Jenish Maharjan **Week 13**

Paper: *Introduction to spiking neural networks: Information processing, learning and applications*

Summary:

Ponulak and Kasinski in their paper on spiking neural networks, present their summary of spiking neurons and spiking networks with a focus on models of spike-based information coding, synaptic plasticity and learning. They also present their review of applications of spiking models ranging from neurobiology to engineering. They present these concepts with the goal of introducing spiking neural networks to audiences from various disciplines interested in spike-based neural processing.

Spiking models are based on the feature of biological neurons that they communicate by generating and propagating electrical pulses known as potentials or spikes. Conceptually, all spiking models process information coming from multiple inputs and produce a single spiking output signal. The probability of generating the output spike increases with excitatory inputs and decreases by inhibitory inputs. Another similarity between spiking models and biological neurons is that their dynamics is characterized by at least one state variable which basically means that the model is supposed to generate one or more spikes when the internal variables of the model reach a certain state. A spiking neural network (SNN) is defined as a finite directed graph (V, E) – a set of input and output neurons V and a set of synapses E.

Three general categories of spiking network architectures are feedforward networks, recurrent networks and hybrid networks. In feedforward networks, the data flow from input to output units is unidirectional with no feedback connections. Recurrent networks have neurons interacting through reciprocal or feedback connections which allows for dynamic temporal behavior. The third category of hybrid networks include networks of both types. The authors describe two main classes of hybrid spiking networks. Synfire chain network is a multi-layered architecture in which spiking activity passes on as a synchronous wave of firing from one layer to successive layers. Reservoir computing benefits from the use of recurrent networks. It is made up of fixed recurrent structure and set of output neurons. The output of the networks is achieved by training only the connections from the reservoir neurons to output neurons simplifying the training.

The authors also discuss how information is encoded and processing in spiking neurons. They also discuss the issue of concerning the neural representation of information known as neural code. They discuss some strategies for neural coding. Time to first spike strategy encodes the model information in the neural systems in the latency between the first stimulus and the time to the first spike. Another strategy Rank-order coding (ROC) encodes the information by the order of spikes in the activity of the neurons. The third strategy Latency code encodes information in the exact timing of a set of spikes relative to each other. Resonant burst model uses an effective mechanism for selective communication between neurons. Coding by synchrony is based on the assumption that neurons that encode different bits of information on the same object fire synchronously. In Phase coding, the times of emitted spikes are referred to the reference time point in a periodic signal and the neurons encode information in the phase of a pulse. The paper also discusses the models of learning for spiking neural networks that explore spike-timing based synaptic plasticity. Both supervised and unsupervised learning models are used with spiking neural networks. Reinforcement learning is another learning model used by spiking neural networks reviewed in the paper.

In the paper, they have also discussed in brief some of the areas of application of spiking neural networks. Many studies have shown the efficacy of spiking networks trained with unsupervised learning in the task of real-world data classification. Image recognition is another area of application where spiking neural networks have had successful implementation. Spiking models of the olfactory system studies by various researchers have also been used for odor recognition by encoding a stimulus by a spatial assembly of quasi-synchronized projection neurons. Spatial navigation and mental exploration of the environment is another interesting area of application discussed in the paper. Other applications are decision making in financial market, decision making and action selection and rehabilitation. The paper presents their survey with introductory concepts on information processing and learning in spiking neural networks successfully.

Strengths:

- Since the target audience constitutes scientists from various disciplines, they have made sure to explain concepts that might be new to scientists from domains new to them.
- The language and the content organization of the paper is really simple and readable.
- Their discussion and survey on the application areas is very elaborate.

Weaknesses:

- The learning sections is packed with a lot of information and has a lot of reviewed work referenced in the section. The organization of contents in the learning section into subsection would have been helpful.

Confusions:

- How do the strategies of latency code and resonant burst model for neural encoding work?
- What is a liquid state network?

Discussion Questions:

- A brief discussion on the various learning models would be helpful.
- An explanation of the navigation maps shown in figure 6 C would be helpful.
- What is the current research direction in spiking neural networks?