Extended Abstract: Attentional Discounting in Gains, Attentional Amplification in Losses

Brenden Eum[1,3], Stephen Gonzalez[2], and Antonio Rangel[1]

[1]California Institute of Technology, Humanities and Social Sciences
[2]Stanford University, Education
[3]Corresponding Author: beum@caltech.edu

June 27, 2023

Introduction

Simple choices between positively valued options are common in our daily lives and are susceptible to robust attentional choice biases [1–5]. Recent evidence has shown that these attentional effects on choices are causal [6]. However, we also encounter choices between negatively valued options. We investigate whether attentional choice biases are similar between choices in gains versus in losses.

Methods

Eye-Tracking Task

Subjects complete 400 trials under two conditions (gain vs. loss; see Fig. 1). In the gain condition, two circles (100 dots each) appear on the left and right. The number of white dots represents the probability of receiving nothing; green dots represent the probability of gaining $10. Loss condition trials are similar, except green dots are replaced with red, representing the probability of losing $10. Subjects have free response time as we track their gaze. 70 subjects were recruited and were paid according to the outcome of two randomly selected trials: 1 gain, 1 loss.

Computational Model

We use the Attentional Drift-Diffusion-Model (aDDM), where value comparison is modulated by the location of one's gaze [2]. Subjects integrate noisy value signals into an evidence accumulator that evolves over time, E_t. Evidence starts at an initial location b. Once E_t crosses one of two pre-specified boundaries (± 1), a choice is made. This process evolves according to:

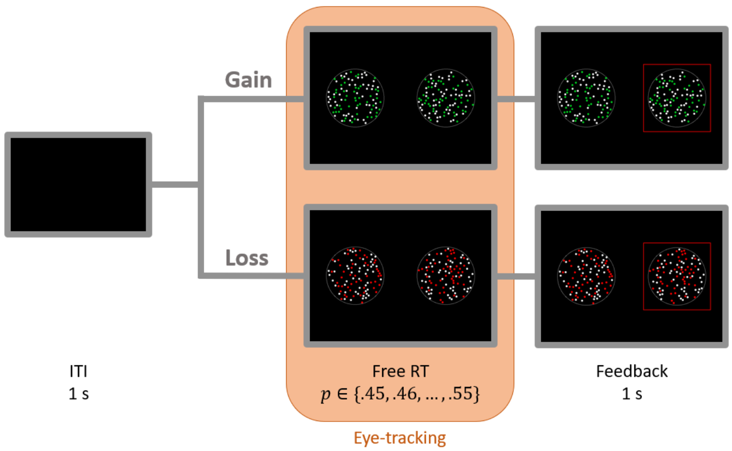

Fig. 1. Task.

$$E_t = E_{t-1} + \mu_t + \epsilon_t \tag{1}$$

where $\epsilon_t \sim N(0, \sigma^2)$. The drift ($\mu_t$) depends on fixation location. If the subject is looking left at time t, then $\mu_t = d(V_L - \theta V_R)$, where d controls the speed of integration, V_i is the value of option i, and θ is an attentional discounting parameter. If the subject is looking right at time t, then drift is instead $\mu_t = d(\theta V_L - V_R)$.

Results

Choice Biases

Consistent with previous findings [1, 2, 4, 5], in Fig. 2 we find evidence of last fixation bias (left) and net fixation bias (right) in the gain trials, shown in blue. However, contrary to the predictions of the aDDM, we find an attentional bias away from the fixated option in losses. In other words, last and net fixation bias are still present in loss trials, shown in red.

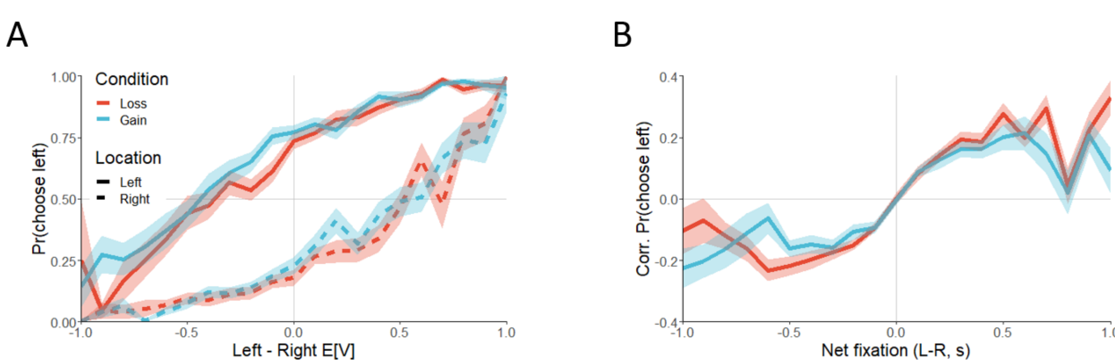

Fig. 2. Choice Biases.

aDDM

We fit the aDDM separately to each subject j by condition (see Fig. 3). Crucially, we find that $\hat{\theta}_j^G < 1$ and $\hat{\theta}_j^L > 1$ for most subjects, meaning that the value of the nonfixated option is "discounted" in gains and "amplified" in losses.

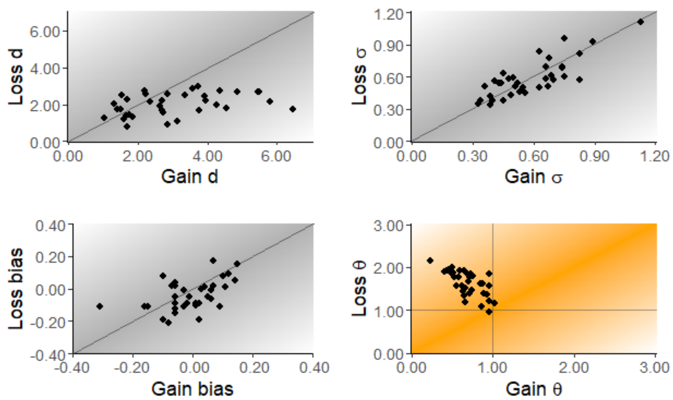

Fig. 3. Comparison of Individual Parameter Estimates.

Discussion

Contrary to the predictions of the aDDM, we found an attentional bias away from the fixated option in losses. That being said, choices and response times can be captured by an aDDM using a non-constant attentional discounting parameter that discounts the value of the nonfixated option in gains ($\theta < 1$) and amplifies this value in losses ($\theta > 1$).

There are several potential explanations of these results. One is that there is a fundamental difference in the role of attention in choices in gains versus in losses. Another is that subjects may be making value comparisons based on the amount of green in gain trials, then switching to the amount of white in loss trials. We are exploring these hypotheses in subsequent work.

References

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