ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Bachelor/Master Thesis

Learning Robust Sequences

A possible explanation of how the human brain stores sequential memories, such as the tones of a melody, the words of a poem or the locations on the way to your friends apartment, is that they get mapped to an already existing sequence of neural activities. This sequence consists of sets or patterns of neurons. The neurons in the first pattern are activated by some stimulus, then the sequence plays, that is, the neurons in the $i+1$-th pattern are activated by the activity in the i-th pattern. Now, in case of remembering a melody, the i-th tone gets mapped to the i-th pattern, meaning that whenever the i-th pattern is active, then the tone is remembered. Of course this procedure only works if the already existing sequence of patterns is very robust. However, robustness in the brain is not a given as neurons are unreliable. It happens that neurons decide to get active spontaneously and that they decide to not turn active though they actually should. The goal of this thesis is to device an unsupervised learning algorithm that forms robust sequences in previously unstructured neural network.

First consider a directed $G_{n,p}$ (each vertex v represents one neuron and an edge (u, v) represents a synapse from neuron u to neuron v), where we assign to every edge e a value $w(e) \in \{0, 1\}$. If the value is $w(e) = 1$ then the synapse is active, and if $w(e) = 0$, then the synapse is silent. Assume a pattern A_0 consisting of m neurons is activated. Now, activity proceeds in rounds $t = 0, 1, 2, \ldots$ and we denote by A_t the active set in round t. In round t all the active vertices send spikes to all their neighbours that are connected with an active synapse to them. The number of spikes x_u that a vertex u receives in round t is thus given by $x_u = \sum_{v \in A_t,(v,u) \in E} w((v, u))$. We now assume that there is an *abstract inhibition* which ensures that in every round exactly m vertices turn active and that there is a *noise level* k. That is A_{t+1} consists of $m-k$ neurons chosen u.a.r. among the neurons that received most spikes (that is$\{v \in V)|x_v \geq z\}$, where z is the smallest number for which $|\{v \in V)|x_v \geq z\}| \geq m$) and k neurons chosen u.a.r. from the rest (that is $\{v \in V)|x_v < z\}$). Due to the noise level k we see every time when we activate A_0 a different sequence of activities. $A_0, A_1, A_2, \ldots$. The goal is to design a learning mechanism that learns a very robust sequence $B_0, B_1, B_2, \ldots$ such that every observed sequence triggered by the activation of A_0 has very high overlap with sequence B_i. The learning rule can adapt the values $w((u, v))$ for every edge in a local way, that is the value of $w((u, v))$ is a function of the activities of the vertices u and v.

In a second part we would like to relax our abstract inhibition a little. Now, vertices get activated, if $x_v \geq z$, where z is some fixed activation threshold. Additionally there are inhibitory neurons that send negative signals and therefore prevent too many neurons to turn active. Such a detailed implementation of inhibition is much less precise. The number of active neurons will not always be m anymore but fluctuate around this value. Can we also learn in this setting a robust sequence?

The thesis consists of a theoretical part (designing and analysing a learning mechanism) and a experimental part (implementing and simulating the learning mechanism). If you are interested in this topic please contact us. We are happy to tell you more about the project!

Prerequisites: Interest in (computational) Neuroscience. Fundamental knowledge in discrete probability theory, graph theory and programming.

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