

Learning in the Social Context:  
Inference, Exploration and Evaluation in Early Childhood

by

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Submitted to the Department of Brain and Cognitive Sciences in partial fulfillment of  
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**Abstract**

Some of the biggest achievements in our lives are made even before we learn to tie our shoes. Within a few years of life, we master a language, acquire cultural norms, and develop naïve, yet rich, abstract, coherent theories about how the world works. How do young learners achieve such a feat? The goal of my thesis is to lay the groundwork for a unified account of a rational inference mechanism that underlies this remarkable human faculty to learn so much, so fast, from so little. The first study (Chapter 2) provides evidence that 16-month-old infants can use co-variation information among agents and objects to infer the cause of their failed actions; depending on their attribution, infants either approached another agent or another object. The second study (Chapter 3) shows that 15-month-old infants consider both the sample and the sampling process to rationally generalize properties of novel objects in the absence of behavioral cues. The results are consistent with the quantitative predictions of a Bayesian model, and suggest that infants' inferences are graded with respect to the probability of the sample. Finally, the third study (Chapter 4) shows that older children make sophisticated inferences about properties of agents; children evaluated an informant based on information he provided, and such evaluations affected how children learned from that informant. These studies provide evidence for rational, probabilistic, domain-general inference mechanisms in preverbal infants, and demonstrate how young learners seamlessly integrate data from different sources in ways that affect their exploration, generalization, and evaluation of both the physical and the social world.

Thesis Supervisor: Laura E. Schulz

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*For Hyora & Dilo,  
and their continued journey.*

# Contents

<b>1. Understanding How We Learn</b>	<b>...11</b>
1.1 Core knowledge and intuitive theories: What we know and what we learn	
1.2 Hierarchical Bayesian models: A formal learning principle	
1.3 Learning from sparse data: What we learn from	
1.4 Towards a unified account of learning from rational inference	
<b>2. Infants rationally infer causes of failed actions from statistical information</b>	<b>...29</b>
2.1 Introduction	
2.2 Experiment 1	
2.3 Experiment 2	
2.4 General Discussion	
<b>3. Infants consider both the sample and the sampling process in inductive generalization</b>	<b>...43</b>
3.1 Introduction	
3.2 A Bayesian Model	
3.3 Behavioral Studies and Comparison with Model Predictions	
3.3.1 Experiment 1	
3.3.2 Experiment 2	
3.3.3 Experiment 3	
3.3.4 Experiment 4	
3.3.5 Experiment 5	
3.3.6 Joint inference vs. strong sampling assumption	
3.4 General Discussion	



<b>4. Who tells the truth, but not the whole truth? Children modulate their inferences based on informant's past omission of relevant information</b>	<b>...75</b>
4.1 Introduction	
4.2 Experiment 1	
4.3 Experiment 2	
4.4 General Discussion	
<b>Chapter 5. Learning in Social Context</b>	<b>...95</b>
5.1. Summary	
5.2 Methodological implications	
5.3. On socially learning from others	
5.4 Conclusion	
<b>References</b>	<b>...107</b>



# Chapter 1

## Understanding How We Learn

Imagine a 2-year-old. She watches her mother flip a switch and sees a light turn on. The toddler tries to flip that switch. Then she turns to a different switch – for example, one on her new toy, and the toy plays music. She now tries a novel action, flipping it back, and the music stops. She finally flips a switch on the vacuum cleaner (which, unbeknownst to the child, is unplugged). Seeing that nothing happens, she turns to her brother to ask why it doesn't work.

From just a few minutes of watching this child play, you can see the whole range of behaviors associated with what we call "learning": observation, imitation, inductive generalization, production of novel interventions, communication with others and even asking for more information. The transition between learning from others and learning from her own exploration of the environment appears seamless, and the child is in command of her own behavior in every aspect. Embedded in the mundane, everyday

activity of a young child is a remarkable ability to flexibly combine a host of ways to maximize learning in a given context.

A fundamental challenge for theories of human learning is to fully appreciate this distinctive human faculty to flexibly learn from others as well as from the physical world, and to provide a unified account that explains how we can learn so much, so quickly, yet so accurately, in a complex, noisy environment. In this thesis, I aim to provide the groundwork for building an account of a learning mechanism that makes this daunting task feasible even for a 2-year-old.

In my dissertation, I continue in the tradition of advancing a unified account of rational inference across areas traditionally thought of as domain-specific knowledge (with respect to both the core systems of knowledge and our intuitive theories) and those traditionally thought of as domain-general processes (e.g., the ability to draw inductive inferences from evidence). As such, my work draws from the cognitive development literature on infants' rich, abstract conceptual repertoire (Spelke, Breinlinger, Macomber, & Jacobson, 1992; Carey & Spelke, 1994) and children's naïve theories in different content domains (Gopnik & Wellman, 1994; Carey, 2009) and the hierarchical Bayesian framework for understanding human cognition (Tenenbaum, Kemp, Griffiths, & Goodman, 2011).

In what follows, I describe the key ideas that constitute the theoretical origins of my work. First I review developmental research on core systems of knowledge and children's naïve theories of the world (1.1). I then briefly introduce hierarchical Bayesian inference mechanisms as a formal learning principle (1.2), and review recent research predating my work that provides cases of learning in which children's rich understanding of the world interacts with powerful inferential capacities to construct

abstract knowledge (1.3). Finally, I conclude Chapter 1 with a discussion of what this dissertation aims to contribute theoretically, methodologically, and empirically, to this research tradition (1.4).

## **1.1 Core knowledge and intuitive theories: What we know and what we learn**

In the past few decades, research in cognitive development has transformed our views about both the content and the form of children's knowledge about the world (Carey, 1985, 2009; Keil, 1989; Gopnik, 1988; Perner, 1991; Gopnik & Wellman, 1992; Wellman, 1990). One direction of this transformation was spurred by hundreds of studies showing how much children know about the world. Especially with the development of looking-time methods, research has revealed that an infant's mind is neither a "blooming, buzzing confusion" (James, 1890) nor a simple sensorimotor machinery that merely reacts to an external stimulus, but much the opposite; even very early in life, infants possess a rich, abstract understanding of their environment that forms the core of the end state of cognitive development. Such initial representational repertoire, referred to as core knowledge (Spelke & Kinzler, 2007) or core cognition (Carey, 2009), is thought to be largely shared by other non-human species (Emlen, Wiltschko, Demong, Wiltschko, & Bergman, 1976; Regolin & Vallortigara, 1995; Mascalzoni, Regolin, & Vallortigara, 2010; Gallistel, 1989; Blaisdell, Sawa, Leising, & Waldmann, 2006) and have distinct evolutionary origins across different domains. These core content domains include: (a) objects, and the kinds of information we bring to bear on understanding events that involve physical entities in space (Spelke, 1990;

Baillargeon & DeVos, 1991; Carey & Xu, 2001), (b) number, with respect to both the magnitude of large numbers (Xu & Spelke, 2000; McCrink & Wynn, 2004; Lipton & Spelke, 2003) and a precise representation of small numbers (Wynn, 1992; Feigenson, Carey, & Spelke, 2002; see Feigenson, Dehaene, & Spelke, 2004, for review), and agents, which include the core principles governing people's perceptions, attention, goals, and their actions (Luo & Johnson, 2009; Johnson, Slaughter, & Carey, 1998; Carpenter, Nagell, Tomasello, Butterworth, & Moore, 1998; Woodward, 1998; Gergely & Csibra, 2003). Armed with such abstract representations of the world, infants already show early signatures of bringing these resources together to make accurate predictions of events that occur among objects and people (Leslie & Keeble, 1987; Muentener & Carey, 2010; Saxe & Carey, 2006; Hamlin, Wynn, & Bloom, 2007). A vast amount of literature now attests to both the richness and sophistication of infants' and young children's system of knowledge that far exceeds the limits that Piaget proposed more than half a century ago.

While it is important to study the earliest possible stages of cognition, it is also important to study how it changes; that is, how children build coherent systems of conceptual knowledge beyond what is in the innate repertoire, and how such representations change and grow. Decades of research in cognitive development has revealed that the structure of representations in young children is coherent and stable, but at the same time, malleable. One prominent approach has likened children's naïve theories to scientific theories (Carey, 1985; Keil, 1989; Gopnik & Wellman, 1992). Such an analogy has been extremely fruitful in characterizing the content and the structure of knowledge in young children as well as their developmental trajectories. Through their interactions with the external environment and interventions on its causal structure,

children develop abstract concepts such as *weight, gravity, birth, interference, or hope*, and construct a system of beliefs (naïve theories) about various domains such as the physical (Baillargeon, 1993), biological (Gelman & Wellman, 1991; Hatano & Inagaki, 1994; Kalish, 1996), and psychological worlds (Flavell, 1999; Perner, 1991; Gopnik & Wellman, 1992). Just like scientists, children not only use their existing knowledge to predict and explain their experience, but in the face of new evidence, they revise and update their theories (Gopnik & Meltzoff, 1998; Carey & Spelke, 1994). Importantly, these revisions are not just tweaks or refinements to existing concepts and theories, but involve fundamental shifts in the child's conceptual repertoire that result in genuine discontinuities in children's understanding of the world (Carey, 1985, 2009).

All these enterprises – discovering the initial representational capacities and their signature limits in core domains, investigating the structure and the content of children's conceptual knowledge about the world, and describing how children's representational resources go through changes in the course of development – have transformed our understandings about what we know (and don't know) about the world, as well as what we learn (and don't learn) about the world. However, even a full description of what infants know and how their knowledge changes would not make a complete picture of learning. The domain-specific core systems of knowledge, grounded in distinct evolutionary origins, might help characterize the initial state but don't address the inferential processes that guide learning. The approach to understanding conceptual development as a process akin to theory acquisition has focused on the content and structure of representations, but there has been little empirical support for the claim that even very young human learners are equipped with rational inferential capacities that allows these representations to change and grow. To

fully capture the faculty for learning in a complex, social environment, we need an account of the inferential processes themselves that support learning from both the social and the physical world in the ordinary course of everyday life.

## **1.2 Hierarchical Bayesian models: A formal learning principle**

The history of cognitive science has provided many different proposals for domain-general learning mechanisms, including operant or classical conditioning, associative learning principles, simple behavioral mirroring, or genetically programmed changes in our perceptual system that occur with relevant input. None of these, however, can fully account for our remarkable ability to develop rich, abstract theories from sparse data. Throughout this thesis, when I refer to a domain-general learning mechanism<sup>1</sup>, I am referring to the capacity to engage in inductive reasoning based on observed evidence and rich prior hypotheses about how the world works, for which principles of Bayesian inference provide a very good formalization.

Consider again the example of the baby who flips the switch on her toy. In order to learn, the child has to assimilate new data into existing representations (schemas, in Piaget's terms) and change her representations to accommodate new data (Piaget, 1929; 1954). Developmental researchers took a less formal approach to qualitatively characterize the learner's representations and to describe the process by which they change through learning. Recent advances in computational approaches to

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<sup>1</sup> In this thesis, I make no theoretical commitments about whether this process should be consciously accessible or not, and discussions about the extent to which this capacity is fundamental for human cognition is beyond the scope of this thesis.



understanding human cognition have offered a way to capture both the representations and the process by which they change in probabilistic models of inference. In particular, hierarchical Bayesian models of human learning have provided elegant formalizations of how abstract knowledge can be learned by updating the learner's degree of belief in hypotheses to account for novel evidence (Tenenbaum, Griffiths, & Kemp, 2006; Tenenbaum et al., 2011).

Bayes' rule expresses how we can infer the probability of a hypothesis given observed data (the *posterior probability* of a hypothesis) by assessing the *prior probability* of the hypothesis given the learner's current theories ( $P(h)$ ), and the degree to which the data are expected under a given hypothesis (*likelihood*,  $P(d|h)$ ). More formally, the posterior probability of a hypothesis is proportional to the product of the prior probability  $P(h)$  and the likelihood  $P(d|h)$ , relative to the all other hypotheses  $h'$  in the learner's hypothesis space  $H$ .

$$P(h|d) = \frac{P(d|h)P(h)}{\sum_{h' \in H} P(d|h')P(h')} \propto P(d|h)P(h)$$

Imagine you just sneezed. Given this piece of evidence, you might entertain a few possible hypotheses: perhaps you have a cold ( $h_1$ ), a stomach flu ( $h_2$ ), or a pollen allergy ( $h_3$ ). If you live in Massachusetts and it's January, your assessment of the prior might quickly rule out  $h_3$  as an explanation; a pollen-induced allergy in January is quite unlikely in Massachusetts. Likelihood  $P(d|h)$ , in contrast, favors  $h_1$  and  $h_3$  over  $h_2$ ; both cold and allergy are likely to induce sneezing whereas a stomach flu is not. Because Bayes' rule scores hypotheses on both their priors and likelihoods, you can easily infer that the most likely explanation for your symptom is  $h_1$ , cold, which scores high on both terms.

Of course, the learner's inference may change with additional data. Suppose you've been sneezing for two weeks straight, with no other symptom. The evidence now seems quite surprising under  $h_1$ , as two weeks of sneezing in the absence of fever is quite unlikely given the hypothesis that the underlying cause is a cold. And if you notice that your orchid plant has been in full bloom for a while, you might now consider  $h_3$  (allergy) as much more plausible than  $h_1$  (cold).

The learner's prior knowledge about the world also plays an important role by providing a rich repertoire of priors over which this inference engine can operate. These priors act as powerful constraints (both for the good and the bad) to quickly eliminate some hypotheses while weighting others more, to allow accurate, robust inference even from sparse data. For example, you could easily rule out  $h_3$  (allergy) because your prior knowledge about the climate of Massachusetts (among many other things) suggested the probability of having pollen-induced allergy in January is quite low; your knowledge about orchid plants provided reasons to consider  $h_3$  despite the season<sup>2</sup>.

As illustrated above, Bayes' rule can capture a variety of inferential practices we exercise every day, formalizing our intuitions about why some hypotheses seem like better explanations for observed evidence than others, how a previously endorsed explanation might become less plausible, or why a piece of evidence appears quite surprising under the currently favored hypothesis. Hierarchical Bayesian models also offer an account for how such theory-like constraints can emerge from data (Kemp & Tenenbaum, 2008; Kemp, Perfors, & Tenenbaum, 2007; Goodman, Ullman, &

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<sup>2</sup> If you sought even more information to confirm your suspicion, you might have discovered that orchid flowers are actually quite an unlikely cause for a pollen-induced allergy!

Tenenbaum, 2011). As the name 'hierarchical' Bayesian model suggests, these inferences not only use acquired data to update local belief representations but operate at multiple levels of knowledge to allow patterns of data to be abstracted further up, ultimately deriving fundamental principles that shape our most abstract theories of how the world works; at the same time, such abstract knowledge constrains inferences at lower levels to facilitate learning. Such simultaneous learning at multiple levels of abstraction (Tenenbaum et al., 2011) provide a powerful account for how learning at so many levels occur from a learner's limited experience with the world.

### **1.3 Rational learning from data: Evidence in early childhood**

One of the hallmarks of cognitive development is the emergence of coherent, abstract, large-scale systems of knowledge within just a few years of life. Understanding the origins and changes in the content and structure of a child's representations is critical for revealing how we achieve such a feat; the current conceptual repertoire of the learner guides her interaction with the world, and her abstract theories about the world interact with her interpretation of new data. However, a full account of learning must also address the properties of the learning processes themselves: their speed, robustness, flexibility, malleability, and ability to deal with incompleteness and uncertainty. By marrying decades of empirical, theoretical endeavors to characterize children's knowledge and the formal framework for understanding human learning as probabilistic inferences at multiple levels of abstraction, researchers have begun to capture early learning as an interaction between systems of rich priors and the operations of a powerful inference engine that perform computations over observed evidence. Such advances have not only added rigor and precision to expressing ideas

like domain-specific knowledge and domain-general learning mechanisms, but have also spawned an interdisciplinary approach to studying early learning in more precise, quantitative, and formal terms. In particular, recent studies have begun to show that children do indeed draw rational inferences from patterns of data, suggesting that abstract knowledge can be acquired from formal properties of input such as statistical information embedded in everyday events (see Schulz, 2012; Gopnik & Wellman, in press; Xu & Tenenbaum, 2007, for reviews).

### **1.3.1 Causal learning from patterns of data**

Recently, a new field of research inspired by the principles of Bayesian inference has begun to reveal children's impressive abilities to draw abstract causal inferences from sparse data. For example, studies have shown that children as young as two years old can use conditional dependencies across objects and their outcomes to make accurate judgments about what causes a machine to activate (Gopnik, Sobel, Schulz, & Glymour, 2001). Along with formal analyses of learning from evidence, studies provided evidence that children's inferences operate across content domains and are rationally influenced by both the evidence and their own prior knowledge about the world (Schulz & Gopnik, 2004; Schulz, Bonawitz, & Griffiths, 2007a). Impressively, based on just a few pieces of evidence, preschoolers inferred abstract physical causal laws behind interactions between novel physical objects, and based on these laws they even inferred the existence of a hidden object (Schulz, Goodman, Tenenbaum, & Jenkins, 2008a).

The data available for learning are not limited to things and events that just happen; children also learn from their own interventions. Schulz, Gopnik, and Glymour

(2007b) looked at preschoolers' ability to distinguish different possible causal structures of a toy from observed evidence. In addition to showing that children correctly infer the correct causal structures from evidence offered by an experimenter, they showed that children's spontaneous free play with the toy, albeit noisy, generates useful evidence that supports accurate learning. For example, after playing with a toy themselves, children were more likely to choose the correct causal chain structure if the toy actually had causal chain structure than when it had common cause structure.

Additionally, children are sensitive to certain formal properties of evidence that can systematically guide their own exploration and intervention, including a sensitivity to confounding (Kushnir & Gopnik, 2005; Schulz & Bonawitz, 2007; Sodian, Zaitchik, & Carey, 1991). For instance, children explore more when evidence is consistent with multiple hypotheses. Schulz and Bonawitz (2007) showed that preschoolers are more likely to override their novelty preference to explore a familiar toy when the toy offers confounded evidence (e.g., two levers pressed together make two toys pop up) than when it offers unambiguous evidence (e.g., two levers pressed separately make each toy pop up). Gweon and Schulz (2008) showed that preschoolers play with a toy more variably upon observing confounded evidence, and that those who generated useful evidence in the course of free play were in fact much more likely to learn the correct causal structure of the toy than children who observed unambiguous evidence from the beginning. Furthermore, children don't simply play more when evidence is ambiguous; they also design effective interventions that offer useful information (Cook, Goodman, & Schulz, 2011). These studies, along with others, have begun to draw attention to the underlying principle that guides children's actions.

### **1.3.2 Learning from statistical information**

One of many exciting aspects of these studies is that they show how children can keep track of events they observe to infer the underlying structure of the world. About a decade ago, a body of infant research had begun to reveal that an impressive sensitivity to statistical information is already present early in life. For example, infants can use transitional probability embedded in a continuous stream of artificial speech for word segmentation (Saffran, Aslin, & Newport, 1996). Numerous reports have corroborated and extended these findings to show that infants reliably represent, extract, and generalize abstract structure of the underlying input across different modalities (Kirkham, Slemmer, & Johnson, 2002; Marcus, Vijayan, Rao, & Vishton, 1999; Marcus, Fernandes, & Johnson, 2007; Johnson et al., 2009; Frank, Slemmer, Marcus, & Johnson, 2009).

Impressively, infants do not require lots of accumulated experience to extract the underlying structure. Xu and Garcia (2008) showed that infants as young as 8 months can form expectations about the properties of a sample (e.g., five ping-pong balls) from a population (e.g., a box full of ping-pong balls) and about a population from a sample. This ability to make generalizations from just a few samples to the whole population is at the core of the ability to draw inductive inference from minimal data. Furthermore, a recent study reports that 12-month-olds can form graded, probabilistic expectations of future events from minimal data, using their abstract understanding of object motion and space (Teglas, Giroto, Gonzalez, & Bonatti, 2007; Téglás et al., 2011). These results are exemplary cases where infants' inferential capacities and the rich constraints work together to reason about events without previous exposure to its elements, and to form

probabilistic representations that reflect the degree to which the observed events are surprising.

In sum, human learners, even before their first birthday, show impressive abilities to (1) extract useful structure embedded in a stream of events they experience, and (2) make predictions about single events from observed statistical properties of the environment. Taken together, the studies reviewed here provide evidence that learning can occur without heavy reliance on accumulated experiences within a content domain; a powerful learning mechanism (along with rich, innate constraints) allows rapid, yet robust, acquisition of abstract knowledge across content domains even from sparse evidence.

While the term ‘statistical learning’ might imply that such formal properties of data are independent of our conceptual understandings of agents and objects, it should be noted that there are no theory-neutral statistical data. Statistics are always *about* something, and the representations children do statistics over are saturated with theories throughout. Nevertheless, the flexibility of this learning mechanism with respect to its input as well as its output suggests that learning need not be constrained either by the content domain to which the information belongs, or by from where the information originates, as is the case with some perceptual processes (e.g., see Scholl & Tremoulet, 2000).

Until recently, evidence for these domain-general inferential capacities in early childhood has been provided almost exclusively in the context of simple physical reasoning. As a result, the rich social environment in which real-world learning actually occurs has received relatively little attention. However, research has begun to show that principles of Bayesian learning can account for inferences in social contexts. Xu and

Tenenbaum (2007a) showed that preschoolers generalize a label for a novel object more conservatively when the exemplars are sampled by a knowledgeable teacher than when they are chosen by the learners themselves. Furthermore, children draw accurate inferences about other people's preferences given apparent violations of the random sampling process. For example, when an agent (i.e., a squirrel puppet) deliberately draws a non-representative sample of toys from the population, preschoolers infer that the agent has a preference for the sampled objects (Kushnir, Xu, & Wellman, 2008). More recently, studies have shown evidence that even infants can use people's preferences to constrain their inferences from population to sample (Denison & Xu, 2009) and use sampling information to infer people's preferences (Ma & Xu, 2011).

These studies, however, only touch the tip of an iceberg; decades of developmental research have documented how social contexts affect what and how children learn. They learn from people's goal-directed actions (Woodward, 1998; Sommerville & Woodward, 2005), and they selectively imitate goal-directed behaviors (Gergely, Bekkering, & Kiraly, 2002; Meltzoff & Brooks, 2001; Lyons, Young, & Keil, 2007). Preschoolers even use information about others' epistemic states (Sabbagh & Baldwin, 2001; Koenig, Clément, & Harris, 2004) to decide whether to accept or reject information provided by others. The scope of behaviors studied in this body of research exemplifies the variety of sources of input a learner must face to learn about the world. This calls for not only empirical endeavors to study core inferential processes that underlie learning from different sources, but also a theoretical account of many phenomena that have been widely considered the results of 'constraints' or 'assumptions' applied specifically to social contexts. How can we use formal inferential principles, as well as our rich, abstract understanding of people, things, events, and their relations, to better



understand how we learn from our environment? In the next section, I present my approach to address some of these questions.

## 1.4 Towards a unified account of learning from rational inference

Theories of social learning have largely focused on domain-specific processes involved in our ability to attend to others' behaviors. By contrast, work on our early-developing sensitivity to statistical information and the capacity to draw inductive inferences from data has been relatively agnostic about the social context in which learning occurs, and the ways in which data are sought after, evaluated, and filtered by the learner.

Motivated and inspired by the idea that humans are rational learners equipped with a powerful inferential mechanism, the studies I present in the following chapters offer empirical support for the central claim of my thesis: human learners engage in core inferential practices via fundamental principles of learning, whether they are engaging in socially learning from others, exploring on their own, generalizing properties of objects, or evaluating information provided by others.

In my approach to understand learning in social contexts, I discuss the following three ideas:

- (1) **Selection:** how learners navigate between different sources of information by carefully monitoring their relative informativeness,
- (2) **Integration:** how learners flexibly utilize information acquired from various sources with different representational format,
- (3) **Construction:** how learners construct a coherent system of knowledge across content domains that, in turn, can support (1) and (2).

There is nothing fundamental or exhaustive about the distinction between these ideas. As in the example of the switch-flipping toddler, each of these aspects of learning are tightly linked to one another, presumably share common representational resources, often operate simultaneously, and affect the learner's behaviors on-line. Nevertheless, the list above provides a useful way to separate out the processes that may serve distinct purposes but together constitute what we call learning: searching for information, integrating information from different sources, and generating robust, abstract representations that guide the learner's behaviors in the world.

In the chapters that follow, I introduce studies that test different populations using different tasks in different contexts. Despite their differences, all these studies ask about selection, integration, and construction by addressing the following aspects of our inferential capacities. First, what is the *input* to this mechanism? That is, what kinds of information do learners make use of? Second, do learners make rational use of this information, drawing accurate *inferences* with respect to their goals that are consistent with predictions of formal models of human cognition? Finally, what is the *output* of this mechanism? How does it affect the learners' real-world behavior, and how do these behaviors contribute to their knowledge? These questions form a useful template that brings together the next three chapters.

The studies I present here are just the beginning steps towards providing a full account of the three ideas above (see Chapter 5 for a discussion about how the studies bear on each of these ideas). Building on prior work showing that learning involves both the operation of a domain-general inference mechanism and rich, structured domain-specific representations, my work extends the idea of rational learning conceptually, developmentally, and methodologically. Conceptually, I extend the scope

of rational inference mechanism to cases where we learn socially from others; developmentally, I provide evidence for some of the earliest signatures of these inferential capacities in late infancy as well as the sophisticated abilities in older children; methodologically, I use computational models to formally characterize children's inferences from data, and present novel ways to measure children's inferential processes that lend themselves well to be compared with predictions of these models.

The next chapter, Chapter 2, will investigate infants' ability to use statistical information embedded in their own and others' interventions. I look at how infants use this information to make accurate causal attributions to themselves versus the external world. Importantly, the study does not stop with showing infants' ability to draw inferences from observed statistical information. The results demonstrate that such attributions also affect their real-world behavior as well as opportunities for subsequent learning.

Chapter 3 shows how statistical information in the environment can be combined with an agent's action to inform infants' inferences about the sampling process underlying the agent's behavior. In this study I look at how inferences about samples and the sampling process by which the samples are generated affect infants' decision about how far to generalize object properties. A simple Bayesian model captures the results across five experiments, and also provides important insights about how to re-evaluate the role of constraints in guiding learning.

Chapter 4 looks at a more explicit case of learning in social contexts. Even in contexts where information is provided by other agents, learners face a problem of figuring out who is helpful and who is not. Two experiments in this chapter reveal

children's ability to actively evaluate other agents based on an abstract understanding of what it means to be helpful, and to flexibly adjust what they learn from these agents based on their evaluation. Even in cases where children are provided with equivalent behavioral information about others' epistemic status, they can reason about how the evidence were sampled and rationally update their beliefs. Importantly, these beliefs are not just about object properties but also about the informants, and they affect how children subsequently learn from these informants.

Chapter 5 summarizes the main findings of the studies, and discusses how they bear onto the three ideas presented in this chapter. Along with a brief review of their methodological contributions, I conclude with the implications of these studies for how we ought to think of our amazing capacity to learn, and what needs to be done to further advance our understanding of it.

## Chapter 2

# 16-month-olds rationally infer causes of failed actions from statistical information to seek help or to explore

Across two experiments, this study shows that sixteen-month-olds use sparse data about the distribution of outcomes among agents and objects to solve a fundamental inference problem: deciding whether event outcomes are due to themselves or the world. Faced with a failed attempt to activate a toy, infants' subsequent actions were guided by their causal attributions. When statistical data suggested that infants themselves are the likely cause of the outcome, infants approached their parent seeking for help; when the data favored the possibility that the object may be the culprit, infants approached another object to explore.

Infants' responses to simple events in this study reflect three different aspects of learning: selection, integration, and construction. They suggest that infants extracted the hidden structure embedded in simple events that involve people and their goal-directed

actions on objects. Notably, the representations over which infants could tabulate the dependencies (and independencies) incorporated not only those between objects and their outcomes but also those of agents and the efficacy of her actions, including the child herself. Using minimal evidence from diverse sources, infants made accurate causal attributions, and critically, such attributions affected the course of infants' real-world actions.

An abbreviated version of the results was presented in Gweon & Schulz, *SCIENCE* 332:1524 (2011). This chapter is a modification/extension of this article and a conference proceeding *Conference Proceeding* (Gweon & Schulz, 2010).

## 2.1 Introduction

Philosophers have long observed that everything we know about the world is a product of our interaction with it; we cannot have unmediated experience of the outside world. In fact, the result of any goal-directed action we perform in the world is determined by not just the causal structure of the world but also our ability to intervene on it. This fundamental inference problem of distinguishing our influence on event outcomes from the impact of the outside world is pervasive in every aspect of our life. Indeed, such distinction has been critical in disciplines ranging from social psychology (Rotter, 1954; Kelley & Michela, 1980) to artificial intelligence (Russell & Norvig, 2009).

This problem becomes especially urgent when our actions fail to achieve expected outcomes. For example, when we try to turn a light and are left in the dark, did we do something wrong (e.g., flip the wrong switch), or is something wrong in the world (e.g., a bulb burned out)? These attributions are important not only because of our desire to find the cause but also because they have different implications for our subsequent actions. If we are the problem, we should change something about the agent (e.g., vary our actions or ask for help finding the switch); if the problem is external, we should try to change the world (or at least the light bulb).

Consistent with previous empirical work showing that children draw accurate inductive inferences from minimal data (Gopnik & Schulz, 2004; Gweon, Tenenbaum, & Schulz, 2010; Xu & Garcia, 2008), we show that much younger children, 13 to 20-month-old infants, can use sparse evidence about the distribution of failed outcomes to attribute the cause of failed actions to either themselves versus the world.

To assess the locus of infants' causal attribution, we looked at the variable on which they intervene. Imagine a situation where a child tries a novel toy and fails to

make it work; the child needs to understand that other people ('the agent' variable), and other toys of the same kind ('the world' variable), can both serve as useful sources of information. A large body of literature on social referencing in infancy suggests that infants readily treat their caregivers as sources of information about the emotional valence of events (Sorace, Emde, Campos, & Klinnert, 1985; Walden & Ogan, 1988) and the referent of adults' attention (Baldwin, 1993; Carpenter et al., 1998). Moreover, infants use the information to regulate their own behavior. In particular, O'Neill (1996) showed that two- year-olds will request help from a knowledgeable (but not ignorant) parent in retrieving a hidden object, suggesting that toddlers not only look to parents for the information they might provide but also actively solicit such information. Children's imitation of object-directed actions is also often interpreted as an indication that children perceive others as agents like themselves (the 'like me' hypothesis, (Meltzoff & Brooks, 2001) and use adult actions for information about how to interact with an object (Gergely et al., 2002; Gopnik & Meltzoff, 1994). Notably, children are more likely to imitate an adult's goal- directed action if they themselves have previously failed to generate a target outcome than if they have succeeded (Williamson, Meltzoff, & Markman, 2008).

Such studies speak to children's understanding of other agents as potential sources of information about objects in the world. What about children's understanding that one object can be informative about other members of the object kind? Previous research has shown that preschoolers generalize non-obvious properties (like squeaking or magnetism) from one member of a kind to others (Gopnik & Sobel, 2000; Nazzi & Gopnik, 2000). Moreover, children maintain this expectation even when one exemplar fails to function as expected (Schulz, Standing, & Bonawitz, 2008b). Indeed, 9-month-



old infants can generalize a property of an object to other identical-looking object after a single exposure (Baldwin, Markman, & Melartin, 1993), and by 15 months infants can even integrate information about how the exemplars are sampled in their inferences about object properties (Gweon et al., 2010). These studies establish that children expect object properties to generalize across similar-looking objects, and maintain that expectation even when they themselves fail to elicit the expected property.

This study shows that infants can use minimal statistical information to infer the cause of their failed actions, and that they rationally plan actions directed towards agents and actions directed towards objects based on their causal attributions. This provides evidence for the youngest age shown to infer causes of events based on co-variation data (Schulz & Gopnik, 2004). Furthermore, this study goes beyond showing that infants consider other agents and objects as useful sources of information; they flexibly choose the potentially more informative source, depending on whether the more likely cause of failure is themselves or the world.

In order to make one cause more likely than the other, we manipulated the statistical information in the demonstration; specifically, we changed the distribution of success and failure within and between objects and agents. We predict that infants should be more likely to direct their actions towards another agent when they themselves are the more probable source of failure and to another object when the more probable culprit is the toy. In Experiment 1, we manipulated whether the outcome of activating a toy co-varied with agents and/or the object.

## 2.2 Experiment 1

### 2.2.1 Method

*Participants* Thirty infants (mean: 16 months, 10 days; range: 14 – 20 months; 47% girls) were recruited from a local children’s museum; infants were randomly assigned to an Within-Object condition (N=15) or a Between-Objects condition (N=15). Nine infants were dropped and replaced due to parental interference, fussing out, experimental error, or failing to pull the cloth to retrieve a toy during the warm-up procedure. (See Procedure.) Two infants (one in each condition) were excluded from analyses because they never showed any of the target behaviors. (See Results)

*Materials* One commercially available toy (a plastic fish) was used during the warm-up period. Three similar-looking novel toys were built by attaching a wooden stick (10 cm in length) to a round plastic container (4 inches in diameter). The toys resembled small hand drums with handles. A square-shaped button (2 x 2 x 1 cm) was attached to the top of the container. This button was inert. Each object was covered with green, red, or yellow electrical tape and felt that was operated by a hidden switch at the bottom of the container: when the toy was laid flat on a hard surface and the fake button was pressed down, the real switch depressed and the toy played a musical tune (creating the appearance that pushing the fake button activated the toy). Children sat in a highchair. The tray on the high chair was covered with white felt, creating a surface that was too soft to activate the real switch at the bottom of the Green toy. The Green toy never worked on this tray when the fake button was pressed. The Red and Yellow toys did not have a musical mechanism inside, but contained play-dough so that all three toys were matched in approximate weight.

*Procedure* All children were tested individually in a quiet room inside the museum. The children sat in the highchair and the parents sat next to them on a chair. (See Figure 2-1 for experimental setup and stimuli.) Parents were instructed not to interact with the toys and only to smile and nod if the child addressed them. They were given a brochure about the study and asked to read it during the experimental procedure. Once the child was positioned in the highchair, the experimenter put a piece of orange felt cloth (approx. 20 x 75 cm) on the table and placed the warm-up toy on one end of the cloth. She pulled the cloth towards herself and retrieved the toy. Then she encouraged the infant to pull the cloth. Infants who did not pull the cloth and retrieve the toy after two demonstrations were excluded from analysis and replaced.

The experimenter removed the warm-up toy and introduced the child to a basket containing the Green, Red, and Yellow toys. She took the Green toy out, put it on the table, and pressed the button on top of the toy to play the music. She demonstrated this three times. Then she showed the child the basket containing the other two toys. She took out the Red toy and placed it on one end of the felt cloth. The toy was approximately 70 centimeters away from the child and was not within direct reach of the child's hands. She placed the other end of the felt cloth on the child's tray within easy reach of the child. Then, the experimenter handed the child either the Green toy (Within-Object condition) or the Yellow toy (Between-Objects condition) and said, "Here you go, you can go ahead and play!" She took the basket with the remaining toy (the Yellow toy in the Within-Objects condition; the Green toy in the Between-Objects condition) out of the child's line of sight.

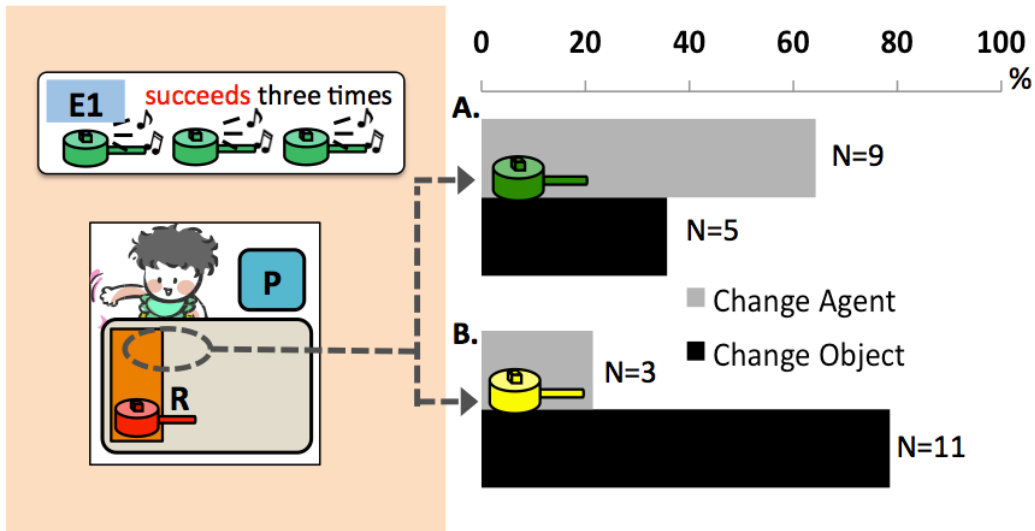


Figure 2- 1. Experimental setup and results from Experiment 1. (A) Within-Object condition, (B) Between-Objects condition. Graphs show the proportion of infants whose first action was agent-directed and object-directed.

## 2.2.2 Results and Discussion

**Preliminary Analyses** We first looked at whether all the children imitated the experimenter's action on the toy and whether they were equally persistent in the Agent condition (where they were given the same toy on which the action had been modeled) and the Object condition (where they had to make an inductive generalization from the Green toy to the Yellow toy). Given previous research suggesting that even 9-month-olds readily make such generalizations (Baldwin et al., 1993), we did not expect any difference in their button-pushing behavior. Indeed, all but one infant immediately (within two seconds) pressed the inert button on the toy in front of them. There was no difference in the frequency of children's button-pushing attempts in the two conditions (Within-Object: mean 3.0 times; Between-Objects: mean 3.2 times,  $p = ns$ ).

**Main Results** To decide whether the problem lies with the agent or the object, infants should consider both the relative plausibility of the two hypotheses and the statistical evidence for each (Griffiths & Tenenbaum, 2009).

In the Within-Object condition, neither hypothesis initially appears very probable: the infant might be doing something subtly wrong (e.g., not pressing hard enough), or something non-obvious might be wrong with the toy (e.g., it might have broken during the transfer). However, the statistical evidence favors the agent hypothesis: the outcome co-varies with the agent independent of the object.

By contrast, in the Between-Objects condition, the statistical evidence is uninformative: the outcome co-varies with both the agent and object. Here however, the object hypothesis is the more plausible on prior grounds: while the infant's actions are not obviously different from the experimenter's, the toy clearly is. Moreover, there are now many ways the toy might have failed (e.g., the yellow toy might have broken at any point, or yellow toys might never work).

As predicted, infants were more likely to try to change the agent (by handing the toy to their parents) than the object (by pulling the cloth or pointing to get the red toy) in the Within than Between-Objects condition (Change Agent vs. Change Object, Within-Object: 64.3% vs. 35.7%; Between-Objects: 21.4% vs. 78.6%,  $p < 0.05$  by Fisher's Exact).

These results confirm that infants rationally use sparse data to make causal attributions. However, other interpretations are possible. Infants who received the experimenter's toy might have been less likely to want a new toy than those who did not. Alternatively, infants in the *Within-Object* condition might have asked for help not because they attributed failure to themselves but because they inferred that the toy was

broken and wanted the parent to fix it. Therefore, in Experiment 2, we manipulated the relative probability of the two hypotheses without varying the object with which infants experienced failure.

## 2.3 Experiment 2

### 2.3.1 Method

*Subjects* Fifty-eight infants (mean: 16 months, 15 days; range: 13 – 20 months; 58% girls) were recruited from a local children’s museum; infants were randomly assigned to an Within-Agent 1 condition (N=20), Within-Agent 2 condition (N=18), or Between-Agents condition (N=20). Using the same criteria as in Experiment 1, twenty-one infants were dropped and replaced due to parental interference, fussing out, experimental error, or failing to pull the cloth to retrieve a toy during the warm-up procedure. Three infants (one in each condition) were excluded from analyses for not showing any of the target behaviors.

*Procedure* Infants were assigned to one of three conditions, identical to the *Within-Object* condition in Experiment 1 except as follows: Within-Agent 1: a single experimenter successfully activated the Green Toy twice and failed twice; Within-Agent 2: two experimenters each activated the Green Toy once and failed once, or Between-Agents: one experimenter activated the Green Toy twice and another experimenter failed twice. The experimenter then gave the Green Toy to the infants, which never activated for them.

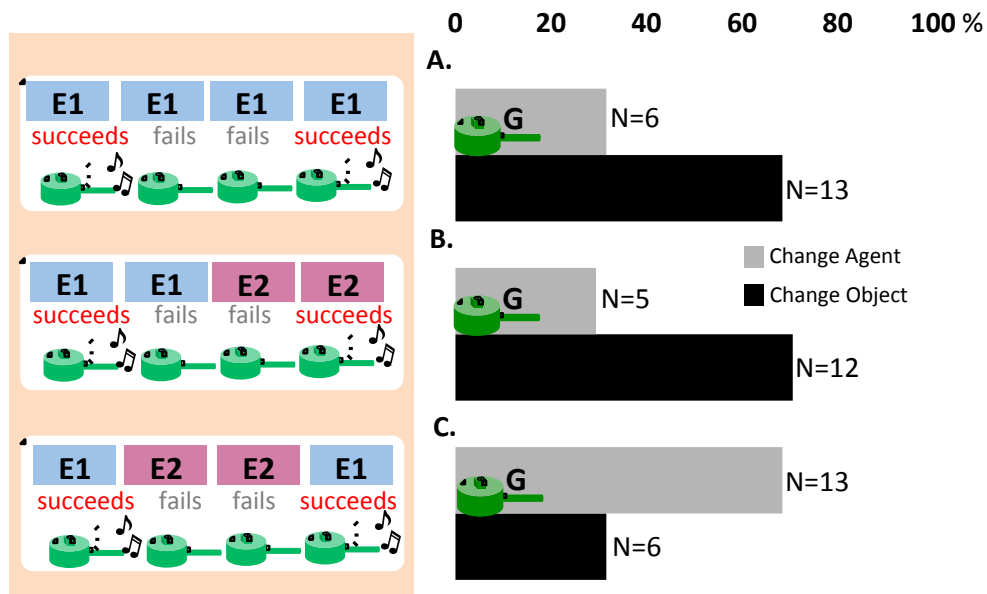


Figure 2- 2. Experiment 2 setup and results. (A) Within-Agent 1, (B) Within-Agent 2, (C) Between-Agents. Graphs represent proportion of infants who changed the agent first (gray bars) and the object first (black bars)

### 3.3.2 Results and Discussion

Consistent with the results in Experiment 1, preliminary analyses showed that infants pressed the button equally often across conditions ( $F(2,51) = 0.59, p = ns$ ). Because all infants received the Green Toy, the three conditions in Experiment 2 differ only with respect to the covariation between the outcome and the agents who performed the action. The outcomes in the Within-Agent 1 and 2 conditions (considering also the infant's failure) vary independent of the agent, suggesting the failure is due to the object; the outcomes in the Between-Agents condition co-vary with the agent, independent of the object, suggesting the failure is due to the agent. As predicted, infants were more likely to first change the agent than the object in the Between-Agents than Within-Agent conditions. (Change Agent vs. Change Object, Within-Agent 1: 31.6% vs. 68.4%; Within-Agent 2: 29.4% vs. 71.6%; Between-Agents: 68.4% vs. 31.6%, both comparisons  $p \leq 0.05$  by Fisher's Exact). See Fig. 2-2.

## 2.4 General Discussion

These results suggest that infants track the statistical dependence between agents, objects, and outcomes and can use minimal data to draw inferences that support rational action. When the infants inferred that they were the source of failure, they sought help; when they believed the failure was due to their object, they explored others. Infants' responses are consistent with formal models of causal induction (Griffiths & Tenenbaum, 2009), suggesting that human learners readily draw rational causal inferences from data even early in life.

There is abundant evidence that young children both ask adults for help (Dunham, Dunham, & O'Keefe, 2000; O'Neill, 1996) and explore objects in the world (Piaget, 1930; Baldwin, Markman, & Melartin, 1993; Bonawitz, Shafto, Gweon, Goodman, Spelke, & Schulz, 2011; Gweon, Tenenbaum, & Schulz, 2010). This study goes beyond previous work in suggesting that infants actively trade-off these two alternatives. Infants not only show rational use of statistical information to attribute the cause of failure to themselves versus the external world, but also choose to approach different sources of information depending on their causal attribution.

Indeed, the purpose of infants' subsequent actions remains an open question for further investigation. Note that although we manipulated the statistical evidence to render either the agent or the object hypothesis much more likely than the other, there was still some ambiguity between the two hypotheses. Therefore, one possibility is that infants in these experiments simultaneously considered both hypotheses and approached different sources to actually deconfound the evidence. However, it is also



possible that children only considered one of the two hypotheses, and wanted to confirm their inference by intervening on the inferred cause. Lastly, it is also possible that infants merely wanted the toy to work and rationally chose the best way to achieve the desired outcome. The current results do not distinguish between the three possibilities.

Nevertheless, these results show that in the face of failure to achieve a goal, children well before their second birthday do not simply look to their parents nor do they simply move on to a new toy. Instead, they are able to infer the likely cause for their failure, and flexibly and rationally adjust their behavior. In solving the problem of assigning causal responsibility to themselves or the world, infants might lay the earliest foundations for scientific inquiry. Furthermore, seeking instruction from others and engaging in exploration are both potentially effective strategies for learning. Infants' differential response to failure depending on the evidence for its causes presents an exemplary case of seamless navigation between social and non-social sources for acquiring useful data.



## Chapter 3

# Infants consider both the sample and the sampling process in inductive generalization

In the experiments in Chapter 2, infants were situated in a naturally social context where experimenters were involved in their own goal-directed actions while still acknowledging the presence of the learner. The question was whether they could figure out the cause of their own failure from interactions between people (others as well as themselves) and objects. The study in this chapter also looks at learning in such social contexts, but in cases in which the experimenters' actions are arguably more directed to the child. One might imagine there would be less inferential burden on the learner in learning from simple goal-directed actions (e.g., squeezing dog toys) that are obviously directed to the child. However, even in such contexts, what is to be inferred from these actions often remains ambiguous; for example, which toys squeak, and which do not? The agent's actions themselves do not specify the sampling process or the properties of an undemonstrated toy, and the output of learning depends on the learner's inferential capacity. The Bayesian model in this chapter offers an exciting possibility that infants

use statistical information, (e.g., distribution of objects in a box and the sample drawn from the box) to infer the sampling process, rather than uniformly apply an assumption about how agents sample objects.

Experiments in this chapter again provide compelling evidence for a learning mechanism that permeates different aspects of learning. The results show that infants combine representations of relative numerosity of objects and people's goal-directed action, and use this to inform their inferences about both the reason behind the agent's action and the property of a novel object. Specifically, their inferences about the object properties affected the degree to which infants expected their actions to generate an outcome. Notably, these representations are graded with respect to their strength of belief in the hypothesis that the objects are squeaky (Experiment 3). Indeed, the exact format of the infants' representations of probability, ratio, and the sampling process need further investigations. Nevertheless, this study shows an impressive ability to jointly infer "something about people" and "something about objects" from brief exposure to people's actions executed on varying distributions of objects.

Experiments 1 and 2 in this chapter were first presented in a conference proceeding (Gweon, Tenenbaum, & Schulz, 2009) and all results have been published in Gweon, Tenenbaum, & Schulz, PNAS 107:9067 (2010).

## Abstract

The ability to make inductive inferences from sparse data is a critical aspect of human learning. However, the properties observed in a sample of evidence depend not only on the true extension of those properties but also on the process by which evidence is sampled. Since neither the property extension nor the sampling process is directly observable, the learner's ability to make accurate generalizations depends on what is known or can be inferred about both variables. In particular, different inferences are licensed if samples are drawn randomly from the whole population (*weak sampling*) than if they are drawn only from the property's extension (*strong sampling*). Given a few positive examples of a concept, only strong sampling supports flexible inferences about how far to generalize as a function of the size and composition of the sample. Here we present a Bayesian model of the joint dependence between observed evidence, the sampling process and the property extension and test the model behaviorally with human infants (mean age: 15 months). Across five experiments, we show that in the absence of behavioral cues to the sampling process, infants make inferences consistent with the use of strong sampling; given explicit cues to weak or strong sampling, they constrain their inferences accordingly. Finally, consistent with quantitative predictions of the model, we provide suggestive evidence that infants' inferences are graded with respect to the strength of the evidence they observe.

### 3.1 Introduction

Human learners can draw rich, abstract inferences from sparse data (Carey, 1985, 2009; Wellman & Gelman, 1992; Gopnik et al., 2004; Keil, 1989; Schulz et al., 2008a). One of the enduring mysteries of cognitive science is why such inferences should be so accurate. The simplest answer is that induction can be accurate as long as the sample is representative of the population. But how do learners know whether a sample is representative? If learners already knew the properties of the population and could see that they were reflected in the sample, they could be confident that the sample was representative. However, it is precisely this information (i.e., the properties of the population) that is in question. Induction is a puzzle because it can hinge on the solution to such chicken-and-egg problems: inferences about the extension of object properties depend on the relationship between the sample and the population, but knowing that may depend on knowing the extension of the object properties.

The problem of how to infer the extension of object properties from small samples of data bedevils much of scientific inquiry. Rock samples from Mars have a high concentration of silica. Is this true for all Martian rocks or just the (dusty) rocks on the surface? Evergreen needles in a forest lie flat along the branch. Is this true for all needles or only those from low-hanging branches? Scientists could use the appearance of the sample (rocky, needle-like) and/or known category labels (“rocks”, “evergreen needles”) to generalize properties within but not across kinds (to other rocks and evergreen needles but not from rocks to evergreen needles). Indeed, even young children can use such cues to constrain their inferences (e.g., children infer that entities that share observable properties and/or category labels with a sample are likely to share other properties as well; (Gelman & Markman, 1986; Gopnik & Sobel, 2000).

However, these cues may not suffice. Whether all Martian rocks have silica or all needles lie flat might depend also on the sampling process.

In scientific inquiry, we can usually either control the sampling process or recognize its biases. If for instance, we *know* that the objects' properties are not independent of the sampling process (because rocks on the surface are both more likely to be dusty and to be sampled; because trees low in the canopy have flat needles to maximize sun exposure), we can use this to restrict our generalizations (in both instances, to the population on or near the ground).

However, the problem becomes more complicated when the nature of the sampling process is unknown. This is often the case in social contexts. When a person chooses a sample, she could randomly sample from the whole population or selectively from any subset of the population, for any number of reasons: because of her preferences, because some objects are easier to reach, because she was told what to do, etc. If the person's goals are not made explicit by linguistic or pragmatic cues, the sampling process may not be obvious. Suppose for instance, a child sees her mother pull a few blue toys from a box of blue and yellow toys. The blue toys squeak. Do all the toys squeak or just the blue ones? How, short of testing all the toys, could the child tell?

As in many problems of induction, the problem of generalization from a sample can be solved either by assuming more constraints on the learner, allowing for relatively simple inferences, or by assuming fewer constraints and more sophisticated inferential abilities. Thus one possibility is that there are early constraints on what infants assume about agents' sampling processes. Infants might for instance assume *weak sampling* (i.e., agents choose items at random from the population, independent of the properties they have) or *strong sampling* (agents sample items selectively, depending on the properties they have) (Tenenbaum, 1999). Alternatively, infants might not have

expectations about sampling processes; rather, they might simultaneously infer both the sampling process and the extension of object properties from data. That is, infants might make joint inferences about the subset of the population that was sampled and the subset to which the property extends, given both the possibility that the subset sampled might be independent of the property's extension and the possibility that it might be coextensive with it.

Whether assumed or inferred, the key question is whether infants consider the sampling process and use it to make accurate generalizations. As the names indicate, weak sampling is a less powerful constraint on induction than strong sampling (Tenenbaum, 1999). If the learner thinks the evidence was sampled from the population as a whole, then both positive and negative evidence (these toys squeak; those toys do not) are needed to constrain inferences to sub-populations (only this kind of toy squeaks). By contrast, under the strong sampling assumption, even a few samples of positive evidence (these toys squeak) can constrain inductive generalizations to sub-populations or kinds (only this kind of toy squeaks). Here we propose a formal model that captures the relationship between the sampling process, the observed data, and the extension of object properties. We present evidence suggesting that infants can flexibly constrain their predictions about the extension of an object property given the assumed, or inferred, sampling process. In particular, we show that in the absence of behavioral cues to the sampling process, infants make inferences consistent with the use of strong sampling. Critically, this is not because infants cannot consider other alternatives; given explicit behavioral cues to weak or strong sampling, infants constrain their generalizations accordingly.

Our studies build on previous work suggesting that infants may be sensitive to each component of the problem in isolation: that is, infants are capable both of inductive



generalization and sensitivity to sampling processes. Young children project properties across entities that share labels and/or perceptual features (Gelman & Markman, 1986; Gopnik & Sobel, 2000), and infants as young as 9-months can generalize otherwise hidden properties of objects (e.g., rattling, squeaking) to identical-looking objects after a single exposure (Baldwin et al., 1993). Infants in their first year can form expectations about the properties of a sample from a population and about a population from a sample (Xu & Garcia, 2008), and these expectations are sensitive to how samples are generated: 11-month-olds expect randomly generated samples to be representative of the population from which they are drawn, but suspend this inference if the sample is clearly generated selectively (e.g., by an experimenter who expresses a preference for particular objects (Xu & Denison, 2009). Older children can make analogous inferences in reverse: they assume that an agent who pulls a non-representative sample from a population must have a preference for members of that sample but they do not make this inference if the agent pulls a representative sample (Kushnir, Xu, & Wellman, 2010). Finally, the scope of preschoolers' generalization about word meanings has been shown to depend on both the sample of evidence provided and the nature of the sampling process, in ways predicted by rational Bayesian models of generalization (Xu & Tenenbaum, 2007a, 2007b): given three labeled examples of a novel object category, preschoolers restricted their generalizations about the label to the tightest category containing the examples, but only when given explicit cues that the examples were generated by strong sampling rather than weak sampling.

Collectively, these results suggest that infants can project properties from samples to populations, recognize when samples are and are not representative of target populations, and recognize that different sampling processes generate different samples. However, in most previous work the sampling process was specified by

explicit social/pragmatic cues (e.g., choosing blindfolded vs. choosing with open eyes and smiling at the chosen items). No previous work has looked at what inferences infants draw when the sampling process is not explicitly cued. Moreover, no previous work has looked at whether infants' generalization of object properties depends on the sampling process. What happens when the probability of drawing a sample and the determination of objects' properties mutually constrain one another? Do infants vary their inferences depending on the relationship between the sample and the population? And can they modulate their generalizations in proportion to how much evidence they have?

Both our model and our experiment follow from the toy box example we outlined above. In the current study, we vary the ratio of blue to yellow balls in a box and the number of blue balls the experimenter pulls from the box. The experimenter squeezes each blue ball in the sample so it squeaks. In all conditions, the question is whether, consistent with different compositions of the sample relative to the population, infants will generalize the squeaking property to the yellow balls. Because the infancy research suggests that babies have abilities presumably prerequisite to such inferences (property projection and sensitivity to sampling processes) by the end of the first year, we look to the beginning of the second year (mean: 15 months) for children's ability to use information about the sample and population to constrain their inferences about the property extension.

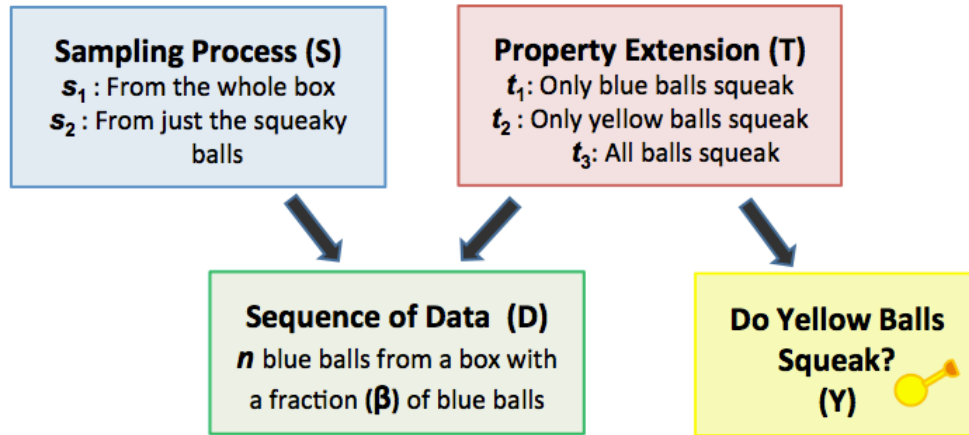


Figure 3- 1. Graphical model of the relationship between the sample, the sampling process, and the true extension of the object properties. Whether or not the yellow balls squeak depends only on the extension of the target property. However, that can only be inferred from the observable data (the ratio  $\beta$  of blue/yellow balls in the box and the  $n$  in the sample), which depends also on the sampling process. Thus to decide whether or not the yellow ball will squeak, children must either assume a particular sampling process, or make a joint inference about both the sampling process and property extension.

### 3.2 A Bayesian Model

Our predictions are informed by a Bayesian inference model that formalizes the claim that inductive inferences about object properties depend on both the sampling process ( $S$ ) and the true extension of the object properties ( $T$ ). This joint dependence can be described in terms of a simple graphical model (Figure 3-1). For simplicity, we consider just three possible property extensions ( $t_1$ : the property applies only to blue balls;  $t_2$ : only to yellow balls;  $t_3$ : to all balls) and two possible sampling processes ( $s_1$ : selectively sampling from just the squeaking set of balls, or strong sampling;  $s_2$ :

randomly sampling from the whole box, or weak sampling).<sup>3</sup> The learner observes data  $D = n$  examples of blue balls that squeak, drawn from a box that appears to contain a fraction  $\beta$  of blue balls and  $1-\beta$  yellow balls. The learner's goal is to predict  $Y$ , the proposition that yellow balls squeak. Note that  $Y$  depends directly on  $T$ , not  $S$  or  $D$ ; given that we know the set of balls that squeak, the observed data or the process by which the data were sampled is irrelevant to predicting whether the yellow balls squeak. However, inferences about  $T$  from  $D$  must take into account the different possible values of  $S$ ; formally, our Bayesian analysis must integrate out  $S$  in scoring each value of  $T$ . Because the learner's data are inconsistent with the hypothesis that only yellow balls squeak ( $t_2$ ), only two hypotheses for  $T$  are relevant to  $Y$  and they make opposite predictions:  $t_1$  predicts that yellow balls do not squeak;  $t_3$  predicts that they do. Following Tenenbaum and Griffiths (2001a), the evidence for one of these hypotheses over the other can be measured by the likelihood ratio,:

$$L = \frac{P(D|t_3)}{P(D|t_1)} = P \frac{(n|t_3, \beta)}{(n|t_1, \beta)}.$$

We posit that children's exploratory behavior - how much they squeeze the yellow ball, expecting a squeak - will be monotonically related to  $L$ . This analysis makes predictions that are independent of the prior probabilities children assign to  $t_1$  or

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<sup>3</sup> It is possible to generate more complex hypotheses for both the sampling process (see General Discussion) and the property extension (e.g., the three blue balls in the sample plus one other ball might squeak, the three balls in the sample plus two other balls might squeak, etc.). Here we model the simplest set of hypotheses needed to explain the range of evidence presented to infants across all five experiments.

$t_3$ , removing a degree of freedom that would otherwise need to be measured or fit empirically to their behavior. These likelihoods can be computed by integrating out the sampling process:

$$P(n | t, \beta) = \sum_{s_i \in \mathcal{S}} P(n | t, s, \beta) P(s).$$

To evaluate these likelihoods we need the following four conditional probabilities:

$$\begin{aligned} P(n | t_1, s_1, \beta) &= 1. \\ P(n | t_1, s_2, \beta) &= \beta^n. \\ P(n | t_3, s_1, \beta) &= \beta^n. \\ P(n | t_3, s_2, \beta) &= \beta^n. \end{aligned}$$

Let  $\alpha$  denote the prior probability  $P(s_1)$ , that the experimenter is sampling from just the squeaky balls:  $P(s_2) = 1 - \alpha$ . We then have:

$$\begin{aligned} P(n | t_1, \beta) &= \sum_{s_i \in \mathcal{S}} P(n | t_1, s, \beta) P(s) \\ &= P(n | t_1, s_1, \beta) P(s_1) + P(n | t_1, s_2, \beta) P(s_2) \\ &= \alpha + \beta^n (1 - \alpha). \end{aligned}$$

$$\begin{aligned} P(n | t_3, \beta) &= \sum_{s_i \in \mathcal{S}} P(n | t_3, s, \beta) P(s) \\ &= P(n | t_3, s_1, \beta) P(s_1) + P(n | t_3, s_2, \beta) P(s_2) \\ &= \beta^n \alpha + \beta^n (1 - \alpha) \\ &= \beta^n. \end{aligned}$$

The likelihood ratio, measuring the evidence in favor of the proposition that yellow balls squeak, is then:

$$L = \frac{P(n | t_3, \beta)}{P(n | t_1, \beta)}$$

$$= \frac{\beta^n}{\alpha + \beta^n(1 - \alpha)}$$

Parameter  $\alpha$  describes the learner's prior probability (degree of belief independent of the data  $D$ ) for selective (or strong) sampling ( $S = s_1$ ). By setting this parameter appropriately, the model can express different possibilities for how infants might take into account sampling in their inductive generalizations. Setting  $\alpha$  to either 0 or 1 encodes a definite assumption about the sampling process. By setting the parameter  $\alpha$  to 0, we can model the possibility that infants expect that evidence is sampled randomly; by setting the parameter  $\alpha$  to 1, we can model the possibility that infants expect that evidence is sampled selectively. Setting  $\alpha = 0.5$  means that the learner has no initial bias for either sampling process and must make a joint inference about sampling and the property's extension from the observed data.

### 3.3 Behavioral Studies and Comparison with Model Predictions

In our behavioral experiments, infants saw an experimenter draw blue ball(s) from a box and were then given the inert yellow ball.<sup>4</sup> In Experiments 1 – 3, we varied the number of balls drawn from the box ( $n$ ) and the ratio of blue to yellow balls in the box ( $\beta$ ) to provide a sample of balls that was either probable or not probable given the

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<sup>4</sup> The model mirrors the task design in distinguishing the sampling phase from the test phase. Because the yellow ball was treated differently from the blue ball(s) (i.e., given directly to the children and not manipulated by the experimenter) we do not treat the yellow ball as part of the sample in the model.

population. Since there is no evidence that infants have initial expectations about the sampling process, we present our data with respect to the joint inference account ( $\alpha = 0.5$ ). We then discuss the relationship of the data to the model predictions under definite assumptions of either random (weak) or selective (strong) sampling ( $\alpha = 0$  or  $1$ , respectively). In Experiments 4 and 5, we provide behavioral cues suggesting that the balls are sampled randomly (Experiment 4) or selectively (Experiment 5) to look at how infants' inferences are affected by explicit evidence about the sampling processes. Figure 4-3 shows the different strengths of evidence (L) predicted by our Bayesian analysis in these different experimental conditions.

### 3.3.1 Experiment 1

#### 3.3.1.1 Methods

*Subjects.* Thirty infants (mean: 15 months, 24 days; range: 13 to 18 months; 53% girls) were recruited from a local children's museum, and randomly assigned to a Blue3balls<sup>5</sup> condition or a Yellow3balls condition. Two participants were dropped and replaced due to (1) fussing out, (2) refusal to touch the stimuli or (3) parental interference.

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<sup>5</sup> The color in the condition name refers to the majority of objects in the box; the number refers to the number of blue balls drawn.

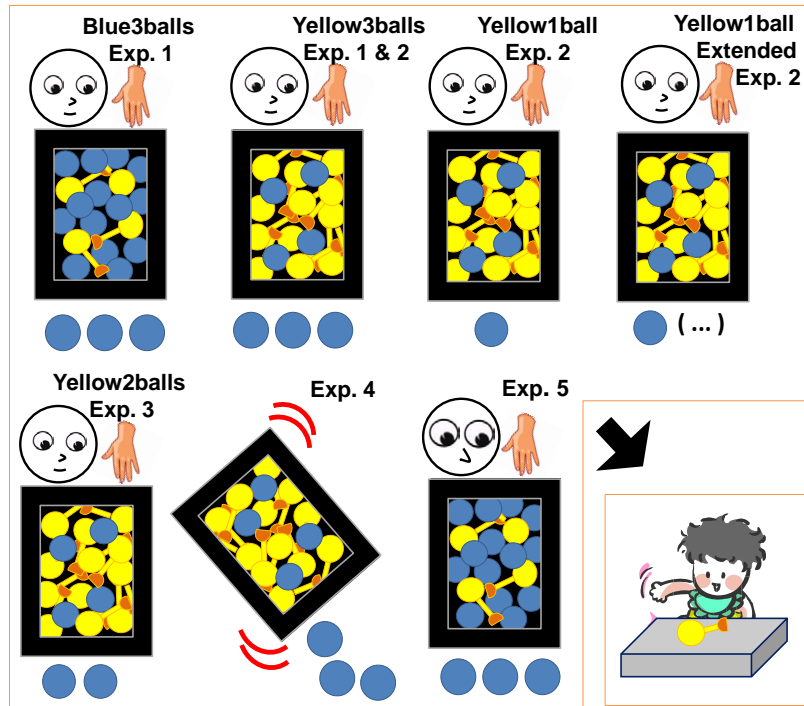


Figure 3- 2. Schematic of design in Experiments 1-5. See text for details.

**Materials** Two foam-board boxes were constructed (30 x 45cm x 30 cm). Each box had a hidden compartment in the back. One box contained 12 blue balls and 4 yellow balls (henceforth the Blue Box), and the other contained 4 blue balls and 12 yellow balls (henceforth the Yellow Box). The front side of the boxes was transparent, and all 16 balls were visible through the transparent window. The blue balls had a squeaking mechanism inside. The squeaking mechanism was removed from the yellow balls so that they were inert. Additionally, the yellow balls had a wooden handle with a bell-shaped object at the end (providing an additional “banging” affordance so the child could readily engage in a behavior other than squeezing the balls). Thus the objects were perceptually similar (an adult would categorize them all as “dog toys” but not identical. The boxes had a small opening at the top, allowing the experimenter to pull



out the balls from the hidden compartment. Thus even when the balls were pulled from the box, the view from the front of the box (showing all 16 balls) stayed constant.

*Procedure* Each participant was tested individually in a quiet lab room at a children’s museum. The child sat on a highchair or on a small stool; the parent sat behind the child, out of the child’s line of sight. In both conditions, children saw a box with a transparent front. In the Blue3Balls condition, 12 blue balls and 4 yellow balls were visible ( $\beta = 0.75$ ); in the Yellow3balls condition, 12 yellow and 4 blue balls were visible ( $\beta = 0.25$ ). The experimenter first drew the child’s attention by pointing to the transparent window and the contents of the box. Then the experimenter took three blue balls from the box, one at a time. Each time she said “Look!” squeezed the ball so that it squeaked, and then set it on the table. Her actions were identical across conditions, so there were no cues to indicate whether she was sampling from a specific subset of balls or from all the balls.

Finally, the experimenter paused, then pulled out a (inert) yellow ball and put it in front of the child saying, “Here you go, you can go ahead and play”. The child was allowed to play with the yellow ball for 30 seconds. If the child did not touch the ball, she encouraged them again. We coded the number of children who squeezed the yellow ball and the number of times each child squeezed the yellow ball. An additional coder, blind to condition, recoded all data in Experiments 1 – 5, and inter-coder reliability averaged 94.7%. Parents provided informed consent; the MIT IRB approved the research.

### 3.3.1.2 Results and Discussion

Under the Bayesian framework, children might consider four joint hypotheses about the sampling process and property extension: H1: sampling = squeaking set ( $s_1$ ),

property = blue ( $t_1$ ); H2: sampling = whole box ( $s_2$ ), property = blue ( $t_1$ ); H3: sampling = squeaking set ( $s_1$ ), property = all ( $t_3$ ); H4: sampling = whole box ( $s_2$ ), property = all ( $t_3$ ).

In both conditions, three blue balls are removed from the box ( $n = 3$ ). In the Blue3balls condition, the data (given that  $\frac{3}{4}$  of the balls in the Blue box are blue;  $\beta = 0.75$ ) fail to distinguish the possibility that the experimenter is sampling from only the squeaky balls ( $s_1$ ) from the possibility that she is randomly sampling from the whole box ( $s_2$ ). Because the inference about the sampling process is tightly coupled to the inference about the property extension, the data also fail to distinguish the inference that only blue balls squeak ( $t_1$ ) from the inference that all balls squeak ( $t_3$ ). Thus all four hypotheses are consistent with the evidence and the status of the yellow toy is unknown. Since the perceptual similarity between the objects supports the property generalization (Baldwin et al., 1993), and the statistical data does not weigh against it, we expected children to squeeze the yellow ball.

By contrast, in the Yellow3balls condition, three blue balls ( $n = 3$ ) are pulled from a box containing only  $\frac{1}{4}$  blue balls ( $\beta = 0.25$ ). The sample is unlikely if the experimenter were randomly sampling from the whole box; it is more probable as a sample from just the squeaky balls. Again, this inference is coupled to the inference about the property extension: given that the balls were most likely sampled from the squeaky balls, the evidence that three blue balls squeak is more likely under the hypothesis that only the blue balls squeak than under the hypothesis that all balls squeak. Thus the data support inference  $s_1$  and  $t_1$ : the joint hypothesis H1 makes the observed sequence of data more probable than any of the other alternatives. In this condition, children should assume that the yellow ball does not squeak and thus should be unlikely to squeeze it. Assuming that two sampling hypotheses ( $s_1$  and  $s_2$ ) are equal a priori ( $\alpha = 0.5$ ), the

likelihood ratio (L; see Supporting Information) is 0.59 for Blue3balls condition and 0.03 for Yellow3balls condition. (See Figure 3-3 for model predictions and results throughout.)

The experimental results confirmed the model predictions: fewer children squeezed the ball in the Yellow3balls than in the Blue3balls condition (33% vs. 80%;  $\chi^2(1, N=30) = 6.65, p < 0.01$ ) and children squeezed the yellow ball less often (0.87 vs. 2.53;  $t(28) = 2.45, p < 0.05$ ). These results suggest that infants constrained their generalization of the squeaking property to the blue balls in the Yellow3balls but not the Blue3balls condition.

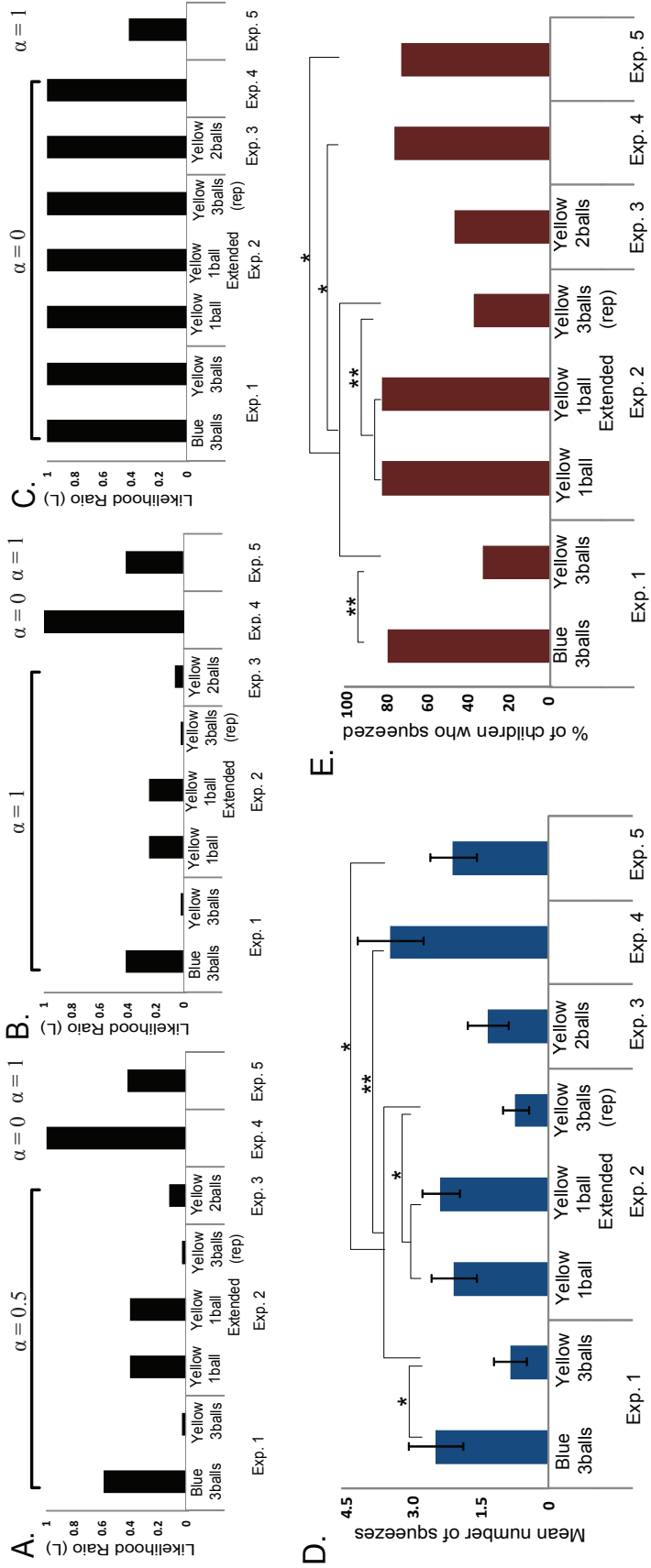


Figure 3-3. Model predictions (A-C) and results for Experiments 1-5 (D, E). A: Model predictions with  $\alpha$  set to 0.5 (joint inference); B:  $\alpha$  set to 0 (assuming weak sampling); C:  $\alpha$  set to 1 (assuming strong sampling). In D and E, asterisks indicate significance in planned comparisons based on model predictions (\*:  $p < 0.05$ ; \*\*:  $p < 0.01$ ). Yellow 3balls (rep) is an exact replication of Yellow3balls condition in Exp 1.

### 3.3.2 Experiment 2

While the results of Experiment 1 are consistent with our formal analysis, it is possible that children simply assumed that properties true of a member of the majority kind could be generalized to the minority kind, but not vice versa. That is, children might generalize from the blue balls to the yellow ball when most balls were blue (in the Blue3balls condition) but not when most balls were yellow (in the Yellow3balls condition). In Experiment 2, we addressed this alternative explanation.

#### 3.3.2.1 Methods

*Subjects.* Fifty-one infants (mean: 15 months, 16 days; range: 13 to 18 months; 47% girls) were recruited from a local children's museum, and were assigned to Yellow3balls, Yellow1ball, or Yellow1ball Extended condition (N=17/condition). Nine participants were dropped and replaced due to fussing out, refusal to touch the stimuli, parental interference, or experimental error.

*Materials* Materials used in Experiment 2 were identical to those used in Experiment 1.

*Procedure* Yellow3balls condition was an exact replication of the same condition in Experiment 1. In Yellow1ball condition, everything was the same except that the experimenter drew just one blue ball out of the mostly yellow box. In Yellow1ball Extended condition, the experimenter drew a single blue ball drawn from the mostly Yellow box, and squeezed the blue ball six times, matching the number of actions and time of exposure to the Yellow3balls condition. See Fig. 3-2.

#### 3.3.2.2 Results and Discussion

Randomly drawing a single blue ball from a mostly yellow box is not particularly improbable and does not discriminate between  $s_1$  and  $s_2$ , or  $t_1$  and  $t_3$ . Although the only difference between the Yellow1ball and Yellow3balls conditions is the number of balls ( $n$ ) drawn from the box, we expected that children should restrict their generalization of the squeaking property to the blue ball significantly more often in the Yellow3balls than in the Yellow1ball condition.

Of course, when children are shown three blue balls squeaking rather than one, they also see more actions on the blue ball and are exposed to the blue balls for a longer time. Mere added experience with the blue balls (rather than the number of blue balls in the sample) could make children less likely to generalize the property to the yellow ball. Yellow1ball Extended condition was designed to address this issue. If children restrict their generalization to the yellow ball based on the length of exposure and number of actions performed on the blue ball, then children in the Yellow1Ball Extended condition should perform like children in the Yellow3balls condition; if instead, children are sensitive to the relationship between the sample and the population, children's performance should mirror that of children in the Yellow1ball condition.

With respect to the model,  $\beta$  was held constant (at 0.25) between the conditions while  $n$  was either 3 or 1. Assuming  $\alpha = 0.5$  as in Experiment 1, the likelihood ratio (L) is 0.40 for the Yellow1ball conditions and 0.03 for Yellow3balls replication. Again, the results were consistent with the model predictions: fewer children squeezed the ball in the Yellow3balls than in the Yellow1ball condition (38% vs. 82%;  $\chi^2(1, N=33) = 6.95, p <$

0.01) and children squeezed less often (0.75 vs. 2.12;  $t(31) = 2.35, p < 0.05$ )<sup>6</sup>. The results of the Yellow3balls condition of Experiment 2 replicated the Yellow3balls condition of Experiment 1 (children squeezing: 33% vs. 38%,  $p = ns$ ; mean squeezes: 0.83 vs. 0.75,  $p = ns$ ) while the results of the Yellow1ball condition of Experiment 2 mirrored those of Blue3balls condition of Experiment 1 (children squeezing: 82% vs. 80%,  $p = ns$ ; mean squeezes: 2.53 vs. 2.12,  $p = ns$ ).

These results were not due simply to children's differential exposure to blue balls in the Yellow3balls and Yellow1ball condition. Children's performance in the Yellow1ball Extended condition was indistinguishable from that of children in the Yellow1ball condition (children squeezing: 82% vs. 82%,  $p = ns$ ; mean squeezes: 2.41 vs. 2.12,  $p = ns$ ) and significantly different from children's performance in the Yellow3balls condition: fewer children squeezed the ball in the Yellow3balls than in the Yellow1ball Extended condition (38% vs. 82%;  $\chi^2(1, N=33) = 6.95, p < 0.01$ ) and children squeezed less often (0.75 vs. 2.41 ;  $t(31) = 2.12, p < 0.05$ ).

These results rule out the alternative explanations of results in Experiment 1. Although blue balls were the minority objects in both conditions of Experiment 2, children generalized the property in the Yellow1ball condition but not the Yellow3balls condition. Moreover, while one might assume that the more often infants see an adult squeezing a ball, the more likely they should be to squeeze themselves, we found the reverse: infants were more likely to squeeze the yellow ball in the Yellow1ball condition (when the experimenter squeezed only one ball) than the Yellow3balls condition (when she squeezed three). While this might suggest the other possibility – that the more often

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<sup>6</sup> One child in Yellow3balls condition in Experiment 2 was an outlier, squeezing the ball 3 standard deviations more than the mean and was excluded from subsequent analysis.

infants see an action on a single object kind, the more likely they are to restrict their actions to this kind – this was also ruled out. Infants in the Yellow1ball Extended condition saw the single blue ball squeezed repeatedly but readily generalized the property to the yellow ball. That is children’s tendency to squeeze was unrelated to the number of times they saw the target action but was well predicted by our model in which generalization from the sample depends jointly on the sampling process and the property extension.

### 3.3.3 Experiment 3

In Experiment 3 we test the prediction that children’s inferences should be graded with respect to the data; that is, children should be progressively less likely to squeeze the yellow ball as the number of balls drawn from the yellow box increases. For instance, setting  $\alpha = 0.5$  ( $s_1$  and  $s_2$  are equally likely a priori) and  $\alpha = 0.25$  ( $\frac{1}{4}$  blue balls in the box), the likelihood ratios (L) are 0.40, 0.12, and 0.03 for  $n = 1$ ,  $n = 2$ , and  $n = 3$ , respectively. The significant differences between children’s performance in the two Yellow1ball conditions (Experiment 2) and the Yellow3balls conditions (Experiments 1 & 2) provide data for cases in which  $n = 1$  and  $n = 3$ . In Experiment 3 we ran the intermediate case, a Yellow2balls condition, in which the experimenter sampled two blue balls from the box containing  $\frac{1}{4}$  blue balls.

#### 3.3.3.1 Methods

*Subjects* Seventeen (mean: 15 months, 17 days; range: 13 to 18 months; 41% girls) were recruited from a local children’s museum. Three participants were dropped and



replaced due to fussing out, refusal to touch the stimuli, parental interference, or experimental error.

**Materials** Materials were identical to those used in Experiments 1 and 2.

**Procedure** Procedures were same as other conditions in Experiments 1 and 2, except that the experimenter drew two blue balls out of the mostly yellow box. See Fig. 3-2.

### 3.3.3.2 Results and Discussion

We predicted that children's tendency to squeeze the yellow ball in this condition would be intermediate between the results of two Yellow1ball and Yellow3balls conditions. The prediction of intermediate responding means that although the results of the Yellow2balls condition might not differ significantly from *either* the Yellow1ball or the Yellow3balls conditions, the model estimates for the five conditions should predict the pattern of results. This is what we found. Numerically, more children squeezed in the Yellow2balls condition of Experiment 3 than either Yellow3balls condition (47% vs. 33%, Experiment 1; 47% vs. 38%, Experiment 2,  $p = ns$ ) and children squeezed the yellow ball more often (1.35 vs. 0.87, Experiment 1; 1.35 vs. 0.75, Experiment 2;  $p = ns$ ). Also, fewer children squeezed the yellow ball in either Yellow2balls condition of Experiment 2 (47% vs. 82% (both conditions);  $\chi^2(1, N=34) = 4.64, p < 0.05$ ), and children squeezed numerically less often (1.35 vs. 2.12 (Yellow1ball), 1.35 vs. 2.41 (Yellow1ball Extended),  $p = ns$ ). Critically, this pattern of results was well predicted by the model (Pearson  $r = 0.98, p < 0.005$ ). Given that this correlation considers only five data points the results should be interpreted with caution. However, they provide suggestive evidence that children's inferences vary in a graded manner with the size of the sample.

### 3.3.4 Experiment 4

In modeling the results so far, we have assumed that the two sampling hypotheses ( $s_1$  and  $s_2$ ) were assigned equal probability a priori ( $\alpha = 0.5$ ). As noted, infants might instead have initial expectations that agents engage in either weak ( $\alpha = 0$ ) or strong sampling ( $\alpha = 1$ ); we address those possibilities in the discussion to follow. In Experiments 4 and 5 however, we consider the case when children are given overt behavioral cues indicating that the sampling process is either random or selective.

#### 3.3.4.1 Methods

*Subjects* Seventeen (mean: 16 months, 9 days; range: 13 to 18 months; 47% girls) were recruited from a local children's museum. Four participants were dropped and replaced due to fussing out, refusal to touch the stimuli, parental interference, or experimental error.

*Materials* Materials were identical to those used in Experiments 1 - 3.

*Procedure* The beginning of the procedure was the same as that in other experiments. However, rather than pulling the balls out, the experimenter shook the box upside down to let the three blue balls fall out. These blue balls were placed in the secret compartment inside the box to allow precise control of which balls will fall out each time. Then she told the child, "The next one is going to be yours". This comment was added to prevent the infants from anticipating that they would get the box to shake (rather than the balls to squeeze). She shook the box again to let a yellow ball fall out and gave it to the child. See Fig. 3-2.

#### 3.3.4.2 Results and Discussion

In Experiment 4, the experimenter drew three blue balls from the box with  $\frac{1}{4}$  blue balls. However, instead of reaching in, she shook the box upside down and let three blue balls fall out. Thus, the evidence (number of balls ( $n$ ) and proportion of blue balls ( $\beta$ )) was the same as in Yellow3balls condition of Experiments 1 and 2 but in this case, the experimenter's action specified that, despite the improbability of the sample, she was sampling from the whole box. Formally, a direct cue to random sampling sets the parameter  $\alpha$  to 0 and raises  $L$  to 1.00, much higher than the  $L = 0.03$  of the Yellow3balls condition. Thus we predicted that children in Experiment 4 should generalize the squeaking property to the yellow ball more than children in Yellow3balls conditions in Experiments 1 and 2. The results were consistent with this prediction: more children squeezed the ball in Experiment 4 than in the Yellow3balls conditions (76% vs. 33%, Experiment 1;  $\chi^2(1, N=32) = 6.03, p < 0.05$ ; 76% vs. 38%, Experiment 2;  $\chi^2(1, N=33) = 5.13, p < 0.05$ ) and children squeezed more often (3.53 vs. 0.87, Experiment 1;  $t(30) = 3.24, p < 0.005$ ; 3.53 vs. 0.75, Experiment 2;  $t(31) = 3.57, p < 0.005$ ).

### 3.3.5 Experiment 5

What are the predictions in the converse case, when children are given explicit cues to selective sampling but a sample that is also likely under random sampling (three blue balls from the mostly blue box)? In Experiment 5, we tested exactly such a case by having the experimenter reach into the mostly blue box with explicit behavioral cues consistent with selective sampling of a specific set of balls.

#### 3.3.5.1 Methods

**Subjects** Fifteen (mean: 16 months, 6 days; range: 13 to 18 months; 60% girls) were recruited from a local children's museum. No participant was dropped or replaced.

**Materials** Materials were identical to those used in Experiments 1 - 4.

**Procedure** The procedure was the same as the Blue3balls condition in Experiment 1. However, when drawing the blue balls from the box, the experimenter peered into the box and took approximately twice as long as in Experiments 1 to pull each blue ball out. As she took the blue ball out, she said, “Aha, here it is, look!” and smiled. After three balls were removed, she said, “The next one is going to be yours” and shook the yellow ball out (matching Experiment 4).

### 3.3.5.2 Results and Discussion

As noted, our model suggests that when  $\beta$  and  $n$  are held constant the likelihood ratio (L) gradually decreases as a function of  $\alpha$ . However, the difference in the likelihood between  $\alpha = 0.5$  and  $\alpha = 1$  is small. With the parameters  $\alpha = 1$ ,  $\beta = 0.75$  and  $n = 3$ , the model predicts only a slightly lower rate of squeezing ( $L = 0.42$ ) in Experiment 5 than in the Blue3balls condition of Experiment 1 ( $L = 0.59$ ) (and thus of course a higher rate of squeezing than in the Yellow3balls conditions of Experiment 1 and 2;  $L = 0.03$ ). Intuitively, this is because explicit cues that the experimenter is selectively sampling from the box (consistent with  $s_1$ ) do not indicate that the yellow balls are not themselves part of the squeaky set that the experimenter is sampling from<sup>7</sup>; thus the inference that the property extends to the yellow balls continues to depend on  $\beta$ , the ratio of blue and yellow balls in the box. We thus predicted that children in Experiment 5 would

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<sup>7</sup> One could of course, provide social/pragmatic cues that would unambiguously establish that the yellow balls were not being sampled (e.g., by picking the yellow ball, frowning, and replacing it with a blue ball). However, in that context, infants’ failure to squeak the yellow ball would be over-determined (i.e., they could directly infer that the yellow ball should be avoided).

generalize the property to the yellow ball, squeezing more than Yellow3balls condition of Experiments 1 and 2 but no differently than children in the Blue3balls condition of Experiment 1.

The results were consistent with our predictions: there were no differences between the results of Experiment 5 and the Blue3balls condition of Experiment 1 with respect to the number of children squeezing (73% vs. 80%,  $p = ns$ ) or the mean number of squeezes (2.12 vs. 2.53,  $p = ns$ ). By contrast, more children squeezed the ball in Experiment 5 than in the Yellow3balls conditions (73% vs. 33%, Experiment 1;  $\chi^2(1, N=30) = 4.82, p < 0.05$ ; 73% vs. 38%, Experiment 2;  $\chi^2(1, N=31) = 4.01, p < 0.05$ ), and children squeezed the ball more often (2.13 vs. 0.87, Experiment 1;  $t(28) = 2.09, p < 0.05$ ; 2.13 vs. 0.75, Experiment 2;  $t(29) = 2.47, p < 0.05$ )

### 3.3.6 Joint inference vs. strong sampling assumption

Thus far we have discussed the joint inference account; we now turn to the possibility that infants might have default assumptions about how agents sample evidence. Our data rule out the possibility that infants assume weak sampling ( $\alpha$  fixed to 0). Under the assumption of weak sampling, the model predicts that infants should squeeze the yellow ball persistently in all five experiments (that is, the results of all five conditions should be identical to that of Experiment 4). By contrast, the likelihood ratios under the strong sampling account ( $\alpha$  fixed to 1) are quite similar to those under joint inference account ( $\alpha = 0.5$ ): Experiment 1 Blue3balls condition  $\alpha = 0.5, L = 0.59$  vs.  $\alpha = 1, L = 0.42$ ; Yellow3balls condition  $\alpha = 1, L = 0.03$  vs.  $\alpha = 1, L = 0.02$ ; Experiment 2 Yellow1ball condition,  $\alpha = 0.5, L = 0.40$  vs.  $\alpha = 1, L = 0.25$ ; Experiment 3 Yellow2balls

condition  $\alpha = 0.5$ ,  $L = 0.12$  vs.  $\alpha = 1$ ,  $L = 0.12$ . Thus our results are consistent with the possibility that infants expect agents to engage in strong sampling. Looking at the overall correlation between the model predictions and the data (mean number of squeezes) across all eight conditions, both the joint inference model and the strong sampling account correlate with the data (joint inference;  $r = 0.97$ ,  $p < 0.001$ ; strong sampling:  $r = 0.92$ ,  $p < .001$ ); the weak sampling account does not ( $r = -.07$ ,  $p = ns$ ). (See Figure 4-3.)

Given that infants might expect agents to engage in strong sampling, why consider the possibility that they engage in joint inference? As noted, one could make assumptions about infants' prior inductive biases allowing for simpler learning, or make no such assumptions and instead credit infants with relatively sophisticated inferential mechanisms. Both the current work (Experiment 4) and previous research (11, 12) establish that infants are sensitive to sampling processes in the presence of explicit behavioral cues. Given that infants recognize that agents can engage in weak sampling, and that there is as yet no evidence that infants nonetheless expect agents to engage in strong sampling, joint inference remains a real possibility. That said, considerable work suggests that infants make assumptions about rational agents with respect to intentional goal-directed actions (Gergely, Nádasdy, Csibra, & Bíró, 1995; Gergely & Csibra, 2003; Woodward, 1998). It would be very interesting if the assumption that agents were likely to engage in selective sampling were part of this repertoire. Thus distinguishing the strong sampling assumption from the joint inference account remains an important direction for future research.

### **3.4 Discussion**

We presented a formal Bayesian account of how inferences about the extension of object properties from a sample of evidence depend on both the true extension of the property and the sampling process. We showed empirically that, given identical samples of evidence, 15-month-old infants make different inferences about the extension of object properties depending on the probability of the sample. In particular, we showed that in the absence of behavioral cues to the sampling process, infants draw inferences consistent with the use of strong sampling; infants were able to draw normative, flexible inferences about the extension of an object property given only a small sample of positive evidence or the property. Additionally, we showed that infants recognize that agents can engage in different sampling processes; given behavioral cues to either weak or strong sampling, infants varied their inferences accordingly. Across the eight conditions, the strength of evidence infants observed for discriminating the two hypotheses about the property extension (all balls squeak vs. only blue balls squeak) predicted their generalizations. Finally, as predicted quantitatively by the Bayesian model, we provided suggestive evidence that infants' inferences are graded with respect to the size of the sample.

We found that both the number of children squeezing and the mean number of squeezes across conditions were consistent with the model predictions. Although the likelihood ratio and these dependent measures were highly correlated, the differences between the group means in the number of squeezes were mainly driven by the children who did not squeeze at all. Additionally, the all-or-none measure of whether a child squeezed or not showed the same qualitative pattern as the mean number of squeezes. Further computational and empirical research might clarify exactly which aspects of behavior the model predicts.

Throughout, we have looked at the probability that a sample might be randomly generated from the whole population. However, it is possible that children are also sensitive to a different measure of likelihood: the degree to which evidence is *representative* of the population (i.e., the degree to which the evidence in the sample distinguishes the target population from alternative populations). Three blue balls for instance, may be the most probable draw from a mostly blue box but this sample fails to distinguish a mostly blue box from an entirely blue box. By contrast, a sample consisting of two blue balls and one yellow ball may be a less probable sample but a more representative one (in that it distinguishes the entirely blue from the mostly blue box). The distinction did not arise in the current work because the samples were never distinctively representative (the sample always consisted of only blue balls although the box contained both blue and yellow balls). However, Bayesian inference models can formally capture this distinction (Tenenbaum & Griffiths, 2001b), and comparing infants' sensitivity to these different measures of likelihood is an intriguing area for future research.

Although we have focused on the distinction between strong and weak sampling assumptions, a variety of more complex models might account for the current data. A child might infer for instance, that the agent intends to sample squeaky balls and knows which balls squeak, believes that all the balls squeak, or believes that some balls squeak but doesn't know which ones. Alternatively, the child might assume that the agent is drawing the sample in order to teach the child which balls squeak. Recent work in computational modeling has suggested formalizations of both such *intentional* and *pedagogical* sampling assumptions (Goodman, Baker, & Tenenbaum, 2009; Shafto & Goodman, 2008). These models make different predictions in a variety of tasks; however in the current paradigm, the predictions are qualitatively the same. Here we



have opted for the simplest model that could explain our data; future research might assess the extent to which infants distinguish more complex sampling assumptions.

Even the current results however, speak to the sophistication of children's reasoning. These findings suggest that infants make accurate generalizations from sparse data, in part because their inferences are sensitive to how the sample of evidence reflects the population. These results are consistent with the theoretical stance that humans are rational learners from the earliest stages of development. Babies who have just learned to say "mama" and may not yet say "ball", may know something about the goals of the former and infer the properties of the latter simply by attending to the rich statistics of everyday life.



## **Chapter 4**

### **Who tells the truth, but not the whole truth? Children modulate their inferences based on informant's past omission of relevant information.**

In Chapters 2 and 3, I provided evidence for early signatures of rational inferential capacities in preverbal infants. In this chapter I present a study with older children that shows how children use patterns of evidence and their knowledge about the world to socially evaluate another agent (e.g., a teacher) in a pedagogical context, and how such evaluation affects the interpretation of information provided by that agent in subsequent encounters. If the previous two studies involved learning about the world while taking into account what other people do, this study is more directly about how children can learn about the world (i.e., what is being taught) and about other agents (i.e., the teacher him/herself) based on information provided by the agent and children's assumptions about what is expected of a helpful teacher.

## **Abstract**

The ability to distinguish competent and incompetent informants is crucial for social learning. Although much is known about children's ability to evaluate informants based on their accuracy, little is known about whether children understand that provision of partial information may constitute a 'sin of omission'. In Experiment 1, we show that children (6- and 7-year-olds) recognize omission of relevant information as a failure to teach effectively by asking them to evaluate informants who provided complete or incomplete information about a toy. In Experiment 2 provides evidence from free-play data that 6-year-old children can modulate their inferences from an informant's demonstration of a toy based on the informant's past history of omitting information. These results show that children are adept and judicious social learners; they evaluate informants based on various properties of information they provide, flexibly adjust their inferences based on such evaluations, and show more self-guided exploration when there is reason to doubt the informant's credibility.

Experiment 1 in this chapter has been presented in a conference proceeding (Gweon, Pelton, & Schulz, 2011).

## 4.1 Introduction

Humans rely heavily on others to acquire new information. In particular, explicit, direct transmission of information via instruction or teaching is one of the unique aspects of human social learning (Csibra & Gergely, 2009; 2011). Implicit in our dependence on others for knowledge, however, is the assumption that people are knowledgeable and helpful.

Although the assumption holds up most of the time, a young learner whose goal is to learn about the world would bear a huge cost if it accepted all socially communicated information as true. The learner may sometimes encounter people who are ignorant about what she wants to learn, people who have false beliefs, or even people who deliberately intend to mislead the learner. For social learning to be a reliable and effective method for acquiring useful information in a complex environment filled with agents with varying degrees of trustworthiness, learners need to be sensitive to the quality of others as informants and selectively avoid those who might jeopardize accurate learning. How does a learner decide if an informant is to be trusted?

Sometimes, there may be explicit cues that indicate others' epistemic status or intent. Previous research suggests that preschoolers can use overt verbal and non-verbal expressions of an agent's uncertainty (Birch, Akmal, & Frampton, 2010) and ignorance (Koenig & Harris, 2005; Sabbagh & Baldwin, 2001), as well as the agent's tendency to deceive (Mascaro & Sperber, 2009) to decide whom to learn from. Furthermore, preschoolers can distinguish informants based on their past accuracy and choose to learn from those who were accurate in the past (Jaswal & Neely, 2006; Koenig & Harris, 2005; Koenig et al., 2004). For example, children are much more likely to endorse a

novel label provided by a teacher who provided a correct label for a familiar object (e.g., calling a cup a cup), than a teacher who provided an incorrect label (e.g., calling a ball a shoe).

In most pedagogical situations, however, teachers rarely express ignorance or uncertainty, and hardly ever provide blatantly false information. Instead, there are more subtle ways in which a teacher might mislead a learner. Imagine someone who claims to know all about an interesting novel toy, states that she wants to teach you how the toy works, and confidently demonstrates one function of the toy. If you were in a position to discover that the toy actually had four functions, would you consider her a “good teacher” and rely on her to learn about another novel toy?

All the explicit cues present in this context indicate that the informant should be trustworthy. Furthermore, the information she provided is true of the toy. Nonetheless, the adult intuition about the effectiveness of teaching would be that the teacher didn’t do a very good job. Why is this so?

In pedagogical contexts, information provided by a teacher can have strong constraints on the learner’s inferences (Bonawitz et al., 2011; Shafto & Goodman, 2008). For example, when a teacher shows one function of a toy, it strongly implies that the toy has just one function, rather than two, three, or four; if there were more, the teacher would have demonstrated them. This constraint can be described as a rational inductive bias; it is predicated on the fact that (a) functions are rare, (b) the informant is knowledgeable about all existing functions of the toy, and (c) that the informant selects the evidence in a way that is intended to help the learner to infer the correct hypothesis. Therefore, partial information provided by a teacher (e.g., showing one out of four properties of a toy) is not only insufficient to support the true hypothesis about the toy’s functions, but it also misleads the learner to believe in the wrong hypothesis.

This inductive constraint explains why we think the teacher in the example above isn't helpful. The teacher's demonstration, albeit true, is *incomplete* and leads the learner to believe that the toy has just one function; she has committed a "sin of omission."

Note that the omission of relevant information is closely related to a violation of the Gricean Maxim of Quantity, which states that a speaker should be as informative as required in communicative contexts (Grice, 1975; Horn, 1984). For instance, a speaker is guilty of violating this maxim if she (accurately) communicates that she ate some of the cookies, when she in fact ate all of them. A large body of literature documents 6-year-olds' failure to reject such under-informative utterances (Barner, Brooks, & Bale, 2011; Noveck & Reboul, 2008; Papafragou & Musolino, 2003). Even when children can distinguish under-informative (yet logically true) utterances from fully informative ones, they still consider them acceptable (Katsos & Bishop, 2011).

Recognizing omission of information as a sin may require a more sophisticated inference than understanding that provision of false information constitutes a "sin of commission." To detect a sin of commission, the learner only needs to recognize whether the presented information is true or false. For sins of omission, however, the information provided is true, and the learner needs to recognize that it nonetheless increases the learner's belief in the wrong hypothesis.

In the current study, we asked whether children accurately evaluate teachers based on their tendency to provide partial information (Experiment 1), and whether children's learning is affected by the informant's past history of committing sins of omission (Experiment 2).

## 4.2 Experiment 1

In Experiment 1, we asked whether children recognize omission of relevant information as a failure to teach effectively by asking them to evaluate teachers who provided complete or incomplete information about a toy. Informed by previous developmental studies on Gricean implicature, and a pilot study of fourteen 5-year-olds<sup>8</sup>, we focused on children between 6 – 7 years of age for this initial investigation.

Previous work established that children make the same inferences from vicarious instruction that they make from direct instruction (Bonawitz et al., 2011). We exploited this fact to create a task in which children first explored a toy to learn all its functions, and then observed a teacher demonstrate the toy to a naïve learner. This design allowed children to objectively evaluate the teacher without being affected by their interest in exploring the toy themselves.

We hypothesized that if children are sensitive to sins of omission in pedagogical contexts, children who saw a teacher demonstrate one of four functions of a multi-function toy would give lower ratings to the teacher compared to those who saw a teacher demonstrate the same function of a single-function toy, even though the behavior of the teachers were identical in both conditions.

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<sup>8</sup> We recruited fourteen five-year-olds ( $M = 5.57$  yrs,  $N=7$  in Teach 1/1 and Teach 1/4 conditions, respectively) as part of a pilot study using the same paradigm used in Experiment 1. We found that regardless of conditions, all but two (one in each condition) children gave the highest possible rating to the Toy Teacher. However, it was unclear whether this result was due to their genuine inability to detect sins of omission, or due to their strong preference for the toy that had cool effects. Therefore, we limited our target age range to six- and seven-year-olds in Experiment 1.





Figure 4-1. Stimuli used in Experiment 1. Left: Single-Function Toy and Four-Function Toy; Right: Puppet teacher, Elmo (naive learner), and rating scale.

#### 4.2.1 Method

**Participants** Fifty-two children between ages 6 and 7 were recruited from a local children’s museum (N=52, M(SD) = 6.93 (0.61) years, 31 girls) and were randomly assigned to either “Teach 1/1”(N=24) or “Teach 1/4”(N=28) conditions. Five children were dropped and replaced for failing to meet the inclusion criteria (see Results).

**Materials** Two yellow, pyramid-shaped novel toys were constructed with foam board and electronic parts. The Four-Function Toy had a purple knob which, when turned, activated a wind-up mechanism that displayed a flapping motion. In addition, a green button activated a spinning mechanism in a transparent plastic globe placed on the apex, a yellow button played music, and an orange button activated two LED lights. The Single Function Toy looked almost identical but had only one functional affordance (purple knob). The rest of the parts did not depress nor function as buttons. This was important to avoid giving the impression that the toy was broken. An Elmo puppet was

used as the naïve learner. Three hand puppets were used as the Toy Teacher (who taught Elmo about the toy), and two other teachers (Correct and Incorrect Teachers) who taught correct or incorrect names of familiar objects (a plastic carrot and corn, a duck, a stuffed rabbit). The rating scale had a ceramic knob that sled from left to right of the scale, with tick marks from 1 - 20 and five color-coded faces (from frowny to smiley) that served as anchor points along the scale.

**Procedure** All children were tested individually in a quiet room inside the museum. The experimenter sat across the table from the child, and the parent was out of the child's line of sight. All (but one by parent's request) sessions were video-recorded. Before beginning the procedure, children were told that they're going to play a "rating game" to see how helpful the teachers are in teaching Elmo, and received a brief training on how to use the sliding scale. Children were then introduced to Elmo (a puppet) who was described as a "silly monster" who didn't know much about toys, and were told that the puppet teachers will teach Elmo about the toys. The experimenter put Elmo away and asked the child to play with the toy first, which indicated the beginning of the Explore phase of the procedure.

1. *Exploration.* Children in Teach 1/1 condition briefly explored the Single-Function Toy, those in the Teach 1/4 condition explored the Four-Function Toy. The functions were readily discoverable; thus all participants entered the study knowing whether the toy had one or four functions.

2. *Teaching.* The experimenter introduced the Toy Teacher who "knew all about the toy", and told the child that he will teach Elmo, a silly monster who knew nothing about these toys. The Toy Teacher's action was identical in both conditions: he said, "I am going to teach you how my toy works", and turned the purple knob on the toy to activate the wind-up mechanism.

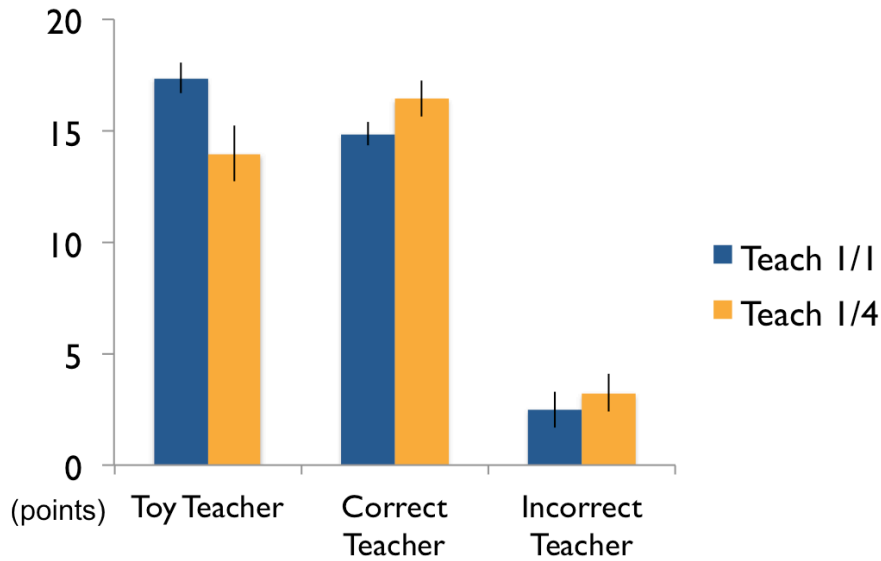


Figure 4- 2. Experiment 1 results.

3. *Rating.* After two demonstrations of the wind-up part, the participant was asked to rate the teacher on the sliding scale. Additionally, the participant rated two more teachers: a “Correct Teacher” who correctly named two familiar objects (i.e., calling a plastic carrot “a carrot”, a rubber duck “a duck”), and an “Incorrect Teacher” who gave wrong names (i.e., calling a stuffed rabbit “a cow”, a plastic corn “a cup”). These additional ratings allowed us to identify children who failed to understand the rating scale, and to calculate an adjusted score for the Toy Teacher calibrated to the child’s own ratings of Correct and Incorrect Teachers (see Results).

#### 4.2.2 Results and Discussion

Five children rated the Incorrect teacher as same as or higher than the Correct Teacher. These children were regarded as not having understood the task instruction or the rating scale, and were excluded from further analysis.

In Teach 1/1 condition, the Toy Teacher's demonstration of the wind-up mechanism provided accurate and complete information about the toy: it was the toy's only function. However, an identical demonstration in Teach 1/4 condition was still accurate of the toy but incomplete: he left three other functions undemonstrated, thereby committing a 'sin of omission'. Therefore, we predicted that children in Teach 1/4 condition would give a lower rating to the Toy Teacher than children in Teach 1/1 condition, but predicted no difference in children's ratings for Correct and Incorrect Teachers (see Figure 4-2).

Children in the Teach 1/1 and Teach 1/4 groups did not differ in their average rating of the Correct Teacher (Teach 1/1:  $M(SD)=14.9(4.0)$  vs. Teach 1/4:  $M(SD) = 16.4(4.5)$ ;  $t(50) = -1.33, p = ns$ ), or the Incorrect Teacher (Teach 1/1:  $M(SD)=2.5(2.6)$  vs. Teach 1/4:  $M(SD) = 3.2(4.3)$ ;  $t(50) = -.71, p = ns$ ).

As predicted, children in Teach 1/4 condition gave lower ratings to the Toy Teacher than those in Teach 1/1 condition (Teach 1/1:  $M(SD) = 17.3(3.5)$  vs. Teach 1/4:  $M(SD) = 14.0(6.7)$ ,  $t(41.7) = 2.32, p = 0.025$ ). To ensure individual differences in children's own references for rating did not affect our results, we calculated adjusted ratings for Toy Teacher using the following formula:  $\text{Adjusted Rating} = (\text{Toy} - \text{Incorrect}) / (\text{Correct} - \text{Incorrect})$ .<sup>9</sup> Children's adjusted scores were significantly higher in Teach 1/1 than in Teach 1/4 condition (Teach 1/1:  $M(SD) = 1.41(0.79)$  vs. Teach 1/4:  $M(SD) = 0.81(0.39)$ ,  $t(50) = 3.59, p = 0.001$ ).

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<sup>9</sup> An adjusted score of 0 or lower indicates that the Toy Teacher was rated as low as, or lower than, the Incorrect Teacher. A score of 1 or higher means that the Toy Teacher was rated as good as, or even higher than, the Correct Teacher.

In fact, children in Teach 1/4 condition rated the Toy Teacher lower than the Correct Teacher (14.0 vs. 16.4;  $t(27) = 2.58, p = 0.016$ ), whereas those in the Teach 1/1 condition rated the Toy Teacher even higher than the Correct Teacher (17.4 vs 14.9;  $t(23) = -2.12, p = 0.045$ )<sup>10</sup>. This pattern also emerged in children's rank order of the three teachers (Toy Teacher, Correct Teacher, and Incorrect Teacher). While 14 of 24 (58.3%) children in the Teach 1/1 condition rated the Toy Teacher the highest of all three, only 5 of 28 (17.9%) children in the Teach 1/4 condition did so ( $p = 0.003$ , Fisher's Exact).

These results suggest that even though the Toy Teacher's demonstrations were identical across conditions, children rated the teacher differently based on whether his demonstration constituted a sin of omission: when the toy had more than one function, children penalized the teacher for not showing additional functions.

### 4.3 Experiment 2

Experiment 1 established that by 6-7 years of age, children recognize informants who provide partial information and evaluate them accordingly. Do children's ratings simply reflect children's transient evaluations of the informant's immediate past behavior, or do children flexibly modify their assumptions about an informant based on

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<sup>10</sup> One might suspect a few reasons for this difference between Toy Teacher and Correct Teacher. One possibility is that one taught about a toy, while the other taught a word label (arguably less fun than a toy); perhaps children assigned extra credit for someone who shows something novel, as opposed to a known word; it is also possible that children valued the amount of effort involved in teaching (i.e., demonstrating a function of a toy versus uttering a sentence). However, this difference was not predicted a priori, and future studies should investigate the factors children might take into account in social evaluations of others in pedagogical contexts.

such behaviors in a way that affects what children learn from these informants? In Experiment 2, we addressed this question by looking at children's exploration of a new toy, to see whether children rationally adjust their inferences about the toy based on the Toy Teacher's past history of committing sins of omission. In addition to testing 6-year-olds, we also tested groups of four-year-olds and five-year-olds to see if children younger than six years of age show signs of such understanding.

### 5.3.1 Methods

**Participants** Seventy-five 6-year-olds (M(SD)= 6.45 (0.29) years, 32 boys), seventy-five 5-year-olds (M(SD)=5.45 (0.26) years, 39 boys), and forty-eight 4-year-olds (M(SD) = 4.58 (0.27) years, 24 boys) were recruited from a local children's museum, and assigned to one of three conditions: Teach 1/1, Teach 1/4, and Teach 4/4. Across all age groups, a total of twenty-seven children (six 6-year-olds, thirteen 5-year-olds, and eight 4-year-olds) were dropped and replaced due to: parental or sibling interference (N=12), experimental error (N=4), not completing the procedure (N=4), or showing little or no play with the final test toy (Play Time < 15 seconds, N=7).

**Stimuli** The two yellow toys (Single-Function and Four-Function Toys), Elmo puppet, and the Toy Teacher puppet from Experiment 1 were used. Additionally, a novel-looking toy (henceforth the Test Toy) with four different non-obvious causal affordances was used (see Bonawitz et al., 2011).

**Procedure** The initial procedure was similar to that in Experiment 1. Children in all conditions played with the yellow toy and discovered all working parts (Teach 1/1: Single-Function Toy, Teach 1/4 and Teach 4/4: Four-Function Toy). Children in Teach 1/1 and Teach 1/4 condition then observed the Toy Teacher demonstrate just one function (wind-up part) of the yellow toy to Elmo, as in Experiment 1. In Teach 4/4

condition, the Toy Teacher showed Elmo all four working parts of the toy. Therefore, the Toy Teacher provided complete information in Teach 1/1 and Teach 4/4 conditions, but omitted three functions in Teach 1/4 condition.

After the demonstration, the experimenter introduced the new Test Toy. She told the participant that Elmo had never seen this toy before, and the Toy Teacher would teach Elmo and the child about the toy. Critically, the Toy Teacher demonstrated just one function in all conditions. He said, “This is my toy. I am going to show you how my toy works” and pulled out a yellow tube from a larger purple tube which generated a squeak sound. After observing this demonstration twice, children were allowed to freely explore the Test Toy for as long as they wanted, for up to 3 minutes.

*Coding* All data were coded initially by the experimenter and then by a trained coder blind to conditions. The main results reported here are coded by the blindcoder . Inter-

Figure 4- 3. Procedure and predicted results. All children played with the Yellow Toy first and observed the teacher demonstrate the Yellow Toy to Elmo. Then the Toy Teacher demonstrated a second toy (Test Toy). The bottom panel illustrates children’s inferences about the number of functions of the Test Toy based on (A) generalizing from the number of functions of the Yellow Toy, and (B) Toy Teacher’s past history of committing a sin of omission. Note that both accounts predict the same pattern of play in Teach 1/1 and Teach 1/4 conditions, but predict different pattern of results in Teach 4/4 condition.

coder discrepancy was very low. For the number of seconds spent playing with the squeaker part during the first 30 seconds of free play; the average of absolute differences in coded data between the Experimenter and the blind coder was 1.73 (SD = 1.79) seconds.

### 5.3.2 Results and Discussion

Based on a previous study (Bonawitz et al., 2011), we assumed that the extent to which children focused on the demonstrated function (the squeaker) of the toy would reflect their inference about the toy's functions. If children consider the teacher's past history of providing complete or incomplete information and adjust their inferences about the Test Toy accordingly, children in Teach 1/1 or Teach 4/4 conditions (in which the Toy Teacher provided complete information about the yellow toy) would show different patterns of free play with the Test Toy than children in Teach 1/4 condition (who observed the Toy Teacher commit a sin of omission with the yellow toy). More specifically, children in Teach 1/1 and Teach 4/4 conditions should infer that the squeaker is the only function of the Test Toy and focus on playing with that function, replicating the effect of pedagogical demonstration in Bonawitz et al. (2011). However, children in Teach 1/4 condition should avoid making strong inferences from information provided by the Toy Teacher and consider the possibility that the Test Toy has additional functions. Therefore, we predicted that children would show less play with the demonstrated part (squeaker) of the Test Toy in Teach 1/4 condition than in Teach 1/1 and Teach 4/4 conditions (see Figure 4-3 for a schematic of design and predictions).

To capture children's initial expectations about the Test Toy immediately following the teacher's demonstration, we limited the scope of our analysis to the earliest portion of free play. We coded the amount of time (in seconds) children spent playing with the squeaker part of the Pipe Toy during the first 30 seconds of children's free play. Because we had a priori hypothesis about the pattern of results across the three conditions, we used planned linear contrasts (see Bonawitz et al., 2011) by applying the weights 1, -2, and 1 for Teach 1/1, Teach 1/4, and Teach 4/4 conditions, respectively.



The pattern of free play in the six-year-old group was consistent with this prediction: children in Teach 1/4 condition spent less time playing with the squeaker than did children in Teach 1/1 and Teach 4/4 conditions (Teach 1/1:  $M(SD) = 20.1(7.7)$ , Teach 1/4:  $M(SD) = 13.4(8.2)$ , Teach 4/4:  $M(SD) = 17.4(6.7)$ ,  $t(72) = 2.87$ ,  $p = 0.005$ ). Further planned comparisons confirmed that children in Teach 1/4 condition spent less time with the squeaker than did children in Teach 1/1 condition ( $t(48) = 2.95$ ,  $p = 0.003$ , one-tailed) and Teach 4/4 condition ( $t(48) = 1.88$ ,  $p = 0.033$ , one-tailed)<sup>11</sup>. However, play time with squeaker did not differ between Teach 1/1 and Teach 4/4 conditions ( $t(48) = 1.29$ ,  $p = ns$ ). See Figure 4-4 for results.

However, five-year-olds' play with the squeaker during the first 30 seconds of free play showed a weak, insignificant trend in the predicted direction (Teach 1/1:  $M(SD) = 17.63(9.5)$ , Teach 1/4:  $M(SD) = 13.57(7.8)$ , Teach 4/4:  $M(SD) = 16.85(5.4)$ ,  $t(72) = 1.93$ ,  $p = 0.058$ ). In fact, children in Teach 1/4 condition showed a trend towards spending less time with the squeaker than did children in Teach 1/1 condition ( $t(48) = 1.65$ ,  $p = 0.053$ , one-tailed) and significantly less than children in Teach 4/4 condition ( $t(48) = 1.72$ ,  $p = 0.046$ , one-tailed)). However, play time with squeaker did not differ between Teach 1/1 and Teach 4/4 conditions ( $t(48) = 0.36$ ,  $p = ns$ ).

Four-year-olds did not show the predicted pattern at all. (Teach 1/1:  $M(SD) = 17.85(7.6)$ , Teach 1/4:  $M(SD) = 16.8(6.4)$ , Teach 4/4:  $M(SD) = 13.09(6.2)$ ,  $t(45) = -0.65$ ,  $p = ns$ ). In fact, pairwise comparisons showed that there was no significant difference between the three conditions.

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<sup>11</sup> All but three children played less than 30 seconds, and the statistical results remain the same when the percent of time spent playing with the squeaker is used.

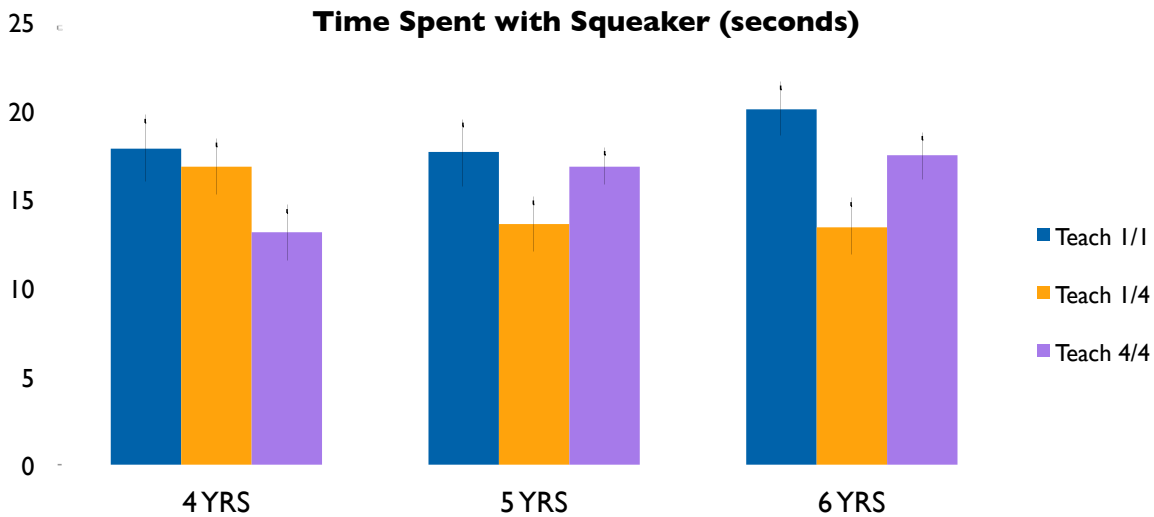


Figure 4- 4. Experiment 2 results for three age groups.

These results suggest that six-year-old children rationally modulate their inference from socially transmitted information based on the informant’s past history of omitting information. Importantly, children did not simply expect teachers to provide all relevant information regardless of his past behavior (which would result in no difference across conditions), nor did they simply generalize the number of functions from the first (yellow) toy to the Pipe Toy disregarding the teacher’s demonstration (which would result in less play with squeaker in Teach 4/4 condition as well as in Teach 1/4 condition). When children observed the Toy Teacher teach all working parts of a toy, children trusted the teacher to provide accurate and complete information about a new toy as well. When they saw the Toy Teacher provide accurate but incomplete demonstration of a toy, his demonstration of a new toy did not place a strong constraint on children’s inferences about the toy; instead, children explored the toy broadly, indicating that they suspected the toy might have other functions.

Five-year-old children showed a similar but a nonsignificant trend. I discuss possible reasons for such weak trend in the general discussion. Interestingly, four-year-

old children's play did not show the predicted pattern at all; instead, children tended to show shorter play with the squeaker in the Teach 4/4 condition compared to the other conditions, but none of the difference between the conditions was significant.

## 5.4 General Discussion

In Experiment 1, we showed that 6-year-old children recognize provision of partial information as a failure to teach effectively and evaluate teachers accordingly. Results from Experiment 2 suggest that children's evaluations of the teacher indicate more than a simple preference; they reflect the extent to which children rationally modify their assumptions about the informant's quality as an effective teacher. When a good, trustworthy teacher tells you "X does Y", a strong inductive bias to interpret it as "X only does Y" can be beneficial for learning. However, if the teacher is likely to have left relevant information out, the learner bears a risk for having such an inductive bias; in fact, children might benefit from further exploration to see if X does more than Y. When socially learning from others in pedagogical contexts, children not only learn about the target of instruction, but also judiciously learn about the quality of others as useful and trustworthy informants.

Of course, not all omissions are considered undesirable. In fact, omission of information is ubiquitous in formal education as well as in everyday communicative interactions. A teacher might deliberately skip teaching what the learner already knows (e.g., the toy is yellow), or what is considered too complicated or unnecessary for the learner's purpose (e.g., the toy is operated by two 1.5-volt alkaline batteries in parallel configuration). A teacher might also provide partial information when a single piece of evidence supports generalization (e.g., if the toy had four identical buttons that work in

the same way, a single demonstration would suffice). However, omission of information constitutes a sin when a teacher demonstrates just one function of a toy that has several interesting functions to a naive learner whose wants to “learn how the toy works.” The current experiments focus on exactly such a case where the consequence of omission is certainly undesirable for the learner: when it leads the learner to make the wrong inference.

Note that provision of partial information may indicate either one’s epistemic status (e.g., the informant doesn’t know about other functions), her intent (e.g., the informant intends to conceal other functions), or perhaps her moral status, and the learner’s attribution may have different implications for the learner’s subsequent inference. Under what circumstances would children exonerate informants from sins of omission? While we purposely created a context in which omission could hardly be justified in this study, it is worth noting that under-informative utterances do not necessarily lead to negative evaluations of the speaker in communicative contexts (Grice, 1975; Clark, 1996; Wilson & Sperber, 2008). We believe that future studies with children may provide useful insights for linking social learning in pedagogical contexts and pragmatic inferences in linguistic communication, and to better understand the cognitive processes that underlie these abilities.

Given preschooler’s success in detecting informants who provide false information (sins of commission, e.g., Koenig & Harris, 2005), the current results from six-year-olds raise a question about the developmental trajectory of children’s sensitivity to others’ quality as useful informants. Arguably, detecting sins of omission in pedagogical contexts may require much more than reasoning about a toy’s function; the learner needs to reason about the *teacher* by using his own knowledge about the toy and the consequence of the inference one would make given the under-informative

demonstration from the teacher. In fact, we found a weak but nonsignificant data in the predicted direction from five-year-olds, and no sign of such pattern in the four-year-old group. The reason for such weak trend in five-year-olds remains to be addressed. One possibility is that younger children are either more likely to forget what the teacher did or lose track of the teachers' behaviors, due to memory and information processing demands of the task. It is also possible that five-year-olds still evaluate the teachers based on sins of omission but their play with a different toy (Test Toy) is much less influenced by such evaluations. For example, the number of functions of the previous toy (Yellow Toy) may interfere with their inference about the Test Toy, as this may require the ability to inhibit irrelevant but salient piece of information (Carlson & Moses, 2001). Another possibility is that the ability to evaluate informants on the basis of their past sins of omission is still developing between five and six years of age. This is consistent with previous studies in pragmatic implicatures (Noveck & Reboul, 2008), and in fact, they may detect the omission but much more forgiving of such sins, as suggested by Katsos & Biship (2011). Our results do not address what it is that develops between four to six years of age. Whether it is due to children's developing ability to reason about others' mental states, better memory of informant's past behavior, or better inhibition of the tendency to generalize the number of functions across toys, is an important open question.

The power of human learning lies in our ability to make inferences from sparse data (Tenenbaum et al., 2011; Gopnik et al., 2004) (see also Schulz, in press). In particular, information selected and provided by knowledgeable, helpful agents can place strong inferential constraints that allow the learner to learn more about the world from less data (Bonawitz et al., 2011; Gweon et al., 2010; Shafto & Goodman, 2008). However, the efficacy of learning from others comes with a cost; the accuracy of

learning hinges on the quality of informants around the learner. Our results suggest that young human learners can successfully detect and evaluate informants who provide accurate but inadequate information about the world, and adjust their inferences accordingly. Even in childhood, social evaluation and learning depend not just on how attractive, friendly, or powerful other agents are, but also on a rational analysis of how likely they are to provide information that supports accurate learning. Critically, such evaluations, in turn, affect what and how we learn from these individuals.

## Chapter 5

### Learning in the Social Context

The studies presented in this thesis provide the groundwork for advancing a formal account of a rational learning mechanism that is core and fundamental to human reasoning and learning. In particular, Chapters 2 and 3 provide compelling evidence that rational inferential capacities are already in place in preverbal infants, allowing them to use minimal statistical information to draw rich, abstract inferences that, in turn, support their behavior. Chapter 4 shows the sophistication of these inferences later in childhood. Although children clearly go through radical developmental shifts in their concepts and knowledge about the world (e.g., Carey, 2009), the current studies provide evidence for developmental continuity in fundamental learning mechanisms. If the previous two studies involved learning about the world while taking into account what other people do, this study asks more directly whether children can learn about other agents based on their behaviors.

## 5.1 Summary

In Chapter 1, I described my approach to understand learning in social contexts as addressing these aspects of learning:

- (1) **Selection:** how learners navigate between different sources of information by carefully monitoring their relative informativeness,
- (2) **Integration:** how learners flexibly and rationally utilize information acquired from various sources with different representational format,
- (3) **Construction:** how learners construct a coherent system of knowledge across content domains that, in turn, can support (1) and (2).

In this section, I first summarize each of the three studies within the template of three basic questions about the way in which statistical inference mechanisms operate in the minds of young learners to support the **selection**, **integration**, and **construction** of knowledge. The first question concerns the *input* to these inferential processes; what kinds information do learners make use of? The second is about the *inference* itself; do learners draw rational inferences from data, in ways that can be formally predicted by computational models of human cognition? The final question concerns the output of these inferences; how do these inferences affect the learners' real-world behavior, and in what ways do they contribute to their knowledge?

In the first study (Chapter 2), infants were able to use a small amount of covariation information embedded across people and objects (*input*). Using such minimal statistical data, they were able to attribute the cause of their failed goal-directed action to either to themselves or to an object (*inference*). These inferences affected their choices of future actions (*output*). When they themselves were the more



likely cause, they approached another agent; when the object was the likely culprit, they approached another object. Notably, they chose the actions that not only offered useful information, but also were more likely to bring about the desired outcome.

The second study showed infants an experimenter who sampled a set of objects from a box. Based on the proportion of the sampled objects in the box, the number of objects in the sample, and the way in which the experimenter drew the sample (*input*), infants were able to rationally generalize a property of the objects to a novel object (*inference*). These inferences affected their exploratory play with the novel object; they squeezed the ball more often when it was likely to generate a sound, but tried other actions when it was unlikely to have that property (*output*).

Finally, in the third study, children saw a teacher who demonstrated the same function of a toy in two different contexts; when the demonstrated function was the toy's only function, and when it was just one of its four functions (*input*). Whether the teacher provided complete or partial information about the toy affected children's evaluation of the teacher (*inference*). Critically, such evaluations modified the way in which children learned from that teacher in the future (*output*); when the teacher's credibility is in doubt, they were much less likely to endorse a strong interpretation of the teacher's demonstration.

Taken together, my work provides evidence for a rational, probabilistic, domain-general inference mechanism that is already in operation from early in life, and suggests that this mechanism **selects** (*input*) and **integrates** data from both the social and the physical world (*inference*) to **construct** knowledge that affect their exploration, generalization, and evaluation in both the physical and the social world (*output*).

## 5.2. Towards a unified account of learning from rational inference

The studies in this thesis are just the first steps towards a unified account of learning from rational inference. Having just considered how each study addressed questions of selection (input), integration (inference), and construction (output), below I review how each of these aspects of learning manifests across the three studies.

### 5.1.1 Selection

Chapters 2, 3, and 4 address *information selection* in somewhat different ways. The first study (Chapter 2) shows children's implicit evaluation of relative informativeness in terms of their approach to either source. Depending on whether the agent (the children themselves) or the object was the more likely culprit of their failures, children directed their actions to either another agent or another object. Chapter 3 indirectly shows that infants make a flexible use of the statistical information present in the environment (i.e., the probability of the sample). Given an explicit cue for a particular sampling process, considering the probability of the sample is not only unnecessary but can even be detrimental for accurate judgments. This study suggests that infants selectively use probability information only when it is useful for determining the population from which the agent was sampling. An interesting question is whether infants actually process the perceptual properties of objects or ratio of the objects to a lesser degree when it is unnecessary to consider the probability of samples. Previous studies have shown that infants are less likely to remember the visual properties of artifacts when they are presented in the context of communicative demonstration of their functions (Futó, Téglás, Csibra, & Gergely, 2010). It is possible that, in general, specifying the purpose of demonstration may reduce infants' attention to information that is less likely to be useful in a given context. Finally, Chapter 4 shows how older

children evaluate other agents as sources of information. Although the task did not involve direct comparisons between teachers, children's relative ratings for teachers can be considered a proxy for their choices. In this study, children not only evaluated teachers on the basis of the property of information provided by these teachers, but they also adjusted their interpretation of the information from the teachers based on how they previously evaluated these teachers.

### 5.1.2 Integration

The work in my thesis attest to the domain-generality of the rational inference mechanisms by showing that inferences operate across domain boundaries, both with respect to the *input* to the learning mechanism as well as its *output* representations. First, all three studies show that children extract information from both the physical and the social world. In the first study (Chapter 2), the information was the conditional dependencies among objects, agents, and events; in the second study (Chapter 3), it was the number of samples and ratios of different populations in the box, as well as the process by which the sample was generated; in the third study (Chapter 4), children had to know about both the agent (e.g., what the Toy Teacher knows) and their own knowledge about the number of functions on the toy to draw rational inferences about sins of omission. Second, with respect to the output of the learning mechanism, I showed that it supports children's approach to either a person or another object (Chapter 2), that it reflects the degree to which children believed that the yellow balls squeak (mediated by the sampling process) (Chapter 3), and that children draw inferences from an agent's interventions on objects to learn about both the object and the agent (Chapter 4).

Some of the earliest evidence for cross-domain integration comes from looking-time studies on infants' understanding of agents as sources of causal power (Saxe, Tenenbaum, & Carey, 2005; Muentener & Carey, 2010). Preschoolers can handle information that is arguably more arbitrary; they use prior-violating evidence that links causes and effects in separate domains (e.g., being scared -> tummy ache) to make accurate causal inferences (Schulz et al., 2007a; Schulz & Gopnik, 2004). The current studies go beyond both lines of literature by showing domain-generality outside the context of prior-violating cross-domain evidence by testing preverbal infants with action measures; preverbal infants' goal-directed behaviors (e.g., approaching, squeezing) reflected their ability to integrate information across domains that are naturally present in our everyday environment, such as people and their actions, physical objects, and even mental states or dispositions of agents such as intent and helpfulness. Furthermore, data from older children (Chapter 4) suggest that the output of these inferences is not limited to causal relations in observed events or properties of physical objects; it can even inform our social evaluations of other agents.

### 5.1.3 Construction

Studies in Chapters 2 and 3 address the *construction* aspect only in a limited sense, by means of showing how the output representations of children's inferences affect their real-world behaviors that, in turn, affect how search for or evaluate informational sources and the kinds of inferences they make. In Chapter 2, their inferences resulted in abstract, causal representations that distinguished the child herself and the target of her actions and assigned causal responsibility to one of them. It remains an open question whether infants can actually learn about the efficacy their own actions or the toy from additional evidence, and is an interesting direction for future research. In Chapter 3,

infants' inferences about the new toy's property affected the extent to which children attempted to reproduce the property with the novel object.

Chapter 4 addresses the construction aspect more explicitly, by showing that children not only learn about properties of objects from others' demonstrations, but they also can use this to learn something about the agent who provided the data. Children's evaluations of the teacher were not transient, temporary impressions of his behavior; they became a part of their coherent, abstract knowledge about that agent which affected their future learning.

## **5.2 Methodological implications**

Cognitive scientists who take on a developmental perspective choose to study children and infants because of the unique insights this population offer about the precise nature of the human mind. In studying children, particularly preverbal infants, finding the right dependent measure is critical for understanding their mental processes. The studies here present some methodological implications for studying infant/child participants. Some of the most frequently used measures in studying children are their binary choices, answers, or actions. However, such all-or-none measures have fundamental limitations in studying the graded, probabilistic nature of their inferences from data. In Chapters 3 and 4, I've devised measures that can better capture these aspects in the course of a child's free play with objects. Particularly in Chapter 3, I offer a Bayesian model to predict children's degrees of beliefs about the novel toy and show that the results using these measures (i.e., number of squeezes) are tightly correlated with the predictions of a Bayesian model. If our cognition is fundamentally probabilistic in nature (e.g., Tenenbaum et al., 2011; Tenenbaum, Griffiths, & Kemp, 2006; Vul, 2010), measures that tap into this nature would be more

informative than averages across many participants. With the recent successes of using looking-time methods (Téglás et al., 2011; Kidd, Piantadosi, & Aslin, 2012) to get to the probabilistic nature of infants' expectations, these methods offer other useful ways in which such aspects can be captured in the naturalistic, spontaneous actions of infants and children.

### **5.3 On socially learning from others**

As the title of the thesis suggests, all three studies look at learning that occur in social contexts; that is, when other agents may provide useful evidence for the learner. In the first study (Chapter 2), infants were situated in a naturally social context where experimenters addressed the child, but at the same time were primarily involved in their own goal-directed actions that were either successful or unsuccessful. From a small amount of contingency information between actions and outcomes, infants quickly distinguished that agents might be a relevant variable in determining the toy's activation. It is possible that infants were able to draw this inference only because there was an agent involved; that is, infants' prior knowledge about agents, goal-directed actions, and their causal power constrained their hypotheses to allow accurate inferences from such sparse data. In the second study (Chapter 3) the experimenter also addressed the child, although in this case, her action was arguably more directed more to the child. One might imagine there would be less inferential burden on the learner when something is simply 'demonstrated' to the learner, compared to when the learner herself has to search for useful information. However, even in contexts where an adult addresses a child and demonstrates an interesting property of an object, it often remains ambiguous as to what is to be inferred from these actions: e.g., what are squeaky toys, and what are not? In this study, the agent's actions themselves were insufficient to

specify neither the sampling process nor the properties of an undemonstrated toy. The results suggest that even a brief exposure to base-rate information (i.e., seeing the ratio of objects) may be enough for preverbal infants to accurately infer object properties. That is, statistical information extended the scope of what the infant can infer from the agent's goal directed action. In the final study, the context was unambiguously pedagogical; it was explicitly stated that the informant is a teacher who knows all about a toy, teaching a naïve learner about it. The results show that even in contexts where an agent is assumed to be knowledgeable and helpful, children do not simply hold onto this initial representation of the informant. In the absence of explicit evidence for the informants' ignorance, false belief, or uncertainty, children used their own knowledge about the toy and the agent's demonstration to re-evaluate this representation, and furthermore, use this to adjust their inferences in subsequent encounters with the same informant.

The distinction between learning from one's own exploration and learning from instructions of others has sometimes been misinterpreted to imply that social learning is a more passive process than learning from evidence generated by one's own actions. The work here suggests that paraphrasing social learning as 'learning from transmission of information' vastly understates the learner's role in learning from others. The learner actively searches for the most useful source for learning, whether it be a person or the external environment, and even intervenes on these sources to initiate learning and generate useful information for her goal. Even when information is directly provided to the learner, the learner selects, filters, interprets, and abstracts the information she is given to construct her own knowledge. As information doesn't come readily digestible even when it originates in another person, what is acquired and how it is used depends on the learner.

One indicator of the extent to which we see social learning as passive is the fact that words like ‘cue’, ‘signal’, or ‘trigger’ pervade theories of social learning. For example, when a baby sees her mom point, smile, and make eye contact with her, she may assume that there is something interesting to be learned and prepare to receive information that is relevant for her in some way (Csibra & Gergely, 2009; 2011). Although human learners might be equipped with early-developing, even innate, mechanisms that trigger their attention under certain contexts, my work suggests that we may be able to break these assumptions down to products of our rich, abstract (but minimal) prior knowledge about agents and the capacity to draw rational, inductive inferences to form probabilistic representations about other people.

On a broader note, learning from others and learning from exploration of the world have been traditionally distinguished as two “primary modes” of learning (Vygotsky, 1978; Piaget, 1929; 1952). The work here suggests that the origin of information may not matter as much as previously thought; learning occurs *through* navigating across both the social and the physical world, and results in learning *about* both the social and the physical world. Underlying these processes are core, fundamental inferential capacities, that allow us to draw rich, abstract inductive inferences from small amounts of data.

## **5.4 Conclusion**

Current theories of cognitive development offer both a rich description of the nature, structure, and the content of knowledge in early childhood, and an explanation for the process by which dramatic shifts and changes in their concepts and theories take place. Hierarchical Bayesian framework offers formal learning principles for how such learning might occur. In addition, social influences have gained increasing attention in



studies of human cognition. While recent interdisciplinary approaches to study reasoning and learning in childhood within this framework have been influential in understanding how children learn rationally from data, the studies I presented here fill in some of the critical gaps. First, I provided some of the earliest hallmarks of rational, probabilistic inference mechanisms by showing sophisticated reasoning abilities in preverbal infants. Second, the studies suggest that these capacities transcend domain boundaries by omnivorously taking in information from both the social and the physical world, drawing inferences about both the social and the physical world. Finally, my work has implications for what has been often considered results of ‘constraints’ or ‘assumptions’ that are specific to learning in social non-social contexts.

Building on the this work, I plan to further contribute to the theoretical, empirical endeavor in advancing the idea that social learning, as with any other kind of learning from observed evidence, is rationally guided by the learners’ abstract, structured representations in various domains. Our ability to socially learn from others reflects fundamental properties of a domain-general learning mechanism. It is indeed a very smart mechanism that extracts useful data from the environment and draws rational inferences to generate rich, abstract, probabilistic representations of the world. But precisely for this reason, social learning isn’t special – it is just part of what we do every day, as we go about learning about the world.



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