Extended Abstract: Attentional Biases in Choices in Gains versus Choices in Losses

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Introduction

We encounter simple choices between positively valued options in our day-to-day lives (e.g. what to buy for dinner at the grocery store, which product we like on an e-commerce website). In these scenarios, previous studies have documented robust attentional choice biases [1–5]. Some of these include last fixation bias (i.e. the tendency to choose the last fixated option), and net fixation bias (i.e. the tendency to choose the option with more relative fixation time). Recent evidence has shown that these attentional effects on choices are causal [6].

However, we also encounter choices between negatively valued options (e.g. which credit card bill to pay off first, whether or not to pay for repairs on a car). We investigate whether attentional choice biases are similar between choices in gains and choices in losses. Based on the Attentional Drift-Diffusion-Model [2], we hypothesized a bias towards choosing the more fixated option in gains, and against choosing the more fixated option in losses. To preview the results, we find evidence of a bias towards choosing the more fixated option, regardless of condition.

Methods

Task

We investigated how attention differentially affects the choice process in the gain and loss domains by using the task depicted in Fig. 1. Subjects begin the trial by fixating on an empty screen for 1 s. In the gain condition, subjects are presented with two grey circles on the left and right sides of the screen. Inside each circle are 100 green or white dots. The number of white dots represents the probability of receiving nothing; the number of green dots represents the probability of gaining $10. Subjects are given free response time to select the lottery they prefer, and after selecting, are given 1 s of feedback about the choice they made. In the loss condition, trials are similar, except the green dots are replaced with red dots, which represent the probability of losing $10. In all trials, the number of green or red dots in either option is drawn uniformly from 45 to 55. The remaining dots are colored white.

Subjects completed 400 trials in the exploratory sample, split into 2 blocks of 200 trials each. 1 block was in the gain condition, the other in the loss condition, randomly ordered.
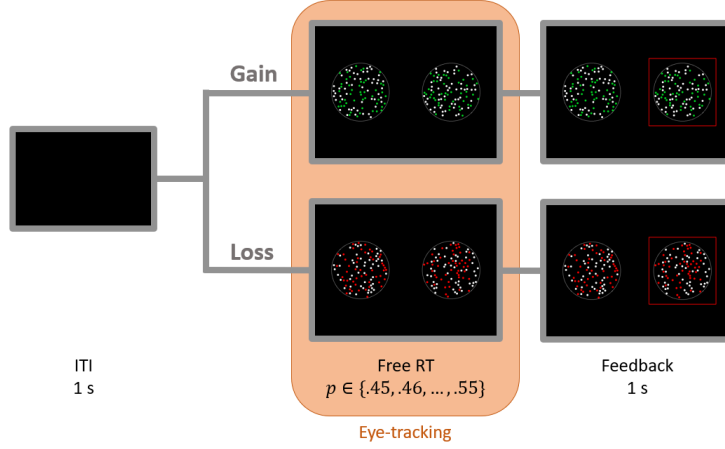

Fig. 1. Task.

Participants

70 subjects were recruited for the study (mean age = 26.4, 41 female). Subjects were paid a \$30 participation fee. After the experiment was over, subjects drew a number between 1 and 200 out of an urn. The lotteries associated with this number in blocks 1 and 2 were played out, and subjects' total pay was adjusted according to the outcome of those lotteries.

Computational Model

We use a variation of the Drift-Diffusion-Model of binary choice [7, 8]. In particular, we use the Attentional Drift-Diffusion-Model (aDDM), where value comparison is modulated by the location of one's gaze. Subjects integrate noisy value signals into an evidence accumulator that evolves over time, E_t. Evidence starts at an initial location b, incorporating some bias towards one of the two options if $b \neq 0$. Once E_t crosses one of two pre-specified boundaries (± 1), a choice is made based on the identity of the boundary (e.g. hitting upper boundary indicates a choice for left option). The evolution of evidence looks like the following diffusion process:

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

where ϵ_t is Gaussian white noise with variance σ^2. The drift (μ_t) in the diffusion process depends on fixation location. If the subject is looking left at time t, then $\mu_t = d(V_L - \theta V_R)$, where d is the drift rate parameter controlling the speed of integration, V_i is the value of option i, and θ is an attentional discounting parameter that discounts the value of the nonfixated option. If the subject is looking right at time t, then drift is instead $\mu_t =$

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$d(\theta V_L - V_R)$. Importantly, the aDDM takes fixations as exogenous to the state of the decision process and is therefore agnostic to modeling fixations.

Results

Basic Psychometrics

There were no meaningful differences in average choices, response times, or number of fixations between the two conditions.

Choice Biases

Consistent with previous findings, 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 evidence in the choice behavior of an attentional bias towards the fixated option in gains and away from the fixated option in losses.
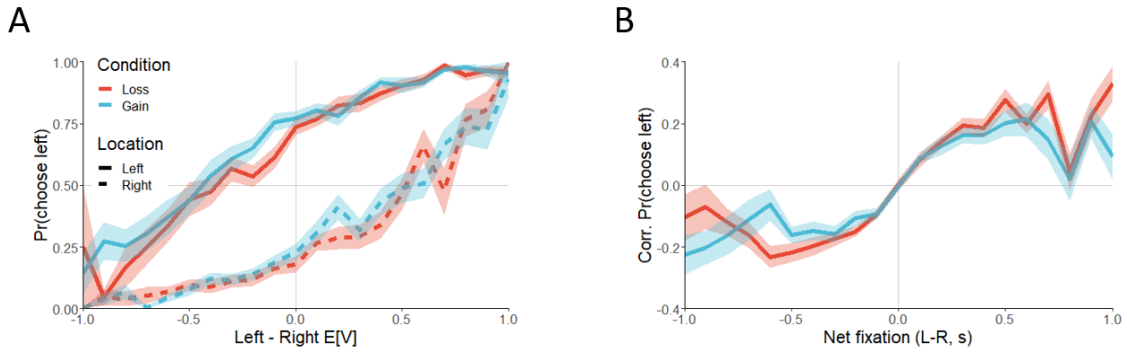

Fig. 2. Choice Biases.

aDDM

We fit the aDDM separately to each subject j, by condition (G,L), and compare estimates across the two conditions (see Fig. 3).

$\hat{\sigma}_j$ and $\hat{b}_j$ remain consistent across the two conditions, while $\hat{d}_j^G > \hat{d}_j^L$ for some subjects. 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.

Discussion

Contrary to the predictions of the aDDM, we found an attentional bias towards the fixated option in gains and 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
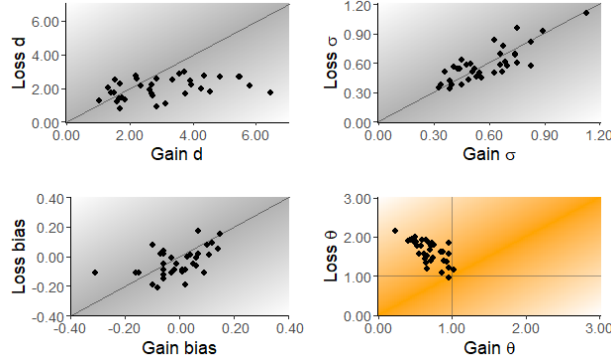
Fig. 3. Comparison of Individual Parameter Estimates.

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. The first is that there is a fundamental difference in the role of attention in choices in gains, and in choices in losses. Second is that subjects may be solving the task by counting the number of green dots in the gain trials, switching to counting the white dots in loss trials, and making value comparisons based on these counts. If so, an aDDM with attentional discounting can explain these results. Another possible explanation is that subjects are evaluating the value of the options with respect to a reference point [9], such as the minimum value between the two options. We are exploring these hypotheses in subsequent work.

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