“What the Brain Tells Us about the Future of Silicon”

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Summary - In this talk I will present recent progress in understanding how biological tissue in the neocortex works. These new insights suggest that many current assumptions about neuromorphic hardware will need to be modified if we want to build systems that work on the same principles as the brain.

Abstract - Many computer and semiconductor manufacturers are looking for new growth opportunities that are not based on traditional von-Neumann architectures. They are also concerned about the potential end of “Moore’s law”. This has led to an increased interest in artificial neural networks, and neuromorphic hardware that can support these systems.

It is well known that the brain is power efficient and naturally fault tolerant. Therefore, much research is being done on how silicon can support neural architectures while achieving greater power efficiency and greater storage density.

I will make two main arguments.

1) Neuron models need to support active dendrites and thousands of synapses

Biological neurons have thousands of synapses which are arranged along dendrites. Dendrites are themselves active processing elements. However, lacking a theory of why neurons have active dendrites, almost all artificial neural networks, such as those used in deep learning, use artificial neurons without active dendrites and with unrealistically few synapses. We now know that active dendrites combined with sparse activations allow individual neurons to recognize hundreds of unique patterns [1], [2]. This enables neurons to learn sequences of patterns which is necessary sensory inference and behavior.

2) Learning in neural tissue is achieved via rewiring, not synaptic weight change

Almost all artificial neural networks are built upon the assumption that learning is achieved via changes in the strength of synapses. However, we now know that most of learning in the cortex occurs via the growth of new synapses [3]. Memory is a rewiring problem, not a storage problem.

I will present a theory of how biological neurons with active dendrites work together in large networks to do inference and prediction in sensory data streams [4], [5]. Such networks are naturally fault tolerant due to the mathematics of sparse representations [6]. I will argue that these networks will form the basis of machine intelligence. To build systems that are as capable as biological brains will require the creation of new HW architectures that support neurons with active dendrites and large-scale rewiring.

References

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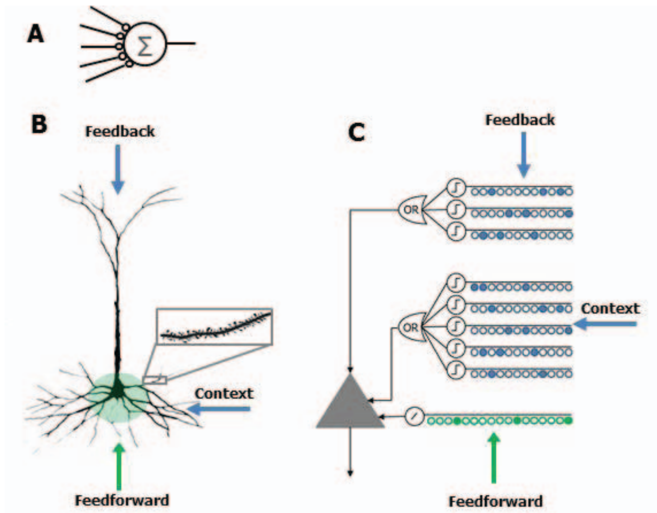

Figure 1 Comparison of neuron models. **A**) The neuron model used in most artificial neural networks has few synapses and no dendrites. **B**) A neocortical pyramidal neuron has thousands of excitatory synapses located on dendrites (inset). The co-activation of a set of synapses on a dendrite will cause an NMDA spike and depolarization at the soma. There are three sources of input to the cell. **C**) An HTM neuron models dendrites and NMDA spikes with an array of coincident detectors each with a set of synapses (only a few of each are shown). HTM neurons have thousands of synapses.

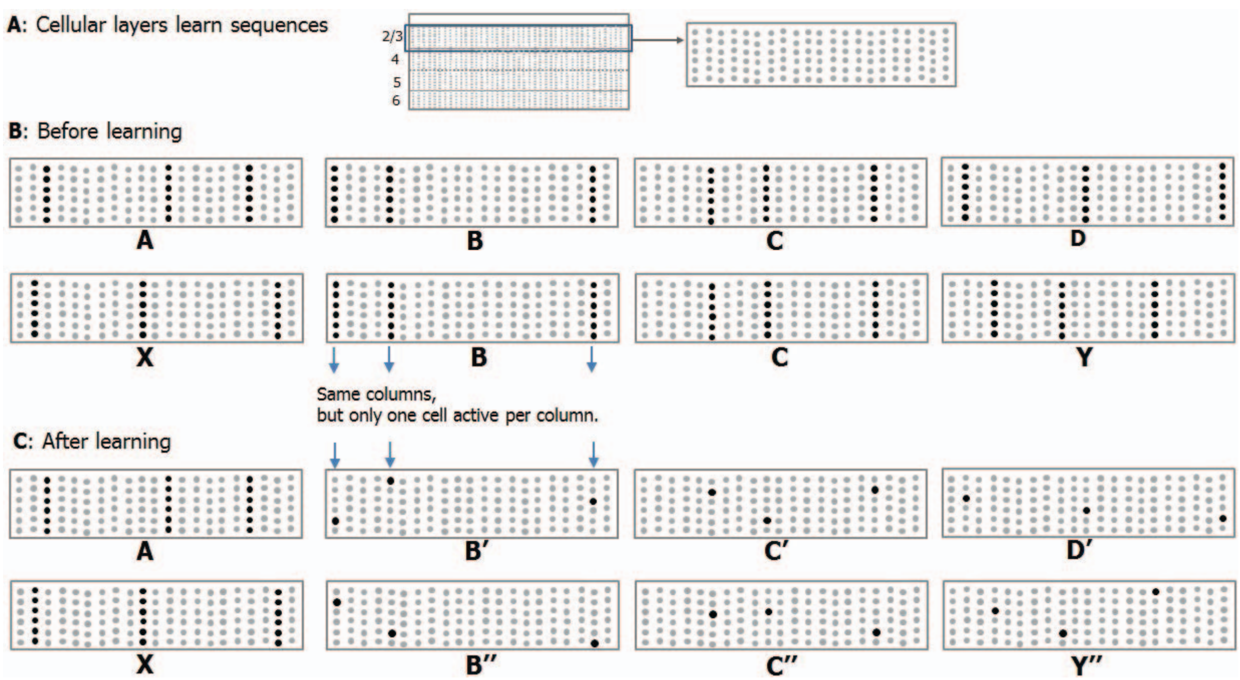

Figure 2 Representing sequences in cortical cellular layers. A) The cortex is divided into cellular layers. The panels in this figure show part of one generic cellular layer. For clarity, the panels only show 21 mini-columns with 6 cells per column. B) Input sequences ABCD and XBCY are not yet learned. Each sequence element invokes a sparse set of mini-columns, three in this illustration. All the cells in a mini-column become active if the input is unexpected, which is the case prior to learning the sequences. C) After learning the two sequences, the inputs invoke the same mini-columns but only one cell is active in each column, labeled B', B'', C', C'', D' and Y''. Because C' and C'' are unique, they can invoke the correct high-order prediction of either Y or D.

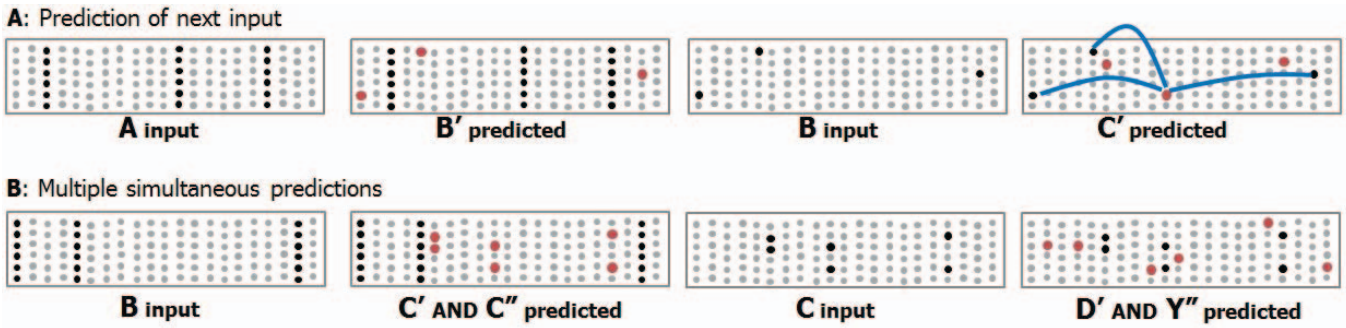

Figure 3 Basal connections to nearby neurons predict the next input. A) Using one of the sequences from figure 2, both active cells (black) and depolarized/predicted cells (red) are shown. The first panel shows the unexpected input A, which leads to a prediction of the next input B' (second panel). If the subsequent input matches the prediction then only the depolarized cells will become active (third panel), which leads to a new prediction (fourth panel). The lateral synaptic connections used by one of the predicted cells are shown. In a realistic network every predicted cell would have 15 or more connections to a subset of a large population of active cells. B) In this example sub-sequence "BC" (which is part of both ABCD and XBCY) is presented to the network. The first panel shows the unexpected input B, which leads to a prediction of both C' and C''. The third panel shows the system after input C. Both sets of predicted cells become active, which leads to predicting both D and Y (fourth panel). In complex data streams there are typically many simultaneous predictions.