EPA 2010 Symposium

“Agentic” Learning: Integrating Developmental, Educational, and Computational Perspectives

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Agentic Learning

Human agency is the capacity for human beings to make choices and to impose those choices on the world.

- Applies not just to the things that we want, but also the data and information that we choose to learn about
An agent-centric view of human learning

- Psychologist and educators alike have long recognized that human learning is, at least in part, an active processes involving the search for new information (c.f., Piaget, 1930; Bruner, 1961; Papert, 1980; Steffe & Gale, 1995).

- However, despite this view of the learner as a *sensemaker* (Klein, Moon & Hoffman, 2006), *question-asker* (Berlyne, 1954), or *intuitive scientist* (Piaget, 1930, Kuhn, 1989, Schultz & Bonawitz, 2007) there has been little attention paid to the implications of self-directed learning on basic cognitive processes.
What do we learn from our actions and choices?

Our actions often dictate what we experience both in terms of what we attend to, what kinds of data we acquire about the world, and what kinds of feedback we receive (e.g., selective sampling, question asking) (Klayman & Ha, 1987; Fazio, Eisner, & Shook, 2004; Castro, et al., 2008, Gureckis & Markant, 2009)

What is that?
What do we learn from our actions and choices?

Given our bounded search time and capacity, places a emphasis on how people reason from samples of evidence that are collected by ones self or by others (Xu & Tenenbaum, 2007; Shafto & Goodman, 2008; Lawson & Kalish, 2009; Rhodes, Gelman, & Brickman, 2010)

Which one has bilirubin?
What do we learn from our actions and choices?

People are often biased to treat the data that they discover themselves as being more useful or informative than data generated from others, or at the very least differently (Kushnir).
What do we learn from our actions and choices?

Educational settings where learners must allocate study time and effort across different materials (Son & Analytis). Do people make adaptive decisions? How do people direct their attention toward different parts of a learning environment?
“...many current theories in cognitive and social psychology still do not incorporate any models of sampling. Consistent with this omission, most experimental tasks lay out all the objects in front of the participants and thereby exclude information search in the first place. This tends to create cognitive theories with a blind spot for how people sample information and when they stop.”

“What’s in a sample?” Gigerenzer, 2006, pg. 251
Key Issues Addressed in the Talks Today

- **Todd Gureckis (NYU)** How do people decide what information they should seek at any point in time? How does allowing learners to select their own learning experiences influence the acquisition of novel concepts?

- **Tamar Kushnir (Cornell)** What is the difference between evidence acquired by one’s own actions versus those obtained by observing someone else?

- **Marjorie Rhodes (NYU)** How do children and adults reason from both the composition and genesis of a data sample or observations to make inferences?

- **Lisa Son (Columbia)** To what degree can people leverage their meta-cognition about what they know they know (or don’t know) to enhance their learning?
Learning Categories by Asking Questions

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Learning by Doing vs. Learning by Observing

Passive Learning

Active Learning
Learning by Doing

• Active learning, discovery learning, inquiry learning have all been advocated as ideal methods for facilitating instruction and learning (c.f., Piaget, 1930; Bruner, 1961; Papert, 1980; Steffe & Gale, 1995).

• This view is at the heart of current thinking in education, but has recently started to have some backlash (Mayer, 2004; Kirschner, Sweller, & Clark, 2006) given the finding that learners sometimes benefit from more direct scaffolding or can be overwhelmed by the demands of designing useful interventions.

• However, surprisingly little basic research in cognition on this issue that directly compares learning under active versus passive conditions in a way that controls for many of the factors that might different between these induction modes.

• Exception is work, all the last few years, examining causal learning from interventions (Lagnado, D., & Sloman, S., 2004; Steyvers, M., Tenenbaum, J. B., Wagenmakers, E., & Blum, B., 2003; Sobel, D., & Kushnir, T., 2006)
Human and Machine Learning Meet

- The basic problem is this: you want to train an artificial learning system to assign items to a category (for example diagnosing some biological samples as toxic or not). However, getting corrective feedback from humans is expensive!

- How can you choose samples to minimize the amount of feedback you need, while still having good categorization accuracy/generalization?

- In other words, is there a way to train on only a subset of the available data in order to optimize learning?

- Various formal proposals (Lindley, 1956; Mackay, 1992) and examples of the practice improvements possible in learning (Hwang, 1990; Mackay, 1992, Cohn, 1992; Castro, et al. 2009)

Yes it works!
Learning Concept Through Queries
Why might learning-by-doing result in better learning than learning-by-observing?

1. “Doers” are free to select which information they want to learn about at any point in time (i.e., they can leverage uncertainty to select better observations)

2. Sequencing of exemplars known to have a dramatic effect on category learning (Elio & Anderson, 1984; Gureckis & Love, 2002; Medin & Bettger, 1994; Mathy & Feldman, 2009)

3. Active learners are often more cognitively engaged in the learning task because planning out useful interventions on the world often requires a deeper consideration of the structure of a learning problem and how various types of information might fit into their understanding of a domain (c.f., Bruner, 1961).
Six Total Conditions (Between-Subjects Design)
Antenna Design

Press the spacebar to begin.
Active Learning

“Actively” Sample Item (self-terminated)

OR

Passive Learning

Item (250ms)
Item+Label (until confirmed)

View Actual Category Label (2000ms)

ITI (500 ms)
"Dial in a stimulus you would like to learn about"

Goal:
Stimulus decoupled from spatial location, movement of mouse (i.e., this is not simply spatial sampling)

Active Learning Interface
Category Structures Tested

- Rule-based (rb)
- Information Integration (ii)

[Diagram showing scatter plots with 'rb' and 'ii' labels, indicating data points for Orientation vs. Radius]
Active Learners out performed Passive Learners in both conditions!

Overall Accuracy During Test Blocks

rb Rule-Based

ii Information-Integration
Not just outliers!

Active
Passive
Passive-yoked

Overall Accuracy (in bins)

Frequency
Consistently better over test blocks!

Accuracy vs Test Block

- **Active**
- **Passive**
- **Passive-Yoked**
Strongest advantage is in the region between the category means

**Rule-Based Learning as a Function of Block**

**Between Category Means**
- **Active**
- **Passive**
- **Passive-Yoked**

**Outside Category Means**
- **Active**
- **Passive**
- **Passive-Yoked**
Rule-Based: Distribution of Samples Aggregated for Each Subject

Samples get closer to true boundary over time.
Example subjects

Subject 35

Subject 43

Subject 46

Block 1  Block 2  Block 3  Block 4  Block 5  Block 6  Block 7  Block 8
Sampling behavior predicts overall accuracy (Pearson $r=-0.45$, $p=0.013$)
Also not just outliers!

Frequency

Overall Accuracy (in bins)

Active
Passive
Passive-yoked
Also consistent across blocks

Active
Passive
Passive-Yoked

Accuracy

Test Block

1 2 3 4 5 6 7 8
Also consistent across blocks

Accuracy

Test Block

Random test block was easier
Main advantage is in the region OUTSIDE the category means
Rule-Based: Distribution of Samples Aggregated for Each Subject

Samples get SOMEWHAT closer to true boundary over time.
Most subjects only approximate boundary sampling, but a few are surprisingly good.
Sampling behavior again predicts accuracy, Pearson r = -0.78, p<0.0001
Why do active participants do better in the task?

Better Samples/Data?  Higher engagement in task?
Basic Modeling Approach

- Based on a generalization of a well known model of categorization known as the Rational model (Anderson, 1991)
- Assumes learners try to infer a set of latent clusters which underlie a category
- The category label (or other missing feature) of an item is assumed to be a weighted average of the likelihood that the items belongs to a particular cluster and the probability that, if it did belong to that cluster, it would have the given feature.
Basic Modeling Approach

- Extension based on Sanborn, et al. (2006) which assumes that learners entertain more than one possible clustering scheme at any given time (but a still a possibly smaller set, such as 10 or so)

- This essentially means that they entertain multiple hypotheses about the true category boundary:
Basic Modeling Approach

- Extension based on Sanborn, et al. (2006) which assumes that learners entertain more than one possible clustering scheme at any given time (but a still a possibly smaller set, such as 10 or so)

- This essentially means that they entertain multiple hypotheses about the true category boundary:

Places where hypotheses disagree are expected to be the most useful samples
Model also predicts strong advantage for Active using more “particles”/”hypotheses”
Model also predicts narrowing gap between Passive and Active over time, despite more particles in the active condition.
Comparison Between the Model’s Sampling Decisions and People’s Samples
Conclusions

• Allowing learners to select their own observations in a well-studied category learning task improved the rate of learning over a passive condition

• This was not simply due to the samples themselves (since passive-yoked participants did not show the same benefit)

• In the rule-based task, participant’s sample help them refine the rule

• In the information-integration task, active learners quickly settled on sub-optimal but workable strategies. Eventually passive learners catch up.

• Performance differences and sampling behavior predicted by a simple category learning model. Key assumption is that learners sample in regions of current uncertainty and that active learning promotes broader hypotheses during learning.
Questions?

http://smash.psych.nyu.edu

doug markant

What is that?