Drift Diffusion Modeling Approaches

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Introduction and Background

Two alternative-force decision processes, otherwise known as diffusion processes, are heavily applied in the fields of psychology and cognitive neuroscience to model the noisy evolution of thought of an individual participating in a binary-choice task. We discuss the application of a specific diffusion process, Drift Diffusion Models, to model Tone Discrimination (TD) in mice. The use of this computational approach on decision making tasks has been shown to gauge a better understanding of underlyign decision-making processes, especially those that are affected by negative biases in mood disorders such as anxiety and depression. The focus of this paper is to explore this modeling approach in the realm of cognitive biases and decision making, as well as discuss the various computational tools for drift diffusion models currently available to researchers in the field.

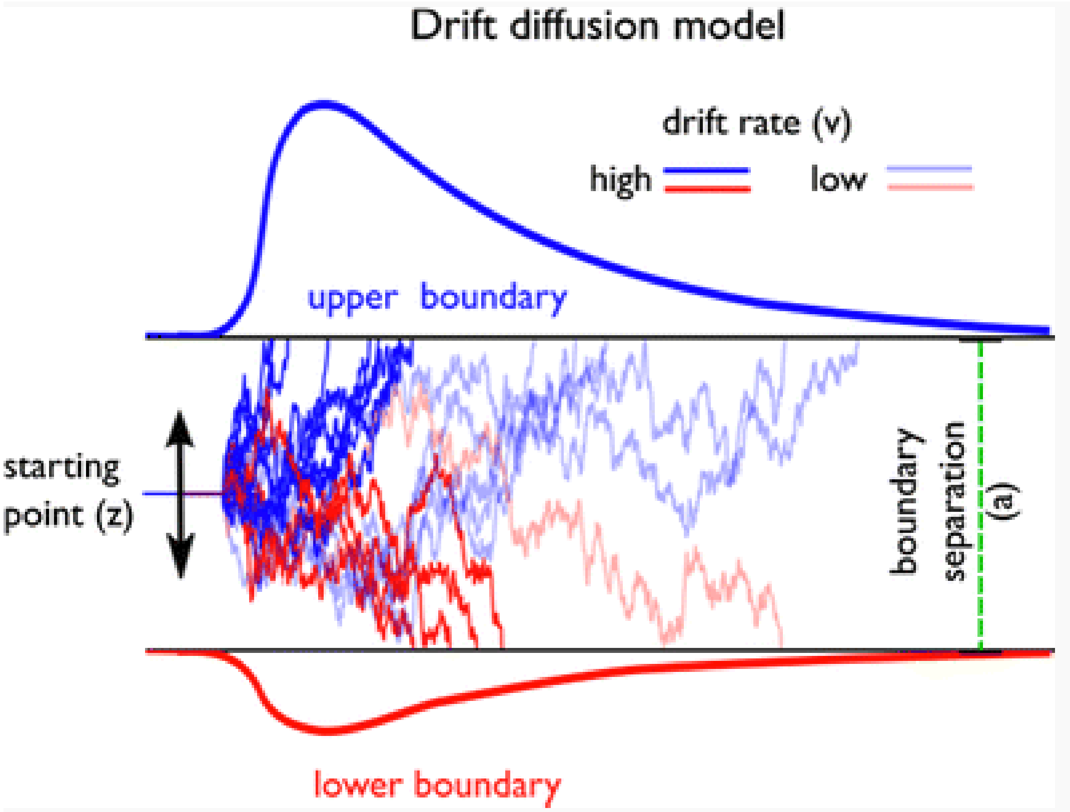
The application of diffusion processes to study choice behavior has been around for more than 40 years, however the use of these diffusion models on the choice reaction time of animal behavior is still yet to be mainstream. Recent advance in computational methods have enabled us to compute a full hierarchical Bayesian posterior distribution of DDM parameters within a cohort, with the aid of Markov Chain Monte Carlo (MCMC) sampling to estimate the joint distribution of free parameters under the model; with the assumption that computing enough parameter estimates across a population can strengthen the recovery of parameters of the individual.

Diffusion models explain the decision making process in several free parameters: including response time (measured to include time for non-decision processes and time from which the decision starting point occurs), decision thresholds (corresponding to lever-presses), and a drift rate as a measure of bias for one decision over another.

Theoretical Formalization

Drift Diffusion models allow for an experimental design with only two alternative options (multi-alternative choice models do exist, however we will not discuss). As first proposed by Ratcliff (1978), subjects noisily fluctuate between two options until a certain decision threshold has been reached, akin to the vibrating frequencies of a tuning fork. This “fluctuation” can be represented by a drift rate; parameterized in the model as v. This slope must have a starting point, which we parameterize as t0. The subject samples between these two alternative options, each having independent decision thresholds, hereonout referred to as A- and A+

Figure 1: Visualization of Drift Diffusion model parameters (CITATION)



Experimental Approach

Experimental Design

Performance in ambiguous-cue interpretation tasks ("ACI") are a frequently used measure of cognitive bias in mice. Negative biases are linked to negative emotional states (Hales, Robinson, Houghton 2016) and thus are hypothesized to be relevant to understanding the etymology and treatment prognosis of mood disorders such as anxiety and depression. In order to test the effectiveness of two DDM tools, we fit data from a Tone-Discrimination task, which is a training precursor performed prior to an ACI task.

Mice were trained on a tone discrimination task, consisting of 50 trials per mouse per day across a period of 5 days. Individual trials involved a lever extension (two levers, one high lever (HL), and one low lever (LL) depending on the trial type). Trials are divided into two types: TD1 denotes trials with a high-frequency tone stimulus, corresponding to a high reward (measured in quantity of food pellets given), and TD2 denotes trials with a low-frequency tone stimulus, corresponding to a lower reward (less amount of food pellets given). Note that during this experimental set-up, only the first response is recorded; e.g. if a mouse's first response is incorrect, any further lever presses within that individual trial, correct or incorrect, will be ignored. Trials with which the animals did not make any lever press responses were categorized as "omissions" and hence not used in the drift diffusion modeling. ### Data Collection Inputs to both modeling tools, HDDM and Fast-DM, are identical. In order to estimate parameter values, a DDM model requires the following: response time (in terms of latency to first lever press), stimulus (tone), response (in terms of a correct or incorrect lever press), and depending on the researcher's needs, you can provide a neurological measure (e.g. EEG) ### Model Application

HDDM

Fast-DM

Discussion

An interesting, relatively recent study by Pedersen, Frank, and Biele described efforts to use drift diffusion model parameters as a choice updating rule in a reinforcement learning model, instead of using the typical expected value choice process via a softmax function. The drawback of regular reinforcement learning models are their inability to capture within-trial decision making processes; modeling the decision process as trial-by-trial accumulation of information. Pedersen et al. aim to combine drift diffusion models, which as we have seen are advantageous when investigating an individuals decision process with respect to choice boundary thresholds, with reinforcement learning parameters, which are useful in describing an individuals overall learning rates and choice sensitivity within their environment. Response latency is usually not encoded into reinforcement learning models, so the integration of response time to RL modeling can provide a more complex explanation of decision processes. ## References 1. Hales, Robinson, Houghton 2. Pedersen,Frank,Biele 3. Wiecki, Sofer, Frank 4. Ratcliff, Smith, Brown, McKoon 5. Ratcliff, Rouder