What Research Do We Do?

We study learning and decisions from experience in dynamic environments. We answer questions such as:

- 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). We answer questions such as:

- How do operators of complex simulatons 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 similar 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.

People of DDMLab

Cleotilde (Coty) Gonzalez, PhD
Research Professor and Founding Director of DDMLab

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Post-Doctoral Fellow

Thuy-Ngoc Nguyen, PhD
Post-Doctoral Fellow

Korosh Mahmoodi, PhD
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Kuldeep Singh, PhD
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Dynamic Decision Making Laboratory

The Dynamic Decision Making Laboratory (DDMLab) was founded in 2002 by Prof. 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 cognitive models 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.

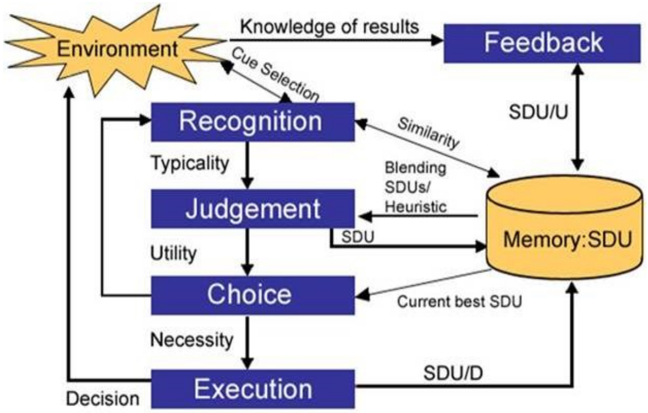
http://www.cmu.edu/ddmlab

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.

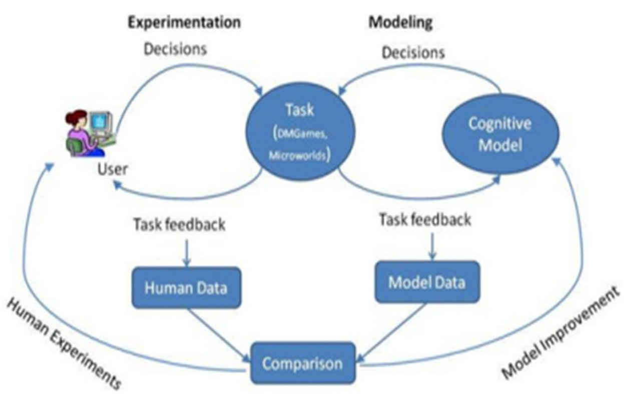
In our research, we address questions such as:

- 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 (called DMGames/Microworlds).
- 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.



Research Program

Collective Behavior

Information Sharing Among Networked Defenders

Funding Source: Army Research Laboratories – Collaborative Research Alliance (ARL-CRA)

Goal: *Understanding the impact of incomplete and imperfect information exchange among collaborative defenders.*

In this project, we assume that the defenders should share information to learn about an ongoing attack, but the information may be corrupted or incomplete. In such scenarios it is important to know which defenders are the most reliable to share information and which information should be shared.

Emergence of Collective Cooperation and Network Connections from Self-Interests

Funding Source: Army Research Office – Network Science Program (ARO-NS)

Goal: *To develop formal cognitive models that combine the interactions of individual dynamic decision-making processes with the emergent dynamics of network structures.*

Selfish Algorithm:
1. A pair of agents is picked randomly from a group of agents (no network structure) to play the PD.
2. Reinforcement: Each agent in the pair makes a decision according to a moving threshold of reinforcement.
3. Trust: Each agent has an option to change its decision by using the decision of the paired agent.
4. The propensity to cooperate or Trust depends on the observed improvement of the agent's own outcomes.
5. The thresholds are moved to decrease/increase the chance of cooperation or Trusting in the future.
6. Connection: The propensity to connect with another agent depends on the observed improvements of the agent's own outcomes.

Human-Machine Teaming

Funding Source: Defense Advanced Research Projects Agency (DARPA) – Artificial Social Intelligence for Successful Teams (ASIST)

Goal: *Design synthetic coaches that would have Machine Theory of Mind (MToM) to support team work and enhance team collaboration.*

- Develop a process of coaching in Human-Machine teams.
- A coach would be able to perceive individual cognitive states and team social states
- Understand the role of humans and other agents in the context of the task environment
- Diagnose team success to design interventions to improve the teamwork.

In the context of Diversity and Inclusion: We designed bots to help reduce biases and increase sensitivity about the challenges that women and minority groups confront in the workplace using a game called Moments@Work.

Research Program

Behavioral Cybersecurity

Funding Source: Army Research Laboratories—Collective Research Alliance (ARL-CRA) and Army Research Office—Multi University Research Initiative (ARO-MURI)

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

A Research Framework for the Design of Dynamic, Adaptive, and Personalized Deception

Goal: *To provide personalized, dynamic, and adaptive deception algorithms for effective and agile defense capabilities.*

- Step 1: Defender uses defense algorithms created from Stackelberg Security Games (SSG) and signaling theory.
- Step 2: Defense algorithms are used in the context of a cybersecurity task (using experimental games).
- Step 3: Human attackers interact with different experimental games.
- Step 4: Cognitive models that represent the attacker's dynamic decision behavior are created for the same task.
- Step 5: The SSGs are adapted using the insights from the cognitive models.

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.
- Defenders 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

Understanding How End-Users Learn to Detect Phishing Emails

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.
- Test their detection capabilities after training.
- Develop cognitive models of end-users to predict their actions ahead of time.

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