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

Brenden Eum, Stephen Gonzalez, and Antonio Rangel

Introduction

Visual attention causally influences choices.

- An increase in the relative attention received by a desirable option increases the frequency with which it is chosen [1–3].

We do not know if visual attention influences choices between losses in the same way that it influences choices between gains.

- Attention to appetitive snacks increases the tendency to overweight the value of fixated options [4–7].
- Attention to the positive outcome of a gamble increases with its probability and amount [8].

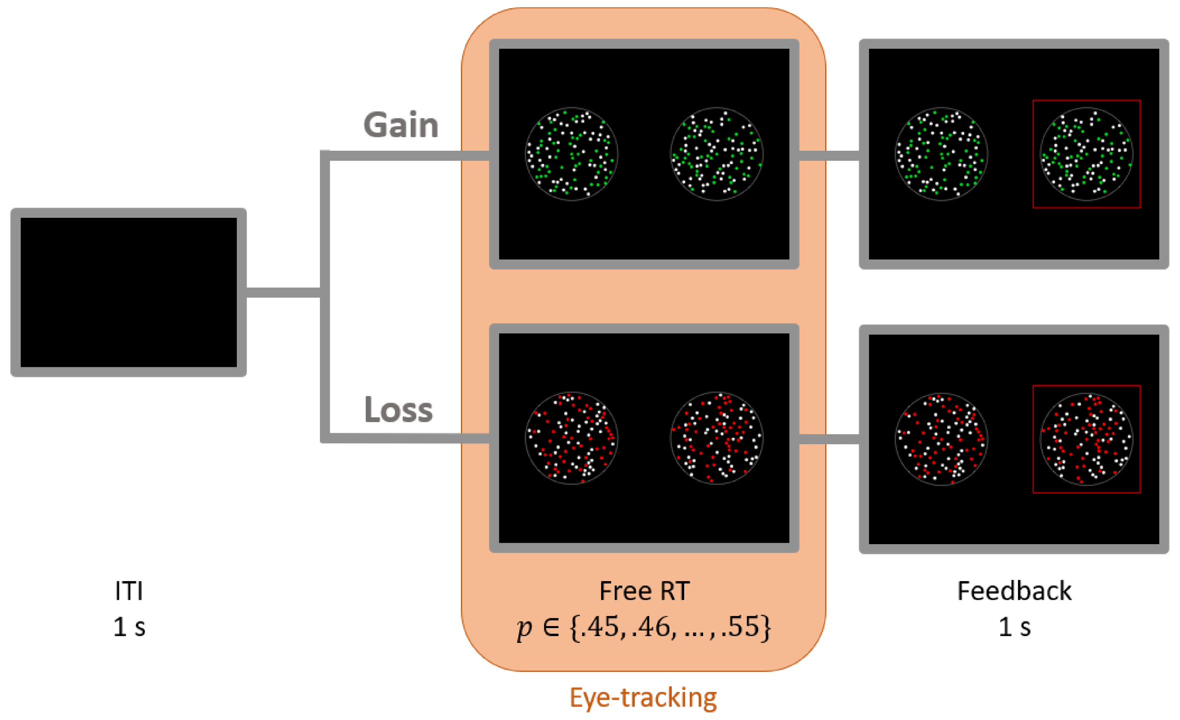
How does visual attention impact choices between negative-outcome lotteries?

H1: Attentional over-weighting of fixated option. ↑ relative attention to option ⇒ ↓ choice frequency.

H2: Attentional under-weighting of fixated option. ↑ rel. attention ⇒ ↑ choice freq.

Eye-Tracking Task

- $N = 25$. Binary choices between lotteries.
- 400 trials, 2 blocks, 2 conditions:
  - Gain: positive-outcome lotteries.
  - Loss: negative-outcome lotteries.



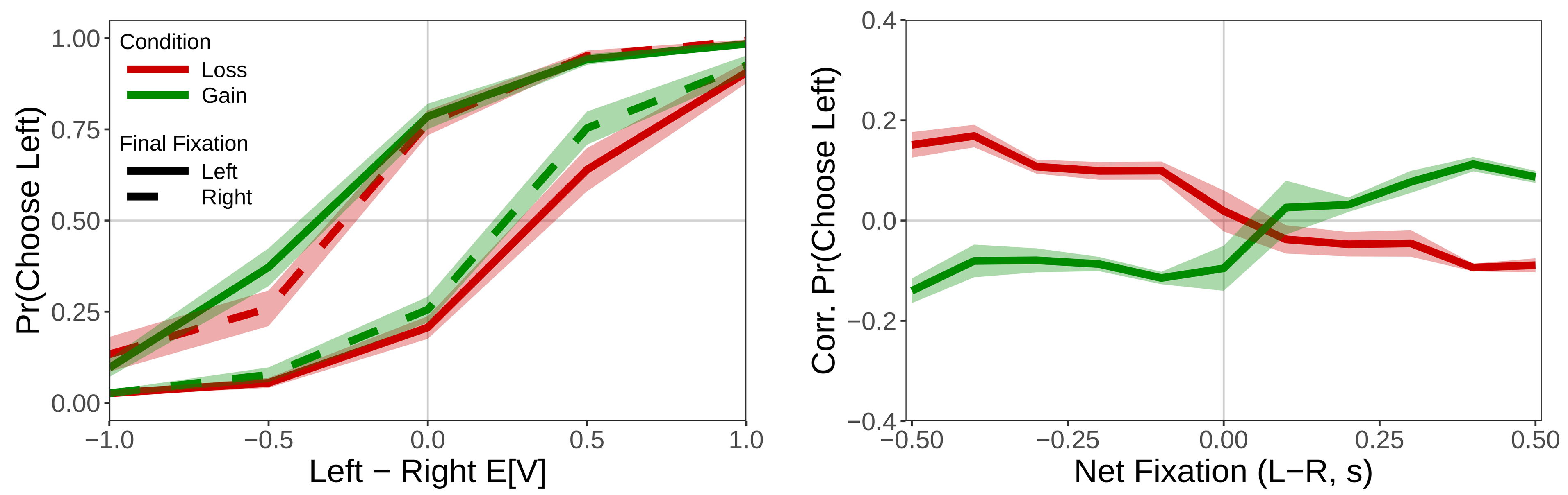
Contact Info

Lab www.rnl.caltech.edu
Web www.brendeneum.com
Email beum@caltech.edu

Results

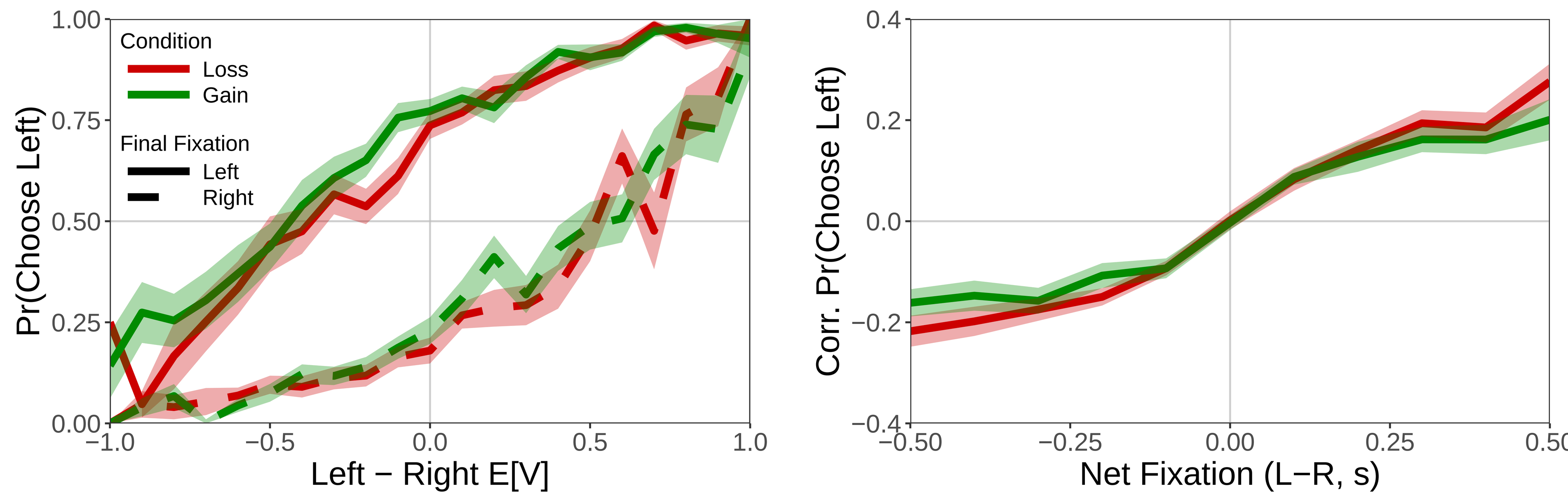
Model Predictions

If there is attentional over-weighting in loss choices ($\theta_{loss} < 1$), then an increase in the relative attention received by an option should decrease the frequency with which it is chosen.



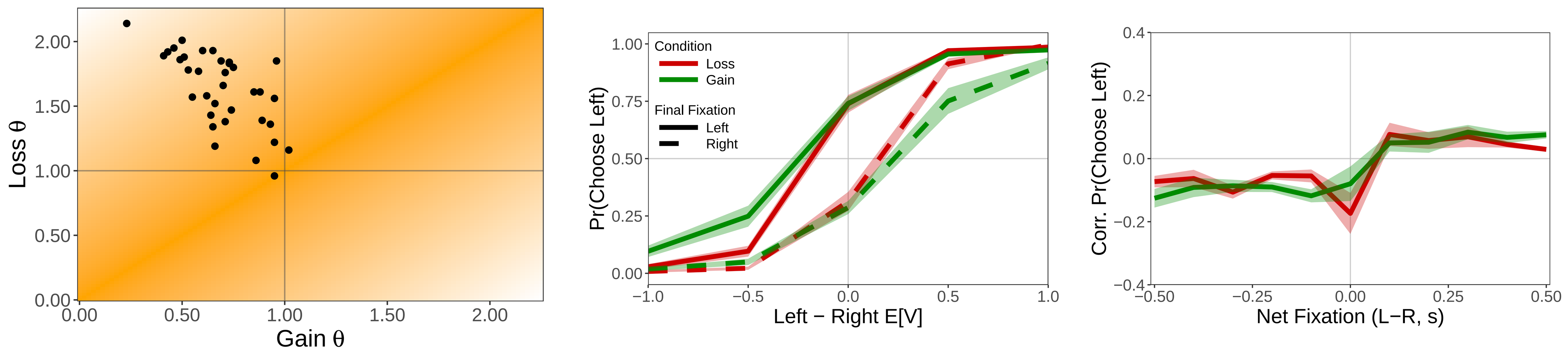
Observed Data

Instead, we find that an increase in the relative attention received by an option still increases the frequency with which it is chosen, just as in gains.



aDDM

Observed data is explained by the aDDM with attentional under-weighting of the fixated option in choices between losses ($\theta_{loss} > 1$) and attentional over-weighting in choices between gains ($\theta_{gain} < 1$).



Hypotheses

H1: Over-weighting in loss; ↑ rel. attention ⇒ ↓ choice freq. (Results, Observed Data)	UNSUPPORTED
H2: Under-weighting in loss; ↑ rel. attention ⇒ ↑ choice freq. (Results, aDDM)	SUPPORTED

Model

Attentional Drift-Diffusion-Model (aDDM)

$$\text{Evidence}_t = \text{Evidence}_{t-1} + \mu_t + \epsilon_t$$

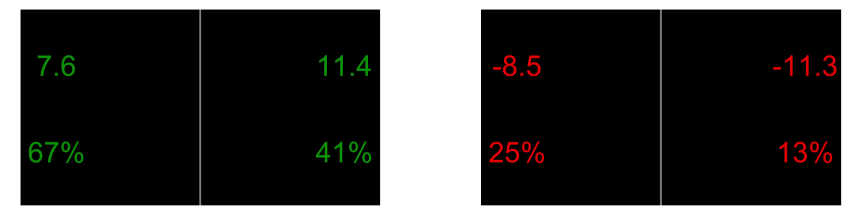
- Evidence accumulation to decision bounds fixed at ± 1.
- Fixated left: $\mu_t = d(V_L - \theta V_R)$
- Fixated right: $\mu_t = d(\theta V_L - V_R)$
- Drift rate: d
- Noise: $\epsilon_t \sim N(0, \sigma^2)$
- Attentional over-weighting: $\theta < 1$
- Attentional under-weighting: $\theta > 1$

Discussion

Choices and response times can be captured by an aDDM using an attentional bias parameter that over-weights the value of the fixated option in gains ($\theta < 1$) and under-weights this value in losses ($\theta > 1$). Potential explanations:

- There is a fundamental difference in the role of attention in gains versus losses.
- Subj. may be treating the task as a perceptual task by counting green dots in gains, white dots in losses, and making value comparisons based on these counts. Then attentional over-weighting explains all results.

Next steps:



References

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