Safe Lifelong Learning: Spiking neurons as a solution to instability in plastic neural networks

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Artificial and Spiking Neural Networks

Artificial neurons are ‘stateless’ and activity is produce via non-linear functions

Spiking neurons accumulate information across the time domain through membrane potential, and spike when a threshold value is reached

**Membrane Potential**

\[ v_j(t + \Delta \tau) = v_j(t) - \alpha_v[v_j(t) - v_{rest}] + R \sum_i W_{i,j}(t)s_i(t), \]

**Spiking Neuron**

\[ s_j(t) = H(v_j(t)) = \begin{cases} 0 & v_j(t) \leq v_{th} \\ 1 & v_j(t) > v_{th} \end{cases}, \]
Synaptic Plasticity as a means toward intra-lifetime learning

• Synaptic plasticity is thought to be one of the primary mechanisms of learning in the brain.
• Plasticity rules change synaptic weight based on local activity

**ABCD Rule**
- Flexible Learning Rule
- Coefficients on joint activity, pre, post and bias
- Learning rate determines magnitude and direction

**Pair-based STDP**
- Precise spike-timing determines weight change
- Depression if more post-without-pre
- Potentiation if more pre-before-post

\[
W^{(l)}(t + \delta t) = W^{(l)}(t) + a_{w}^{(l)} \odot \Delta_{ABCD}(t)
\]

\[
\Delta_{ABCD}(t) = (A_{w}^{(l)} + B_{w}^{(l)} + C_{w}^{(l)} + D_{w}^{(l)}) (t)
\]

\[
A_{w}^{(l)} (t) = A^{(l)} \odot (x^{(l)}(t)^{T} \times x^{(l-1)}(t))
\]

\[
B_{w}^{(l)} (t) = B^{(l)} \odot (x^{(l)}(t)^{T} \times 1_{(l-1)})
\]

\[
C_{w}^{(l)} (t) = C^{(l)} \odot (1_{l}^{T} \times x^{(l-1)}(t))
\]

\[
m_{+} \frac{dx}{dt} = -x_{j} + a_{+} (x_{j}) \sum_{\text{pre}} \delta (t - t_{j}^{\text{pre}})
\]

\[
m_{-} \frac{dy}{dt} = -y_{j} - a_{-} (y) \sum_{\text{post}} \delta (t - t_{j}^{\text{post}})
\]

\[
\Delta W_{j}^{(l)} = A_{+} (W_{j}) x(t) \sum \delta (t - t^{n}) - A_{-} (W_{j}) y(t) \sum \delta (t - t_{j}^{f})
\]
Evolve the initial weights and synaptic plasticity parameters for a population of neural networks.

Algorithm 1 Evolution Strategies

1: **Input:** Learning rate $\alpha$, noise standard deviation $\sigma$, initial policy parameters $\theta_0$
2: for $t = 0, 1, 2, \ldots$ do
3: Sample $\epsilon_1, \ldots, \epsilon_n \sim \mathcal{N}(0, I)$
4: Compute returns $F_i = F(\theta_t + \sigma \epsilon_i)$ for $i = 1, \ldots, n$
5: Set $\theta_{t+1} \leftarrow \theta_t + \alpha \frac{1}{n \sigma} \sum_{i=1}^{n} F_i \epsilon_i$
6: end for

$$x^{(l)}(t) = \sigma \left( W^{(l)}(t) \times x^{(l-1)}(t) \right),$$

$$\tau \frac{dy}{dt} = -y_j + a_-(y) \sum_{post} \delta(t - t^{post})$$

$$\Delta W_j^{(l)} = A_+(W_j)x(t) \sum \delta(t - t^n) - A_-(W_j)y(t) \sum \delta(t - t^f)$$
The problem of finite lifespan

- Time-dependent parameters are being optimized across a (short) time horizon.

- Does intra-lifetime learning generalize to the time domain?
A reinforcement learning experiment

- PANNs are shown to degrade in performance instantaneously after the trained time horizon.
- PSNNs are shown to continue collecting positive reward, which improved in generalization with a greater time horizon.

**Artificial Neurons (ABCD)**

**Spiking Neurons (ABCD)**
An experiment in long-term control stability

**Artificial Neurons**

- PANNs are shown to have a linear relationship between the time-horizon and the amount of time balanced
- PSNNs are shown to be capable of balancing the pole indefinitely for any time horizon beyond 400 for all tested plasticity types and with recurrent PSNNs

**Spiking Neurons**
Conclusion

- The purpose of synaptic plasticity is to allow learning to occur within and beyond the training period of a neural network, and hence it is necessary to consider the ability to generalize not only in the task domain but also in the time domain.

- Spiking neurons seem to generalize better in the time domain on robotic control tasks.