Computational Cognitive Neuroscience. Lab 3

Modelling behavioural data. Drift diffusion process. February 2025

Lecturer: Peggy Seriès
Teaching Assistant: Lars Werne

Tutorial Objectives

In this tutorial, you will:

- Learn to implement a model of binary decision making – a Drift Diffusion Process.
- Explore the model can be adjusted for prior information affecting its decisions.
- Interpret performance differences between clinical populations in behavioural experiments, using statistics and logical reasoning.

Introduction

Depression is associated with numerous cognitive deficits, including deficits in executive functioning, memory and attention (1). Additionally, we have learned that one of the symptoms of a major depressive episode is "psychomotor agitation or retardation nearly every day (observable by others, not merely subjective feelings of restlessness or being slowed down)" (2). Sometimes we therefore observe worse performance in depressed patients as compared to healthy control participants (e.g. in the tasks of the second and third parts of this assignment). Other times, we observe similar performance in terms of correctness, but slower response times from depressed participants. We can model the dynamics of decision processes using a random walk model or a diffusion process (see lectures slides, and (3) for a review). This model starts from the basic principle of accumulation of information. When an individual is asked to make a binary choice on the basis of an available stimulus, the assumption is that evidence from the stimulus is accumulated over time and a decision is made as soon as an upper or lower boundary is reached. Which boundary is reached determines which response is given and the time required to reach it determines the response time (RT). In this part, we will use a drift diffusion model to model responses of depressed and healthy participants in some (for our purposes arbitrary) experiment.

Drift Diffusion Models (DDMs)

We model a decision process between two hypotheses, which we call h^- and h^+. A Wiener diffusion process W_t with drift rate v and variance s^2 can be simulated using the following equation (4):

$$W(t + dt) = W(t) + v \times dt + s \times \eta \tag{1}$$

When $W(t) < 0$, a decision in favour of h^- is made. On the contrary if $W(t) > a$, a decision in favour of h^+ is made. dt denotes the time step used to simulate the process. η represents a Gaussian noise process with standard deviation $\sqrt{dt}$. Note the square root! We write $\eta \sim \mathcal{N}(0, dt)$.

The parameters are

- The mean drift rate v,
- The separation of the boundaries a,
- The starting point $W(0) = z$.

The drift rate v models the amount of evidence in favour of each of the hypotheses. If $v > 0$, there is more evidence in favour of h^+ (**which is then the correct decision**). On the contrary, if $v < 0$, there is more evidence in favour of h^-.

Tasks

1. **Initial Simulations**: Simulate the model with the following values: $v = 0.03, a = 0.12, s = 0.04, z = a/2, dt = 0.001(s)$.

   That is, write a function that accepts these parameters as inputs and returns the model's final decision, its *history* or *path* – all values that state W takes until a decision is reached, as well as a list of time points, matching the length of the path. Implement a 'timeout' of a maximum of 2000 steps, at which point the simulation should terminate without a final decision being made.

   Hint: In Python, you can return multiple values by separating them with commas in the return statement.

   Repeat the simulation multiple times and

   (a) Plot example paths.
   (b) Plot the three response time distributions (h^+, h^- and overall histograms).
   (c) Report and discuss the percentage of correct and incorrect responses and timeouts. Can you infer anything about the experiment?

2. **Exploring parameter settings**: Explore different settings of these values for v and a (always set $z = a/2$). Illustrate and describe how changes in parameter settings influence accuracy, response times and their trade-off.

3. **Prior information** Assume that a subject knows that one hypothesis is more likely than the other, for example the prior $p(h_+) = 2 \times p(h_-)$. How can this information be included in the model. Illustrate and explain.

4. **Group differences** Assume we collected data from two different experiments (with different participant groups). Each experiment included a participant group suffering from major depressive disorder and a healthy control group. Discuss the following scenarios:

   - Using two separate statistical tests to compare groups in terms of accuracy and response time, we did not find a significant difference for either test. We then fitted a drift diffusion model and compared the estimated parameters of the two groups. Is it possible that we would find significant differences between the groups' parameters? Why, or why not?
   - We find that (compared to controls) patients responded slower during the task but with similar accuracy. We suspect that this is related to one of two things: (a) A difficulty in the evidence accumulation and/or integration due to some cognitive deficits, or (b) a 'slowing down' of their perception and/or movement initiation and execution. How could we test for these two possibilities using our model and/or an extension of the model?

References

[1] Rock PL, Roiser JP, Riedel WJ, Blackwell A. Cognitive impairment in depression: a systematic review and meta-analysis. Psychological medicine. 2014;44(10):2029-40.

[2] DSM-IV-TR A. Diagnostic and statistical manual of mental disorders. American Psychiatric Association Washington, DC; 2000.

[3] Smith PL, Ratcliff R. Psychology and neurobiology of simple decisions. Trends in neurosciences. 2004;27(3):161-8.

[4] Ratcliff R, Rouder JN. Modeling response times for two-choice decisions. Psychological science. 1998;9(5):347-56.