What Research Do We Do?

We study learning and decisions from experience in situations involving repeated, interdependent decisions in dynamic environments.

- How does experience influence our decisions?
- What kinds of experiences would produce better decisions and better adaptation?
- How does experience transfer to new situations?

We also study humans making decisions in a wide range of decision contexts that we bring to the laboratory in the form of dynamic simulations (MicroWorlds or DMGames).

- How do operators of complex industrial plants make dynamic allocations of limited resources?
- How can forensic examiners be more accurate at identifying matches between physical samples?
- How might cybersecurity analysts improve their detection of cyberattacks?

Our driving theory is the Instance-Based Learning Theory (IBLT), which in essence proposes that people make choices by retrieving the best outcomes from their past experience. The process involves:

- Retrieving memories (*instances*) that resemble the current situation (instances are triplets: situation-decision-utility)
- Filtering memories according to their maximum experienced expected value (utility or *blended value*)
- Evaluating and storing new instances reflecting each possible option in the decision situation
- Selecting the option with the maximum blended value

Carnegie Mellon University

People of DDMLab

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Dynamic Decision Making Laboratory

The Dynamic Decision Making Laboratory (DDMLab) was founded in 2002 by Dr. Cleotilde Gonzalez to investigate decision making in complex dynamic environments. Such environments are characterized by the need for people to make multiple, interdependent, real-time decisions in reaction to both external changes, as well as the effects of their past decisions.

At the DDMLab, we seek to build models and methods that help explain, predict, and draw recommendations for improving decision making in dynamic environments. We use multiple research methods, but notably, we rely on laboratory experiments where we collect human behavior using dynamic simulations (Decision Making Games) and on computational cognitive models based on Instance-Based Learning Theory (IBLT) and the ACT-R cognitive architecture to understand and predict such behavior.

Practical applications of our research extend from front-end system design activities to back-end training and decision-support. On the front-end, we can provide principled guidance and empirical support for the design of systems that exploit DDM strengths. On the back-end, we can help decision makers exploit system strengths. In this respect, DDM theory and methods are particularly suited for the design of training interventions. But the closely related activity of decision support design is no stretch for the skill set our multidisciplinary team provides.

The laboratory consists of post-doctoral fellows, research-programmers, doctoral students and research assistants. Lab members come from different fields, including Behavioral Decision Research, Psychology, and Computer Science.

The DDMLab is part of the Social and Decision Sciences Department at Carnegie Mellon University.

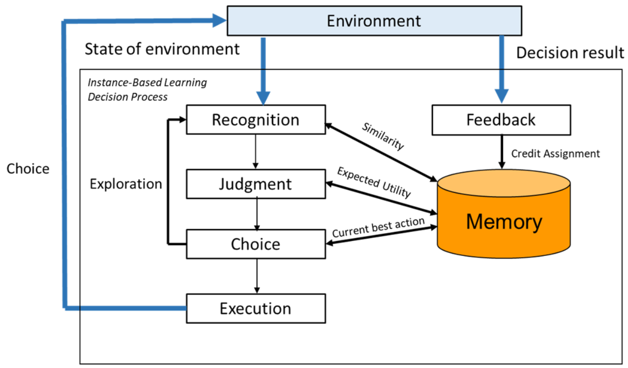
http://www.cmu.edu/ddmlab

How Do We Do Research?

Our research approach includes laboratory experiments and cognitive models, which form a learning cycle that compares human data from experiments against theory-informed data from computational models.

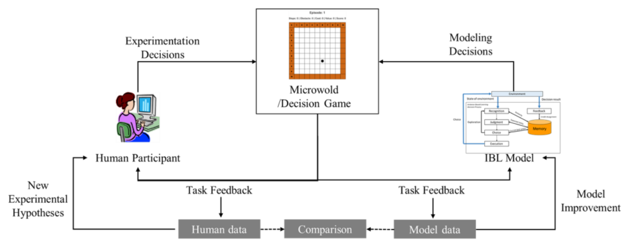
In our research, we address questions such as:

- How does experience influence our decisions?
- What kinds of and how much experience produces better performance and better adaptation to novel environments?



Our research approach includes laboratory experiments and cognitive models, which form a learning cycle that compares human data from experiments against theory-informed data from computational models.

- We collect behavioral data using complex, dynamic simulations.
- Our experiments often involve extended practice to help us understand how experience develops, changes, and transfers to new situations.
- We create cognitive models that rely on IBLT and the mechanisms proposed in the ACT-R cognitive architecture to represent and predict human behavior in decision making tasks.
- Our theory and methods are applied to many domains that deal with the prediction of behavior in complex systems.



The DDMLab is constantly upgrading its systems for computational modeling. A fantastic new addition is SpeedyIBL, a Python library that allows to create single or multiple IBL agents with fast processing and response time without compromising the performance.

- SpeedyIBL utilizes fast processing and response time without compromising performance compared to the traditional implementations.
- SpeedyIBL can be used to create IBL agents that can do a wide range of decision games.

SpeedyIBL

Research Program

Human-Machine Teaming

Funding Source: Defense Advanced Research Projects Agency (DARPA) and Air Force Research Laboratory (AFRL)

Long-term Goal: Long-term goal: *Design synthetic coaches that would have Machine Theory of Mind to support team work and enhance team collaboration.*

Developing Human-like AI Agents

Goal: *To investigate which temporal credit assignment mechanisms can account for behavior under different levels of uncertainty in goal-seeking navigation tasks.*

- *Provide humans with different levels of uncertainty, represented by different visual representations of the same tasks.*
- *Develop cognitive models with different credit assignment mechanisms.*
- *Compare each of the mechanisms with collected human data.*

Learning in Cooperative Multiagent Systems

Goal: *To develop cognitive machine models for stochastic scenarios in cooperative multiagent systems (CMS).*

- *Introduce three models: Greedy, Hysteretic, and Lenient Multiagent IBL models for CMS*
- *Conduct experiments on four stochastic scenarios of Coordination Multiagent Object Transportation Problem*
- *Compare our models with three deep reinforcement learning models*

Complexity and Uncertainty on Learning

Goal: *To investigate which temporal credit assignment mechanisms can account for behavior under different levels of uncertainty in goal-seeking navigation tasks.*

- Develop an interactive simulated search and rescue mission called Minimap.
- Provide human subjects with different degrees of structural complexity coupled with uncertainty in Minimap.
- Analyze different aspects of human behavior in terms of various metrics.

Cognitive Models in Sequential Decision Tasks

Goal: *To understand how people make sequential decisions in various tasks involving balancing exploration and exploitation, and to develop cognitive models of their behavior in these tasks.*

- Develop an interactive simulated search and rescue mission.
- Provide human subjects with different degrees of structural complexity coupled with uncertainty in Minimap.
- Analyze different aspects of human behavior in terms of various metrics.

Cognitively Aware Reinforcement Learning

Goal: *To investigate how cognitive models can be used in tandem with reinforcement learning (RL) agents to learn policies that complement human behavior.*

- We incorporate cognitive models into the RL training and testing pipelines to see how such models can improve performance in cooperative tasks.
- We test these models with human proxies and real humans, and analyze their behavior using collaborative fluency metrics, to see how well they learn collaborative policies.

Research Program

Behavioral Cybersecuirty

Funding Source: Army Research Laboratories—Collective Research Alliance (ARL-CRA) and Army Research Office—Multi University Research Initiative (ARO-MURI) on cyber deception and MURI-AUS on Human-Bot cyber defense teams

Long-term goal: *To design effective defense techniques informed directly by dynamics of human behavior, emergent cognitive biases, and psychological deception strategies.*

Deception Through Signaling and Masking

Goal: *Design dynamic and personalized deception strategies using cognitively-informed algorithms for defense.*

- Defenders strategically reveal information to the attackers to influence their decisions and can use a combination of truthful and deceptive signals to protect unprotected resources.
- Defenders can also use masking strategies to manipulate features of real machines.
- Cognitive algorithms learn the attacker's behavior and inform game theoretic models to adapt the defense

Learning of End-Users in Phishing Training

Goal: *To determine the effect of cognitive factors on the detection of phishing emails through experiential learning.*

- Train end-users with different frequency, recency, and content of phishing emails.
- Provide different kinds of feedback during training and test their detection capabilities after training.
- Develop cognitive models of end-users to predict their actions ahead of time.

Defense Strategies in Binary Choice Tasks

Goal: To design defense strategies to influence human choices in the box game, a repeated binary choice task.

- Attackers repeatedly attempt to find a treasure in one of two boxes.
- Defenders provide a potentially deceptive signal about the protection of the chosen box.
- Attackers decide whether to advance or withdraw, then observe the outcome.
- Defenders use defense strategies informed by cognitive algorithms, in which the attacker's behavior is used to adjust the strategy dynamically.

Autonomous Adaptive Defense Agents

Goal: *To study the integration of IBL models for improving Trust and Mental Models sharing in Human-Autonomy teams for cybersecurity.*

- Develop a framework for Human-AI collaboration research for cyber-defense.
- Develop Cognitive models of Human defenders to predict their decisions.
- Test Human defenders in an Interactive Defense Game.
- Test Human-AI (ML & IBL) collaboration in similar scenario.