Decision Making: Studying the Drift-Diffusion Model For Perceptual Decision Making

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1 Introduction

The drift-diffusion model (DDM) is a fundamental framework for understanding perceptual decision-making processes in neuroscience. This model describes how evidence accumulates over time until a decision threshold is reached, making it particularly relevant for two-alternative forced choice (2AFC) tasks. The DDM has its roots in the 1970s, when Roger Ratcliff introduced it to model two-choice decision-making tasks. Building upon earlier concepts of evidence accumulation, Ratcliff's model provided a quantitative framework to explain both the accuracy and reaction time distributions observed in such tasks. Over the years, the DDM has been extensively validated and refined, becoming a cornerstone in cognitive psychology and neuroscience for modeling decision-making processes.

In this report, we analyze the DDM through computational simulations, examining how various parameters influence decision outcomes and reaction times.

2 Results

2.1 Simulate the dynamics

We simulated the drift-diffusion process for 10 trajectories using the parameters $I_A = 0.95$, $I_B = 1.0$, $\sigma = 7$, and $\mu = 20$. All simulations started from the initial condition $x_0 = 0$ and were run for a maximum of 10,000 time steps. The Euler-Maruyama method was used for numerical integration with a time step of $dt = 0.1$.

For the stochastic differential equation, the discrete update rule is:

$$x_{t+1} = x_t + (I_A - I_B) \cdot dt + \sigma\sqrt{dt} \cdot \xi_t \tag{1}$$

where ξ_t is a standard normal random variable.

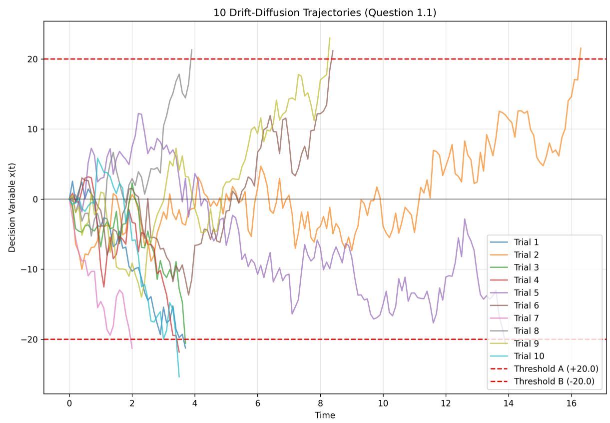

Figure 1: Ten trajectories of the drift-diffusion process. Red dashed lines indicate decision thresholds at ± 20. Each trajectory shows the evolution of the decision variable $x(t)$ over time until a decision is reached or the maximum simulation time is exceeded.

The trajectories demonstrate the stochastic nature of the decision-making process. Due to the negative evidence ($E = I_A - I_B = -0.05$), there is a slight bias toward decision B, though individual trajectories can still reach either threshold due to noise fluctuations.

2.2 Store the outcomes

From 1,000 simulation trials with identical parameters, we obtained the following outcome distribution:

Outcome	Count
Decision A	485
Decision B	515
No Decision	0

Table 1: Distribution of outcomes from 1,000 drift-diffusion simulations. The slight bias toward decision B reflects the negative evidence value. The results confirm the expected bias toward decision B due to the negative evidence ($E = -0.05$), while the presence of no-decision trials indicates that some trajectories failed to reach either threshold within the simulation time limit.

2.3 Vary the parameters

Threshold Variation

We investigated how the decision threshold μ affects outcome frequencies by varying μ from 1 to 100 while keeping other parameters constant ($I_A = 0.95$, $I_B = 1.0$, $\sigma = 7$).

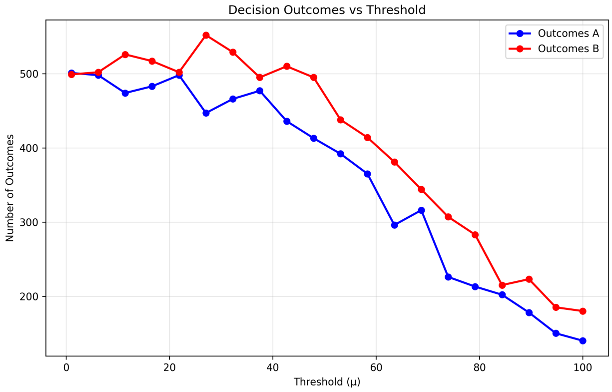

Figure 2: Effect of decision threshold μ on outcome frequencies. Higher thresholds require more accumulated evidence, leading to fewer total decisions but potentially higher accuracy.

The analysis reveals that increasing the decision threshold leads to fewer overall decisions (more no-decision outcomes), longer decision times (representing a higher accuracy-speed trade-off), and maintained bias toward the favored alternative due to $E = -0.05$ (decision B in this case).

Evidence Variation

We examined how evidence strength $E = I_A - I_B$ influences decision bias by varying E from -0.5 to 0.5 while maintaining $I_B = 1.0$, $\sigma = 7$, and $\mu = 20$.

Figure 3: Effect of evidence strength $E = I_A - I_B$ on decision outcomes. Positive evidence favors decision A, while negative evidence favors decision B. The transition is smooth and approximately sigmoidal.

The evidence variation analysis demonstrates strong relationship between evidence direction and decision bias, and it depicts a symmetric response around $E = 0$ (no bias condition) and a transition between decision preferences. Additionally, evidence strength determines the steepness of the preference transition.

2.4 Reaction times distributions

We analyzed reaction time distributions for three different evidence levels: $E = 0$, $E = 0.01$, and $E = 0.05$, using parameters $I_B = 1.0$, $\sigma = 7$, and $\mu = 20$.

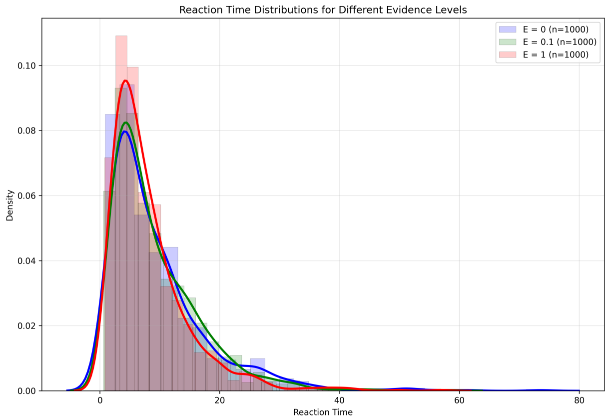

Figure 4: Reaction time distributions for different evidence levels. The distributions show how evidence strength affects both the speed and variability of decision-making.

Evidence (E)	Mean RT	Std RT
0.0	9.52	8.39
0.1	9.18	7.21
1.0	8.14	6.58
5.0	4.27	2.79

Table 2: Reaction time statistics for different evidence levels. RT = Reaction Time.

The reaction time analysis reveals several key findings. Higher evidence levels lead to significantly faster mean reaction times, while simultaneously reducing reaction time variability (lower standard deviation). Stronger evidence also increases the proportion of trials reaching a decision within the time limit. The reaction time distributions consistently show positive skew, which aligns with empirical findings in perceptual decision-making literature. These results demonstrate how evidence strength directly influences both the speed and consistency of the decision-making process.

3 Conclusions

This computational analysis of the drift-diffusion model demonstrates its effectiveness in capturing fundamental aspects of perceptual decision-making. Key findings include: (1) the model successfully reproduces the stochastic nature of decision processes (Fig 1); (2) decision thresholds create a speed-accuracy trade-off, with higher thresholds leading to more accurate but slower decisions due to higher evidence requirements and lower variance (Fig 2); (3) evidence strength directly influences both choice bias and reaction time characteristics (Fig 3); and (4) reaction time distributions show the expected positive skew and systematic variation with evidence strength (Fig 4).

The drift-diffusion model remains a cornerstone framework for understanding decision-making in neuroscience, providing quantitative predictions that can be tested against behavioral and neural data. Its simplicity and mathematical tractability make it an excellent starting point for more complex models of cognitive processes.