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Editorial

Current topics in Computational Cognitive Neuroscience

1. Editorial

Computational Cognitive Neuroscience is a discipline at the intersection of psychology, neuroscience and artificial intelligence. At its core is the development and comparison of computational models that allow the prediction of behavior, cognition and brain activity, with the long-term goal of providing a neurophysiologically plausible characterization of the underlying brain structure or function (Ashby and Helie, 2011; Kriegeskorte and Douglas, 2018; Love, 2015; O'Reilly and Munakata, 2000). Fueled by recent developments with machine learning techniques that solve cognitive tasks such as object recognition, decision making, or language processing (Krizhevsky et al., 2012; Mikolov et al., 2013; Mnih et al., 2015), computational cognitive neuroscientists have started to link these artificial intelligence approaches to neural processes (Huth et al., 2016; Stachenfeld et al., 2017; Yamins et al., 2014). This, in turn, has led to applications of computational modeling in neuroscience that have become increasingly sophisticated. Today, the field is moving fast, and hardly a year goes by without discoveries that seem like a true expansion of our horizon. These exciting developments motivated us to bring to life this Special Issue on Computational Cognitive Neuroscience.

Rapid developments in research, however, do not come without challenges. Not only is building useful models hard, new models also require experimental designs well-suited for these models (Görgen et al., 2018) and often warrant novel methods of data analysis. Apart from model development and experimental design, another challenge is how to connect the data produced by model simulations with the empirical data observed in experiments. One problem arises because model predictions often don't capture the details of the data-generating process. For example, it is unclear how a latent cognitive variable (e.g. prediction error) is exactly translated to measured magnetoencephalography recordings that offer high temporal but low spatial resolution, or functional MRI responses that offer high spatial but low temporal resolution. How can we relate model predictions and the different forms of measured data points? One approach to this challenge lies in finding new data analytical techniques that allow us to compare models and data on a more abstracted level. A prime example is model-based MEG-fMRI fusion based on representational similarity analysis (Hebart et al., 2018; Cichy; Oliva, 2020), which focuses on the predicted similarity between measurement modalities rather than the actual activation patterns, while being able to incorporate assumptions about latent model variables.

This Special Issue mirrors these challenges and reflects recent advances not only in model development, but also in the accompanying data analysis and experimentation tools. The articles included in this issue therefore highlight the progress in the development of advanced statistical analysis techniques and computational modeling approaches in the cognitive neurosciences. The reviews and original research articles demonstrate how progress in methodology and theory has often interacted in a synergistic manner. Further, advances in the statistical analysis of neuroimaging data (e.g. multivariate decoding) have broadened the spectrum of testable experimental hypotheses, and conversely, pressing theoretical questions have led to important methodological developments. These developments include encoding models that allow inferring the presence of navigation-related directional tuning in neuronal populations (Nau et al., 2020), or MEG and fMRI techniques that investigate fast neural sequences called replay (Kurth-Nelson et al., 2016; Schuck; Niv, 2019), to name just a few. With a focus on this interrelation, this issue aims at bringing together articles that advance our understanding of analysis techniques of neuroimaging data and studies using theory-driven computational modeling to test specific hypotheses using neuroimaging and behavioral data.

Two important families of models discussed in the field of Computational Cognitive Neuroscience are (1) sequential sampling models that have been central to our understanding of the mechanisms of decision-making in brain and behavior, as well as (2) reinforcement learning models for understanding how previous interactions between agents and the environment affect future behavior. Miletic and colleagues (Miletić et al., 2020) review theoretical work and empirical evidence on how these model families can be combined effectively to better account for choice behavior, response times, and brain responses. Another interesting phenomenon in the field is that while many laboratories may work on somewhat related topics, this can lead to several models that account for behavior in different tasks, each offering a valid contribution that is difficult to link to other models. This, in turn, raises another question: what do all these models and tasks have in common, and how can their similarities be captured? Rusch and colleagues (Rusch et al., 2020) ask this question for the field of Theory of Mind. Reviewing existing tasks and computational approaches, they propose that these can be viewed as characterized along two dimensions, interactivity and uncertainty. Rusch et al. further argue that the internal representation of others' goals is strongest if a situation requires maximal interaction and is maximally uncertain, and relate their ontology of Theory of Mind processes to neuroimaging findings.

Not only are models important in Computational Cognitive Neuroscience, the methods used to derive these models are also of considerable importance. Important methodological goals of Computational Cognitive Neuroscience are therefore (1) to make inferences about latent variables, (2) to reveal how they relate to each other, and (3) to demonstrate how they lead to observed responses in brain and behavior.

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One approach, reviewed by Cai and colleagues (Cai et al., 2020), is the use of probabilistic graphical models. These models make explicit the assumptions of how latent variables are related to each other. They model different sources of noise explicitly and allow the incorporation of prior knowledge, making them a powerful and often interpretable tool with a wide range of possible applications. While Bayesian models have been used widely in cognitive psychology (Etz and Vandekerckhove, 2018; Kruschke, 2010; Ma, 2012), their use has recently been growing in popularity in the cognitive neurosciences. In this Special Issue, Cai and colleagues (Cai et al., 2020) showcase the benefits and limitations of probabilistic graphical models for fMRI data, focusing on several recent empirical examples.

But how can we be sure the methods we use produce the expected results? A nice example of how simulations can inform common methodology in Computational Cognitive Neuroscience is provided by Ramírez and colleagues (Ramírez et al., 2020). The authors tested to what degree fine-scale brain response patterns can be compared across subjects by means of anatomical alignment and leave-one-subject-out cross-validation. To this end, they used a shallow neural network to simulate brain responses as would be measured with fMRI. The results demonstrate that seemingly arbitrary analysis choices such as demeaning can drastically alter the pattern of brain responses and that using anatomical alignment biases the results towards the total signal. The authors propose hyperalignment as an alternative to pattern similarity analysis because hyperalignment is less sensitive to these issues when the strength of the signal for each condition is estimated.

What, then, are possible applications of computational modeling to cognitive neuroscience research? Koch and colleagues (Koch et al., 2020) show how Cognitive Computational Neuroscience can be useful in the study of cognitive aging. Applying multivariate decoding techniques to brain imaging data acquired during a spatial navigation task, they asked whether the decline of spatial abilities is reflected in changed neural representations of walking direction. Drawing from models of neural population coding (Pouget et al., 2000), they tested specifically if evidence for a flattened tuning curve of direction signals in older adults can be found, rather than just reduced decoding performance. Their analyses reveal that the shape of tuning functions appears broader in older adults' visual cortex, while no such differences could be found in retrosplenial complex, where direction encoding is less stimulus-bound. In a related fashion, Glenn and colleagues (Glenn et al., 2020) demonstrate in their article how representational similarity analysis can be used for the study of development and disease. Studying high and low trait anxiety children, Glenn and colleagues first conducted a threat conditioning and extinction test. Three weeks later, they studied brain responses when children were presented with blends of the threat and safe stimuli. Their core question was whether neural responses reflected children's threat generalization, and if such a neural generalization effect differs between the low versus high anxiety groups. This was indeed the case in vmPFC.

Finally, Momennejad and colleagues (2020) highlight another facet of Computational Cognitive Neuroscience: the formulation of normative models. In their paper the authors ask how humans can efficiently pursue multiple goals by keeping a future task in mind while doing something else (using prospective memory). The model proposed by Momennejad and colleagues shows how humans can turn noisy observations into optimal actions under such conditions, even when their capacity for holding information in working and long-term memory are limited. A comparison of model predictions against a set of canonical observations in prospective memory tasks shows that their account of a boundedly rational use of memory captures human behavior well. In addition, the authors lay out how their model could be applied to the study of psychiatric disorders.

Together, we believe this Special Issue provides an intriguing overview of current research trends in Computational Cognitive Neuroscience research, showcasing a variety of recent computational approaches, highlighting their advantages, but also exposing their limitations. We are certain that the field of cognitive neuroscience as a whole can benefit from a wider adoption of computational methods, and in turn the field of computational modeling can find important inspiration from cognitive neuroscience research.

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References

Ashby, G.F., Helie, S., 2011. A tutorial on computational cognitive neuroscience: modeling the neurodynamics of cognition. J. Math. Psychol. 55, 273–289. https://doi.org/10.1016/j.jmp.2011.04.003.

Cai, M.B., Shvartsman, M., Wu, A., Zhang, H., Zhu, X., 2020. Incorporating structured assumptions with probabilistic graphical models in fMRI data analysis. Neuropsychologia 144, 107500. https://doi.org/10.1016/j.neuropsychologia.2020.107500.

Cichy, R.M., Oliva, A., 2020. A M/EEG-fMRI fusion primer: resolving humam brain responses in space and time. Neuron. https://doi.org/10.1016/j.neuron.2020.07.001.

Etz, A., Vandekerckhove, J., 2018. Introduction to Bayesian inference for psychology. Psychon. Bull. Rev. 25, 5–34. https://doi.org/10.3758/s13423-017-1262-3.

Glenn, D.E., Fox, N.A., Pine, D.S., Peters, M.A.K., Michalska, K.J., 2020. Divergence in cortical representations of threat generalization in affective versus perceptual circuitry in childhood: relations with anxiety. Neuropsychologia 142, 107416. https://doi.org/10.1016/j.neuropsychologia.2020.107416.

Görgen, K., Hebart, M.N., Allefeld, C., Haynes, J.-D., 2018. The same analysis approach: practical protection against the pitfalls of novel neuroimaging analysis methods. NeuroImage 180, 19–30. https://doi.org/10.1016/j.neuroimage.2017.12.083. New advances in encoding and decoding of brain signals.

Hebart, M.N., Bankson, B.B., Harel, A., Baker, C.I., Cichy, R.M., 2018. The representational dynamics of task and object processing in humans. eLife 7, e32816.

Huth, A.G., de Heer, W.A., Griffiths, T.L., Theunissen, F.E., Gallant, J.L., 2016. Natural speech reveals the semantic maps that tile human cerebral cortex. Nature 532, 453–458. https://doi.org/10.1038/nature17637.

Koch, C., Li, S.-C., Polk, T.A., Schuck, N.W., 2020. Effects of aging on encoding of walking direction in the human brain. Neuropsychologia 141, 107379. https://doi.org/10.1016/j.neuropsychologia.2020.107379.

Kriegeskorte, N., Douglas, P.K., 2018. Cognitive computational neuroscience. Nat. Neurosci. 21, 1148–1160. https://doi.org/10.1038/s41593-018-0210-5.

Krizhevsky, A., Sutskever, I., Hinton, G.E., 2012. ImageNet classification with deep convolutional neural networks. In: Pereira, F., Burges, C.J.C., Bottou, L., Weinberger, K.Q. (Eds.), Advances in Neural Information Processing Systems, vol. 25. Curran Associates, Inc., pp. 1097–1105

Kruschke, J.K., 2010. What to believe: Bayesian methods for data analysis. Trends Cognit. Sci. 14, 293–300. https://doi.org/10.1016/j.tics.2010.05.001.

Kurth-Nelson, Z., Economides, M., Dolan, R.J., Dayan, P., 2016. Fast sequences of non-spatial state representations in humans. Neuron 91, 194–204. https://doi.org/10.1016/j.neuron.2016.05.028.

Love, B.C., 2015. The algorithmic level Is the bridge between computation and brain. Top. Cognit. Sci. 7, 230–242. https://doi.org/10.1111/tops.12131.

Ma, W.J., 2012. Organizing probabilistic models of perception. Trends Cognit. Sci. 16, 511–518. https://doi.org/10.1016/j.tics.2012.08.010.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G.S., Dean, J., 2013. Distributed representations of words and phrases and their compositionality. In: Burges, C.J.C., Bottou, L., Welling, M., Ghahramani, Z., Weinberger, K.Q. (Eds.), Advances in Neural Information Processing Systems, vol. 26. Curran Associates, Inc., pp. 3111–3119

Miletić, S., Boag, R.J., Forstmann, B.U., 2020. Mutual benefits: combining reinforcement learning with sequential sampling models. Neuropsychologia 136, 107261. https://doi.org/10.1016/j.neuropsychologia.2019.107261.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., Hassabis, D., 2015. Human-level control through deep reinforcement learning. Nature 518, 529–533. https://doi.org/10.1038/nature14236.

Nau, M., Navarro Schröder, T., Frey, M., Doeller, C.F., 2020. Behavior-dependent directional tuning in the human visual-navigation network. Nat. Commun. 11, 3247. https://doi.org/10.1038/s41467-020-17000-2.

O'Reilly, R.C., Munakata, Y., 2000. Computational Explorations in Cognitive Neuroscience: Understanding the Mind by Simulating the Brain. MIT Press, Cambridge, MA.

Pouget, A., Dayan, P., Zemel, R., 2000. Information processing with population codes. Nat. Rev. Neurosci. 1, 125–132. https://doi.org/10.1038/35039062.

Ramírez, F.M., Revsine, C., Merriam, E.P., 2020. What do across-subject analyses really tell us about neural coding? Neuropsychologia 143, 107489. https://doi.org/10.1016/j.neuropsychologia.2020.107489.

Rusch, T., Steixner-Kumar, S., Doshi, P., Spezio, M., Gläscher, J., 2020. Theory of mind and decision science: towards a typology of tasks and computational models. Neuropsychologia 146, 107488. https://doi.org/10.1016/j.neuropsychologia.2020.107488.

Schuck, N.W., Niv, Y., 2019. Sequential replay of nonspatial task states in the human hippocampus. Science 364. https://doi.org/10.1126/science.aaw5181.

Stachenfeld, K.L., Botvinick, M.M., Gershman, S.J., 2017. The hippocampus as a predictive map. Nat. Neurosci. 20, 1643–1653. https://doi.org/10.1038/nn.4650.

Yamins, D.L.K., Hong, H., Cadieu, C.F., Solomon, E.A., Seibert, D., DiCarlo, J.J., 2014. Performance-optimized hierarchical models predict neural responses in higher visual cortex. Proc. Natl. Acad. Sci. Unit. States Am. 111, 8619–8624. https://doi.org/10.1073/pnas.1403112111.

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