Title: **Modelling systematic changes in diffusion model parameters across time**

H: **Psychological constructs are dynamic**

* As we spend time on a task, our psychological states and cognitive capacities change.
  + People learn, become habituated, get bored, etc.

H: **Psychological constructs are dynamic**

* Most approaches that attempt to model these constructs assume they do not change over time.
* Evidence accumulation models are a typical example of this.
  + Give us a single estimate of cognitive constructs for the whole experiment.
    - Information processing efficiency
    - Bias
    - Caution
  + Good reason for this -- improves reliability of estimates.
  + But unlikely that these things are constant across time.

H: **Previous work: practice function on RT**

* Previous studies suggest response times confirm to mathematical functions during practice.
  + Power (e.g., Anderson, 1981)
  + Exponential (Heathcote, 2000),
  + Transition (Evans et al., 2018)
  + **Positive:** You get extremely fine-grained estimates (i.e., trial-level) of how people’s performance changes over time.
  + **Limitation:** It’s only in terms of response time, and the parameters don’t have clear psychological meanings like those of the DDM parameters

H: **Previous work: block level changes**

One previous approach has been to look at block level changes.

* Estimating a value each block:
  + Dutilh et al. (2009) showed that estimates of almost all the diffusion model parameters seemed to vary across blocks in their paradigm.
  + Evans et al. (2017): Different thresholds in each block, comparing the effect of either receiving feedback on block 4 (bottom) or not (top).
  + **Positive:** You get estimates of how cognitive constructs change over time.
  + **Limitation:** It’s not very fine-grained, as the focus is on the block level, and you completely miss any learning that happens within-blocks (such as at the very start of the experiment)

H: **Previous work: psychological “state” switching**

* Able to show that people switch between different psychological states across time.
  + Identified 2 states: a more cautious state and a more urgent state (mapping on to thresholds in the LBA).
  + Found that a model assuming trial-level state switching outperformed models assuming block-level switching.
* **Positive:** You get estimates of different states that people may be in on different trials.
* **Limitation:** Doesn’t really tell us about learning (or other time-dependent dynamics), as the states don’t change, and people can swap back and forth whenever

H: **Previous work: Reinforcement learning + diffusion model**

Only other research I have found that looks at more systematic changes in DDM parameters are models that integrate DDM parameters with reinforcement learning models.

* E.g., Pedersen et al., 2016: Developed RL+DDM Models where threshold and drift rate could be power functions.
* **Positive:** You get fine-grained estimates of learning in cognitive constructs
* **Limitation:** You need some aspect of the stimulus to constrain the parameter changes according to, meaning that it can only be used for certain paradigms (such as RL).

H: **Previous work: Neural superstatistics estimation**

* Schumacher et al. (2022)
  + Introduce a deep learning method for estimating trial by trial variation in model parameters.
  + **Positive:** Fine-grained estimates of learning where you don’t need to constrain the model according to the **stimulus**
  + **Limitation:** You don’t have enough constraint, meaning these changes don’t seem to be well identified (see below)

H: **Previous work: Estimating DDM Across Time**

Cochrane et al. (2023) showed the potential for estimating DDM parameter changes across time.

* Were interested in Across trial changes and across day changes (participants tested in multiple sessions over multiple days).
* Tested threshold (caution) and drift rate (efficiency).
* Found evidence that drift rate changed exponentially across trials, whereas threshold changed across days.
* **Limitations:** 
  + Only looked at exponential functions.
  + Did not look at block level changes.
  + Did not examine the measurement properties of the models.

H: **Our Study**

**Introduce a general framework for modelling diffusion model parameters as trial varying mathematical functions.**

H: **Five general research questions:**

1. Is a model predicting systematic changes in parameters better than the standard model in typical experimental psychology experiments?
2. If so, does it look like multiple parameters seem to vary or just one?
3. Are these changes trial dependent or block dependent?
4. What are the measurement properties of these models?
5. Do time-varying process affect the measurement properties of the standard diffusion model?

H: **The basic idea**

In the standard diffusion model, we can think of parameters as a *constant* value across trials. E.g.:

a = a

But what if instead, threshold increased linearly as people became more confident in the task? We could model changes in a across trials using a linear function:

a = b \* trial + c

**In this study we focus on threshold (a) and drift rate (v), because these could feasibly vary in any multi-trial experiment.** But the framework could be applied to all DDM parameters.

We had three different kinds of functions to test each of these possibilities: 1. Trial-level functions that varied systematically as a function of the trial. 2. Block level functions that assumed a different value of the construct across blocks, but no changes within blocks. 3. Trial + Block functions that assumed both block and trial level changes.

**H: Trial Level Functions**

1. Linear
2. Exponential
3. Exponential-Transition