# 1-100. Evolving to learn: discovering interpretable plasticity rules for spiking networks

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How do we learn? Whether we are memorizing the way to a lecture hall or mastering a sport, our central nervous system is able to retain the relevant information over extended periods of time. Adjustments of the interaction strength between neurons are a key component in this process. How these can be mathematically described at the phenomenological level, as so called “plasticity rules”, is essential both for understanding biological information processing and for developing cognitively performant artificial systems.

We suggest an automated approach for discovering biophysically plausible plasticity rules. By evolving compact symbolic expressions we ensure the discovered plasticity rules are amenable to intuitive understanding. This is fundamental for successful communication and human-guided generalization, for example to different network architectures or task domains.

We apply out method to three learning paradigms. In a reward-driven learning scenario we demonstrate that, in contrast to the prevailing view (e.g., Fremaux et al., 2010), agents with no estimate of the expected reward outperform agents who make use of such information. In an error-driven learning scenario a set of discovered plasticity rules can be interpreted as variations on the dendritic prediction of somatic spiking (Urbanczik & Senn, 2014). In a correlation-driven learning scenario, the evolutionary search discovers a variety of STDP kernels and associated homeostatic mechanisms that are functionally indistinguishable. This suggests to reconsider the STDP variations reported in the experimental literature from a point of functional equivalence.

We view the presented methods as a machinery for generating, testing, and extending hypotheses on learning in spiking networks driven by problem instances and prior knowledge and constrained by experimental evidence. We believe this approach can accelerate progress towards deep insights into information processing in physical systems, both biological and biologically inspired, with immanent potential for the development of powerful artificial learning machines.