# Hebbian Plasticity based Networks for Pattern Reconstruction and Classification

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## Motivation

- Plasticity is one of the most essential component of biological neural networks
- Most state-of-the-art Deep Learning methods do not incorporate plasticity
- Analysis of incorporation of plasticity in conventional neural networks is necessary so as to mimic biological neural networks more closely
- Training plastic neural networks using back-propagation would help us use existing tools of conventional ANNs for getting better performance

## Overview

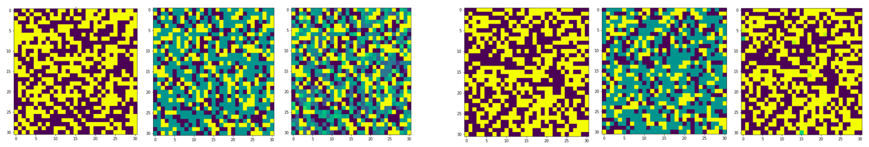
- Plasticity in networks implies that the synaptic weights have two components, fixed and plastic, the latter being the product of learning rate and the Hebbian trace.
- Hebbian between the pre-neuron and post-neuron activity is used to change the strength of the connection between two neurons as shown in equations below.

$$x_j(t) = \sigma\Big(\sum_{i \in inputs} [w_{i,j} x_i(t-1) + \alpha_{i,j} H_{i,j}(t) x_i(t-1)]\Big)$$

$$H_{i,j}(t+1) = \eta x_i(t-1) x_j(t) + (1-\eta) H_{i,j}(t)$$

## Pattern reconstruction

- Using the primitive Hebbian trace update rule, the problem of reconstructing the given input to a desired output with minimum loss is solved.
- The results are listed below.

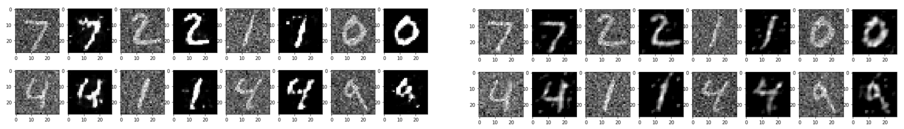


(a) (b)

Figure 1: Reconstruction of a given input pattern after (a) 10 epochs, Mean loss = 0.0239, (b) 930 epochs, Mean loss = 0.0001

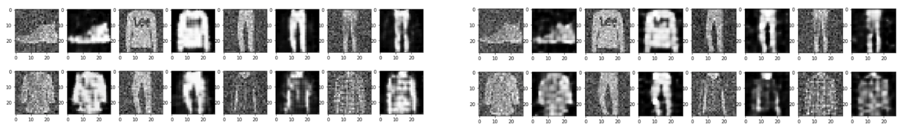
## Reconstruction in presence of noise

- The Encoder-decoder network shown in figure 1 was presented with episodic batch of images, corrupted with Gaussian noise
- A fully connected plastic layer was incorporated after each of auto-encoder and decoder layers. Results are listed below.



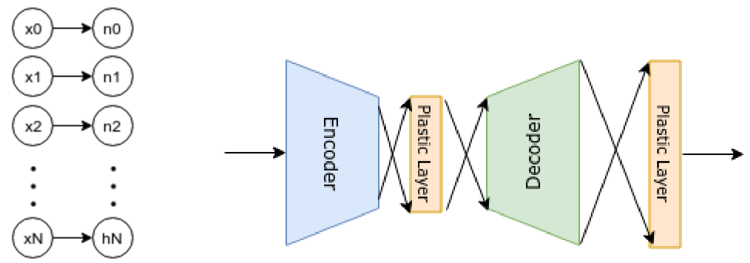
(a) (b)

Figure 2: Denoising using (a) plasticity based, (b) similar DNN based Autoencoder-decoder network on MNIST dataset



(a) (b)

Figure 3: Denoising using (a) plasticity based, (b) similar DNN based Autoencoder-decoder network on FMNIST dataset

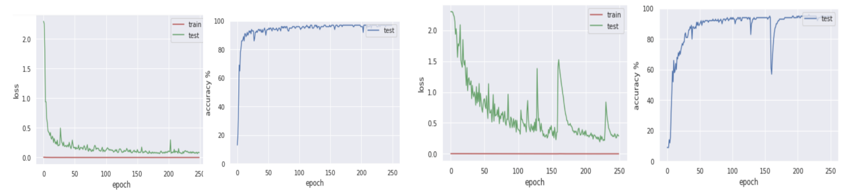



(a) (b)

Figure 4: Network for (a) Pattern Reconstruction (*fully connected*), (b) Plasticity based Autoencoder-decoder for denoising (*crossed lines represent fully connected layers*)

## Classification performance: plastic vs non-plastic

- Classifying MNIST images using plastic and non-plastic deep learning model (similar networks)
- **Number of training samples < 25,000**



(a) (b) (c) (d)

Figure 5: (a) or (c) train and test set loss using non-plastic or plastic deep model. (b) or (d) test set accuracy using non-plastic or plastic deep model.

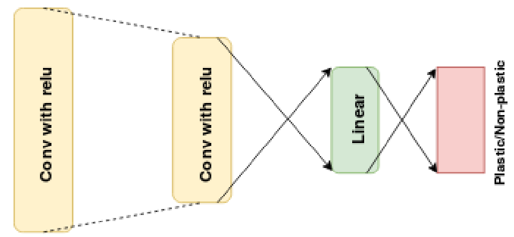



Figure 6: Network for classifying images, last layer can be plastic or non-plastic. Dashed line represents max-pooling, crossed solid lines represents fully connected layers

## Conclusions

- Proposed synaptic plasticity in current form doesn't perform well in batches making the learning much slower than the corresponding non-plastic version
- Performs well for certain specific tasks, however when we put it to test for some of the generic tasks it fails to improve the learning (in contrast to what was proposed by author)
- Learning more unstable with plasticity for generic vision tasks such as classification and denoising