Title: A model of top-down processing and temporal predictions in cortex

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Summary:

Unlike classical models of information processing, computation in the cortex is bidirectional. There is increasing evidence that top-down processes play critical functional roles even in early sensory regions. Pyramidal neurons in cortex primarily receive top-down feedback input onto their apical dendrites and recent experimental evidence suggests that both basal and apical inputs are critical for determining a neuron's response (Larkum, 2013). However the exact functional role of top-down input in processing a temporal stream of sensory information is unclear. In this paper we describe a computational model of top-down processing using a large network of neurons with apical dendrites operating on sparse distributed representations. The two-layered network is able to learn and predict temporal sequences in the lower layer using a recently proposed sequence memory model (Hawkins and Ahmad, 2016), and form stable sparse representations of those sequences in the upper layer. The upper layer projects back to the apical dendrites of cells in the lower layer and acts as a context-specific bias. We compare performance under various scenarios, focusing on processing complex temporal sequences under noisy and ambiguous conditions. Our results show that networks of neurons can use feedback to disambiguate sensory inputs and sequences. The network also shows increased noise robustness when feedback is enabled, and can retain temporal context even in the presence of significant temporal variations. Furthermore we show a disproportionate benefit of feedback under increasingly complex and ambiguous scenarios. Our results are consistent with a large body of experimental literature, and the model leads to a number of specific predictions. We propose that feedback projections bias an entire layer of cells, that this bias is learned through experience, and that top-down information significantly improves the ability of the cortex to function effectively while receiving complex, ambiguous temporal information.

Additional Details

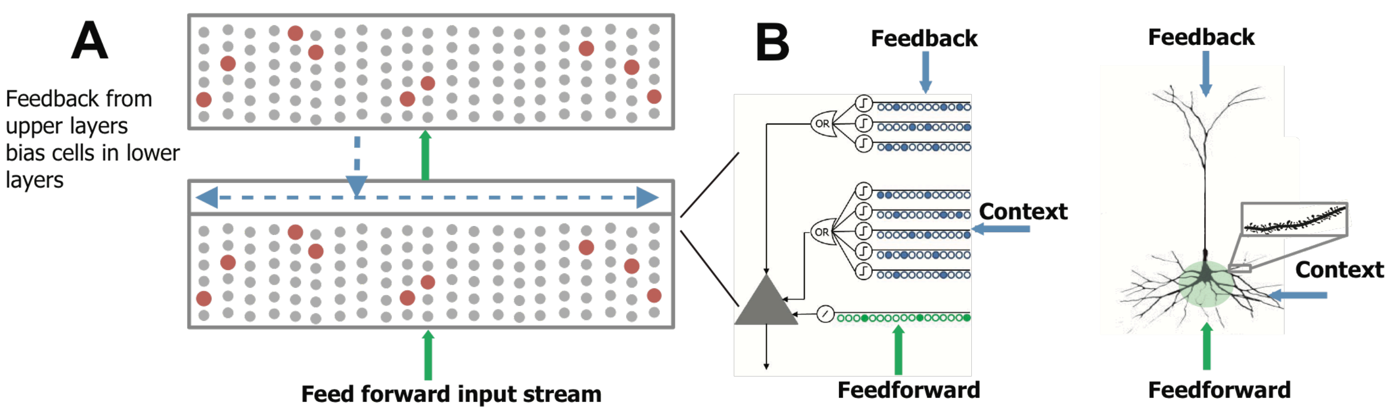

Figure 1. A. Our model consists of two large layers of recurrently connected pyramidal cells, approximately 10,000 cells total, analogous to two cortical layers. The lower layer learns to model and predict high Markov-order temporal sequences in its input stream. Through lateral recurrent connections (not shown in figure) the layer forms sparse contextual representations of sensory sequences, which are fed into the upper layer. The upper layer forms stable sparse representations of predictable sequences. It projects back to the apical dendrites of cells in the lower layer (shown in blue) and acts as a bias for future predictions. **B.** Model neurons in each layer incorporate known active dendritic properties of pyramidal cells. Each cell learns receptive fields of feed forward patterns in specific temporal contexts, similar to the model detailed in (Hawkins and Ahmad, 2016). Apical dendrites act as a predictive bias such that cells with both bottom-up and top-down support fire more strongly (Siegel et al., 2000; Larkum, 2013), and inhibit cells without such support.

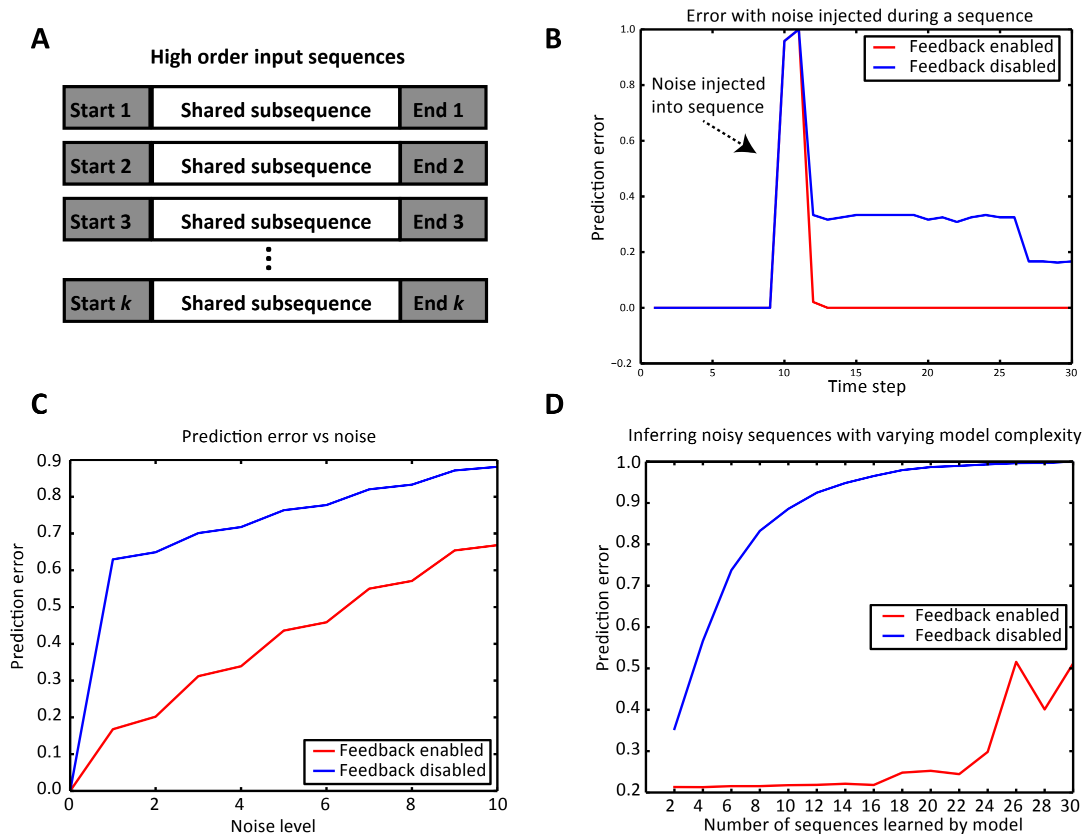

Figure 2. Simulation results. **A.** Structure of high-order test sequences fed to the network. Each sequence contains a number of elements. The elements at the start and end of each sequence are unique but the middle portion contains elements shared with other sequences. Making accurate predictions with such sequences requires maintaining temporal context throughout. Each sequence has a length of 30 elements. **B.** Plot demonstrates network error while inferring an example sequence. Noise is injected in the middle, at time step 10. Without feedback the network loses context once noise is encountered and is unable to predict the rest of the sequence accurately. With feedback enabled, the network is able to maintain context. Prediction error quickly returns to zero. **C.** Normalized prediction error when inferring an entire sequence as a function of the amount of injected noise. We injected varying amounts of temporal noise into the input stream and measured average prediction error throughout the stream. Types of noise included skipping elements, swapping successive elements, inserting random elements, and adding spatial noise to each element. (This specific chart shows error with varying numbers of successive elements swapped.) With all noise types, the network was far more sensitive to noise with feedback disabled. When feedback is enabled the network is able to predict much more reliably. **D.** We trained the model on increasingly complex tasks by varying numbers of high-order sequences with shared subsequence. The chart plots average prediction error while inferring noisy sequences. The plot shows that the more complex and ambiguous the scenario, the larger the benefit of feedback, up to a point. Without feedback, networks trained on more sequences have a disproportionately high error in the presence of noise, whereas networks with feedback are significantly better at maintaining context and predicting well.

References

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