Title: Modelling Systematic Changes in Diffusion Model Parameters Across Time

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Introduction

Psychological Constructs are Dynamic

As people engage in tasks over extended periods, their psychological states change. These changes can be attributed to various factors, such as learning, habituation, or boredom, and can significantly impact task performance. In the field of psychology, particularly cognitive psychology, researchers often seek to capture different psychological constructs by having participants perform repetitive tasks— sometimes hundreds of times. This approach serves an important purpose, as multiple observations from a single participant enhance the measurement properties of a construct. However, traditional models attempting to capture these constructs typically assume their constancy throughout an experiment, which is unlikely to hold true.

A prominent example of such a model is evidence accumulation models, which use response time and accuracy data to infer a range of cognitive constructs including bias, task efficiency, and caution. These models have emerged as the leading theoretical framework for understanding decision-making in cognitive psychology and have gained popularity as measurement tools across various disciplines (SOURCE). Nonetheless, despite requiring a substantial number of trials for reliable fitting (SOURCE), these models offer only a single estimate of a given construct for the entire duration of an experiment, failing to account for potential changes in these constructs over time.

In this study, we present and evaluate a modelling framework for estimating the temporal dynamics of constructs measured in evidence accumulation models, specifically the diffusion decision model (DDM). We start by providing an overview of relevant previous work, followed by detailing our research questions and the specifics of the different models that we investigated.

Previous Work Describing How Cognitive Processes Change Across Time

One popular method for investigating the nature of time-varying cognitive processes has focused on the relationship between response times and practice. Researchers have aimed to describe a "law of practice" by identifying a single mathematical function that explains the reduction in response times with increased practice. Several candidate functions have been proposed, including power functions (e.g., Anderson, 1981) and exponential functions (Heathcote, 2000). These functions account for the general trend of rapid reductions in response times during initial trials, followed by diminishing reductions towards an asymptote as practice continues. Recently, transition functions have also been introduced as a candidate for this law, as they can explain periods of slow learning initially, followed by the discovery of a more optimal strategy which results in a higher rate of response time decrease (Evans et al., 2018). This approach to understanding how cognitive processes change over time is valuable because it provides detailed estimates of individuals' performance changes. However, these parameters lack clear psychological interpretations compared to thos of process models, such as evidence accumulation models.

Another approach to studying changes in constructs over time is through the examination of block-level changes. One way to achieve this using evidence accumulation models is by estimating parameter values within each block of an experiment. For instance, Dutilh et al. (2009) used this approach to demonstrate that most diffusion model parameters did appear to vary across blocks in their paradigm. Moreover, Evans et al. (2017) demonstrated how different levels of feedback influence the extent to which caution changes throughout an experiment. This approach offers insights into how cognitive constructs change over time but lacks granularity as it focuses on the block level and overlooks within-block learning dynamics. Furthermore, estimates in each block are not constrained and can freely vary across blocks, limiting its usefulness as a theoretical tool.

Another approach, as explored by Gunnowan et al. (2023), involves examining how individuals transition between different psychological states during an experiment. They employed a hidden Markov model to identify two distinct states that participants switched between: a cautious state and an urgent state. These states aligned with thresholds in evidence accumulation models, specifically the linear ballistic accumulator model (SOURCE). By comparing models assuming trial-level and block-level state switching, Gunnowan et al. suggested that the switches were more likely to occur at the trial level. While this approach provides estimates of different psychological states on individual trials and blocks, it does not capture learning dynamics or other time-dependent phenomena, as the states remain constant and can be interchanged arbitrarily.

Integrating reinforcement learning models with diffusion model parameters has been another avenue to investigate systematic changes over time. For example, Pedersen et al. (2016) integrated a reinforcement learning model and a diffusion model, where the threshold (caution) and drift rate (efficiency) parameters were constrained to follow power functions over time. This approach provides fine-grained, theoretically informed estimates of how learning influences cognitive constructs. However, it relies on stimulus-specific constraints, limiting its application to certain paradigms like reinforcement learning.

A more general method that is not constrained to any particular paradigm was introduced by Schumacher et al. (2022) who introduced a deep learning method for estimating trial-by-trial variations in model parameters. This approach offers fine-grained estimates of learning without requiring constraints based on the stimulus. However, the lack of sufficient constraints results in poorly identified parameter changes, meaning that it is not possible to tell whether changes estimated by their model are due to actual time varying properties of the parameters or measurement error.

One approach to strike a balance between the theoretical constraints and granularity of the reinforcement learning + diffusion model and the general applicability of the state switching and deep learning models is to constrain the standard diffusion model using mathematical functions. Cochrane et al. (2023) demonstrated the potential of this method by constraining diffusion model parameters with exponential functions to assess their variations across trials and different days of the experiment. They found evidence that the drift rate increased exponentially at the trial level, while the threshold was more likely to vary across days rather than trials. However, their investigation was limited to exponential functions and did not consider other potential change functions that could be influencing these parameters. Additionally, they did not explore block-level changes or examine the measurement properties of their models.

In our current study, we build upon the method of constraining diffusion model parameters with mathematical functions. We aim to assess various functions that account for trial-level changes, block-level changes, and a combination of both trial and block-level changes. Our focus is primarily on two psychological constructs that we expect to vary in most multi-trial tasks: task efficiency (drift rate) and caution (threshold). However, the framework we discuss can be applied to any diffusion model parameter.

Our study addresses five core research questions:

1. Is a model that predicts systematic changes in parameters superior to the standard model in typical experimental psychology experiments?
2. If systematic changes exist, do multiple parameters exhibit variation, or is it primarily confined to a single parameter?
3. Do these changes occur on a trial-by-trial basis or a block-by-block basis?
4. What are the measurement properties of the proposed models?
5. How do time-varying processes affect the measurement properties of the standard diffusion model?

By addressing these research questions, we aim to provide insights into whether time varying models outperform the standard diffusion model even in contexts where time varying constructs (e.g., learning) have not been explicitly manipulated. We also intend to shed light in their ability to detect temporal dynamics in contexts where time varying processes have been manipulated (e.g., feedback tasks). We also intend to uncover the temporal scale at which these changes occur, the extent to which the models and parameters we propose are identifiable, and whether time-varying processes affect the measurement properties of the standard diffusion model.