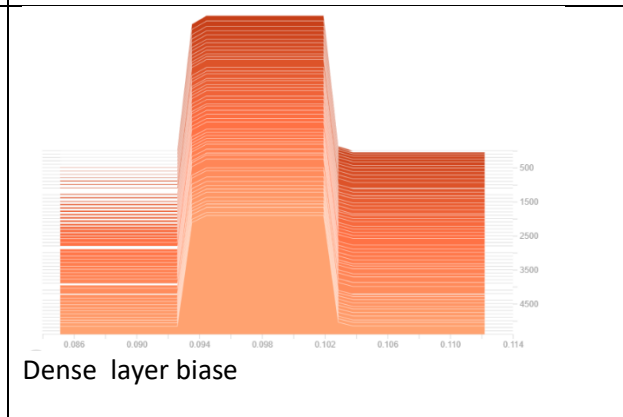
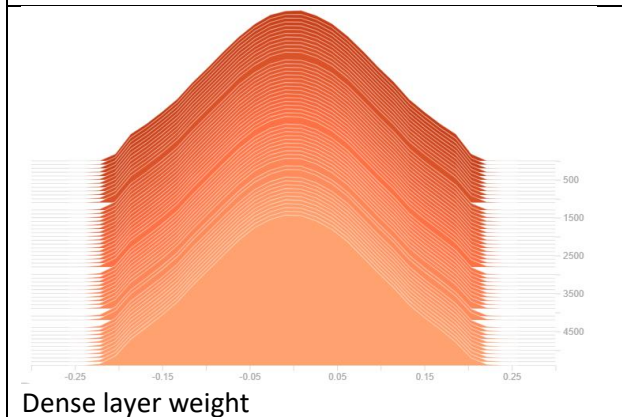
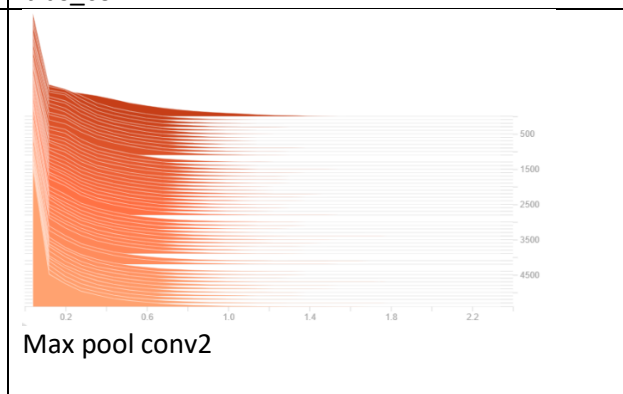
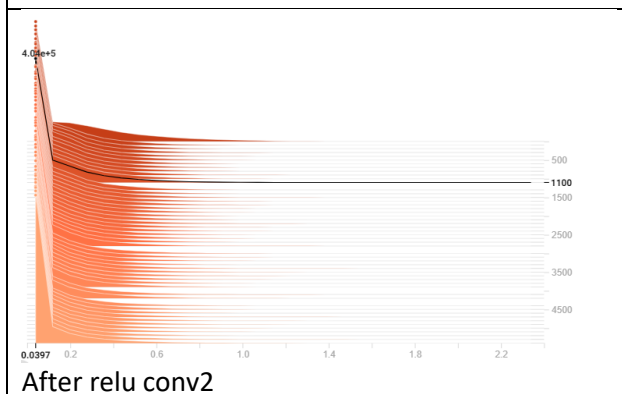
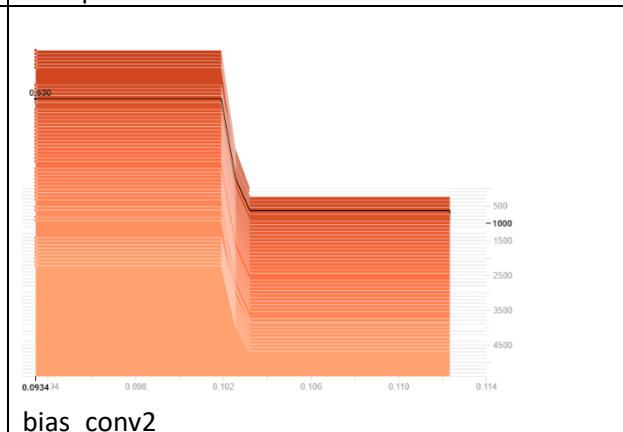
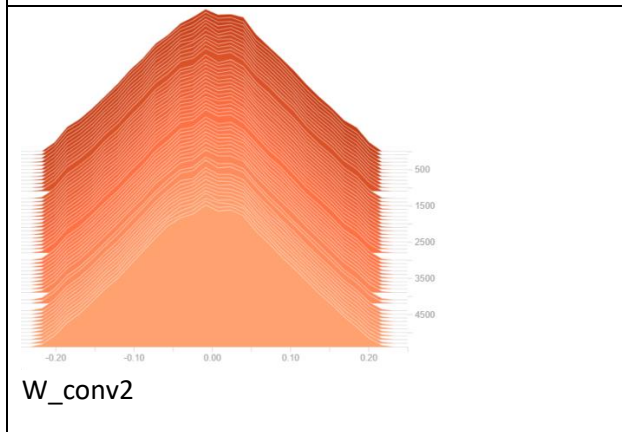
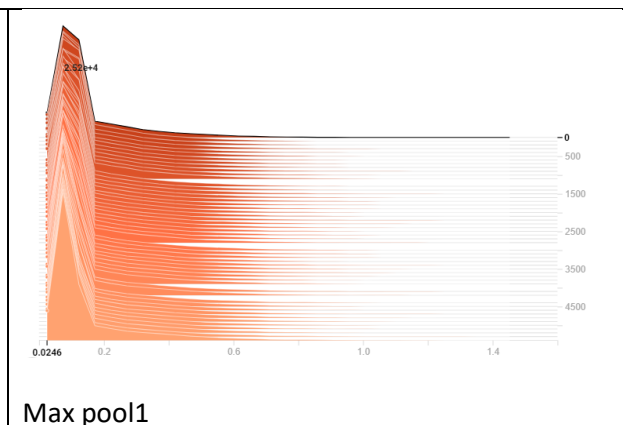
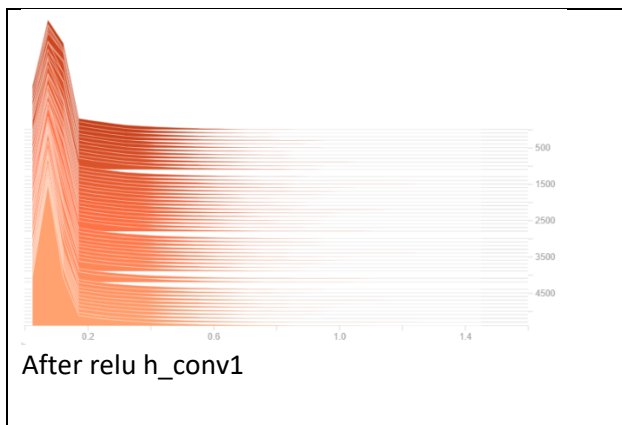


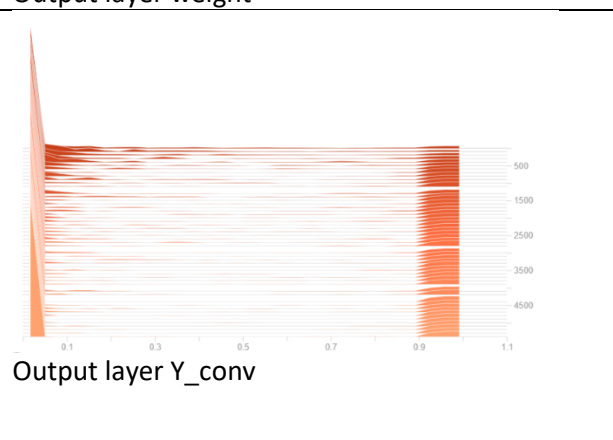
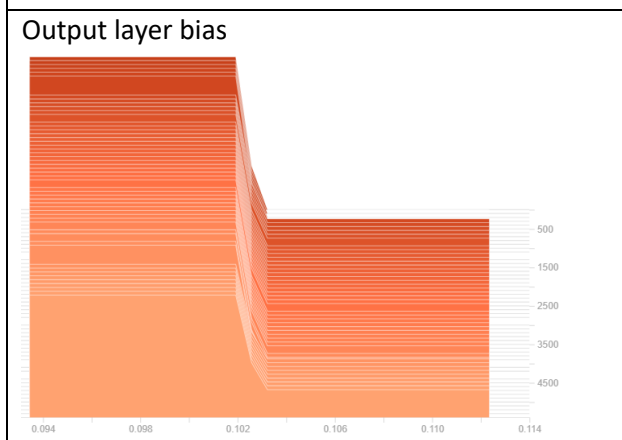
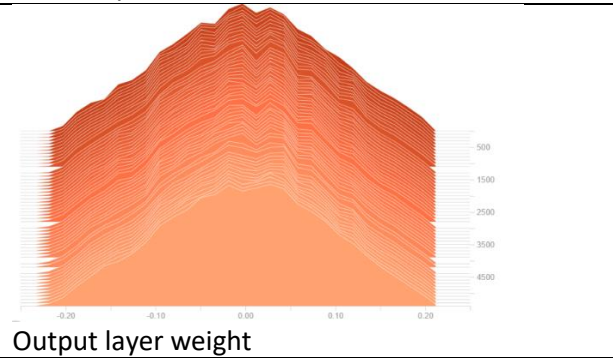
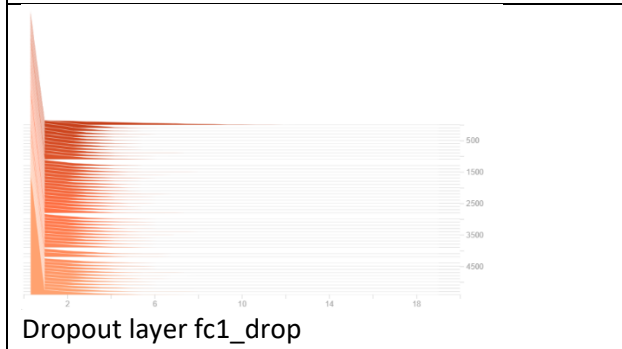
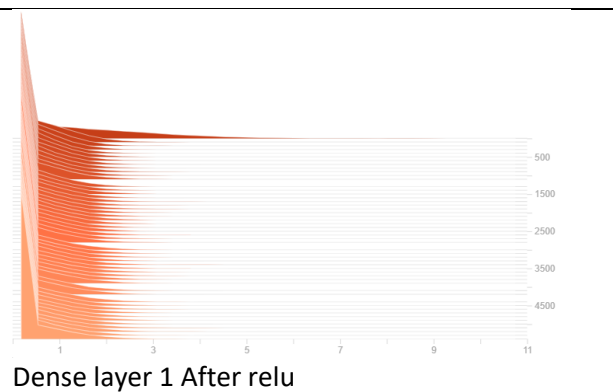
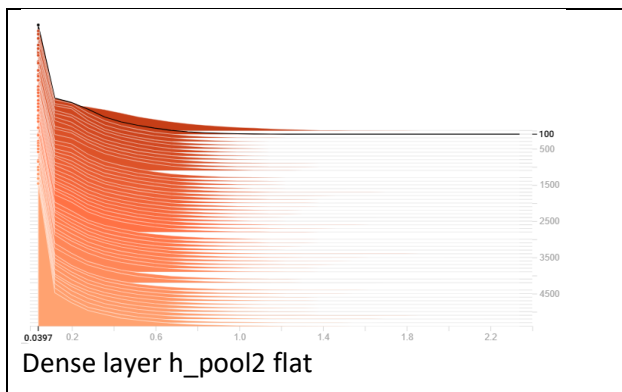




Histogram Plots:







(c)

For network architecture for this part of the problem is:

conv1(5 - 5 - 1 - 32) - leaky-ReLU - maxpool(2 - 2) - conv2(5 - 5 - 32 - 64)
- leaky-ReLU - maxpool(2 - 2) - fc(1024) - leaky-ReLU - DropOut(0.5) - Soft-
max(10).

I used Xavier initialization technique and Monemtum optimizer to train this network. The figure 9 shows the training, test and validation loss and accuracy curve for this network.

The test accuracy after at was approximately 98.23% and it the training takes 121.732510 second to finish, where the network training in part (a) takes 64.156681 second to finish and the accuracy is 98.73.

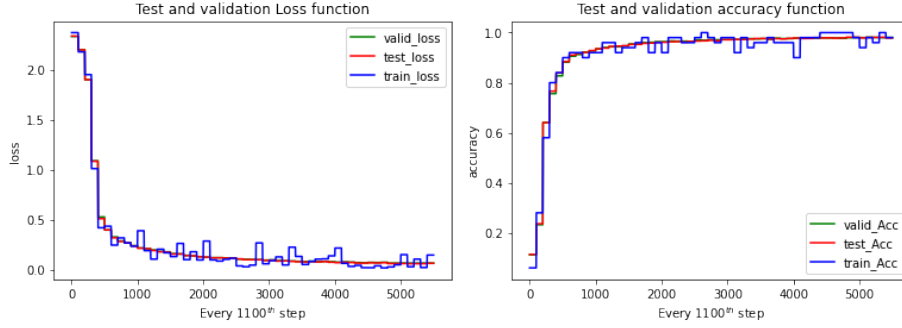
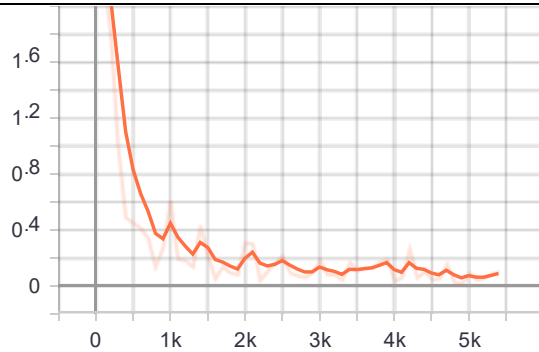
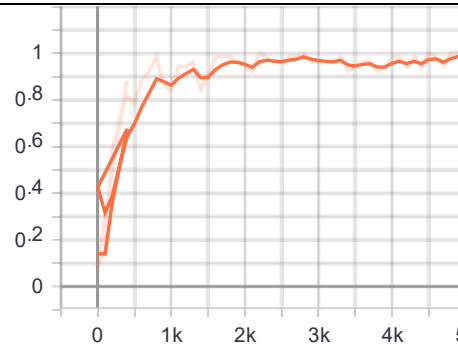


Figure 9: The loss and accuracy plots of training, validation and test

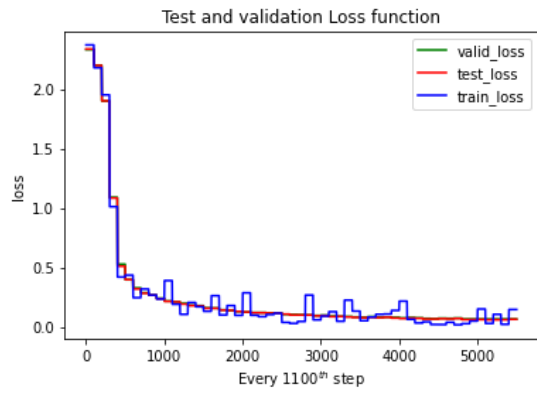
Part C:



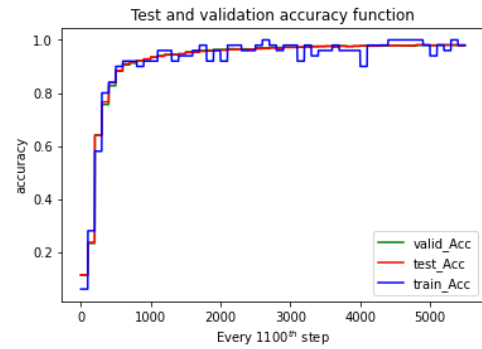
Train loss



Train accuracy

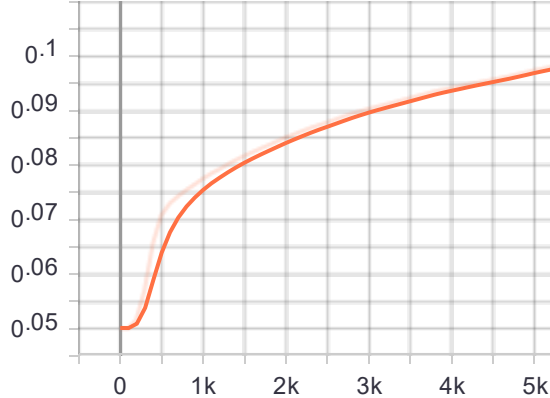


Train, test and validation loss

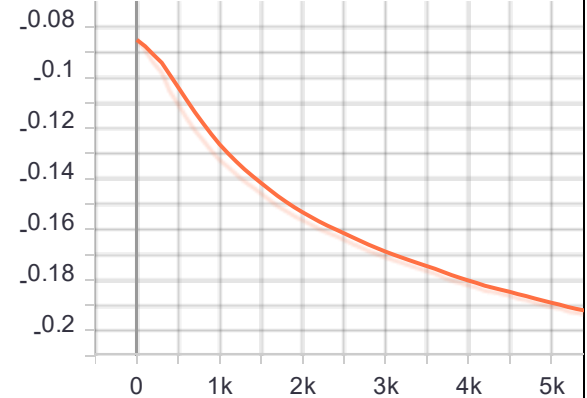


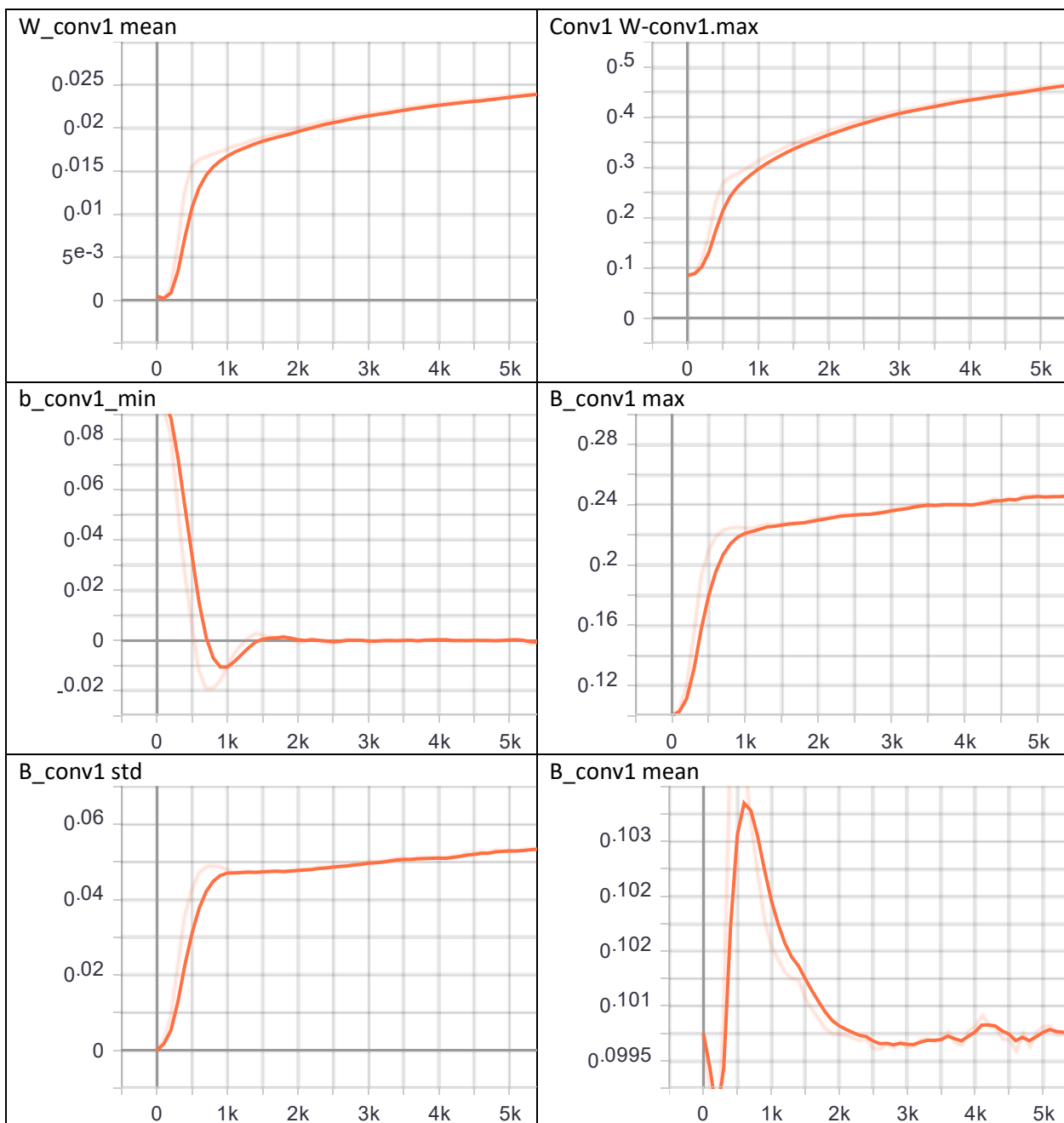
Train, test and validation accuracy

W_conv1 std

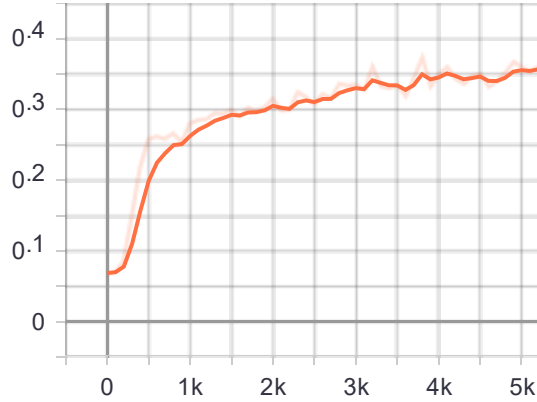


W_conv1 min

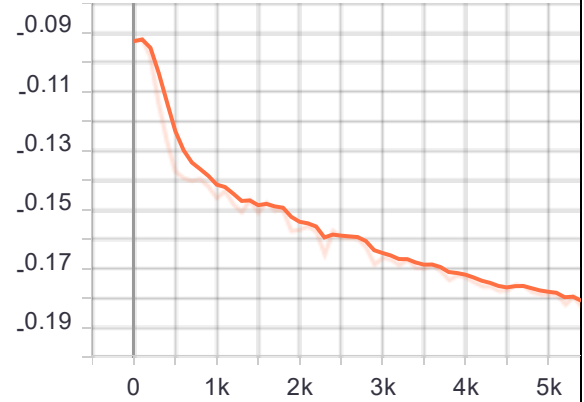




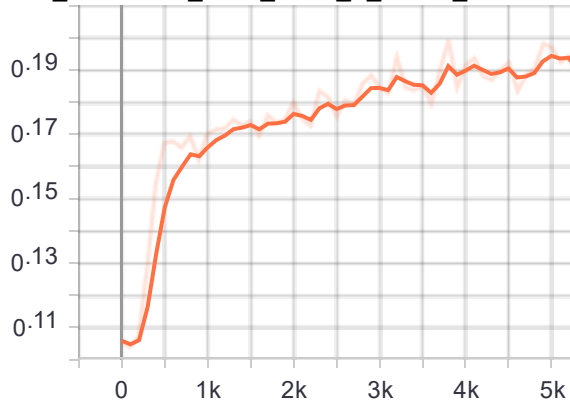
Conv1 after ReLU: h_conv1_std



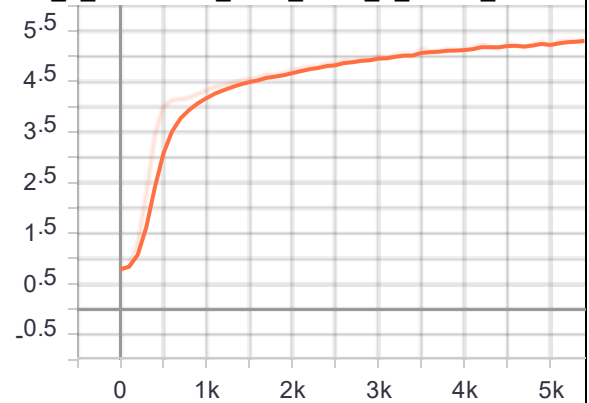
Activation_after_ReLU_h_conv1_min



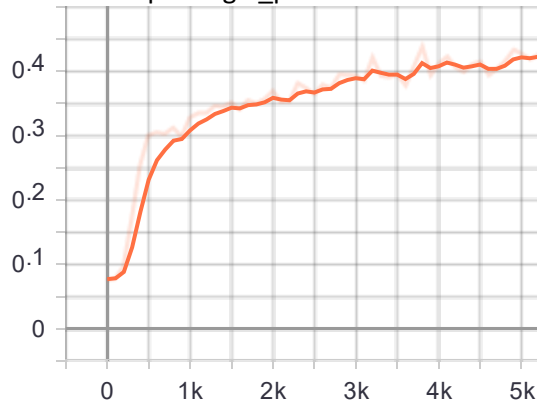
Conv1_Activation_after_ReLU_h_conv1_mean



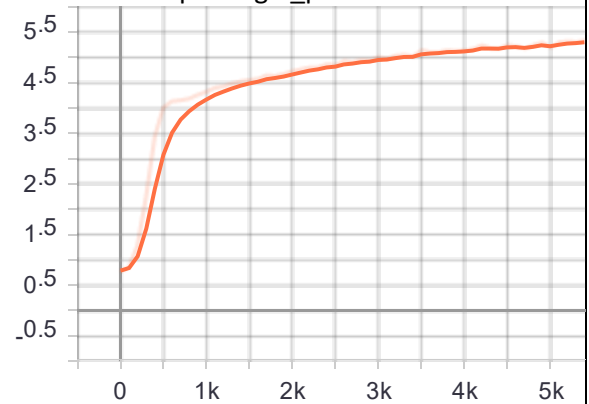
Conv1_2_Activation_after_ReLU_h_conv1_max

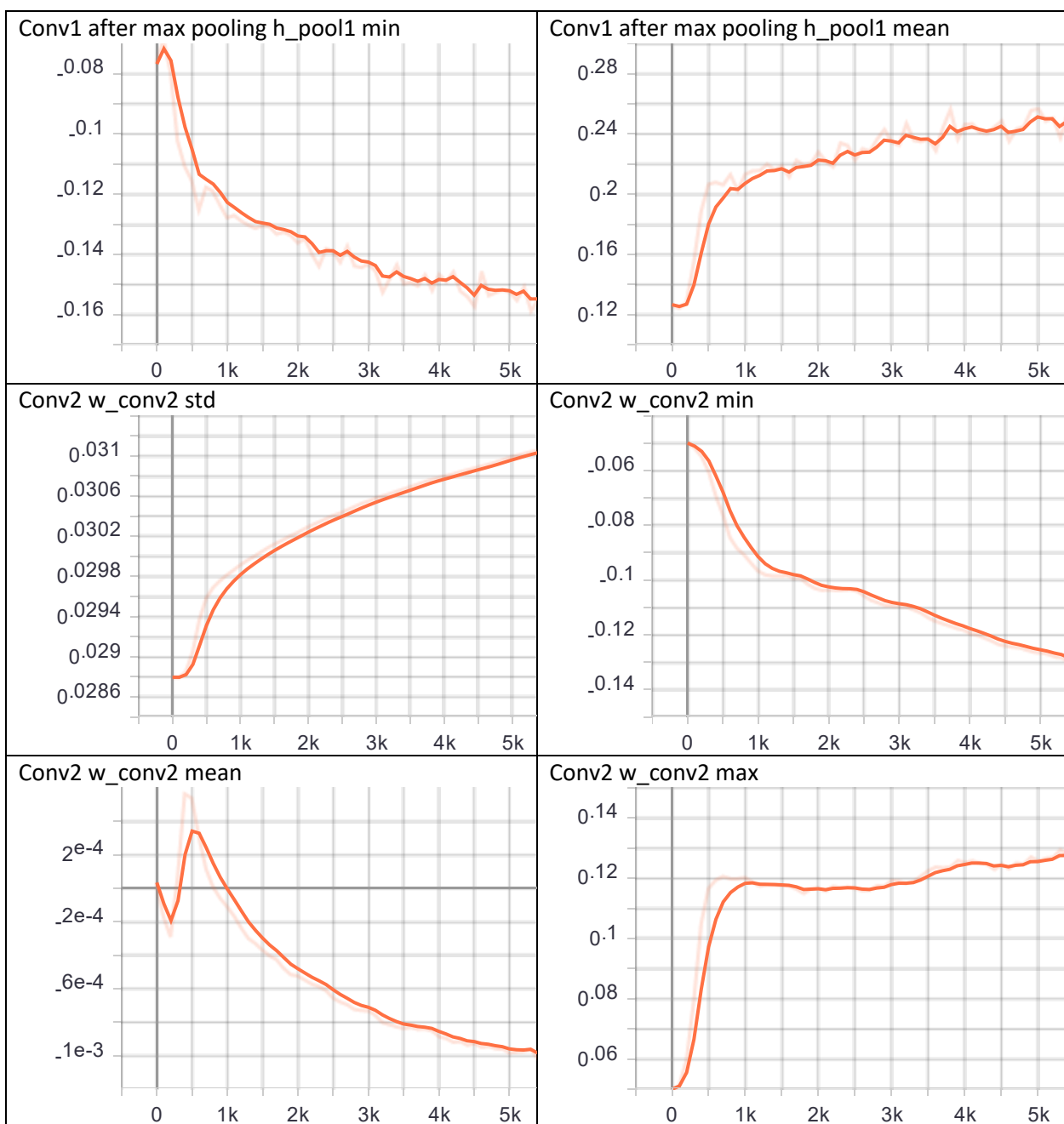


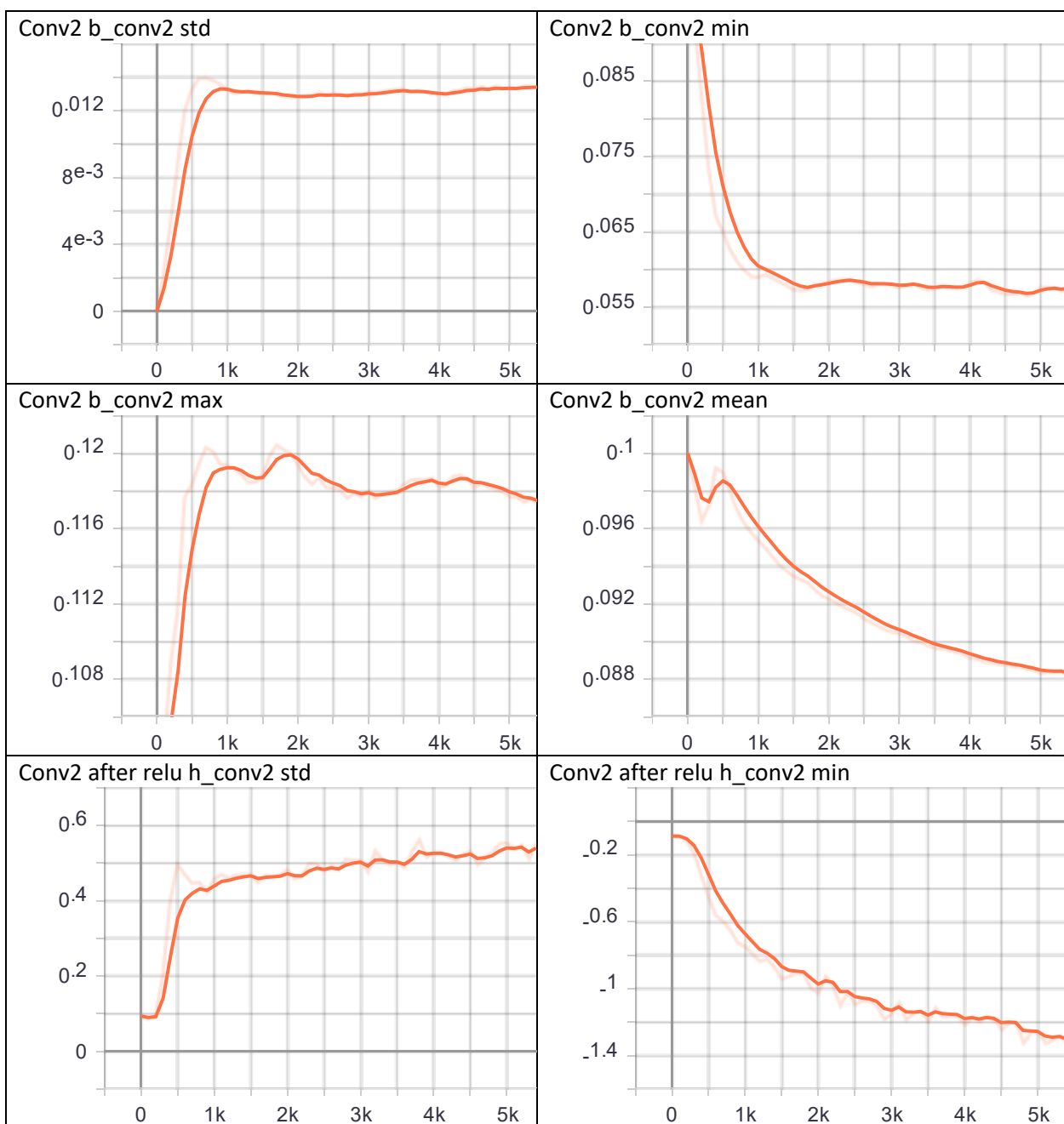
Conv1 after max pooling h_pool1_std



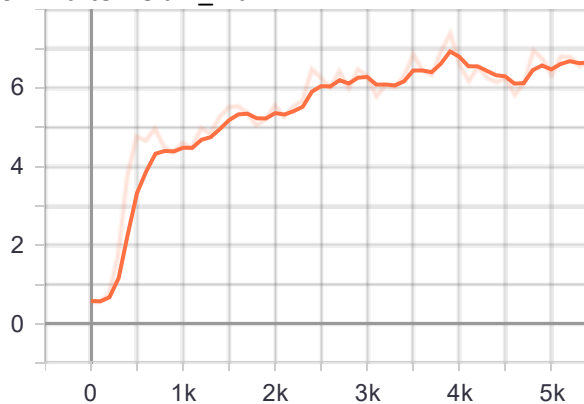
Conv1 after max pooling h_pool1 max



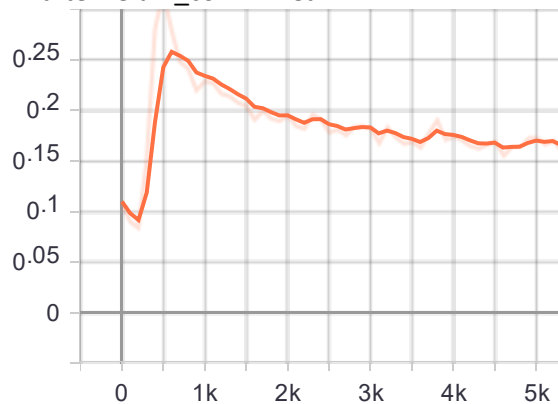




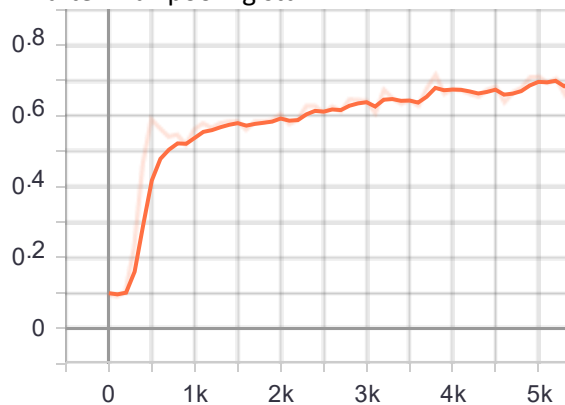
Conv2 after relu h_max



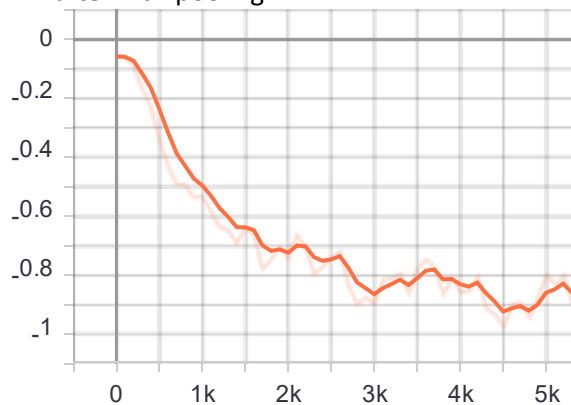
Conv2 after relu h_conv2 mean



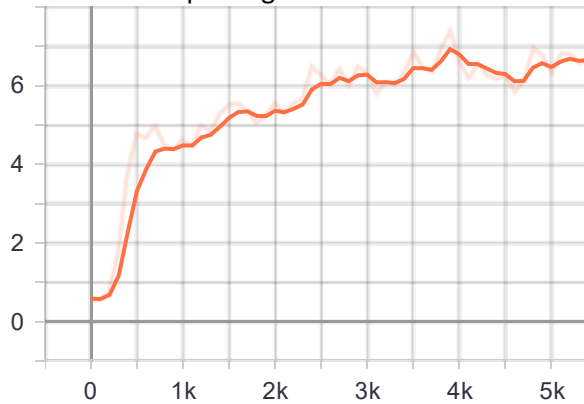
Conv2 after max pooling std



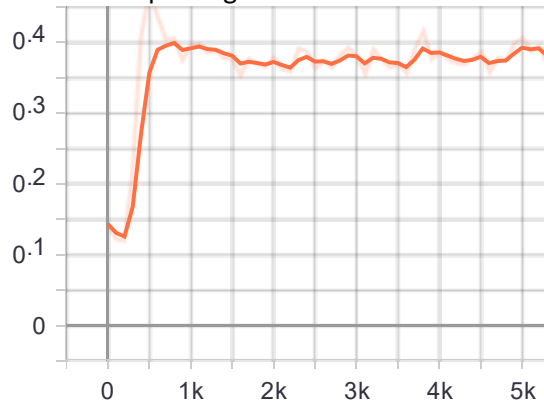
Conv2 after max pooling min

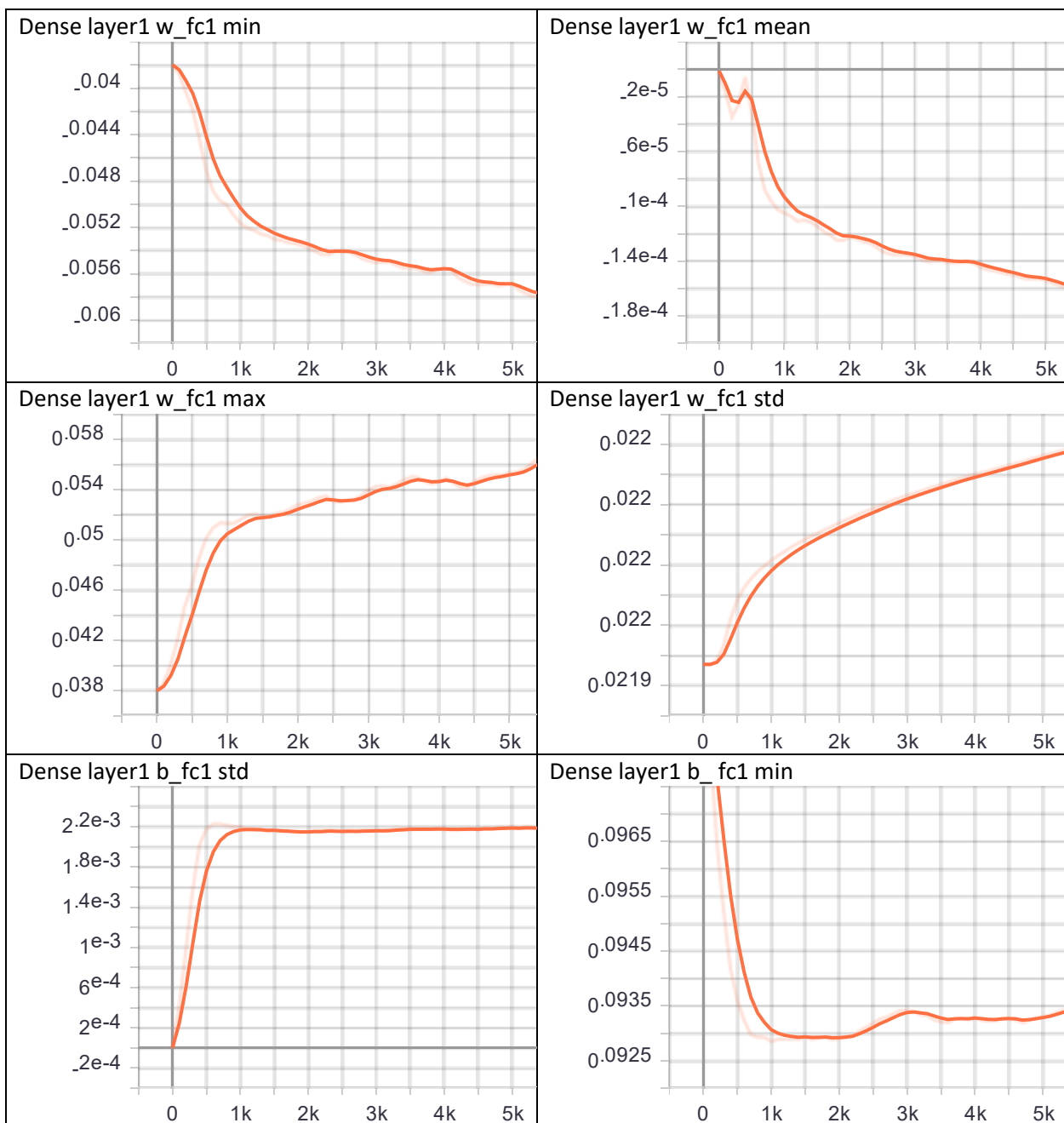


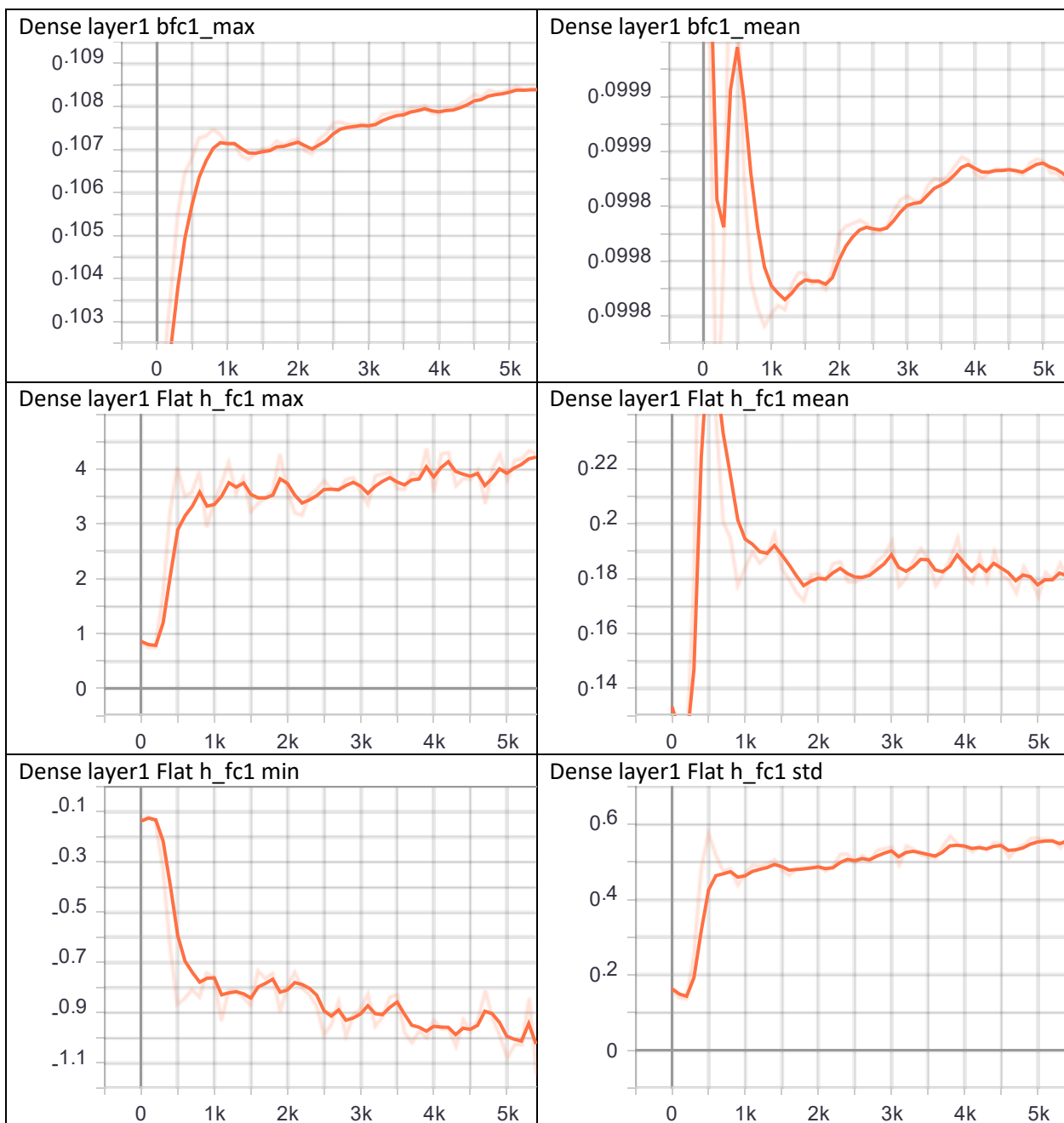
Conv2 after max pooling max

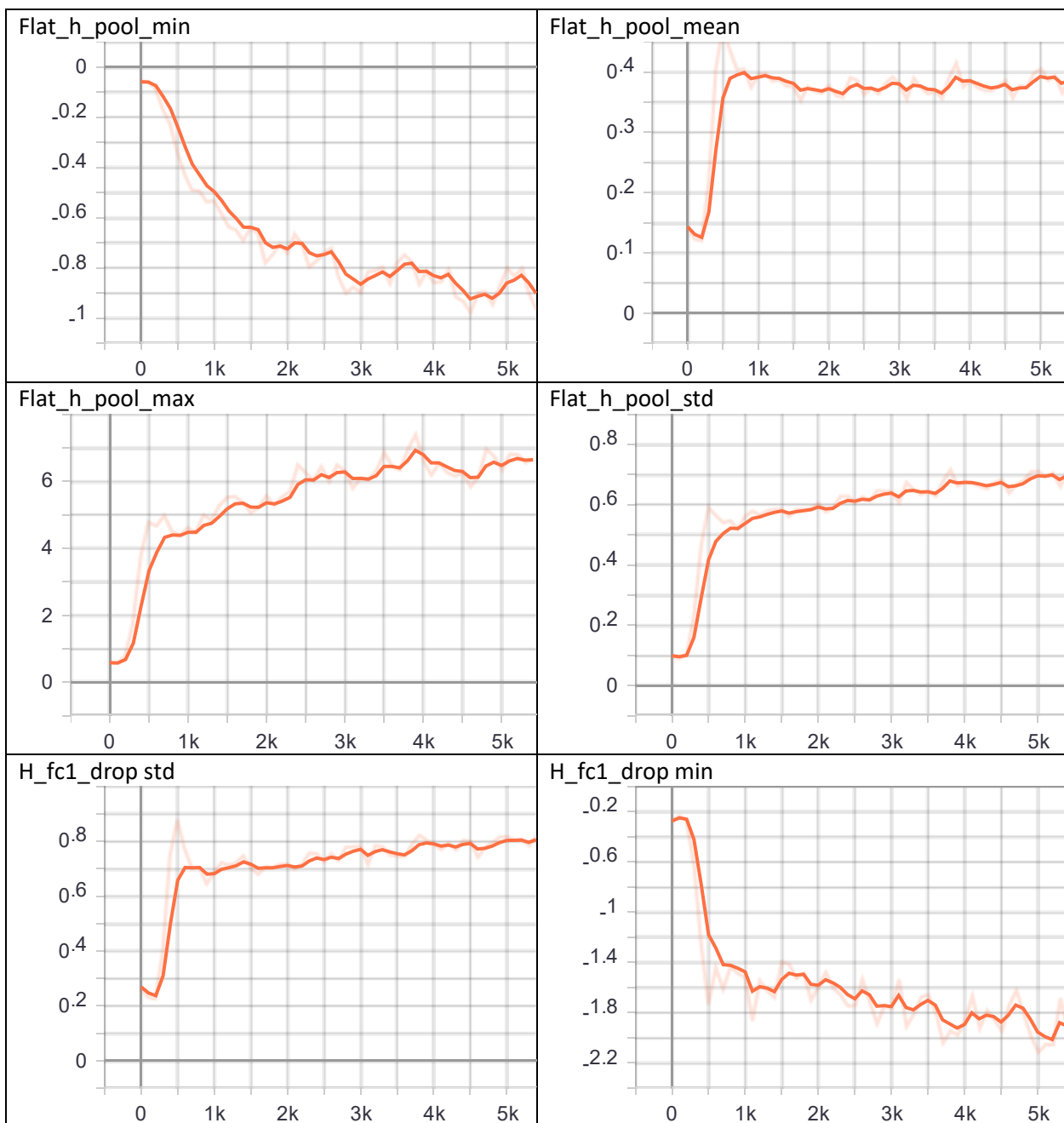


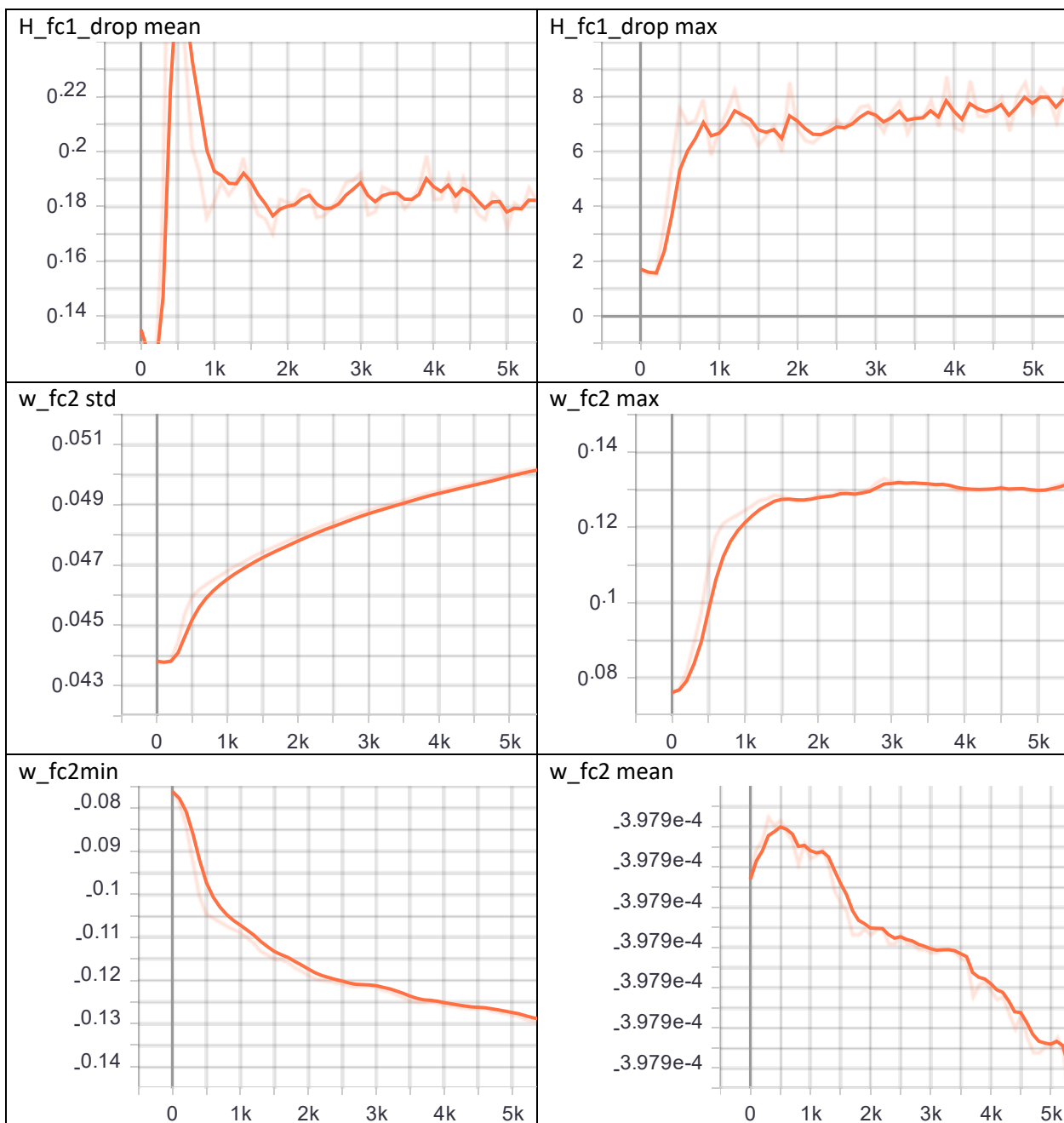
Conv2 after max pooling mean

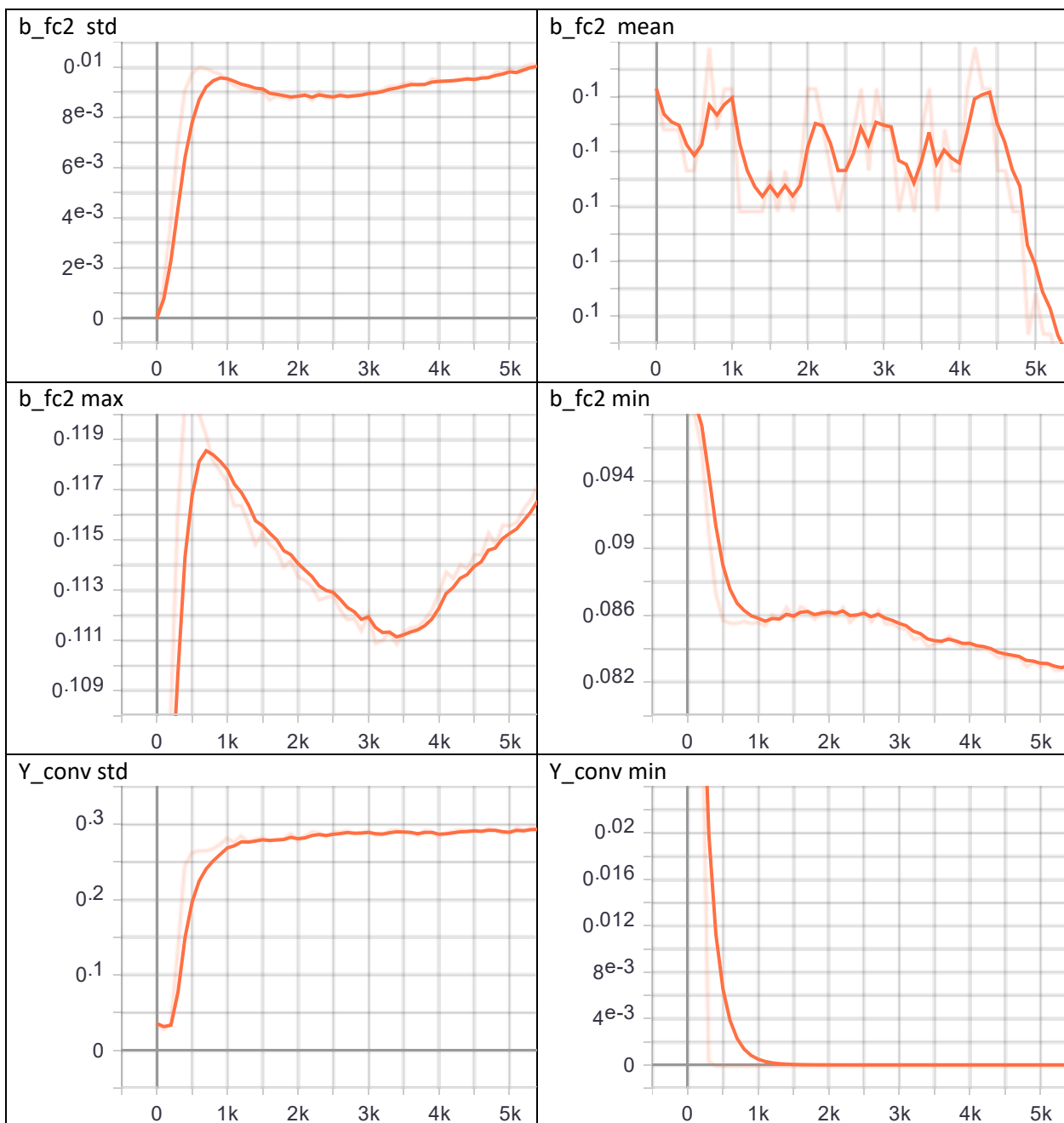


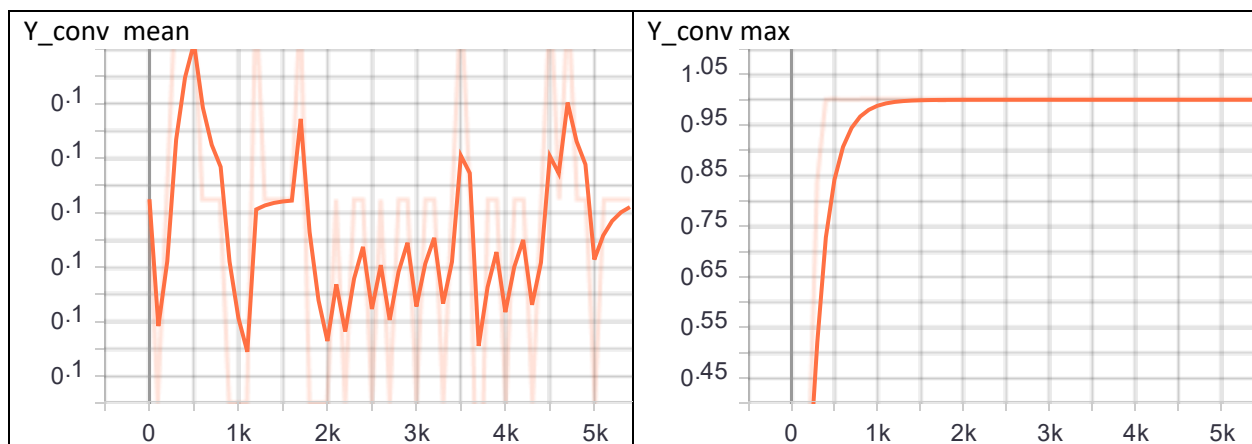




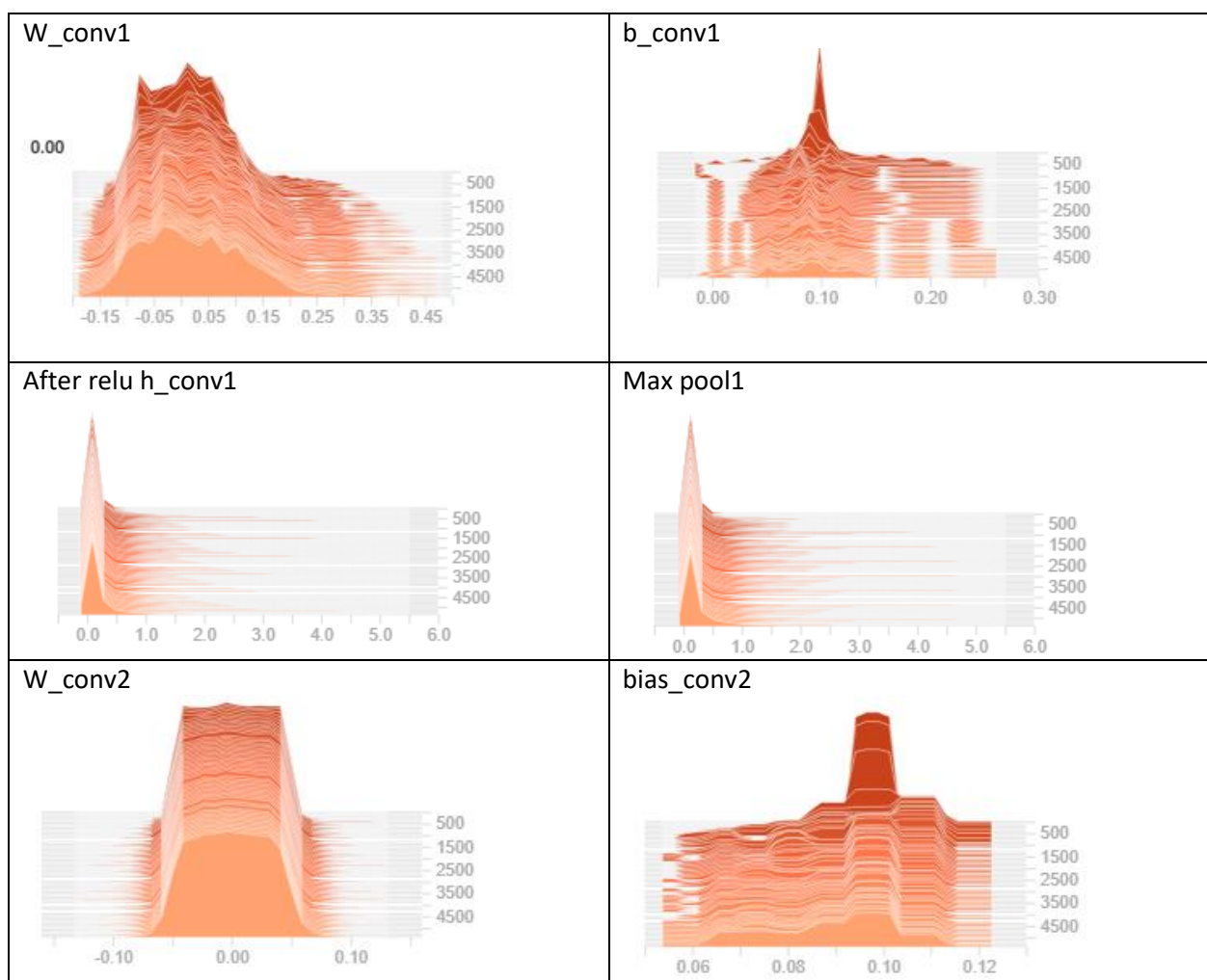




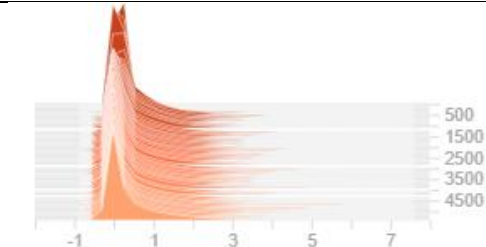
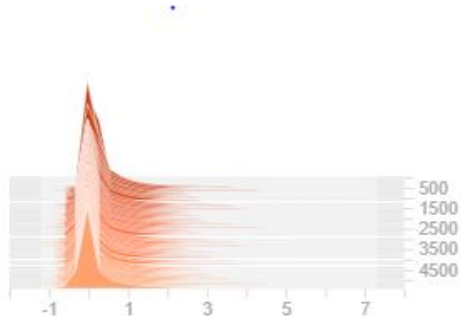




Histogram Plots:

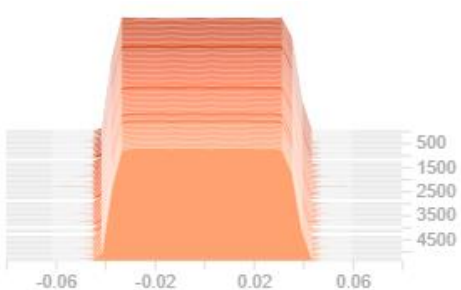


After relu conv2

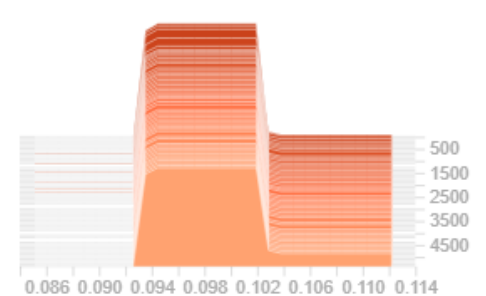


Max pool conv2

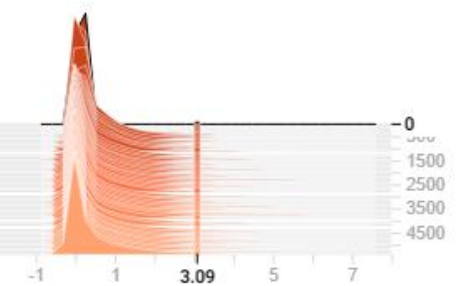
Dense layer weight



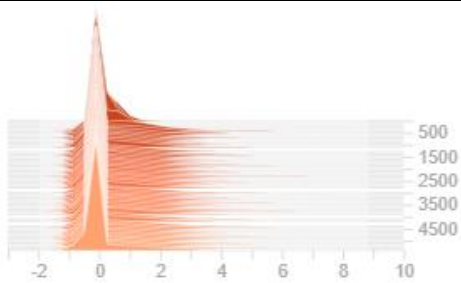
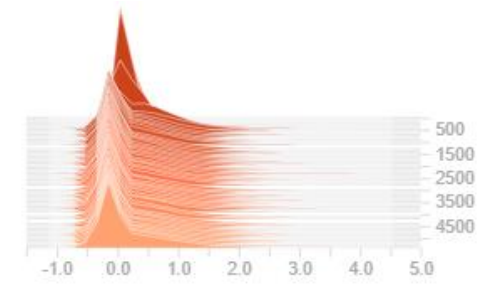
Dense layer biase



Dense layer h_pool2 flat

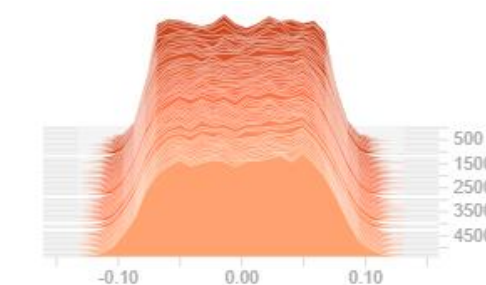


Dense layer 1 After relu

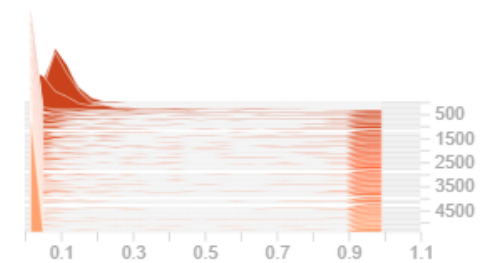
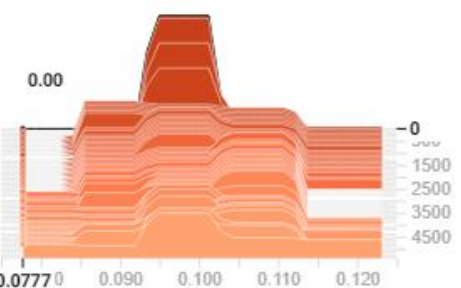


Dropout layer h_fc1_drop

Output layer weight



Output layer bias



Output layer Y_conv

2.1 Resources I used to work on this HW:

1. Introduction to Deep Learning Lectures
2. Multi-Layer Neural Network
3. How the backpropagation algorithm works
4. Mysteries of Neural Networks Part III
5. Neural Networks Tutorial – A Pathway to Deep Learning