A conversation with Prof. Barak Pearlmutter, September 23, 2019

Participants

- Barak Pearlmutter, PhD - Professor of Computer Science, Maynooth University
- Joseph Carlsmith - Research Analyst, Open Philanthropy

Note: These notes were compiled by Open Philanthropy and give an overview of major points made by Prof. Pearlmutter.

Summary

Open Philanthropy spoke with Prof. Barak Pearlmutter of Maynooth University as part of its investigation of what we can learn from the brain about the computational power ("compute") sufficient to match human-level task performance. The conversation focused on the compute required to model different processes in the brain.

Complexity of brain modeling

Neuroscientific uncertainty

Mr. Carlsmith asked Prof. Pearlmutter about his views about the level of modeling detail necessary to create brain models that can replicate task performance. Prof. Pearlmutter suggested that "the truth is: we don't know," and that while we may have intuitions, science has shown us that intuitions are not very reliable.

Prof. Pearlmutter's own intuition is that the gaps in our neuroscientific understanding are primarily to do with understanding the organizing principles of the brain, rather than with understanding low level biological details. Optimal information compression is an example of an organizing principle operative in the brain that has proven useful to neuroscience.

Sources of possible compute

Mr. Carlsmith suggested the possibility of breaking down the different mechanisms in the brain into four categories: neurons receiving synaptic inputs and deciding whether to fire an action potential, the biophysical changes involved in learning, various alternative signaling mechanisms, and other unknowns.

Prof. Pearlmutter thought that it sounded fairly reasonable to frame the question in these terms. However, it might result in an overly pessimistic compute estimate, as there might be tricks you can do on computers that the brain can't make use of, and the brain might be devoting some of its budget to maintenance that computers don't have to do.

Spikes through synapses

Mr. Carlsmith asked what Prof. Pearlmutter thought about the idea that a spike through a synapse could be modeled using a single floating point operation (FLOP), reflecting the impact of the spike on the post-synaptic membrane potential. Prof. Pearlmutter said that this is how it is done in deep neural networks, but that in the actual brain there is a strong temporal component to the process, and the probability of synaptic release depends on the recent history of spiking at that synapse. Prof. Pearlmutter was unsure how many more FLOPs this would implicate, though he thought it might not be that much, given that a synapse is probably storing very little state.

Prof. Pearlmutter suggested that budgeting 100 full-precision FLOPs per spike through synapse is pretty pessimistic, because you can probably code the state in many fewer bits, and one floating point operation is a lot of four-bit operations. For lower-precision FLOPs, he suggested that 1-100 FLOPs sounds about right, and that it's hard to be too wrong with an estimate like that.

Firing decisions

Prof. Pearlmutter thought that the compute for firing decisions would be "in the noise" relative to compute for spikes through synapses, because there are so many fewer neurons than synapses.

Prof. Pearlmutter was sympathetic to the idea that the tree-structure of dendrites would limit the compute burdens that dendritic computation could introduce. There is an important distinction between causal models that are tree-structured and ones that are not tree-structured. Non-tree structured causal model can have cycles that quickly become very computationally expensive, whereas tree structured models are comparatively easy to compute. He suggested that this type of consideration applies to dendrites as well (including in the context of feedbacks between the dendrites and the soma).

Prof. Pearlmutter thought it a fairly good intuition that dendritic computation would only implicate a small constant factor increase in required compute, though very complicated local interactions could introduce uncertainty.

Learning

Prof. Pearlmutter's best-guess estimate was that the learning overhead (that is, the compute increase from moving from a non-adaptive system to an adaptive system) would be a factor of two. It could be more or less, but this is a number we actually understand, because the existing learning algorithms that we know work for large-scale systems, and that we have put effort into optimizing -- for example, backpropagation -- implicate roughly this type of overhead. Prof. Pearlmutter also mentioned work by one of his post-docs on automatic differentiation, which implicates at worst a factor of six overhead.

Prof. Pearlmutter was comfortable using spikes through synapses as the basis for an estimate of the compute costs of non-adaptive processing.

Alternative signaling mechanisms

Mr. Carlsmith and Prof. Pearlmutter also discussed the compute implicated by various possible alternative signaling mechanisms in the brain:

- Prof. Pearlmutter characterized the comparatively minimal number of gap junction as the "bottom line" with respect to their computational role. And he took the fact that gap junctions are roughly linear, and that they don't involve time delays, as evidence they would be easy to model.
- He also suggested that ephaptic effects would be "in the noise" because they are bulk effects, representation of which would involve one number that covers thousands of synapses.
- Prof. Pearlmutter also mentioned the possibility that the delays introduced by axons of different lengths might introduce additional storage requirements and communication complexities.

Comparisons with computer vision

Prof. Hans Moravec attempted to derive estimates of the computational capacity of the brain from examination of the retina. Prof. Pearlmutter thought that Moravec's estimates for the computational costs of robotic vision were likely accurate, given Moravec's expertise in vision.

Prof. Pearlmutter was wary about comparing the visual processing in the brain with the visual processing performed by deep neural networks. For example, the fact that deep neural networks seem to require so many layers (maybe more layers than the brain has available) might suggest that we're missing something about how to build image recognition systems.

Computing power and AI progress

The "AI winter", which was a period of 20-30 years of comparatively little AI progress, strikingly coincided with a period in which spending on computer power per AI researcher decreased, such that the computing power available per researcher was roughly flat. As more compute became available, the rate of progress rapidly improved. To Prof. Pearlmutter, this suggests that available computing power may have been the main factor determining progress.

Overall compute

Overall, Prof. Pearlmutter thought that an estimate based on 100 FLOPs per spike through synapse, with a factor of two for learning, sounded fairly reasonable.

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