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A tutorial on joint models of neural and behavioral measures of cognition[☆]

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HIGHLIGHTS

- A tutorial on jointly modeling neural and behavioral measures is presented.
- Simulated data from Directed and Hierarchical models are used.
- A real-world example is used containing data from a perceptual discrimination task.
- User-friendly JAGS code is provided in all examples.

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ABSTRACT

A growing synergy between the fields of cognitive neuroscience and mathematical psychology has sparked the development of several unique statistical approaches exploiting the benefits of both disciplines (Turner, Forstmann et al., 2017). One approach in particular, called joint modeling, attempts to model the covariation between the parameters of "submodels" intended to capture important patterns in each stream of data. Joint models present an interesting opportunity to transcend conventional levels of analyses (e.g., Marr's hierarchy; Marr, 1982) by providing fully integrative models (Love, 2015). In this manuscript, we provide a tutorial of two flavors of joint models — the Directed and Covariance approaches. Computational procedures have been developed to apply these approaches to a number of cognitive tasks, yet neither have been made accessible to a wider audience. Here, we provide a step-by-step walkthrough on how to develop submodels of each stream of data, as well as how to link the important model parameters to form one cohesive model. For convenience, we provide code that uses the Just Another Gibbs Sampler (Plummer, 2003) software to perform estimation of the model parameters. We close with a demonstration of the approach applied to actual data from a contrast discrimination task where activation parameters of early visual areas are directly mapped to the drift rate parameter in a simplified version of the diffusion decision model (Ratcliff, 1978).

1. Introduction

The evolution of technology for measuring brain signals, such as electroencephalography (EEG) and functional magnetic resonance imaging (fMRI), has provided exciting new opportunities for studying mental processes. Today, scientists interested in studying cognition are faced with many options for relating experimentally-derived variables to the dynamics underlying a cognitive process of interest. While conceptually the presence of these new "modalities" of cognitive measures could have immediately spawned an interesting new integrative discipline, the emergence of such a field has been slow relative to the rapid advancements made in these new technologies. Until a little over a decade ago, much of our understanding of cognition had been advanced by two dominant but virtually non-interacting groups. The largest group, cognitive neuroscientists, relies on statistical models to understand patterns of neural activity brought forth by the new technologies. The models used by cognitive neuroscientists are typically data-mining

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techniques, and these models often disregard the computational mechanisms that might detail a cognitive process. The other group, mathematical psychologists, is strongly motivated by *theoretical* accounts of cognitive processes, and instantiates these theories by developing formal mathematical models of cognition. The models often assume a system of computations and equations intended to characterize the processes assumed to take place in the brain. As a formal test of their theory, mathematical psychologists usually rely on their model's ability to fit and predict behavioral data relative to the model's complexity.

Although both groups are concerned with explaining behavior, cognitive neuroscientists and mathematical psychologists tend to approach the challenge from different vantage points. To appreciate the distinction between the fields, we can use Marr's (1982) levels of analysis, where our understanding of the mind can be advanced by considering a computational, algorithmic, and implementational level. At the computational level, our goal is to understand what a system does, and more importantly, why the system does what it does. At the algorithmic level, our goal is to understand exactly how a system does what it does, specifically what types of representations are used to perform the task. At the implementational level, our goal is to understand how the system can be physically realized, or how the representations in the algorithmic level could be created given biological constraints. Mathematical psychologists tend to focus on the computational and algorithmic levels, whereas cognitive neuroscientists tend to focus on the implementation level. Although progress can be made by maintaining a tight focus on one level, many important opportunities are lost (Love, 2015). For example, without an overarching theory explaining how the mind generally solves problems, such as a theory that might be developed at the computational level, it can be difficult to aggregate neuroscientific results from various experimental paradigms that focus on the implementational or algorithmic levels (cf. Coltheart, 2006).

As a remedy, new work has endeavored to integrate the levels of analysis in an effort to relate mechanisms assumed by mathematical models to the neural computations supporting task-specific behavior within the brain. However, integrating the two fields is made difficult by the fact that mechanisms in mathematical models are often necessarily abstract, whereas neurophysiological measures are physical realizations of cognitive processes (Turner, 2015). The importance of solving the integration problem has created several entirely new statistical modeling approaches developed through collaborations between mathematical psychologists and cognitive neuroscientists, collectively forming a new field often referred to as "model-based cognitive neuroscience" (e.g., Boehm, Van Maanen, Forstmann, & Van Rijn, 2014; Daw & Doya, 2006; Daw, Niv, & Dayan, 2005; Forstmann & Wagenmakers, 2014; Forstmann, Wagenmakers, Eichele, Brown, & Serences, 2011; Frank, Seeberger, & O'Reilly, 2004; Love, 2015; Mack, Preston, & Love, 2013; Palmeri, Schall, & Logan, 2015; Turner, Forstmann et al., 2013; Turner, Van Maanen, & Forstmann, 2015; van Maanen et al., 2011).

At this point, there are several approaches for integrating neural and behavioral measures via cognitive models, and these approaches are neither restricted to any particular kind of neural or behavioral measure, nor to any particular cognitive model (see de Hollander, Forstmann, & Brown, 2016; Turner, Forstmann, Love, Palmeri, & Van Maanen, 2017 for reviews). A convenient taxonomy for organizing these approaches can be built from considering a researcher's goals in relating the measures to one another (Turner, Forstmann et al., 2017). One goal might be to use the neural data to constrain a behavioral model. Another goal might be to identify patterns of neural data that are consistent with specific computations carried out in the behavioral model. The final goal, which is the focus of the current article, is to enforce statistically reciprocal relationships between the neural measures and the parameters of a behavioral model by modeling these random variables simultaneously (see Forstmann et al., 2011 for some motivation).

One successful method of performing simultaneous modeling has been the "joint modeling" approach (Cassey, Gaut, Steyvers, & Brown, 2016; Turner, 2015; Turner, Forstmann, et al., 2013; Turner, Rodriguez, Norcia, Steyvers, & McClure, 2016; Turner et al., 2015; Turner, Wang, & Merkel, 2017). Joint models were developed as an alternative to the "two-stage" correlation approaches, where parameters of a fitted cognitive model were simply correlated with a neural measure of interest. While a two-stage correlation approach does give insight into how parameters of a cognitive model are related to brain data, this approach misses an opportunity to enforce a constraint on the model parameters based on the random variation in the neural data. In other words, if one treats the neural data as a covariate, the estimates of the behavioral model parameters can be better informed. This simple covariate approach gives joint models some advantages in articulating brain-behavior relationships. Specifically, joint models are better equipped to (1) handle mismatching (i.e., when the size of the neural data is different from the size of the behavioral data) and missing data, (2) perform inference on the magnitude of brain-behavior relationships (i.e., they are not subject to Type I errors as in the two-stage approach), (3) compare different brain-behavior relationships across models, and (4) make predictions about either neural or behavioral data.

At their highest level, joint models simply require an expression specifying the joint distribution of the measures N obtained by using cognitive neuroscience techniques (e.g., EEG, fMRI) to measures of behavior B (e.g., choice, response time). Given this intentionally vague definition, there are many "classes" of joint models that vary in the way N is structurally related to B. For the purposes of this article, we narrow our focus to three types of joint models: Integrative, Directed, and Covariance. As many of our research efforts have modeled the covariation between N and B via the Covariance approach, we may have given the impression that joint models are inherently structured in a specific way, but this is not the case. Here, we present a more comprehensive account of different types of models that we collectively refer to as "joint models". Three types of joint models are illustrated in Fig. 1 via graphical diagrams, where observed variables (e.g., N and B) are shown as filled square nodes, and parameters are shown as empty circles. Paths between the nodes in the graph indicate dependency among the nodes, where an arrow pointing from one node to another indicates a "parent-to-child" ancestry (Pearl, 1988). In other words, the node being pointed at depends on the node from which the arrow originates. Although the three types of joint models can be illustrated with similar graphical diagrams, the structures introduce different constraints, which have major implications for a joint model's complexity relative to the observed data. We now discuss each of the three classes of joint models in Fig. 1.

1.1. Integrative approach

The first joint modeling approach we will focus on is the Integrative approach, where a single cognitive model is developed to predict neural and behavioral measures simultaneously. The Integrative approach is depicted on the left side of Fig. 1. Here, the neural data N and the behavioral data B are explained together through a single set of parameters θ, indicated by the connections from θ to both N and B. Alternatively, Integrative joint models can use a set of modulators to transform an internal state of a model into a prediction about the precise functional form of the neural measures. For example, different modulators would be necessary to make predictions for a blood oxygenated level dependent (BOLD) response in an fMRI study versus predictions for