

INI Retreat 2023 Decision making and adaptation

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Overview

- 1. Drift-Diffusion model and related models
- 2. Why are these models useful?
- 3. How can decision making be adapted?
- 4. How are these models connected to neuroscience?

Drift-Diffusion model and related models

The diffusion model



Basic model as a stochastic differential equation:

drift term

$$dx = \nu dt + \sigma dW$$

change in decision variable

noise term (Wiener process)

Main Parameters:

- Upper threshold (a) ("conservatism")
- Starting point (z) ("Bias")
- Drift rate (v)

Other Parameters:

- Response time constant (t₀)
- Diffusion constant (s)
- Inter-trial variability of parameters (typically standard deviation of drift rate)

Voss, A., Rothermund, K., & Voss, J. (2004). Interpreting the parameters of the diffusion model: An empirical validation. Memory & cognition, 32, 1206-1220. Bogacz, R., Brown, E., Moehlis, J., Holmes, P., & Cohen, J. D. (2006). The physics of optimal decision making: a formal analysis of models of performance in two-alternative forced-choice tasks. Psychological review, 113(4), 700.

Some related models

(there is a bit of a zoo of very similar models...)



Why are these models useful?

Main idea behind model-based analysis

- Instead of analysing behavioural data (reaction times, accuracy,...) directly, we describe the behavioural data in terms of model parameters
- So behavioural data, from a given participant and task condition, is used to fit model parameters
- Each participant would be associated with a set of model parameters; and often each participant would be associated with a different set of parameters for task conditions of interest
- The data analysis is then done on the model parameters
- Advantages:
 - Compressing large amounts of behavioural data
 - Removing noise and idiosyncratic patterns (considered irrelevant here)
 - Interpretation of results in terms of theoretical frameworks
 - Connection to neuroscience



- Example here: how to fit the drift rate to empirical data?
- Assumption: drift rate is a random variable that we sample in each trial from a normal distribution
- Brute force:
 - try out normal distributions with different means and standard deviations
 - For each, you obtain a model reaction time distribution that you can compare with the empirical distribution
 - Pick the one that fits best and you have found your parameters for the slope!



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- Different fitting methods available
- Maximum likelihood estimation
- Chi-square and weighted leastsquare methods
- Statistic of the Kolmogorov-Smirnov test
- R packages, e.g.:
 - code: <u>https://github.com/</u> igmmgi/DMCfun
 - paper: https://doi.org/ 10.1016/ j.metip.2021.100074)



Adaptation

Adaptation of decision making

- An interesting aspect of decision making is how it adapts to different demands, situations, and conditions
- Wide range of possible applications of model-based analysis
- Identifying pathological decision making, e.g. comparing distribution of model parameters between Patients and Controls
- Characterising the effects of drug use
- Within-participant comparison of model parameters across different blocks in a task, e.g. task blocks with a high/low probability of a 'Conflict' (see Simon and Flanker tasks)
 - Possible project for this workshop: design a Simon/Flanker task variant with 'High' and 'Low' conflict blocks; how does decision making adapt, e.g. with an increase in the threshold (boundary) for high conflict?



Example: Post-Error Slowing

- In many tasks, after subjects make an error, they have a longer reaction time in the following trial
- There are different explanations for this phenomenon
- These have been proposed to map onto different parameters in the diffusion model
- Fitting diffusion model parameters for 'post-correct' and 'post-error' trials indicated that post-error slowing is due to an increase in the threshold ('boundary separation'), interpreted as 'response caution'



How are these models connected to neuroscience?

Neurophysiology of reaction time variability

- Recordings in the frontal eye fields of monkeys performing a reaction time task
- Examination of neurons increasing their firing rate before saccades
- Neurons in the frontal eye field indicate that reaction times vary due to the drift parameter!



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Beta oscillations can transiently increase decision thresholds



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