Agreement and Clustering in Spiking Neural Networks

Goals: Devise algorithm for agreement and neural clustering in neural spiking networks.

Tools: Logic, mathematics, algorithmic reasoning.

Prerequisites: Curiosity, taste for novel models and problems, basic knowledge of distributed algorithms, (preferably) basic knowledge of neural networks, math background (probability theory).

This is an interdisciplinary project in the intersection of neural networks and distributed computing.

A neural network can be seen as a distributed system, where neurons and synapses connecting them are modeled as a graph of finite state automata. Neurons communicate by firing in discrete pulses, in stochastic response to a sufficiently high number of received (over the incoming graph edges) pulses.

It has been shown that the problem of *Winner-Take-All* (WTA, also known as test-and-set or leader election in the distributed computing literature) has an efficient neural circuit [2]. Later the results were formally restated in the novel stochastic spiking neural network (SNN) [1] and generalized to solving k-WTA (or k-TAS) [3].

The problem of (k-)winner-take-all is a classical example of *symmetry breaking*: splitting the system in two classes: (up to k) leaders and everybody else. The problem of *agreement* naturally complements this class of problems. In k-set agreement, every participating process is expected to converge to up to k values, satisfying certain validity conditions. In the special case of *majority* consensus ($k = 1$), every process is expected to output the value of the majority of inputs.

On the other hand, we can naturally consider the WTA problem in the dynamic setting. Indeed, the original SNN model is static in the sense that the synaptic structure of the circuit is constant. It is very interesting to see what can be done in systems where synapse weights are functions of the firing pattern, which gives rise to a generalization of WTA, known as the *neural clustering* problem.

Goals

The project intends to explore two directions:

(1) Neural agreement.

Take the task of majority agreement: instead of selecting a bounded subset of neurons to fire, we try to make the neurons agree on whether to fire or not, depending on the number of fired neurons in the initial state. The goal is to find an agreement algorithm and study its complexity.

(2) Neural clustering.

Define the neural clustering model. Intuitively, the probability distribution of input vectors (determining the firing probability for each neuron) is split into clusters, and each elected leader must map to one of the clusters. The goal is to propose a solution in the dynamic spiking neural network and study its complexity.

Milestones

1. Study the recent literature on the algorithmic face of neural networks, starting from [1–3].

2. State the neural agreement problem and study its solvability and complexity bounds.

3. Define a dynamic variant of the SNN model, state the clustering problem, find its solution and analyse its complexity.

Contact

Petr Kuznetsov
`http://www.infres.enst.fr/~kuznetso/`
`petr.kuznetsov@telecom-paristech.fr`
INFRES, Télécom Paris

Denis Sheynikhovich
`http://www.aging-vision-action.fr/people/denis-sheynikhovich/`
`denis.sheynikhovich@upmc.fr`
UPMC, Sorbonne University

References

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[3] L. Su, Chia-Jung, and N. Lynch. Spike-based winner-take-all computation: Fundamental limits and order-optimal circuits. *Neur. Comput.*, 2019. `https://arxiv.org/pdf/1904.10399.pdf`.