MOD201: Decision Making

Ciprian Bangu

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2 The Drift Diffusion Model

The decision making process in the 2AFC task described above can be approximated by 'drift-diffusion' model. This model is given by the following equation:

$$\frac{dx(t)}{dt} = (I_A - I_B) + \sigma\eta(t) \tag{1}$$

where x is a decision variable, I_A and I_B are the neural signals to make decision A and B respectively, σ is the noise level, and $\eta(t)$ is a Gaussian white noise process with zero mean and unit variance. The decision of the subject, either A or B is represented by the crossing of the decision variable of some threshold: μ in the case the subject decides for outcome A, or $-\mu$ in the case the subject decides for outcome B. The differnce $I_A - I_B$ can be thought of as the evidence, E, the subject has for deciding in eithe direction. If this difference is positive, the subject is more likely to decide in favor of A, and if it is negative, the subject is more likely to decide in favor of B.

The idea is that this model captures the process of the integration by neurons in the Lateral Intraparietal area (LIP) of signals of motion direction in either the A or B direction as reported by direction sensitive neurons in the Medio-Temporal visual cortex.

2.1 Simulating the DDM

To get a sense of the dynamics of the stochasitc process produced by the model, we can simulate the model and plot the decision variable $x(t)$ as a function of time. Figure 1 below illustrates 10 trials of the model, given the initial conditions: $I_A = 0.95$, $I_B = 1$, $\sigma = 7$, $\mu = 20$, $x(0) = 0$, $dt = 0.1$, and possible timesteps = 10000.

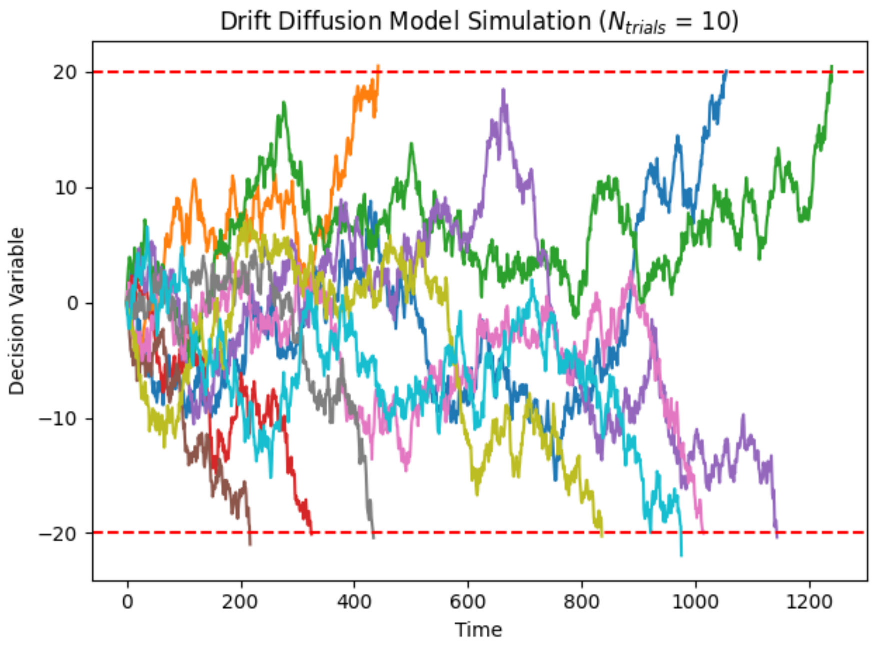

Figure 1: Simulation of the Drift Diffusion Model with $I_A = 0.95$, $I_B = 1$, $\sigma = 7$, $\mu = 20$, $x(0) = 0$, $dt = 0.1$, possible timesteps = 10000. Different trials are indicated by different colors. The dashed red lines indicate the decision variable thresholds.

As we can see from figure 1, the decision variable evolves randomly over time thanks to the gaussian noise in the model. Moreover, while it does not evolve in the same way every time, the decision variable eventually meets or crosses one of the thresholds, ending the trial, for every trial. **IS THERE ANYTHING ELSE TO SAY HERE?**

Recall that we introduced the notion of evidence E as the difference between the signals I_A and I_B. In Figure 1, we see that there are 3 trials where the decision variable crosses the threshold for A and 7 trials where the decision variable crosses the threshold for B. This is consistent with the fact that $I_B > I_A$. We can see the impact of this difference in evidence for one decision over another by looking at the number of trials that end in favor of one decision over the other, over more simulations of the model.

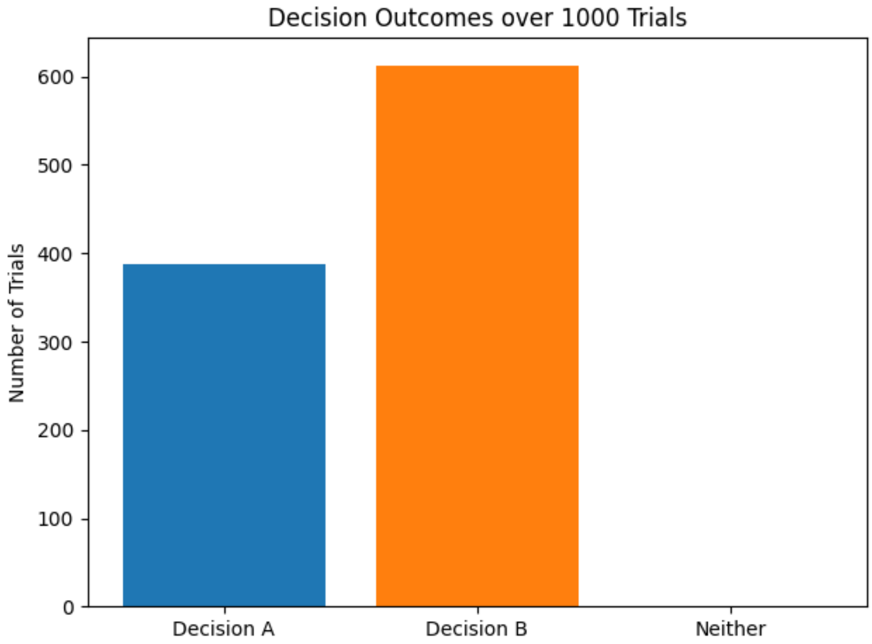

Figure 2: Outcomes of the Drift diffusion model over 1000 simulations. $I_A = 0.95$, $I_B = 1$, $\sigma = 7$, $\mu = 20$, $x(0) = 0$, $dt = 0.1$. The number of trials that end in favor of decision A is plotted in blue, and the number of trials that end in favor of decision B is plotted in orange.

Figure 2 above illustrates the distribution of the number of outcomes for each decision over 1000 simulations of the model. From Figure 2, we can see that the split between decisions A and B is about 60:40 in favor of decision B. Thus, for this model, even a small difference in the evidence in favor of one decision over another can lead to a significant difference in the number of trials that end in favor of one decision over the other. In this case a 0.05 evidence advantage for B led to a 50% increase in the number of trials that ended in favor of B over A.

2.2 Varying other parameters

We have seen how a small differential in the evidence can impact the distribution of outcomes for the model. However, there are more parameters we can vary to get differential behavior. In this section, we will vary μ σ and E to observe how the distribution of outcomes changes.

2.2.1 Varying μ

First, let us vary the threshold parameter of the model, μ. Recall, the threshold parameter, and its negative, are the values at which, once x reaches (or crosses) either of them, the simulation stops and the subject is said to have decided in favor of the corresponding decision. In Figure 3 below, we keep the same intial conditions as before, but vary μ from 1 to 100. Given the small amount of simulations, the difference in the number of trials that end in favor of B rather than A is initially small, and in some cases negative. However, as μ increases, there begins to be a clear advantage for decision B over A. This is because the evidence imablance combined with the higher threshold makes it less likely that x will reach or cross μ on any given trial. From the figure, we see that this decrease in A decisions is linear as μ increases. However, the relationship between increases in μ (or, really, increases in the *magnitude* of μ, since it is negative for decision B) is parabolic. Initially, increases in μ have a positive imapct on the number of trials that end in favor of B. However, this effect flattens out around $\mu = 50$, after which the number of trials that end in favor of B begins to decrease (although it remains higher than the number in favor of A). This is because the model is less likely to cross any threshold as μ increases, since it only has a finite amount of time to reach μ, which will take longer as μ increases.

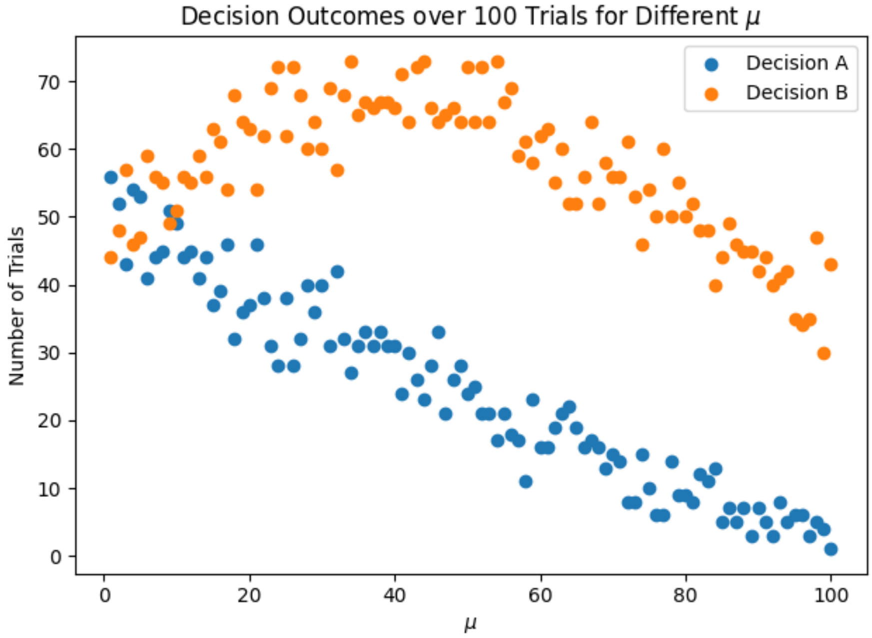

Figure 3: Number of trials that end in favor of decision A and B over 100 simulations of the DDM, varying μ from 1 to 100. $I_A = 0.95$, $I_B = 1$, $\sigma = 7$, $x(0) = 0$, $dt = 0.1$, possible timesteps = 10000.

2.2.2 Varying σ

Now, let us vary σ, or the magnitude of the noise in the model. In Figure 4 below, we keep the same initial conditions as before, but vary σ from 0 to 50, simulating the model for 100 trials.