# SEEKING VISUAL INFORMATION DURING SIGNED AND SPOKEN LANGUAGE COMPREHENSION AND WORD LEARNING

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# Abstract

Children's rapid language development is one of the more remarkable features of human cognition. How do they learn so much despite ambiguous input and limited processing capabilities? Social learning theories argue for the importance of acquiring language from more knowledgeable adults who constrain the learning task. Statistical learning accounts emphasize the role of pattern detection and structure in children's language environment. Finally, active learning explanations focus on children's skill in seeking information to support their own learning. This thesis presents an integrative framework for unifying key ideas from these accounts, followed by a diverse set of case studies of eye movements during language processing and word learning. The empirical work highlights how children's gaze patterns can flexibly adjust to the demands of very different learning environments.

Chapter 1 uses the formalization of Optimal Experiment Design (OED) to provide an integrative account of information seeking within social contexts. Chapter 2 presents the first case study: children's eye movements during real-time processing of American Sign Language (ASL) where objects and language compete for visual attention. Chapter 3 provides a direct comparison of eye movements during signed and spoken language comprehension, proposing an information-seeking explanation of why ASL-learners are slower to shift gaze away from their social partners and to named objects. Chapters 4 and 5 generalize the information seeking explanation to the domain of novel word learning. Chapter 4 presents a series of large-scale word learning experiments, showing that the presence of social cues can change how adults distribute attention and memory during statistical learning. Finally, Chapter 5 presents an eye tracking study measuring how children's decisions to gather visual information about social partners vs. objects changes as a function of their knowledge of word-object links.

# Dedication

I dedicate this dissertation to the memory of my grandmother, Sheila Paget. Thank you for being my greatest supporter and for always encouraging me to ask questions.

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# Introduction

Word learning seems simple. An adult produces a word about something in the surrounding context (e.g., "look at the ball") and the child connects what they hear with the round object that they see in front of them. This characterization of word learning via association belies the complexity of the acquisition challenge faced by children. Consider that even to learn the meaning of concrete nouns children have to extract the correct units from a continuous stream of linguistic information and map them on another continous stream of visual information. The word-to-meaning mapping task becomes even more complex if we consider that a speaker's intended meaning is largely unconstrained by the co-occurring context; a point made famous by W.V. Quine's example of a field linguist trying to select the target meaning of a new word ("gavagai") from the set of possible meanings consistent with the event of a rabbit running (e.g., "white," "rabbit," "dinner," etc.) (Quine, 1960). Remarkably, children's word learning proceeds rapidly, with estimates of adult vocabularies ranging from 50,000 to 100,000 distinct lexical concepts (P. Bloom, 2002).

The number of word meanings children will acquire is not the only impressive feature of their lexical development. As children accumulate word knowledge, they also gain the ability to access the conceptual representation connected with a word quite rapidly. Consider that children are able to understand language even though adults speak at a rate of three words per second. Moreover, empirical work shows that both adults and young children shift their visual attention to a familiar object in the scene within hundreds of milliseconds upon hearing its name (Allopenna, Magnuson, & Tanenhaus, 1998; Spivey, Tanenhaus, Eberhard, & Sedivy, 2002; Tanenhaus, Spivey-Knowlton, Eberhard, & Sedivy, 1995). The speed of lexical access is highlighted when compared with the slower retrieval of other learned, arbitrary facts (e.g., phone numbers) (Pinker, 2003).

Taken together, these facts make children's lexical comprehension and acquisition important topics of study for cognitive science. How is it that nearly all children growing up under typical circumstances acquire language quite rapidly despite noise and an in principle unlimited amount of referential uncertainty in the input? What learning mechanisms could account for the robustness and flexiblity of language development?

Social learning accounts point out that each child does not have to re-invent language on their own. Instead, children are typically surrounded by parents, other knowledgeable adults, or older peers – all of whom know the target language and want to facilitate their learning (P. Bloom, 2002; Clark, 2009; Hollich et al., 2000). Statistical learning theories propose that children possess powerful pattern detection skills that can learn the consistent structure in their input and reduce ambiguity in the learning task (Roy & Pentland, 2002; Siskind, 1996; Yu & Smith, 2007). More recent theories highlight the role child as active learner, controlling aspects of their own learning via the selection of behaviors – for example, asking questions or choosing where to allocate visual attention – that change the content, pacing, and sequence of their learning experiences (Gopnik, Meltzoff, & Kuhl, 1999; L. Schulz, 2012). A common thread in the three accounts – social, statistical, and active – is that children have access to information that *constrains* their inferences about new word meanings, thus reducing the problem of indeterminancy.

While the study of these learning accounts have typically proceeded in parallel, in real-world learning, these mechanisms do not operate in isolation. Thus, it is important to develop integrative accounts that try to explain how different sources of information might mutually influence one another to support lexical development. But how should we integrate these proposals? In this thesis, I argue that answering this question represents a significant step towards a more complete theory of early language acquisition since children's word learning often unfolds within socially grounded learning contexts. Put simply, children acquire language from other people, creating a scenario where they can integrate social information with their prior knowledge of word meanings to decide what actions to take.

Chapter 1 presents the details of an integrative account of how children's active learning might be shaped by information present in social contexts. I use the computational framework of Optimal Experiment Design (Emery & Nenarokomov, 1998; Lindley, 1956) as a conceptual tool to bring social learning processes into contact with the underlying decision making that supports active learning. The key insight is that learning in the presence of other people plays a direct role in determining

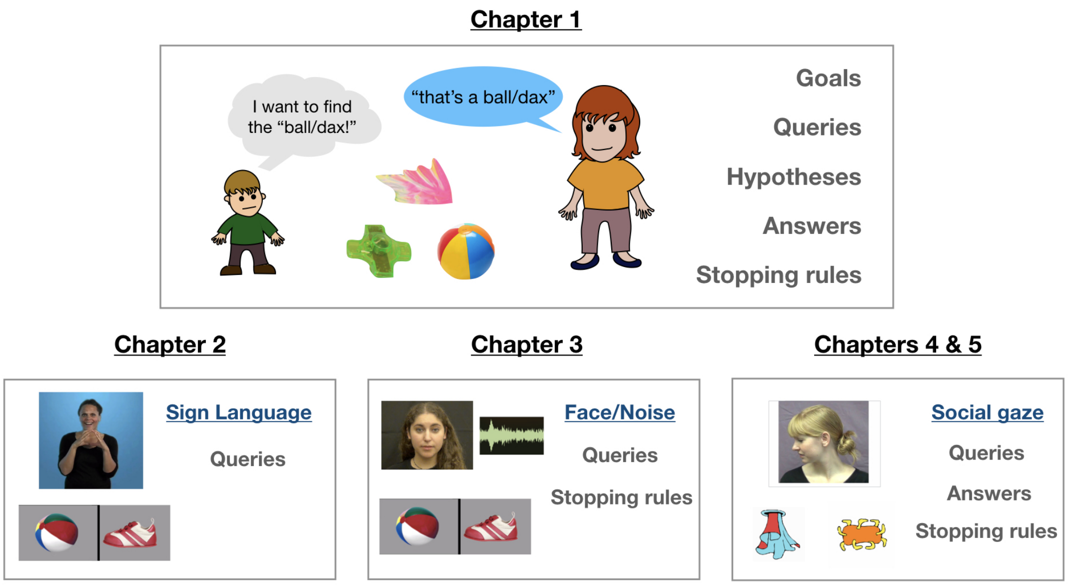


Figure 1: The upper panel shows a schematic overview of the components of an integrative framework of active language comprehension and and word learning within a social context. The lower panels show the different case studies and pieces of the general model that correspond to each chapter of the disseration.

the *usefulness* of different actions. Using this framework allows us to ask how social and statisical information might selectively affect the different underlying components of children's information selection during lexical comprehension and word learning. In Chapters 2-5, I present a diverse set of case studies of children and adult's eye movements during real-time familiar language comprehension and novel word learning. The empirical work focuses on eye movements as one instantiation of an active learning behavior that is particularly relevant for early lexical development. That is, decisions about visual fixation can be cast as a type of question-asking where perceivers deploy their gaze to reduce uncertainty about the world and to maximize their expected future rewards with respect to some goal (Hayhoe & Ballard, 2005). Morever, eye movements, as opposed to verbal question asking, are a behavior that children can control relatively early in development and map well on to the ecological task of interest: linking linguistic and visual information about concrete objects, which are perceived via the visual channel. Overall, the goal fo the empierical work is to ask how children's real-time visual information selection adapts to the information available in very different processing contexts.

Chapter 2 presents the first case study, which explores how children's eye movements during real-time language comprehension adapt to the context of processing a signed language. In this case, both the referents (objects) and the linguistic signal (signs) are visual and can compete for children's fixations. How do children learning sign choose to divide their visual attention between signers and objects?

Chapter 3 builds on the sign language work and directly compares children's gaze dynamics during signed and spoken language comprehension. Morever, Chapter 3 compares spoken language learners' eye movements when processing language produced by a video of a speaker's face to language coming from a disembodied voice. This comparison allows us to ask how the presence of social partner changes how listeners choose to gather visual information from objects vs. faces. Finally, Chapter 3 presents an information-seeking explanation of the differences in gaze dynamics between spoken and signed language learners. This explanation draws ideas directly from the conceptual analysis of active learning within social contexts proposed in Chapter 1.

Finally, Chapters 4 and 5 generalize the information seeking explanation to the domain of novel word learning. Chapter 4 presents a series of large-scale word learning experiments, showing that the presence of social cues can change how adults choose to distribute attention and memory during statistical word learning. Finally, Chapter 5 presents an eye tracking study that attempts to bring together elements of all three pieces of the integrative account – social, statistical, and active – presented in Chapter 1. We measured how children's active decisions about whether to look at a social target (a speaker's face) or at novel objects changes as a function of gaining more exposure to statistical information about word-object links.

# Chapter 1

# Active learning within social contexts

## 1.1 Introduction

The rate of children's early cognitive development is remarkable. Consider that children, despite limitations on their processing capabilities and ambiguity in the input, rapdily acquire new lexical concepts, eventually reaching an adult vocabulary ranging from 50,000 to 100,000 words (P. Bloom, 2002). And they accomplish this all while also developing motor skills, learning social norms, and building causal knowledge. How can we explain children's prodigious learning abilities?

Social learning accounts point out that children do not solve these problems on their own. Instead, they are typically surrounded by parents, other knowledgeable adults, or older peers – all of whom are likely to know more than they do and want to facilitate their learning. Social learning accounts also emphasize how social contexts can bootstrap children's learning via several, distinct mechanisms. For example, work on early language acquisition shows that social partners provide input that is tuned to children's cognitive abilities (Eaves Jr, Feldman, Griffiths, & Shafto, 2016; Fernald & Kuhl, 1987), that guides children's attention to important features in the world (Yu & Ballard, 2007), and increases levels of sustained attention, which results in better learning outcomes (Kuhl, 2007; Yu & Smith, 2016).

Social contexts can also change the inferences that support children's learning from evidence.

Recent work in the fields of concept learning and causal intervention suggests that the presence of another person engages a set of psychological reasoning where the learner thinks about *why* other people performed specific actions. The critical insight comes from knowing that another person has intentionally selected examples, which allows children to make stronger inferences that speed learning (Bonawitz & Shafto, 2016; Frank, Goodman, & Tenenbaum, 2009; Shafto, Goodman, & Griffiths, 2014). For example, children learn at different rates after observing the same evidence depending on whether they thought the actions that generated that evidence were accidental (less informative) or intentionally selected (more informative). Moreover, adults and children will make even stronger inferences if they believe that another person selected their actions with the goal of helping them to learn (i.e., teaching) (Shafto, Goodman, & Frank, 2012b).

However, children are not passive recipients of information – from people or the world. Instead, they actively select behaviors – for example, asking questions or choosing where to allocate visual attention – that can change the content, pacing, and sequence of their learning experience. Recent theories of cognitive development have proposed the metaphor of the "child as scientist" and characterized early learning as a process of exploration and hypothesis testing following principles of the scientific method (Gopnik et al., 1999; L. Schulz, 2012). Moreover, empirical work across a variety of domains – education (Grabinger & Dunlap, 1995), machine learning (Castro et al., 2009; Settles, 2012), and cognitive science (D. B. Markant & Gureckis, 2014) – has directly compared learning trajectories in self-directed contexts (active learning) as compared to settings where the learner has less control (passive learning). The upshot of this work is that active contexts often lead to faster learning because of enhanced attention and arousal or because the learners selects information that is closely linked to their current goals, beliefs, and interests (see Gureckis & Markant (2012) for a review).

Thus, children are capable of selecting actions that support their own learning, and a large body of work shows that social partners can create particularly good contexts for learning. This research, however, has often proceeded in parallel, focusing on the isolated effects of either active or social processes on children's learning. This stands in contrast to the ecological context in which language acqusition unfolds. That is, children acquire their first language from interactions with other people. And in these social interactions, they they are able to select actions – where to look, where to point, what question to ask – that influence the content and pacing of conversation. Taken together, these facts about the ecological context in which children learn highlight the need for integration across the active and social theoretical accounts.

But how can we begin to integrate these two proposals, which often contain definitional issues and a lack of formal foundations? In this chapter, I argue that a formal integrated account of active learning within social contexts is an important step towards a more complete account of early cognitive development. To connect the active and social learning proposals, I use the computational frameworks of Optimal Experiment Design (Emery & Nenarokomov, 1998; Lindley, 1956) and Bayesian models of social reasoning (@ Goodman & Frank, 2016). The key insight is that the presence of another person can modulate the *availability* and *usefulness* of different actions that the active learner could select. Specifically, social interactions can shape learners' goals, hypotheses, actions, answers, and decisions about when to stop gathering information.

The chapter is organized as follows. First, I provide definitions of active and social learning to clarify the behaviors and phenomena that the integrative account can address (Part I). Then, I review the theory of Optimal Experiment Design (OED) (Part II), highlighting its role as a formal framework for understanding human active learning. I also discuss the behavioral evidence for OED-like reasoning in both adults' and children's learning. Finally, I conclude by presenting an integrative account of how social contexts can shape active learning (Part III). In the final section, I also highlight a series of novel links between the social and active accounts, which present a way forward for empirical work that could shed light on how children's active learning processes operate over fundamentally social input.

## 1.2 Part I: Learning from others and learning on your own

A diverse set of scholars, theories, and empirical work has considered the contributions of active and social processes to children's learning. One consequence of this range of approaches is that the terms "active" and "social" have become associated with a vareity of meanings. Before integrating the two accounts, it is worth defining what we mean by active learning and social contexts. By providing definitions, this section aims to clarify the behaviors and phenomena that the integrative account attempts to explain.

### 1.2.1 Social learning

Learning can be social in a variety of ways. First, children could learn with another person present but without attending to or directly interacting with them. Research in social psychology shows that the mere presence of other people can facilitate performance of simple tasks and impair the performance of complex tasks (N. B. Cottrell, Wack, Sekerak, & Rittle, 1968; Uziel, 2007). Second, children could learn by looking to others as a guide by observing or imitating their behavior. In fact, children's capacity for faithful imitation is a critical feature separating human from non-human learning (Call, Carpenter, & Tomasello, 2005). Finally, children could both attend to the person and directly interact with them, entering a communicative learning context that engages psychological reasoning processes that alter the course of learning (Frank & Goodman, 2014; Goodman & Frank, 2016; Shafto et al., 2012b).

For this integrative account, I define a social context as a learning environment where another agent is present. This definition includes all of the social learning behaviors – observation, imitation, and learning from direct interaction – discussed above. This broad definition highlights the diverse pathways through which social information could interact with children's active learning. Moreover, this definition captures the diverse set of ecological contexts in which children develop, where in some cultures children experience high amounts of child-centered interactions while in others contexts they are expected to learn mostly through observation (Rogoff et al., 1993).

Social learning theories emphasize that children's rapid conceptual development is facilitated by the uniquely human capacity to transmit and acquire information from other people. A primary benefit of learning from others is that children gain access to knowledge that has accumulated over many generations; information that would be far too complex for any individual to figure out on their own (Boyd, Richerson, & Henrich, 2011). In addition to the cumulative effects, social contexts facilitate in-the-moment learning since more knowledgeable others can select input that is most useful for children's learning (Kline, 2015; Shafto et al., 2012b) and information that is likely to generalize beyond the current context (Csibra & Gergely, 2009).

There is a large body of empirical work on social learning across a variety of domains including language acquisition, causal learning, and concept learning. For example, newborn infants prefer to look at face-like patterns compared to other abstract configurations (Farroni, Csibra, Simion, & Johnson, 2002; Johnson, Dziurawiec, Ellis, & Morton, 1991), to listen to speech over non-speech

(Vouloumanos & Werker, 2007), their mother's voice over a stranger's (DeCasper, Fifer, Oates, & Sheldon, 1987), and infant-directed speech over adult-directed speech (Cooper & Aslin, 1990; Fernald & Kuhl, 1987; Pegg, Werker, & McLeod, 1992). Moreover, these attentional biases lead to differential learning in the presence of another person. 4-month-olds show better memory for faces that gazed directly at them (Farroni, Massaccesi, Menon, & Johnson, 2007), for an object if an adult gazed at that object during learning (Cleveland, Schug, & Striano, 2007; Reid & Striano, 2005), and perform better at tasks such as word segmentation from infant-directed speech compared to adult-directed speech (Thiessen, Hill, & Saffran, 2005). Kuhl (2007) refer to these effects as "social gating" phenomena since the presence of another person activates or enhances children's underlying computational learning mechanisms.

In addition to enhancing attention and memory, social contexts can facilitate learning by generating useful information that is tailored to the child's current developmental stage (Vygotsky, 1987). Empirical work shows that caregivers alter their communication style when speaking to children (e.g.,exaggerating prosody, reducing speed), which in turn can help children learn vowel sounds (Adriaans & Swingley, 2017; De Boer & Kuhl, 2003), segment the speech stream (Fernald & Mazzie, 1991; Thiessen et al., 2005), recognize familiar words (Singh, Nestor, Parikh, & Yull, 2009), and learn new lexical concepts (Graf Estes & Hurley, 2013). Additional evidence comes from Goldstein & Schwade (2008)'s study where they found that infants modified their babbling to produce more speech-like sounds after interacting with caregivers who provided contingent responses, suggesting that contingent, social input was particularly useful because it was closer in time and easier to compare discrepancies between the child's vs. adult's speech sound. Finally, converging support comes from research on children's early word learning, which shows that social partners actively reduce the complexity of the visual scene by using gaze/pointing/holding actions to make a single object dominant in the visual field (Yu & Smith, 2013; Yu, Ballard, & Aslin, 2005) and by producing labels for objects that children are already attending to (i.e., "follow-in" labeling) (Tomasello & Farrar, 1986).

Anbother feature of social interactions is that other people's actions are not random; instead they are intentionally selected with respect to some goal (e.g., to communicate information). And if children are sensitive to *why* someone else performed an action, they can use this information to facilitate learning. Recent empirical and modeling work has formalized this idea as a process of belief updating that is dependent in Bayesian models of cognition (Frank & Goodman, 2014; Goodman & Frank, 2016; Shafto et al., 2012b). For example, adults are more likely to think that pressing both buttons is necessary to activate a toy if that action was demonstrated by someone who knew how the toy worked as compared to the same action but demonstrated by someone accidentally pressing the buttons (Goodman, Baker, & Tenenbaum, 2009). Shafto et al. (2012b) interpreted these results as a psychological reasoning process such as: "if the other person were knowledgeable and wanted to generate the effect, then he would perform both actions." This finding also suggests that learners assume that others' goal-directed behaviors will be efficient and they should avoid performing unnecessary actions (e.g., pressing two buttons when pressing one would have been sufficient).

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

Finally, information learned from other people is more likely to generalize beyond the current context. Several accounts of cultural learning argue that an assumption of *generalizability* is fundamental to the human communication system and allows for the accumulation of cultural knowledge (Boyd et al., 2011; Csibra & Gergely, 2009; Kline, 2015). In these explanations, adults generate ostensive signals such as direct gaze, infant-directed speech, and infant-directed actions, which, in turn, direct infants' attention and bias them to expect generalizable information. Experimental work testing predictions of a "Natural Pedagogy" account shows that children tend to think that information presented in communicative contexts is generalizable (Butler & Markman, 2012; J. M. Yoon et al., 2008), and corpus analyses show that generic language (e.g., "birds fly") is common in everyday adult-child conversations (Gelman, Goetz, Sarnecka, & Flukes, 2008).

The work on social learning reviewed in this section highlight several points that are important for theories of cognitive development. First, from an early age, children are surrounded by other people who know more than they do. Moreover, these more knowledgeable others are invested in children's development and can provide good learning opportunities. Second, children are motivated to interact with other people, and these interactions engage and guide attention to relevant information. Finally, social contexts can trigger a set of psychological reasoning mechanisms that lead to stronger inferences, allowing children to get more information out of the same amount of input.

However, social learning accounts often reflect a relatively passive construal of the learner. It is clear that children are not just passive recipients of input from the world or other people. Instead, they actively process information and select behaviors that change what they learn. A parallel body of research on this topic – under the umbrella term of "active learning" – has developed alongside social learning theories.

### 1.2.2 Active learning

Learning can be active in a variety of ways. First, a child could be physically active, and this movement could change what information they extract from the experience. There is a large body of research that explores the effects of action experience on infants' learning (see Kontra, Goldin-Meadow, & Beilock (2012) for a review of work on embodied cognition). One classic example from Needham, Barrett, & Peterman (2002) shows that infants who physically hold and manipulate objects will outperform a control group on measures of object attention and exploration. Second, active learning could refer to children's contribution to processing incoming information. For example, young learners do not just passively accept other people's claims and will reject answers that conflict with their knowledge (Pea, 1982). Third, children might engage in self-generated active explanations. Lombrozo (2006) review evidence that 'self-explanation'can lead to better learning. Finally, active learning could refer to a decision-making process where children select, sequence, and pace their own learning experiences.

For the integrative account, I focus on active learning effects that arise via children's decisions about what action to take next. The key assumption is that active learners are trying to take actions that maximize the amount of information they can get in return. By scoping the account to decisions, I do not aim to ignore the importance of other types of active engagement; instead, the goal is to constrain the space of connections between active and social learning theories. Moreover, children's action selections capture a rich set of behaviors, including pointing, eye movements, verbal question asking, and causal interventions. Finally, focusing on active decisions connects work on children's learning to a rich tradition of computational and experimental research in the fields of machine learning, decision theory, and statistics.

The idea that children's actions are important for cognitive development has been an influential aspect of both classic (Berlyne, 1960; e.g., Bruner, 1961; Piaget & Cook, 1952) and modern (Gopnik et al., 1999; L. Schulz, 2012) theories of learning. Moreover, the effects of active processes have been studied in education (Grabinger & Dunlap, 1995; Prince, 2004), machine learning (Ramirez-Loaiza, Sharma, Kumar, & Bilgic, 2017; Settles, 2012), and cognitive psychology (Castro et al., 2009; Chi, 2009). One common thread across these diverse literatures is that active contexts lead to different (and often more rapid) learning outcomes because they (a) enhance learners' attention and memory and (b) allow learners to structure experiences that are tuned to their own goals, beliefs, and capabilities (see D. B. Markant, Ruggeri, Gureckis, & Xu (2016) for a review).

One compelling example of how to study these kinds of effects related to self-directed choice comes from D. Markant, DuBrow, Davachi, & Gureckis (2014)'s study of "deconstructed" active learning. Adults were asked to memorize the identities and locations of objects hidden in a grid and given different levels of control. They could select: (1) next location to search, (2) item to reveal, (3) duration of the trial, and/or (4) time between trials. D. Markant et al. (2014) also included a "yoked" control group who saw exactly the same training data that was generated by the active learning group, thus equating the experience while varying the level of control. Across the board, there was a memory advantage for active control, providing evidence for the benefits of being able to coordinate the timing of information with internal attentional processes.

Developmental experiments have shown similar active learning advantages. For example, Ruggeri, Markant, Gureckis, & Xu (2016) found that active control over the timing of new information led to better spatial memory in 6- to 8-year-olds (Ruggeri et al., 2016); Partridge, McGovern, Yung, & Kidd (2015) showed similar effects in the domain of word learning (see also Kachergis, Yu, & Shiffrin (2013) for evidence in adults); and L. Schulz (2012) found active learning benefits for preschoolers' understanding of new causal structures. Even 16-month-olds show better memory for objects they pointed to compared to an object that they had not actively engaged with (Begus, Gliga, & Southgate, 2014).

### 1.2.3 The scope of the integrative account

In sum, the empirical work reviewed in this section shows that both social and active processes can change learning by enhancing attention, memory, and inferential processes and by generating particularly "useful" learning data. The integrative account that I present in the rest of this chapter is scoped to focus on children's active learning *decisions* within social contexts. I argue that this is a useful step forward because it allows researchers to ask how specific pieces of social learning affect separate underlying components of decision making.

One major challenge of integrating these two proposals is that there are a large number of factors that could influence how active learning interacts with social reasoning, which in turn creates a large space of possibilities for researchers to test. One way forward is to constrain the space of hypotheses by using a formal model of information seeking and taking an ideal-observer approach (Geisler, 2003). The ideal-observer model allows researchers to focus on defining the structure of the learning task and asking how well learners can take advantaqge of the information available in the environment. Moreover, this approach forces researchers to explicitly define the processes of active and social learning as separable, underlying components, which can then become targets for empirical work.

Research in developmental and cognitive psychology has used the ideal-observer approach to understand active learning. One particularly useful model has been a formal account of scientific reasoning that falls under the umbrella term: Optimal Experiment Design (OED). The OED model was orginally designed to help scientists select the best experiment from the set of possible experiments, where "best" is defined as the experiment that leads to the highest amount of information gained. Using this formalization, researchers have been able to ask whether people's intuitive information seeking looks similar to predictions from OED models.

Moreover, OED uses the same mathematical framework as recently-developed models of social learning: Bayesian ideal-observer models of psychological reasoning during learning and communication (Frank et al., 2009; Goodman & Frank, 2016; Shafto et al., 2012a). These parallel formalizations suggest a way ot integrate active and social learning theories. This point is the primary focus of the integative account that I present in Part III of this chapter. Before discussing the details of the account, I provide a brief overview of the OED formalization.

## 1.3 Part II: A formal account of active learning

Optimal Experiment Design (OED) (Emery & Nenarokomov, 1998; Lindley, 1956; Nelson, 2005) is a statistical framework for quantifying the usefulness of experiments. Lindley (1956) described the approach as a transition from viewing statistics as binary decision making to a practice of gathering information about the "state of nature" (p. 987). The concrete proposal is to design studies that maximize expected information gain (a measure borrowed from Information Theory and discussed in more detail below) and continue to collect data until the information gained reaches a pre-determined threshold.

The OED approach allows scientists to make design choices that maximize the effectiveness of their experiments, reducing inefficiency and cost. Consider the following toy example borrowed from Ouyang, Tessler, Ly, & Goodman (2016) where a researcher is interested in designing the best experiment to figure out whether people think a coin is fair or biased (i.e., a trick coin). Here the researcher's hypotheses correspond to different models of the coin [$M_{fair} : Bernoulli(p = 0.5)$] and [$M_{bias} : Bernoulli(p)$ where $p \sim Uniform(0, 1)$] and the experiments correspond to different sequences of coin flips that she could select as stimuli. Imagine that the researcher has limited time or resources and can only show a sequence of four coin flips, creating a space of 16 possible experiments. An OED model allows the researcher to select the best experiment that maximally differentiates the two hypotheses. For example, OED provides an answer to the question: how much better would it be to use [$HHHH$] versus [$HTHT$]? Here, [$HHHH$] is more informative because both the bias and the fair coin models make the same predictions for the [$HTHT$] experiment, meaning we would not learn much from this test.

Nelson, McKenzie, Cottrell, & Sejnowski (2010) demonstrate the usefulness of taking an OED approach for differentiating competing theories of information seeking in adults' category learning. They created an OED model of their task, which included the design choices (what combination of features to show participants) and the relevant behavioral hypotheses (the different theories of category learning). They used the model to simulate the outcomes of using different stimulus sets, allowing them to choose stimuli for which the competing theories made very different predictions, speeding the rate of discovery.

Coenen, Nelson, & Gureckis (2017) provide a thorough review of the OED framework and its links to human information seeking. They outline the four critical parts of an OED model that are

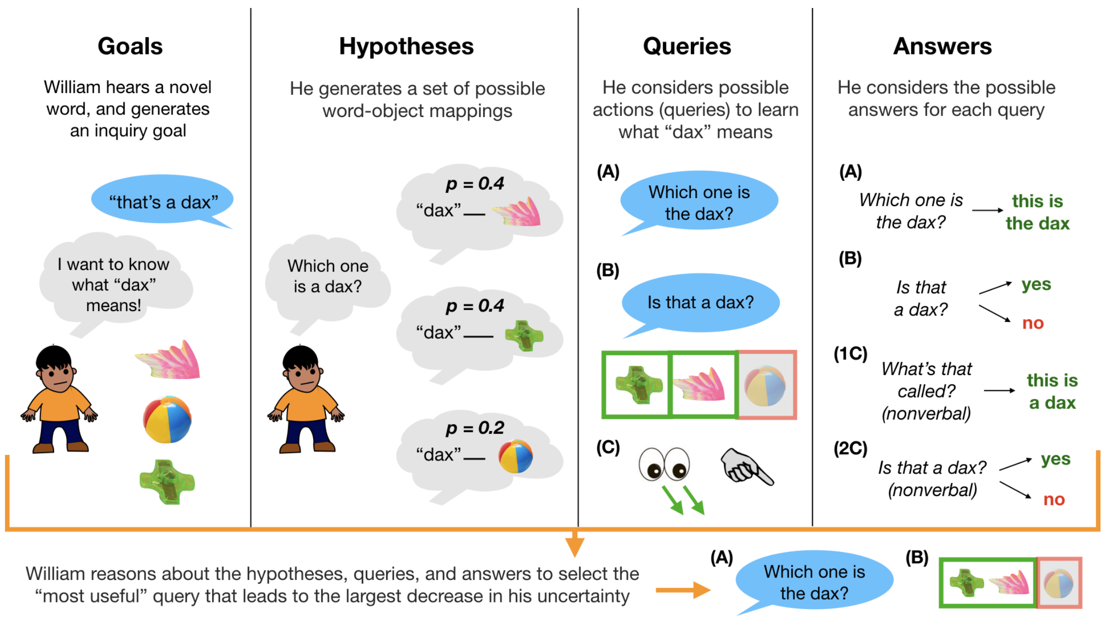


Figure 1.1: Schematic of an active word learning context using the decomposition of Optimal Experiment Design. Social input (hearing a novel word) triggers an inquiry goal. Then the learner considers potential hypotheses for the candidate word-object links, weighting each hypothesis by its prior probability. In this case, the learner thinks that the new word is less likely to refer to the familiar object BALL. Next, he considers possible queries (actions) and the potential outcomes of those actions. In the word learning context, the child must direct queries towards a social partner, which provides the learner with more possible queries: both verbal (questions) and nonverbal (eye gaze; pointing). Note that the social partner must interpret the goal of the child's nonverbal queries. If the learner selects the action to maximize expected utility, then he would ask the most informative question, which removes all uncertainty for the meaning of 'dax' – 'What's that called?' If he does select the relatively less informative action of asking about a single object, he would be unlikely to ask about the familiar object BALL since there is less information to be gained from this query based on his prior beliefs.

necessary to compute the expected value of an information seeking action: (1) a set of hypotheses, (2) a set of queries (i.e., actions) to learn about the hypotheses, (3) a generative model of the types of answers that each query could elicit, and (4) a way to score each answer with respect to the learning goal.[1] There are also two components that are external to the utility computation but important for an account of human inquiry. First, having a goal to learn, which instantiates the hypotheses, questions, and answers that a learner considers. And second, having a stopping rule, which refers to a threshold that causes people to stop seeking information and generate a response.

### 1.3.1 Evidence of OED-like reasoning in human behavior

A growing body of psychological research has used the OED framework as a metaphor for active learning. The idea is that when people make decisions, they engage in a similar process of evaluating the usefulness of different actions relative to their learning goals. Using this evaluation process, learners can then select behaviors that maximize the potential for gaining information. A success of the OED account is that it can capture a wide range of information seeking behaviors, including verbal question asking (Ruggeri & Lombrozo, 2015), planning interventions in causal learning tasks (C. Cook, Goodman, & Schulz, 2011), and decisions about where to look during scene understanding (Najemnik & Geisler, 2005). Figures 1 and 2 present schematic overviews of how OED principles could shape the learning process for two of these domains – causal learning (Figure 1) and word learning (Figure 2).

One compelling use case of OED metaphor as a model of human behavior comes from Nelson (2005) study of eye movements during novel concept learning. Their model combined Bayesian probabilistic learning, which represents current knowledge as a probability distribution over concepts, with an OED model that calculated the usefulness of different patterns of eye movements. Here, eye movements were modeled as a type of question-asking behavior that gathered visual information about the target concept. Nelson (2005) found that participants' eye movements aligned with predictions from the OED model. Specifically, participants changed the dynamics of eye movements depending on how well they learned the target concepts. Early in learning, when the concepts were unfamiliar, the model generated a broader, less efficient distribution of fixations to explore all candidate features that could be used to categorize the stimulus. However, after the model began

[1] See Appendix A for the mathematical details of the OED model.

to learn the target concepts, eye movement patterns shifted to become more efficient and focused on a single stimulus dimension to maximize accuracy. This shift from exploratory to efficient eye movements matched adult performance on the task, suggesting that people's behavior was sensible given the structure of the learning problem and the uncertainty in the context.

Recent developmental work has used OED models to ask whether children are capable of selecting efficient behaviors that maximize learning goals. For example, Legare, Mills, Souza, Plummer, & Yasskin (2013) used a modified question asking game where 4- to 6-year-old children saw 16 cards with a drawing of an animal on them. The animals varied along several dimensions, including type, size, and pattern. Children could ask the experimenter yes/no questions to figure out which animal card was hidden in a box. Legare et al. (2013) coded questions as constraint-seeking (narrowing the set of possible cards by gathering information about a particular dimension (e.g., "Is it red?"), confirmatory (questions that provided redundant information), or ineffective that did not provide any useful information (e.g., "Does it have a tail?"). All children produced a high proportion of the more useful, constraint-seeking questions. Moreover, the number of constraint-seeking questions was correlated with accuracy in guessing the identity of the hidden card. Legare et al. (2013) interpreted these results as evidence for OED-like reasoning in children's question asking. Other work using the question-game finds that children prefer to direct questions to someone who is knowledgeable compared to someone who is inaccurate or ignorant, providing additional support for the OED hypothesis (Mills, Legare, Bills, & Mejias, 2010; Mills, Legare, Grant, & Landrum, 2011).

Another developmental example comes from C. Cook et al. (2011) study of causal learning . They showed preschoolers a device that played music when beads were placed on top of it and manipulated the usefulness of different actions that children could take to test the device. Half of the children saw evidence that all types of beads could make the machine work, while the other half learned that only specific types of beads (defined by color) could make it go. Next, children could choose one of two sets of beads to test the machine. In one set the beads were stuck together, in the other, they could be separated. Children who learned that only some of the beads worked were twice as likely to select the separable beads. This finding suggests that children were reasoning about the amount of information they could gain by choosing the detachable beads since this choice would allow them to test each bead independently. In contrast, the children who believed that all beads worked had less to gain by picking the separable set. This result is compelling because it provides evidence that children's were reasoning about a decision (separable vs. stuck together beads) that would influence a future opportunity to generate useful information.

Although the OED approach has provided a formal account of seemingly unconstrained information seeking behaviors, there are several ways in which it falls short as an explanation of human self-directed learning. Coenen et al. (2017) argue that OED models make several critical assumptions about the learner and the learning task, including (1) the hypotheses/questions/answers under consideration, (2) that people are actually engaging in some expected utility computation in order to maximize the goal of knowledge acquisition, and (3) that the learner has sufficient cognitive capacities to carry out the calculations. In the next section, I argue that limitations of the OED approach can be productively reconstrued as opportunities for understanding how learning from other people could scaffold children's active learning. I focus on integrating research and theory on social learning with five key components of the OED model: goals, hypotheses, questions, answers, and stopping rules (see Figure **??** for a schematic overview of the account).

## 1.4 Part III: Active learning within social contexts

Why should we situate active learning within research on the effect of social learning contexts? First, children do not re-invent knowledge of the world, and while they can learn a tremendous amount from their own actions, much of their generalization and abstraction is shaped by input from other people. Moreover, social learning can be the only way to learn something (e.g., first language acquisition). Finally, children are often surrounded by parents, other adults, and older peers – all of whom may know more about the world than they do, creating contexts where the opportunity for social learning is ubiquitous.

Second, there is a body of empirical work showing that active learning can be biased and ineffective in systematic ways. For example, work by Klahr & Nigam (2004) found that elementary school-aged children were less effective at discovering the principles of well-controlled experiments from their self-directed learning, but were capable of learning these principles from direct instruction. D. B. Markant & Gureckis (2014) showed that active exploration provided no benefit over passive input in category learning when there was a mismatch between the target concept and adults' prior hypotheses going into the learning task. And McCormack, Bramley, Frosch, Patrick, & Lagnado (2016) found that 6-7 year-olds showed no benefit from active interventions on a causal system compared to observing another person perform the interventions.

In a comprehensive review of the self-directed learning literature, Gureckis & Markant (2012) point out that the quality of active exploration is linked to the learner's understanding of the task: if the representation is poor, then self-directed learning will be biased and ineffective. Coenen et al. (2017) continue this line of argument and propose a series of specific challenges for research on active learning. Here is a sample of those open questions that are most relevant to the integrative account proposed in this chapter:

- What triggers inquiry behaviors in the first place?
- How do people construct a set of hypotheses?
- How do people generate a set of queries?
- What makes a "good" answer?
- How do people generate and weight possible answers to their queries?
- How does learning from answers affect query selection and belief change?

In the rest of this chapter, I argue that ideas from research on social learning can address these challenges. I start from the OED model, and use it as a conceptual tool to integrate social contexts and active learning. The contribution of this formalization is that it makes the different components of active learning explicit, highlighting the aspects that might be particularly challenging for young learners. Moreover, the "challenges" to the OED account can be reconstrued as opportunities for understanding the benefits of learning from other people. In each of the following sub-sections, I first define a challenge for active learning. Then, I discuss how social contexts could address each challenge, highlighting prior empirical work that connects active and social learning accounts (see **??** for an overview).

### 1.4.1 Goals

In the OED framework, an inquiry goal refers to the underlying motivation for information seeking. This is often operationalized as a search for the target hypothesis amongst a set of candidate hypotheses. Some examples of inquiry goals that children might hold are:

- What is this speaker referring to? (word learning)
- What types of objects are called "daxes"? (category learning)
- How does this toy work? (causal learning)

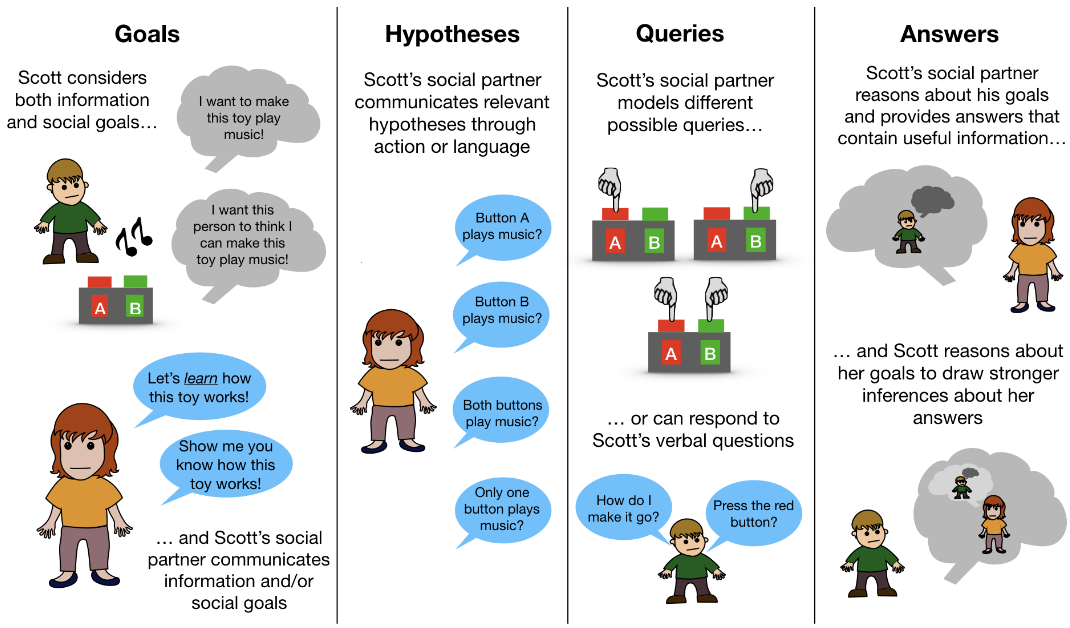


Figure 1.2: Schematic of active learning within a social context. Each panel shows how social information could influence a different component of the active learning process. These social effects occur in-the-moment of learning or over developmental time. Also, the cause of the social effect varies from the mere presence of another person to triggering a sophisticated psychological reasoning process about others' goal-directed behaviors. Note that the panels correspond to the different sub-sections in Part IV of the text.

- Is this person reliable? (selective learning)

Learning goals are important since without them the learner will struggle to evaluate whether an action leads to learning progress. Coenen et al. (2017) illustrate this point by saying,

> The importance of such goals is made clear by the fact that in experiments designed to evaluate OED principles, participants are usually instructed on the goal of a task and are often incentivized by some monetary reward tied to achieving that goal. Similarly, in developmental studies, children are often explicitly asked to answer certain questions, solve a particular problem, or choose between a set of actions. (p. 32-33)

Characterizing children's goals is not trivial they could consider a range of goals at any moment with no guarantee that learning progress be one of them. In fact, one line of theorizing about the OED hypothesis argues that effective information seeking should only occur in the presence of precise tasks and goals. Consider the situation where a parent gives their child a new toy with several buttons on it and says, "Let's figure out how this toy works!" In this case, it becomes possible to ask whether the child selects actions that are more or less useful with respect to understanding the toy's causal structure.

This scenario illustrates how interactions with other people can trigger learning goals and information seeking. Empirical work shows how the actions of a social partner can increase children's tendency to detect their own uncertainty (see Lyons & Ghetti (2010) for a review). The upshot of this research is that children's ability to realize when they do not know something is relatively slow to develop. For example, Markman (1979) showed that elementary school-aged children were unable to detect obvious inconsistencies in written paragraphs (e.g., "fish can't see without light, and there's no light at the bottom of the ocean, but some fish at the bottom of the ocean only know their food by its color."). Interestingly, if the experimenter gave children an explicit warning or challenge to find a problem with the essay, then they were more likely to monitor uncertainty and asked more clarifying questions. This finding can be reconstrued as the social context shifting children's expectations, highlighting the learning goal, and facilitating their information seeking actions. Converging evidence comes Kim, Paulus, Sodian, & Proust (2016), which showed that in an "opt-out" task, 3- to 4-year-olds who were told they woulid have to teach another person about the contents of a opaque box showed higher rates of uncertainty monitoring compared to children who were not expecting to interact with anyone else (see also Lombrozo (2006)).

In addition to triggering inquiry goals, social partners can communicate the *value* of learning goals relative to other goals that children may pursue. This connection draws on theoretical and empirical work exploring how children's environments can shape their intuitive frameworks for processing information and generating goals (i.e., intuitive theories) (Dweck & Leggett, 1988). These accounts propose that if children believe that abilities are malleable, they will want to increase their competence (prioritize learning goala) as opposed to demonstrate their fixed abilities (prioritize performance goals). Empirical work shows that when adults emphasize a learning goal (e.g., "If you pick the task in this box, you'll probably learn a lot of new things." vs. "If you pick this box, although you won't learn new things, it will really show me what kids can do."), children tend to seek out the more difficult task [elliott1988goals]. Moreover, both lab-based experiments and observational work provide evidence that the language adults use when praising children influences their tendency adopt inquiry goals (Cimpian, Arce, Markman, & Dweck, 2007; Gunderson et al., 2013).

While social interactions can emphasize learning, they can also engage psychological reasoning about others' mental states and elicit social goals that take priority over learning goals. Consider the "goals" panel of the schematic active-social learning context shown in **??**. If the learner is worried about what his social partner thinks of him, then he might prioritize actions that reduce the chance of making mistakes and may not even ask for a novel label. Moreover, he could seek out easy tasks that demonstrate his competence at the expense of selecting actions that help him learn. The OED framework typically focuses on informational goals with progress measured as reduction in uncertainty. However, recent empirical and modeling work has begun to move beyond informations-specific utiilty functions to include other goals learners may have (e.g., saving time, money, or cognitive resources) [meder2012information].

Recent work modeling pragmatic communication[2] provides a way to integrate social goals within the OED framework. For example, T. Yoon Erica J & Frank (2017) model speakers' decisions to use polite speech as opposed to direct speech (e.g., indirect language such as "I don't think that dress looks phenomenal on you" as opposed to "It looks terrible") as a tradeoff between maximizing informational and social goals, showing that speakers are in fact balancing these two goals when deciding what to say.

In both OED and RSA, people are assumed to select actions that maximize utility, but the

[2]Rational Speech Act (RSA) framework for pragmatic reasoning. The RSA approach models language comprehension and production as, "a process of recursive reasoning about what speakers would have said, given a set of communicative goals" (p.819) (Goodman & Frank, 2016)

politeness model allows social information in the utility computation. An intriguing possibility for future research would be to adapt the utility-theoretic approach used by T. Yoon Erica J & Frank (2017) to model information seeking behaviors in social contexts that vary how much they emphasize learning goals. The presence of another person could be modeled as an increase in the weight that children place on maximizing social goals, leading children to select easier tasks where they can appear competent(see E. J. Yoon, MacDonald, Asaba, Gweon, & Frank (2018) for an example of this approach in causal learning). Moreover, this builds on the goal-orienting accounts reviewed above (Dweck & Leggett, 1988) since behavior is modeled as an output of a mixture of goals as opposed to chlidren holding either a performance or a learning goal.

Another open question for research on children's learning goals is how often children experience contexts where learning goals are apparent or emphasized in their everyday experience. We do not yet have an estimate of the prevalence of situations that would lead children to generate learning goals. One exception, however, is research on *guided participation* by Rogoff et al. (1993) provides evidence that parents from a diverse set of cultural backbgrounds produce high rates of structuring and goal-orienting behaviors during activities such as cooking, shopping, working, etc. It is interesting to consider whether variability in children's exposure to goal-orienting behaviors could influence children's tendency to spontaneously generate learning goals.

### 1.4.2 Hypotheses

Once children have a learning goal, the next step in the OED model is to figure out what hypotheses to consider. Intuitively, a hypothesis is a candidate explanation about how the world works. For example, consider the schematic learning context shown in **??**. Here, the child might generate the following hypotheses about the meaning of a new word "dax": (1) dax = object A, (2) dax = object B, or (3) dax = object C.[3]

The set of hypotheses under consideration is critical for quantifying effective self-directed learning in the OED account. The usefulness function of expected information gain outlined in Part II works by comparing the learner's uncertainty over hypotheses before and after they see an answer ($U(a) = ent(H) - ent(H|a)$). Without a defined hypothesis space, it is challenging to select the best action to reduce uncertainty. Put another way; the OED framework does not readily deal

[3]This hypothesis space is simplified since it only considers the possibility of one-to-one word-object mappings and that the new word refers to the co-occurring visual context.

with situations where learners might have to consider a large space of hypotheses, might hold the wrong hypotheses, or might perform actions without considering any hypotheses at all. This is an especially important challenge for developmental accounts that draw on OED principles since these scenarios seem plausible for young learners. Social partners, however, can address this challenge by providing children with a constrained set of possible explanations that facilitate comparison of different information seeking actions.

Consider the case of children's early word learning where even the simplest of words, concrete nouns, are often used in complex contexts with multiple possible referents, which in turn have many conceptually natural properties that a speaker could talk about. This ambiguity creates the potential for an (in principle) unlimited number of hypotheses that children could entertain when trying to figure out word meanings (Quine, 1960). Social-pragmatic theories of lexical development often start from the idea that adults constrain the learning task by providing social cues (eye gaze, pointing, etc.) that map words to their referents during labeling (P. Bloom, 2002; Clark, 2009; Hollich et al., 2000). Some of our own empirical work shows that the number and fidelity word-object hypotheses that word learners store tracks with the strength of social cues available during the labeling moment. (MacDonald, Yurovsky, & Frank, 2017b). Other empirical wor shows that even children as young as 16 months prefer to map novel words to objects that are the target of a speaker's gaze and not their own (D. A. Baldwin, 1993), and analyses of naturalistic parent-child labeling events shows that young learners tended to retain labels accompanied by clear referential cues, which served to make a single object dominant in the visual field (Yu & Smith, 2012).

Social input can also influence the hypotheses that children generate by revising their intuitive theories about the world. Gerstenberg & Tenenbaum (2017) describe an intuitive theory as, "an ontology of concepts, and a system of (causal) laws that govern how the different concepts interrelate. . . " (p. 3). Importantly, these theories shape how children interpret incoming information and, in turn, the set of candidate explanations (hypotheses) they could explore. Empirical work on conceptual change across development has explored the ways that children integrate input from other people with their current theories (Gelman, 2009). For example, elementary school-aged children tend to hold a mixture of beliefs about the shape of the earth, ranging from a flat earth theory to the adult-like, sphere model (Vosniadou & Brewer, 1992). Interestingly, some children hold intermediate beliefs such as a theory where there are two earths, suggesting that they actively integrate aspects of their initial theory with the information they get from other people (see Opfer & Siegler (2004) for another example from intuitive theories of biological concepts).

In sum, research on children's hypotheses suggest that the space of explanations children consider are likely quite different from adults and that their hypotheses can be shaped by social information both during the moment of learning (e.g., referential gaze during word learning) and over a developmental timescale (e.g., intuitive theory revision). Critically, social partners can facilitate active learning by constraining the set of hypotheses under consideration, which makes comparing the utility of exploring each hypothesis more tractable. An open question for future research is how children's information seeking changes as a function of the size of the hypothesis space. Moreover, there is a need to move beyond lab-based studies towards observational research that measures how children's everyday social interactions constrain the hypotheses they decide to target with their exploration behaviors.

### 1.4.3 Queries

Queries in the OED framework refer to the set of experiments that a scientist could conduct to gather information about their hypotheses. In human active learning, queries are the set of actions people can take to gather information. Empirical work on active learning has explored a variety of behaviors, including verbal questions, pushing a button to figure out how a toy works, and decisions about where to look. One of the strengths of the OED account is that it provides general principles that could explain such a wide range of behaviors.

The challenge for young learners, however, is to discover what behaviors are available and of those actions which one might be particularly useful for learning. One way for children to address this challenge is to look to older peers and adults to figure out what actions can help then learn. Moreover, social learning context change the query space by adding a the option of querying a social partner, which dramatically expands the set of possible learning-related actions the child could take.

Research on verbal question asking provides insight into how social input can model information seeking queries. First, the very act of asking a question in natural language requires that children have acquired a conventionalized symbolic system, which must have been learned from social input. Second, both experimental work and corpus analyses provide evidence that children's question-asking becomes more varied and productive over the first years of life as they get exposed to more complex language input. Finally, observational studies have found that that parents' use of wh-questions predicts children's later vocabulary and verbal reasoning outcomes (Rowe, Leech, & Cabrera, 2017) and children of parents who were trained to ask "good" questions during book reading episodes at home had children who asked better questions during book reading sessions at school (Birbili & Karagiorgou, 2009). One explanation for these associations is that wh-questions challenge children to produce more complex responses that build verbal abilities. However, another intriguing causal pathway is that the frequency and type of questions that parents use provides children with a templates for how to ask useful questions.

Even if children have the capacity to generate multiple queries, they still have to evaluate the relative usefulness of each action with respect to their learning goal. In fact, empirical work with adults shows a substantial gap between people's question-generating and question-evaluation skills. For example, Rothe, Lake, & Gureckis (2015) used an OED model to measure the expected information gain of adults' natural language questions in a modified "Battleship" game, and found that people rarely produced high information gain questions. In a follow-up experiment, however, Rothe et al. (2015) showed that when a different group of adults had access to the list of questions generated by the participants in the unconstrained version, they were quite good at recognizing and selecting high information gain questions.

Developmental work provides additional evidence of this production-comprehension asymmetry. For example, children younger than the age of three have difficulty generating useful verbal questions compared to their older peers in "Twenty Questions" style tasks that are designed to measure question-asking skill (Mills et al., 2010, 2011), but even the youngest children in that sample are capable of using information elicited by others' questions to succeed at the task (Mills, Danovitch, Grant, & Elashi, 2012). Moreover, Mills et al. (2011) directly manipulatted whether children were exposed to a training phase where adults modeled useful questions and found that this helped the youngest children produce useful questions at a much higher rates. Converging evidence comes from research showing that direct instruction (i.e., understanding the objectives of inquiry and identifying good questions) was necessary for elementary-school-aged children to develop skill in designing informative experiments to learn about physics concepts (Kuhn & Pease, 2008).

In addition to providing a model of useful queries, social contexts also expand the set of possible queries by adding a "social target" for information seeking actions. That is, the child has an additional choice: to gather information from the non-social world or other people. The "Questions" panel in Figure 3 shows a child playing with a set of concrete objects. If there is no social partner present, they could still interact with the objects to learn about their shape, texture, or functional properties. But if another person is present, the child now has the option to ask verbal questions or to seek information from the other speaker by gathering their nonverbal cues (e.g., pointing, eye gaze, or facial expressions).

Recent empirical work has explored the factors that influence children's decisions to seek information from other people. For example, Fitneva, Lam, & Dunfield (2013) showed that children know when to query other people to gain information that they could not get on their own (e.g., invisible properties of a novel social category). Additional evidence comes from work by Lockhart, Goddu, Smith, & Keil (2016) where they showed that 5- to 11-year-olds could reliably determine the kinds of things a person "growing up on their own" could learn from personal experience (that the sky is blue) vs. required interactions with other people (that the earth is round). Finally, work on children's help-seeking behaviors shows that both preschoolers and even infants seek help systematically when completing a task, turning to a social target to request information or acting on the world depending on which information source was more likely to help them achieve their current goal (Gweon & Schulz, 2011; Vredenburgh & Kushnir, 2016).

Some of our work has explored how the presence of another person changes the set of information seeking behaviors available (MacDonald, Blonder, Marchman, Fernald, & Frank, 2017a; MacDonald, Marchman, Fernald, & Frank, 2018) by asking how social targets change children's real-time selection of visual information via their eye movements. In a real-time familiar language processing task, we found that children learning a visual-manual language gathered more visual information from a signer compared to children processing spoken language from a a speaker. We interpreted this behavior within an information seeking framework, hypothesizing that sign learners were sensitive to the higher value of fixating on the source of language; whereas spoken language learners could shift visual attention more rapidly while still gathering linguistic information through the auditory channel. We followed up on this finding by showing a similar pattern of results in children and adults processing spoken language in noisy auditory environments where gathering more visual information could compensate for the less reliable linguistic signal. Critically, listeners would not have been able to gather this information if the speaker was not present (e.g., listening to a noisy recording).

### 1.4.4 Answers

OED defines answers as the possible states of the world after the learner generates a query. An answer is useful if it decreases uncertainty about the learners' hypotheses. The challenge for the child as active learner can be separated into two parts: (1) figure out what which answers (outcomes) are likely for each query (action) and (2) decide how much to update beliefs after seeing each answer. In this section, I discuss the ways that social contexts can affect each component of the answer evaluation process.

Defining a "good" answer is challenging. Intuitively, a good answer provides the learner with information that they did not already know, that they were interested in learning, and that is likely to be useful beyond the current context. Even within the formal OED framework, there have been a variety of ways to instantiate this utility function (e.g., information gain, probability gain, and Kullback-Leibler divergence) (Nelson, 2005). These information-theoretic utility functions take into account the learner's prior beliefs, which are represented as probability distributions over hypotheses and compute the effect of each answer on the learner's beliefs, which is represented as a conditional probability distribution.

Social learning theories often start from the idea that interactions with other people increase the probability of getting good information. For example, evolutionary models argue that knowledge transfer between generations allows for the gradual accumulation of small improvements that eventually led to complex tools, beliefs, and practices that would be difficult, if not impossible, for any individual to discover on their own (Kline, 2015). Boyd et al. (2011) provide the example of a hunter stumbling across the link between the color/texture of ice and its stability, saying that this type of rare information would be much harder for individuals to re-discover on their own. But social transmission allows humans to pass these discoveries down to subsrequent enerations, allowing humans to move beyond the information that the world is likely to provide.

Csibra & Gergely (2009)'s theory of "Natural Pedagogy" argues that an assumption of *generalizability* is a fundamental component of the answers that children get when they interact with adults. Under their account, when adults provide ostensive cues (eye gaze or child-directed speech) to signal generalizable knowledge children update their beliefs differently. Empirical work shows that infants are more likely to generalize the valence of an object to a new person if this information was learned in the presence of an ostensive, pedagogical cue (Gergely, Egyed, & Király, 2007). Moreover, infants are more likely to encode the stable features of an object, as opposed to its location in space, if a communicative signal such as a point guided their attention to that object (J. M. Yoon et al., 2008).

In addition to to increasing the chance of seeing generalizable information, features of the social context can also modulate the way active learners evaluate possible answers. This link is one of the more developed connections between the OED and social learning accounts. That is, researchers have made progress in modeling the influence of different assumptions that a learner could make about the process through which other people generate answers. Shafto et al. (2012b) describe these different sampling assumptions, placing them along a continuum that varies in terms of how much a learner should update their beliefs:

- *Weak sampling*: answers generated at random from the set of all possible answers (independent of target hypothesis)
- *Strong sampling*: answers generated at random from the set of answers that are true of the correct hypothesis (linked to target hypothesis)
- *Pedagogical sampling*: answers generated that maximize the learner's belief in the correct hypothesis (linked to target hypothesis and consider alternative hypotheses)

If the learner assumes strong or pedagogical sampling, then they can make stronger inferences that speed learning. For example, if we see someone press two buttons to activate a device, we are more likely to think that both buttons were necessary if that person knew how the machine worked and wanted to communicate to us how it worked. Otherwise, if one of the buttons would have been sufficient, then it would not make sense for them to perform the less efficient action of pressing both buttons. The effects of these sampling assumptions are fundamentally psychological. They require the learner to reason about others' goals and to reason about whether other people are thinking about their goals.[4]

Empirical support for the pedagogical sampling account comes from a range of domains/tasks, including word learning (Frank et al., 2009), pragmatic inference (Frank & Goodman, 2012), and causal reasoning (Bonawitz et al., 2011). These empirical findings connect directly to the OED model, Consider Xu & Tenenbaum (2007a) finding that when a knowledgeable teacher generates object labels, learners assumed the examples indicated the true word meaning, making it more likely that three examples would be drawn from the larger, basic category (as opposed to the smaller

[4]See the "Answers" panel of Figure XXX for an illustration of this recursive reasoning process within an active learning context.

subordinate category). This effect was modeled by modifiying the likelihood function in a Bayesian cognitive model. In this case, the likelihood function for the teacher-driven condition was designed to capture the idea that learners should prefer more restrictive hypotheses if they are confident that the teacher generated labels based on the actual word meaning. This formalization makes direct contact with the OED model of human inquiry since learners consider how much answers will update their beliefrs, capturing the idea that responses generated to help us learn carry more information.

Another line of empirical work has focused on children's decisions about whom to learn from. Even young infants are capable of *selective* learning, rejecting answers that conflict with their knowledge (Pea, 1982) and seeking information from people who tend to provide good information in the past (Koenig, Clement, & Harris, 2004). For example, Chow, Poulin-Dubois, & Lewis (2008) found that 14-month-olds are less likely to follow the gaze of a person who had consistently directed gaze towards an empty location. Moreover, children prefer to learn from familiar over unfamiliar adults (Corriveau & Harris, 2009), adults over peers (Rakoczy, Hamann, Warneken, & Tomasello, 2010), and ingroup over outgroup members (MacDonald, Schug, Chase, & Barth, 2013). In fact, Gweon, Pelton, Konopka, & Schulz (2014) found that 14-month-olds explore objects more after interacting with a teacher who had been under-informative in their previous demonstrations, providing evidence of an early ability to link the quality of answers to active learning decisions.

Interestingly, the outcome measures in these studies of selective learning – whom to direct questions towards or how long to explore a novel toy – are information-gathering decisions. While this is an implicit link to the OED account, selective learning phenomena have also been formally modeled as modifications to the likelihood function in Bayesian cognitive models. For example, Shafto et al. (2012a) developed a model in which children reason about both the helpfulness and knowledgeability of speakers when deciding whom to learn from and were able to capture several qualitative findings from the selective trust literature. This approach parallels the word learning and pedagogical sampling models reviewed above. It is interesting tha same modeling approach can account for children's behavior in different domain, suggesting that social reasoning effects should be considered when chracterizing the utility of answers from other people.

One candidate for future research is to ask how social contexts change children's decisions about whether to initiate information seeking behaviors in the first place. That is, if their social partners are unlikely to provide useful answers, then active learning (even if children are capable of selecting informative actions) becomes less valuable. The dual consideration of costs and benefits in active learning has been the focus of much research in machine learning, which tries to select the set of questions to ask taking into account how long it will take a human to respond (Haertel, Seppi, Ringger, & Carroll, 2008). Moreover, recent lab-based studies and theorizing in social cognition suggest that children are capable of "intuitive utility maximization" reasoning that others take actions to increase rewards while minimizing costs in terms of time, effort, etc (Jara-Ettinger, Gweon, Tenenbaum, & Schulz, 2015). It would be interesting to bring these cost-based approaches to bear on questions about how social contexts modify children's active learning.

### 1.4.5 Stopping rules

A stopping rule describes a threshold that causes people to cease information seeking and generate a behavior. The concept draws on ideas from probability theory that have been used to model how random variables change as a function of time. Rules can be information or time-based. For example, when researching for a paper, a student might generate the time-based stopping rule – read for two hours – or a more information-based rule – read until I understand this concept. The learner's goal is to figure out the stopping rule that balances achieving the inquiry goal with reducing unnecessary time/effort put into the task.

Studies of children's information seeking have primarily focused on measuring whether children persist if their initial request is not satisfied. For example, Frazier, Gelman, & Wellman (2009) analyzed parent-child question-answer exchanges from the CHILDES database to see if children show evidence of seeking causal explanations when they ask *how* and *why* questions. To address this hypothesis, Frazier et al. (2009) measured the probability of children re-asking the same question and the likelihood of asking a different, follow-up question after receiving either an explanatory response (e.g., CHILD: "Why you put yogurt in there?" ADULT: "Yogurt's part of the ingredients") or a non-explanatory response (e.g., CHILD: "How do you get sick?" ADULT: "I don't know."). Children were more than twice as likely to re-ask a question after getting a non-explanatory response (24%) compared to an explanatory answer (9.4%), providing evidence that they continued to collect information until their inquiry goal was satisfied.

Converging evidence comes from Deborah, Louisa Chan, & Holt (2004)'s work exploring children's intended meaning when they ask "What is it?" about objects. Children's propensity for asking follow-up questions was measured after they were given either a name or a functional explanation in response to an ambiguous request ("What is it?" Or "What's this?"). Similar to Frazier et al. (2009)'s findings, 2- to 4-year-olds asked more follow-up questions when adults provided an object label, suggesting that they intended to ask about the object's function and persisted to get this information. Children were also more likely to change the form of their ambiguous questions to more specifically target functional explanations in the object label condition. Together, these studies suggest that young children are sensitive to when they have gathered sufficient information to address their questions. In the majority of this work, the social context influenced children's stopping decisions by giving them the information they desired.

However, social contexts can shape children's stopping decisions in other ways. A recent body of research shows that adults' demonstrations of pedagogy directly influence children's decisions about whether to persist in exploration. For example, Bonawitz et al. (2011) showed that preschoolers spend less time exploring an object and are less likely to discover alternative object-functions after an adult explicitly taught a single function (Bonawitz et al., 2011). The explanation for this effect is similar to the pedagogical inference work reviewed in the "Answers" section. A pedagogical demonstration by a knowledgeable teacher provides evidence for that function and against the existence of other functions; otherwise, the teacher would have demonstrated the other features. We can construe this finding as an effect of social input on children's stopping rules. When the social context indicates that there is less to learn, children adopt a lower threshold for ending their search.

It is not the case that information acquired in social contexts always reduces information search. In fact, Butler & Markman (2012) study of children's inductive inferences provides evidence that a pedagogical demonstration leads to an increase in exploration. Preschoolers saw an unfamiliar object and learned a novel causal property (that the object could magnetically pick up paper clips). In one condition, the experimenter demonstrated the property with a pedagogical framing ("Look, watch this!"). In the other condition, it was an accidental demonstration ("Oops!"). After the pedagogical demonstration, children spent more than twice as much time exploring the objects and generated three times as many attempts to make the objects pick up the paper clips.

These are seemingly contradictory effects of pedagogy on children's stopping rules. However, they both arise because socially transmitted information is more informative and warrants stronger inferences. In the causal learning case, the stronger inference is about the lack of alternative object-functions, leading to less exploration. In the inductive inference case, the stronger inference is about the generalizability of the causal property, leading to more exploration. These findings also highlight the useful distinction between social information available in the moment and social input acquired from previous interactions.

Understanding why children decide to stop gathering information is a promising area for future research. Studies could focus on children's developing capacity to reason about the cost of actions for themselves and others. This cost term is critical to deciding when it is not worth gathering additional information. In fact, recent theorizing in the field of social cognition proposes that intuitive reasoning about the costs/benefits of others actions is the core of our social cognition. Jara-Ettinger, Gweon, Schulz, & Tenenbaum (2016) describe this idea as a Naive Utility Calculus where, "... human social cognition is structured around a basic understanding of ourselves and others as intuitive utility maximizers." (p. 589).

There has also been a growing interest in developing "cost-sensitive" active learning algorithms in the field of machine learning (Haertel et al., 2008), with researchers beginning to define costs in increasingly sophisticated ways. For example, Settles, Craven, & Friedland (2008) point out that the cost of information gathering should not be measured as a reduction in the number of training trials if those training trials vary in length because specific questions are more challenging to answer. Thus, an efficient active learner should want to ask questions that maximize information gain, but they should also take into account the cost incurred by others (e.g., time or mental effort) to provide that information. This idea is fundamentally psychological in that it expands the utility computation to include some measure of how our behavior affects others' actions and/or mental states. Another open question is how children develop skill in reasoning about more complex costs (e.g., reputation management), and how children integrate their costs with the costs incurred by others.

## 1.5 Conclusions

In this chapter, I proposed a way forward for integrating active and social learning theory. I argued that the formal framework of Optimal Experiment Design (OED) is a useful way to characterize the effects of social contexts on children's active learning. The OED framework defines information seeking as a process of expected utility maximization for gaining information. There are four model components – goals, hypotheses, questions, and answers – and other factors that are important but exist outside the model such as stopping rules. I used the OED decomposition to bring social learning phenomena into contact with active learning theory, and I suggested that the social context can influence children's active learning by:

1. communicating and/or triggering a diverse set of goals both informational and/or social
2. shaping the content of children's hypothesis spaces both in-the-moment and/or over a developmental timescale
3. serving as a model of possible and useful queries for children to imitate
4. providing useful and generalizable answers to children's queries
5. modulating when children decide to stop collecting information

The heart of this proposal is that an integrative account of active learning within social contexts represents a valuable step towards understanding cognitive development. I have tried to argue that the social and active learning accounts have much to be gained by considering the other. Active learning accounts benefit by understanding how learners function within social contexts. This social information can allow researchers to create more sophisticated utility functions that take into account the social goals that people consider when deciding what to learn. This seems especially important for characterizing children's active learning since observational studies of learning environments suggest that opportunities to learn from social interaction are ubiquitous. On the other hand, researchers interested in social learning can benefit from advances in the field of active learning by connecting their ideas to the rich traditions of machine learning, decision theory, and statistics. Moreover, children's information seeking decisions are often used as dependent variables in studies of social learning phenomena. Thus, a secondary benefit would be a deeper understanding of the factors that influence the measurement of social learning effects.

Finally, I think research on active learning could move beyond studies that lack a social context and begin to document the presence of learning goals, constrained hypothesis spaces, and the quality of answers in children's everyday experiences. This line of inquriy falls out of the integrative approach emphasized In this chapter. It will require a shift from relying on highly-controlled lab experiments of children's active learning skill to leveraging large-scale, observational datasets. And while this approach adds complexity to our experiments and models, I think that the benefit will be a far greater understanding of how children's active learning operates over fundamentally social input.

# Chapter 2

# Eye movements during American Sign Language comprehension

## 2.1 Introduction[1]

Finding meaning in a spoken or a signed language requires learning to establish reference during real-time interaction – relying on audition to interpret spoken words, or on vision to interpret manual signs. Starting in infancy, children learning spoken language make dramatic gains in their efficiency in linking acoustic signals representing lexical forms to objects in the visual world. Studies of spoken language comprehension using the looking-while-listening (LWL) procedure have tracked developmental gains in language processing efficiency by measuring the timing and accuracy of young children's gaze shifts as they look at familiar objects and listen to simple sentences (e.g., "Where's the ball?") naming one of the objects (Fernald, Zangl, Portillo, & Marchman, 2008; Law & Edwards, 2014; Venker, Eernisse, Saffran, & Ellis Weismer, 2013). Such research finds that eye movements to named objects occur soon after the auditory information is sufficient to enable referent identification, and often prior to the offset of the spoken word (Allopenna, Magnuson, & Tanenhaus, 1998). Moreover, individual differences in the speed and accuracy of eye movements in response to familiar words predict vocabulary growth and later language and cognitive outcomes (Fernald,

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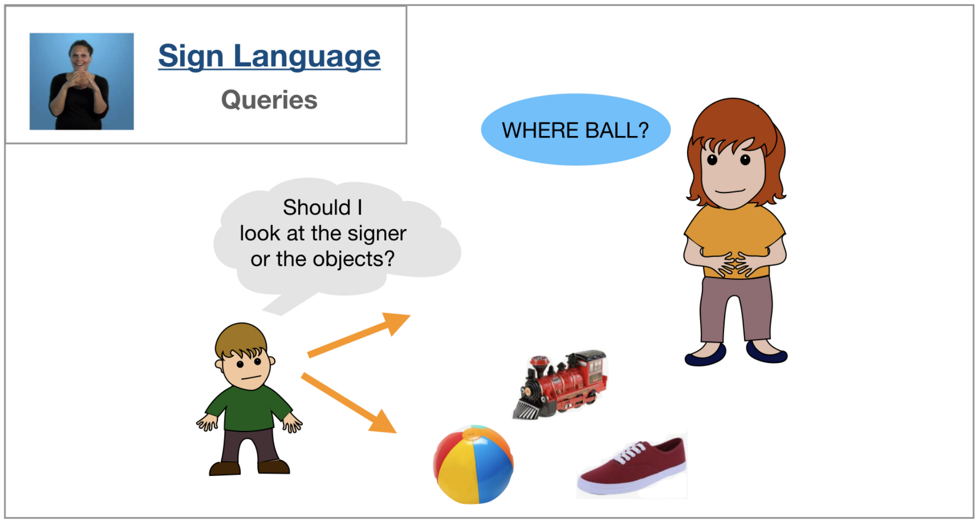



Figure 2.1: A schematic showing the components of the OED model captured by the case studies in Chapter 2.

Perfors & Marchman, 2006; Marchman & Fernald, 2008). Together, these results suggest that gaze shifts to objects in response to spoken language reflect a rapid integration of linguistic and visual information, and that variability in the timing of these gaze shifts provides researchers a way to measure the efficiency of the underlying integration process.

Much less is known about how language influences visual attention during sign language comprehension, especially in young learners. Given the many surface-level differences between signed and spoken languages, it is not immediately clear whether the findings from spoken language will generalize to signed languages or whether they are specific to mechanisms of language comprehension in the auditory modality. In particular, studies with children learning spoken languages find that these skills undergo dramatic developmental changes over the 2nd and 3rd years of life. Moreover, there are significant relations between variation in efficiency in online language processing, as indexed by language-driven eye movements, and measures of linguistic achievement, such as vocabulary size and scores on standardized tests (Fernald et al., 2006; Marchman & Fernald, 2008). Will individual variation in language processing among children learning a signed language also be related to their age and vocabulary outcomes, as observed in children learning a spoken language?

Here we address this question by developing precise measures of speed and accuracy in real-time sign language comprehension by children learning American Sign Language (ASL). First, we estimate the extent to which adults and children tend to shift visual attention to a referent and away from the language source prior to the offset of a sign naming an object in the visual scene. Will signers wait until the end of the signed utterance, perhaps to reduce the probability of missing upcoming linguistic information? Or will signers shift gaze incrementally as the signs unfold in time, initiating saccades soon after there is enough information in the signal to identify the referent, similar to children and adults processing spoken language? Another related possibility is that signers would produce incremental gaze shifts to the named objects while still monitoring the linguistic signal in the periphery. This analysis provides an important first step towards validating the linking hypothesis that eye movements generated in our task reflect efficiency of sign recognition, rather than some other process, such as attending to the objects after the process of sign comprehension is complete. If children and adults produce rapid gaze shifts prior to target sign offset, this would provide positive evidence of incremental ASL processing.

Next, we compare the time course of ASL processing in deaf and hearing native ASL-learners to ask whether having the potential to access auditory information in their day-to-day lives would change the dynamics of eye movements during ASL processing. Do deaf and hearing native signers show parallel patterns of looking behavior driven by their similar language background experiences and the in-the-moment constraints of interpreting a sign language (i.e., fixating on a speaker as a necessary requirement for gathering information about language)? Or would the massive experience deaf children have in relying on vision to monitor both the linguistic signal and the potential referents in the visual world result in a qualitatively different pattern of performance compared to hearing ASL learning, e.g., waiting until the end of the sentence to disengage from the signer? This analysis is motivated by prior work that has used comparisons between native hearing and deaf signers to dissociate the effects of learning a visual-manual language from the effects of lacking access to auditory information (e.g., Bavelier, Dye, & Hauser, 2006).

Finally, we compare timing and accuracy of the eye movements of young ASL-learners to those of adult signers, and ask whether there are age-related increases in processing efficiency that parallel those found in spoken languages. We also examine the links between variability in children's ASL processing skills and their expressive vocabulary development. A positive association between these two aspects of language proficiency, as previously shown in children learning spoken languages, provides important evidence that skill in lexical processing efficiency is a language-general phenomenon that develops rapidly in early childhood, regardless of language modality.

### 2.1.1 ASL processing in adults

Research with adults shows that language processing in signed and spoken languages is similar in many ways. As in spoken language, sign recognition is thought to unfold at both the lexical and sub-lexical levels. Moreover, sign processing is influenced by both lexicality and frequency; non-signs are identified more slowly than real signs (Corina & Emmorey, 1993) and high frequency signs are recognized faster than low frequency signs (Carreiras, Gutiérrez-Sigut, Baquero, & Corina, 2008). Recent work using eye-tracking methods found that adult signers produce gaze shifts to phonological competitors, showing sensitivity to sub-lexical features, and that these shifts were initiated prior to the offset of the sign, showing evidence of incremental processing (Lieberman, Borovsky, Hatrak, & Mayberry, 2015). In addition, Caselli and Cohen-Goldberg (2014) adapted a computational model, developed for spoken language (Chen & Mirman, 2012), to explain patterns of lexical access in sign languages, suggesting that the languages share a common processing architecture.

However, differences between spoken and signed languages in both sub-lexical and surface features of lexical forms could affect the time course of sign recognition (for reviews, see Carreiras, 2010 and Corina & Knapp, 2006). For example, Emmorey and Corina (1990) showed deaf adults repeated video presentations of increasingly longer segments of signs in isolation and asked them to identify the signs in an open-ended response format. In the same study, English-speaking adults heard repeated presentations of increasingly longer segments of spoken words. Accurate identification of signs required seeing a smaller proportion of the total sign length compared to words (see also Morford & Carlsen, 2011), suggesting that features of visual-manual languages, such as simultaneous presentation of phonological information, might increase speed of sign recognition. Moreover, Gutierrez and colleagues (2012) used EEG measures to provide evidence that semantic and phonological information might be more tightly linked in the sign language lexicon than in the spoken language lexicon. Thus there is evidence for both similarities and dissimilarities in the processes underlying spoken-word and manual-sign recognition. However, with a few exceptions (e.g. Lieberman et al., 2015, 2017), most of this work has relied on offline methods that do not capture lexical processing as it unfolds in time during naturalistic language comprehension. In addition, no previous studies have characterized how young ASL-learners choose to divide visual attention between a language source and the nonlinguistic visual world during real-time language comprehension.

### 2.1.2 Lexical development in ASL

Diary studies show that ASL acquisition follows a similar developmental trajectory to that of spoken language (Lillo-Martin, 1999; Mayberry & Squires, 2006). For example, young signers typically produce recognizable signs before the end of the first year and two-sign sentences by their 2nd birthday (Newport & Meier, 1985). And as in many spoken languages (Waxman et al., 2013), young ASL-learners tend first to learn more nouns than verbs or other predicates (Anderson & Reilly, 2002).

However, because children learning ASL must rely on vision to process linguistic information and to look at named objects, it is possible that basic learning processes, such as the coordination of joint visual attention, might differ in how they support lexical development (Harris & Mohay, 1997). For example, in a study of book reading in deaf and hearing dyads, Lieberman, Hatrak, and Mayberry (2015) found that deaf children frequently shifted gaze to caregivers in order to maintain contact with the signed signal. Hearing children, in contrast, tended to look continuously at the book, rarely shifting gaze while their caregiver was speaking. This finding suggests that the modality of the linguistic signal may affect how young language learners negotiate the demands of processing a visual language while simultaneously trying to fixate on the referents of that language.

This competition for visual attention in ASL could lead to qualitatively different looking behavior during real-time ASL comprehension, making the link between eye movements and efficiency of language comprehension in ASL less transparent. On the one hand, demands of relying on vision to monitor both the linguistic signal and the named referent might cause signers to delay gaze shifts to named objects in the world until the end of the target sign, or even the entire utterance. In this case, eye movements would be less likely to reflect the rapid, incremental influence of language on visual attention that is characteristic of spoken language processing. Another possibility is that ASL-learners, like spoken language learners, will shift visual attention as soon as they have enough linguistic information to do so, producing saccades prior to the offset of the target sign. Evidence for incremental language processing would further predict that eye movements during ASL processing could index individual differences in speed of incremental comprehension, as previously shown in spoken languages.

### 2.1.3 Research questions

Adapting the LWL procedure for ASL enables us to address four questions. First, to what extent do children and adult signers shift their gaze away from the language source and to a named referent prior to the offset of the target sign? Second, how do deaf and hearing ASL-learners compare in the time course of real-time lexical processing? Third, how do patterns of eye movements during real-time language comprehension in ASL-learners compare to those of adult signers? Finally, are individual differences in ASL-learners' processing skill related to age and to expressive vocabulary development?

## 2.2 Methods

Participants were 29 native, deaf and hearing ASL-learning children (17 females, 12 males) and 16 fluent adult signers (all deaf), as shown in Table 1. Since the goal of the current study was to document developmental changes in processing efficiency in native ASL-learners, we set strict inclusion criteria. The sample consisted of both deaf children of deaf adults and hearing Children of Deaf Adults (CODAs), across a similar age range. It is important to note that all children, regardless of hearing status, were exposed to ASL from birth through extensive interaction with at least one caregiver fluent in ASL and were reported to experience at least 80% ASL in their daily lives. Twenty-five of the 29 children lived in households with two deaf caregivers, both fluent in ASL. Although the hearing children could access linguistic information in the auditory signal, we selected only ASL-dominant learners who used ASL as their primary mode of communication both within and outside the home (10 out of 13 hearing children had two deaf caregivers). Adult participants were all deaf, fluent signers who reported using ASL as their primary method of communication on a daily basis. Thirteen of the 16 adults acquired ASL from their parents and three learned ASL while at school.

Our final sample size was determined by our success over a two-year funding period in recruiting and testing children who met our strict inclusion criteria – receiving primarily ASL language input. It is important to note that native ASL-learners are a small population. The incidence of deafness at birth in the US is less than .003%, and only 10% of the 2-3 per 1000 children born with hearing loss have a deaf parent who is likely to be fluent in ASL (Mitchell & Karchmer, 2004). In addition to the 29 child participants who met our inclusion criteria and contributed adequate data, we also recruited and tested 17 more ASL-learning children who were not included in the analyses, either because it was later determined that they did not meet our stringent criterion of exposure to ASL from birth (n = 12), or because they did not complete the real-time language assessment due to inattentiveness or parental interference (n = 5).

Table 2.1: Age (in months) of hearing and deaf ASL-learning participants

| **Hearing status** | **n** | **Mean** | **SD** | **Min** | **Max** |
|---|---|---|---|---|---|
| deaf | 16 | 28.0 | 7.5 | 16 | 42 |
| hearing | 13 | 29.4 | 11.2 | 18 | 53 |
| all children | 29 | 28.6 | 9.2 | 16 | 53 |

### 2.2.1 Measures

Expressive vocabulary size: Parents completed a 90-item vocabulary checklist, adapted from Anderson and Reilly (2002), and developed specifically for this project to be appropriate for children between 1.5 and 4 years of age. Vocabulary size was computed as the number of signs reported to be produced by the child.

ASL Processing: Efficiency in online comprehension was assessed using a version of the LWL procedure adapted for ASL learners, which we call the Visual Language Processing (VLP) task. The VLP task yields two measures of language processing efficiency, reaction time (RT) and accuracy. Since this was the first study to develop measures of online ASL processing efficiency in children of this age, several important modifications to the procedure were made, as described below.

### 2.2.2 Procedure

The VLP task was presented on a MacBook Pro laptop connected to a 27" monitor. The child sat on the caregiver's lap approximately 60 cm from the screen, and the child's gaze was recorded using a digital camcorder mounted behind the monitor. To minimize visual distractions, testing occurred in a 5' x 5' booth with cloth sides. On each trial, pictures of two familiar objects appeared on the screen, a target object corresponding to the target noun, and a distracter object. All picture pairs were matched for visual salience based on prior studies with spoken language (Fernald et al., 2008). Between the two pictures was a central video of an adult female signing the name of one of the pictures. Participants saw 32 test trials with five filler trials (e.g. "YOU LIKE PICTURES? MORE WANT?") interspersed to maintain children's interest.

Coding and Reliability. Participants' gaze patterns were video recorded and later coded frame-by-frame at 33-ms resolution by highly-trained coders blind to target side. On each trial, coders indicated whether the eyes were fixated on the central signer, one of the images, shifting between pictures, or away (off), yielding a high-resolution record of eye movements aligned with target noun onset. Prior to coding, all trials were pre-screened to exclude those few trials on which the participant was inattentive or there was external interference. To assess inter-coder reliability, 25% of the videos were re-coded. Agreement was scored at the level of individual frames of video and averaged 98% on these reliability assessments.

### 2.2.3 Stimuli

*Linguistic stimuli.* To allow for generalization beyond characteristics of a specific signer and sentence structure, we recorded two separate sets of ASL stimuli. These were recorded with two native ASL signers, using a different alternative grammatical ASL sentence structures for asking questions (see Petronio and Lillo-Martin, 1997):

- Sentence-initial wh-phrase: "HEY! WHERE [target noun]?"
- Sentence-final wh-phrase: "HEY! [target noun] WHERE?"

Each participant saw one stimulus set which consisted of one ASL question structure, with roughly an even distribution of children across the two stimulus sets (16 saw sentence-initial wh-phrase structure; 13 saw the sentence-final wh-phrase structure). To prepare the stimuli, two female native ASL users recorded several tokens of each sentence in a child-directed register. Before each sentence, the signer made a hand-wave gesture commonly used in ASL to gain an interlocutor's attention before initiating an utterance. These candidate stimuli were digitized, analyzed, and edited using Final Cut Pro software, and two native signers selected the final tokens. The target nouns consisted of eight object names familiar to most children learning ASL at this age.

Table 2.2: Iconicity scores (1 = not iconic at all; 7 = very iconic) and degree of phonological overlap (out of 5 features) for each sign item-pair. Values were taken from ASL-LEX, a database of lexical and phonological properties of signs in ASL.

| **Item Pair (iconicity score 1-7)** | **Number of matched features** | **Matched features** |
|---|---:|---|
| bear (3.0) – doll (1.2) | 1 | Movement |
| cat (4.6) – bird (4.5) | 3 | Selected Fingers, Major Location, Sign Type |
| car (6.2) – book (6.7) | 4 | Selected Fingers, Major Location, Movement, Sign Type |
| ball (5.7) – shoe (1.5) | 4 | Selected Fingers, Major Location, Movement, Sign Type |

*Visual stimuli.* The visual stimuli consisted of colorful digitized pictures of objects corresponding to the target nouns presented in four fixed pairs (cat—bird, car—book, bear—doll, ball—shoe). See Table 2 for information about the degree of phonological overlap in each item-pair and the degree of iconicity for each sign (values were taken from ASL-LEX [Caselli et al., 2017]).[2] Images were digitized pictures presented in fixed pairs, matched for visual salience with 3–4 tokens of each object type. Each object served as target four times and as distracter four times for a total of 32 trials. Side of target picture was counterbalanced across trials.

### 2.2.4 Trial Structure

Figure 1 shows the structure of a trial with a sentence-final wh-phrase, one of the two question types in the VLP task. On each trial, children saw two images of familiar objects on the screen for 2 s before the signer appeared, allowing time for children to inspect both images. Next, children saw a still frame of the signer for one second, so they could orient to the signer prior to sentence onset. The target sentence was then presented, followed by a question and 2-s hold, followed by an exclamation to encourage attention to the task. This structure is nearly identical to the auditory LWL task, differing only in the addition of the 2-s hold. The hold was included to give participants additional time to shift gaze from the signer to the objects.

[2]We did not find evidence that these features were related to the speed or accuracy of participants' eye movements in our task. However, this study was not designed to vary these features systematically. See Appendix XX for the analysis.

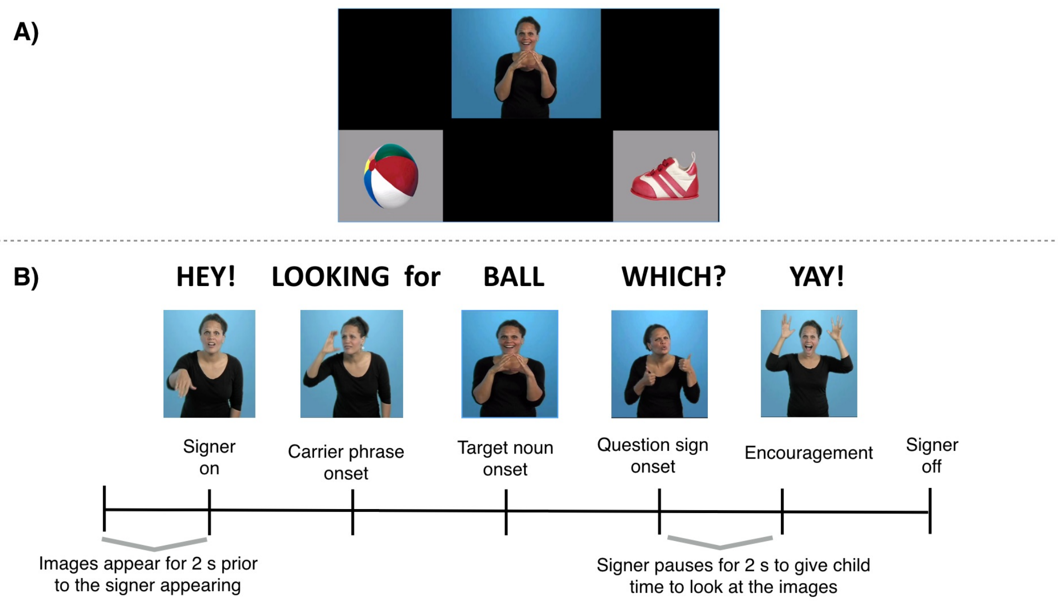



Figure 2.2: Configuration of visual stimuli (1A) and trial structure (1B) for one question type (sentence final wh-phrase) shown in the central video on the VLP task.

### 2.2.5 Calculating measures of language processing efficiency

*Computing target sign onset and offset.* In studies of spoken language processing, target word onset is typically identified as the first moment in the auditory signal when there is acoustic evidence of the target word. However, in signed languages like ASL, phonological information is present in several components of the visual signal simultaneously – for example, in one or both hands as well as in the face of the signer - making it difficult to determine precisely the beginning of the target sign. Because sign onset is critical to operationalizing speed of ASL comprehension in this task, we applied an empirical approach to defining target-sign onset. We used a gating task in which adult signers viewed short videos of randomly presented tokens that varied in length. Two native signers first selected a sequence of six candidate frames for each token, and then 10 fluent adult signers unfamiliar with the stimuli watched videos of the target signs in real-time while viewing the same picture pairs as in the VLP task. Participants indicated their response with a button press. For each sign token, the onset of the target noun was operationalized as the earliest video frame? at which adults selected the correct picture with 100% agreement. To determine sign offset, two native signers independently marked the final frame at which the handshape of each target sign was no longer identifiable. Agreements were resolved by discussion. Sign length was defined as sign offset minus sign onset (Median sign length was 1204 ms, ranging from 693-1980 ms).

*Reaction Time.* Reaction time (RT) corresponds to the latency to shift from the central signer to the target picture on all signer-to-target shifts, measured from target-noun onset. We chose cutoffs for the window of relevant responses based on the distribution of children's RTs in the VLP task, including the middle 90% (600-2500 ms) (see Ratcliff, 1993). Incorrect shifts (signer-to-distracter [19%], signer-to-away [14%], no shift [8%]) were not included in the computation of median RT. The RT measure was reliable within participants (Cronbach's $\alpha = 0.8$).

*Target Accuracy.* Accuracy was the mean proportion of time spent looking at the target picture out of the total time looking at either target or distracter picture over the 600 to 2500 ms window from target noun onset. We chose this window to be consistent with the choice of the RT analysis window. This measure of accuracy reflects the tendency both to shift quickly from the signer to the target picture in response to the target sign and to maintain fixation on the target picture. Mean proportion looking to target was calculated for each participant for all trials on which the participant was fixating on the center image at target-sign onset. To make accuracy proportion scores more suitable for modeling on a linear scale, all analyses were based on scores that were scaled in log space using a logistic transformation. The Accuracy measure was reliable within participants (Cronbach's $\alpha = 0.92$)

*Proportion Sign Length Processed Prior to Shifting.* As a measure of incremental processing, we used the mean proportion of the target sign that children and adults saw before generating an initial eye movement away from the central signer. Because target signs differed in length across trials, we divided each RT value by the length of the corresponding target sign. Previous research on spoken language suggests that at least 200 ms is required to program an eye-movement (Salverda, Kleinschmidt, & Tanenhaus, 2014), so we subtracted 200 ms from each RT to account for eye movements that were initiated during the end of the target sign (proportion target sign = $\frac{(RT-200\text{ms})}{\text{Sign Length}}$). Mean proportion of sign processed was computed for each token of each target sign and then averaged over all target signs within participants, reflecting the amount of information signers processed before generating an eye movement, on average. A score of $\geq 1.0$ indicates that a signer tended to initiate eye movements to the target pictures after sign offset. An average $< 1.0$ indicates eye-movements were planned during the target sign, reflecting the degree to which signers showed evidence of incremental language processing.

### 2.2.6 Analysis Plan

We used Bayesian methods to estimate the associations between hearing status, age, vocabulary, and RT and accuracy in the VLP task. Bayesian methods are desirable for two reasons: First, Bayesian methods allowed us to quantify support in favor of a null hypothesis of interest – in this case, the absence of a difference in real-time processing skills between age-matched deaf and hearing ASL learners. Second, since native ASL learners are rare, we wanted to use a statistical approach that allowed us to incorporate relevant prior knowledge to constrain our estimates of the strength of association between RT/accuracy on the VLP task and age/vocabulary.

Concretely, we used prior work on the development of real-time processing efficiency in children learning spoken language (Fernald et al., 2008) to consider only plausible linear associations between age/vocabulary and RT/accuracy, thus making our alternative hypotheses more precise. In studies with adults, the common use of eye movements as a processing measure is based on the assumption that the timing of the first shift reflects the speed of their word recognition (Tanenhaus, Magnuson, Dahan, & Chambers, 2000).[3] However, studies with children have shown that early shifts are more likely to be random than later shifts (Fernald et al., 2008), suggesting that some children's shifting behavior may be unrelated to real-time ASL comprehension. We use a mixture-model to quantify the probability that each child participant's response is unrelated to their real-time sign recognition (i.e., that the participant is responding randomly, or is "guessing"), creating an analysis model where participants who were more likely to be guessers have less influence on the estimated relations between RT and age/vocabulary. Note that we use this approach only in the analysis of RT, since "guessing behavior" is integral to our measure of children's mean accuracy in the VLP task, but not to our measure of mean RT. The Supplemental Material available online provides more details about the analysis model, as well two additional sensitivity analyses, which provide evidence that our results are robust to different specifications of prior distributions and to different analysis windows. We also provide a parallel set of analyses using a non-Bayesian approach, which resulted

[3] The assumption that first shifts reflects speed of incremental word recognition depends on the visual display containing candidate objects with minimal initial phonological overlap. If there are phonological competitors present (e.g., candy vs. candle), then participants' early shifting behavior could reflect consideration of alternative lexical hypotheses for the incoming linguistic information.

in comparable findings.

To provide evidence of developmental change, we report the strength of evidence for a linear model with an intercept and slope, compared to an intercept-only model in the form of a Bayes Factor (BF) computed via the Savage-Dickey method (Wagenmakers et al., 2010). To estimate the uncertainty around our estimates of the linear associations, we report the 95% Highest Density Interval (HDI) of the posterior distribution of the intercept and slope. The HDI provides a range of plausible values and gives information about the uncertainty of our point estimate of the linear association. Models with categorical predictors were implemented in STAN (Stan Development Team, 2016), and models with continuous predictors were implemented in JAGS (Plummer, 2003). Finally, we chose the linear model because it a simple model of developmental change with only two parameters to estimate, and the outcome measures – mean RT and Accuracy for each participant – were normally distributed. All of the linear regressions include only children's data and take the form: *processing measure* *age* and *processing measure* *vocabulary*.

## 2.3 Results

The results are presented in five sections addressing the following central questions in this research. First, where do ASL users look while processing sign language in real-time? Here we provide an overview of the time course of looking behavior in our task for both adults and children. Second, would young ASL-learners and adult signers show evidence of rapid gaze shifts that reflect lexical processing, despite the apparent competition for visual attention between the language source and the nonlinguistic visual world? In this section, we estimate the degree to which children and adults tended to initiate eye-movements prior to target sign offset, providing evidence that these gaze shifts occur prior to sign offset and index speed of incremental ASL comprehension. Third, do deaf and hearing native signers show a similar time course of eye movements, despite having differential access to auditory information in their daily lives? Or would deaf children's daily experience relying on vision to monitor both the linguistic signal and the potential referents in the visual world result in a qualitatively different pattern of performance, e.g., their waiting longer to disengage from the signer to seek the named object? Fourth, do young ASL-learners show age-related increases in processing efficiency that parallel those found in spoken languages? Here we compare ASL-learners' processing skills to those of adult signers and exploring relations to age among the children. Finally,

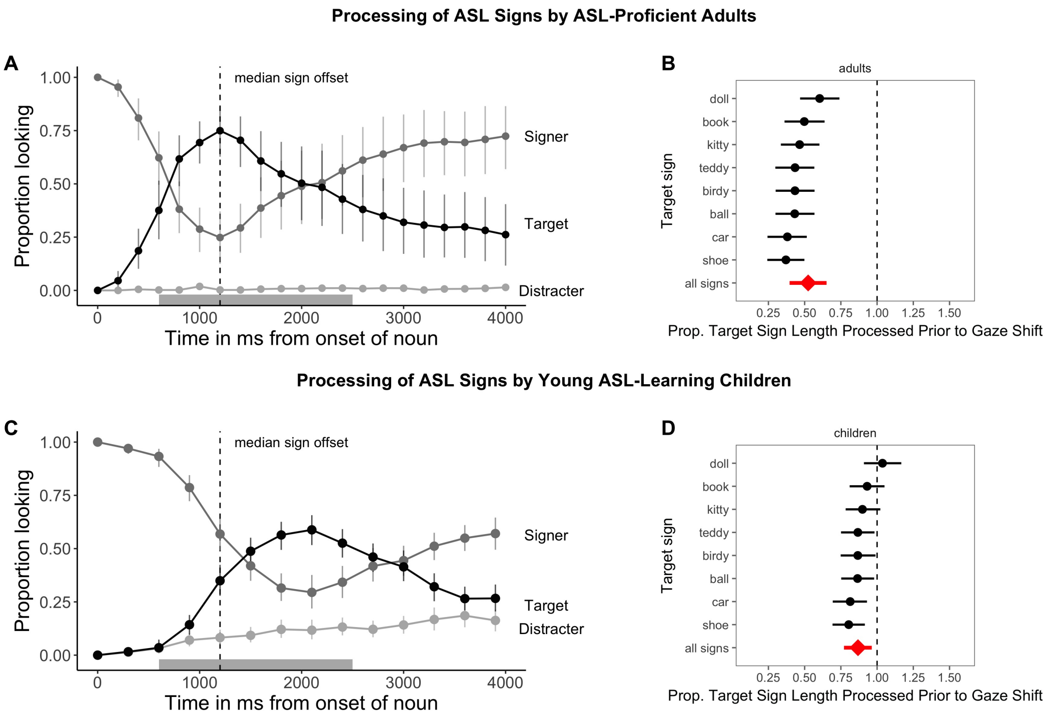



Figure 2.3: The time course of looking behavior for ASL-proficient adults (2A) and young ASL-learners (2C). The curves show mean proportion looking to the signer (dark grey), the target image (black), and the distracter image (light grey). The grey shaded region marks the analysis window (600-2500ms); error bars represent +/- 95% CI computed by non-parametric bootstrap. The mean proportion of each target sign length (see the Methods section for details on how sign length was defined) processed prior to shifting visual attention away from the language source to a named object for adults (2B) and children (2D). The diamond indicates the mean estimate for all signs. The dashed vertical line corresponds to a median proportion of 1.0. Error bars represent 95% Highest Density Intervals.

is individual variation in children's ASL processing efficiency related to the size of their productive ASL vocabularies?

### 2.3.1 Overview of looking behavior during real-time ASL comprehension

The first question of interest was where do ASL users look while processing sign language in real-time? Figure 2 presents an overview of adults (2A) and children's (2B) looking behavior in the VLP task. This plot shows changes in the mean proportion of trials on which participants fixated the signer, the target image, or the distracter image at every 33-ms interval of the stimulus sentence. At target-sign onset, all participants were looking at the signer on all trials. As the target sign unfolded, the mean proportion looking to the signer decreased rapidly as participants shifted their gaze to the target or the distracter image. Proportion looking to the target increased sooner and reached a higher asymptote, compared to proportion looking to the distracter, for both adults and children. After looking to the target image, participants tended to shift their gaze rapidly back to the signer, shown by the increase in proportion looking to the signer around 2000 ms after target-noun onset. Adults tended to shift to the target picture sooner in the sentence than did children, and well before the average offset of the target sign. Moreover, adults rarely looked to the distractor image at any point in the trial. This systematic pattern of behavior – participants reliably shifting attention from the signer to the named object and back to the signer – provides qualitative evidence that the VLP task is able to capture interpretable eye movement behavior during ASL comprehension.

### 2.3.2 Evidence that eye movements during ASL processing index incremental sign comprehension

One of the behavioral signatures of proficient spoken language processing is the rapid influence of language on visual attention, with eye movements occurring soon after listeners have enough information to identify the named object. Our second question of interest was whether young ASL-learners and adult signers would also show evidence of rapid gaze shifts in response to signed language, despite the apparent competition for visual attention between the language source and the nonlinguistic visual world. Or would signers delay their shifts until the very end of the target sign, or even until the end of the utterance, perhaps because they did not want to miss subsequent linguistic information?

To answer these questions, we conducted an exploratory analysis, computing the proportion of each target sign that participants processed before generating an eye movement to the named object. Figure 2 shows this measure for each target sign for both adults (2B) and children (2D). Adults shifted prior to the offset of the target sign for all items and processed on average 51% of the target sign before generating a response (M = 0.51, 95% HDI [0.35, 0.66]). Children processed 88% of the target sign on average, requiring more information before shifting their gaze compared to adults. Children reliably initiated saccades prior to the offset of the target sign overall (M = 0.88, 95% HDI [0.79, 0.98]) and for five out of the eight signed stimuli.

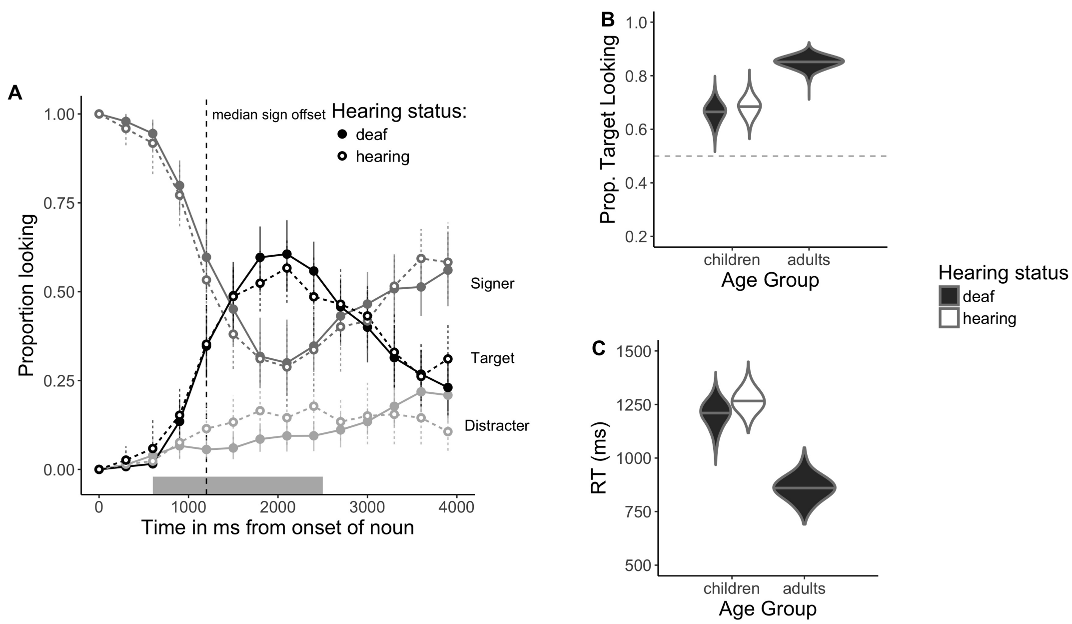



Figure 2.4: The time course of looking behavior for young deaf and hearing ASL-learners (3A). Filled circles represent deaf signers, while open circles represent hearing signers; All other plotting conventions are the same as in Figure 2. Panels B and C show full posterior distributions over model estimates for mean Accuracy (3B) and Reaction Time (3C) for children and adults. Fill (white/black) represents children's hearing status. (Note that there were no hearing adult signers in our sample).

These results suggest that young signers as well as adults process signs incrementally as they unfold in time (for converging evidence see Lieberman et al., 2015, 2017). It is important to point out that we would not interpret signers waiting until the end of the sign or the end of the sentence as evidence against an incremental processing account since there could be other explanations for that pattern of results such as social norms of looking at a person until they finish speaking. However, this result provides positive evidence that eye movements in the VLP task provide an index of speed of incremental ASL comprehension, allowing us to perform the subsequent analyses that estimate (a) group differences in looking behavior and (b) links between individual variation in speed and accuracy of eye movements during ASL processing and variation in productive vocabulary.

### 2.3.3 Real-time ASL comprehension in deaf and hearing children and deaf adults

The third question of interest was whether deaf and hearing native signers show a similar time course of lexical processing, driven by their similar language experiences and the in-the-moment constraints of interpreting a sign language in real time? Or would deaf children's daily experience relying on vision to monitor both the linguistic signal and the potential referents in the visual world result in a qualitatively different pattern of performance, e.g., their waiting longer to disengage from the signer to seek the named object?

Figure 3A presents the overview of looking behavior for deaf and hearing children. At target-sign onset, all children were looking at the signer on all trials. Overall, deaf and hearing children showed a remarkably similar time course of looking behavior: shifting away from the signer, increasing looks to the target, and shifting back to the signer at similar time points as the sign unfolded. To quantify any differences, we compared the posterior distributions for mean accuracy (Figure 3B) and mean RT (Figure 3C) across the deaf and hearing groups. We did not find evidence for a difference in mean accuracy ($M_{hearing} = 0.68$, $M_{deaf} = 0.65$; $\beta_{diff} = 0.03$, 95% HDI $[-0.07, 0.13]$) or RT ($M_{hearing} = 1265.62$ ms, $M_{deaf} = 1185.05$ ms; $\beta_{diff} = 78.32$ ms, 95% HDI $[-86.01ms, 247.04ms]$), with the 95% HDI including zero for both models. These parallel results provide evidence that same-aged hearing and deaf native ASL-learners showed qualitatively similar looking behavior during real-time sentence processing, suggesting that decisions about where to allocate visual attention are not modulated by differential access to auditory information, but rather are shaped by learning ASL as a first language (see Bavelier et al., 2006 for a review of the differential effects of deafness compared to learning a visual language on perception and higher-order cognitive skills). Moreover, these results provide additional justification (over and above children's highly similar language background experience) for analyzing all the native ASL-learning children together, regardless of hearing status, in the subsequent analyses. Next, we compared real-time processing efficiency in ASL-learners and adult signers. Returning to the overview of looking behavior shown in Figure 2, we see that adults tended to shift to the target picture sooner in the sentence than did children, and well before the average offset of the target sign. Moreover, adults rarely looked to the distractor image at any point in the trial. To quantify these differences we computed the full posterior distribution for children and adults' mean Accuracy (Figure 3B) and RT (Figure 3C). Overall, adults were more

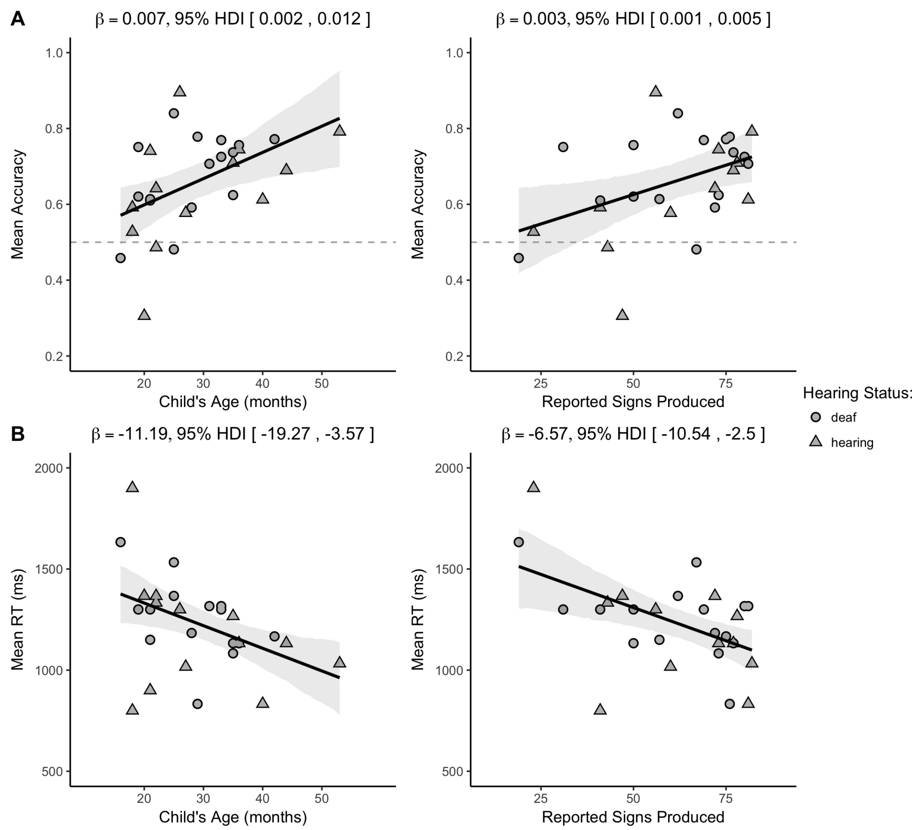



Figure 2.5: Scatterplots of relations between children's age and vocabulary and measures of their mean accuracy (4A) and mean RT (4B) in the VLP procedure. Shape represents children's hearing status. The solid black line is the maximum a posteriori model estimate for the mean accuracy at each age point. The shaded gray regions represent the 95% Highest Density Interval (range of plausible values) around the regression line.

accurate ($M_{adults} = 0.85$, $M_{children} = 0.68$, $\beta_{diff} = 0.17$, 95% HDI for the difference in means [0.11, 0.24]) and faster to shift to the target image compared to children ($M_{adults} = 861.98$ ms, $M_{children} = 1229.95$ ms; $\beta_{diff} = -367.76$ ms, 95% HDI for the difference in means [-503.42 ms, -223.85 ms]). This age-related difference parallels findings in spoken language (Fernald et. al., 2006) and shows that young ASL learners are still making progress towards adult-levels of ASL processing efficiency.

### 2.3.4 Links between children's age and efficiency in incremental sign comprehension

The fourth question of interest was whether young ASL-learners show age-related increases in processing efficiency that parallel those found in spoken languages. To answer this question, we estimated relations between young ASL learners' age-related increases in the speed and accuracy with which they interpreted familiar signs (see Table 3 for point and interval estimates). Mean accuracy was positively associated with age (Figure 4A), indicating that older ASL learners were more accurate than younger children in fixating the target picture. The Bayes Factor (BF) indicated that a model including a linear association was 12.8 times more likely than an intercept-only model, providing strong evidence for developmental change. The $\beta$ estimate indicates that, for each month of age, children increased their accuracy score by 0.007, i.e., an increase of ˜1% point, meaning that over the course of one year the model estimates a ˜12% point gain in accuracy when establishing reference in the VLP task. Mean RTs were negatively associated with age (Figure 4A), indicating that older children shifted to the target picture more quickly than did younger children. The BF was ˜14, providing strong evidence for a linear association. The model estimates a ˜11 ms gain in RT for each month, leading to a ˜132 ms gain in speed of incremental ASL comprehension over one year of development.

Together, the accuracy and RT analyses showed that young ASL learners reliably looked away from the central signer to shift to the named target image in the VLP task. Importantly, children varied in their response times and accuracy, and this variation was meaningfully linked to age. Thus, like children learning spoken language, ASL learners improve their real-time language processing skills over the second and third years of life as they make progress towards adult levels of language fluency.

Table 2.3: Summary of the four linear models using children's age and vocabulary size to predict accuracy (proportion looking to target) and reaction time (latency to first shift in ms). BF is the Bayes Factor comparing the evidence in favor of linear model to an intercept-only (null) model; Mean Beta is the mean of the posterior distribution for the slope parameter for each model (i.e., the linear association); and the Highest Density Interval (HDI) shows the interval containing 95% of the plausible slope values given the model and the data.

| **Model specification** | **Bayes Factor** | **Mean Beta** | **95% HDI** |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Accuracy ~ Age | 12.8 | 0.007 | [0.002, 0.012] |
| Accuracy ~ Vocab | 6.8 | 0.003 | [0.001, 0.005] |
| RT ~ Age | 14.4 | -11.2 ms | [-19.3 ms, -3.6 ms] |
| RT ~ Vocab | 18.7 | -6.6 ms | [-10.5 ms, -2.5 ms] |

### 2.3.5 Links between children's incremental sign comprehension and productive vocabulary

The final question of interest was whether individual differences in processing skills were related to the size of children's ASL vocabularies. As shown in Figure 4B, children with higher accuracy scores also had larger productive vocabularies (BF = 6.8), with the model estimating a 0.003 increase for each additional sign known. Moreover, children who were faster to recognize ASL signs were those with larger sign vocabularies (BF = 18.7), with each additional sign resulting in a ~7 ms decrease in estimated RT. Taken together, older children and children with larger expressive vocabularies were more accurate and efficient in identifying the referents of familiar signs. It is important to point out that the independent effect of vocabulary size on ASL processing could not be assessed here given the correlation between age and vocabulary (r = 0.76) in our sample of children ages one to four years. However, these findings parallel results in the substantial body of previous research with monolingual children learning spoken languages, such as English (Fernald et al., 2006) and Spanish (Hurtado, Marchman, & Fernald, 2007).

## 2.4 Discussion

Efficiency in establishing reference in real-time lexical processing is a fundamental component of language learning. Here, we developed the first measures of young ASL learners' real-time language comprehension skills. There are five main findings from this research.

First, both adults and children showed a similar qualitative pattern of looking behavior as signs unfolded in time. They began by looking at the signer to gather information about the signed sentence, before shifting gaze to the named object, followed by a return in looking to the signer. All signers allocated very few fixations to the distractor image at any point during the signed sentence.

Second, children and adults tended to shift their gaze away from the signer and to the named referent prior to sign offset, providing evidence of incremental ASL processing. This rapid influence of language on visual attention in ASL is perhaps even more striking since premature gaze shifts could result in a degraded the linguistic signal processed in the periphery or in missing subsequent linguistic information altogether. Furthermore, evidence of incremental gaze shifts suggests that eye movements during ASL processing index efficiency of lexical comprehension, as previously shown in spoken languages, which is important for future work on the psycholinguistics of early sign language acquisition.

Third, deaf and hearing native signers, despite having differential access to auditory information, showed remarkably similar looking behavior during real-time ASL comprehension. Even though the deaf and hearing children had differential access to auditory information in their daily lives, this experience did not change their overall looking behavior or the timing of their gaze shifts during ASL comprehension. Instead, both groups showed parallel sensitivity to the in-the-moment constraints of processing ASL in real time. That is, both deaf and hearing children allocated similar amounts of visual attention to the signer, presumably because this was the only fixation point in the visual scene that also provided information with respect to their goal of language comprehension. This is in stark contrast to what hearing children could potentially do in a similar grounded language comprehension task where a speaker was a potential visual target. In that case, the hearing listener could choose to look at the speaker or to look elsewhere, without losing access to the incoming language via the auditory channel. Thus, they can look while they listen.

Fourth, like children learning spoken language, young ASL-learners were less efficient than adults in their real-time language processing, but they showed significant improvement with age over the first four years. Moreover, although all target signs were familiar to children, older children identified the named referents more quickly and accurately than younger children. This result suggests that the real-time comprehension skills of children who are learning ASL in native contexts follow a similar developmental path to that of spoken language learners, as has been shown in previous work on ASL production (Lillo-Martin, 1999; Mayberry & Squires, 2006). By developing precise measures of real-time ASL comprehension, we were able to study children's language skills earlier in development as compared to other methods.

Fifth, we found a link between ASL processing skills and children's productive vocabularies. ASL-learning children who knew more signs were also faster and more accurate to identify the correct referent than those who were lexically less advanced. These results are consistent with studies of English- and Spanish-learning children, which find strong relations between efficiency in online language comprehension and measures of linguistic achievement (Fernald et al., 2006; Marchman & Fernald, 2008).

### 2.4.1 Limitations and open questions

This study has several limitations. First, while the sample size is larger than in most previous studies of ASL development, it is still relatively small compared to many studies of spoken language acquisition - an unsurprising limitation, given that native ASL-learners are a rare population. Thus more data are needed to characterize more precisely the developmental trajectories of sign language processing skills. Second, testing children within a narrower age range might have revealed independent effects of vocabulary size on ASL processing, which could not be assessed here given the correlation between age and vocabulary size in our broad sample of children from one to four years. To facilitate replication and extension of our results, we have made all of our stimuli, data, and analysis code publicly available (`https://github.com/kemacdonald/SOL`).

Third, we did not collect measures of age-related gains in children's general cognitive abilities. Thus, it is possible that our estimates of age-related changes in lexical processing are influenced by children's developing efficiency in other aspects of cognition, e.g., increased control of visual attention. Work on the development of visual attention from adolescence to early adulthood shows that different components of visual attention (the ability to distribute attention across the visual field, attentional recovery from distraction, and multiple object processing) develop at different rates (Dye and Bavelier, 2009). Moreover, work by Elsabbagh et. al., (2013) shows that infants become more efficient in their ability to disengage from a central stimulus to attend to a stimulus in the periphery between the ages 7 months and 14 months. However, there is a large body of work showing that features of language use and structure (e.g., the frequency of a word, a word's neighborhood density, and the amount of language input a child experiences) affect the speed and accuracy of eye movements in the Looking-While-Listening style tasks (see Tanenhaus et al., 2000 for a review). Thus, while it possible that age-related improvements in general cognitive abilities are a factor in our results, we think that the strength of the prior evidence suggests that more efficient gaze shifts in the VLP task are indexing improvements in the efficiency of incremental ASL comprehension.

A fourth limitation is that characteristics of our task make it difficult to directly compare our findings with previous work on ASL processing by adults. For example, in contrast to prior gating studies (e.g., Emmorey & Corina, 1990; Morford & Carlsen, 2011), our stimuli consisted of full sentences in a child-directed register, not isolated signs, and we used a temporal response measure rather than an open-ended untimed response. However, it is interesting to note that the mean reaction time of the adults in our task (M = 862 ms) is strikingly close to the average performance of native adult signers in Lieberman et al.'s (2015) "unrelated" condition (M = 844 ms). In addition, we did not select stimuli that parametrically varied features of signs that may influence speed of incremental ASL comprehension, including iconicity and degree of phonological overlap. However, we were able to use a recently created database of lexical and phonological properties of 1000 signs (Caselli et. al., 2017) to explore this possibility. We did not see evidence that iconicity or degree of phonological overlap influenced speed or accuracy of eye movements in children or adults in our sample of eight target signs (see Figures S4 and S5 in the online supplement).

We also cannot yet make strong claims about processing in signed vs. spoken languages in absolute terms because the VLP task included the signer as a central fixation, resulting in different task demands compared to the two-alternative procedure used to study children's spoken language processing (e.g., Fernald et al. 1998). However, a direct comparison of the timecourse of eye movements during signed and spoken language processing is a focus of our ongoing work (MacDonald et al., 2017). Nevertheless, the current results reveal parallels with previous findings showing incremental processing during real-time spoken language comprehension (see Tanenhaus et al., 2000) and sign language comprehension in adults (Lieberman et al., 2015). Moreover, we established links between early processing efficiency and measures of vocabulary in young ASL-learners, suggesting that parallel mechanisms drive language development, regardless of the language modality.

Finally, our sample is not representative of most children learning ASL in the United States. Since most deaf children are born to hearing parents unfamiliar with ASL, many are exposed quite inconsistently to sign language, if at all. We took care to include only children exposed to ASL from birth. The development of real-time ASL processing may look different in children who have inconsistent or late exposure to ASL (Mayberry, 2007). An important step is to explore how variation in ASL processing is influenced by early experience with signed languages. Since children's efficiency in interpreting spoken language is linked to the quantity and quality of the speech that they hear

(Hurtado, Marchman, & Fernald, 2008; Weisleder & Fernald, 2013), we would expect similar relations between language input and outcomes in ASL-learners. We hope that the VLP task will provide a useful method to track precisely the developmental trajectories of a variety of ASL-learners.

## 2.5 Conclusion

This study provides evidence that both child and adult signers rapidly shift visual attention as signs unfold in time and prior to sign offset during real-time sign comprehension. In addition, individual variation in speed of lexical processing in child signers is meaningfully linked to age and vocabulary. These results contribute to a growing literature that highlights parallels between signed and spoken language development when children are exposed to native sign input, suggesting that it is the quality of children's input and not features of modality (auditory vs. visual) that facilitate language development. Moreover, similar results for deaf and hearing ASL-learners suggest that both groups, despite large differences in their access to auditory information in their daily lives, allocated attention in similar ways while processing sign language from moment to moment. Finally, these findings indicate that eye movements during ASL comprehension are linked to efficiency of incremental sign recognition, suggesting that increased efficiency in real-time language processing is a language-general phenomenon that develops rapidly in early childhood, regardless of language modality.

# Chapter 3

# Information seeking eye movements during language comprehension

## 3.1 Introduction[1]

[1]Parts of this chapter were published as MacDonald et al. (2017a) An information-seeking account of eye movements during spoken and signed language comprehension and MacDonald et al. (2018) Adults and preschoolers seek visual information to support language comprehension in noisy environments. Proceedings of the 39th and 40th Annual Meetings of the Cognitive Science Society.

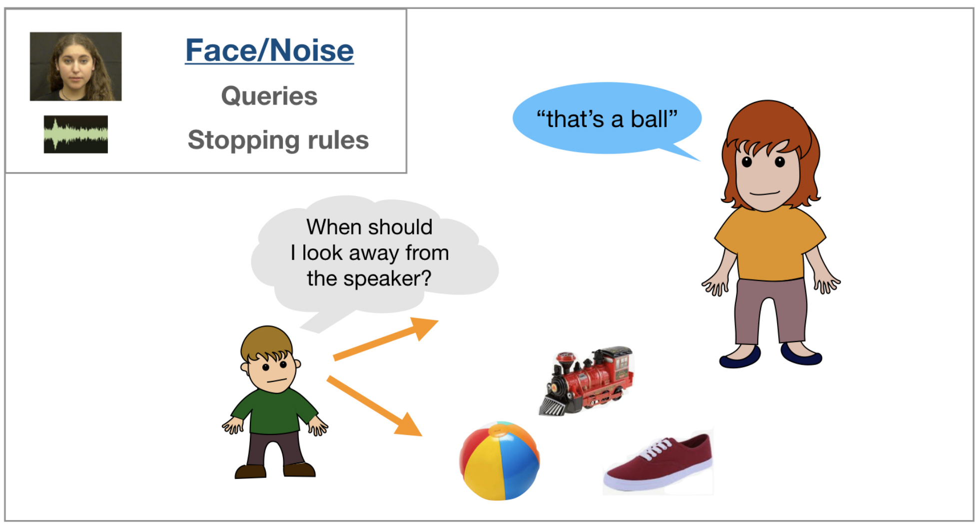



Figure 3.1: A schematic showing the components of the OED model captured by the case studies in Chapter 3.

# Chapter 4

# Social information and word learning

## 4.1 Introduction[1]

Learning the meaning of a new word should be hard. Consider that even concrete nouns are often used in complex contexts with multiple possible referents, which in turn have many conceptually natural properties that a speaker could talk about. This ambiguity creates the potential for an (in principle) unlimited amount of referential uncertainty in the learning task.[2] Remarkably, word learning proceeds despite this uncertainty, with estimates of adult vocabularies ranging between 50,000 to 100,000 distinct words (P. Bloom, 2002). How do learners infer and retain such a large variety of word meanings from data with this kind of ambiguity?

Statistical learning theories offer a solution to this problem by aggregating cross-situational statistics across labeling events to identify underlying word meanings (Siskind, 1996; Yu & Smith, 2007). Recent experimental work has shown that both adults and young infants can use word-object co-occurrence statistics to learn words from individually ambiguous naming events (Smith

[1]This chapter is published in MacDonald et al. (2017b). Social cues modulate the representations underlying cross-situational learning. *Cognitive Psychology* , 94, 67-84.

[2]This problem is a simplified version of Quine's *indeterminacy of reference* (Quine, 1960): That there are many possible meanings for a word ("Gavigai") that include the referent ("Rabbit") in their extension, e.g., "white," "rabbit," "dinner." Quine's broader philosophical point was that different meanings ("rabbit" and "undetached rabbit parts") could actually be extensionally identical and thus impossible to tease apart.

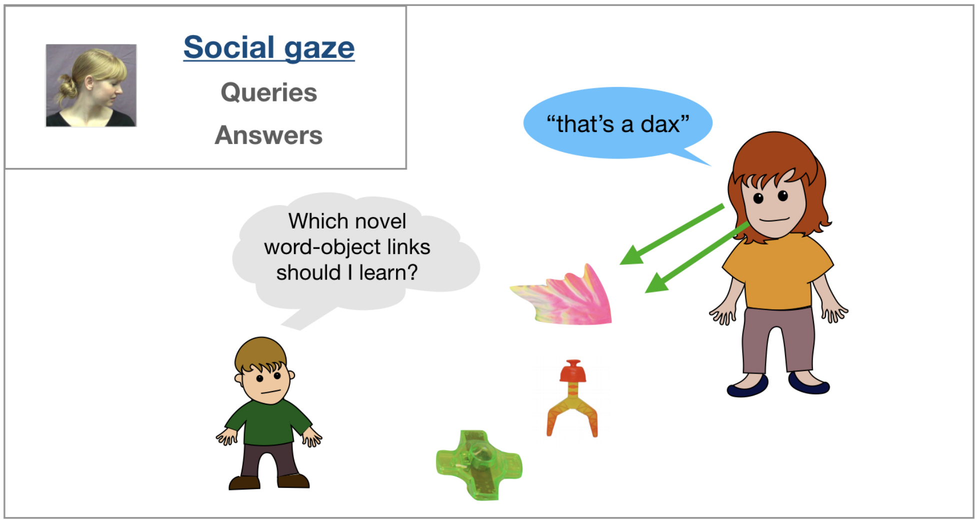



Figure 4.1: A schematic showing the components of the OED model captured by the case studies in Chapter 4.

& Yu, 2008; Vouloumanos, 2008). For example, Smith and Yu (2008) taught 12-month-olds three novel words simply by repeating consistent novel word-object pairings across 10 ambiguous exposure trials. Moreover, computational models suggest that cross-situational learning can scale up to learn adult-sized lexicons, even under conditions of considerable referential uncertainty (K. Smith, Smith, & Blythe, 2011). Although all cross-situational learning models agree that the input is the co-occurrence between words and objects and the output is stable word-object mappings, they disagree about how closely learners approximate the input distribution (for review, see Smith, Suanda, & Yu 2014). One approach has been to model learning as a process of updating connection strengths between multiple word-object links (McMurray, Horst, & Samuelson, 2012), while other approaches have argued that learners store only a single word-object hypothesis (Trueswell, Medina, Hafri, & Gleitman, 2013). In recent experimental and modeling work Yurovsky and Frank (2015) suggest an integrative explanation: learners allocate a fixed amount of attention to a single hypothesis and distribute the rest evenly among the remaining alternatives. As the set of alternatives grows, the amount of attention allocated to each object approaches zero.

In addition to the debate about representation, researchers have disagreed about how to characterize the ambiguity of the input to cross-situational learning mechanisms. One way to quantify the uncertainty in a naming event is to show adults video clips of caregiver-child interactions and measure their accuracy at guessing the meaning of an intended referent (Human Simulation Paradigm: HSP [Gillette, Gleitman, Gleitman, and Lederer, 1999]). Using the HSP, Medina, Snedeker, Trueswell, and Gleitman (2011) found that approximately 90% of learning episodes were ambiguous (< 33% accuracy) and only 7% were relatively unambiguous (> 50% accuracy). In contrast, Yurovsky, Smith, and Yu (2013) found a higher proportion of clear naming events, with approximately 30% being unambiguous (> 90% accuracy). Consistent with this finding, Cartmill, Armstrong, Gleitman, Goldin-Meadow, Medina, and Trueswell (2013) showed that the proportion of unambiguous naming episodes varies across parent-child dyads, with some parents rarely providing highly informative contexts and others' doing so relatively more often.[3]

Thus, representations in cross-situational word learning can appear distributional or discrete, and the input to statistical learning mechanisms can vary along a continuum from low to high ambiguity. These results raise an interesting question: could learners be sensitive to the ambiguity of the input and use this information to alter the representations they store in memory? In the current line of work, we investigated how the presence of referential cues in the social context might alter the ambiguity of the input to statistical word learning mechanisms.

Social-pragmatic theories of language acquisition emphasize the importance of social cues for word learning (P. Bloom, 2002; Clark, 2009; Hollich et al., 2000). Experimental work has shown that even children as young as 16 months prefer to map novel words to objects that are the target of a speaker's gaze and not their own (D. A. Baldwin, 1993). In an analysis of naturalistic parent-child labeling events, Yu and Smith (2012) found that young learners tended to retain labels that were accompanied by clear referential cues, which served to make a single object dominant in the visual field. And correlational studies have demonstrated strong links between early intention-reading skills (e.g., gaze following) and later vocabulary growth (Brooks & Meltzoff, 2005, 2008; Carpenter, Nagell, Tomasello, Butterworth, & Moore, 1998). Moreover, studies outside the domain of language acquisition have shown that the presence of social cues: (a) produce better spatial learning of audiovisual events (Wu, Gopnik, Richardson, & Kirkham, 2011), (b) boost recognition of a cued object (Cleveland et al., 2007), and (c) lead to preferential encoding of an object's featural

[3]The differences in the estimates of referential uncertainty in these studies could be driven by the different sampling procedures used to select naming events for the HSP. Yurovsky, Smith, and Yu (2013) sampled utterances for which the parent labeled a co-present object, whereas Medina, Snedeker, Trueswell, et al. (2011) randomly sampled any utterances containing concrete nouns. Regardless of these differences, the key point here is that variability in referential uncertainty across naming events exists and thus could alter the representations underlying cross-situational learning.

information (J. M. Yoon et al., 2008). Together, the evidence suggests that social cues could alter the representations stored during cross-situational word learning by modulating how people allocate attention to the relevant statistics in the input.

The goal of our current investigation was to ask whether the presence of a valid social cue – a speaker's gaze – could change the representations underlying cross-situational word learning. We used a modified version of Yurovsky and Frank (2015)'s paradigm to provide a direct measure of memory for alternative word-object links during cross-situational learning. In Experiment 1, we manipulated the presence of a referential cue at different levels of attention and memory demands. At all levels of difficulty, learners tracked a strong single hypothesis but were less likely to track multiple word-object links when a social cue was present. In Experiment 2, we replicated the findings from Experiment 1 using a more ecologically valid social cue. In Experiment 3, we moved to a parametric manipulation of referential uncertainty by varying the reliability of the speaker's gaze. Learners were sensitive to graded changes in reliability and retained more word-object links as uncertainty in the input increased. Finally, in Experiment 4, we equated the length of the initial naming events with and without the referential cue. Learners stored less information in the presence of gaze even when they had visually inspected the objects for the same amount of time. In sum, our data suggest that cross-situational word learners are quite flexible, storing representations with different levels of fidelity depending on the amount of ambiguity present during learning.

## 4.2 Experiment 1

We set out to test the effect of a referential cue on the representations underlying cross-situational word learning. We used a version of Yurovsky and Frank (2015)'s paradigm where we manipulated the ambiguity of the learning context by including a gaze cue from a schematic, female interlocutor. Participants saw a series of ambiguous exposure trials where they heard one novel word that was either paired with a gaze cue or not and selected the object they thought went with each word. In subsequent test trials, participants heard the novel word again, this time paired with a new set of novel objects. One of the objects in this set was either the participant's initial guess (Same test trials) or one of the objects was *not* their initial guess (Switch test trials). Performance on Switch trials provided a direct measure of whether referential cues influenced the number of alternative word-object links that learners stored in memory. If learners performed worse on Switch trials after an exposure trial with gaze, this would suggest that they stored fewer additional objects from the initial learning context.

### 4.2.1 Method

#### Participants

We posted a set of Human Intelligence Tasks (HITs) to Amazon Mechanical Turk. Only participants with US IP addresses and a task approval rate above 95% were allowed to participate, and each HIT paid 30 cents. 50-100 HITs were posted for each of the 32 between-subjects conditions. Data were excluded if participants completed the task more than once or if participants did not respond correctly on familiar object trials (131 HITs). The final sample consisted of 1438 participants.

#### Stimuli

Figure 1 shows screenshots taken from Experiment 1. Visual stimuli were black and white pictures of familiar and novel objects taken from Kanwisher, Woods, Iacoboni, and Mazziotta (1997). Auditory stimuli were recordings of familiar and novel words by an AT&T Natural Voices ™(voice: Crystal) speech synthesizer. Novel words were 1-3 syllable pseudowords that obeyed all rules of English phonotactics. A schematic drawing of a human speaker was chosen for ease of manipulating the direction of gaze, the referential cue of interest in this study. All experiments can be viewed and downloaded at the project page: `https://kemacdonald.github.io/soc_xsit/`.

#### Design and Procedure

Participants saw a total of 16 trials: eight exposure trials and eight test trials. On each trial, they heard one novel word, saw a set of novel objects, and were asked to guess which object went with the word. Before seeing exposure and test trials, participants completed four practice trials with familiar words and objects. These trials familiarized participants to the task and allowed us to exclude participants who were unlikely to perform the task as directed, either because of inattention or because their computer audio was turned off.

After the practice trials, participants were told that they would now hear novel words and see novel objects and that their task was to select the referent that "goes with each word." Over the course of the experiment, participants heard eight novel words two times, with one exposure trial and one test trial for each word. Four of the test trials were *Same* trials in which the object that participants selected on the exposure trial was shown with a set of new novel objects. The other four test trials were *Switch* trials in which one of the objects was chosen at random from the set of objects that the participant did not select on exposure.

Participants were randomly assigned to one of the 32 between-subjects conditions (4 Referents X 4 Intervals X 2 Gaze conditions). Participants either saw 2, 4, 6, or 8 referents on the screen and test trials occurred at different intervals after exposure trials: either 0, 1, 3, or 7 trials from the initial exposure to a word. For example, in the 0-interval condition, the test trial for that word would occur immediately following the exposure trial, but in the 3-interval condition, participants would see three additional exposure trials for other novel words before seeing the test trial for the initial word. The interval conditions modulated the time delay and the number of intervening trials between learning and test, and the number of referents conditions modulated the attention demands present during learning.

Participants were assigned to either the Gaze or No-Gaze condition. In the Gaze condition, gaze was directed towards one of the objects on exposure trials; in the No-Gaze condition, gaze was always directed straight ahead (see Figure 1 for examples). At test, gaze was always directed straight ahead. To show participants that their response had been recorded, a red box appeared around the selected object for one second. This box always appeared around the selected object, even if participants' selections were incorrect.

### 4.2.2 Results and Discussion

#### Analysis plan

The structure of our analysis plan is parallel across all four experiments. First, we examined accuracy on exposure trials in the Gaze condition and then we compared response times on exposure trials across the Gaze and No-Gaze conditions. These analyses tested whether learners were (a) sensitive to our experimental manipulation and (b) altered their allocation of attention in response to the presence of a social cue. Accuracy on exposure trials was defined as selecting the referent that was the target of gaze in the Gaze condition. (Note that there was no "correct" behavior for exposure trials in the No-Gaze condition.) Next, we examined accuracy on test trials to test whether learners' memory for alternative word-object links changed depending on the ambiguity of the learning context. Accuracy on test trials (both Same and Switch) was defined as selecting the referent that was present during the exposure trial for that word.

The key behavioral prediction of our hypothesis was that the presence of gaze would result in reduced memory for multiple word-object links, operationalized as a decrease in accuracy on Switch test trials after seeing exposure trials with a gaze cue. To quantify participants' behavior, we used mixed-effects regression models with the maximal random effects structure justified by our experimental design: by-subject intercepts and slopes for each trial type (Barr, 2013). We limited all models to include only two-way interactions because the critical test of our hypothesis was the interaction between gaze condition and trial type, and we did not have theoretical predictions for any possible three-way or four-way interactions.

In the main text, we only report effects that achieved statistical significance at the $\alpha = .05$ threshold. In the Appendix, we report the full model specification and output for each of the models in the paper. All models were fit using the lme4 package in R (Bates, Maechler, Bolker, & Walker, 2013), and all of our data and our processing/analysis code can be viewed in the version control repository for this paper at `https://github.com/kemacdonald/soc_xsit`.

### Exposure trials

To ensure that our referential cue manipulation was effective, we compared participants' accuracies on exposure trials in the Gaze condition to a model of random behavior defined as a Binomial distribution with a probability of success $\frac{1}{NumReferents}$. Correct performance was defined as selecting the object that was the target of the speaker's gaze. Following Yurovsky and Frank (2015), we fit logistic regressions for each gaze, referent, and interval combination specified as `Gaze Target` $\sim$ `1 + offset(logit(1/Referents))`. The offset encoded the chance probability of success given the number of referents, and the coefficient for the intercept term shows on a log-odds scale how much more likely participants were to select the gaze target than would be expected if participants were selecting randomly. In all conditions, participants used gaze to select referents on exposure trials more often than expected by chance (smallest $\beta = 1.4$, z = 9.38, $p < .001$). However, the mean proportion of gaze following varied across conditions (overall $M = 0.84$, range: 0.77–0.93).

We were also interested in differences in participants' response times across the experimental conditions. Since these trials were self-paced, participants could choose how much time to spend inspecting the referents on the screen, thus providing an index of participants' attention. To quantify the effects of gaze, interval, and number of referents, we fit a linear mixed-effects model that predicted participants' inspection times as follows: `Log(Inspection time)` $\sim$ `(Gaze * Log(Interval) + Log(Referents))`$^2$ `+ (1 | subject)`. We found a significant main effect of the number of referents ($\beta$ = 0.34, p < .001) with longer inspection times as the number of referents increased, a significant interaction between gaze condition and the number of referents ($\beta$ = -0.27, p < .001) with longer inspection times in the No-Gaze condition, especially as the number of referents increased, and a significant interaction between gaze condition and interval ($\beta$ = -0.08, $p$ = 0.004) with longer inspection times in the No-Gaze condition, especially as the number of intervening trials increased (see the top row of Figure 2). Shorter inspection times on exposure trials with gaze provide evidence that the presence of a referential cue focused participants' attention on a single referent and away from alternative word-object links.

### Test trials

Next, we explored participants' accuracy in identifying the referent for each word in all conditions for both kinds of test trials (see the bottom row of Figure 2). We first compared the distribution of correct responses made by each participant to the distribution expected if participants were selecting randomly defined as a Binomial distribution with a probability of success $\frac{1}{NumReferents}$. Correct performance was defined as selecting the object that was present on the exposure trial for that word. We fit the same logistic regressions as we did for exposure trials: `Correct` $\sim$ `1 + offset(logit(1/Referents))`. In 31 out of the 32 conditions for both Same and Switch trials, participants chose the correct object more often than would be expected by chance (smallest $\beta$ = 0.36, $z$ = 2.44, $p$ = 0.01). On Switch trials in the 8-referent, 3-interval condition, participants' responses were not significantly different from chance ($\beta$ = 0.06, z = 0.33, $p$ = 0.74). Participants' success on Switch trials replicates the findings from Yurovsky and Frank (2015) and provides direct evidence that learners encoded more than a single hypothesis in ambiguous word learning situations even under high attentional and memory demands and in the presence of a referential cue. To quantify the effects of gaze, interval, and number of referents on the probability of a correct response, we fit the following mixed-effects logistic regression model to a filtered dataset where we removed participants who did not reliably select the object that was the target of gaze

| Predictor | Estimate | Std. Error | $z$ value | $p$ value | |
|---|---|---|---|---|---|
| Intercept | 3.01 | 0.29 | 10.35 | $< .001$ | *** |
| Switch Trial | -1.36 | 0.24 | -5.63 | $< .001$ | *** |
| Gaze Condition | 0.12 | 0.26 | 0.47 | 0.64 | |
| Log(Interval) | -0.45 | 0.11 | -4.08 | $< .001$ | *** |
| Log(Referents) | 0.23 | 0.11 | 2.02 | 0.04 | * |
| Switch Trial*Gaze Condition | -1.09 | 0.12 | -9.07 | $< .001$ | *** |
| Switch Trial*Log(Interval) | 0.52 | 0.05 | 9.50 | $< .001$ | *** |
| Switch Trial*Log(Referent) | -0.59 | 0.09 | -6.49 | $< .001$ | *** |
| Gaze Condition*Log(Interval) | 0.06 | 0.06 | 1.00 | 0.32 | |
| Gaze Condition*Log(Referent) | 0.20 | 0.09 | 2.15 | 0.03 | * |
| Log(Interval)*Log(Referent) | -0.04 | 0.04 | -1.02 | 0.31 | |

Table 4.1: Predictor estimates with standard errors and significance information for a logistic mixed-effects model predicting word learning in Experiment 4.1.

on exposure trials:[4] `Correct` $\sim$ `(Trial Type + Gaze + Log(Interval) + Log(Referents))`$^2$ `+ offset(logit(`$^1/_{Referents}$`)) + (TrialType | subject)`. We coded interval and number of referents as continuous predictors and transformed these variables to the log scale.[5]

Table 1 shows the output of the logistic regression. We found significant main effects of the number of referents ($\beta = 0.23$, $p < .001$) and interval ($\beta = -0.45$, $p < .001$), such that as each of these factors increased, accuracy on test trials decreased. We also found a significant main effect of trial type ($\beta = -1.36$, $p < .001$), with worse performance on Switch trials. There were significant interactions between trial type and interval ($\beta = 0.52$, $p < .001$), trial type and referents ($\beta = -0.59$, $p < .001$), and gaze condition and referents ($\beta = 0.2$, $p < .05$). These interactions can be interpreted as meaning: (a) the interval between exposure and test affected Same trials more than Switch trials, (b) the number of referents affected Switch trials more than Same trials, and (c) participants performed slightly better at the higher number of referents in the Gaze condition. The interactions between gaze condition and referents and between referents and interval were not significant. Importantly, we found the predicted interaction between trial type and gaze condition ($\beta = -1.09$, $p < .001$), with participants in the Gaze condition performing worse on Switch trials. This interaction provides direct evidence that the presence of a referential cue reduces participants' memory for alternative word-object links.

[4] We did not predict that there would be a subset of participants who would not follow the gaze cue, thus this filtering criterion was developed posthoc. However, we think that the filter is theoretically motivated because we would only expect to see an effect of gaze if participants actually used the gaze cue. The filter removed 94 participants (6% of the sample). The key inferences from the data do not depend on this filtering criterion.

[5] If we allowed for three-way interactions in the model, the key interaction between gaze condition and trial type remained significant ($\beta$ = -1.3, $p$ = 0.006).

We were also interested in how the length of inspection times on exposure trials would affect participants' accuracy at test. So we fit an additional model where participants' inspection times were included as a predictor. We found a significant interaction between inspection time and gaze condition ($\beta = -0.17$, $p = 0.01$) such that longer inspection times provided a larger boost to accuracy in the No-Gaze condition. Importantly, the key test of our hypothesis, the interaction between gaze condition and trial type, remained significant in this alternative version of the model ($\beta$ = -1.02, $p$ = p < .001).

Taken together, the inspection time and accuracy analyses provide evidence that the presence of a referential cue modulated learners' attention during learning, and in turn made them less likely to track multiple word-object links. We saw some evidence for a boost to performance on Same trials in the Gaze condition at the higher number of referent and interval conditions, but reduced tracking of alternatives did not always result in better memory for learners' candidate hypothesis. This finding suggests that the limitations on Same trials may be different than those regulating the distribution of attention on Switch trials.

There was relatively large variation in performance across conditions in the group-level accuracy scores and in participants' tendency to *use* the referential cue on exposure trials. Moreover, we found a subset of participants who did not reliably use the gaze cue at all. It is possible that the effect of gaze was reduced because the referential cue that we used – a static schematic drawing of a speaker – was relatively weak compared to the cues present in real-world learning environments. Thus we do not yet know how learners' memory for alternatives during cross-situational learning would change in the presence of a stronger and more ecologically valid referential cue. We designed Experiment 2 to address this question.

## 4.3 Experiment 2

In Experiment 2, we set out to replicate the findings from Experiment 1 using a more ecologically valid stimulus set. We replaced the static, schematic drawing with a video of an actress. While these stimuli were still far from actual learning contexts, they included a real person who provided both a gaze cue and a head turn towards the target object. To reduce the across-conditions variability that we found in Experiment 1, we introduced a within-subjects design where each participant saw both Gaze and No-Gaze exposure trials in a blocked design. We selected a subset of the conditions from Experiment 1 and tested only the 4-referent display with 0 and 3 intervening trials as between-subjects manipulations. Our goals were to replicate the reduction in learners' tracking of alternative word-object links in the presence of a referential cue and to test whether increasing the ecological validity of the cue would result in a boost to the strength of learners' recall of their candidate hypothesis.

### 4.3.1 Method

#### Participants

Participant recruitment and inclusion/exclusion criteria were identical to those of Experiment 1. 100 HITs were posted for each condition (1 Referent X 2 Intervals X 2 Gaze conditions) for a total of 400 paid HITs (33 HITs excluded).

#### Stimuli

Audio and picture stimuli were identical to Experiment 1. The referential cue in the Gaze condition was a video (see Figure 1). On each exposure trial, the actress looked out at the participant with a neutral expression, smiled, and then turned to look at one of the four images on the screen. She maintained her gaze for 3 seconds before returning to the center. On test trials, she looked straight ahead for the duration of the trial.

### 4.3.2 Design and Procedure

Procedures were identical to those of Experiment 1. The major design change was a within-subjects manipulation of the gaze cue where each participant saw exposure trials with and without gaze. The experiment consisted of 32 trials split into 2 blocks of 16 trials. Each block consisted of 8 exposure trials and 8 test trials (4 Same trials and 4 Switch trials) and contained only Gaze or No-gaze exposure trials. The order of block was counterbalanced across participants.

### 4.3.3 Results and Discussion

We followed the same analysis plan as in Experiment 1. We first analyzed inspection times and accuracy on exposure trials and then analyzed accuracy on test trials.

| Predictor | Estimate | Std. Error | $z$ value | $p$ value | |
|---|---|---|---|---|---|
| Intercept | 4.04 | 0.18 | 21.97 | $< .001$ | *** |
| Switch Trial | -2.99 | 0.19 | -16.11 | $< .001$ | *** |
| Gaze Condition | -0.10 | 0.16 | -0.63 | 0.53 | |
| Log(Interval) | -0.93 | 0.10 | -9.23 | $< .001$ | *** |
| Switch Trial*Gaze Condition | -0.71 | 0.16 | -4.49 | $< .001$ | *** |
| Switch Trial*Log(Interval) | 0.79 | 0.10 | 8.03 | $< .001$ | *** |
| Gaze Condition*Log(Interval) | 0.15 | 0.08 | 2.05 | 0.04 | * |

Table 4.2: Predictor estimates with standard errors and significance information for a logistic mixed-effects model predicting word learning in Experiment 4.2.

**Exposure trials**

Similar to Experiment 1, participants' responses on exposure trials differed from those expected by chance (smallest $\beta$ = 3.39, z = 31.99, $p < .001$), suggesting that gaze was effective in directing participants' attention. Participants in Experiment 2 were more consistent in their use of gaze with the video stimuli compared to the schematic stimuli used in Experiment 1 ($M_{Exp1} = 0.8$, $M_{Exp2} = 0.91$), suggesting that using a real person increased participants' willingness to follow the gaze cue.

We replicated the findings from Experiment 1. Inspection times were shorter when gaze was present ($\beta$ = -1.1, $p < .001$) and in the 3-interval condition ($\beta$ = -0.48, $p < .001$). The interaction between gaze and interval was not significant, meaning that gaze had the same effect on participants' inspection times at both intervals (see Panel A of Figure 3).

**Test trials**

Across all conditions for both trial types, participants selected the correct referent at rates greater than chance (smallest $\beta$ = 0.58, z = 9.32, $p < .001$). We replicated the critical finding from Experiment 1: after seeing exposure trials with gaze, participants performed worse on Switch trials, meaning they stored fewer word-object links ($\beta = -0.71$, $p < .001$).[6] Participants were also less accurate as the interval between exposure and test increased ($\beta$ = -0.93, $p < .001$) and on the Switch trials overall ($\beta = -2.99$, $p < .001$).

In addition, there was a significant interaction between trial type and interval ($\beta$ = 0.79, $p < .001$), with worse performance on Switch trials in the 3-interval condition. The interaction between gaze condition and interval was also significant ($\beta$ = 0.15, $p$ = 0.041), such that participants in the

[6] As in Experiment 1, we fit this model to a filtered dataset removing participants who did not reliably use the gaze cue.

gaze condition were less affected by the increase in interval. Similar to Experiment 1, we did not see evidence of a boost to performance on Same trials in the gaze condition.

Next, we added inspection times on exposure trials to the model. Similar to Experiment 1, the key interaction between gaze and trial type remained significant in this version of the model ($\beta$ = -0.54, $p < .001$). We also found an interaction between inspection time and trial type ($\beta = 0.21$, $p = 0.05$), with longer inspection times providing a larger boost to performance on Switch trials (i.e., stronger memory for alternative word-object links). This result differs slightly from Experiment 1 where we found an interaction between trial type and inspection time, with longer inspection times providing a larger boost to accuracy in the No-Gaze condition. Despite this subtle difference, we speculate that inspection times likely played a similar role in both experiments, with longer inspection times leading to better performance on Switch trials since these trials depended on encoding multiple word-object links. It is also possible that the interaction between gaze condition and inspection time that we found in Experiment 1 was influenced by the different number of referents and interval conditions.

The results of Experiment 2 provide converging evidence for our primary hypothesis that the presence of a referential cue reliably focuses learners' attention away from alternative word-object links and shifts them towards single hypothesis tracking. Moving to the video stimulus led to higher rates of selecting the target of gaze on exposure trials, but did not result in a boost to performance on Same trials. This finding suggests that the level of attention and memory demand present in the learning context might modulate the effect of gaze on the fidelity of learners' single hypothesis.

Thus far we have shown that people store different amounts of information in response to a categorical manipulation of referential uncertainty. In both Experiments 1 and 2, the learning context was either entirely ambiguous (No-Gaze) or entirely unambiguous (Gaze). But not all real-world learning contexts fall at the extremes of this continuum. Could learners be sensitive to more subtle changes in the quality of the input? In our next experiment, we tested a prediction of our account: whether learners would store more word-object links in response to graded changes in referential uncertainty during learning.

## 4.4 Experiment 3

In Experiment 3, we explored whether learners would allocate attention and memory flexibly in response to *graded* changes in the referential uncertainty that was present during learning. To test this hypothesis, we moved beyond a categorical manipulation of the presence/absence of gaze, and we parametrically varied the reliability of the referential cue. We manipulated cue reliability by adding a block of familiarization trials where we varied the proportion of Same and Switch trials. If participants saw more Switch trials, this provided direct evidence that the speaker's gaze was a less reliable cue to reference because the gaze target on exposure trials would not appear at test. This design was inspired by a growing body of experimental work showing that even young children are sensitive to the prior reliability of speakers and will use this information to decide whom to learn novel words from (e.g., Koenig, Clement, & Harris, 2004).

### 4.4.1 Method

#### Participants

Participant recruitment and inclusion/exclusion criteria were identical to those of Experiment 1 and 2 (27 HITs excluded). 100 HITs were posted for each reliability level (0%, 25%, 50%, 75%, and 100%) for total of 500 paid HITs.

#### Design and Procedure

Procedures were identical to those of Experiments 1 and 2. We modified the design of our cross-situational learning paradigm to include a block of 16 familiarization trials (8 exposure trials and 8 test trials) at the beginning of the experiment. These trials served to establish the reliability of the speaker's gaze. To establish reliability, we varied the proportion of Same/Switch trials that occurred during the familiarization block. Recall that on Switch trials the gaze target did not show up at test, which provided evidence that the speaker's gaze was not a reliable cue to reference. Reliability was a between-subjects manipulation such that participants either saw 8, 6, 4, 2, or 0 Switch trials during familiarization, which created the 0%, 25%, 50%, 75%, and 100% reliability conditions. After the familiarization block, participants completed another block of 16 trials (8 exposure trials and 8 test trials). Since we were no longer testing the effect of the presence or absence of a referential cue, all exposure trials throughout the experiment included a gaze cue. Finally, at the end of the task, we asked participants to assess the reliability of the speaker on a continuous scale from "completely unreliable" to "completely reliable."

### 4.4.2 Results and Discussion

#### Exposure trials

Participants reliably chose the referent that was the target of gaze at rates greater than chance (smallest $\beta = 2.62$, z $= 31.99$, $p < .001$). We fit a mixed effects logistic regression model predicting the probability of selecting the gaze target as follows: `Correct-Exposure` $\sim$ `Reliability Condition * Subjective Reliability + (1 | subject)`. We found an effect of reliability condition ($\beta = 3.28$, $p = 0.03$) such that when the gaze cue was more reliable, participants were more likely to use it ($M_{0\%} = 0.83$, $M_{25\%} = 0.82$, $M_{50\%} = 0.87$, $M_{75\%} = 0.9$, $M_{100\%} = 0.94$). We also found an effect of subjective reliability ($\beta = 7.26$, $p < .001$) such that when participants thought the gaze cue was reliable, they were more likely to use it. This analysis provides evidence that participants were sensitive to the reliability manipulation both in how often they used the gaze cue and in how they rated the reliability of the speaker at the end of the task.

#### Test trials

Next, we tested whether the reliability manipulation altered the strength of participants' memory for alternative word-object links in the second block of test trials that followed the initial familiarization phase. Across all conditions, participants selected the correct referent at rates greater than chance (smallest $\beta = 0.42$, z $= 3.69$, $p < .001$). Our primary prediction was an interaction between reliability and test trial type, with higher levels of reliability leading to worse performance on Switch trials (i.e., less memory allocated to alternative word-object links). To explore this prediction, we performed four complementary analyses: our primary analysis, which tested the effect of the reliability manipulation, and three secondary analyses, which explored the effects of participants' (a) use of the gaze cue, (b) subjective reliability assessments, and (c) inspection time on exposure trials.

### Reliability condition analysis

To test the effect of reliability, we fit a model predicting accuracy at test using reliability condition and test trial type as predictors. We found a significant main effect of trial type ($\beta = -3.95$, $p < .001$), with lower accuracy on Switch trials. We also found the key interaction between reliability condition and trial type ($\beta$ = -0.76, $p$ = 0.044), such that when gaze was more reliable, participants performed worse on Switch trials (see Panel A of Figure 4). This interaction suggests that people store more word-object links as the learning context becomes more ambiguous. However, the interaction between reliability and trial type was not particularly strong, and – similar to Experiment 1 – performance varied across conditions (see the 50% reliable condition in Panel A of Figure 4). So to provide additional support for our hypothesis, we conducted three follow-up analyses.

### Gaze use analyses

We would only expect to see a strong interaction between reliability and trial type if learners chose to use the gaze cue during exposure trials. To test this hypothesis, we fit two additional models that included two different measures of participants' use of the gaze cue. First, we added the number of exposure trials on which participants chose to use the gaze cue as a predictor in our model. We found a significant interaction between use of the gaze cue on exposure trials and trial type ($\beta = -1.43$, $p$ $< .001$) with worse performance on Switch test trials when participants used gaze on exposure trials (see Panel B of Figure 4). We also found an interaction between gaze use and reliability ($\beta$ = 0.97, $p$ = 0.004) such that when gaze was more reliable, participants were more likely to use it. The $\beta$ value for the interaction between trial type and reliability changed from -0.76 to -0.62, ($p$ = 0.086). This reduction suggests that participants' tendency to use the gaze cue is a stronger predictor of learners' memory for alternative word-object links compared to our reliability manipulation.[7]

We also hypothesized that the reliability manipulation might change how often individual participants chose to use the gaze cue throughout the task. To explore this possibility, we fit a model with the same specifications, but we included a predictor that we created by binning participants based on the number of exposure trials on which they chose to follow gaze (i.e., a gaze following score). We found a significant interaction between how often participants chose to follow gaze on exposure trials and trial type ($\beta = -0.26$, $p < .001$), such that participants who were more likely to

[7]We are grateful to an anonymous reviewer for suggesting this analysis, but we would like to note that it is exploratory.

use the gaze cue performed worse on Switch trials, but not Same trials (see Panel A of Figure 5).[8] Taken together, the two analyses of participants' use of the gaze cue provide converging evidence that when the speaker's gaze was reliable participants were more likely to use the cue, and when they followed gaze, they tended to store less information from the initial naming event.

### Subjective reliability analysis

The strong interaction between use of the gaze cue and memory for alternative word-object links suggests that participants' subjective experience of reliability in the experiment mattered. Thus, we fit the same model but substituted subjective reliability for the frequency of gaze use as a predictor of test trial performance. We found a significant interaction between trial type and participants' subjective reliability assessments ($\beta = -1.63$, $p = 0.01$): when participants thought the speaker was more reliable, they performed worse on Switch trials, but not Same trials (see Panel B of Figure 5).

### Inspection time analyses

Finally, we analyzed the effect of inspection times on exposure trials, fitting a model using inspection time, trial type, and reliability condition to predict accuracy at test. We found a main effect of inspection time ($\beta = 0.31$, $p = 0.001$), with longer inspection times leading to better performance for both Same and Switch trials. The interaction between inspection time and reliability condition was not significant. The key interaction between reliability condition and trial type remained significant in this version of the model ($\beta$ = -0.58, $p$ = 0.048).

Next, we explored the factors that influenced inspection time on exposure trials by fitting a model to predict inspection times as a function of reliability condition and participants' use of the gaze cue. We found a main effect of participants' use of the gaze cue (-0.32, $p < .001$) with shorter inspection times when participants followed gaze. The main effect of reliability condition and the interaction between reliability and use of gaze were not significant. These analyses provide evidence that inspection times were similar across the different reliability conditions and that use of the gaze cue was the primary factor affecting how long participants explored the objects during learning.

Together, these four analyses show that when the speaker's gaze was more reliable, participants were more likely to: (a) use the gaze cue, (b) rate the speaker as more reliable, and (c) store

[8] We found this interaction while performing exploratory data analyses on a previous version of this study with an independent sample (N = 250, $\beta = -0.24$, $p < .001$). The results reported here are from a follow-up study where testing this interaction was a planned analysis.

fewer word-object links, showing behavior more consistent with single hypothesis tracking. These findings support and extend the results of Experiments 1 and 2 in several important ways. First, similar to Experiment 2, participants' performance on Same trials was relatively unaffected by changes in performance on Switch trials. The selective effect of gaze on Switch trials provides converging evidence that the limitations on Same trials may be different than those regulating the distribution of attention on Switch trials. Second, learners' use of a referential cue was a stronger predictor of reduced memory for alternative word-object links compared to our reliability manipulation. Although we found a significant effect of reliability on participants' use of the gaze cue, participants' tendency to use the cue remained high. Consider that even in the 0% reliability condition the mean proportion of gaze following was still 0.82. It is reasonable that participants would continue to use the gaze cue in our experiment since it was the only cue available and participants did not have a strong reason to think that the speaker would be deceptive.

The critical contribution of Experiment 3 is to show that learners respond to a graded manipulation of referential uncertainty, with the amount of information stored from the initial exposure tracking with the reliability of the cue. This graded accuracy performance shows that learners stored alternative word-object links with different levels of fidelity depending on the amount of referential uncertainty present during learning.

Across Experiments 1-3, learners tended to store fewer word-object links in unambiguous learning contexts when a clear referential cue was present. However, in all three experiments, participants' responses on exposure trials controlled the length of the trial, meaning that when participants used the gaze cue, they also spent less time visually inspecting the objects. Thus, we do not know whether there is an independent effect of referential cues on the representations underlying cross-situational learning, or if the effects found in Experiments 1-3 are entirely mediated by a reduction in inspection time. In Experiment 4, we addressed this possibility by removing participants' control over the length of exposure trials, which made the inspection times equivalent across the Gaze and No-Gaze conditions.

## 4.5 Experiment 4

In Experiment 4, we asked whether a reduction in visual inspection time in the gaze condition could completely explain the effect of social cues on learners' reduced memory for alternative word-object links. To answer this question, we modified our paradigm and made the length of exposure trials equivalent across the Gaze and No-Gaze conditions. In this version of the task, participants were shown the objects for a fixed amount of time regardless of whether gaze was present. We also included two different exposure trial lengths in order to test whether gaze would have a differential effect at shorter vs. longer inspection times. If the presence of gaze reduces learners' memory for multiple word-object links, then this provides evidence that referential cues affected the underlying representations over and above a reduction in inspection time.

### 4.5.1 Method

#### Participants

Participant recruitment and inclusion/exclusion criteria were identical to those of Experiments 1, 2, and 3. 100 HITs were posted for each condition (1 Referent X 2 Intervals X 2 Inspection Time conditions) for a total of 400 paid HITs (37 HITs excluded).

#### Stimuli

Audio, picture, and video stimuli were identical to Experiments 2 and 3. Since inspection times were fixed across conditions, we wanted to ensure that participants were aware of the time remaining on each exposure trial. So we included a circular countdown timer located above the center video. The timer remained on the screen during test trials but did not count down since participants could take as much time as they wanted to respond on test trials.

### 4.5.2 Design and Procedure

Procedures were identical to those of Experiment 1-3. The design was identical to that of Experiment 2 and consisted of 32 trials split into 2 blocks of 16 trials. Each block consisted of 8 exposure trials and 8 test trials (4 Same trials and 4 Switch trials) and contained only Gaze or No-Gaze exposure trials. The order of block was counterbalanced across participants.

The major design change was to make the length of exposure trials equivalent across the Gaze and No-Gaze conditions. We randomly assigned participants to one of two inspection time conditions: Short or Long. Initially, the length of the inspection times was based on participants' self-paced inspection times in the Gaze and No-Gaze conditions in Experiment 2 (Short = 3 seconds; Long

= 6 seconds). However, after pilot testing, we added three seconds to each condition to ensure that participants had enough time to respond before the experiment advanced (Short = 6 seconds; Long = 9 seconds). If participants did not respond in the allotted time, an error message appeared informing participants that time had run out and encouraged them to respond within the time window on subsequent trials.

### 4.5.3 Results and Discussion

We did not see strong evidence of an effect of the different inspection times. Thus, all of the results reported here collapse across the short and long inspection time conditions. For all analyses, we removed the trials on which participants did not respond within the fixed inspection time on exposure trials (0.05% of trials).

#### Exposure Trials

Participants' responses on exposure trials differed from those expected by chance (smallest $\beta = 2.95$, z = 38.08, $p < .001$), suggesting that gaze was again effective in directing participants' attention. Similar to Experiment 2, participants were quite likely to use the gaze cue when it was a video of an actress ($M_{0-interval} = 0.93$, $M_{3-interval} = 0.95$).

#### Test Trials

Figure 6 shows performance on test trials in Experiment 4. In the majority of conditions, participants selected the correct referent at rates greater than chance (smallest $\beta = 0.2$, z = 2.2, $p < .05$). However, participants' responses were not different from chance on Switch trials after exposure trials with gaze in the 3-interval condition ($\beta = 0.17$, $p = 0.06$).

We replicate the key finding from Experiments 1-3: after seeing exposure trials with gaze, participants were less accurate on Switch trials ($\beta = 0.9$, $p < .001$). Since inspection times were fixed across the Gaze and No-Gaze conditions, this finding provides evidence that the presence of a referential cue did more than just reduce the amount of time participants' spent inspecting the potential word-object links. In contrast to Experiments 2 and 3, visual inspection of Figure 6 suggested that the referential cue provided a boost to accuracy on Same trials. To assess the simple effect of gaze on trial type, we computed pairwise contrasts using the *lsmeans* package in R with a Bonferroni correction for multiple comparisons (Lenth, 2016). Accuracy was higher for Same trials in the Gaze condition ($\beta$ = 0.49, $p < .001$), but lower for Switch trials ($\beta$ = -0.41, $p < .001$). The boost in accuracy on Same trials differs from Experiments 2 and 3 and suggests that making inspection times equivalent across conditions allowed the social cue to affect the strength of learners' memory for their candidate hypothesis.

The results of Experiment 4 help to clarify the effect of gaze on memory in our task, providing evidence that the presence of a referential cue did more than just reduce participants' visual inspection time. Instead, gaze reduced memory for alternative word-object links even when people had the same opportunity to visually inspect and encode them. We also found evidence of a boost for learners' memory of their candidate hypothesis in the gaze condition, an effect that we saw at the higher number of referents and the longer intervals in Experiment 1, but that we did not see in Experiments 2 or 3. One explanation for this difference is that in Experiment 4, since participants' use of gaze was independent of the length of exposure trials, inspection times in the gaze condition were longer compared to those in Experiments 1-3. Thus, it could be that the combination of a gaze cue coupled with the opportunity to continue attending to the gaze target led to a boost in performance on Same trials relative to trials without gaze.

## 4.6 General Discussion

Tracking cross-situational word-object statistics allows word learning to proceed despite the presence of individually ambiguous naming events. But models of cross-situational learning disagree about how much information is actually stored in memory, and the input to statistical learning mechanisms can vary along a continuum of referential uncertainty from unambiguous naming instances to highly ambiguous situations. In the current line of work, we explore the hypothesis that these two factors are fundamentally linked to one another and to the social context in which word learning occurs. Specifically, we ask how cross-situational learning operates over social input that varies the amount of ambiguity in the learning context.

Our results suggest that the representations underlying cross-situational learning are quite flexible. In the absence of a referential cue to word meaning, learners tended to store more alternative word-object links. In contrast, when gaze was present learners stored less information, showing behavior consistent with tracking a single hypothesis (Experiments 1 and 2). Learners were also sensitive to a parametric manipulation of the strength of the referential cue, showing a graded increase in the tendency to use the cue as reliability increased, which in turn resulted in a graded decrease in memory for alternative word-object links (Experiment 3). Finally, learners stored less information in the presence of gaze even when they were shown the objects for the same amount of time (Experiment 4).

In Experiments 2 and 3 reduced memory for alternative hypotheses did not result in a boost to memory for learners' candidate hypothesis. This pattern of data suggests that the presence of a referential cue selectively affected one component of the underlying representation: the number of alternative word-object links, and not the strength of the learners' candidate hypothesis. However, in Experiments 1 and 4, we did see some evidence of stronger memory for learners' initial hypothesis in the presence of gaze: at the higher number of referents and interval conditions (Experiment 1), and when the length of exposure trials was equivalent across the Gaze and No-Gaze conditions (Experiment 4). We speculate that the relationship between the presence of a referential cue and the strength of learners' candidate hypothesis is modulated by how the cue interacts with attention. In Experiment 1, gaze may have provided a boost because, in the absence of gaze, attention would have been distributed across a larger number of alternatives. And, in Experiment 4, gaze may have led to better memory because it was coupled with the opportunity for sustained attention to the gaze target. More work is needed in order to understand precisely when the presence of gaze affects this particular component of the representations underlying cross-situational learning.

In Experiments 1-3, longer inspection times (i.e., more time spent encoding the word-object links during learning) led to better memory at test. We did, however, find slightly different interaction effects across our studies. In Experiment 1, longer inspection times led to higher accuracy in the No-Gaze condition for both Same and Switch trials. In Experiment 2, longer inspection times provided a larger boost to performance on Switch trials compared to Same trials, regardless of gaze condition. Despite these differences, we speculate that inspection time played a similar role across these studies: When a social cue was present, learners' attention was focused and inspection times tended to be shorter, which led to worse performance on Switch trials (i.e., reduced memory for alternative word-object links). Interestingly, in Experiment 4, we found an effect of social cues on memory for alternatives even when participants were given the same opportunity to visually inspect the objects, suggesting that gaze does more than just modulate visual attention during learning.

### 4.6.1 Relationship to previous work

Why might a decrease in memory for alternatives fail to increase the strength of learners' memory for their candidate hypothesis? One possibility is that participants did not shift their cognitive resources from the set of alternatives to their single hypothesis, but instead chose to use the gaze information to reduce inspection time, thus conserving their resources for future use. Griffiths, Lieder, and Goodman (2015) formalize this behavior by pushing the rationality of computational-level models down to the psychological process level. In their framework, cognitive systems are thought to be adaptive in that they optimize the use of their limited resources, taking the cost of computation (e.g., the opportunity cost of time or mental energy) into account. For example, Vul, Goodman, Griffiths, and Tenenbaum (2014) showed that as time pressure increased in a decision-making task, participants were more likely to show behavior consistent with a less cognitively challenging strategy of matching, rather than with the globally optimal strategy. In the current work, we found that learners showed evidence of altering how they allocated cognitive resources based on the amount of referential uncertainty present during learning, spending less time inspecting alternative word-object links and reducing the number of links stored in memory when uncertainty was low.

Our results fit well with recent experimental work that investigates how attention and memory can constrain infants' statistical word learning. For example, Smith and Yu (2013) used a modified cross-situational learning task to show that only infants who disengaged from a novel object to look at both potential referents were able to learn the correct word–object mappings. Moreover, Vlach and Johnson (2013) showed that 16-month-olds were only able to learn from adjacent cross-situational co-occurrence statistics, and unable to learn from co-occurrences that were separated in time. Both of these findings make the important point that only the information that comes into contact with the learning system can be used for cross-situational word learning, and this information is directly influenced by the attention and memory constraints of the learner. These results also add to a large literature showing the importance of social information for word learning (P. Bloom, 2002; Clark, 2009) and to recent work exploring the interaction between statistical learning mechanisms and other types of information (Frank et al., 2009; Koehne & Crocker, 2014; Yu & Ballard, 2007). Our findings suggest that referential cues affect statistical learning by modulating the amount of information that learners store in the underlying representations that support learning over time.

Is gaze a privileged cue, or could other, less-social cues (e.g., an arrow) also affect the representations underlying cross-situational learning? On the one hand, previous research has shown that gaze cues lead to more reflexive attentional responses compared to arrows (Friesen, Ristic, & Kingstone, 2004), that gaze-triggered attention results in better learning compared to salience-triggered attention (Wu & Kirkham, 2010), and that even toddlers readily use gaze to infer novel word meanings (D. A. Baldwin, 1993). Thus, it could be that gaze is an especially effective cue for constraining word learning since it communicates a speaker's referential intent and is a particularly good way to guide attention. On the other hand, the generative process of the cue – whether it is more or less social in nature – might be less important; instead, the critical factor might be whether the cue effectively reduces uncertainty in the naming event. Under this account, gaze is placed amongst a set of many cues that could produce similar effects as those reported here. Future work could explore a wider range of cues to see if they modulate the representations underlying cross-situational learning in a similar way.

How should we characterize the effect of gaze on attention and memory in our task? One possibility is that the referential cue acts as a filter, only allowing likely referents to contact statistical learning mechanisms (Yu & Ballard, 2007). This 'filtering account' separates the effect of social cues from the underlying computation that aggregates cross-situational information. Another possibility is that referential cues provide evidence about a speaker's communicative intent (Frank et al., 2009). In this model, the learner is reasoning about the speaker and word meanings simultaneously, which places inferences based on social information as part of the underlying computation. A third possibility is that participants thought of the referential cue as pedagogical. In this context, learners assume that the speaker will choose an action that is most likely to increase the learner's belief in the true state of the world (Shafto et al., 2012b), making it unnecessary to allocate resources to alternative hypotheses. Experiments show that children spend less time exploring an object and are less likely to discover alternative object-functions if a single function is demonstrated in a pedagogical context (Bonawitz et al., 2011). However, because the results from the current study cannot distinguish between these explanations, these questions remain topics for future studies specifically designed to tease apart these possibilities.

### 4.6.2 Limitations

There are several limitations to the current study that are worth noting. First, the social context that we used was relatively impoverished. Although we moved beyond a simple manipulation of the presence or absence of social information in Experiment 3, we nevertheless isolated just a single cue to reference, gaze. But real-world learning contexts are much more complex, providing learners access to multiple cues such as gaze, pointing, and previous discourse. In fact, Frank, Tenenbaum, and Fernald (2013) analyzed a corpus of parent-child interactions and concluded that learners would do better to aggregate noisy social information from multiple cues, rather than monitor a single cue since no single cue was a consistent predictor of reference. In our data, we did see a more reliable effect of referential cues when we used a video of an actress, which included both gaze and head turn as opposed to the static, schematic stimuli, which only included gaze. It is still an open and interesting question as to how our results would generalize to learning environments that contain a rich combination of social cues.

Second, we do not yet know how variations in referential uncertainty during learning would affect the representations of young word learners, the age at which cross-situational word learning might be particularly important. Recent research using a similar paradigm as our own did not find evidence that 2- or 3-year-olds stored multiple word-object links; instead, children only retained a single candidate hypothesis (Woodard, Gleitman, & Trueswell, 2016). However, performance limitations on children's developing attention and memory systems (Colombo, 2001; Ross-sheehy, Oakes, & Luck, 2003) could make success on these explicit response tasks more difficult. Moreover, our work suggests that different levels of referential uncertainty in naturalistic learning contexts (see Medina, Snedeker, Trueswell, & Gleitman, 2011; Yurovsky & Frank, 2015) might evoke different strategies for information storage, with learners retaining more information as ambiguity in the input increases. Thus, we think that it will be important to test a variety of outcome measures and learning contexts to see if younger learners show evidence of storing multiple word meanings during learning.

In addition, previous work with infants has shown that their attention is often stimulus-driven and sticky (Oakes, 2011), suggesting that very young word learners might not effectively explore the visual scene in order to extract the necessary statistics for storing multiple alternatives. It could be that referential cues play an even more important role for young learners by filtering the input to cross-situational word learning mechanisms and guiding children to the relevant statistics in the input. In fact, recent work has shown that the precise timing of features such as increased parent attention and gesturing towards a named object and away from non-target objects were strong predictors of referential clarity in a naming event (Trueswell et al., 2016). It could be that the statistics available in these particularly unambiguous naming events are the most useful for cross-situational learning.

Finally, the current experiments used a restricted cross-situational word learning scenario, which differs from real-world language learning contexts in several important ways. One, we only tested a single exposure for each novel word-object pairing; whereas, real-world naming events are best characterized by discourse where an object is likely to be named repeatedly in a short amount of time (Frank, Tenenbaum, & Fernald, 2013; Rohde & Frank, 2014). Two, the restricted visual world of 2-8 objects on a screen combined with the forced-choice response format may have biased people to assume that all words in the task must have referred to one of the objects. But, in actual language use, people can refer to things that are not physically co-present (e.g., Gleitman, 1990), creating a scenario where learners would not benefit from storing additional word-object links in the absence of clear referential cues. Finally, we presented novel words in isolation, removing any sentential cues to word meaning (e.g., verb-argument relations). In fact, previous work with adults has shown that cross-situational learning mechanisms only operate in contexts where sentence-level constraints do not completely disambiguate meaning (Koehne & Crocker, 2014). Thus, we need more evidence to understand how the representations underlying cross-situational learning change in response to referential uncertainty at different timescales and in richer language contexts that more accurately reflect real-world learning environments.

## 4.7 Conclusions

Word learning proceeds despite the potential for high levels of referential uncertainty and despite learners' limited cognitive resources. Our work shows that cross-situational learners flexibly respond to the amount of ambiguity in the input, and as referential uncertainty increases, learners tend to store more word-object links. Overall, these results bring together aspects of social and statistical accounts of word learning to increase our understanding of how statistical learning mechanisms operate over fundamentally social input.

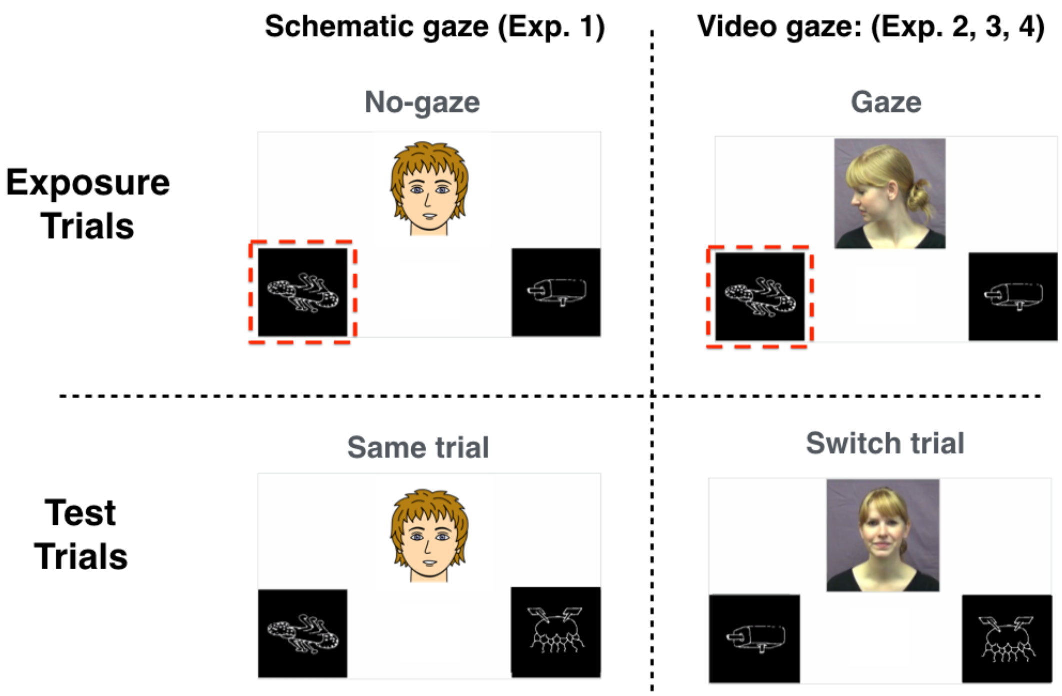



Figure 4.2: Screenshots of exposure and test trials from Experiments 1-4. The top left panel shows an exposure trial in the No-gaze condition using the schematic gaze cue (Experiment 4.1). The top right panel shows an exposure trial in the Gaze condition using the video gaze cue (Experiments 4.2-4.4). Participants saw either Gaze or No-gaze exposure trials depending on condition assignment, and participants saw both types of test trials: Same (bottom left panel) and Switch (bottom right panel). On Same trials, the object that participants chose during exposure appeared with a new novel object. On Switch trials the object that participants did not choose appeared with a new novel object. Participants either saw 2, 4, 6, or 8 referents on the screen depending on condition assignment.

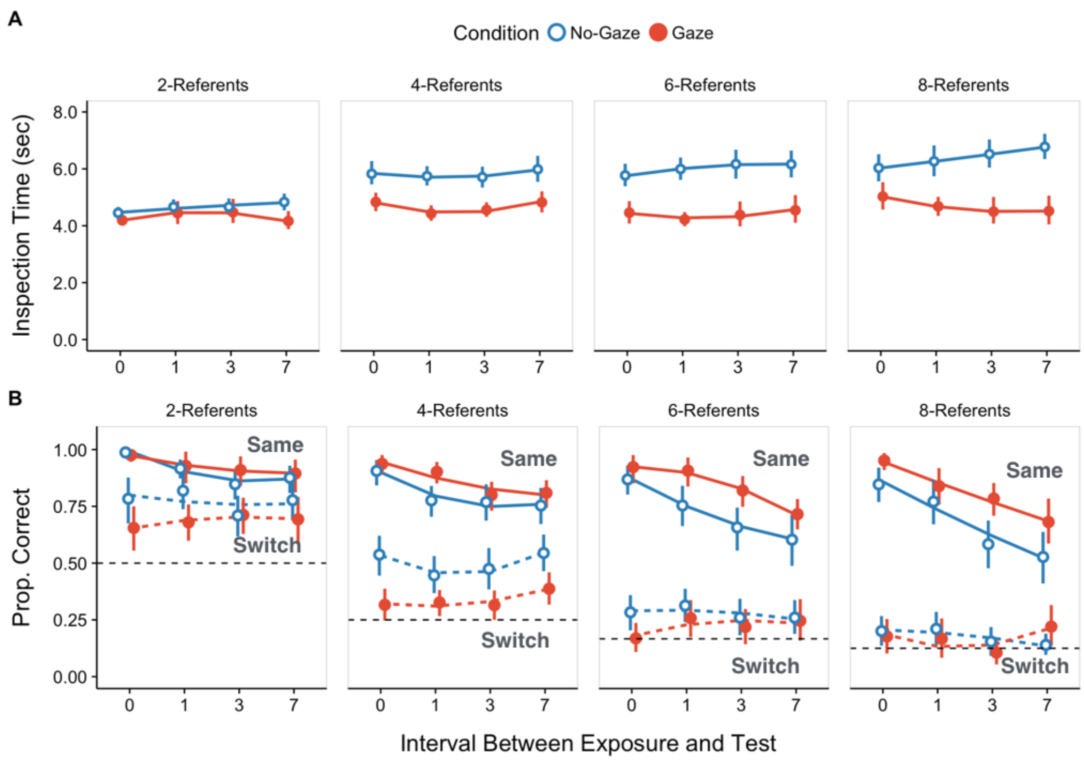



Figure 4.3: Experiment 4.1 results. The top row shows average inspection times on exposure trials for all experimental conditions as a function of the number of trials that occurred between exposure and test. Each panel represents a different number of referents, and line color represents the Gaze and No-Gaze conditions. The bottom row shows accuracy on test trials for all conditions as a function of the number of intervening trials. The horizontal dashed lines represent chance performance for each number of referents, and the type of line (solid vs. dashed) represents the different test trial types (Same vs. Switch). Error bars indicate 95% confidence intervals computed by non-parametric bootstrap.

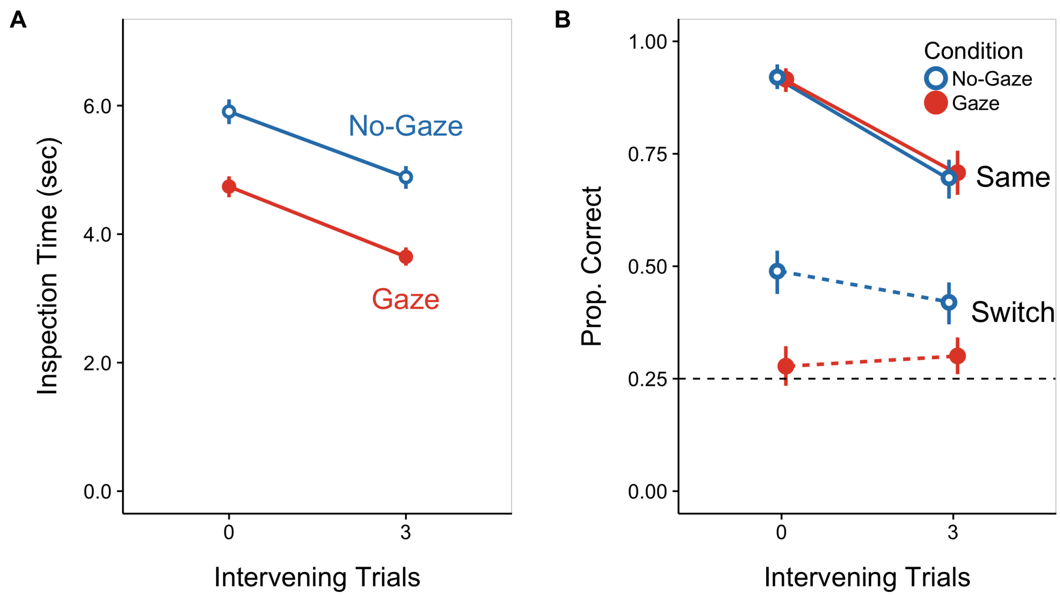



Figure 4.4: Experiment 2 results. Panel A shows inspection times on exposure trials with and without gaze. Panel B shows accuracy on Same and Switch test trials. All plotting conventions are the same as in Figure 2. Error bars indicate 95% confidence intervals computed by non-parametric bootstrap.

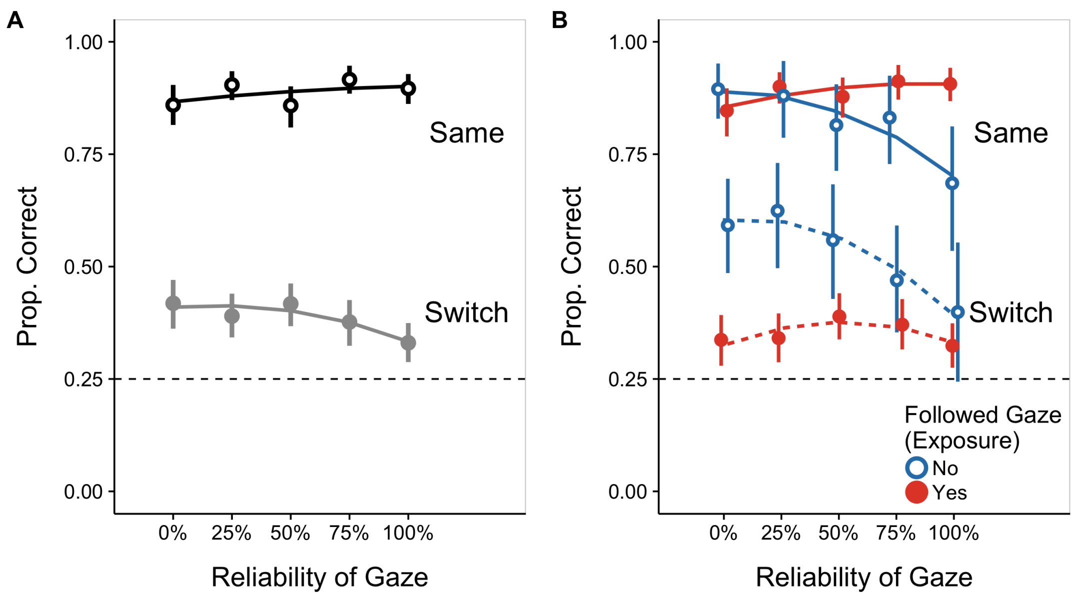



Figure 4.5: Primary analyses of test trial performance in Experiment 3. Panel A shows performance as a function of reliability condition. Panel B shows performance as a function of reliability condition and whether participants chose to follow gaze on exposure trials. The horizontal dashed lines represent chance performance, and error bars indicate 95% confidence intervals computed by non-parametric bootstrap.

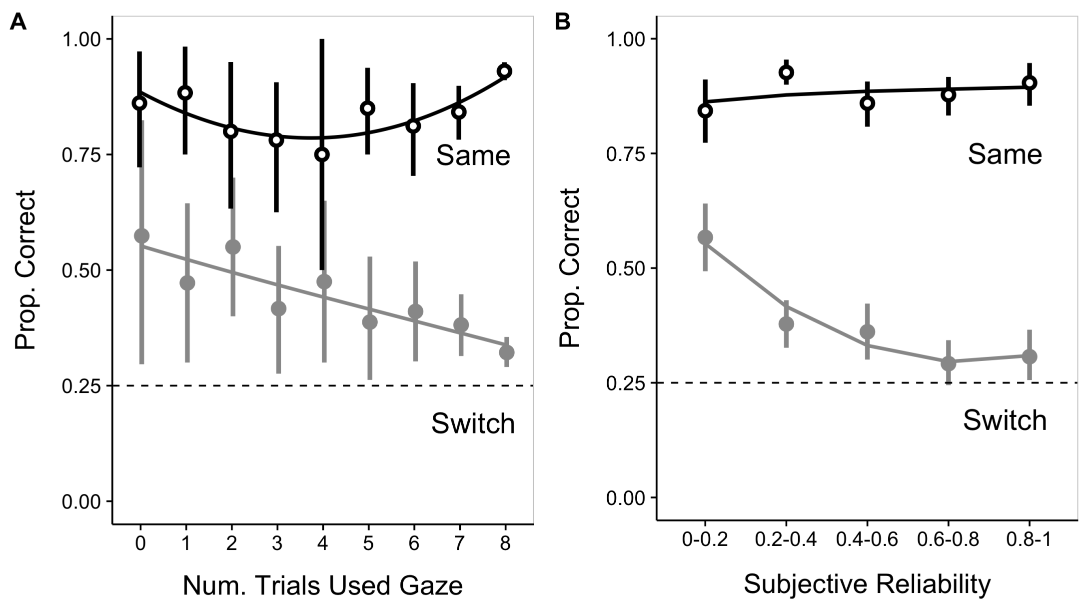



Figure 4.6: Secondary analyses of test trial performance in Experiment 3. Panel A shows accuracy as a function of the number of exposure trials on which participants chose to use the gaze cue. Panel B shows accuracy as a function of participants' subjective reliability judgments. The horizontal dashed lines represent chance performance, and error bars indicate 95% confidence intervals computed by non-parametric bootstrap.

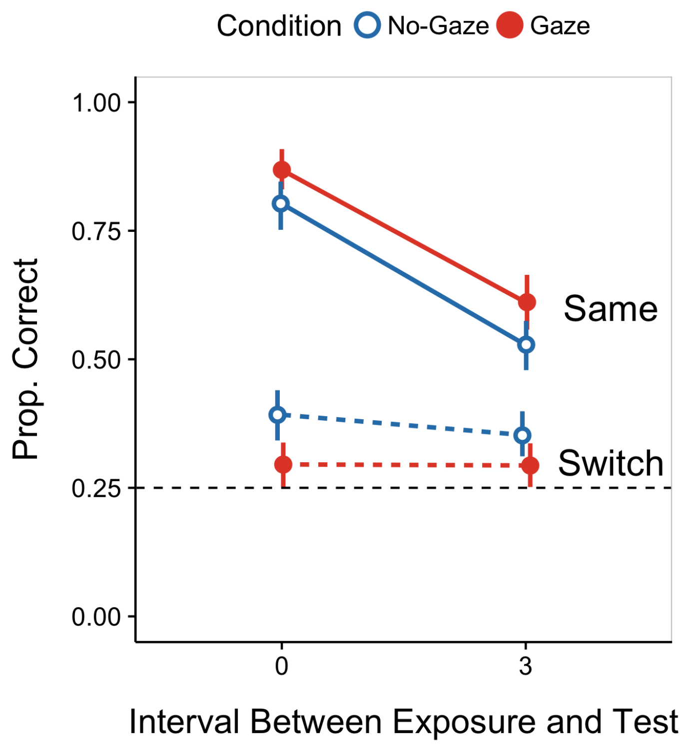



Figure 4.7: Experiment 4.4 results. Accuracy on test trials in Experiment 4 collapsed across the Long and Short inspection time conditions. The dashed line represents chance performance. Color and line type indicate whether there was gaze present on exposure trials. Error bars indicate 95% confidence intervals computed by non-parametric bootstrap.

# Chapter 5

# Seeking social and statisical information during word learning

# Conclusion

If we don't want Conclusion to have a chapter number next to it, we can add the `{-}` attribute.

**More info**

And here's some other random info: the first paragraph after a chapter title or section head *shouldn't be* indented, because indents are to tell the reader that you're starting a new paragraph. Since that's obvious after a chapter or section title, proper typesetting doesn't add an indent there.

# Appendix A

# Supplementary materials for Chapter 1

## A.1 Mathematical details of Optimal Experiment Design

This supplement contains the mathematical details of the OED approach as described in Coenen et al. (2017). The goal is to provide a concrete foundation for the conceptual analysis of how social learning contexts can influence different components of active learning.

The OED model quantifies the *expected utility* of different information seeking actions. Formally, the set of queries is defined as $Q_1, Q_2, ..., Q_n = \{Q\}$. The expected utility of each query ($EU(Q)$) is a function of two factors: (1) the probability of obtaining a specific answer $P(a)$ weighted by (2) the usefulness of that answer for achieving the learning goal $U(a)$.

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

There are a variety of ways to define the usefulness function to score each answer. An exhaustive review is beyond the scope of this paper (for a detailed analysis of different approaches, see Nelson (2005)). One standard method is to use *information gain*, which is defined as the change in the learner's overall uncertainty (difference in entoropy) before and after receiving an answer.

$$U(a) = ent(H) - ent(H|a)$$

Where $ent(H)$ is defined using Shannon entropy[1] (MacKay, 2003), which provides a measure of the overall amount of uncertainty in the learner's beliefs about the candidate hypotheses.

$$ent(H) = -\sum_{a \in A} P(h) log_2 P(h)$$

The conditional entropy computation is the same, but takes into account the change in the learner's beliefs after seeing an answer.

$$ent(H|a) = -\sum_{h \in H} P(h|a) log P(h|a)$$

To calculate the change in the learner's belief in a hypothesis $P(h|a)$, we use Bayes rule.

$$P(h|a) = \frac{P(h)P(a|h)}{P(a)}$$

If the researcher defines all these parts of the OED model (hypotheses, questions, answers, and the usefulness function), then selecting the optimal query is straightforward. The learner performs the expected utility computation for each query in the set of possible queries and picks the one that maximizes utility. In practice, the learner considers each possible answer, scores the answer with the usefulness function, and weights the score using the probability of getting that answer.

Before reviewing the behavioral evidence for OED-like reasoning in adults and children, I will present a worked example of how to compute the expected utility of a single query. The goal is to provide simple calculations that illustrate how reasoning about hypotheses, questions, and answers can lead to selecting useful actions. This example is slightly modified from Nelson (2005).[2]

Imagine that you are a biologist, and you come across a new animal that you think belongs to one of two species: "glom" or "fizo." You cannot directly query the category identity, but you can gather information about the presence or absence of two features (eats meat? or is nocturnal?) that you

[1]Shannon entropy is a measure of unpredictability or amount of uncertainty in the learner's probability distribution over hypotheses. Intuitively, higher entropy distributions are more uncertain and harder to predict. For example, if the learner believes that all hypotheses are equally likely, then they are in a state of high uncertainty/entropy. In contrast, if the learner firmly believes in one hypothesis, then uncertainty/entropy is low.

[2]In the appendix, I include example code for instantiating the OED calculations as functions in the R programming language.

know from prior research are more or less likely for each of the species. The following probabilities summarise this prior knowledge:

- $P(eatsMeat \mid glom) = 0.1$
- $P(eatsMeat \mid fizo) = 0.9$
- $P(nocturnal \mid glom) = 0.3$
- $P(nocturnal \mid fizo) = 0.5$

You also know from previous research that the probability of seeing a glom or a fizo in the wild is:

- $P(glom) = 0.7$
- $P(fizo) = 0.3$

Which feature should you test: eats meat? or sleeps at night? Intuitively, it seems better to test whether the creature eats meat because an answer to this question provides good evidence about whether the animal is a fizo since $P(eatsMeat \mid fizo) = 0.9$. However, the OED computation allows the biologist to go beyond this intuition and compute precisely how much better it is to ask the "eats meat?" question. All the scientist has to do is pass her knowledge about the hypotheses and features through the expected utility computation.

Here are the steps of the OED computation for calculating the utility of the "eats meat?" question. First, we use Bayes rule to calculate how much our beliefs would change if we received a "yes" or a "no" answer.[3]

$$P(glom \mid eatsMeat) = \frac{P(eatsMeat \mid glom) \times P(glom)}{P(eatsMeat)} = \frac{0.1 \times 0.7}{0.34} = 0.21$$

Next, we calculate the uncertainty over the Species hypothesis before doing any experiment. We do this by computing the prior entropy.

[3]Note that the $P(eatsMeat)$ term is computed by taking $P(eatsMeat) = [P(eatsMeat \mid glom)\ timesP(glom)] + [P(eatsMeat \mid fizo) \times P(fizo)] = (0.1 \times 0.7) + (0.9 \times 0.3) = 0.34$

$$
\begin{aligned}
ent(Species) &= -\sum_{h \in H} P(h) \times log_2 P(h) \\
&= [-P(glom) \times log_2 P(glom)] + [-P(fizo) \times log_2 P(fizo)] \\
&= [-(0.7 \times log_2(0.7)] + [-(0.3 \times log_2(0.3)] \\
&= 0.88
\end{aligned}
$$

To calculate information gain, we also need to compute our uncertainty over hypotheses conditional on seeing each answer, or the posterior entropy. First, for the "yes" answer:

$$
\begin{aligned}
ent(Species|eatsMeat = yes) &= -\sum_{a \in A} P(Species \mid eatsMeat = yes) \times log_2 P(species \mid eatsMeat = yes) \\
&= [0.21 \times log_2(0.21)] + [0.79 \times log_2(0.79)] \\
&= 0.73
\end{aligned}
$$

We use the difference between the prior and posterior entropy to compute the utility of the "yes" answer.

$$
\begin{aligned}
U(a = yes) &= ent(Species) - ent(Species \mid eatsMeat = yes) \\
&= 0.88 - 0.73 \\
&= 0.15
\end{aligned}
$$

Next, we do the same process for the "no" answer. First, we calculate the posterior entropy.

$$
\begin{aligned}
ent(Species|eatsMeat = no) &= -\sum_{a \in A} P(Species \mid eatsMeat = no) \times log_2 P(species \mid eatsMeat = no) \\
&= [0.95 \times log_2(0.95)] + [0.05 \times log_2(0.05)] \\
&= 0.27
\end{aligned}
$$

Again, we use the difference between the prior and posterior entropy to compute the utility of the "no" answer.

$$
\begin{aligned}
U(a = no) &= ent(Species) - ent(Species \mid eatsMeat = no) \\
&= 0.88 - 0.27 \\
&= 0.61
\end{aligned}
$$

Note that the $U(a = no) > U(a = yes)$. This captures the intuition that learning that the animal does not eat meat would provide strong evidence against the "fizo" hypothesis since $P(eatsMeat \mid fizo) = 0.9$. Finally, to compute the overall expected information gain for the **"eats meat?" question**, we weight the utility of each answer by its probability:

$$
\begin{aligned}
EU(Q = eatsMeat) &= \sum_{a \in A} P(a)U(a) \\
&= [P(eatsMeat = yes) \times U(eatsMeat = yes)] + \\
&\qquad [P(eatsMeat = no) \times U(eatsMeat = no)] \\
&= [0.34 \times 0.15] + [0.66 \times 0.61] \\
&= 0.46
\end{aligned}
$$

If we performed the same steps to calculate the expected utility of the "sleeps at night?" question, we get $EU(Q = sleepsNight) = 0.026$. So if the biologist wants to maximize the chance of gaining useful information, she should select the "eats meat?" experiment since $EU(Q = eatsMeat) > EU(Q = sleepsNight)$.

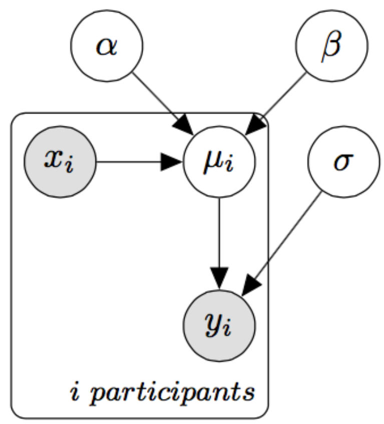
# Appendix B

# Supplementary materials for Chapter 2

In this appendix, we present four pieces of supplemental information. First, we provide details about the Bayesian models used to analyze the data. Second, we present a sensitivity analysis that provides evidence that the estimates of the associations between age/vocabulary and accuracy/reaction time (RT) are robust to different parameterizations of the prior distribution and different cutoffs for the analysis window. Third, we present the results of a parallel set of analyses using a non-Bayesian approach to show that these results are consistent regardless of choice of analytic framework. And fourth, we present two exploratory analyses measuring the effects of phonological overlap and iconicity on RT and accuracy. In both analyses, we did not see evidence that these factors changed the dynamics of eye movements during ASL processing

## B.1 Model Specifications

Our key analyses use Bayesian linear models to test our hypotheses of interest and to estimate the associations between age/vocabulary and RT/accuracy. Figure S1 (Accuracy) and S2 (RT) present graphical models that represent all of the data, parameters, and other variables of interest, and their dependencies. Latent parameters are shown as unshaded nodes while observed parameters and data are shown as shaded nodes. All models were fit using JAGS software (Plummer, 2003) and adapted




$$\alpha \sim \text{Gaussian}(0,\, 10)$$
$$\beta \sim \text{TruncatedGaussian}_+(0,\, 1)$$
$$\sigma \sim \text{Uniform}(1/1000,\, 1000)$$
$$\mu_i \leftarrow \alpha + \beta * x_i$$
$$y_i \sim \text{Gaussian}(\mu_i,\, \sigma)$$

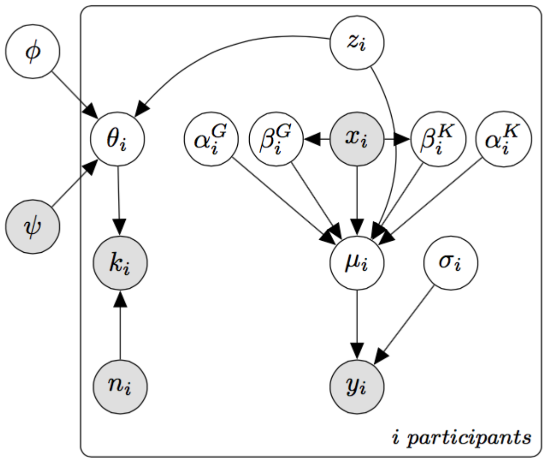
Figure B.1: Graphical model representation of the linear regression used to predict accuracy. The shaded nodes represent observed data (i.e., each participant's age, vocabulary, and mean accuracy). Unshaded nodes represent latent parameters (i.e., the intercept and slope of the linear model).

from models in Kruschke (2014) and Lee and Wagenmakers (2014).

### B.1.1 Accuracy

To test the association between age/vocabulary and accuracy we assume each participant's mean accuracy is drawn from a Gaussian distribution with a mean, $\mu$, and a standard deviation, $\sigma$. The mean is a linear function of the intercept, $\alpha$, which encodes the expected value of the outcome variable when the predictor is zero, and the slope, $\beta$, which encodes the expected change in the outcome with each unit change in the predictor (i.e., the strength of association).

For $\alpha$ and $\sigma$, we use vague priors on a standardized scale, allowing the model to consider a wide range of plausible values. Since the slope parameter $\beta$ is critical to our hypothesis of a linear association, we chose to use an informed prior: that is, a truncated Gaussian distribution with a mean of zero and a standard deviation of one on a standardized scale. Centering the distribution at zero is conservative and places the highest prior probability on a null association, to reduce the chance that our model overfits the data. Truncating the prior encodes our directional hypothesis that accuracy should increase with age and larger vocabulary size. And using a standard deviation of one constrains the plausible slope values, thus making our alternative hypothesis more precise. We constrained the slope values based on previous research with children learning spoken language




$$
\begin{aligned}
&\alpha \sim \text{Gaussian}(0,\ 10)\\
&\beta \sim \text{TruncatedGaussian}_{-}(0,\ 1)\\
&\sigma_i \sim \text{Uniform}(1/1000,\ 1000)\\
&z_i \sim \ \text{Bernoulli}(0.5)\\
&\phi \sim \ \text{Uniform}(0.5,\ 1)\\
&\psi \leftarrow \ 0.5\\
&\theta_i \leftarrow \begin{cases} \phi & \text{if } z_i = 1\\ \psi & \text{if } z_i = 0 \end{cases}\\
&k_i \sim \ \text{Binomial}(\theta_i,\ n_i)\\
&\mu_i \leftarrow \begin{cases} \alpha_i^K + \beta_i^K * x_i & \text{if } z_i = 1\\ \alpha_i^G + \beta_i^G * x_i & \text{if } z_i = 0 \end{cases}\\
&y_i \sim \ \text{Gaussian}(\mu_i,\ \sigma_i)
\end{aligned}
$$

Figure B.2: Graphical model representation of the linear regression plus latent mixture model (i.e., guessing model). The model assumes that each individual participant's first shift is either the result of guessing or knowledge. And the latent indicator $z_i$ determines whether that participant is included in the linear regression estimating the association between age/vocabulary and RT.

showing that the average gain in accuracy for one month of development between 18-24 months to be ˜1.5% (Fernald, Zangl, Portillo, & Marchman, 2008).

### B.1.2 Reaction Time

The use of RT as a processing measure is based on the assumption that the timing of a child's first shift reflects the speed of their incremental language comprehension. Yet, some children have a first shift that seems to be unassociated with this construct: their first shift behavior appears random. We quantify this possibility for each participant explicitly (i.e., the probability that the participant is a "guesser") and we create an analysis model where participants who were more likely to be guessers have less of an influence on the estimated relations between RT and age/vocabulary.

To quantify each participant's probability of guessing, we computed the proportion of signer-to-target (correct) and signer-to-distracter (incorrect) shifts for each child. We then used a latent mixture model in which we assumed that the observed data, k_i, were generated by two processes (guessing and knowledge) that had different overall probabilities of success, with the "guessing group" having a probability of 50%, $\psi$, and the "knowledge" group having a probability greater than 50%, $\phi$. The group membership of each participant is a latent indicator variable, $z_i$, inferred based on that participant's proportion of correct signer-to-target shifts relative to the overall proportion of correct shifts across all participants (see Lee & Wagenmakers (2014) for a detailed discussion of this modeling approach). We then used each participant's inferred group membership to determine whether they were included in the linear regression. In sum, the model allows participants to contribute to the estimated associations between age/vocabulary and RT proportional to our belief that they were guessing.

As in the Accuracy model, we use vague priors for $\alpha$ and $\sigma$ on a standardized scale. We again use an informed prior for $\beta$, making our alternative hypothesis more precise. That is, we constrained the plausible slope values based on previous research with children learning spoken language showing that the average gain in RT for one month of development between 18-24 months to be ˜30 ms (Fernald, Zangl, Portillo, & Marchman, 2008).

## B.2 Sensitivity Analysis: Prior Distribution and Window Selection

We conducted a sensitivity analysis to show that our parameter estimates for the associations between accuracy/RT and age/vocabulary are robust to decisions about (a) the analysis window and (b) the specification of the prior distribution on the slope parameter. Specifically, we varied the parameterization of the standard deviation on the slope, allowing the model to consider a wider or narrower range of values to be plausible a priori. We also fit these different models to two additional analysis windows +/- 300 ms from the final analysis window: 600-2500 ms (the middle 90% of the RT distribution in our experiment). Figure S3 shows the results of the sensitivity analysis, plotting the coefficient for the $\beta$ parameter in each model for the three different analysis windows for each specification of the prior. All models show similar coefficient values, suggesting that inferences about the parameters are not sensitive to the exact form of the priors. Table S1 shows the Bayes Factors for all models across three analysis windows and fit using four different vales for the slope prior. The Bayes Factor only drops below 3 when the prior distribution is quite broad (standard deviation of 3.2) and only for the longest analysis window (600-2800 ms). In sum, the strength of evidence for a

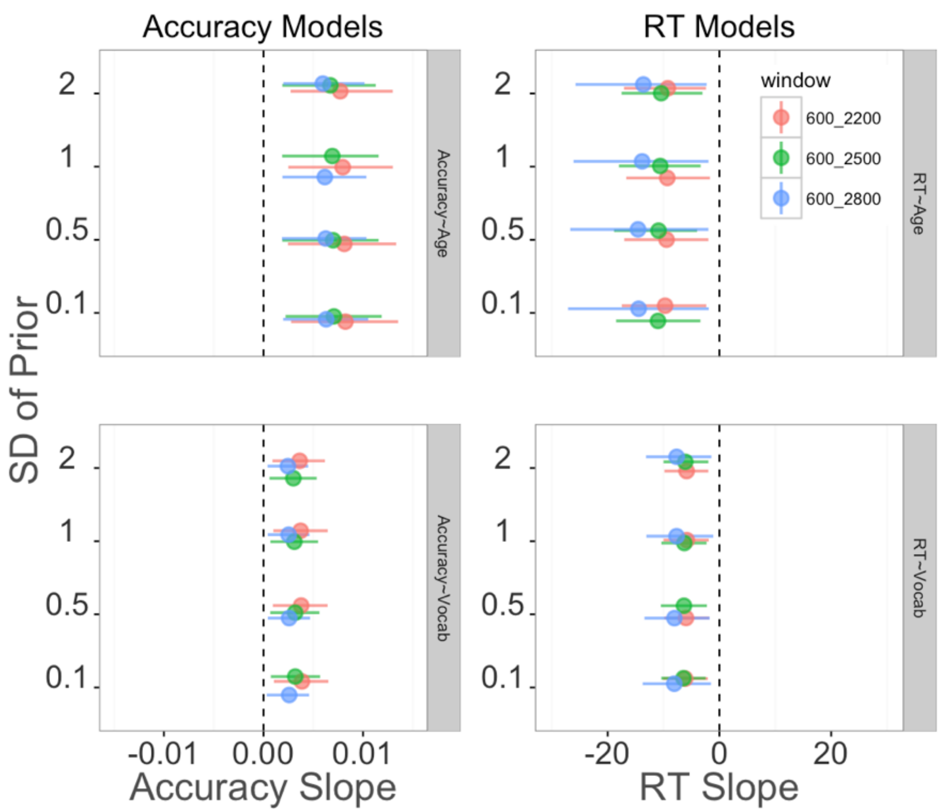



Figure B.3: Coefficient plot for the slope parameter for four different parameterizations of the prior and for three different analysis windows. Each panel shows a different model. Each point represents a coefficient measuring the strength of association between the two variables. Error bars are 95% HDIs around the coefficient. Color represents the three different analysis windows.

linear association is robust to the choice of analysis window and prior specification.

## B.3 Parallel set of non-Bayesian analyses

First, we compare Accuracy and RT of native hearing and deaf signers using a Welch Two Sample t-test and do not find evidence that these groups are different (Accuracy: $t(28) = 0.75$, $p = 0.45$, 95% CI on the difference in means [-0.07, 0.14]; RT: $t(28) = 0.75$, $p = 0.46$, 95% CI on the difference in means [-125.47 ms, 264.99 ms].

Second, we test whether children and adults tend to generate saccades away from the central signer prior to the offset of the target sign. To do this, we use a One Sample t-test with a null

Table B.1: Bayes Factors for all four linear models fit to three different analysis windows using four different parameterizations of the prior distribution for the slope parameter.

| **Analysis window** | **SD Slope** | **Acc˜Age** | **Acc˜Vocab** | **RT˜Age** | **RT˜Vocab** |
|---|---|---|---|---|---|
| 600 – 2200 ms | 3.2 | 6.2 | 3.7 | 2.4 | 4.1 |
| NA | 1.4 | 14.1 | 5.5 | 3.5 | 8.6 |
| NA | 1.0 | 19.4 | 8.9 | 5.0 | 9.2 |
| NA | 0.7 | 22.7 | 11.6 | 7.8 | 17.0 |
| 600 – 2500 ms | 3.2 | 11.0 | 2.3 | 5.6 | 6.1 |
| NA | 1.4 | 9.7 | 4.0 | 13.8 | 10.5 |
| NA | 1.0 | 12.8 | 6.8 | 12.5 | 18.2 |
| NA | 0.7 | 15.6 | 6.8 | 17.9 | 20.7 |
| 600 – 2800 ms | 3.2 | 6.0 | 1.1 | 1.2 | 1.4 |
| NA | 1.4 | 10.7 | 2.6 | 3.5 | 4.7 |
| NA | 1.0 | 13.5 | 4.0 | 3.7 | 4.0 |
| NA | 0.7 | 15.2 | 4.6 | 5.5 | 5.6 |

hypothesis that the true mean is not equal to 1, and we find evidence against this null (Children: M = 0.88, t(28) = -2.92, p = 0.007, 95% CI [0.79, 0.96]; Adults: M = 0.51, t(15) = -6.87, p < 0.001, 95% CI [0.35, 0.65])

Third, we fit the four linear models using MLE to estimate the relations between the processing measures on the VLP task (Accuracy/RT) and age/vocabulary. We follow recommendations from Barr (2008) and use a logistic transform to convert the proportion accuracy scores to a scale more suitable for the linear model. Table XXX shows the results.

## B.4 Analyses of phonological overlap and iconicity

First, we analyzed whether phonological overlap of our item-pairs might have influenced adults and children's RTs and accuracy. Signs that are higher in phonological overlap might have been more difficult to process because they are more confusable. Here, phonological overlap is quantified as the number of features (e.g., Selected Fingers, Major Location, Movement, Sign Type) that both signs shared. Values were taken from a recently created database (ASL-LEX) of lexical and phonological properties of nearly 1,000 signs of American Sign Language (Caselli et al., 2017). Our item-pairs varied in degree of overlap from 1-4 features. We did not see evidence that degree of phonological overlap influenced either processing measure in the VLP task. Next, we performed

Table B.2: Results for the four linear models fit using Maxiumum Likelihood Estimation. All p-values are one-sided to reflect our directional hypotheses about the VLP measures improving over development.

| Model specification | Mean Beta value | std. error | t-statistic | p-value |
|---|---|---|---|---|
| logit(accuracy) ~ age + hearing status | 0.003 | 0.012 | 2.59 | 0.008 |
| logit(accuracy) ~ vocabulary + hearing status | 0.002 | 0.006 | 2.27 | 0.015 |
| RT ~ age + hearing status | -10.050 | 4.620 | -2.17 | 0.019 |
| RT ~ vocabulary + hearing status | -6.340 | 2.180 | -2.91 | 0.003 |

a parallel analysis, exploring whether the iconicity of our signs might have influenced adults and children's RT and accuracy. It is possible that highly iconic signs might be easier to process because of the visual similarity to the target object. Again, we used ASL-LEX to quantify the iconicity of our signs. To generate these values, native signers were asked to explicitly rate the iconicity of each sign on a scale of 1-7, with 1 being not iconic at all and 7 being very iconic. Similar to the phonological overlap analysis, we did see evidence that degree of iconicity influenced either processing measure for either age group in the VLP task.

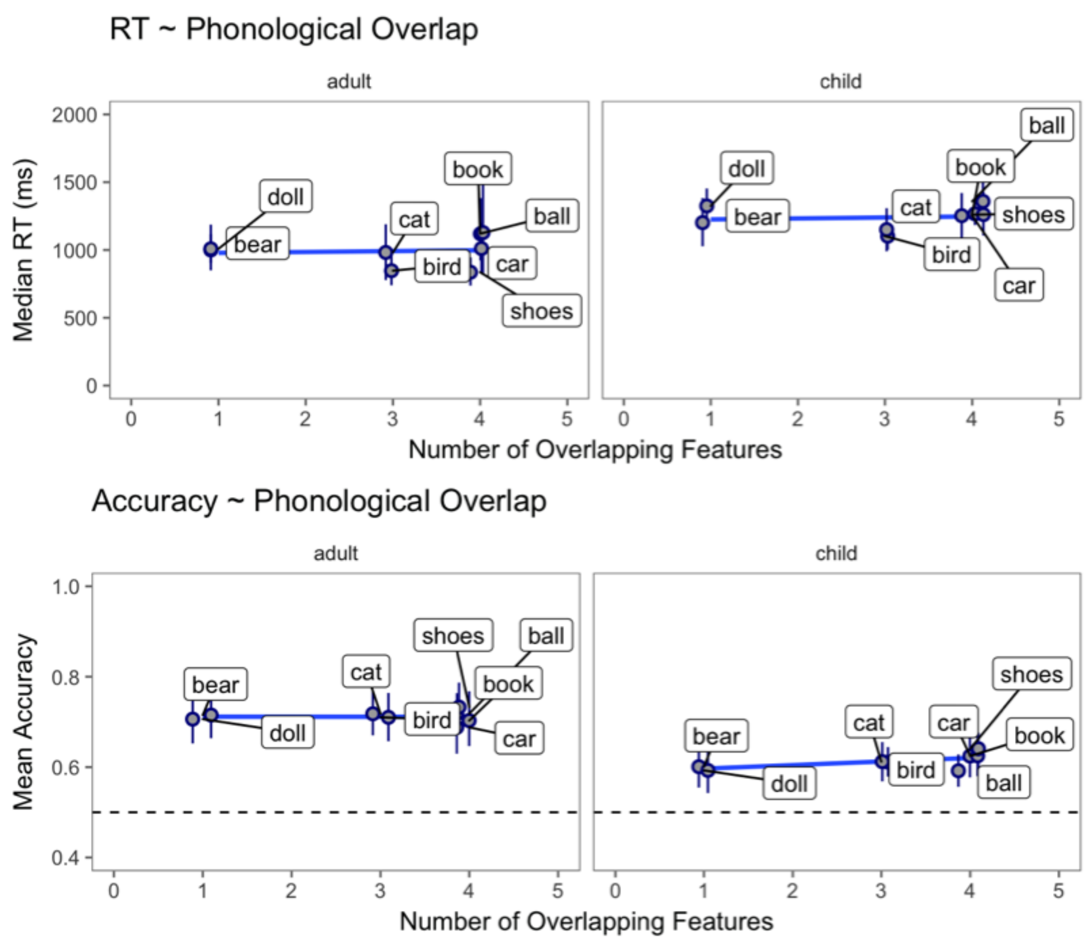



Figure B.4: Scatterplot of the association between degree of phonological overlap and RT (top row) and accuracy (bottom row) for both adults (left column) and children (right column). The blue line represents a linear model fit.

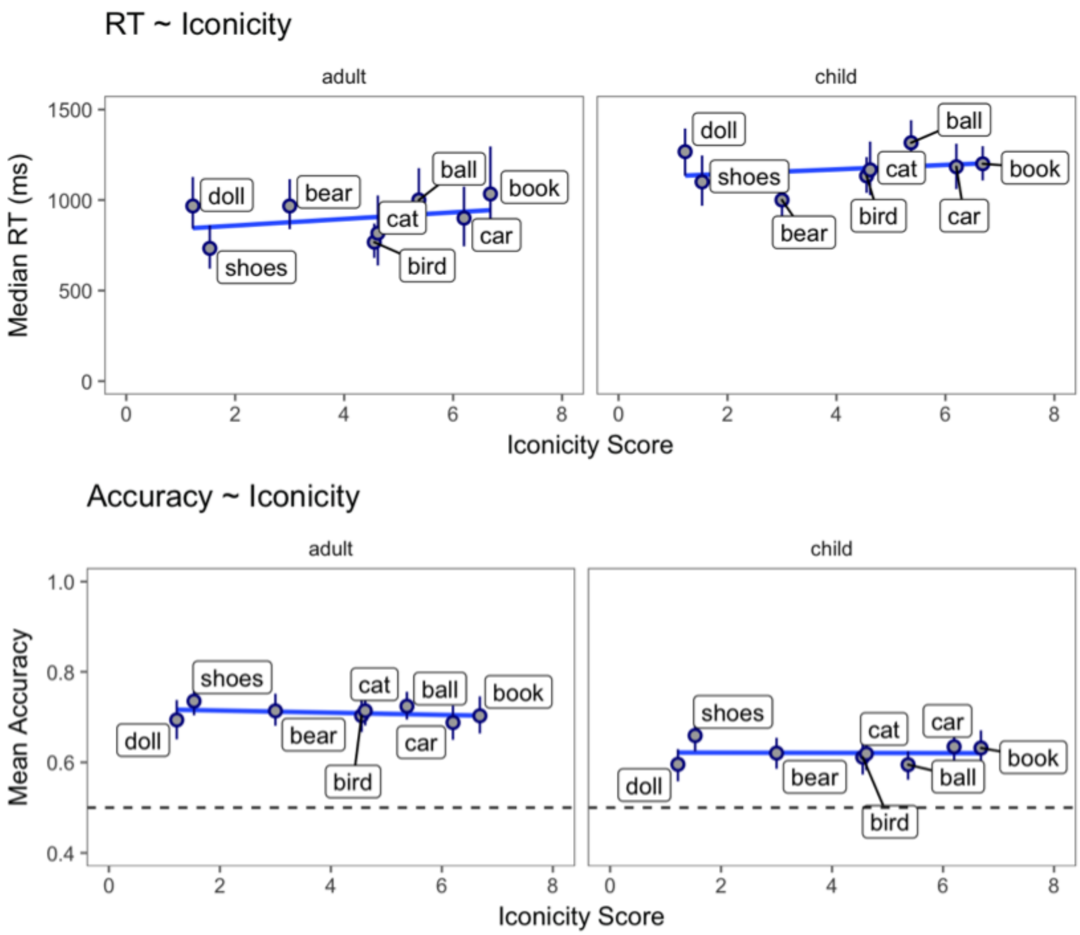



Figure B.5: Scatterplot of the association between degree of iconicity and RT (top row) and accuracy (bottom row) for both adults (left column) and children (right column). The blue line represents a linear model fit.

# Appendix C

# Supplementary materials for Chapter 4

## C.1 Analytic model specifications and output

### C.1.1 Experiment 1

### Table A1. Length of inspection times on exposure trials in Experiment 1 as a function of gaze, interval, and number of referents

`Log(Inspection time)` $\sim$ `(Gaze + Log(Interval) + Log(Referents))`$^2$ `+ (1 | subject)`

| term | estimate | std.error | t.value | p.value | |
|---|---|---|---|---|---|
| Intercept | 0.83 | 0.10 | 8.19 | < .001 | *** |
| Gaze Condition | 0.16 | 0.11 | 1.48 | 0.138 | |
| Log(Interval) | 0.06 | 0.05 | 1.33 | 0.184 | |
| Log(Referents) | 0.34 | 0.04 | 7.91 | < .001 | *** |
| Gaze Condition*Log(Interval) | -0.08 | 0.03 | -2.86 | 0.004 | ** |
| Gaze Condition*Log(Referent) | -0.27 | 0.04 | -6.01 | < .001 | *** |
| Log(Interval)*Log(Referent) | -0.00 | 0.02 | -0.19 | 0.849 | |

# Table A2. Accuracy on test trials in Experiment 1 with inspection times on exposure trials included as a predictor

`Correct` $\sim$ `(Trial Type + Gaze + Log(Interval) + Log(Referents) +`

`Log(Inspection Time))`$^2$ `+ offset(logit(`$^1/_{Referents}$`)) + (TrialType | subject)`

| term | estimate | std.error | z.value | p.value | |
|---|---|---|---|---|---|
| Intercept | 2.89 | 0.34 | 8.49 | < .001 | *** |
| Switch Trial | -1.45 | 0.25 | -5.76 | < .001 | *** |
| Gaze Condition | 0.12 | 0.27 | 0.43 | 0.669 | |
| Log(Interval) | -0.47 | 0.11 | -4.15 | < .001 | *** |
| Log(Referents) | 0.05 | 0.14 | 0.39 | 0.693 | |
| Log(Inspection Time) | 0.20 | 0.15 | 1.38 | 0.169 | |
| Switch Trial*Gaze Condition | -1.02 | 0.13 | -7.86 | < .001 | *** |
| Switch Trial*Log(Interval) | 0.52 | 0.06 | 9.39 | < .001 | *** |
| Switch Trial*Log(Referent) | -0.62 | 0.09 | -6.67 | < .001 | *** |
| Switch Trial*Log(Inspection Time) | 0.09 | 0.07 | 1.36 | 0.174 | |
| Gaze Condition*Log(Interval) | 0.09 | 0.06 | 1.61 | 0.107 | |
| Gaze Condition*Log(Referent) | 0.36 | 0.10 | 3.68 | < .001 | *** |
| Gaze Condition*Log(Inspection Time) | -0.17 | 0.07 | -2.55 | 0.011 | * |
| Log(Interval)*Log(Referent) | -0.05 | 0.04 | -1.26 | 0.207 | |
| Log(Interval)*Log(Inspection Time) | 0.02 | 0.03 | 0.54 | 0.589 | |
| Log(Referents)*Log(Inspection Time) | 0.05 | 0.05 | 0.94 | 0.345 | |

### C.1.2 Experiment 2

## Table A3. Length of inspection times on exposure trials in Experiment 2 as a function of gaze and interval

`Log(Inspection time) ~ Gaze * Log(Interval) + (1 | subject)`

| term | estimate | std.error | t.value | p.value | |
|---|---|---|---|---|---|
| Intercept | 3.90 | 0.08 | 50.69 | $< .001$ | *** |
| Gaze Condition | -1.10 | 0.05 | -20.90 | $< .001$ | *** |
| Log(Interval) | -0.48 | 0.05 | -8.77 | $< .001$ | *** |
| Gaze Condition*Log(Interval) | -0.02 | 0.04 | -0.60 | 0.549 | |

## Table A4. Accuracy on test trials in Experiment 2 with inspection times on exposure trials included as a predictor

$\texttt{Correct} \sim \texttt{(Trial Type + Gaze + Log(Interval) + Log(Inspection Time))}^2\ \texttt{+}$
$\texttt{offset(logit(}{}^{1}/_{Referents}\texttt{)) + (TrialType | subject)}$

| term | estimate | std.error | z.value | p.value | |
|---|---|---|---|---|---|
| Intercept | 3.51 | 0.29 | 12.13 | $< .001$ | *** |
| Gaze Condition | 0.13 | 0.23 | 0.58 | 0.559 | |
| Switch Trial | -3.12 | 0.26 | -12.21 | $< .001$ | *** |
| Log(Interval) | -0.88 | 0.14 | -6.34 | $< .001$ | *** |
| Log(Inspection Time) | 0.15 | 0.13 | 1.14 | 0.255 | |
| Switch Trial*Gaze Condition | -0.54 | 0.17 | -3.21 | 0.001 | ** |
| Gaze Condition*Log(Interval) | 0.16 | 0.09 | 1.85 | 0.064 | . |
| Gaze Condition*Log(Inspection Time) | -0.14 | 0.10 | -1.37 | 0.172 | |
| Switch Trial*Log(Interval) | 0.77 | 0.10 | 8.00 | $< .001$ | *** |
| Switch Trial*Log(Inspection Time) | 0.21 | 0.11 | 1.96 | 0.05 | . |
| Log(Interval)*Log(Inspection Time) | 0.04 | 0.06 | 0.77 | 0.44 | |

### C.1.3 Experiment 3

## Table A5. Accuracy on exposure trials in Experiment 3 as a function of reliability condition and participants' subjective reliability judgments

`Correct-Exposure` $\sim$ `Reliability Condition * Subjective Reliability + offset(logit(`$^1/_{Referents}$`)) + (1 | subject)`

| term | estimate | std.error | z.value | p.value | |
|---|---|---|---|---|---|
| Intercept | 3.07 | 0.98 | 3.14 | 0.002 | ** |
| Reliability Condition | 3.28 | 1.50 | 2.19 | 0.028 | * |
| Subjective Reliability | 7.26 | 1.72 | 4.22 | $<$ .001 | *** |
| Reliability Condition*Subjective Reliability | -4.58 | 2.72 | -1.69 | 0.092 | . |

## Table A6. Accuracy on test trials in Experiment 3 as a function of reliability condition

`Correct` $\sim$ `Trial Type * Reliability Condition + offset(logit(`$^1/_{Referents}$`)) + (Trial Type | subject)`

| term | estimate | std.error | z.value | p.value | |
|---|---|---|---|---|---|
| Intercept | 4.70 | 0.36 | 13.09 | $<$ .001 | *** |
| Trial Type | -3.95 | 0.36 | -10.91 | $<$ .001 | *** |
| Reliability Condition | 0.38 | 0.37 | 1.03 | 0.302 | |
| Reliability Condition*Trial Type | -0.76 | 0.38 | -2.01 | 0.044 | * |

## Table A7. Accuracy on test trials in Experiment 3 as a function of reliability condition and participants' use of gaze on exposure trials

`Correct` $\sim$ `(Trial Type + Reliability Condition + Correct-Exposure)`$^2$

`+ offset(logit(`$^1/_{Referents}$`)) + (Trial Type | subject)`

| term | estimate | std.error | z.value | p.value | |
|---|---|---|---|---|---|
| Intercept | 4.50 | 0.39 | 11.58 | $< .001$ | *** |
| Correct Exposure | 0.07 | 0.29 | 0.26 | 0.796 | |
| Trial Type | -2.70 | 0.38 | -7.07 | $< .001$ | *** |
| Reliability Condition | -0.43 | 0.44 | -0.98 | 0.325 | |
| Correct Exposure*Trial Type | -1.43 | 0.27 | -5.41 | $< .001$ | *** |
| Correct Exposure*Reliability | 0.97 | 0.33 | 2.92 | 0.004 | ** |
| Reliability Condition*Trial Type | -0.62 | 0.36 | -1.72 | 0.086 | . |

## Table A8. Accuracy on test trials in Experiment 3 as a function of each participants' accuracy on exposure trials

`Correct` $\sim$ `Trial Type * Total Correct Exposure + offset(logit(`$^1/_{Referents}$`)) +`

`(Trial Type | subject)`

| term | estimate | std.error | z.value | p.value | |
|---|---|---|---|---|---|
| Intercept | 2.73 | 0.39 | 7.01 | $< .001$ | *** |
| Total Exposure Correct | 0.14 | 0.06 | 2.49 | 0.013 | * |
| Trial Type | -1.39 | 0.39 | -3.55 | $< .001$ | *** |
| Total Exposure Correct*Trial Type | -0.26 | 0.06 | -4.66 | $< .001$ | *** |

## Table A9. Accuracy on test trials in Experiment 3 as a function of each participants' subjective reliability judgment

`Correct` $\sim$ `Trial Type * Subjective Reliability + offset(logit(`$^1/_{Referents}$`)) + (Trial Type | subject)`

| term | estimate | std.error | z.value | p.value | |
|---|---|---|---|---|---|
| Intercept | 4.54 | 0.44 | 10.33 | $<$ .001 | *** |
| Subjective Reliability | 0.40 | 0.58 | 0.69 | 0.493 | |
| Trial Type | -3.44 | 0.44 | -7.81 | $<$ .001 | *** |
| Subjective Reliability*Trial Type | -1.63 | 0.59 | -2.78 | 0.005 | ** |

## Table A10. Accuracy on test trials in Experiment 3 as a function of reliability condition and inspection time on exposure trials

`Correct` $\sim$ `(Trial Type + Reliability condition + Trial Type + Log(Inspection Time))`$^2$ `+ offset(logit(`$^1/_{Referents}$`)) + (Trial Type | subject)`

| term | estimate | std.error | z.value | p.value | |
|---|---|---|---|---|---|
| Intercept | 3.11 | 0.20 | 15.94 | $<$ .001 | *** |
| Log(Inspection Time) | 0.31 | 0.09 | 3.31 | 0.001 | ** |
| Trial Type | -2.75 | 0.20 | -13.64 | $<$ .001 | *** |
| Reliability Condition | 0.50 | 0.30 | 1.66 | 0.097 | . |
| Log(Inspection Time)*Trial Type | 0.03 | 0.09 | 0.34 | 0.736 | |
| Log(Inspection Time)*Reliability Condition | -0.20 | 0.11 | -1.83 | 0.067 | . |
| Trial Type*Reliability Condition | -0.58 | 0.29 | -1.97 | 0.048 | * |

### C.1.4 Experiment 4

## Table A11. Accuracy on test trials in Experiment 4 as a function of gaze and interval

`Correct` $\sim$ `(Trial Type + Gaze + Log(Interval))`$^2$ `+ offset(logit(`$^1/_{Referents}$`)) + (Trial Type | subject)`

| term | estimate | std.error | z.value | p.value | |
|---|---|---|---|---|---|
| Intercept | 3.37 | 0.16 | 21.32 | $< .001$ | *** |
| Trial Type | -3.18 | 0.16 | -19.93 | $< .001$ | *** |
| Gaze Condition | -0.48 | 0.14 | -3.52 | $< .001$ | *** |
| Log(Interval) | -0.84 | 0.10 | -8.59 | $< .001$ | *** |
| Trial Type*Gaze Condition | 0.90 | 0.14 | 6.63 | $< .001$ | *** |
| Trial Type*Log(Interval) | 0.80 | 0.09 | 8.71 | $< .001$ | *** |
| Gaze Condition*Log(Interval) | -0.01 | 0.07 | -0.10 | 0.917 | |

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