

Feedback Promotes Learning and Knowledge of the Distribution of Values Hinders Exploration in an Optimal Stopping Task

Erin H. Bugbee and Cleotilde Gonzalez

{ebugbee, coty}@cmu.edu





Summary

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

- How do feedback and knowledge of the distribution of option 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?

Introduction

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

Methods

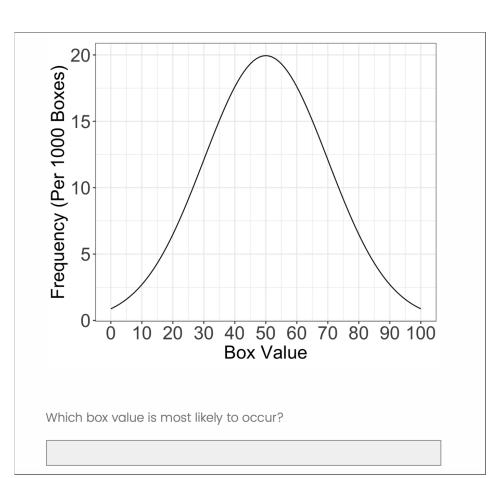
Human Participants

- Participants: 256 from Amazon Mechanical Turk
- Design: Between-subjects
- Conditions: 2 (Knowledge of the Distribution: Known or Unknown) x 3 (Feedback: No Feedback, Outcome, or Detailed)

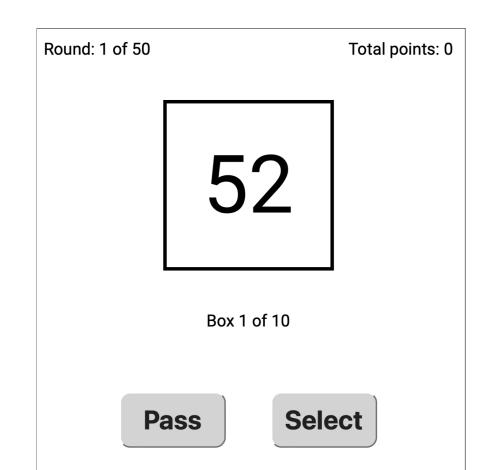
Model Agents

• Simulate 256 IBL model and optimal agents

Optimal Stopping Task



(a) Known Distribution Condition



(b) Choice

Feedback Conditions

• No Feedback:

You chose **Box** [Number] with a value of [Value].

• Outcome Feedback:

Your choice was [Correct/Wrong]. You chose Box [Number] with a value of [Value].

• Detailed Feedback:

Your choice was [Correct/Wrong]. You chose Box [Number] with a value of [Value]. The maximum value box was Box [Number] with a value of [Value].

Cognitive Model: Instance-Based Learning Model

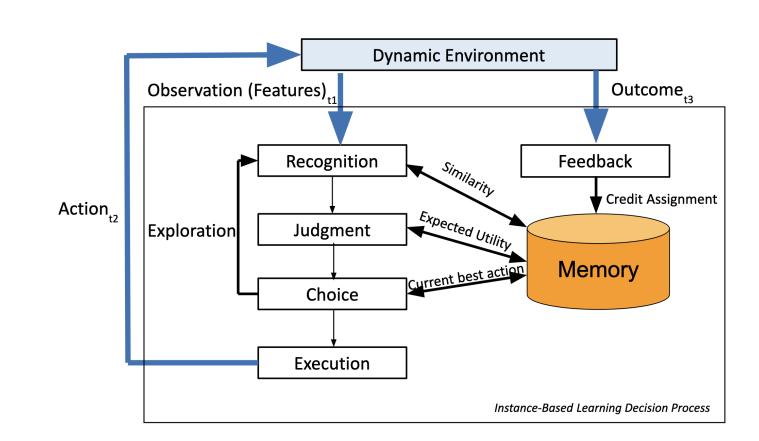
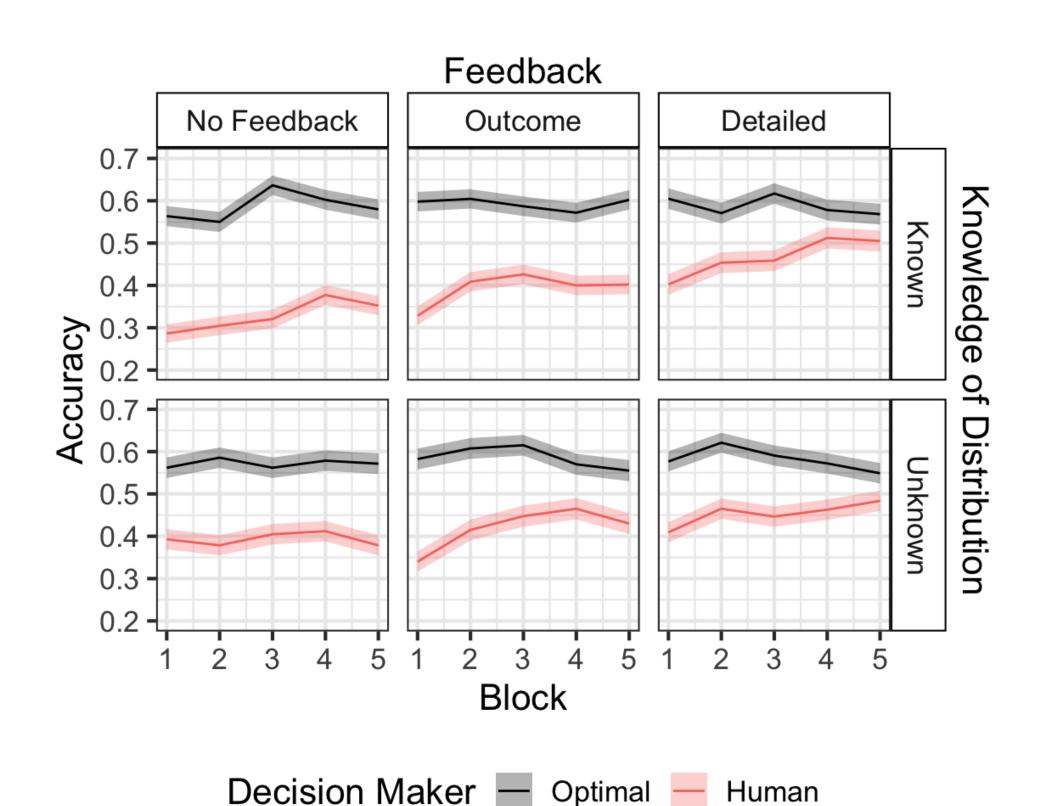


Figure 2: Instance-Based Learning Theory [4]

- 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 retrieved instances.
- The agent *chooses* the option with the highest BV.

	State	Action	Utility
Value	Boxes Remaining	{Select, Pass}	$\{0, 1\}$
Table 1: Instance Structure			

Results



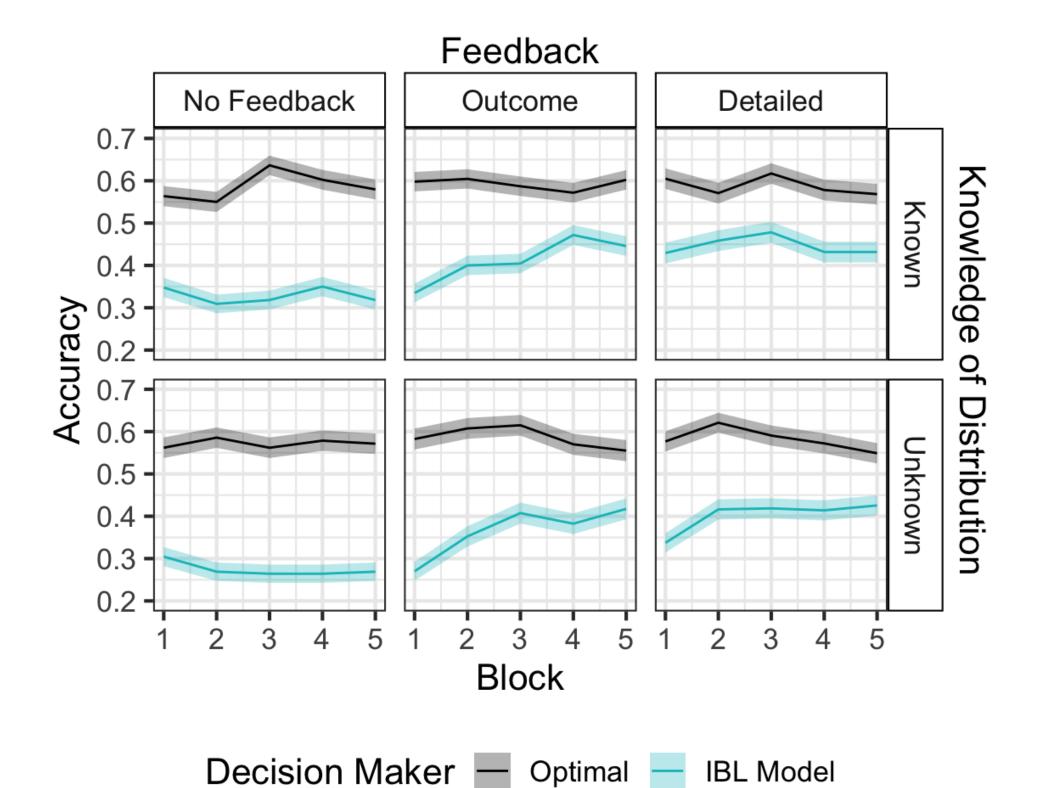


Figure 3: Accuracy for Human Participants (top, red), IBL Agents (bottom, blue), and Optimal Agents (both, black) over Blocks of 10 Problems

Conclusion

Key Findings:

- Feedback Promotes Learning: Participants in the feedback conditions stopped closer to the optimal position and achieved higher accuracy.
- Knowledge of the Distribution Hinders Exploration: Participants with distribution knowledge explored less by stopping earlier than those without this knowledge.
- Model Predictive Accuracy: The IBL model accurately predicted human stopping behavior across conditions.

Future Work:

• Investigate additional factors (variability of sequence length, crowd decisions)

References

- [1] Christiane Baumann, Henrik Singmann, Samuel J. Gershman, and Bettina von Helversen. A linear threshold model for optimal stopping behavior. Proceedings of the National Academy of Sciences, 117(23):12750–12755, June 2020.
- [2] Erin H. Bugbee and Cleotilde Gonzalez.
- Deciding When to Stop: Cognitive Models of Sequential Decisions in Optimal Stopping Tasks.

2022. Publisher: Carnegie Mellon University. Under review.

- [3] Daniel G. Goldstein, R. Preston McAfee, Siddharth Suri, and James R. Wright. Learning When to Stop Searching. Management Science, 66(3):1375–1394, March 2020.
- [4] Cleotilde Gonzalez, Javier F. Lerch, and Christian Lebiere. Instance-based learning in dynamic decision making. Cognitive Science, 27, 2003.
- [5] Maime Guan, Ryan Stokes, Joachim Vandekerckhove, and Michael D. Lee. A cognitive modeling analysis of risk in sequential choice tasks. Judgment and Decision Making, 15(5):823–850, September 2020.

Additional Information

- Lab Website: cmu.edu/ddmlab
- Personal Website: erinbugbee.com
- For Materials, Paper, Poster: Scan QR code

