# Unsupervised learning in Spiking Convolutional Neural Networks using STDP

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## Introduction

Spiking neural networks more closely mimic the behavior of biological neurons and are important in modelling real brains (within the discipline of Computational Neuroscience) and provide new opportunities to achieve the goal of human-like intelligence.

In ANNs the standard training method is backpropagation, where after presenting an input example, each neuron receives its specific error signal which is used to update the weight matrix. It seems unlikely that such a neuron-specific error signal would be implemented in the brain instead evidence is more pointing toward unsupervised learning methods like spike timing-dependent plasticity (STDP).

By modifying synaptic strengths Spike-timing-dependent plasticity (STDP) leads to adjustment of the strength of connections and the reorganization of connections within a neural network and under certain conditions may result in the emergence of new functions, such as input clustering, pattern recognition,etc.

This project is based on the paper by Diehl, P et al.,2019 and provides an unsupervised learning method for image classification that makes use of biologically plausible spike timing-dependent plasticity (STDP) method.

## Methodology

There are many different models of spiking neurons that can be used. The one used in this project is the following LIF (Leaky Integrate and Fire) neuron model.

$$\tau \frac{dV}{dt} = (E_{rest} - V) + g_e(E_{exc} - V) + g_i(E_{inh} - V)$$

Inputs to spiking neurons are given in the form of spike trains. Fig 1 shows an example of a spike train.

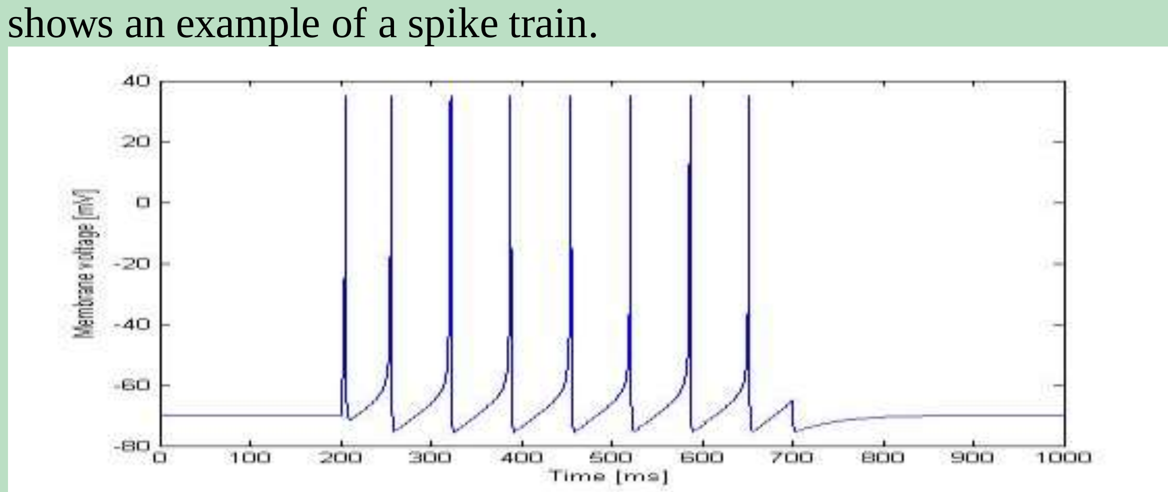


Fig. 1. Spike train provided as an input to the neurons

In order to provide an image as input to the network we convert the images into Poisson spikes inputs with firing rates proportional to the intensity of corresponding pixels. We then can visualize the firing rates of all 784 neurons (28 x 28) using raster plots (refer Fig. 2). In the raster plots the vertical axis indicates the neuron index and the horizontal axis indicates time. The intensity values of the 28 × 28 pixel MNIST images are converted to Poisson-spike inputs with firing rates proportional to the intensity of the corresponding pixel.

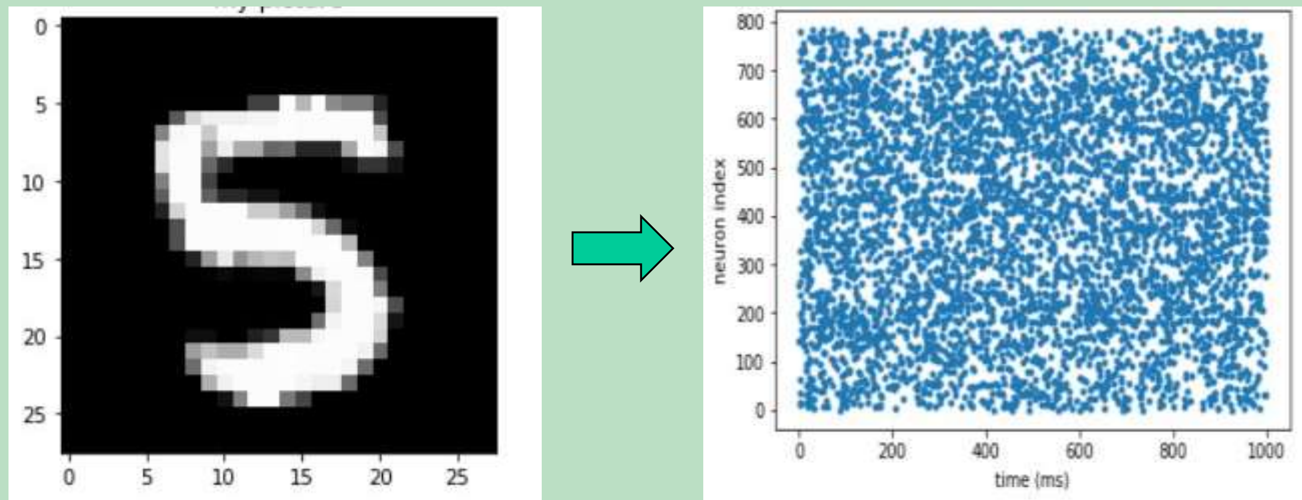


Fig. 2. Conversion of image input to Poisson spike inputs

Those Poisson-spike trains are fed as input to excitatory neurons in an all-to-all fashion. In Fig. 3 the blue shaded area shows the input connections to one specific excitatory example neuron.

Excitatory neurons are connected to inhibitory neurons via one-to-one connections, as shown for the example neuron. The red shaded area denotes all connections from one inhibitory neuron to the excitatory neurons.

Each inhibitory neuron is connected to all excitatory neurons, except for the one it receives a connection from. Class labels are not presented to the network, so the learning is unsupervised. Excitatory neurons are assigned to classes after training, based on their highest average response to a digit class over the training set .

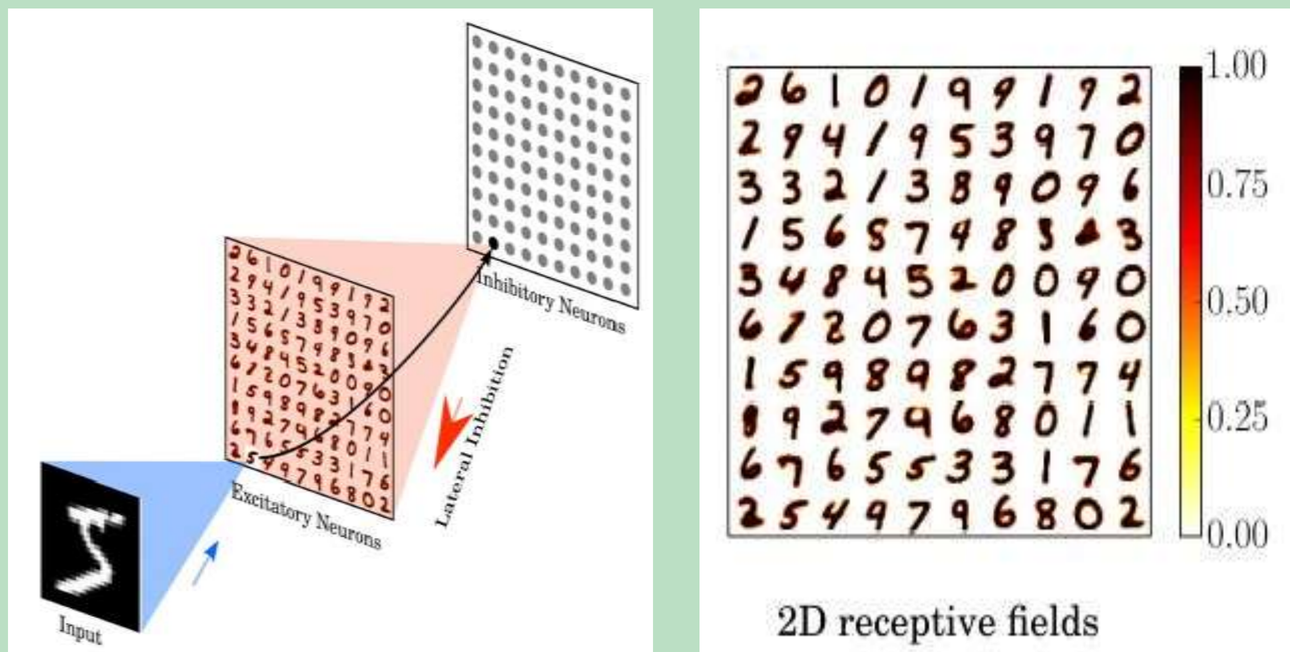


Fig. 3 Network Architecture

No additional parameters are used to predict the class, specifically no linear classifier or similar methods are on top of the SNN. All synapses from input neurons to excitatory neurons are learned using STDP. When a postsynaptic spike arrives at the synapse the weight change is calculated based on the presynaptic trace

$$\Delta w = \eta(x_{pre} - x_{tar})(w_{max} - w)^{\mu}$$

Further methods like Homeostasis and modifying input encodings can help increase accuracy.

## Results and Important Conclusions

Diehl and Cook trained and tested using 40,000 MNIST images and using 100 ,400,1600 and 6400 excitatory neurons. It was found that the accuracy increases with the increase in number of excitatory neurons. Fig. 4 shows the trend of accuracy with increasing number of neurons. Similarly Fig. 5 shows the trend of accuracy with increasing number of input images and Fig. 6 shows the confusion matrix of the results.

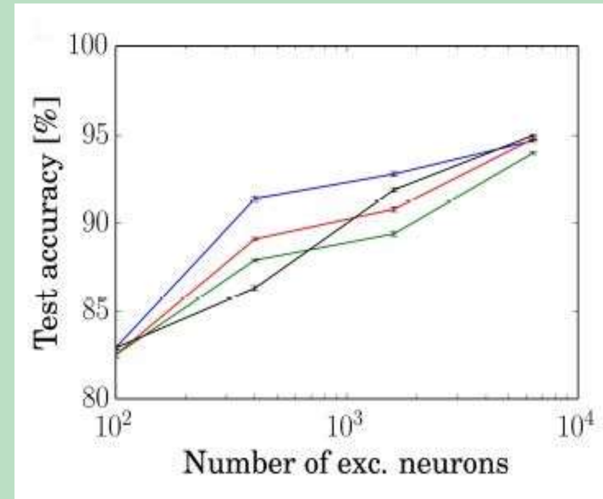


Fig. 4 Performance as a function of number of excitatory neurons

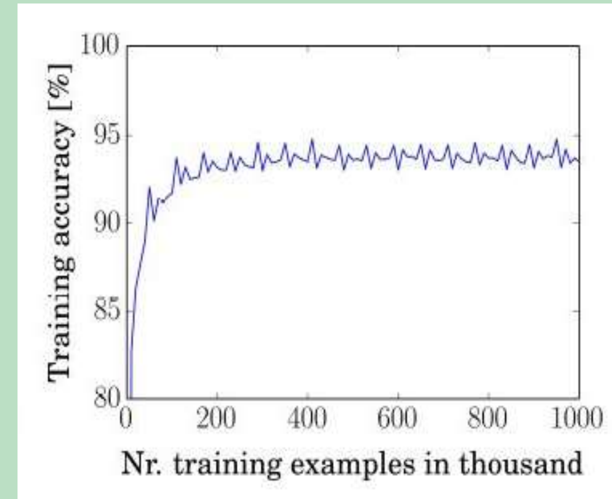


Fig. 5 Performance as a function of number of input images

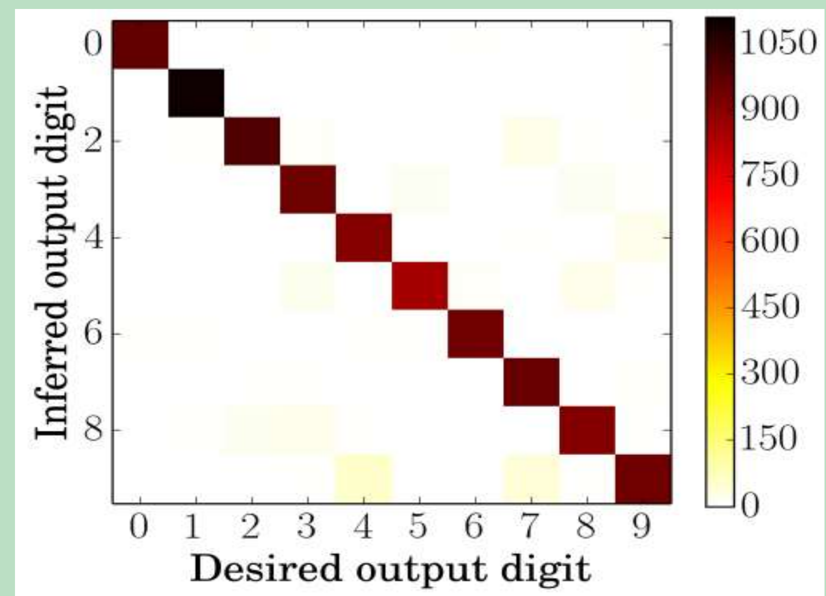


Fig. 6. Average confusion matrix of the testing results over ten presentations of the 10,000 MNIST test set digits.

## References

[1] Diehl, P. and Cook, M. (2015). Unsupervised learning of digit recognition using spike-timing-dependent plasticity.

[2] Jug, F. (2012). On Competition and Learning in Cortical Structures. Ph.D. thesis, Diss., Eidgenssische Technische Hochschule ETH Zrich, Nr. 20194, 2012

[3] Ponulak, Filip Kasiski, Andrzej. (2011). Introduction to spiking neural networks: Information processing, learning and applications. Acta neurobiologiae experimentalis. 71. 409-33.

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