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On the efficiency of neurally-informed cognitive models to identify latent cognitive states[☆]

Guy E. Hawkins[a,*], Matthias Mittner[b], Birte U. Forstmann[a], Andrew Heathcote[c]

[a] Amsterdam Brain and Cognition Center, University of Amsterdam, Amsterdam, The Netherlands
[b] Department of Psychology, University of Tromsø, Tromsø, Norway
[c] School of Medicine – Division of Psychology, University of Tasmania, Hobart, Tasmania, Australia

HIGHLIGHTS

- Explores the recovery of cognitive models that are informed with neural data.
- Contrasts two frameworks for using neural data to identify latent cognitive states.
- Neural data have more power to recover discrete versus continuous latent states.
- Reliably identifying latent cognitive states depends on effect size in neural data.

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ABSTRACT

Psychological theory is advanced through empirical tests of predictions derived from quantitative cognitive models. As cognitive models are developed and extended, they tend to increase in complexity – leading to more precise predictions – which places concomitant demands on the behavioral data used to discriminate between candidate theories. To aid discrimination between cognitive models and, more recently, to constrain parameter estimation, neural data have been used as an adjunct to behavioral data, or as a central stream of information, in the evaluation of cognitive models. Such a model-based neuroscience approach entails many advantages, including precise tests of hypotheses about brain–behavior relationships. There have, however, been few systematic investigations of the capacity for neural data to constrain the recovery of cognitive models. Through the lens of cognitive models of speeded decision-making, we investigated the efficiency of neural data to aid identification of latent cognitive states in models fit to behavioral data. We studied two theoretical frameworks that differed in their assumptions about the composition of the latent generating state. The first assumed that observed performance was generated from a mixture of discrete latent states. The second conceived of the latent state as dynamically varying along a continuous dimension. We used a simulation-based approach to compare recovery of latent data-generating states in neurally-informed versus neurally-uninformed cognitive models. We found that neurally-informed cognitive models were more reliably recovered under a discrete state representation than a continuous dimension representation for medium effect sizes, although recovery was difficult for small sample sizes and moderate noise in neural data. Recovery improved for both representations when a larger effect size differentiated the latent states. We conclude that neural data aids the identification of latent states in cognitive models, but different frameworks for quantitatively informing cognitive models with neural information have different model recovery efficiencies. We provide full worked examples and freely-available code to implement the two theoretical frameworks.

1. Introduction

Quantitative models that explicate the cognitive processes driving observed behavior are becoming increasingly complex,

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* Correspondence to: Amsterdam Brain and Cognition Center, University of Amsterdam, Nieuwe Achtergracht 129, Amsterdam 1018 WS, The Netherlands.

E-mail address: guy.e.hawkins@gmail.com (G.E. Hawkins).

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leading to finer-grained predictions for data. Although increasingly precise model predictions are undoubtedly a benefit for the field, they also increase the demands placed on data to discriminate between competing models. The predictions of cognitive models have traditionally been tested against behavioral data, which is typically limited to choices and/or response times. Such behavioral data have been extremely useful in discriminating between model architectures (e.g., Anderson et al., 2004; Brown & Heathcote, 2008; Forstmann, Ratcliff, & Wagenmakers, 2016; Nosofsky & Palmeri, 1997; Ratcliff & Smith, 2004; Shiffrin & Steyvers, 1997; Tversky & Kahneman, 1992). As model predictions increase in precision, however, we approach a point where behavioral data have limited resolution to further constrain and discriminate between the processes assumed by the models of interest.

The problem of behavioral data providing limited constraint is compounded when one aims to study non-stationarity. Cognitive models typically assume a stationary generative process whereby trials within an experimental condition are treated as independent and identically distributed random samples from a probabilistic model with a specified set of parameters. This assumption has proven extremely useful, both practically and theoretically, but is not supported by fine-grained empirical analysis (e.g., Craigmile, Peruggia, & Van Zandt, 2010; Wagenmakers, Farrell, & Ratcliff, 2004). Recent work in the study of stimulus-independent thought, or mind wandering, provides a psychological mechanism that can explain these findings, at least in part, in terms of observed performance arising from two or more latent data-generating states. One prominent theory proposes that ongoing performance is driven by two distinct phases: perceptual coupling – where attentional processes are directed to incoming sensory input and completing the ongoing task – and perceptual decoupling – where attention is diverted from sensory information toward inner thoughts (for detailed review, see Smallwood & Schooler, 2015). The perceptual decoupling hypothesis of mind wandering proposes, therefore, that observed behavior is the end result of a mixture of discrete latent data-generating states. To gain insight into the processes underlying the phases of perceptual coupling and decoupling, the goal of the cognitive modeler is to use the available data to determine the optimal partition of trials into latent states.

On the basis of behavioral data alone, such as choices and response times, reliably identifying discrete latent states can be difficult or near impossible. In an example of this approach, Vandekerckhove, Tuerlinckx, and Lee (2008) aimed to identify *contaminant* trials – data points not generated by the process of interest – in a perceptual decision-making experiment. They defined a latent mixture model in a Bayesian framework that attempted to partition trials that were sampled from the (diffusion model) process of interest from contaminant trials distributed according to some other process. In attempting to segment trials to latent classes, the diffusion model was only informed by the same choice and response time data it was designed to fit. For a representative participant, only 0.6% of their 8000 trials were classified as contaminants, indicating either a remarkable ability of the participant to remain on task (which is unlikely; see, e.g., Killingsworth & Gilbert, 2010), or, more likely, to the limited ability of behavioral data alone to segment trials into latent states.

Rather than relying solely on behavioral data, here we examine whether augmenting cognitive models with an additional stream of information – such as neural data, whether that involves single cell recordings, EEG, MEG, or fMRI – aids identification of latent data-generating states underlying observed behavior. Our aim is to investigate whether the addition of neural data can improve our account of the behavioral data, and in particular the identification of latent states, rather than accounting for the joint distribution of behavioral and neural data (for joint modeling approaches, see Turner, Forstmann et al., 2013). To this end, we condition on neural data; that is, we do not consider generative models of neural data. Rather, we explore tractable and simple methods that augment cognitive models using neural data as covariates in order to gain greater insight into cognition than is possible through consideration of behavioral data in isolation.

Throughout the manuscript, we position our work within the theoretical context of mind wandering. Over the past decade, the scientific study of mind wandering has received great interest from behavioral (e.g., Bastian & Sackur, 2013; Cheyne, Solman, Carriere, & Smilek, 2009) and neural (e.g., Andrews-Hanna, Reidler, Sepulcre, Poulin, & Buckner, 2010; Christoff, Gordon, Smallwood, Smith, & Schooler, 2009; Weissman, Roberts, Visscher, & Woldorff, 2006) perspectives, though there have been few attempts to integrate the two streams of information in a model-based cognitive neuroscience framework (for an exception, see Mittner et al., 2014). The study of mind wandering is particularly relevant to our aim of identifying latent cognitive states as it is a phenomenon that has been studied under various, qualitatively distinct, hypotheses about how latent states give rise to observed performance (Smallwood & Schooler, 2006, 2015), which we expand upon below. Mind wandering, therefore, serves as an excellent vehicle through which to demonstrate our methodological approach. Our working hypothesis is that mind wandering is a neural state or process that affects the parameters of cognitive models, which in turn affect observed behavioral performance (Hawkins, Mittner, Boekel, Heathcote, & Forstmann, 2015). Our approach inverts this chain of causation: we fit behavioral data with cognitive models that are informed with neural data, and compare their fit to cognitive models that are not informed with neural data. This allows us to assess what can be learnt about mind wandering in a way that is not feasible without the discriminative power of the neural data.

Through the lens of cognitive models of speeded decision-making, we consider two approaches that use neural data to constrain cognitive models, which in turn helps to identify both when people mind wander and the effect it has on task performance. We note, however, that our methods generalize to any domain of study that utilizes neural data – or any additional stream of data, for that matter – to aid identification of latent data-generating states and fit the behavioral data arising from those states with cognitive models.

We consider two general approaches to incorporating mind wandering within a modeling framework. The first approach assumes that observed behavior arises from a mixture of discrete latent states, which may have partially overlapping or unique sets of data-generating parameters. We refer to this as the *Discrete State Representation*. One might think of the latent states as reflecting an *on-task* state, where attention is directed to external stimuli, or task-related thoughts, and an *off-task* state, where attention is directed to internal stimuli, or task-unrelated thoughts, similar to the perceptual decoupling hypothesis (Smallwood & Schooler, 2015). Alternatively, the latent states might reflect *executive control*, where an executive system oversees maintenance of goal-directed behavior, and *executive failure*, which occurs when the executive control system fails to inhibit automatically cued internal thoughts that derail goal-directed behavior (McVay & Kane, 2010). Regardless of the labels assigned to the latent states, models assuming a discrete state representation aim to first identify the mutually exclusive latent states and then estimate partially overlapping or distinct sets of model parameters for the discrete states (for a similar approach, see Mittner et al., 2014). We note that a discrete state representation is also considered outside the context of mind wandering. For example, Borst and Anderson (2015) developed a hidden semi-Markov model approach that used a continuous stream of EEG data to identify discrete stages of processing in associative retrieval.

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