Lab 4 Exercise - Fun with MLPs & MNIST

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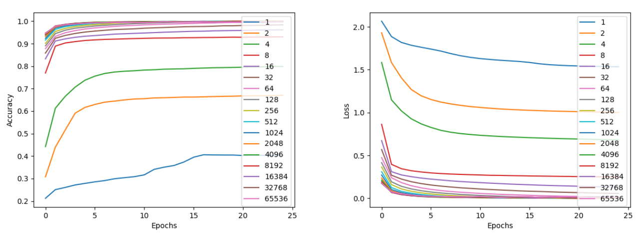
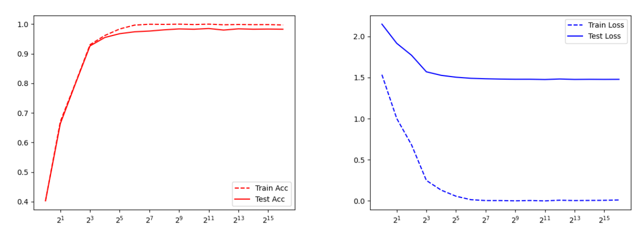
n	Hidden Layer Size	Parameters	Train Accuracy	Test Acc
1	2	1,600	0.403	0.407
2	4	3,190	0.691	0.686
3	8	6,370	0.864	0.861
4	16	12,730	0.929	0.923
5	32	25,450	0.965	0.957
6	64	50,890	0.987	0.969
7	128	101,770	0.998	0.975
8	256	203,530	1.000	0.980
9	512	407,050	1.000	0.982
10	1024	814,090	1.000	0.983
11	2,048	1,628,170	1.000	0.985
12	4,096	3,256,330	1.000	0.987
13	8,192	6,512,650	0.999	0.985
14	16,384	13,025,290	0.996	0.979
15	32,768	26,050,570	0.997	0.979
16	65,536	52,101,130	0.998	0.980



(a) Accuracy **(b) Loss**

Figure 1: Showing training accuracy and loss across all models



(a) Accuracy **(b) Loss**

Figure 2: Showing accuracy and loss on a log scale of hidden nodes

1 EXERCISE 1

1.1 Wide MLPs on MNIST

To conduct this experiment, a range of single layered MLP's were trained with hidden layer's sized 2^n from $n = 1$ until $n = 16$, for a max hidden layer size of 65,536 neurons. The Adam optimiser was used to train at a default learning rate over 25 epochs.

With 60,000 samples in the MNIST training dataset, with anything over $2^7 = 128$ nodes in the hidden layer, there will be 101,770 learnable parameters in the network, more than enough to start to overfit to the dataset.

Investigating the training curves shown in Figure 1, it is clear to see small networks with 1-2 hidden nodes struggling to learn with maximum accuracies at 0.4 and 0.6 respectively. For any MLP above 32 hidden units the training accuracy and loss quickly converge to close to perfect scores over the training data.

With the scale of data presented, it is much easier to present the loss and accuracy compared to hidden unit on a logarithmic scale. The data shown in Figure 2 show how the the final training and testing accuracy stays tightly bound until 2^3, at which point the training accuracy started to overtake the testing accuracy. This could be a sign of the network starting to overfit to the data, but I find it hard to claim that the network has failed to generalise to the dataset as the accuracy is still above 0.95.

The loss curves per hidden unit shown in Figure 2b are an interesting addition to this data. The loss shown in these curves start to level off past 2^3, indicating the network is not able to utilise the extra width past this point.

Over the course of this investigation I found it very hard to find clear signs of the models overfitting, even with hidden layers as wide as 65,536 neurons, the MNIST dataset may be a reasonably easily linearly seperable problem which would make it hard to overfit to.