

A Practical Analysis of the Convergence of Back Propagation

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Objectives

- Implement a fully connected neural network.
- Analyze the effects on performance and convergence of several improvements to back propagation, including those proposed by LeCun's 1998 paper *Efficient BackProp* [1].
- Perform practical tests on the MNIST data set.

MNIST



Figure 1: Sample digits from the MNIST dataset [2].

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Input Normalization

Average of the input training data should be close to 0.

$$x \leftarrow x - \bar{x} \quad (1)$$

Variance of the input training data should be the same for each feature (≈ 1).

$$x_i \leftarrow \frac{x_i}{\sigma_{x_i}} \quad (2)$$

Sigmoid

Logistic sigmoid:

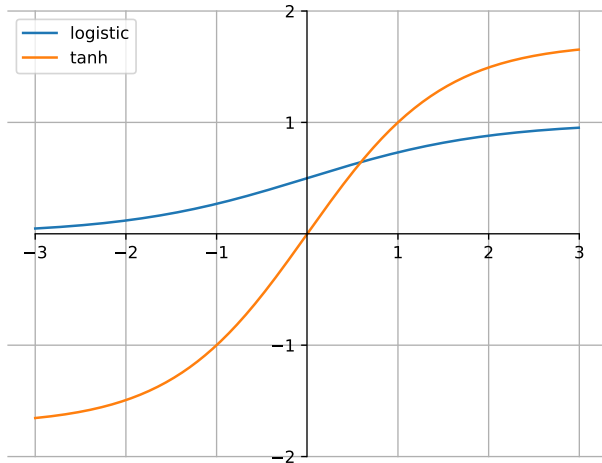
$$f_{logistic}(x) = \frac{1}{1 + e^{-x}} \quad (3)$$

Tanh sigmoid:

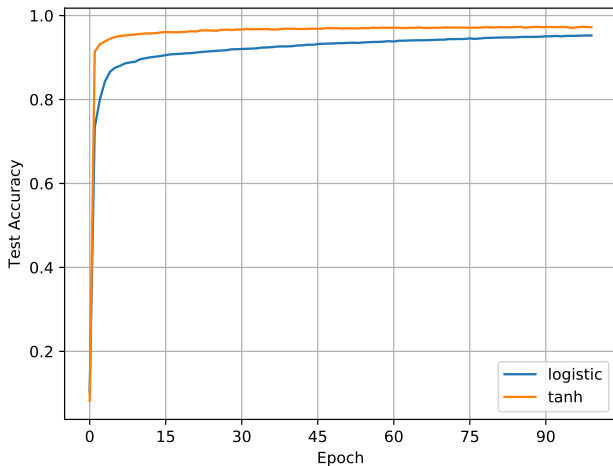
$$f_{tanh}(x) = 1.7159 \tanh\left(\frac{2}{3}x\right) \quad (4)$$

- Symmetric about the origin.
- $f(\pm 1) = \pm 1$.
- Second derivative maximum at $x = 1$.
- Output variance close to 1 if input is normalized.

Sigmoid



Sigmoid



Weight Initialization

Initial weights should be randomly drawn from a distribution with zero mean and standard deviation σ_w (m : fan-in).

$$\sigma_w = m^{-1/2} \quad (5)$$

This ensures that the initial weights range over the sigmoid's linear region (assuming input normalization and tanh sigmoid).

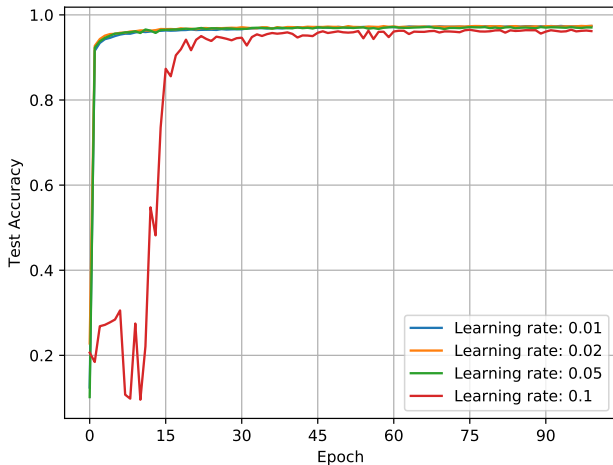
- Gradients large enough for learning to proceed.
- Linear learning occurs before more difficult nonlinear learning.
- Distribution of outputs of each node has $\sigma \approx 1$.

Learning Rate

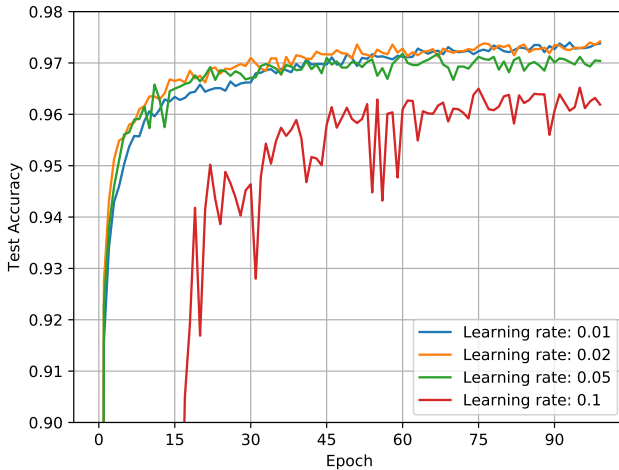
$$w_i \leftarrow w_i - \eta_i \frac{\partial E}{\partial w_i} \quad (6)$$

- η_i : learning rate for weight w_i .
- Large learning rate: oscillations.
- Small learning rate: slow learning.

Learning Rate



Learning Rate



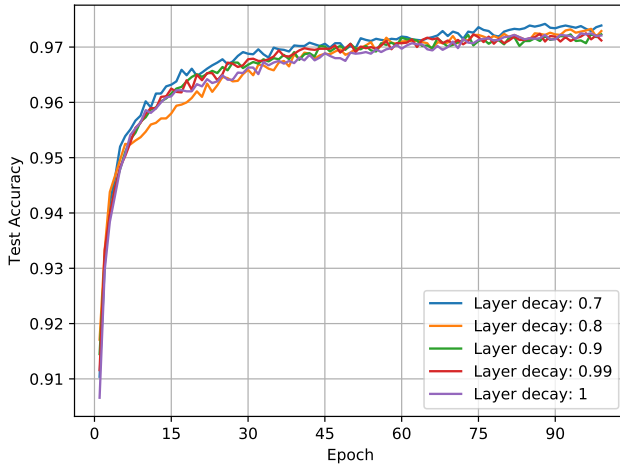
Layer Decay

Learning rate for weights in lower layers should be larger than for those in higher layers.

$$\eta_i = \delta \eta_{i-1} \quad (7)$$

- η_i : learning rate in layer i (layer i is higher than layer $i - 1$).
- δ : layer decay ($0 < \delta \leq 1$).

Layer Decay

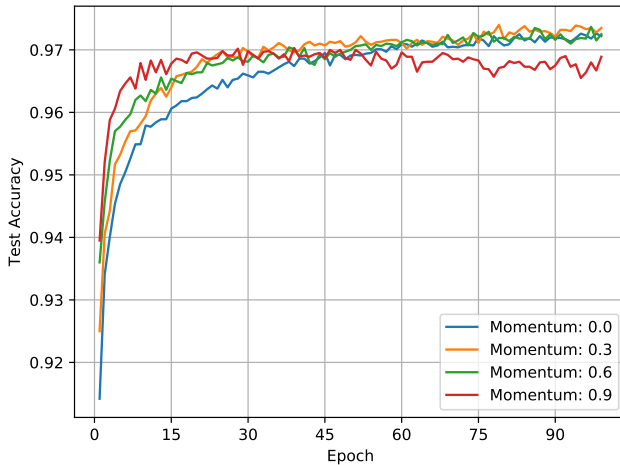


Momentum

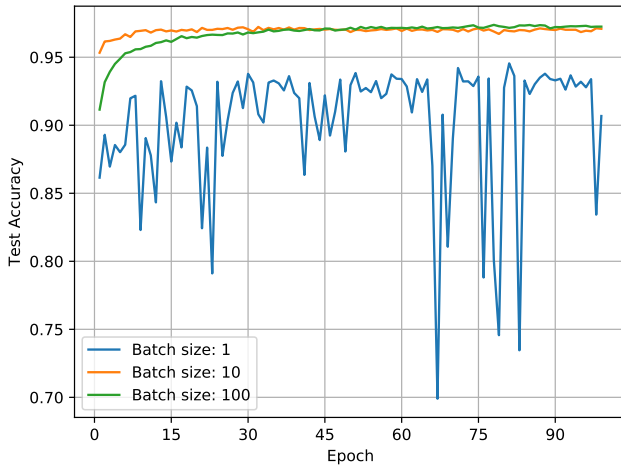
$$\Delta w(t+1) \leftarrow -\eta \nabla E + \mu \Delta w(t) \quad (8)$$

- μ : momentum.
- Avoids getting stuck in local minima.
- Large momentum: overshoot the minimum.
- Small momentum: slow learning.

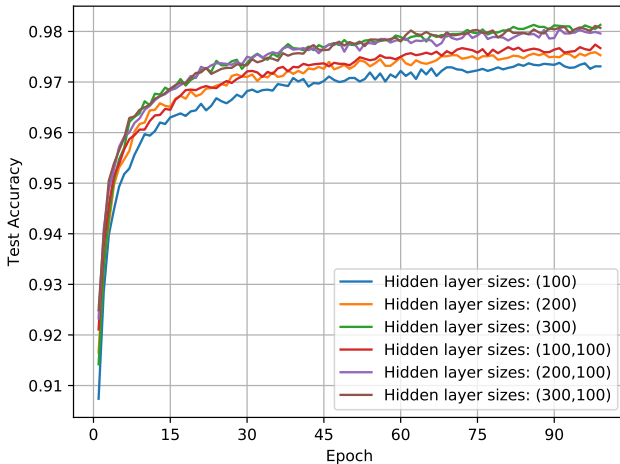
Momentum



Batch Size



Layer Sizes



Comparison to Other Approaches

- Deep convolutional network using TensorFlow [3].
- Learns localized features of the input.
- Learned features are translation invariant.
- Better for image recognition problems (like MNIST).

Comparison to Other Approaches

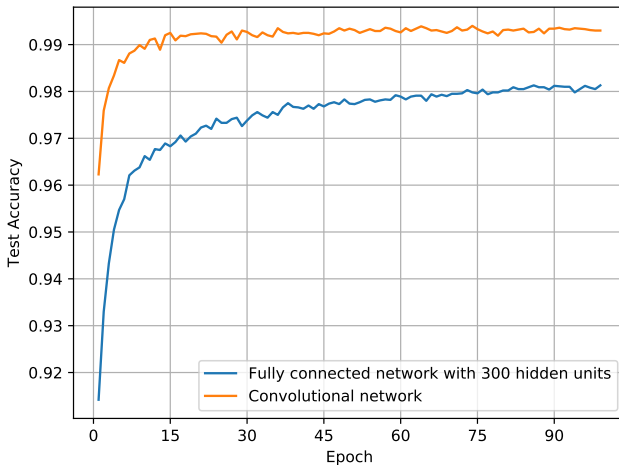


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Demo

- Inspired by the OCHRE applet [4].

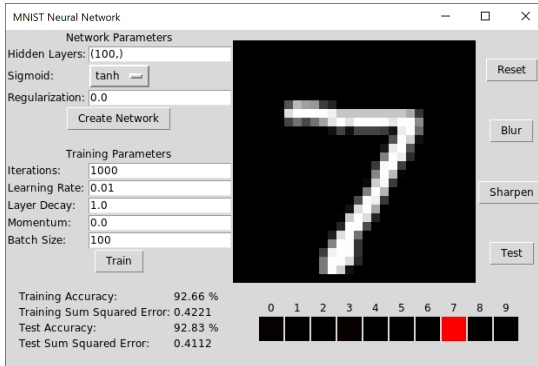






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