GENMOD - Generative models of human cognition

A fundamental issue in the study of human cognition is what computations are carried out by the brain to implement cognitive processes. The connectionist framework assumes that cognitive processes are implemented in terms of complex, nonlinear interactions among a large number of simple, neuron-like processing units that form a neural network. This approach has been successfully used in cognitive psychology to produce highly detailed simulations of human skilled performance and its breakdown following brain damage. However, much of this work has been carried out using models that have no biological plausibility beyond the metaphor of “neuron-like” processing and where learning (typically by "error backpropagation”) is supervised. The latter implies subscription to the dubious assumption that learning is mostly discriminative (e.g. classification or association) and that an external teaching signal is available at each learning event. The aim of the present research program was to exploit the latest findings in machine learning research to develop generative connectionist models of cognition. Implemented as stochastic recurrent networks, these models learn internal representations of the sensory data without any supervision or reward. When combined with a hierarchical structure (a deep network with many layers), learning can lead to the emergence of increasingly more complex and abstract representations across layers. Generative models are also appealing because they represent plausible models of cortical learning and are consistent with neurobiological theories that emphasize the mixing of bottom-up and top-down interactions in the brain. We applied these methods to three different cognitive domains: numerical cognition, spatial cognition, and written language processing. For each of these domains, we developed connectionist models that were systematically evaluated, both qualitatively and quantitatively, to empirical data that span from the behavioral (reaction times and errors) to the neuronal (single-cell responses) level. The results show that generative models provide an excellent match to both psychological and neurophysiological data. For example, we showed that a visual “number sense” (i.e. numerosity perception) can spontaneously emerge in a deep network that learned without supervision to efficiently encode images of object sets. The model accounts for classic human psychophysical data as well as for the activity pattern of “number neurons” in the posterior parietal cortex of the primate brain. Moreover, the model can explain changes in numerosity perception ability, also known as “number acuity”, from infancy throughout elderhood. Number acuity during learning improves in a way that mirrors the developmental trajectory of typically developing children, whereas the atypical developmental pattern observed in dyscalculia can be simulated by limiting the number of available neurons (in line with the finding of reduced gray matter density in the dyscalculic brain). Our approach represents an important step forward for the computational modeling of human cognition, because it is based on a more plausible model of cortical learning and it offers a way to bridge the gap between emergentist connectionist models and structured Bayesian models of cognition.

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