Attentional Over-Weighting in Gains, Attentional Under-Weighting in Losses

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Introduction

Simple choices between positively valued options are common in our daily lives and are susceptible to robust attentional choice biases [1–5]. We investigate whether attentional choice biases are similar in choices between negatively valued options.

Methods

Task 70 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.

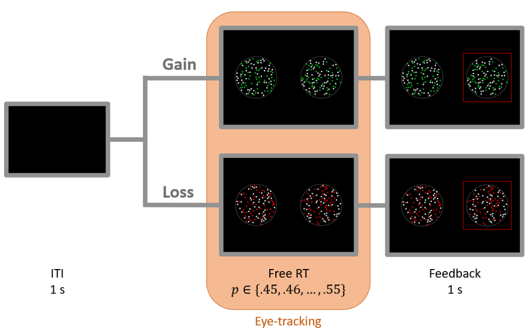

Figure 1: Task

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:

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

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

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 green. 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.

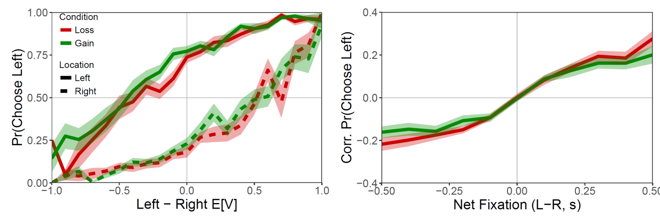

Figure 2: Choice Biases.

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 fixated option is over-weighted in gains and under-weighted in losses.

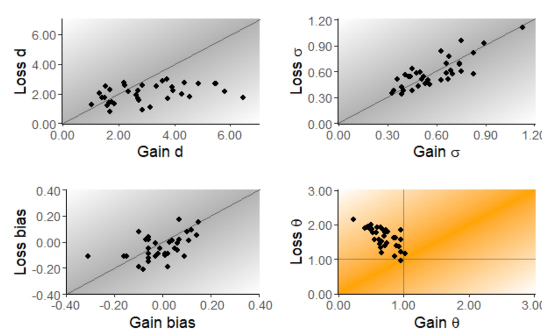

Figure 3: Comparison of Individuals' Estimates.

Conclusion

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 ($\theta > 1$).

References

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