Children's active learning is social learning

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Author Note

Conceptual Analysis of Dissertation Area. Readers: Michael C. Frank, Hyowon Gweon, and Anne Fernald

Abstract

Children's rapid conceptual development is one of the more remarkable features of human cognition. How do they learn so much so quickly? Social learning theories argue for the importance of learning from more knowledgeable others. In contrast, active learning accounts focus on children's knowledge acquisition via self-directed exploration. In this paper, I argue that an important step towards a more complete theory of early learning is to understand how active learning behaviors unfold in social learning contexts. To integrate the two theoretical accounts, I use ideas from theories of rational decision making that emphasize the expected utility and cost of different actions in order to explain choice behavior. The key insight is that the costs and benefits of active learning behaviors (e.g., metacognitive monitoring, information seeking, and question asking) are fundamentally shaped by interactions with other people.

Keywords: human learning, active learning, social learning, decision making, theory

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Introduction

Human learning is remarkable. Consider that children, despite limitations on their general processing capabilities, are able to acquire new concepts at a high rate, eventually reaching an adult vocabulary ranging between 50,000 to 100,000 words (P. Bloom, 2002). And they accomplish this while also developing motor skills, learning social norms, and building causal knowledge. What sorts of processes can account for children's prodigious learning abilities?

Social learning theories offer a solution by pointing out that children do not solve these problems on their own. And although children learn a great deal from observation, they are typically surrounded by parents, other knowledgeable adults, or older peers – all of whom likely know more than they do. These social contexts can bootstrap learning via several mechanisms. For example, work on early language acquisition shows that social partners provide input that is tuned to children's cognitive abilities (Eaves Jr, Feldman, Griffiths, & Shafto, 2016; Fernald & Kuhl, 1987), that guides children's attention to important features in the world (Yu & Ballard, 2007), and that increases levels of arousal and sustained attention, which lead to better learning (P. K. Kuhl, 2007; Yu & Smith, 2016).

Social contexts can also change the computations that support children' learning from evidence. Recent work on both concept learning and causal intervention suggests that the presence of another person leads the learner to reason about *why* people perform certain actions. The key insight is that knowledge of the underlying process that generates examples allows learners to make more appropriate inferences that speed learning (Bonawitz & Shafto, 2016; Frank, Goodman, & Tenenbaum, 2009; Shafto, Goodman, & Griffiths, 2014). For example, people will draw different inferences from observing the same actions depending on whether they think that the behavior was accidental or intentional. Moreover, adults and children will make even stronger inferences if they think an action was selected with the goal to help them learn (i.e., teaching) (Shafto, Goodman, & Frank, 2012).

However, children are not merely passive recipients of information – from people or from the world. Instead, children actively select behaviors (e.g., asking questions or choosing where to allocate attention) that change the content, pacing, and sequence of the information that they receive. In fact, recent theorizing and empirical work characterizes early learning as a process of exploration and hypothesis testing similar to the scientific method (Gopnik, Meltzoff, & Kuhl, 1999; Schulz, 2012). Moreover, recent empirical work across a variety of domains (education, machine learning, and cognitive science) has begun to explore the benefits of self-directed choice for speeding learning outcomes by increasing learners' attention/arousal or by providing learners with better information that is more tightly linked to their current cognitive state and interests (Castro et al., 2009; D. B. Markant & Gureckis, 2014; Settles, 2012).

Thus, both social and active contexts can facilitate cognitive development by activating distinct learning processes and by providing the learner with better information. However, real-world learning involves a mixture of these processes where young learners must consistently integrate information that they generate with information provided by other peopole. Thus, one of the fundamental challenges for increasing our understanding of human learning is to precisely characterize the interplay between social contexts and self-directed learning behaviors.

In this paper, I use the framework of Optimal Experiment Design (CITE) to integrate ideas from the active and social learning accounts. The key insight is that social learning contexts can *constrain* the decision processes that the self-directed learner makes. I argue that taking into account the effects of social context provides a way to explain a diverse set of findings on children's uncertainty monitoring (markman; kim et al.), information seeking (begus), and question asking (katz et al. (2010). Before presenting the integrative framework of active learning within social contexts, it is useful to review evidence showing how both social contexts and self-directed behaviors can modulate learning outcomes.

Part I: Learning from other people

Social learning theories argue that children's rapid conceptual development is facilitated by humans' unique capacity to transmit and acquire information from other people.[1] One of the primary benefits of cultural learning is that children gain access to knowledge that has accumulated over many generations; information that would be far too complex for any individual person to figure out on their own (Boyd, Richerson, & Henrich, 2011). In addition to these cumulative effects, social contexts facilitate learning because more knowledgeable others select the input that could best support children's learning (Kline, 2015; Shafto et al., 2012), providing learning opportunities for generalizable information (Csibra & Gergely, 2009).

There is now a large body of empirical work on children's learning that show the effect of social contexts across a variety of domains. These learning effects manifest via different pathways such as guiding attention, increasing arousal, providing better information, and changing the strength of children's inferences. In this section, I briefly

[1] In this paper, I define "social" contexts as learning environments where another agent is present. This definition includes a broad range of social learning behaviors: e.g., observation, imitation, and learning from direct pedagogy.

review the evidence for the role of each of these social learning processes, with the goal of providing a high-level taxonomy of social learning effects. Outlining these social learning effects will set the stage for the discussion of how they shape self-directed learning behaviors in Part III.

Social interactions enhance attention. From infancy humans preferentially attend to social information. For example, newborn infants will choose to look at face-like patterns compared to other abstract configurations (Johnson, Dziurawiec, Ellis, & Morton, 1991) and will even show a preference for faces that make direct eye contact compared to faces with averted gaze (Farroni, Csibra, Simion, & Johnson, 2002). In the auditory domain, newborns prefer to listen to speech over non-speech (Vouloumanos & Werker, 2007), their mother's voice over other voices (DeCasper, Fifer, Oates, & Sheldon, 1987), and infant-directed speech over adult-directed speech (Cooper & Aslin, 1990; Fernald & Kuhl, 1987; Pegg, Werker, & McLeod, 1992). And recent work by Yu & Smith (2016) using head-mounted eye trackers to record parent-child interactions found that one-year-olds will sustain visual attention to an object longer when their parents' had previously looked at that object.

These early attentional biases can lead to differential outcomes when learning occurs with another person present. For example, 4-month-olds' show better memory for faces if that face gazed directly at them as compared to memory for a face with averted gaze (Farroni, Massaccesi, Menon, & Johnson, 2007) and for objects if an adult gazed at that object during learning (Cleveland, Schug, & Striano, 2007; Reid & Striano, 2005). Moreover, 7-month-olds perform better at word segmentation if the words are presented in infant-directed speech compared to adult-directed speech (Thiessen, Hill, & Saffran, 2005).

P. K. Kuhl (2007) refer to these effects as "social gating" phenomena since the presence of another person activates or enhances children's underlying computational learning mechanisms such as attention. One particularly striking piece of evidence for the social gating hypothesis comes from P. K. Kuhl, Tsao, & Liu (2003)'s study of infants' foreign-language phonetic learning. In this experiment, 9-10 month-old English-learning infants listened to Mandarin speakers either via live interactions or via audiovisual recordings and their ability to discriminate Mandarin-specific phonemes was assessed two months later. Only the infants who were exposed to Mandarin within social interactions were able to succeed on the phonetic discrimination task and infants in the audiovisual recording condition showed no evidence of learning. P. K. Kuhl et al. (2003) also provided evidence that infants in the social interaction condition showed higher rates of visual attention to the speaker, suggesting that the social contexts enhanced learning by increasing children's attention to the input.

The common thread across these findings is that the presence of another person is a particularly good way to increase attention. In this model, social input becomes more salient and therefore more likely to come into contact with general learning mechanisms. However, increases in arousal, attention, and memory are only one way that social contexts can influence learning. In fact, one of the defining features of early learning environments is the presence of other people who know more than the child, creating opportunities for more knowledgeable others to select learning experiences that are particularly beneficial – either because the information is tuned to children's current cognitive abilities or because the information is likely to be generalizable.

Social interactions provide "good" information. The notion that children's input might be shaped to facilitate their learning is a key tenet of several influential theories of cognitive development (e.g., Zone of Proximal Development (Vygotsky, 1987), Guided Participation (Rogoff et al., 1993), and Natural Pedagogy (Csibra & Gergely, 2009)). But how do social interactions provide particularly useful information for children's learning?

A particularly compelling set of evidence comes from studies of how caregivers alter the way they communicate with young children. That is, adults do not speak to children in the same way as they speak to other adults; instead, they exaggerate prosody, reduce speed, shorten utterances, and elevate both pitch and affect (for a review, see (Fernald & Simon, 1984)). And subsequent empirical work has shown that these features of "infant-directed speech" facilitate vowel learning (Adriaans & Swingley, 2017; De Boer & Kuhl, 2003), word segmentation (Fernald & Mazzie, 1991; Thiessen et al., 2005), word recognition (Singh, Nestor, Parikh, & Yull, 2009), and word learning (Graf Estes & Hurley, 2013).

Work on infants' early vocal production also provides evidence for the importance social feedback, highlighting the feature of *contingency*. For example, Goldstein & Schwade (2008) measured whether infants modified their babbling to produce more speech-like sounds after interacting with caregivers who either provided contingent or non-contingent responses to infants' babbling. They found that only infants in the contingent feedback condition changed their vocalization behavior to produce more adult-like language forms. Goldstein & Schwade (2008) hypothesized that the contingency effect was driven by infants' receiving input that was particularly useful for solving this learning problem since the feedback was close in time to infants' vocalizations, making it easier for them to compare discrepancies between the two.

A third piece of evidence comes from research on children's early word learning. Social-pragmatic theories of language acquisition have emphasized the importance of social cues for reducing the (in principle) unlimited amount of referential uncertainty present when children are trying to acquire novel words (P. Bloom, 2002; Clark, 2009;

Hollich et al., 2000). Empirical work by Yu & Smith (2012) shows that young learners tend to retain words that are accompanied by clear referential cues, which serve to make a single object dominant in the visual field (see also (Yu & Smith, 2013; Yu, Ballard, & Aslin, 2005). Moreover, correlational studies show positive links between early vocabulary development and parents' tendency to refer to objects that children are already attending to (i.e., "follow-in" labeling) (Tomasello & Farrar, 1986).

Thus far, I have reviewed evidence showing that social information can benefit learning because it enhances attention and it contains features that make it easier to learn. Learning from other people also changes learning by engaging distinct social reasoning processes that change how learners interpret and learn from evidence.

Social interactions change inferences and generalization. Perhaps one of the defining features of human social learning is that teachers and learners' actions are not random. Instead, people select behaviors with respect to some goal (e.g., to communicate a concept), and learners reason about *why* someone chose to perform a particular action. The key point is that this reciprocal process of reasoning about others' goal-directed actions can change how people interpret superficially similar behaviors, altering the learning process.

In recent empirical and modeling work, Shafto et al. (2012) formalized this social reasoning process within the framework of Bayesian models of cognition. In these models, learning is a process of belief updating that depends on two factors: what the learner believed before seeing the data and what the learner thinks about the process that generated the data. The key insight is that if the learner assumes that information is generated with the intention to communicate/teach, then they can make "stronger" inferences.[2]

[2]Formally, these models change the form of the likelihood term in Bayes theorem in order to capture

For example, Goodman, Baker, & Tenenbaum (2009) presented adults with causal learning scenarios with the following structure: either the participant or someone else who knows the causal structure generates an effect (e.g., growing flowers) by performing two actions at the same time (e.g., pouring a yellow liquid and a blue liquid). The participant's task was to identify the correct causal structure. Results showed that when participants thought the other person was knowledgeable, they were more likely to infer that performing *both* actions was necessary. In contrast, when the participant performed the action on their own (and did not know the causal structure), adults were less sure that both actions were necessary. Shafto et al. (2012) interpreted these results as learners going through a psychological reasoning process such as "if the other person was knowledgeable and wanted to generate the effect, he would definitely perform both actions if that was the correct causal structure."

Similar psychological reasoning effects have been shown in the domains of word learning (Frank & Goodman, 2014; Xu & Tenenbaum, 2007), selective trust in testimony (Shafto, Eaves, Navarro, & Perfors, 2012), tool use (Sage & Baldwin, 2011), and concept learning (Shafto et al., 2014). Moreover, there is evidence that even young learners are sensitive to the presence of others' goal-directed behaviors. For example, Yoon, Johnson, & Csibra (2008) showed that 8-month-olds will encode an object's identity if their attention was directed by a communicative point, but they will encode an object's spatial location if their attention was directed by non-communicative reach. And Senju & Csibra (2008) found that infants will follow another person's gaze only if the gaze event was preceded by the person providing a relevant, communicative cue (e.g., infant-directed speech or direct eye contact).

In addition to being easier to learn, information acquired in social contexts is also

a person's theory of how data are generated.

more likely to generalize and be useful beyond the current learning context. Csibra & Gergely (2009) argue that this assumption of *generalizability* is a fundamental component of "Natural Pedagogy" – a uniquely human communication system that allows adults to efficiently pass along cultural knowledge to children. Experimental work testing predictions from this account shows that children are biased to think that information presented in communicative contexts is generalizable (Butler & Markman, 2012; Yoon et al., 2008), and corpus analyses provide evidence that generic language (e.g., "birds fly") is common in everyday adult-child conversations (Gelman, Goetz, Sarnecka, & Flukes, 2008).

Across all of these studies, learners interpreted similar information in different ways depending on their assumptions about other people's goals. These effects are different from the attentional and informational explanations reviewed above in that the inferences based on social information are part of the underlying computations that support learning. This account fits well with evolutionary models that emphasize the importance of pedagogy for the accumulation of human cultural knowledge (Boyd et al., 2011; Kline, 2015) and theories of cognitive development that emphasize the adult's role as providing children with generalizable information (Csibra & Gergely, 2009).

Part II: Learning on your own

Another key ingredient for children's rapid conceptual development is their ability to learn on their own. That is, children are not just passive recipients of information; instead, they actively seek knowledge via their own actions. This model of the child as an "active" learner has been an influential idea in many classic theories of cognitive development (e.g., Bruner (1961); Berlyne (1960); and piaget_cite). And recent theorizing has characterized cognitive development as a process of active hypothesis testing and theory revision following principles similar to the scientific method (Gopnik et al., 1999; Schulz, 2012).

In addition to playing a prominent role in developmental theory, the potential benefits of "active"[3] learning have been the focus of a great deal of empirical work in education (Grabinger & Dunlap, 1995; Prince, 2004), machine learning (Ramirez-Loaiza, Sharma, Kumar, & Bilgic, 2017; Settles, 2012), and cognitive psychology (Castro et al., 2009; Chi, 2009). The common finding across these studies is that active learning contexts – where people have control over some aspect of the learning environment – lead to better outcomes when compared to passive contexts where people do not have control over the information that they receive.

But what makes active control a useful way to learn about the world? In this section, I present evidence for two mechanisms – enhanced attention/memory and higher quality information – through which active control can improve learning outcomes. I then review work that formalizes human inquiry as a process of "optimal experiment design" (OED) to ask when and how human self-directed learning deviates from optimal information gathering principles. I conclude Part II with a discussion of what makes optimal active learning difficult and why this is an intresting point of contact with research on children's social learning.

Active control enhances attention and memory. A growing body of work has explored the effect of active control on basic processes underlying learning and memory. In these tasks, outcomes for active and passive learning experiences are

[3]The term "active learning" has been used to describe a wide variety of behaviors such as question asking, increased physical activity, or active memory retrieval. In this paper, I focus on a specific subset of these behaviors: the *decisions* that people make, or could make, during learning. This definition captures several ways that people can exert control over their learning experiences, including the selection, sequencing, and/or pacing of new information.

directly compared across a variety of tasks, such as episodic memory, casual learning, and concept learning. D. B. Markant, Ruggeri, Gureckis, & Xu (2016) review this diverse literature and suggest that the active learning advantage found across these domains is caused by an increase in attention and memory with the precise pathway determined by the type of control in the study. For example, one effect of active control is that is allows people to coordinate the timing of incoming information with their current cognitive state, including attention and readiness to learn.

One nice illustration of this effect comes from a study by D. Markant, DuBrow, Davachi, & Gureckis (2014). In this task, participants memorized the identities and locations of objects that were hidden in a grid (adapted from Voss et al. (2011)). D. Markant et al. (2014) varied the *level* of control across conditions and compared the performance of active learners to a group of "yoked" participants who saw training data that was generated by the active group. Across conditions, participants could either control: (a) the next location in the grid, (b) the next item to be revealed, (c) the duration of each learning trial, and/or (d) the time between learning trials (i.e., inter-stimulus-interval or ISI). Results showed an active learning advantage for all levels of control, including the lowest amount of control in the ISI-only condition. D. Markant et al. (2014) interpreted these results as providing evidence that active control allowed people to, "optimize their experience with respect to short-term fluctuations in their own motivational or attentional state."

Developmental studies have extended this work on adults' spatial memory to 6- to 8-year old children, showing similar advantages for conditions of active control (Ruggeri, Markant, Gureckis, & Xu, 2016). Other work has found similar benefits of active control in word learning (Partridge, McGovern, Yung, & Kidd (2015); see also Kachergis, Yu, & Shiffrin (2013) for evidence in adults) and understanding causal structures (Schulz, 2012). Sobel and Kushnir (2006) showed that learners who designed their own interventions on a causal system learned better than yoked participants who either passively observed the same sequence of actions or re-created the same choices made by others. Moreover, even young infants seem to benefit from active engagement with the learning environment. For example, Begus, Gliga, & Southgate (2014) showed that 16-month-old infants show evidence of stronger memory for information that was provided about an object they had previously pointed to as opposed to information about an object they had previously ignored.

Additional evidence that active control enhances attention and memory comes from research on children's engagement with educational technology (for a review, see Hirsh-Pasek et al. (2015)). For example, Calvert, Strong, & Gallagher (2005) exposed preschool-aged children to two sessions of reading a computer storybook with an adult, and manipulated whether the adult or the child controlled the mouse and could advance the story. Children in the adult-control condition showed a decrease in attention to the storybook materials in the second session; in contrast, children who were given control over the experience maintained similar levels of attention across both sessions. Other research shows that when adults interact with an avatar that is controlled by a real person rather than a computer, people experience higher levels of arousal, learn more, and pay more attention (Okita, Bailenson, & Schwartz, 2008). And work by Roseberry et al. (2014) showed children learned equally well from interactions with a person in a video chat (e.g., Skype) when social contingency was established, but they did not learn from watching a digital interaction between the adult and another child.

These results parallel the literature on attention/memory effects in social learning reviewed in Part 1. That is, both active and social processes can modulate attention and memory to facilitate in-the-moment learning. However, as in social learning, the effects of active control operate through multiple mechanisms, going beyond changes in lower-level cognitive processes to changing the quality of *information* that learners get from the world.

Active control provides "good" information. Active learning allows people to gather information that is particularly "useful" for their own learning. This benefit relies on the fact that learners have better access to their own prior knowledge, current hypotheses, and ability level, which they can leverage to create more helpful learning contexts (e.g., asking a question about something that is particularly confusing). Research on this compoenent of active learning focuses on how people take actions to create learning experiences that are more useful compared to entirely passive contexts where the learner has little control.

For example, Castro et al. (2009) directly compared human active and passive category learning to predictions from statistical learning theory under conditions of varying difficulty. They found that human active learning was always superior to passive learning, but did not reach the performance of the optimal model and the advantage for active control decreased in the more difficult (i.e., noisier) learning tasks. Using a similar model-based approach, D. B. Markant & Gureckis (2014) investigated the effects of active vs. passive hypothesis testing on the rate of adults' category learning. They varied the difficulty of the learning task by testing two different types of category structures: a rule-based category, which varied along 1 dimension (easier to learn), and an information-integration category, which varied along 2 dimensions (harder to learn). In the active condition, the learner chose specific observations from the category to test his or her beliefs, whereas in the passive condition, the data were generated randomly by the experiment. Participants in the active condition learned the category structure faster and achieved a higher overall accuracy rate compared to participants in the passive learning condition, but only for the simpler, rule-based category.

Together, the Castro et al. (2009) and D. B. Markant & Gureckis (2014) results illustrate several important points about active learning. First, the quality of active exploration was fundamentally linked to the learner's understanding of the task: if the representation was poor, then self-directed learning was biased and ineffective. Second, the benefits of active control were tied to the aspects of the individual learner – i.e., their prior knowledge and the current hypotheses under consideration – such that the same sequence of data did not provide "good" information for another learner. And third, the benefits of active learning diminished with increased task difficulty, perhaps because learners struggled to generate "helpful" examples.

These findings help to illusrate the complexity of human self-directed learning. That is, it is not the case that active learning functions similarly across individuals, contexts, and learning domains. However, the multitude of factors that could influence active learning create a complicated set of possibilities to explore. One useful approach to understanding this complexity is to compare human behavior to formal models of scientific inquiry that were developed by statisticians to quantify the usefulness of a particular experiment.

Optimal Experiment Design: A formal account of active learning. Optimal Experiment Design (OED) (Emery & Nenarokomov, 1998; Nelson, 2005) is a statisical framework that attempts to quantify the "usefulness" of a set of possible experiments relative to the experimenter's current goal and understanding of the problem. The benefit of using an OED approach is that it then allows the scientist to make design choices that maximize the effectiveness of their experiment, thus reducing the cost of additional experimentation. For example, Nelson, McKenzie, Cottrell, & Sejnowski (2010) used OED principles to differentiate competing theories of information seeking during adults' category learning. To do this, they created an OED model of the task and found the experiments in the space of possible experiments that maximized disagreement between the competing theories, or the experiments that were most likely to provide a useful answer.

A growing body of psychological research has used the OED framework as a metaphor for human active learning. The idea is that when people make decisions about how to act on the world, they are engaging in a similar process of evaluating the "goodness" of these different actions relative to some learning goal, and in turn, select behaviors that maximize the potential for gaining information about the world. One of the major successes of the OED model is that it can be used to account for a wide range of information seeking behaviors, including verbal question asking (CITE), planning interventions in causal learning tasks (CITE), and decisions about visual fixations during scene understanding (Najemnik).

What are the key ingredients of an OED model? Coenen, Nelson, & Gureckis (2017) provide a thorough review of the OED framework and its links to research in psychology. In their review, they lay out four key pieces of an OED model: 1) a set of hypotheses, 2) a set of questions to learn about the hypotheses, 3) a way to model the types of answers that each question could elicit, and 4) a way to score each of the possible answers with respect to change in belief about the hypotheses. They also highlight the importance of learners' *inquiry goals* (e.g., "What's that object called?") for engaging in OED-like reasonsing. The key point is that without a clear learning goal, then it becomes difficult to instantiate the hypotheses, questions, and answers that a learner will consider when deciding how to act.

Together, these four pieces allow an OED model to quantify the *expected utility* of each question $EU(q)$ in the set of questions that a person could ask $q_1, q_2, ..., q_n = \{Q\}$.

This expected value is a function of two values: 1) the probability of obtaining a certain answer given a question $P(a|q)$ and 2) the usefulness of that answer for achieving the learner's goal $U(a)$. Then, we can define the expected utility for a specific question as the average utility over all the possible answers to that question.

$$EU(q) = \sum_{a \in q} P(a|q)U(a)$$

There are a variety of ways to define the usefulness function to score each answer. An exhaustive review is beyond the scope of this paper, but for a detailed analysis of different approaches and their match to human behavior, see Nelson (2005). One common approach is to use the change in uncertainty in a specific hypothesis after receiving a particular answer or *information gain*. This can be calculated as the change in entropy after seeing a particular answer.

$$P(h|a) = ent(h) - ent(h|a)$$

Finally, to select the best question, an OED learner must perform the expected utility computation for each possible question. This involves considering all of the possible answers for each question, scoring the answers using some usefulness function, and then weighting each score by the probability of getting that answer.

There are several benefits of the OED formalization for understanding human active learning. First, it makes researchers define the different components of an active learning problem, thus making their assumptions about the phenomenon more explicit. Second, if researchers can develop an OED model, then they can ask whether people's behavior matches or deviates from the optimal behavior predicted by the model. Finally, casting information seeking as rational *choice* links psychology with several rich literatures (economics, statistics, computer science) that have attempted to formalize the decision-making process as a process of utility analysis that can include both the costs of information acquisition and the benefits of choosing a particular behavior.

One nice demonstration of this approach comes from Nelson (2005) model of eye movements during novel concept learning. The model combines Bayesian probabilistic learning, which represents the learner's current knowledge as a probability distribution over a concept, with an OED model of the usefulness of a particular eye movement (modeled as a type of question-asking behavior) for gathering additional information about the target concept from the visual world. Together, these model components allowed Nelson (2005) to predict changes in the pattern of eye movements at different points in the learning task. Specifically, they found that early in learning, when the concepts were unfamiliar, the model predicted a wider, less efficient distribution of fixations to all candidate features that could be used to categorize the stimulus. However, after the model learned the target concepts, eye movement patterns shifted, becoming more efficient and focusing on a single stimulus dimension.

Another promising aspect of the OED models is that recent developmental work has provided evidence that even young children appear to select behaviors that efficiently maximize learning goals. For example, there is evidence that children from a young age use verbal questions to gather information from other people. In a corpus analysis of four children's parent-child conversations, Chouinard, Harris, & Maratsos (2007) found that children begin asking questions early in development (18 months) and at an impressive rate, ranging from 70-198 questions per hour of conversation. Chouinard et al. (2007) also coded the intent of children's questions, finding that 71% were for the purpose of gathering information, as opposed to attention getting or clarifications. Other corpus analyses provide converging evidence that question asking is a common behavior in parent-child conversations (Davis, 1932), that children are seeking knowledge with their questions (Bova & Arcidiacono, 2013), and that children will persist in asking questions if they do not receive a satisfactory explanation (Frazier, Gelman, & Wellman, 2009).

Experimental work has investigated the quality of children's question asking by measuring the quality of questions in constrained problem-solving tasks. For example, Legare, Mills, Souza, Plummer, & Yasskin (2013) used a modified question asking game where 4- to 6-year-old children saw 16 cards with a drawing of an animal on them. The animals varied along several dimensions, including type, size, and pattern on the animal. The child's task was to ask the experimenter yes-no questions in order to figure out which animal card the experimenter had hidden in a special box. Legare et al. (2013) coded whether children asked *constraint-seeking* questions that narrowed the set of possible cards by increasing knowledge of a particular dimension or dimensions (e.g., "Is it red?"), *confirmatory* questions that provided redundant information, or *ineffective* questions that did not provide any useful information (e.g., "Does it have a tail?"). Results showed that all age groups asked a higher proportion of the effective, constraint-seeking questions relative to the other question types, and that the number of constraint-seeking questions was correlated with children's accuracy in guessing the identity of the card hidden in the special box. Legare et al. (2013) interpret these results as evidence that children can use questions to solve problems in a efficient manner. Converging evidence in support of this interpretation comes from experimental work using this approach finding that children prefer to direct questions to someone who is knowledgeable compared to someone who is inaccurate or ignorant (Mills, Legare, Bills, & Mejias, 2010; Mills, Legare, Grant, & Landrum, 2011),

Although the OED approach has provided a formal account of seemingly uncontstrained information seeking, there are several ways in which it falls short as an explanation of human self-directed learning. Coenen et al. (2017) argue that in practice OED models make several critical assumptions about the learner and the problem, including the hypotheses/questions/answers under consideration, that people are actually engaging in some kind of expected utility compuation in order to maximize the goal of knowledge acquisition, and the cognitive capacities of the learner to carry out these computations. For the purpose of our argument, there are two limitations that are most relevant for connecting social learning contexts with the OED model of self-directed learning: (1) assumptions about the hypotheses, questions, and answers that children take into consideration during learning and (2) the role of resource constraints on children's cognitive capacities that limit their ability to engage in OED-like reasoning.

In the next section, I intergrate social and active learning acounts using expected utility and OED framework to structure the argument. I focus on a subset of the nine open questions about human inquiry put forth by Coenen et al. (2017). I argue that learning from others provides one path to setting up a tractable space of hypotheses, questions, and answers. The crux of the argument is that learning from more knowledgable others plays an important role in providing the fundamental building blocks that are required for children to engage in effective OED reasoning in the moment of learning. # Part III: How social contexts can shape active learning

Hypothesis space.

Generating questions.

Generating answers.

Reputation management.

Stopping rules.

Social information seeking. Active social learning - seek information from social targets. Models of seeking information from social targets:

- Baldwin & Moses (1998): The Ontogeny of Social Information gathering
- Chouinard (2007): Children's questions as learning mechanism
- Hyo's and Liz Bonawitz's work

These studies of the benefits of active information selection connect nicely to developmental work on children's question asking. Verbal questions are a spontaneous behavior that occurs in everyday interactions that could allow children to seek information that is directly relevant to their current interests and misconceptions. Moreover, asking a good question is complex: the child must know what they don't know, how to ask about it, who to ask about it, and be able to assimilate new information. However, other work has focused on the social context in which question asking occurs.

Part IV: Resource constraints in active-social learning

Active learning takes into account a utility structure that can include both the costs of data acquisition and the rewards of choosing an example (e.g., in terms of information acquisition/uncertainty reduction relative to some longer term learning goal).

Focusing on *choices* is useful since there is a rich literature that has formalized decision-making process, which can be used to describe behaviors made by both more knowledgeable others and by learners. The interesting question is how costs/benefits of active learning behaviors are altered by the social context and how reasoning about learners as active might change the social context.

Process:

- analyze costs and benefits of behavior

`- planning models that take into account long-term value`

`- decisions in the brain and in non-human primates`

Active learning in social contexts. The presence of another agent can change the cost/benefit structure of choices made for learning and therefore models of self-directed learning should include this information. In contrast, these models often view the learner as moving back and forth between active exploration and passive reception. This type of active learning account does not leave room for social reasoning processes (i.e., naive utility calculus, goal reasoning) to change the utility of active learning behaviors.

Metacognition.

Question asking.

Conclusions and a way forward

Models of self-directed learning should include information the social-communicative context in which learning often occurs. Reasoning about other people modulate the choices that learners make: whether it's who to talk to, what to look at, or what questions to ask.

Models of social learning should take into account the choice behaviors available to the learner. i.e., think about teaching as reasoning about another person's active learning or setting up a social learning context where the learner selects actions

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