The Effect of Feedback and Knowledge of the Distribution of Option Values on Learning in Sequential Search

Erin H. Bugbee and Cleotilde Gonzalez
{ebugbee, coty}@cmu.edu
Department of Social and Decision Sciences, Carnegie Mellon University

Summary

In many naturalistic situations such as deciding on an apartment to rent or selecting a life partner, people can explore options before making a selection. We investigate the following:

How do **feedback** and **knowledge of the distribution of options values** affect **learning** in sequential search?

How do people **deviate from optimal** based on these factors, and can this be modeled with a **cognitive model** of decisions from experience?

Goals:

1. Determine how factors influence decisions and learning within a sequential search task
2. Create a general paradigm for studying stopping decisions

Introduction

- Previous work indicates that people are suboptimal at stopping such exploration phase and often stop earlier than optimal [1, 5]
- Recent work shows that people can learn to stop at the optimal time with experience [3]
- We investigate factors that may influence learning in stopping decisions and extend our previous modeling work [2] to this task

Methods

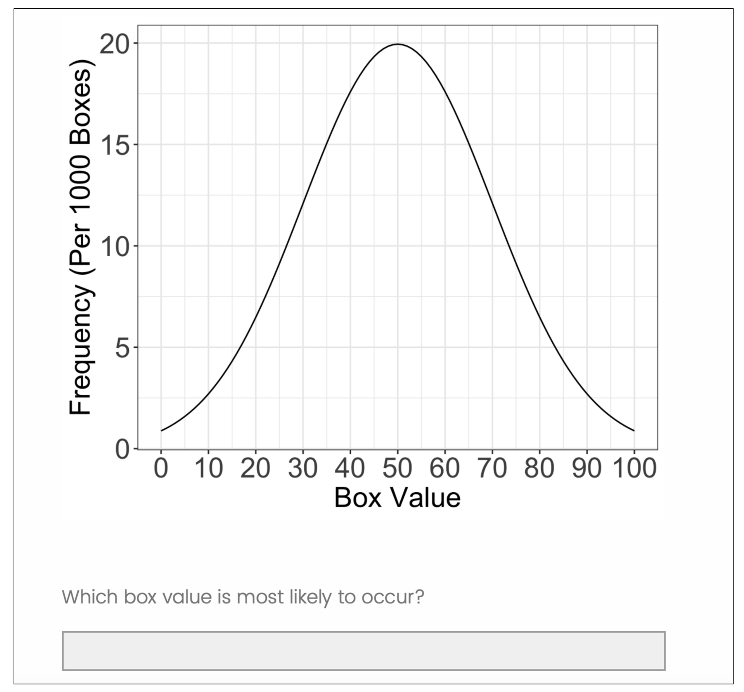
Human Participants

- *Participants*: 226 from Amazon MTurk
- *Design*: Randomly assigned to a condition in a between-subjects design
- *Conditions*: 2 (Knowledge of the Distribution: Known or Unknown) x 3 (Feedback: Outcome, Detailed, or No Feedback)

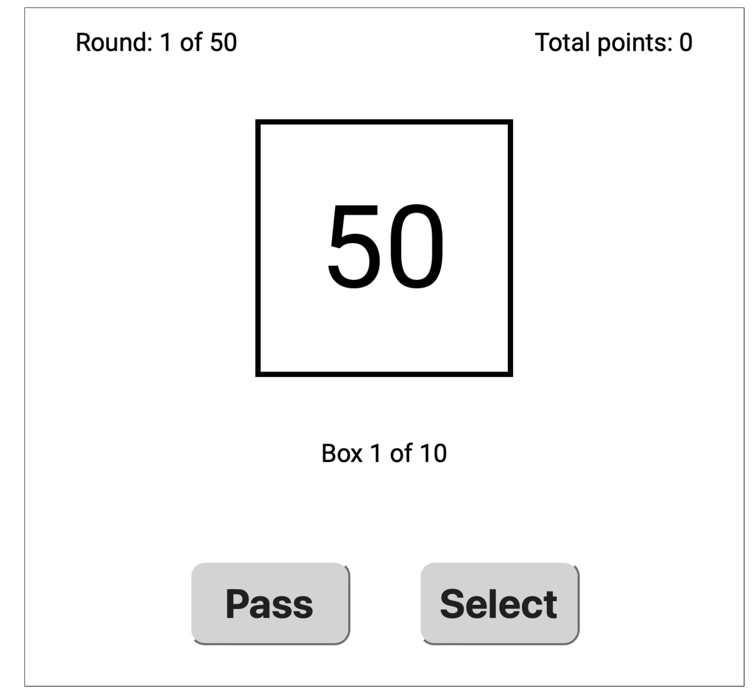
Model Agents

- Simulate 300 IBL model and optimal agents completing the same task

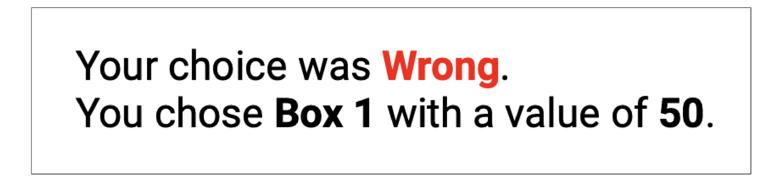
Optimal Stopping Task



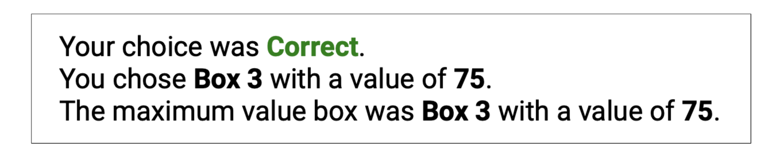
(a) Distribution Known



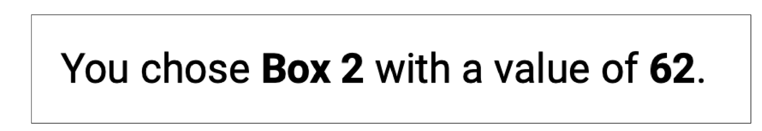
(b) Stopping Decision



(c) Outcome Feedback



(d) Detailed Feedback



(e) No Feedback

Cognitive Model: Instance-Based Learning Model

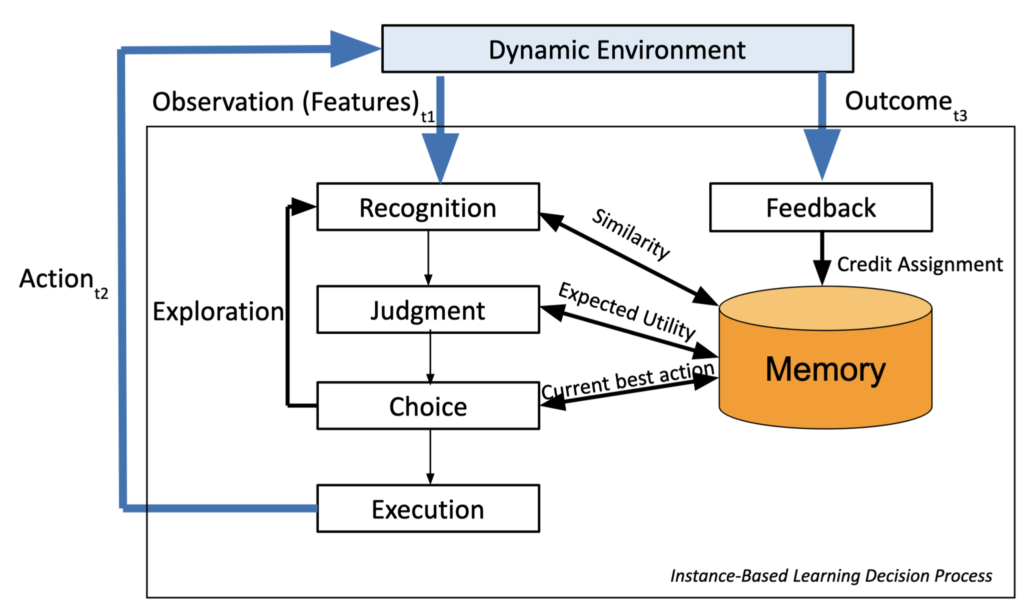


Figure 2: Instance-Based Learning Theory [4]

- Learning occurs through the accumulation of memory units called *instances*
- Past instances are *retrieved* based on *similarity* to the current situation, frequency, and recency
- A *blended value* (BV) is calculated based on the *utility* of the retrieved instances
- The agent *chooses* option with the highest BV

State		Action	Utility
Value	Boxes Remaining	{Select, Pass}	{0, 1}

Table 1: Instance Structure

Results

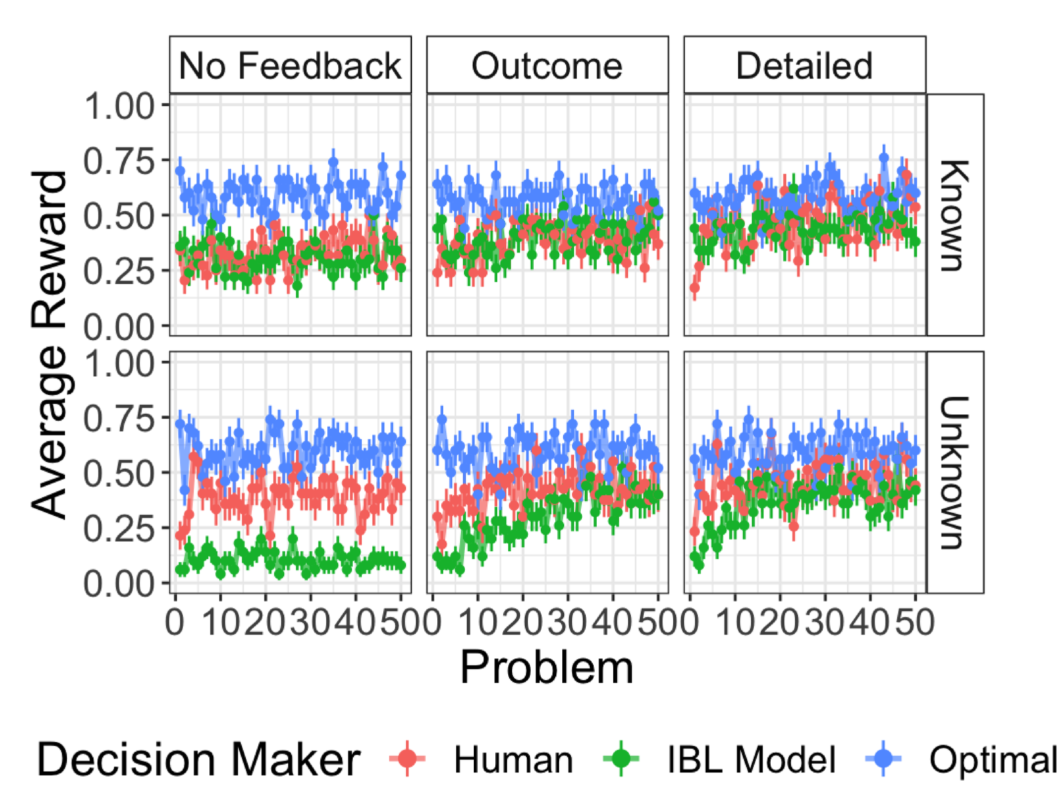


Figure 3: Average Reward for Human, IBL Model, and Optimal Agents for Problems 1 through 50

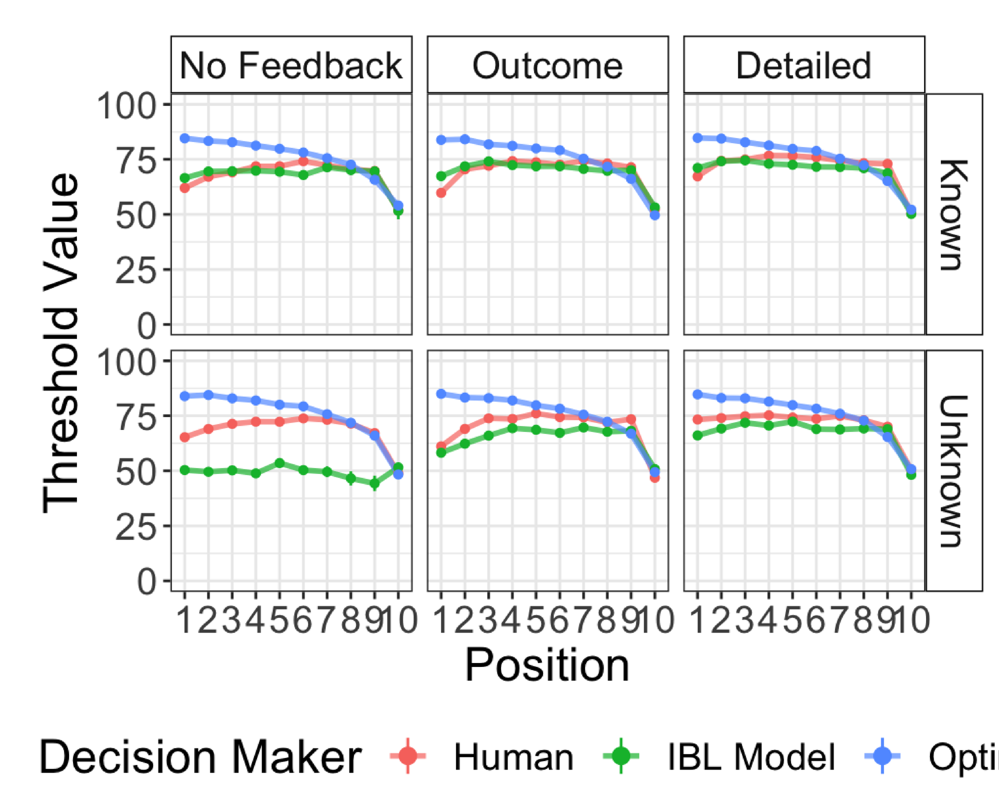


Figure 4: Threshold Values for Human, IBL Model, and Optimal Agents for Positions 1 through 10

Conclusion

- We develop a **novel optimal stopping task** to investigate the impact of various factors on stopping decisions in sequential search
- We find that human participants and IBL model agents have **lower thresholds (stop earlier) than optimal**
- We find evidence that people **learn more (choose the best option) when provided feedback** relative to no feedback, and when they do not know the distribution relative to knowing
- ***Future Work***: Investigate additional factors (variability of sequence length, crowd decisions)

References

[1] Baumann, C., Singmann, H., Gershman, S. J., and von Helversen, B. A linear threshold model for optimal stopping behavior. *Proceedings of the National Academy of Sciences 117*, 23 (June 2020), 12750–12755.

[2] Bugbee, E., and Gonzalez, C. Deciding When to Stop: Cognitive Models of Sequential Decisions in Optimal Stopping Tasks. Publisher: Carnegie Mellon University. Under review.

[3] Goldstein, D. G., McAfee, R. P., Suri, S., and Wright, J. R. Learning When to Stop Searching. *Management Science 66*, 3 (Mar. 2020), 1375–1394.

[4] Gonzalez, C., Lerch, J. F., and Lebiere, C. Instance-based learning in dynamic decision making. *Cognitive Science 27* (2003).

[5] Guan, M., Stokes, R., Vandekerckhove, J., and Lee, M. D. A cognitive modeling analysis of risk in sequential choice tasks. *Judgment and Decision Making 15*, 5 (Sept. 2020), 823–850.

Contact Information

- **Email:** ebugbee@cmu.edu
- **Lab Website:** cmu.edu/ddmlab
- **Personal Website:** erinbugbee.com