On Neural Network Initialization

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ABSTRACT

This is a report describing the experimental results on the performance of a shallow neural network on MNIST digits dataset with different weight initialization schemes.

NETWORK STRUCTURE

We built a shallow neural network with one hidden layer with *tanh* activation units as recommended in (LeCun et al. 2012)

$$1.7159 * \tanh\left(\frac{2}{3}x\right)$$

and an output layer with $softmax$ activation units to model the problem as a multinomial classification problem:

$$P(y = j|x) = \frac{e^{x^T w_j}}{\sum_{k=1}^{K} e^{x^T w_k}}$$

The input layer has 784 units and the output layer has 10 units corresponding to the ten target classes. All the units in each layer are fully connected.

TRAINING METHOD

The neural Network is trained using mini-batch stochastic gradient descent (SGD) back propagation with a batch size of 32. A constant learning rate of 0.01 is used. SGD is run for a fixed number of iterations and the model that performs best on the validation set at any time during training is used as the final model.

WEIGHT INITIALIZATION

Neural Networks are commonly initialized with weights sampled randomly from a uniform distribution such that the network begins operating in its linear regime. This ensures that the gradients are large enough when the training begins. In addition, it also helps the network to learn the linear features first and harder

non-linear features next. Weights at each layer are initialized at each layer using the following heuristic:

$$W_{ij} = U\left[-\frac{1}{\sqrt{n}}, \frac{1}{\sqrt{n}}\right]$$

where $U[-a, a]$ is the uniform distribution in the interval $(-a, a)$ and n is the size of the previous layer (Erhan et al. 2009). The biases are set to zero or initilized from the same uniform distribution as the weights.

EXPERIMENTS

We performed several experiments with the shallow neural network and MNIST digits dataset. The mnist training data set is split into two— a set of 50000 examples is used for training set and and the set of other 10000 examples is used for the validation. The standard mnist test set is used for testing the performance of the neural network. The dataset is standardized to have a mean of zero and variance of one in all features.

Shallow Neural Network

We set up a shallow neural network as described in section 1 with 300 hidden units. The weights were initialized as described in section 3. The network was trained with mini-batch SGD back propagation. The network converges to zero error after 30 passes through the dataset and achieves an error of 0.036 on the test set. The Training and Validation errors over training epochs are show in figure 1. We also plot the distribution of weights and biases to monitor the change over training epochs in figure 2. Finally figure 4 shows the distribution of activations that units in hidden layer output.

FIG. 1. Training and Validation Error

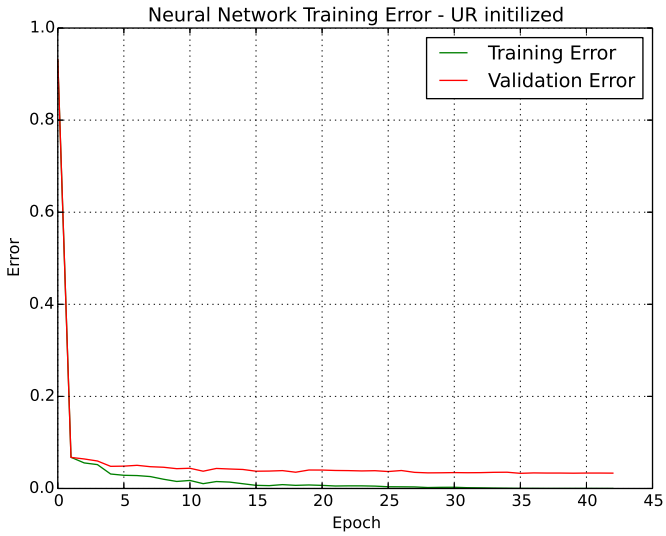
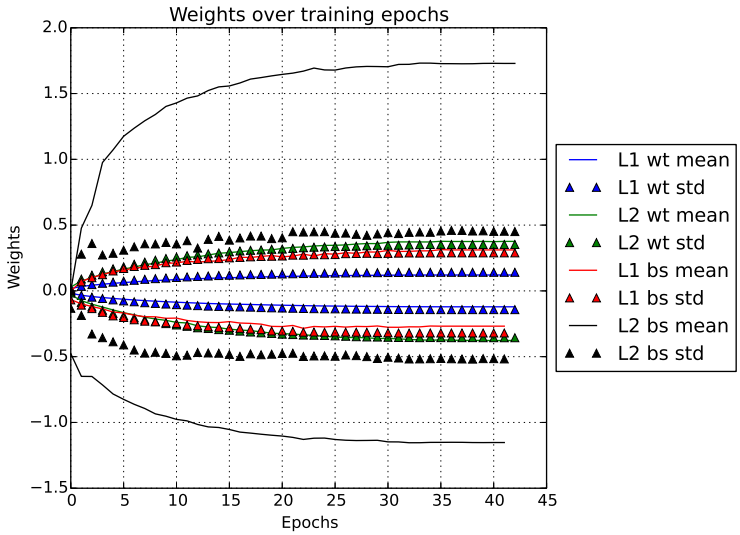


FIG. 2. Weight Distribution



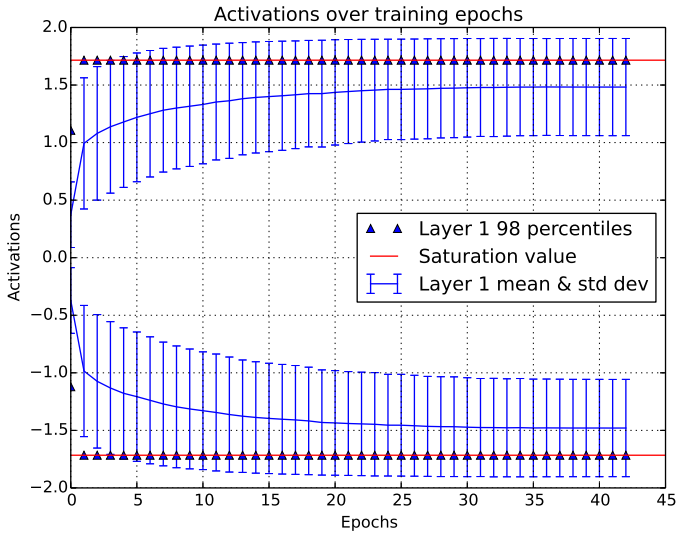


FIG. 3. Layer 1 Activations

Random Features Network

We performed an experiment to determine the performance of neural network with random (linear and non linear) features. This is done by keeping the weights that map the input layer to the hidden layer (IHL) fixed, while changing only the weights that map the hidden layer to the output layer (HOL) using Back Propagation. The weights in HOL initialized as mentioned in section 3 while the weights in IHL are sampled randomly from a uniform distribution $U[-a, a]$ where

a is varied from 0.01 to 3.0. The hidden layer is set to have 300 hidden units. The network is trained using back propagation for 10 epochs with a fixed learning rate and batch size as mentioned in section 2. The error obtained on the test set is recorded in table 1

a	$TestError$
0.01	0.0885
0.035	0.0853
0.1	0.1072
0.3	0.129
0.9	0.1488
3.0	0.1554

TABLE 1. Random Feature Shallow Network with 300 Hidden Units

REFERENCES

Erhan, D., Manzagol, P.-A., Bengio, Y., Bengio, S., and Vincent, P. (2009). "The difficulty of training deep architectures and the effect of unsupervised pre-training." *International Conference on Artificial Intelligence and Statistics*, 153–160.

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References