Methods in Computational Neuroscience

# Decision making: studying the drift-diffusion model and training recurrent neural networks

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03.05.2024

## 1. The drift-diffusion model for perceptual decision making

In a two-alternative forced choice task (2AFC-task), subjects are asked to choose between two alternative actions. We will here consider the case where a subject receives a visual motion stimulus (a set of points on a screen that are moving in different directions) and then needs to indicate whether the points were moving upwards or downwards. If such a motion stimulus is ambiguous or "noisy", the task can be quite difficult. This scenario is well described by the "drift-diffusion-model":

$$\frac{dx(t)}{dt} = (I_A - I_B) + \sigma\eta(t) \tag{1.1}$$

where $x$ is the decision variable, $I_A$ and $I_B$ are the decision inputs, $\eta(t)$ is a noise term (Gaussian white noise with unit standard deviation), and $\sigma$ is the noise magnitude.
If the decision variable $x$ surpasses a threshold $\mu$, then the subject decides for outcome A; if $x$ decreases below a threshold $-\mu$, then the subject decides for outcome B.

**1.1** Simulate the dynamics Simulate the stochastic process defined in eq (1.1) for 10000 time steps. Use $dt = 0.1$. Use $I_A = 0.95$, $I_B = 1$, $\sigma = 7$ and a decision threshold $\mu = 20$. Simulate and plot the process 10 times, starting from the same initial condition $x_0 = 0$.

**1.2** Store the outcomes. Simulate the process 1000 times, starting from the same initial condition $x_0 = 0$. Store the outcomes: how many times decision A is taken? How many times decision B is taken? How many times there is no decision? (in the simulation interval)

**1.3** Vary the parameters Now we want to vary the parameters of the model, discuss their meaning and see how they affect the decision process. For the following points, simulate the dynamics 100 times. Plot the number of outcomes A and B as the parameter varies.
• Vary $\mu$ in $(1, 100)$. Use $I_A = 0.95$, $I_B = 1$ and $\sigma = 7$.

- Vary $E = I_A - I_B$ in $(-0.5, 0.5)$. Use $\sigma = 7$ and $\mu = 20$.

Explain the results and the meaning of these parameters. [For each point, you are asked to plot 2 curves: 'number of outcomes A' and 'number of outcomes B', as function of the parameter.]

### 1.4 Reaction times distribution

For different values of the evidence, $E = 0$, $E = 0.01$ and $E = 0.05$, simulate the dynamics 1000 times and collect the reaction times. Plot the reaction times distribution and explain the results for the 3 different cases. Do they differ for different evidence values? Use $I_B = 1$, $\sigma = 7$ and a decision threshold $\mu = 20$. [As an alternative to the classical histogram plot, you may check the function *sns.displot* with the command *kind="kde"*, from the Seaborn library in Python.]

## 2. Modeling decision making with Recurrent Neural Network (RNN)