“Cognitive Models as Bridge between Brain and Behavior”

Bradley C. Love
University College London

How can disparate neural and behavioral measures be integrated? Turner and colleagues propose joint modeling as a solution. Joint modeling mutually constrains the interpretation of brain and behavioral measures by exploiting their covariation structure. Simultaneous estimation allows for more accurate prediction than would be possible by considering these measures in isolation.

main text: 988 words
figures/tables: 0
references: 7

Contact:

Bradley C. Love (b.love@ucl.ac.uk)
Experimental Psychology
University College London
London, UK WC1H 0AP

Acknowledgments:

This work was supported by the Leverhulme Trust (Grant RPG-2014-075) and Wellcome Trust Investigator Award (Grant WT106931MA).

Perhaps the key theoretical challenge in cognitive neuroscience is to bridge levels of analysis, linking brain and behavior in a mutually explanatory manner. This integration would help answer fundamental questions like how neural activity gives rise to behavior and what basic processes underlie unique human abilities. Unfortunately, the chasm between behavior and neural activity is wide. Moreover, the “languages” of these two types of data are different. Behavior is measured in terms of choice and response time, whereas neural activity is measured by spiking activity, BOLD signal in fMRI, etc.

One possible bridge between behavior and brain are cognitive models. Cognitive models are simple mathematical formalisms that embody psychological principles and are often evaluated by their ability to account for behavioral data. The mechanisms in these models can both be related to behavior and to neural measures (see [1] for a recent review), thus providing a possible bridge.

One straightforward bridging method is to fit a cognitive model to a participant's behavioral data, such as the responses made during a learning task. Then, internal measures from the cognitive model, such as the degree the model updates internal representations on a learning trial, can be related to brain activity using standard statistical techniques (e.g., [2]). Brain areas that show a rise and fall in activity along with the model measure are possible candidates for implementing that mental process.

Related techniques, such as Representational Similarity Analysis [3], can evaluate the agreement between a model and a brain region in a multivariate manner. Other approaches ground aspects of cognitive models in specific brain regions and use measurements from these regions to adjust parameter values in the model, which in turn drives the behavioral predictions of the model (e.g., [4]). Finally, model decoding approaches decipher patterns of brain activation to select which model out of a set of competing cognitive models is most consistent with brain activity [5].

All of these approaches are useful in bridging the chasm between brain and behavior and have their place. However, none of these approaches allow for simultaneous inferences to be made about brain and behavior. For example, fitting a cognitive model to behavioral data and then using a model measure to help analyze brain activity is a staged analysis in which information flows in one direction, namely from behavior to model parameter values to brain analysis. In some situations, it would be advantageous to make simultaneous inferences about both behavior and brain measures.

Recent work by Turner and colleagues addresses this challenge with a powerful new method, joint modeling, that allows for simultaneous integration of behavioral and multiple neural measures [6]. The hope of joint modeling is that simultaneous integration will enable multiple imperfect measures to mutually constrain one another. For example, EEG and fMRI have complementary strengths and weaknesses in terms of temporal and spatial resolution. Integrating these two brain measures, along with behavior, may provide a more accurate assessment than would be possible by considering each measure in isolation.

Joint modeling is sophisticated in that it is formulated within a hierarchical Bayesian framework, but its basic premise is straightforward -- Simple correlations across different measures drive prediction. To make an analogy, knowing someone's weight can be useful in inferring the person's height. Likewise, given noisy measurements of both height and weight, one could use prior information about what people's heights and weights tend to be and how they correlate in order to adjust estimates of both measures to improve accuracy. Joint modeling is not limited to two measures, such that other measures (e.g., gender) could also be included in the covariation structure. Joint modeling's linkage of disparate measures via covariation structure allows for the simultaneous interpretation of multiple measures and for assessment of how different measures relate (e.g., how a cognitive model's parameter correlates with brain activity in some region).

In Turner and colleagues' contribution, joint modeling is applied to an intertemporal choice task in which participants choose between an immediate reward and a larger delayed reward. Three “submodels” are considered, one for behavior, EEG, and fMRI data. The behavioral data (choice and response time) is fit by a cognitive model, the Linear Ballistic Accumulator (LBA; [7]), that links a parameter value to predicted behavior. Typically, LBA is fitted to behavior without consideration of brain measures. The other two submodels for the EEG and fMRI data involve standard statistical analyses.

These multiple measures are linked through their covariation structure. As experimental conditions are altered (e.g., the payoff for a delayed reward increases), the parameters in the cognitive model will change along with brain activity in dorsal medial frontal cortex (dmFC) as measured by EEG and fMRI. Using the correlations across these three measures, one can gleam a more accurate estimate of each measure than by considering the measures in isolation. For example, higher dmFC activity on a trial may imply that the cognitive model parameter should be adjusted upward, which will improve the quality of model's prediction for that trial. Indeed, Turner and colleagues demonstrate that behavior is better predicted through joint modeling than fitting the cognitive model to behavior alone. Furthermore, using the covariation structure, missing neural measures can be predicted using the remaining information (e.g., the EEG signal can be inferred using observed behavioral and fMRI information).

In summary, joint modeling offers an exciting method for simultaneously integrating multiple disparate measures to improve prediction. Rather than information flowing in one direction (e.g., from cognitive model to brain analysis or vice versa), joint modeling involves simultaneous estimation. When this mixing and linkage of data sources (e.g., fMRI and behavior) is desirable, joint modeling provides leverage for measures that correlate. In other cases, depending on one's goal, staging analyses using other methods may be preferable. What is clear is that joint modeling is an exciting development in the innovative and burgeoning area of model-based cognitive neuroscience. The overarching goal of this area of work is to bridge brain and behavior by utilizing both theoretical and data constraints across levels of analysis.

References

1. Turner BM, Forstmann BU, Love BC, J.Palmeri T, Maanen LV. Approaches to Analysis in Model-based Cognitive Neuroscience. J Math Psychol. in press.
2. Davis T, Love BC, Preston AR. Learning the exception to the rule: model-based FMRI reveals specialized representations for surprising category members. Cereb

Cortex. 2012;22(2):260-73. Epub 2011/06/15. doi: 10.1093/cercor/bhr036. PubMed PMID: 21666132.
3. Kriegeskorte N, Kievit RA. Representational geometry: integrating cognition, computation, and the brain. Trends Cogn Sci. 2013;17(8):401-12. Epub 2013/07/24. doi: 10.1016/j.tics.2013.06.007. PubMed PMID: 23876494; PubMed Central PMCID: PMC3730178.
4. Purcell BA, Heitz RP, Cohen JY, Schall JD, Logan GD, & Palmeri TJ. Neurally-constrained modeling of perceptual decision making. Psychol Rev. 2010;117.
5. Mack ML, Preston AR, Love BC. Decoding the Brain's Algorithm for Categorization from its Neural Implementation. Current Biology. 2013;23:2023-7.
6. Turner BM, Rodriguez CA, Norcia TM, McClure SM, Steyvers M. Why more is better: Simultaneous modeling of EEG, fMRI, and behavioral data. Neuroimage. 2016;128:96-115. doi: 10.1016/j.neuroimage.2015.12.030. PubMed PMID: 26723544.
7. Brown SD, Heathcote A. The simplest complete model of choice response time: Linear ballistic accumulation. Cogn Psychol. 2008;57(3):153-78.