How does the neocortex support learning? We explore a new framework where the superficial and deep neocortical layers play distinct but interrelated functional roles. The superficial layers engage in high-bandwidth, higher-frequency continuous bidirectional interactions, that can be computationally characterized in terms of parallel constraint satisfaction and attractor dynamics in the classic tradition of the Hopfield network, Boltzmann machine, and interactive-activation and competition (IAC) models. The deep layers function as a kind of outer-loop to the superficial-layer inner loop of processing, imposing more slowly evolving attentional constraints on the superficial-layer dynamics. The deep layers update roughly every 100 msec (i.e., alpha frequency) to reflect the evolving “understanding” emerging in the superficial layer representations, along with top-down task/goal constraints coming from higher layers. Computationally, the entire superficial-deep dynamic can be understood in terms of the expectation-maximization (EM) algorithm, which has the same nested inner-outer loop structure.

This framework also incorporates the widely-explored idea that people learn continuously from each moment of experience through predictive learning, learning from the differences between expectations and actual outcomes. This form of learning does not require special coincidences of inputs, and instead operates continuously on bottom-up sensory input to develop increasingly accurate internal models of the environment. Our specific proposal is that predictive learning operates within the 10Hz alpha-frequency dynamics of the deep layers and thalamocortical loops, with each 100 msec iteration of deep layer / thalamic updating supporting one expectation / outcome predictive learning cycle. More specifically, the TRC neurons of the thalamus, which receive signals from the deep layers of the neocortex, act as the visible neurons of a predictive auto-encoder (the input/output patterns). The thalamus receiving “first” from the layer 6 neurons of some area, for example V2 in visual cortex, what amounts to the prediction, and “second”, 100 msec later, the signal from layer 5 of the preceding area, in this example V1, the input signal. The difference is the error and training signal. The idea that the brain imposes an internal discretization of experience for the purposes of learning (and attentional updating) helps to resolve the otherwise thorny problem of how the brain knows the difference between the minus and plus phases of error-driven learning: it is just built-in to the basic dynamics.

We will present an implementation of this model for visual object recognition.

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