Bocconi

16 JANUARY 2025
12:00 PM
Room 2-E4-SR03
Via Röntgen 1, Milan, 2° floor

Brains v. machines – what can AI learn from neuroscience?

Speaker

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Abstract

Biological nervous systems can be aptly described as directionally interconnected networks of neurons, each emitting binary signals (spikes) when the combined inputs received from other neurons exceeds a threshold. The connection (synapse) between two neurons changes its weight continuously in an activity-dependent manner, but its sign remains constant and is uniquely determined by the excitatory or inhibitory nature of the sending neuron. In this traditional "neural network" model, spatial-temporal neural patterns (which neurons spike and when) represent the content – memories, decisions, plans, etc. – whereas synaptic plasticity (weight changes) underlie learning. It is also broadly recognized that sparse activity is key to energy efficiency: fewer than 1% of the neurons spike at a time. A less understood organizational principle of nervous systems is that brain connectivity is also extremely sparse: a typical mammalian neuron "only" contacts ~10k other neurons, i.e. less than 0.01% of the whole network even in small rodent brains. Moreover, connectivity is exquisitely specific and structurally plastic. In other words, (1) any given neuron has a limited pool of partners (typically ~100k or ~0.1% of all neurons) that it can possibly connect to, defining a crucial blueprint of that particular functional circuit (say, visual recognition vs. spatial navigation); and (2) which 10% of its 'partner pool' a neuron actually contacts varies over time based on their activity, providing a core substrate for memory storage and retrieval. An even less appreciated architectural principle of biological neural circuits is that long-range connection pathways typically remain computationally segregated when they converge on individual neurons. On the one hand, this feature combinatorially increases neural information capacity. On the other, it allows every circuit to precisely align inhibition for the selective control of each independent processing stream. Artificial neural networks such as deep learning can emulate certain elements of such an organization by layered all-to-all connectivity and a majority of quasi-zero weights, but fail to capture other potentially essential aspects. I will discuss how to quantify the key computational parameters from well-studied neural systems. Whether and how incorporating these neuroscience principles in next-gen machine learning designs could lead to technological and scientific breakthroughs remains an open question.

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