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A confirmatory approach for integrating neural and behavioral data into a single model[☆]

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HIGHLIGHTS

- An overview of joint modeling of behavioral and neural data.
- A joint modeling account of mental rotation behavioral data and ERP data.
- A formal comparison of several joint modeling alternatives.
- Drift rate is capable of simultaneously explaining behavioral data and neural data.

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ABSTRACT

Recent decades have witnessed amazing advances in both mathematical models of cognition and in the field of cognitive neuroscience. These developments were initially independent of one another, but recently the fields have started to become interested in joining forces. The resulting joint modeling of behavioral and neural data can be difficult, but has proved fruitful. We briefly review different approaches used in decision-making research for linking behavioral and neural data, and also provide an example. Our example provides a tight link between behavioral data and evoked scalp potentials measured during mental rotation. The example model illustrates a powerful hypothesis-driven way of linking such data sets. We demonstrate the use of such a model, provide a model comparison against interesting alternatives, and discuss the conclusions that follow from applying such a joint model.

Like many areas of scientific enquiry, cognitive psychology began with verbally-specified theories and gradually progressed to quantitative accounts over time. This resulted in mathematical models to describe memory (e.g., Atkinson & Shiffrin, 1968; Raaijmakers & Shiffrin, 1981), categorization (e.g., Nosofsky, 1986; Nosofsky & Palmeri, 1997), speeded and unspeeded decision making (e.g., Ratcliff, 1978; Wagenmakers, 2009), and many other paradigms (for reviews, see Lee & Wagenmakers, 2013; Lewandowsky & Farrell, 2010). A separate and at first mostly unrelated development was the advent of cognitive neuroscience. This field sought to map changes in the brain as they related to cognition, using neural measurements obtained through event-related potentials (ERPs; e.g., Hillyard, Hink, Schwent, & Picton, 1973; Sutton, Braren, Zubin, & John, 1965), the magnetoencephalogram (MEG; e.g., Brenner, Williamson, & Kaufman, 1975), functional magnetic resonance imaging (fMRI; e.g., Belliveau et al., 1991), and single-unit recordings in non-human primates (e.g., Hanes & Schall, 1996; Schall, 2001; Shadlen & Newsome, 1996). As progressively more precise measures of the inner workings of the brain became available, researchers have become increasingly capable at understanding the neural determinants of cognitive processes.

Some research paradigms have well-specified and tractable mathematical models of cognition, and also well-developed methods for neural measurement, for example, simple decision-making and reinforcement learning. Researchers interested in such paradigms started investigating ways to link the neural and behavioral data more carefully. The latest developments include so-called *joint models*, in which data of one kind can inform the model fit of the other kind and vice versa (e.g., Anderson & Fincham, 2014; Purcell et al., 2010; Turner, Forstmann, Love, Palmeri, & van Maanen, in press; Turner, Forstmann et al., 2013). These accounts aim for the most explicit and careful links, by simultaneously modeling neural recordings and behavioral outputs, allowing both kinds of data to inform model

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selection and parameter estimation. Joint modeling provides an important theoretical contribution: it allows a researcher to examine common denominators underlying both behavioral data and neural data.

In this paper, we provide an example of how to jointly model behavioral and neural data from simple decision-making. As an illustrative example, we apply a joint model of behavioral responses and EEG recordings to data from an experiment based on the classic Shepard–Metzler mental rotation task (Shepard & Metzler, 1971). However, before describing the model, we review different approaches to linking behavioral and neural data, with a focus on decision-making research.

An important change in the development of decision-making models over the past twenty years has been a steady "tightening" of the link between neural and behavioral data (for reviews and discussion of linking behavioral and neural data, see Teller, 1984). Early models of simple decision-making linked behavioral and neural data loosely, by constraining the development of behavioral models to respect data from neural measurements. For example, the leaky competing accumulator model developed by Usher and McClelland (2001) was structurally constrained to include components supported by neural investigations, such as lateral inhibition between accumulating units, and passive decay of accumulated evidence. These links were included as part of the model development process, and thereafter there was no further attempt to link neural with behavioral data.

Subsequent models tested the links via qualitative comparisons between predictions for corresponding neural and behavioral data sets. This kind of linking was very common in early research into decision-making with fMRI methods, in which predictions were based on the assumption that an experimental manipulation will influence one particular model component, which leads naturally to predictions for the behavioral data, and also for the neural data (via the hypothesized link). Predictions most frequently take the form "in condition A vs. B, behavioral measure X should increase while neural measure Y decreases". Support for the predictions is taken as evidence in favor of the model, including the hypothesized link. As an example, Ho, Brown, and Serences (2009) tested predictions generated from decision-making models via hypothesized neural links. In one part of their study, Ho et al. manipulated the difficulty of a decision-making task and hypothesized that this should result in a change in the speed of evidence accumulation in a sequential sampling model. By examination of the model coupled to a standard model for hemodynamic responses, Ho et al. generated predictions for the blood–oxygen-level dependent (BOLD) response profile within regions that are involved in perceptual decision making. These predictions were compared with data from an fMRI experiment, which lent support to some accounts over others.

Linking via the testing of qualitative hypotheses was later surpassed by quantitative approaches, which provided a tighter link between neural and behavioral data. The most common example of quantitative linking in decision-making models takes parameters of the decision-making model, estimated from behavioral data, and compares them against the parameters of a descriptive model estimated from the neural data. For example, Forstmann et al. (2008) correlated individual subjects' model parameters, estimated from behavioral data, against blood–oxygen-level dependent (BOLD) parameter estimates; subjects with large changes in threshold parameters also showed similarly large changes in BOLD responses.

Most recently, there have been efforts to link neural and behavioral decision-making data even more tightly, by combining both data sets in a single model-based analysis. This approach has culminated in models such as that developed by Purcell et al. (2010) which uses neural measurements as a model input in order to predict both behavioral measurements and a second set of neural measurements. This provides a simultaneous description of neural and behavioral data sets, as well as explicating the links between them. A less detailed, but more general approach was developed by Turner, Forstmann et al. (2013) and extended by Turner et al. (in press) in this volume. In their method, neural and behavioral models are joined by allowing their parameters to covary. Turner, Forstmann, et al.'s approach is a "joint" model, in the sense that it allows symmetric information flow: behavioral data can influence the neural parameter estimates, and neural data can influence the behavioral parameter estimates. This information flow is achieved via a covariance matrix for the model parameters. This structure allows the identification of covariance between model parameters associated with neural processes and model parameters associated with behavioral processes. However, Turner, Forstmann, et al.'s approach differs from our analyses in its focus. The covariance matrix of Turner, Forstmann, et al.'s approach means that any and all parameters of the behavioral model are allowed to link with any and all parameters of the neural model, although all these links are required to be linear. Our approach is less general, but more pointed, because it requires the specific instantiation of a single, precise link between one parameter of the neural model and one parameter of the behavioral model.[1]

The joint modeling approach of Turner, Forstmann et al. (2013) is complementary to the approach we use. For paradigms in which there exist precise hypotheses about the links between neural and behavioral models, our approach offers a straightforward way of instantiating and testing these hypotheses. For paradigms in which this is not the case, Turner, Forstmann, et al.'s approach offers a powerful tool for exploration. What both approaches have in common is that they *jointly* fit the neural and behavioral data, which allows behavioral data to influence parameters on the "neural side" of the model, and vice versa. A joint model in this sense is able to identify a compromise between the two streams of data. This means that, compared to an otherwise-identical model that is fit solely to the behavioral (or neural) data, a joint model will always fit more poorly. Coherently managing the compromise between fitting neural and behavioral data streams is a strength of the joint modeling approach. For example, suppose one was examining a joint model for behavioral and neural data, but was not fitting the model in a "joint" manner. Instead, imagine the model was examined by fitting first to behavioral data alone, and then later evaluating the model by comparing its subsequent predictions for neural effects against the neural data. One problem with this approach arises if the model had two sets of parameters (say, A and B) which both provided very good fits to the behavioral data, but very different fits to the neural data. Suppose that parameter set A provided slightly better behavioral fits, but also terrible neural fits, while parameter set B provided good fits to the neural data. Fitting to the behavioral data alone would lead the researcher to choose parameter set A, and then to reject the model because of the terrible fit to neural data. Joint fitting allows identification of compromise parameters (such as set B) which provide good fits to both data streams.

The two-stage approach to model evaluation, in which the flow of information between the two types of data is mostly one-way, was employed by Purcell et al. (2010) (they used two different neural data streams, only one of which was a fitting target). While we hope that a joint modeling approach has some strengths that the two-stage approach does not, Purcell et al.'s work included

[1] While it is true that Turner, Forstmann, et al.'s method could, in theory, be restricted to produce our approach (e.g. by setting almost all priors on the covariance matrix components to zero, and by adding in nonlinear parameter link functions) in practice this has not been done.

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