HUMBOLDT-UNIVERSITÄT ZU BERLIN

BERNSTEIN CENTER FOR

COMPUTATIONAL NEUROSCIENCE

Humboldt-Universität zu Berlin
Philippstr. 13 House 6

Phone: 030/2093-9110
Fax: 030/2093-6771
webpage: http://www.bccn-berlin.de/

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Project 6: Temporal Pattern Learning

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Background

The tempotron, in analogy the perceptron, is a neuron that is able to distinguish between different temporal input patterns. It should respond with an action potential for some input patterns, but not for others. Importantly, for all input patterns, the tempotron can receive input from the same cells, but only the relative timing of these inputs is different for different input patterns. Read the original paper (Gütig and Sompolinsky, 2006) to understand the details on the tempotron algorithm.

The model neuron and its inputs

The tempotron is a leaky integrate-and-fire neuron that receives input from n cells. An input spike evokes a postsynaptic potential in the membrane potential of the tempotron. The summed postsynaptic potentials of all inputs define the membrane potential of the tempotron:

$$V(t) = \sum_i \omega_i \sum_{t_i} \kappa(t - t_i) + V_{rest}$$

with t_i being the spike time of the ith input cell and $\kappa(t - t_i)$ being the normalized postsynaptic potential evoked by an input spike (for $t - t_i \geq 0$, otherwise $\kappa = 0$):

$$\kappa(t - t_i) = V_0(e^{-(t-t_i)/\tau} - e^{-(t-t_i)/\tau_s})$$

V_0 is a normalization constant, so that the amplitude is given by ω_i. τ and τ_s are time constants for the membrane and synaptic currents, respectively. They determinine the decay and rise time of the postsynaptic potentials. For $\tau/\tau_s = 4$, V_0 equals 2.12.

1. Implement a basic version of the tempotron. Start with very few input cells with different synaptic strengths ω_i. Check a few voltage traces to ensure that your implementation is correct.

2. Generate a set of random input patterns. Each pattern occurs within a time window of 500 ms. Each input cell fires only once per input pattern. The time of the input spike for each input cell is uniformly-distributed within the 500 ms window.

3. Vary the synaptic weights and the number of input cells.

Tempotron learning

So far, the response of the tempotron does not change because the synaptic weights are fixed. Now, we want to use a rule that modifies the synaptic weights when a temporal pattern is presented. The goal is that the tempotron produces an output spike for some patterns ('+' patterns) but not for others ('-' patterns). To determine whether an output spike is produced, we simply check whether the membrane potential $V(t)$ exceeds a certain threshold for a given pattern. Intuitively, the synaptic weights should be increased if we want our tempotron to fire an action potential for a certain pattern. Conversely, the synaptic weights should be decreased if we do not want to fire a spike for a certain pattern. However, as the input patterns mainly differ in the timing of the input, we need a sophisticated learning rule. The tempotron learning rule is:

$$\Delta\omega_i = \lambda \sum_{t_i < t_{max}} \kappa(t_{max} - t_i)$$

where $\lambda > 0$ is a learning rate and t_{max} is the time when $V(t)$ is maximal. Weights are only changed for incorrect responses of the tempotron. Weights are increased by $\Delta\omega_i$ if no spike was elicited (although there should have been one). Weights are decreased by $\Delta\omega_i$ if a spike was elicited (although there should have been none).

1. Train your tempotron on two patterns (one '+' and one '-' pattern). Compare the synaptic weights before and after learning. Switch the identities of the '+' and '-' pattern and learn again.

2. Generate a larger training set and reproduce some results of Gütig and Sompolinsky (2006).

3. Change some aspects of the learning paradigm (e.g. the temporal structure of the input patterns, the shape of postsynaptic potentials, the learning parameters,...) and examine the effect on learning performance.

4. For what types of learning could the tempotron learning rule be used by the brain? Try to illustrate your idea(s) with simulations using the tempotron. Are there problems or weaknesses of the algorithm that need to be addressed by the brain?

Create labeled figures for all your main findings and summarize your results.

Literature

R. Gütig and H. Sompolinsky (2006). The tempotron: a neuron that learns spike timing-based decisions. *Nat Neurosci* 9(3):420-8.

Contact

Richard Kempter	Phone: 2093-8925	Email: r.kempter(at)biologie.hu-berlin.de
Robert Schmidt	Phone: 2093-8926	Email: r.schmidt@biologie.hu-berlin.de
Bartosz Telenczuk	Phone: 2093-8838	Email: b.telenczuk@biologie.hu-berlin.de