Title: **Maintaining stable perception during active exploration**

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Our sensory input changes dramatically as the result of our own behavior, including eye movements, head turns, and body movements. Despite these rapid sensory changes, our perception of the world is amazingly stable, and we can reliably discriminate between different patterns. This suggests that we learn stable but distinct representations through active exploration. There is reason to believe that efference copy, an internal copy of the motor signal, is critical for such sensorimotor learning. However the exact brain mechanisms underlying these computations remain unknown. In this study, we propose a computational model of sensorimotor learning and prediction. Sparse distributed representations of visual scenes are built up incrementally by pooling together predictable temporal transitions during exploration. To enable accurate predictions during active exploration, we modified the Hierarchical Temporal Memory sequence-learning algorithm to use both sensory inputs and efference copy signals. To enable forming stable representations of scenes, we implemented a novel temporal pooling learning rule that allows downstream neurons to form connections with upstream neurons that are predicting correctly. The overall model is unsupervised and the architecture is consistent with several important aspects of thalamocortical circuits. We tested the algorithm on a set of simulated environments, as well as a robotics test bed. In both cases the model achieves two desired properties: 1) prediction of future sensory inputs during behavior, and 2) emergence of stable and distinct representations for learned patterns. After learning, the sparse activity of cells in downstream regions is stable despite sensor movements, while different images lead to distinct representations. These results demonstrate how efference copy can be used in sensory cortex to make predictions during behavior. We propose temporal pooling as a novel computational principle for forming invariant representations during unsupervised learning and active exploration.

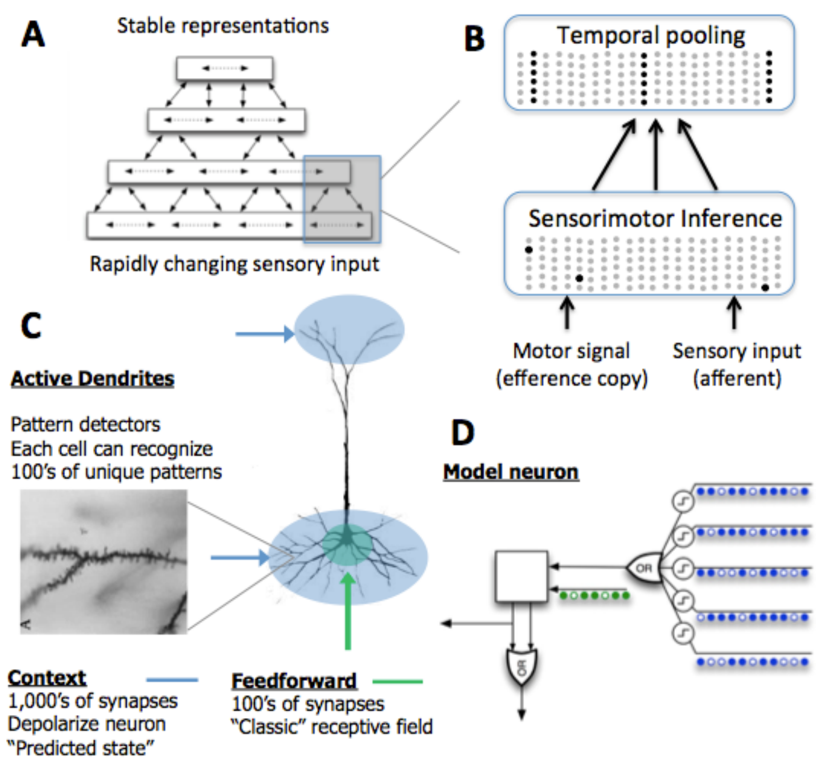

Figure 1. **Modeling framework**. **A.** The HTM network contains a hierarchy of regions. Higher levels form stable representations of the external world despite rapidly changing sensory input to lower levels. **B.** At each level, the model uses current sensory input and efference motor copy[1,6] as contextual inputs to predict future sensory inputs. If the input is correctly predicted, the temporal pooling algorithm learns to form stable representations at the next level. **(C-D)** Single neuron model in the network. In addition to feedforward inputs, pyramidal neurons receive thousands of contextual inputs via distal dendrites (C). Moreover, recent studies suggest dendrites are active structures that can initiate

dendritic spikes[2]. We propose that the depolarization caused by contextual inputs turns neuron into a "predicted state", and makes neurons more excitable upon feedforward activation[3]. Schematic of our model neuron is shown in (D). We also incorporated various inhibitory mechanisms into the model, so that predicted neurons will fire first and inhibit other neurons within the same cortical column. Lateral inhibition across columns generates a sparse distributed representation of sensory inputs[4].

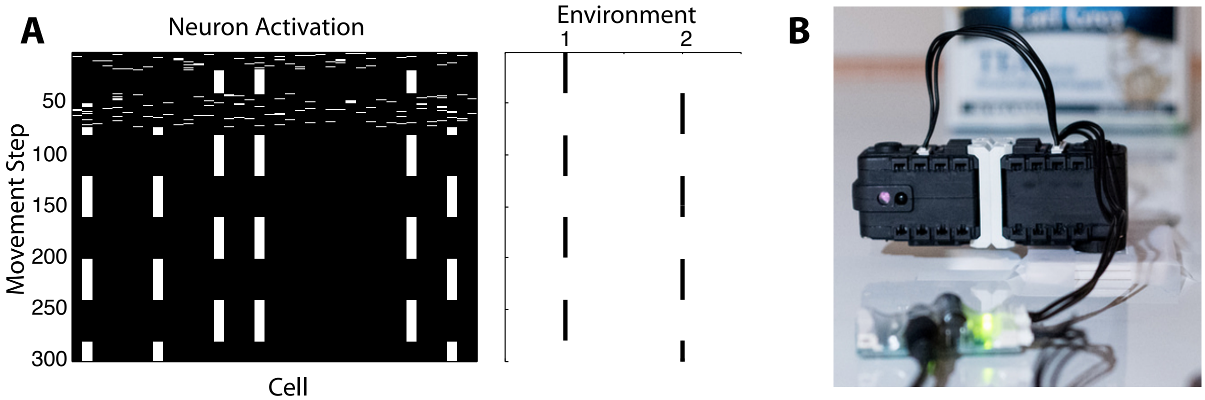

Figure 2. **Experimental tests of the algorithm**. **A.** In an example experiment, the robot actively explores two environments with different spatial configurations using random motions. Neuronal activations are shown across time (vertical axis). This figure shows a transition from an initially random, unstable representation to stable and distinct sparse representations for two test patterns despite rapid sensor movements. **B.** Robotics test bed. The robot has an infrared sensor to sense distance to an object, and a servo motor to rotate within a plane. The robot explored several environments with different spatial configurations. We verified that in all cases stable and distinct representations were learned for each environment[5].

References

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