

A mixed-feedback recurrent neural network to create spikes

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Modern AI systems are achieving more and more impressive results in a wide range of fields. They even sometimes overtake human performance. On the other hand, biological brains are much more energy-efficient than usual AI models. The lack of energy-efficiency in current AI models prevents them to be used in areas where computational power is less available, like in embedded systems for instance. One considered solution comes directly from the biological brains. Indeed, the communication between biological neurons is mostly done by *spikes*, which are perturbations of their membrane potential. In a higher level of abstraction, spikes can be seen as discrete and sparse events. This kind of communication leads to event-based computation, where neurons are only active when events are generated. This allows to save energy, among other things. Recent research has therefore been done in order to design artificial neural networks in which neurons create and communicate with spikes, as well as specific hardware to run them. Such networks are called *Spiking Neural Networks (SNNs)*. While some good results have been obtained, training such networks is known to be difficult, especially for deep ones. Artificial spiking neurons are usually derived from simple spiking neuron models used in computational neuroscience to which are added learnable weights. These neurons are then organized in layers to form a network. A variation of the classical backpropagation is finally used to train them.

To try a different approach, we have started from the other side, i.e. the Machine Learning side. We have derived a spiking neuron, called the *Spiking Recurrent Cell (SRC)*, from usual artificial neural networks. The type of neural networks which is the closest to SNNs is the *Recurrent Neural Network (RNN)*. RNNs have originally been designed to process sequential data, like time-series or sentences. As their name suggests, RNNs use their previous output as part of their input, creating a recurrent connection. This input/output is usually referred to as the *hidden state*. But RNNs can also be seen as non-linear dynamical systems, where inputs are perturbations and feedbacks can occur through the recurrent connections. Moreover, it is known that spikes can be generated by a fast local positive feedback followed by a slow negative one. Therefore, it

is feasible to create a spiking RNN by tuning the feedbacks occurring inside it.

To derive such network, we started from the *Bistable Recurrent Cell (BRC)* [1], itself derived from the well-known *Gated Recurrent Unit (GRU)* [2]. BRC creates bistability through a local positive feedback. This feedback can thus be used to generate the ascending side of the spike. Adding a second one, which is slower and negative, allows to finish the spike. The equations of the spike generation of the SRC can be written as:

$$\begin{aligned}h[t] &= \tanh(x[t] + r \odot h[t-1] + r_s \odot h_s[t-1] + b_h) \\h_s[t] &= z_s \odot h_s[t-1] + (1 - z_s) \odot h[t-1]\end{aligned}$$

where h is the first hidden state and mimics the membrane potential of biological neurons, h_s is the second hidden state that slowly follows h , x represents the input, r (> 0) and r_s (< 0) are the feedbacks parameters, b_h is the bias to control the propensity to spike and z_s is the parameter that controls the convergence speed of h_s .

This is not the full set of equations of SRC, as the integration of the input spikes must still be described, but it is the core. Experiments with SNNs made of SRCs have been made on classical SNN benchmarks and good results have been obtained. More importantly, SRC allows to train deep SNNs of 10+ layers quite easily while classical SNNs failed to learn with so many layers.

References

- [1] Vecoven, N., et al. "A Bio-Inspired Bistable Recurrent Cell Allows for Long-Lasting Memory." PLOS ONE 16, no. 6 (June 8, 2021).
- [2] Cho, K., et al. "Learning Phrase Representations Using RNN Encoder-Decoder for Statistical Machine Translation." In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), 1724–34.

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