PROJECT DESCRIPTION

Early childhood is ubiquitous with choices for exploring, question asking, and consequently learning about the world. Whether children are picking among books to read at night before bed, deciding which exhibit to visit next at the museum, choosing among toys to play with, or performing spontaneous interventions like blowing bubbles in milk or testing the angle of repose of pile of peas, children are drivers of their own discovery. Since Piaget (1930), and even earlier, people have suggested that children learn through actively exploring their environment (Bruner, Jolly, & Sylva, 1976; Singer, Golinkoff, & Hirsh-Pasek, 2006). Indeed, in education research the benefits of self-directed learning have been strongly supported by data on children's exploratory play (Berlyne, 1960; Papert, 1980). Similarly, in cognitive psychology active exploration is seem as an important component in learning; exploration leads to "interventions" which help deconfound variables. To this end, researchers have stressed the analogy between children and scientists (Carey 1985; Gopnik & Meltzof, 1997; Keil, 1992; Wellman & Gelman, 1992), suggesting that, like scientists, children have *intuitive* theories that are shaped by evidence, such as observations of causal interventions (Cook, Goodman, & Schulz, 2011; Schulz, Kushnir, & Gopnik, 2007; Schulz, Gopnik, & Glymore, 2007; Schulz, 2012).

Children clearly learn from their own actions, but how do children decide what to act on? The world is vastly under-constrained; there are infinitely many possible options to explore. So, where should an active learner begin? One possibility is that children are motivated to explore when there is high expectation in "Information Gain" – the degree to which a learner can expect to update her beliefs. Information Gain helps solve the problem of 'infinite possible actions', because it provides a model for the most efficient action to take: the one that will maximize the opportunity for learning.

In this proposal, I bring a modeling perspective to bear on understanding exploratory biases in childhood. I suggest that the statistical information theory of "Information Gain" and rational choice models can inform our understanding of whether children are effective active learners. The modeling provides qualitative predictions that motivate five studies investigating children's active learning. These begin with the question of whether children track probability information and are able to used expected reward to drive decisions. The second set of studies investigate whether children are motivated to explore an object longer and more variably when they believe learning about it will be more difficult (have higher information gain). The remaining experiments examine children's choices between two uncertain outcomes. One set of studies assess whether children consider the effects of evidence prior to exploring events with potential information gain. The second set of studies looks at information gain in the context of children's beliefs – specifically, whether children who are transitioning between beliefs are more motivated (as compared to children who are more confidently rooted in their current beliefs) to seek information that will help them learn. In all studies, developmental differences are explored. **The goal is to use a model of information gain and choice to provide a framework for efficient active exploration in childhood.** To understand the role of children's early exploratory experiences in learning, we must begin with formal models that help us understand what kinds of events are ideal for supporting learning. By investigating the degree to which children's choices converge with the predictions of these models, we can develop effective educational interventions that exploit children's natural preferences and even come to understand the factors that might lead to developmental learning disabilities.

AIMS	
1	Employ a formal framework of information gain to understand the development of effective active exploration.
2	Investigate the factors that lead to expectations of information gain.
3	Empirically investigate whether children are sensitive to these factors.
4	Explore the development of effective active exploration.

BACKGROUND

Children in the earliest stages of life are able to observe the world, form theories about how the world works, predict possible consequences of their theories, and intervene to test their predictions. Previous work has supported the theory theory claim that children have coherent, causal representations that constrain the interpretation of evidence but that are also defeasible (Carey 1985; Gopnik & Meltzof, 1997; Keil, 1992; Wellman & Gelman, 1992). More recently, researchers have applied probabilistic computational models to predictions from this theory theory framework, demonstrating that children can make near optimal predictions, interventions, and even counterfactual claims (Gopnik & Schulz, 2004; Gopnik, Sobel, Schulz, & Glymour, 2001; Schulz & Gopnik, 2004; Shultz & Mendelson, 1975; Siegler & Liebert, 1975; Sobel, 2004). For example, preschool-aged children can learn from ambiguous patterns of evidence, revising strong prior beliefs as evidence increases (Schulz, Bonawitz, & Griffiths, 2007).

Thus, research suggests that children often update their beliefs in ways consistent with "optimal models". But, do children *seek out* events that are optimal for learning? Education research has demonstrated that individuals who are more curious are more likely to learn because they seek out uncertainty, engage longer, and are thus more likely to generate evidence to support learning (Beswick, 1971, Boyle, 1983). Despite this substantial agreement that children learn through play (e.g., Bruner, Jolly, & Sylva, 1976), less is known about whether children use exploration as an effective way to support inferences. Although young children do not design controlled experiments, they can use patterns of presented evidence to update their beliefs and guide generalization and exploration (Gweon & Schulz, 2011; Gweon, Tenenbaum, & Schulz, 2010; Schulz & Gopnik, 2004). Cognitive developmentalists have stressed the role of these intuitive theories and evidence in guiding hypothesis testing (e.g. Gopnik, 1996). But we do not know when children seek out potential evidence that supports efficient learning or what kinds of events might be ideal for exploratory learning.

For an unbiased learner, there are many kinds of events worth exploring. Novelty is always potentially informative because – by its very definition – nothing is known about the novel item and so there is something to be learned. Indeed, it has long been established that children (and many nonhuman animals) prefer novel stimuli over familiar ones (Berlyne, 1960; Dember & Earl, 1957; Henderson & Moore, 1980; Hutt & Bhaynani, 1972; Pavlov, 1927). However, it is difficult to evaluate what optimal exploration would mean if a learner simply sought novelty, although recent research suggests a "sweet spot" for events that are neither too simple or complex (Kidd, Piantadosi, & Aslin, 2012, 2014). Nonetheless, infinitely many objects and events are novel, so a complete rational story of this preference would require clarification on how and what directed attention to *particular* novel experiences.

Surprise is another factor that may influence exploration. A learner who has a strong belief, but then observes evidence that stands in conflict with that belief has an excellent opportunity for learning. Either something about the evidence was misinterpreted or can be explained away, or the initial belief was incorrect and must be revised. Either way, these cases of "causal ambiguity from surprise" provide opportunity for learning from further investigation (Bonawitz & Schulz, 2007). In previous research, past collaborators and I have found that when faced with evidence that conflicts with their beliefs, children are more likely to explore and also to appeal to hidden variables to "explain away" this data that conflict with strongly held beliefs (Bonawitz et al, 2012; see also van Schijndel, Visser, van Bers, & Raijmakers, 2015; Cook, Goodman, & Schulz, 2011). Even infants seem to engage in surprise-based hypothesis testing: When 11-month-olds observe events that violate their expectations about object solidity, they attempt to bang the object, but when they observe events that violate expectations about support, they attempt to release-drop objects (Stahl & Feigenson, 2015).

A third opportunity arises for learning when an observer faces uncertainty. In these cases, there are multiple possible explanations for a set of observed evidence for which the observer does not have strong prior beliefs. That is, unlike causal ambiguity, which follows a surprising outcome, uncertainty arises from weak initial commitments and insufficient evidence. For example, consider a jack in the box with two levers and two toys. Nothing about the position of the levers can be used to discern which lever causes which toy to rise. Observing both levers pressed simultaneously, with both toys rising in the center of the box, provides no new information as to which level causes which toy. Thus, such a confounded observation leads to a case of causal uncertainty (Schulz & Bonawitz, 2007). A preference for exploring uncertain events is related in many ways to a preference for novelty. However, although novel stimuli likely involves uncertainty, uncertainty does not require novelty. Children may be motivated to explore uncertain events regardless of their novelty because exploration could lead to causal explanatory information. Indeed, research suggests that children are interested in exploring when evidence is confounded (Schulz & Bonawitz, 2007; Gweon & Schulz, 2008). Learners may be motivated towards uncertainty because they enjoy learning new things – the "learning and discovery" is a reward. Indeed, research suggests that resolving uncertainty can have physiological reward associated with it (Wittmann, Daw, Seymour, & Dolan, 2008). Converging evidence from cognitive neuroscience suggests that there are specialized circuits for rewarding events that have not been explored (Kakade & Dayan, 2002).

The exploratory opportunities following ambiguous or uncertain information are driven by a response to evidence (either because evidence is surprising or insufficient). In previous work, Bonawitz and Schulz (2007) presented a formal model of these two kinds of opportunities for learning, and demonstrated that children are more exploratory (favoring ambiguous or uncertain events over novelty). However, these accounts tell just a part of the story. For one, learners may be interested in tangible, non-epistemic rewards, so actions may not always be driven by a desire to learn – they may also be driven by desire to observe an effect, or to enjoy a piece of candy, etc. There are also many instances in which a learner can experience uncertainty or ambiguity, but there is no possibility for learning (because interventions will not be informative). Thus, an effective actor must be able to evaluating the conditions under which learning will be possible. Furthermore, an effective learner need not only be reflexive to evidence as is the case for ambiguity- and uncertainty-driven exploration. Effective learners may make choices about what to act on *prior to observing any evidence*. Such a learner must be able to evaluate the probability of reward in the environment, consider the opportunity for learning in the current case, and even make choices among competing opportunities for investigation.

Model of efficient exploration

Computational models provide a means by which researchers can formalize their theories. Models also force researchers to be explicit about the assumptions and constraints that must be considered. The work proposed in this grant is *qualitatively* informed by a modeling approach. Empirical predictions are driven by expected general trends from the models, rather than quantitatively matching precise response output between participants and models.

Active exploration is an important topic for understanding human behavior and also for developing intelligent machine algorithms. To this end, there have been numerous models capturing various aspects of how and when a learner should explore. A large set of models are based on reinforcement learning (RL) theories (e.g. see Kaebling, 1993 for a review); these theories depend on many, many trials of learning, though algorithms that only depend on the most recently observed evidence are often employed ("Markov Decision Processes", MDPs; Bellman, 1957). These theories assume that a learner is using statistics to estimate the utility of taking certain actions (for a review see Kaebling, Littman, & Moore, 1996). Other approaches allow learners to search a series of behaviors over time, in order to find the one that performs best in a particular environment (Schmidhuber, 1996). These are both informative approaches to the problem of learning and planning multiple actions over time.

Here we focus on a different approach to active learning, the question of "what" one wants to learn about. We ask how a learner makes an *initial choice* between (at least) two possible options. Such a task requires a learner to consider which of the outcomes is most likely to produce a reward. Rewards, of course, can be tangible "payoffs" – such as money or prizes. In this grant we ask a crucial question for active learning in development: do children treat "Information Gain" (the degree to which something new is learned, as measured by changes in beliefs) as rewarding? Are children more motivated to explore events that have greater Information Gain?

To ask this question, we turn to a formal measure of information gain. This measure is known as the Kullback-Leibler divergence (KL Divergence, see Eq. 1). 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.

$$D_{KL} = \sum_{\alpha} p(\alpha|\text{prior})[\log p(\alpha|\text{prior}) - \log p(\alpha|\text{post})] \quad \text{Eq. 1}$$

Importantly, KL Divergence is about how a learner updates their beliefs about the world, and is not the same as the degree to which a learner is *surprised* by evidence they have just observed. Indeed, in information theory, this degree of surprise measure is known as Shannon Information:

$$I_S(\alpha) = -\log p(\alpha|\text{prior}) \quad \text{Eq. 2}$$

Shannon information might reasonably be considered a useful measure for certain developmental findings, such as how long an infant might look after seeing an unexpected event, or whether a child is more interested in exploring a theory-violating event over a novel one. The relationship between KL Divergence and Shannon information is that KL Divergence is the probability-weighted average change in the Shannon Information across all possible data as a consequence of updating the model.

Utility calculations of these sorts depend on the assumption that the learner experiences *reward* from (e.g.) maximizing KL divergence. I refer to this as "epistemic reward" to note the degree of utility in gaining some amount of new knowledge. This kind of reward can be contrasted with non-epistemic reward, relating to tangible rewards in the environment, such as enjoying the outcome of an event, a toy, or candy, or even praise. (Though event outcomes and praise are not "tangible" I will group them together with the others here for practical purposes.) To consider both kinds of reward, which may conflict with each other, rational choice theory provides a framework by which we can evaluate the impact of different types of reward to lead to optimal action. Similar approaches have been used recently to model adult trial-by-trial information gathering with great success (Gureckis & Markant, 2009; Markant & Gureckis, 2012; Nelson, 2008). These computational approaches allow for a weighted mixture of choice between tangible rewards and epistemic rewards, and demonstrate the adult participants combine both factors in their decision making, but also show great individual variation (Coenen, Rehder, & Gureckis, 2014).

But why would an individual ever choose to learn something new over enjoying an immediate tangible reward? Efficient active learners may choose to explore because the act of maximizing information gain provides its own sense of rewarding satisfaction (Wittmann, Daw, Seymour, & Dolan, 2008). Is this experience of reward optimal? The computational level of analysis (Marr, 1982) suggests one rational explanation for this epistemic-reward response*:* it could be rational to prefer to explore more (even if there is some certainty about less reward) if a learner expects that they may return to this environment later and thus require knowledge of its utility (after current, alternative rewards are exploited). This "long-run" expectation is a given in classic N-arm bandit problems (Robins, 1952; Gittins, 1979), when the learner knows that they will have many trials and can expect that reward probabilities will be stable. It is less clear how learners, and children in particular, might respond in other explore-exploit situations that do not include this long-run expectation, and it is interesting to ask whether a preference to explore is observed even when there is no long-run payoff, unlike bandit problems.

To summarize, in order to model children's active learning, we must consider both the expected value of the information gain (the KL divergence), which is a way of measuring the reduction of uncertainty in one's beliefs, and also any non-epistemic reward that is experienced. As discussed above, most past work of children's learning have considered how children respond *after having observed evidence*, but information gain measures the choices an individual should make *prior to observing evidence* in order to maximize the expected potential for learning. Thus, information gain provides a novel approach to considering children's exploration of the environment, and rational choice theory allows us to evaluate how the reward from IG and non-epistemic rewards should be considered together.

In this proposal I ask two broad questions. First, how does children's exploration correspond with a rational model of efficient active learning? Second, I ask: are there developmental differences in the efficiency of children's active learning? There are some hints from other fields that suggest that exploratory approaches undergo developmental changes. Anthropological research has suggested that "costly", exploratory play in early childhood has important developmental benefits and changes with age (Bock & Johnson, 2004; Kaplan, Hill, Lancaster, & Hurtado, 2000). Studies in decision making have similarly shown changes over older-children's exploration choice strategies (Davidson, 1991). However, research in cognitive development has not yet focused on how efficient exploration might change with age in younger populations. Thus, to better understand the core cognitive factors that drive discovery in early childhood we must understand the degree to which young children's behavior corresponds with these efficient-explorer predictions, and whether this behavior changes with development.

APPROACH

The theoretical perspective described above highlights several factors to which an efficient active learner must be sensitive. These factors raise three primary hypotheses that are empirically explored in this proposal. The goal is to establish the constraints and abilities of young children's active exploration, to help us understand the ways in which behavior approximates "optimal" solutions to the problem of choice in exploration and also the ways in which behavior diverges from these solutions and changes with development. The hypotheses are now discussed in detail.

Hypothesis 1: Optimal actors must be sensitive to probability of reward in the environment and choose effectively among expected rewards.

The rational choice model depends on an actor's ability to represent and respond to expected reward in the environment. Are children sensitive to the probability of reward in their environment? How does this change with development? To assess this quantitatively, we can ask whether children are able to trade off immediate reward with expected gain. In Studies 1 and 2, children are given information about the probability of reward in the environment and must choose between an uncertain (but computable) expected reward and a known reward. This trade-off is referred to as exploration-exploitation.

There is some evidence that children are sensitive to probabilities and can rationally choose between outcomes in simple decision-making contexts. Children are able to integrate multiple pieces of information to make probabilistically-sensitive judgments (Gregan-Paxton, & John,1995; Schlottmann & Anderson, 1994; Schlottmann, 2000, 2001), though preschoolers sometimes struggle in these decisions when probability information must be integrated with other cues (Betsch, & Lang, 2013). These approaches are used typically as a way to explore normative models of decision making, such as Subjective Expected Utility Theory. However, these approaches are rarely extended to preschoolers. Preschooler's can integrate probability information with prior expectations to guide their causal explanations (Bonawitz & Lombrozo, 2012; Denison, Bonawitz, Gopnik, & Griffiths, 2013; Schulz, Bonawitz, & Griffiths, 2007), but the question of exploration and exploitation in these younger children's decision making has not been studied in these contexts. Thus, past studies provide promising support for the claim that children use probability information in their decision making, but they leave open the question of how and whether younger children employ rational strategies in exploration-exploitation.

Exploration and exploitation trade-offs have been extensively studied in multiple disciplines including ecology and foraging theory (Stephens & Krebs, 1986), epistemological philosophy (e.g. Kvanvig, 2007), machine learning and computer science (e.g. Kaebling, 1993), a anthropology (Bock & Johnson, 2004; Kaplan, Hill, Lancaster, & Hurtado, 2000). There is less research on human exploration in psychology, although it has been demonstrated that adults can learn about the distribution of rewards in physical locations and search accordingly (Smith, Hood, & Gilchrist, 2010). Given reinforcement, children can also learn probabilistic information about environments to efficiently search physical spaces, dependent on the development of their spatial working memory (Smith, Glichrist, & Hood, 2005).

Thus, children's appear able to learn about environments through longer periods of reinforcement and appropriately take advantage of reward in their environments; this demonstrates children's ability to learn from, and act on, statistical data from trial and error. However, less is known about how children use expectations about rewards in the environment in "one-shot" learning to decide between explore-exploit options. That is, can children use probabilistic information to rationally choose between outcomes? Specifically, *can children use expectations about reward to decide between competing alternatives*? If so, children should be more likely to explore when the environment is likely to produce higher rewards.

Hypothesis 2. The effort and variability in exploration should increase as expectations about information gain increase, leading to greater discovery.

Investigation of hypothesis 1 will establish children's sensitivity to probability information and how this trades-off with utilities in reward. This is a critical first step before we can establish whether information gain will compete with these utilities. However, effective active learners must also be motivated by degree of information gain. Where-as Studies 1 and 2 will establish children's sensitivity to probability information to choice between tangible rewards, Study 3 controls for probability and tangible reward. The only variable manipulated is expected information gain, allowing investigation of whether children's exploration changes as a function of potential for learning.

How might information about a toy's potential shape exploration? Recent works suggest that children's exploratory play is sensitive to the manor in which evidence is presented about the to-be-explored toy. Preschoolers can use the knowledge and intent of a teacher to draw stronger inferences then are afforded by the data alone (Bonawitz, Shafto et al., 2011; Buchbaum et al., 2011; Shafto, Bonawitz, Landrum, & Yu, *in review*). For example, following direct instruction about one function of a toy, children will restrict their play to that function, rather than exploring more broadly (as they do following accidental or other non-pedagogical cues; Bonawitz, Shafto et al., 2011). Children also use the probability of an observed sample to make inferences that shape the degree and type of play with sampled items (Schulz, Standing, & Bonawitz, 2008; Gweon, Pelton, Konopka, & Schulz, 2014; Gweon & Schulz, 2011; Gweon, Tenenbaum, & Schulz, 2010). These studies demonstrate that children's exploration of a particular object is sensitive to how information about that object is presented, however they were not designed to explore whether expected information gain is a driving force in exploratory choices, and they do not investigate these questions across years in early-childhood.

Hypothesis 3. **Given a choice between two uncertain outcomes, effective active learners should select the outcome with higher information gain.**

To recap: Study 3 investigates whether action over a single event varies as a function of expected information gain, though does not require the learner to choose between two outcomes prior to action. Studies 1 and 2 assess whether children are sensitive to probability information in the choice between expected tangible rewards, but do not require children to consider competing information about knowledge gain. The final set of proposed studies explore the combined question of choice and information gain, to see whether children choose to explore events with the highest information gain.

In simple contexts children seem to recognize the difference between informative and uninformative evidence when it is presented to them (Masnick & Klahr, 2003; Sodian, Zaitchik, & Carey, 1991; Nelson et al, 2014; Ruggeri & Lombrozo, 2015). However, this previous research has not looked at whether children privilege more informative information over less informative information. That is, given two opportunities in which either choice will result in resolution of uncertainty, do children privilege the action that has the potential to yield *more* information? We explore two factors that can influence the degree of information gain. The first (Study 4) investigates whether children consider the potential effect of evidence prior to exploration. The second (Study 5) investigates whether a child's current degree of certainty in her beliefs influences her choice to gain information that could provide support for or against that belief. That is, are children who are in a transitional state between beliefs more likely to seek out evidence than children who are convicted in their beliefs? The model predicts an interesting U-shaped developmental effect, with "middle, transitional" children showing a strong preference for information about their domain of uncertainty, but young children (who are confident in their *incorrect* beliefs) and older children (who are confident in their correct beliefs) preferring to investigate other uncertain options.

PROPOSED STUDIES

This proposal focuses on preschool- and early-school aged children (3- to 7-years-old), but the principles and methods developed should be broadly applicable across the life-span. Focusing on children at this age has principal benefits. The background knowledge that young children bring to bear on any given situation is more uniform, due to their relatively limited experiences in life. Critically, children at this age have not yet experienced formal schooling, allowing insight into early developing mechanisms that support efficient active learning, prior to instruction. Furthermore, exploring this age allows me to adopt tasks for which there is a well-established developmental trajectory. This in turn allows us to make more informed inferences about what is and is not being learned.

Science is only as robust as the sample of participants is representative of the whole population. Our lab works to maintain connections to extremely varied populations and is supported by a large University initiative to focus on outreach and engagement with our inner-city community. The University is located in Essex County, which has one of the sharpest contrasts between rich and poor in the nation (2010 US Census Bureau), as well as extremely varied racial and cultural backgrounds. This affords inspection across a range of different populations despite regional and government similarities. The lab currently has ongoing collaborations with science museum, child play centers, libraries, and zoos in this and neighboring counties. The connections we have to these diverse populations also allow for "purposeful sampling" in research collection and design. That is, if there appear to be differences between communities, we can systematically explore them. This provides an important improvement on typical samples in developmental psychology research, which must then not only temper the broader applicability of results from overly narrow populations, but that often struggle with reaching the very communities that could most benefit from and inform the generalizability of their findings.

Hypothesis 1: Optimal actors must be sensitive to probability of reward in the environment and choose effectively among expected rewards.

My general method for examining children's exploration in probabilistic environments involves a force-choice paradigm in a relatively abstract decision task. Although it is important to extend these questions to tasks that more closely resemble "real world" experiences (e.g. Studies 3, 6), the approach here affords important regulation on the statistics in the environment. At a minimum, the statistics in the proposed tasks are presented as larger sets of frequencies, which more closely resembles how humans intuitively encode information from the environment (Hoffrage, Gigerenzer, Krauss, & Martingnon 2002; Gigerenzer, 1998). The basic-science approach proposed here is critical because it allows us to control and isolate the contribution of each of the exploratory biases described above. Only by first using basic science approaches to establish the factors that lead to exploration in childhood, can we then design more practical applications in academic and informal learning environments.

Model of choice between expected rewards

A child is asked to choose between an object for which the reward is known and an object for which the reward is unknown. For example, she is collecting marbles and one red box has two marbles in it, the other blue box is closed, and so the number of marbles is hidden. However, the child observes that the closed blue box was drawn from a group of blue boxes where the general distribution of marbles is known. She knows that these closed blue boxes can have 0, 1, 2, 3, or 4 marbles in them, and this box was drawn from a particular set of eight boxes each containing the following number of marbles [0 1 1 1 3 3 3 4]. Thus, although the exact number of marbles in this particular blue box is unknown, she can have an *expectation* about the likely mean number of marbles in this box sampled from the set.

So, how does this child choose between the known quantity of 2 marbles in the red box and the unknown quantity in the blue box? Given a set of observed rewards and random drawing of a single sample, the expected reward is simply the mean of the observed values. This equation becomes slightly more nuanced if options are not equally likely to be drawn from the set. For the experiments presented here however, random sampling is established in the methods so all options would be assumed to be equally likely. Therefore, if an agent is presented with the following options (**Fig. 1,** below), then the value of the red box is known to be "2". The 8 blue boxes include the following rewards [0 1 1 1 3 3 3 4]. If one box is randomly drawn, the expected value for that box is (0 + 1 + 1 + 1 + 3 + 3 + 3 + 4) = 16/(number of boxes = 8) = "2" (See also Anderson's Information Integration approach: e.g. Anderson, 1980). Thus, although no particular blue box has an actual reward of 2 marbles, the *expected value* of a randomly sampled blue box is 2.

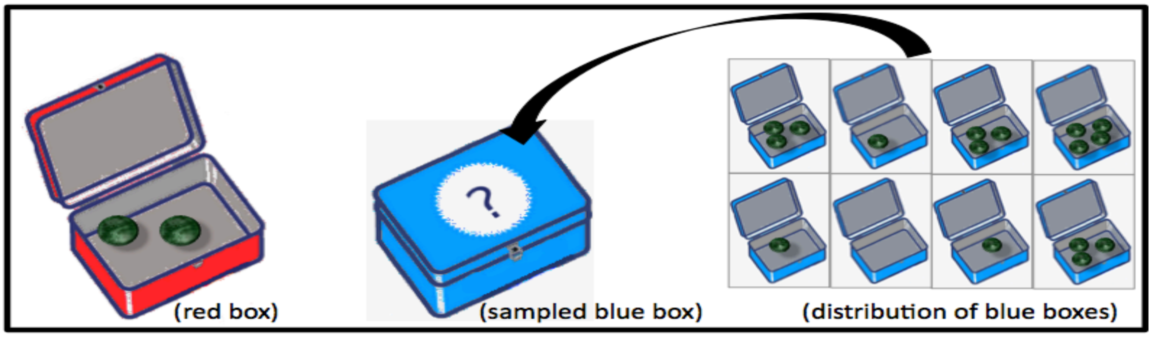


Fig. 1. Studies 1 & 2: learners choose between the known reward in the red box and the unknown reward in the blue box. The blue box is sampled randomly from a known distribution, so expected value of the blue box is computable.

In this example, the known red box and the sampled blue box both have an expected reward of 2; the next question is which option should the learner choose given this information? There is a long history in decision sciences about how a learner should choose between competing options, given some expectation about reward. One of the simplest forms of choice is Luce choice (1959). There is a host of literature considering context effects that may influence choice behavior, (see also Shafto & Bonawitz, 2015), but for the relatively straight-forward 2-choice alternative task here, Luce is likely to be an acceptable model of human behavior. The main intuition with Luce choice is that an agent's choice is probabilistic – an agent chooses an option with probability proportional relative to its value. Luce choice is related to Sutton and Barto's (1998) softmax rule in exploration-exploitation paradigm (where choice depends on an weighted exponential transform of the utility) and also the Sampling Hypothesis developed by myself and my post-doctoral mentors (where children generate a response probabilistically in proportion to the option's posterior probability, see **Relationship to prior NSF support**, e.g. Bonawitz, Denison, Griffiths, & Gopnik, 2014). Thus, there is strong converging support from explore-exploit models and cognitive developmental studies that this probabilistic choice model will likely correspond to older preschooler's responses on the tasks presented here.

Given these predictions, we can evaluate possible response patterns of children (in aggregate) as the expected reward in the unknown box is varied. That is, in different trials, we can teach children new information about different sets of boxes – leading to cases when the known box has significantly higher predicted reward and other cases when the known box has significantly lower predicted reward. An important question then becomes, given different trials in which the ratio of expected reward between the known an unknown box move from lower reward for the uncertain box to higher reward, do children also begin to choose the uncertain box with higher probability? A linearly increasing result tells us that children are sensitive to the statistics in the environment, rationally sample a guess for the uncertain box, and make choices proportional to these expectations.

Study 1: Sensitivity to probability information: Individual differences in exploration strategies and coherence over time

The goal of this study is to explore whether preschool-aged children can use information about the expected reward in the environment to make decisions between a known reward and an uncertain outcome. The approach allows examination of individual differences in drive to explore. Follow-up tasks provide a preliminary look at whether these strategies are coherent over time as well as whether strategy preference correlates with other measures.

Participants and Design: Three-, four-, and five-year-olds participate in an initial testing session with 10 marble-box trials. Approximately one month later, they are visited a second time to participate in a follow-up marble-box task, and on a third visit they participate in battery of tasks described below. Assuming medium sized correlations (r = .50), power = .80, and α = .05, power analyses suggests 30 participants per age group should be tested.

	4:1	2:1	1:1	1:2	1:4
Marbles in the Known Box	2	2	2	2	2
	3	3	3	3	3
Marbles in pre-sampled set	0 0 0 0 0 0 1 3	0 0 1 1 1 1 1 3	0 1 1 1 3 3 3 4	1 4 4 4 4 5 5 5	1 8 8 8 9 10 10 10
	0 0 0 0 0 1 1 4	1 1 1 1 1 1 2 4	1 2 2 2 4 4 4 5	2 5 6 6 6 6 6 7	2 12 12 12 14 14 15 15
Expectation of sampled box	.5	1	2	4	8
	.75	1.5	3	6	12

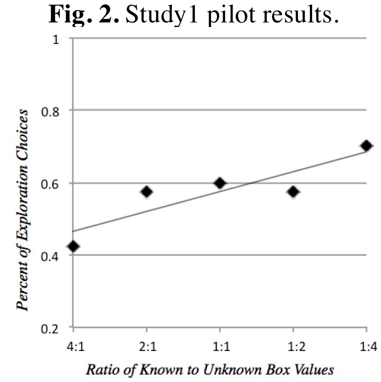
Table 1. Distributions for marbles in boxes. Columns capture ratio between known reward in one box to the expected reward in the sampled box. There are two different trials at each ration. In one set of trials the known box always has 2 marbles; the corresponding sets of marbles are given for these 2-marble-trials in the top row of each cell. In the other set of trials the known box always has 3 marbles; the corresponding marbles for the unknown set shown in the bottom row of each cell.

Procedure: Participants are introduced to a set of boxes, each containing a number of marbles that vary. (Marbles correspond to a reward that will be obtained at the end of the experiment.) Another box with a known reward is also presented. Participants then decide whether they would like to choose the reward in the observed box or whether they would like to uncover the uncertain, sampled box (see **Fig. 1**). This task is repeated, each time changing the sets of boxes (noted by different colors and designs), which allows comparison of exploration given difference distributions and thus trade-off between the reward in the known and uncertain box. Children complete the 10 trials on the first visit.

Coherence measure: We return four weeks later to provide children with a second set of box-marble trials, slightly varying the distributions of marbles. This will allow us to examine whether children's exploration-exploitation strategies are stable over time.

Pilot data: We have piloted this method on 20 four- and five-year-olds in the marble-box tasks. Children were able to follow the method and found the game interesting. Overall, the aggregate pattern of children's responses reflect sensitivity to the probability of expected reward in the environment (**Fig. 2**). The group average shows increasing preference for the uncertain box as that choice becomes higher in reward. Our pilot results also suggest we will find developmental differences. Rather than all children showing this aggregate pattern of responding, preschoolers employed one of three different strategies for choice: a bias to almost always choosing the 'known' box (N=7); a bias to choose the 'unknown' box (N=4); or responding with a mix of 'known' and 'unknown' choices (N=9). Children who are showing a bias to explore the unknown box are significantly younger than the other two groups. The behavior of the mixed-responders on aggregate directly correlates to the probability ratios of known to expected rewards, demonstrating that children rationally trade-off exploration and exploitation in response to probability information. Furthermore, our results are showing that these patterns appear stable over time, with individuals "sticking" with their strategies on the follow-up visits ($r = .68$, $p < .01$).

Fig. 2. Study1 pilot results.



Predictions and contributions. I expect that the pilot results will continue to bare-out: children on aggregate will reflect sensitivity to the probability of expected reward, with a bias towards exploration for younger children. These results would have important implications for understanding the literature on individual differences in children's curiosity and exploration more generally, with indications that younger children may by both more promiscuous explorers, and older children showing more nuanced sensitivity to reward in the environment.

Study 2. Evaluating developmental differences for risk and uncertainty in exploratory strategies

Preliminary data from Study 1 suggests that there may be developmental differences in evaluating probability information when acting to maximize expected reward. In economics, researches have noted differences between uncertainty and risk, where-by "uncertainty" arises when the reward-probability is unknown, and risk is given by the variance of the probability distribution (Epstein, 1999; Huettel et al., 2006; Christopoulos et al., 2009; Tobler et al., 2009; O'Neill & Schultz, 2010). Where-as resolving uncertainty may drive exploration (Dayan & Sejnowski, 1996; Dearden et al., 1998; Daw et al., 2006; Esber & Haselgrove, 2011), risk avoidance may drive individuals *away* from exploration. Study 2 controls for these competing factors to explore how each might contribute to developmental differences in exploratory choice.

Participants and Design: Three-, four-, and five-year-old children participate in 10 marble-box trials with 5 ratios, two of each type (5:1, 3:1, 1:1, 1:3, 1:5). For each ratio five trials are "high variance" trials, in which risk is high, and five trials are "low variance", in which risk is lower. Children in each age group are then randomly assigned to one of two between-subject conditions: Knowledge-control or Knowledge-gained. Power analyses based on preliminary data from Study 1 were performed to determine appropriate sample size. Assuming a mean difference of .2 and standard deviations of .3, 20 participants in each age group, for each condition will be tested, totaling 120 children.

Procedure: In the Knowledge-control condition, children are told that regardless of their decision (to explore or exploit) they will get to see the reward in the uncertain box (though they only get to keep the reward from the box that is selected). Thus, this condition controls for uncertainty in that children do not need to select the uncertain box in order to see its outcome. This allows us to evaluate the role of risk in driving exploratory choices in early development. In the Knowledge-gained condition, children are told they will see the outcome of the uncertain box only if it is selected (as with Study 1). After ten trials of choosing between these outcomes, children are rewarded with the marble game (as described above.)

Predictions: If younger children are insensitive to probability information and simply driven to prefer uncertainty, then regardless of Condition and Distribution of expected value in the unknown boxes, three-year-olds should always select the uncertain box. However, if these youngest children are sensitive to probability information, highly information seeking, but simply not risk averse, then three-year-olds should show different patterns of responses in the Knowledge-gained and Knowledge-control conditions. When the drive to resolve uncertainty is controlled for because it will be resolved regardless of choice (in the Knowledge-control condition) children's exploratory choices should reflect sensitivity to the distribution of expected reward, with children being more likely to choose the uncertain box as its expected value increases as compared to the known box. In contrast, when uncertainty is only contingently resolved (Knowledge-gained Condition), then three-year-old children should always favor the uncertain box regardless of expected value.

Based on preliminary data from Study 1, the predicted pattern of results for older children are as follows. If older children are risk averse, then results between "high variance" and "low variance" condition should differ, with children being more likely to choose the uncertain box on "low variance" trials than on "high variance". If older children are also sensitive to uncertainty, then results between the Knowledge-gained and Knowledge-control condition should also differ, with children showing an overall decrease in choosing the uncertain box in the Knowledge-control condition. Taken together, this design allows for multiple patterns of results; all allow us to reveal the factors that lead to developmental differences in risk-aversion and uncertainty biases influencing exploration-exploitation trade-offs.

Hypothesis 2: The effort and variability in exploration should increase as expectations about information gain increase, leading to greater discovery.

Study 3: Do children use information about task difficult to drive exploration?

Study 3 investigates whether children are motivated to explore an object longer and more variably when they believe learning about it will be more difficult (have higher information gain). In this study, we gave children a causal learning task, to "figure out how it works" because causal learning may play a privileged role in exploration. Gopnik (1998) has argued that the act of generating causal explanations for events may actually lead to positive physiological sensations. Alvarez and Booth (2011) have demonstrated that preschoolers prefer to uncover causal information about an item, rather than other (e.g. perceptual) details, suggesting a bias for children to uncover causally explanatory information. Children even treat causal information as a reward, persisting through a tedious task if promised causal information in return (Alvarez & Booth, 2014).

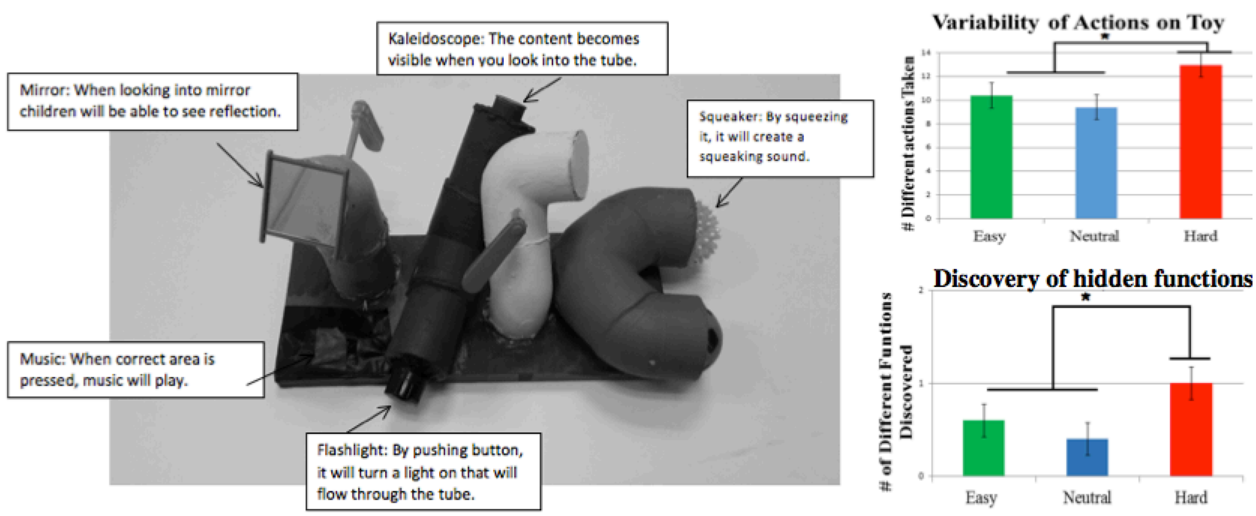


Figure 3. The novel toy used in Study 3 (left), preliminary results from four-year-old children (right). Children in the Difficult condition explored more variably (right top) and discovered more hidden functions of the toy (left top).

Participants and Design: Three- to five-year-old children participate in an Easy, Neutral, or Hard condition. Power analyses based on preliminary data from four-year-olds were performed to determine appropriate sample size. Assuming results follow these means and extrapolating SD, power = .80, and α = .05, 20 participants in each age group, for each condition will be tested, totaling 120 children.

Procedure. Children play an initial short warm-up task with an experimenter and are then told that they will get to play with another toy. In the Easy condition, children are told "This toy is easy, most children figure out all there is to learn about it." In the Neutral condition, children are told "I do not know if this toy is easy or hard because you are the first person to play with it." In the Hard condition children are told "This toy is hard, most children do not figure out all there is to learn about it." This "easy/hard" language is chosen in order to provide cues to information gain, without explicitly instructing the children that there was more to do and learn. Following these instructions the child is asked to "figure out how the toy works" and left to play with the toy until they stated they were finished, or an eight-minute time period expired. Following "free play" standards in other novel toy exploration paradims (e.g. Bonawitz, Shafto et al, 2011), if children stop playing with the toy for more than fifteen seconds, the experimenter prompts "Are you all done or would you like to keep playing with that toy?" If children say they are done, the experimenter returns to conclude the session. If the child says she would like to continue, she is left to play until she either says she would like to stop, or if she again stops interacting with the toy for more than fifteen seconds. Following the second cessation, the experimenter concludes the session.

Predictions: The variability of children's action (how many different kinds of actions they take) as well as learning (how many of the original functions they discover) are coded from video. Our preliminary results suggest that children take information about the difficulty of a toy into account during exploratory play. Children who are told that task is "hard" show more variability in their play and find more hidden functions than children who were told the toy is easy or for children who are given no information about the toy. If younger children have a stronger preference to explore uncertainty, then results should reveal developmental differences in exploration of the toy. Overall, younger children might be more likely to generate more variable exploration of the toy and play longer than older children.

Hypothesis 3. Given a choice between two uncertain outcomes, effective active learners should select the outcome with higher information gain.

Study 4. Do children consider the effects of evidence on information gain prior to choosing an outcome? Does this ability develop in the preschool years?

Study 4 investigates whether there are developmental differences in children's use of information gain to inform choice. Children are shown three bags and taught about the distribution of their contents.

One bag has only red marbles in it, one only blue marbles, and the third has equal parts red and blue marbles mixed together. The experimenter shuffles just the single-color bags and draws a marble from one of the shuffled bags. The experimenter then draws a marble from the two-color bag. The child is given the option to observe just one of the two marbles. Both samples are uncertain and have equal probability of red or blue marbles, so children will learn something about the immediate marble that was observed. However, if the child chooses the marble drawn from the shuffled bags, they gain greater information: the outcome will simultaneously inform the child as to which of the two shuffled bags is which because the child knows which of the two shuffled bags the marble was drawn (and that the bags are uniform). The task is partly inspired by early studies on uncertainty and risk, which employed a similar urn-sampling method with adults (Ellsberg, 1961), and also by a method employed in my own work (Denison et al, 2014), in which an option is blindly selected from one of two randomized bags, thus leading to unbiased sampling.

Participants and Design: Three-, four-, and five-year-old children participate in one of two studies. Power analyses using preliminary data from three- and four-year-olds was performed to determine appropriate sample size. Assuming results follow these trends, power = .80, and $\alpha = .05$, 18 participants in each age group, for each condition will be tested, totaling 54 children.

Procedure. Children are asked to make a choice to learn about one of two marbles, sampled as described above. After the outcome has been revealed, children are asked to report the bag's contents.

Preliminary results and predictions: Our preliminary results with 5 three-, 9 four- and 6 five-year-olds reveal a strong developmental effect consistent with predictions. All three-year-olds choose to observe the marble with lower information gain (from the known bag), the majority of fours choose the marble with higher information gain, and all five-year-olds selecting the marble with higher information gain. For the fours and fives that selected to learn about the high IG marble from the unknown bag, most five-year-olds were then able to use that information to report the color-contents of the bag, however four-year-olds reporting from this evidence is at chance. These preliminary results suggest that where-as three-year-olds do not select the bag with higher information gain, four-year-olds do, but are unable to use this information to dynamically update their knowledge. Only five-year-olds seem able to both select the bag with higher information gain and then use this knowledge to inform their uncertainty.

Study 5. Are children who are transitioning between beliefs more motivated to explore uncertain outcomes when the information from those outcomes informs those beliefs?

While the previous study has focused on how particular data can be more or less informative, these studies look at whether the current state of the learner's beliefs influences the expected information gain. If one has greater uncertainty about their current beliefs, than any new information can be highly informative. However, if one has strong certainty about their beliefs, then the probability of unlikely and thus informative information is low, and so seeking out data under certainty is suboptimal. Throughout development, children are constantly revising their beliefs, sometimes moving from strong beliefs that are inaccurate, to transition states when there is high uncertainty, to strong beliefs with higher accuracy. These changes occur in children's theories about other minds (Goodman et al, 2006; Wellman & Liu, 2004), psychosomatic events (Notaro, Gelman, & Zimmerman, 2001; Bonawitz, Fischer, & Schulz, 2012), knowledge about biological kinds and germs (Carey, 1985; Kalish, 1996), and forces and physical systems such as balance (Bonawitz et al, 2014; Inhelder & Piaget, 1958, 2013; Karmiloff-Smith & Inhelder, 1975; Siegler 1976). In the proposed study, we leverage the finding the children transition between knowledge states in these domains and that there are individual developmental differences in these transitions. A five-year-old child who is transitioning between an understanding of germ transmission might simultaneously be strongly convicted in their *correct* understanding of false-belief events, but also strongly convicted in their *incorrect* beliefs about the role of distance on torque in balance scale tasks. Thus, this child might pass-up opportunities to learn outcomes of false-belief or balance-scale tasks but be interested in observing outcomes from ambiguous contamination events.

Participants and Design: Three- to six-year-old children participate in several sessions over a one month period. Measures include both discrete forced choice responding and continuous (mean number of book choices) values as compared across three categorical groups based on children's belief states (early incorrect conviction, transitional state, late correct conviction). Power assume power = .80, and α = .05, require 20 participants in each age group (totally 60 participants). However, because these groups cannot be discerned prior to testing, we assume some noise in the distributions, conservatively test 80 children.

Procedure. Children are visited at their daycare or school three times, and a follow-up with parents is conducted 2 weeks after the child's third visit. The first visit consists of administering the false-belief battery (Wellman & Liu, 2004) as well as a germ battery, assessing children's understanding of contagions. On the second visit children participate in an assessment of their balance scale knowledge (Siegler, 1976) as well as an assessment of their beliefs about psychosomatic events (Notoro, Gelman, & Zimmerman, 2001). Children are not given any feedback or training following their responses to these batteries. Children's responses on the batteries on visits one and two will be used to classify children's belief states for each domain (false-belief, germ, psychosomatic, and balance). On the third visit, children are given four trials, one from each domain. Children are also introduced to four objects, each with an uncertain outcome. For example, one object is a jack-in-the-box with two levers (either lever might cause a toy to pop up) and children are shown one trial in which evidence is confounded (both levers depressed simultaneously so it is unknown which lever causes which toy; see Schulz & Bonawitz, 2007). Another toy involves a "Plinko-like" machine, with a ball that can bounce to drop down one of a few possible tracks. (Pilot testing ensures that these toys are not so interesting as to always trump the domain-specific uncertainty tasks.) Children are then given a scenario in one of the four domains. For example, for the false-belief domain, children read a Sally-Anne book about a character Sally who places her toy in a basket; Anne moves the toy while Sally is away, and then Sally is about to come back to the room to look for her toy. Children are given the option of either (a) finding out where Sally goes to look for her toy, *or* (b) observing the outcome of a trial on the matched "uncertainty" toy. For the balance scale domain, children are shown a balance with three weights placed on the final (fifth peg) and three weights placed on the first peg – a stand holds the balance in place while the weights are being placed. Children either have the choice of observing the outcome of the balance when the stand is removed or they can observe the outcome of the 2nd uncertainty toy. And so on for the other two domains.

Following the third session children are read four short books that provide a story and causal mechanism information about each domain (e.g. see Bonawitz, Fischer, & Schulz, 2012). These books are then sent home with parents. Parents are instructed on how to offer to read their child the books (without inducing bias) over the course of two weeks. Each day children may choose from any of the books and may choose multiple books. Parents are given stickers to mark the back page of the book each time it is selected by and read to the child. At the end of two weeks, parents are contacted to report on the number of times each book was requested by the child.

Predictions. Information gain predicts that children with greater uncertainty in their current beliefs should be more interested to explore and learn outcomes to ambiguous events in those transitional domains. Thus, we predict that in test trials children who are "transitional" (as given by pre-tests) will be more likely to choose to see the outcome from that domain over other domain-general toys with uncertain outcomes. Children should also be more interested in reading books and learning causal relevant information in those transitional domains, as compared to domains where children have conviction in their beliefs (either because they are pre-transitional or because they are post-transitional). This research allows us to investigate the degree to which children drive their own cognitive development, through actively seeking out information in domains that are associated with uncertainty both in laboratory settings and also in natural "wild" parent-child settings at home.

Relationship to prior NSF support

Although I have not had direct NSF support myself, I have had the experience of helping write a grant that supported my post-doctoral training (*Causal learning as sampling*: BCS-1023875, 9/1/10 to 8/30/13, under PIs Alison Gopnik and Thomas Griffiths). Because there is some relevance of these past findings to the current proposal, I briefly discuss them here. Gopnik and Griffith's grant focused on the question of whether children's minds sample. If they do, that might help to explain how children approach learning from probabilities, and specifically how they are able to choose hypotheses given the computational complexity of evaluating probabilities when the space of hypotheses is large. Our grant explored whether children "sample" hypotheses from a probability distribution. For example, in one study we showed children a box full of red and blue chips in different proportions, and asked them to guess the color of a chip invisibly selected at random. Children's responses were variable: the same child would sometimes say red and sometimes say blue. However, as we varied the proportion of red and blue chips across condition, the proportion of "red" or 'blue" responses also closely tracked the probability of the relevant hypotheses: children said "red" more often when that was more likely to be the correct answer. Additional experiments showed that children were employing a more sophisticated strategy than frequency matching, instead responding proportional to the predicted posterior distribution. This "matching to the posterior" is a signature of sampling (Denison, Bonawitz, Gopnik, & Griffiths, 2010, 2013). Additional studies explored different specific sampling rules that children and adults might employ in simple causal learning paradigms (Bonawitz, Denison, Gopnik, and Griffiths, 2011; 2014), and how these approaches help us understand conceptual search in larger hypothesis spaces (Bonawitz et al. 2012).

Broader Impacts. The proposal involved an interdisciplinary collaboration between developmental psychology and computational modeling. The development of a WSLS algorithm contributed to machine learning. The research has also given us new insights into the relation between early childhood cognition and scientific thinking, with relevance for science education, in general, and early childhood education, in particular (see Gopnik, 2012).

Bonawitz Publications directly resulting from the previous grant (11). Bonawitz, Denison, Chen, Griffiths, & Gopnik (2011); Bonawitz, Denison, Gopnik, & Griffiths (2014); Bonawitz, Denison, Griffiths, & Gopnik (2014); Bonawitz, Gopnik, Denison, & Griffiths (2012); Bonawitz & Griffiths, (2010, *in revision*); Bonawitz, Ullman, Gopnik, & Tenenbaum (2012; Bonawitz et al. (*in revision*); Denison, Bonawitz, Gopnik, & Griffiths (2010, 2013); Gopnik & Bonawitz (2014).

Relationship of prior support to proposed work. The sampling approach connects to the rational choice models proposed here. For example, learners may be variable in their exploration, but – as the sampling hypothesis suggests, this variability may be also be systematically related to the expectation about rewards in the environment. This previous research also provides a story about how learners might actually carrying out the computational demanding task of evaluating information gain. This prior work supports the claim that children are sensitive to probabilistic information in the environment and approximate optimal solutions by sampling a hypothesis from this information. Thus, children's behavior on aggregate approximates these computational models, but does not require an individual learner to be able to exhaustively evaluate the potential outcomes of intervention on full probability distributions.

BROADER IMPACTS OF THE PROPOSED WORK

Bridging disciplines

In addition to the benefits of this collaboration for the researchers involved, it is anticipated that carrying out this project will lead to: (1) New laboratory methods for studying questions in developmental psychology and information theory; (2) A deeper understanding of how children may be approaching the problem of efficient active learning, with a focus on the factors that influence learning, exploring the role of information gain and its implications for motivation and training in education. (3) Connections between state-of-the-art methods in machine learning, computer science, statistics, economic theory, and accounts of children's exploration.

Most importantly, this work attempts to bridge disparate literatures, including developmental cognitive psychology, education, decision sciences, and computational modeling. All too often studies in one field have the potential to inform our understanding of concepts in other fields, but are overlooked. This proposed research plan provides a vehicle to improve that dialog. For example, a difficulty in education relates to the challenges of exploring the theoretical underpinnings of behavior; bringing together the strengths of multiple disciplines has the potential to resolve these issues. In particular, choice and information theories developed in economics and the decision sciences inform our understanding of children's cognitive choices to explore. The cognitive and mathematically rigorous approach that establishes the precise factors that drive exploratory biases can lead to educational practices that take advantage of these individual drives. And, the extension of these theories to under-represented populations can not only help us understand how broader societal constraints can lead to early individual differences – with possible snow-balling consequences in later cognitive development and academic performance, but can help us to develop early interventions that improve the lives of these populations.

Plan for Dissemination of Results

Given the interdisciplinary nature of this research, the goal is to disseminate results across the different disciplines contributing to it. To this end, results will be presented to the following audiences: Developmentalists (through presentations at Society for Research in Child Development and the Cognitive Development Society); Cognitive scientists (Annual Conference of the Cognitive Science society); Decision Scientists (Society for Judgment and Decision making conference)*;* Computer scientists (Neural Information Processing Systems). Publications describing this work will be submitted to journals that target a broad audience, such as the *Proceedings of the National Academy of Sciences*, as well as more specialized journals in the disciplines identified above (e.g. *Cognition, Cognitive Science, Journal of Behavioral Decision Making, Developmental Psychology, and Child Development*). The PI also has a history of publishing in open access journals, and will continue this practice.

Broader Public: Parents and early childhood educators provide a particularly important population for learning about this work, and the PI will continue her public outreach efforts. This includes dissemination parent newsletters with results written in lay language to local daycares and public spaces where we often recruit and give informal presentations. These spaces include science museums, play centers, zoos, libraries, and fairs such as the Rutgers Day fair which includes an average outreach to over 100 families. I often discuss my research with journalists and will also disseminate my work to the media.

Perhaps most importantly, our lab works with underprivileged communities. Members of these communities may not typically engage with researchers who are studying early learning. These communities offer important perspective for basic science researchers, because they help us understand the unique constraints these populations face and the degree to which our theories generalize to broader communities. Thus, outreach allows us to work towards a better understanding of how to best engage diverse populations in research on active exploration, the role of parental involvement, and education more broadly. And, by connecting with early educators and parents in under-privileged communities we can help educate members about the most effective early childhood interventions.

Interactions with Education and Training

The primary use of funds will be to support a postdoctoral researcher with a background in cognitive development in acquiring new skills in the methods of computational modeling (see **Postdoctoral Training Plan**). I also teach large undergraduate classes in cognitive science, and graduate courses including Introduction to Cognitive Science and Computational Models of Cognition; all emphasize connections between cognitive science and developmental psychology. These classes provide the first exposure to cognitive science and computational methods for many students, some of whom go on to work as research assistants in my lab (currently there are 12 students in my group). The proposed research would provide these students with exposure to ideas from developmental psychology and cognitive science, and experience in research.

This research will also provide a vehicle to train women and minorities, who make up a large percentage of the population in our department, in computational skills necessary that may transform education and science more broadly. The PI has a record of facilitating these experiences, through her own expertise as a female computational developmentalist and as one who has trained numerous female and minority maters students and senior honors undergraduate students, who have gone on to apply computational approaches in their advanced degrees and professional positions. The proposed research will bring us closer to having a formal, evidence-based understanding when and why epistemic hunger can be deployed toward educational goals, while facilitating attainment of computational skills by women and minorities.