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# Active learning: Cognitive development, education, and computational models

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## Generating data for learning

*Behold! Human beings living in an underground den, which has a mouth open towards the light and reaching all along the den; here they have been from their childhood, and have their legs and necks chained so that they cannot move, and can only see before them, being prevented by the chains from turning round their heads. ...they see only their own shadows, which the fire throws on the opposite wall of the cave... To them truth would be literally nothing but the shadows of the images.*

-Plato's Republic

Socrates' point was to show that, like his prisoners, none of us can ever be sure about the truth of the world. However, unlike his prisoners who passively watch the shadows on the wall, we are equipped with the ability to drive our own learning. From infancy on, our lives are filled with self-directed opportunities for acquiring information about the world. Active learning encompasses many of these self-directed opportunities. It includes attending to a particular event in our environment over another, mentally searching for explanations, asking questions and knowing who to ask, or taking actions. Although there are numerous contexts for which *active learning* applies, they are united by the broader goal of generating data for learning. The factors that influence active learning may be crucial to human intelligence – they afford purposeful data gathering by the learner.

Active learning is not only an important topic for understanding human behavior, but also for developing intelligent machine algorithms. There have been numerous computational approaches towards capturing aspects of how and when a learner might benefit by generating further data. These include algorithm that favor novelty, surprising events (Shannon information), and ambiguity (e.g. as in when Bayesian posteriors equally support multiple hypotheses).

One well-studied computational approach to optimally generating data for learning is known as information gain, or the Kullback-Leibler divergence (KL Divergence)

Simply, the KL Divergence measures the degree to which one's beliefs after having seen the evidence differ from the beliefs they held just prior to observing the evidence. An optimal learner takes actions so as to maximize this information gain.

Although computational approaches have begun to lay the foundation for optimal approaches to active learning, less is known about how children and adults approach the problem of data generation. What are the cognitive mechanisms that influence active learning? Are learners systematic? Rational? Are their decisions captured by information gain? How does active learning interact with teaching and instruction?

In this workshop, we invite speakers from a variety of approaches to broadly inform our understanding of active learning, including cognitive development, education, and computational modeling. We examine what "active" means in active learning, and present talks on the cognitive mechanisms that might support active learning, including attention, hypothesis-generation, explanation, pretend play, and question asking. We also explore how efficient learners are when planning and executing actions in the service of learning, and whether there are developmental or socio-economic differences in active learning. We integrate the problem of active learning with teaching to investigate the similarities and differences involved in selecting evidence for oneself and others. Throughout we ask how we can capture these processes with computational models that spell out the underlying assumptions and potential algorithms.

Identifying factors that influence active learning is important because it could lead to understanding broader individual differences in drive for learning, with direct consequences for the development of informal and formal educational practices. Interdisciplinary research leveraging tools from computational and developmental science toward educational goals has the potential for generating critical insights for each of the fields involved. The proposed workshop will bring together these different communities, to encourage interdisciplinary dialog in this important topic.

In active learning we are broken free from the chains of passive observation, affording self-generated discovery of the true nature of the shadows on the wall.

## Topics and Speakers

The workshop is divided into three main themes, with speakers from education, modeling, and developmental backgrounds in each. After each set of talks, we schedule ample time for discussion lead by a panel moderator who is an expert in the field, encouraging participants to fully engage with the speakers. The workshop concludes with a final discussion broad discussion on open questions and the future of active learning research.

### Opening remarks

#### Cognitive mechanisms in active learning

1. *Switches in attention reflect a strategy for optimizing learning.* Madeline Pelz & Celeste Kidd. (University of Rochester)

2. *Hypothesis generation processes and how they guide active exploration.* Doug Markant. (Center for Adaptive Rationality, Max Planck Institute for Human Development).

3. *Mechanisms in children's active learning: self-generated explanations.* Caren Walker & Tania Lombrozo (University of California, San Diego; University of California, Berkeley).

4. *Progress in building a machine that can ask interesting and informative questions.* Anselm Rothe, Brenden Lake & Todd Gureckis\* (New York University) \*presenter.

5. Panel Discussion

#### Development of active learning (Part 1)

1. *5- and 7-year-olds benefit from selection learning in a category-learning task.* Zi L. Sim, & Fei Xu. (UC Berkeley)

2. *Five-year-old children identify the most informative questions.* Azzurra Ruggeri. Azzurra Ruggeri\*, Zi Lin Sim\*, & Fei Xu. (Max Planck Institute for Human Development, Berlin, Germany; University of California, Berkeley) \*contributed equally.

3. *Children's selective social referencing during word learning.* Emily Hembacher and Michael C. Frank (Stanford University)

4. Invited Panel Moderator Laura Schulz

#### Development of active learning (Part 2)

1. *Can preschoolers direct their learning based on difficulty? Evidence from word learning.* Stephanie Denison (University of Waterloo).

2. *Cognitive heuristics for computing information gain in children and adults.* Elizabeth Lapidow & Elizabeth Bonawitz. (Rutgers University – Newark)

3. *Socioeconomic status and exploratory play in early childhood.* Julia Leonard, John D.E. Gabrieli, & Laura Schulz (Massachusetts Institute of Technology)

4. Invited Panel Moderator Fei Xu

#### Active learning and teaching

1. *Cost-and-benefit analysis in planning and helping others learn.* Hyowon Gweon (Stanford University)

2. *Teaching versus active exploration: A computational analysis of conditions that affect learning.* Scott Cheng-Hsin Yang & Patrick Shafto (Rutgers University – Newark)

3. *Why guided play is a form of active learning.* Deena Weisberg, Roberta M. Golinkoff, Kathy Hirsh-Pasek, and Marcia Shirilla (University of Pennsylvania, University of Delaware, Temple University)

4. *The grandparent method: A computational model of experience-based guided learning.* Sophia Ray Searcy, Yue, Yu, Scott Cheng-Hsin Yang, & Patrick Shafto (Rutgers University – Newark)

5. Invited Panel Moderator Kathy Hirsch-Pasek

### Closing remarks