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Anonymous CogSci submission

Abstract

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Introduction

Whether to keep looking at a current target of attention is one of the most fundamental decisions we make, whether we are trying to find our way in a busy street or swiping through Tik-Tok. Even young infants constantly decide whether to keep looking or move on. In fact, infant research has long capitalized on infants' ability to endogenously control their attention, making inferences about infants' learning and mental representations from changes in their looking duration (Aslin, 2007; Sim & Xu, 2019). In a typical experiment, infants decrease their looking duration upon seeing the same stimulus repeatedly (i.e. habituation). Then, infants' often recover interest when seeing a novel stimulus (i.e. dishabituation). While these phenomena are well-documented, the mechanisms underlying them remain poorly understood. A better understanding of what shapes habituation and dishabituation is of both methodological and theoretical significance. Methodologically, assumptions about habituation and dishabituation underpin many other claims about infants' cognitive repertoire (Paulus, 2022; Tafreshi, Thompson, & Racine, 2014). Theoretically, it would shed light on infants' active role in shaping their own learning and reveal principles that guide human information-seeking behavior in general (Raz & Saxe, 2020; Smith, Jayaraman, Clerkin, & Yu, 2018). Here we provide a model of the basic decision faced by infants in a standard looking paradigm. To do so, we model looking as rational active selection of noisy perceptual samples for learning. Our goal is to describe the proximal computations that could underlie the moment-to-moment decision of whether to keep looking at the current stimulus, or look away to find a different stimulus.

Classical theory of infant looking posits that infants look at stimuli in order to learn or encode them, so the dynamics of looking time are driven by the dynamics of learning (Hunter & Ames, 1988). The more an infant has already been exposed to a stimulus, the less they have to learn about it (i.e. increasing exposure time should decrease looking). The more complicated a stimulus is, the more that would still remain to learn after any given exposure time (i.e. increasing complexity should increase looking). Individual infants may also differ in how long it takes them to learn a given stimulus (e.g. older infants may habituate after less exposure. Although this theory is influential, little empirical work has examined it systematically (for exceptions, see Hunter, Ames, & Koopman, 1983) and the lack of quantitative details in the theory has made it impossible to offer precise predictions.

In contrast to the classical verbal theory, recent work has attempted to describe infants' looking behaviors through computational modeling. In pioneering work, Kidd, Piantadosi, & Aslin (2012) developed a paradigm in which infants are shown sequences of events. Infants' look-away probabilities away from the stimuli are compared with surprisal, a measure of information content, derived from a rational learner model that keeps track of the probabilities of each event. The study shows that infants' pay most attention to event sequences that are neither too high nor too low in surprisal, resulting in a 'Goldilocks' effect of attention. A recent study by Poli, Serino, Mars, & Hunnius (2020) offered an alternative linking hypothesis between the model and behavior: the study used a similar paradigm and model to show that infants' looking time can be predicted by 'learning progress', formalized as the Kullback-Leibler (KL) divergence between the the model's knowledge before and after each stimulus. These attempts to connect information theoretic measures to infants' looking time resonate with previous literature on information foraging that postulates human exploratory behaviors are driven by maximizing information gain (Hills et al., 2015; Pirolli & Card, 1999) as well as the emerging literature on curiosity in developmental robotics and reinforcement learning (Haber, Mrowca, Fei-Fei, & Yamins, 2018; Oudeyer, Kaplan, & Hafner, 2007), as well as information foraging . Curiosity-driven artificial agents' exploratory behaviors can be guided by optimizing expected information gain (EIG), a measurement that has been shown to be related to curiosity-driven learning in human children and adults (e.g., Liquin, Callaway, & Lombrozo, 2021).

However, there are several limitations to the existing mod-

els. First, current models do not capture the noisy nature of perceptual learning (Callaway, Rangel, & Griffiths, 2021; Kersten, Mamassian, & Yuille, 2004). That is, the models were assumed to acquire perfect representation of each event in the sequence. This assumption leads to the second limitation: While surprisal and KL-divergence have been shown to correlate with infants' looking behaviors, current models do not provide an account of how these measurements might be linked mechanistically to infants' behavior. Previous models show that infants might be sensitive to the information-theoretic variability in their learning environment, but they do not provide an account of how they are related to infants' real-time sampling behavior. Finally, the event sequence paradigm used to evaluate these models are not representative of classical infant looking time paradigms. As the key phenomena described in the Hunter & Ames (1988) theory were not captured, the extent to which we can extrapolate current model fits to behavior in a typical looking time experiment remains limited.

Here we present steps toward overcoming these limitations. Our goal is to provide a unifying quantitative account of looking behaviors as arising from optimal decision-making over noisy perceptual representations (Bitzer, Park, Blankenburg, & Kiebel, 2014; Callaway et al., 2021). To do so, we present the "rational action, noisy choice for habituation" (RANCH) model. RANCH works by a) accumulating noisy samples from the stimulus, and b) rationally choosing what to look at using different information-theoretic linking hypotheses (surprisal, KL-divergence, and EIG). Finally, we evaluate RANCH with adult looking time data collected from a paradigm that captures habituation, dishabituation, and complexity effects.

Experiment

To evaluate how well these models can explain looking time changes, we developed a stimuli set and an experimental paradigm to reproduce the key looking time patterns in adult participants. There are two advantages to evaluating models with adult looking time data: 1) it is relatively easy to acquire adult looking time data to reach sufficient power; 2) adult looking time data can speak to the developmental endpoints of the principles guiding looking time behaviors.

Methods

Stimuli We created the animated creatures using Spore (a game developed by Maxis in 2008). There were forty creatures in total, half of which have low perceptual complexity (e.g. the creatures do not have limbs, additional body parts, facial features, or textured skin), and half of which have high perceptual complexity (i.e. they do have the aforementioned features; see Fig 2 for examples). We used the "animated avatar" function in Spore to capture the creatures in motion.

Procedure The experiment was a web-based, self-paced visual presentation task. Participants were instructed to look at a sequence of animated creatures at their own pace and an-
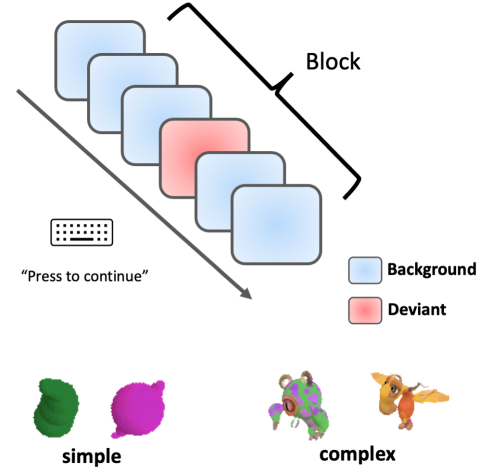

Figure 1: Experimental design and examples of simple and complex stimuli. In each block, a deviant could appear on the second, fourth (as depicted here) or sixth trial or not at all. Stimuli within a block were either all simple or all complex.

swer some questions throughout. On each trial, an animated creature showed up on the screen. Participants could press the down arrow to go to the next trial whenever they wanted to, after a minimum viewing time of 500 ms.

Each block consisted of six trials. Unbeknownst to the participants, each trial was either a background trial (B) or a deviant trial (D). A background trial presented a creature repeatedly, and the deviant trial presented a different creature from the background trial in the block. Two creatures in the blocks were matched for visual complexity. There were four sequences of background trials and deviant trials. Each sequence appeared twice, once with high complexity stimuli and once with low complexity stimuli. The deviant trial could appear at either the second (BDBBBB), the fourth (BBBDBB), or the sixth trial (BBBBBD) in the block. Two blocks did not have deviant trials (BBBBBB). The creatures presented in the deviant trials and background trials were matched for complexity. Each participant saw eight blocks in total, half of which used creatures with high perceptual complexity, and half of which used creatures with low perceptual complexity.

To test whether behavior was related to task demands, participants were randomly assigned to one of three attention check conditions, differing in the type of questions asked following each block: Curiosity, Memory, and Math. In the Curiosity condition, participants were asked to rate "How curious are you about the creature?" on a 5-point Likert scale. In the Memory condition, a forced-choice recognition question followed each block ("Have you seen this creature before?"). The creature used in the question in both conditions was either a creature presented in the preceding block or a novel creature matched in complexity. In the Math condition, the participants were asked a simple arithmetic question ("What is 5 + 7?") in a multiple-choice format.

At the end of the eight blocks, participants were asked to rate the similarity between pairs of creatures and complexity of creatures they encountered on a 7-point Likert scale. We used responses to these questions to make sure our complexity manipulation was successful.

Participants We recruited 449 participants (Age $M = 30.83$; $SD = 17.44$) on Prolific. They were randomly assigned to one of the three conditions of the experiment (Curiosity: $N = 156$; Memory: $N = 137$; Math: $N = 156$). Participants were excluded if they showed irregular reaction times or their responses in the filler tasks indicates low engagement with the experiment. All exclusion criteria were pre-registered. The final sample included 380 participants.

Results

The sample size, methods, and main analyses were all pre-registered and are available at [LINK]. Data and analysis scripts are available at [LINK]. We first checked the basic complexity manipulations were successful. Complex animated creatures were rated as more perceptually complex ($M = 4.63$; $SD = 1.08$) than the simple animated creatures ($M = 1.06$; $SD = 1.06$; $t < 0.001$).

Three criteria were selected to evaluate whether the paradigms successfully captured the characteristic looking time patterns observed in infant literature: habituation (the decrease in looking time for a stimulus with repeated presentations), dishabituation (the increase in looking time to a new stimulus after habituated to one stimulus), and complexity effect (longer looking time for perceptually more complex stimuli). The visualization of our results suggests that we reproduce the phenomena qualitatively (Fig. 3, row1).To evaluate the phenomenon quantitatively, we ran a linear mixed effects model with maximal random effect structure. The predictors included in the model were a three-way interaction term between the trial number (modeled as an exponential decay, Kail, 1991), the type of trial (background vs. deviant) and the complexity of the stimuli (simple vs. complex). The model failed to converge, so we pruned the model following the pre-registered procedure. The final model included per-subject random intercepts. All predictors except for the three-way interaction were significant from the model (all $t < .001$), providing a quantitative confirmation that our paradigm successfully captured the key looking time patterns.

Model

We reasoned that, habituation, dishabituation and complexity effects are consequences of encoding. For example, habituation occurs when each repetition of a stimulus refines the representation of a concept until encoding is complete. Dishabituation then occurs when a stimulus deviates from the concept learned during habituation. And complex stimuli might be harder to encode, which slows down encoding. We therefore formalized the learning problem that participants face in a simple habituation experiment as a form of Bayesian concept learning (Goodman, Tenenbaum, Feldman, & Griffiths,

2008; Tenenbaum, 1999). In this setting, learners are tasked with learning a concept by observing samples from it, and each concept has a set of features that can be either on or off, to represent complexity the number of features being on.

Learning

RANCH's goal is to learn a concept θ, which is a set of probabilities for independent binary features $\theta_{1,2,..,n}$, where n is the number of features. θ in turn generates exemplars y: instantiations of $\bar{\theta}$, where each feature $y_{1,2,...,n}$ is either on or off. Each feature θ_i and its corresponding exemplar y_i form a Beta-Bernoulli process:

$$p(\theta_i) \sim Beta(\alpha_i, \beta_i) \qquad (1)$$
$$p(y_i|\theta_i) \sim Bernoulli(\theta_i) \qquad (2)$$

Since the features are independent, this relationship holds for the entire concept θ.

This formulation mirrors the models proposed previously to account for infant looking behavior, but it assumes that stimuli are encoded perfectly and instantaneously(Kidd et al., 2012; Poli et al., 2020). However, to model the precise time course of attention, we instead suggest that participants gather repeated noisy samples $\bar{z}$ from the exemplars, instead of directly observing them. For any sample z from an exemplar y there is a small probability ε to misperceive the feature as off when it was actually on, and vice versa.

Therefore, by making noisy observations $\bar{z}$, the learner obtains information about the true identity of the exemplar y, and by extension, about the concept θ. By Bayes' rule:

$$P(\theta|\bar{z}) \quad = p(\bar{z}|y)p(y|\theta)p(\theta)/p(\bar{z}) \qquad (3)$$

where $p(\bar{z}|y_i)$ is fully described by ε, and $p(y|\theta)$ by Bernoulli processes as in Eq. 2. Figure 1 shows the plate diagram illustrating the RANCH's model architecture.
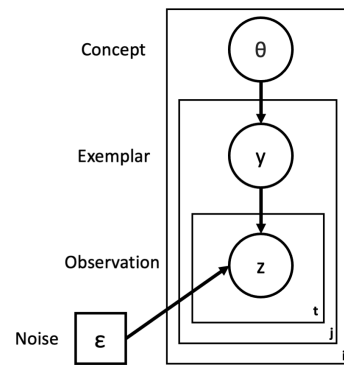

Figure 2: Graphical representation of RANCH. Circles indicate random variables. The square indicates fixed model parameters.

Sampling

The formulation of the model as taking noisy samples from exemplars allows us to do two things: First, we can explicitly model the learner's on-the-fly decisions by asking the model to decide, after every sample z, whether it wants to continue sampling from the same stimulus or not. This is in contrast to previous work which describes how entire stimuli affect an ideal learner model (Kidd et al., 2012; Poli et al., 2020). In these cases, we can only link information-theoretic measures to looking data, but not provide a mechanism for how these measures could control moment-to-moment sampling decisions. Second, a consequence of making a decision at every time step is that we can study the behavior of another information-theoretic measure: the expected information gain (EIG). EIG is commonly used in rational analyses of information-seeking behavior - that is to assess whether information-seeking is optimal with respect to the learning task (Markant & Gureckis, 2012; Oaksford & Chater, 1994). Importantly, EIG is a forward-looking measure that considers the potential for learning from the next sample. Since previous models operate on the level of a whole stimulus, rather than a series of incomplete, noisy individual samples, EIG would look forward to the next stimulus in these models, rather than to the next sample, and therefore not capture the in-the-moment decision of whether to keep looking. Relating EIG to looking time is therefore only possible in models with temporally extended perception.

RANCH computes EIG by weighing the information gain from each possible next observation by the probability of that observation. We defined information gain as the KL-divergence between the hypothetical posterior after observing a future sample z_{t+1} and the current posterior:

$$EIG(z_{t+1}) = \sum_{z_{t+1} \in [0,1]} p(z_{t+1}|\theta_t) * D_{KL}(\theta_{t+1}||p(\theta_t)) \qquad (4)$$

Finally, to get actual sampling behavior from the model, it has to convert EIG into a binary decision about whether to continue looking at the current sample, or to advance to the next trial. The model does so using a Luce choice between the EIG from the next sample and a constant EIG from looking away.

$$p(look) = \frac{EIG(z_{t+1})}{EIG(z_{t+1}) + EIG(world)} \qquad (5)$$

The basic structure of the model can therefore be described in the following pseudocode:

Experimental Setting

To model the behavioral experiment, we first represented the stimuli as binary-valued vectors indicating the presence (1) or absence (0) of each feature. All stimuli vectors were chosen to be length 6 to provide sufficient representational flexibility. Complex stimuli were represented as having three 1s and simple stimuli were represented as having one 1, with the rest of the elements 0s. Individual stimuli are then assembled into

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RANCH model
> **for** each exemplar y
> > $continue \leftarrow T$
> > **while** $continue$ take another sample z
> > > update posterior $P(\theta|z)$
> > > compute EIG of next sample z_{t+1}
> > > flip $coin$ with $p(lookaway) = \frac{EIG(z_{t+1})}{EIG(z_{t+1}) + EIG(env)}$
> > > **if** $coin = T$
> > > > $continue \leftarrow F$

---

sequences to reflect the stimuli sequences in the behavioral experiment. We ran four types of sequences, differing in the position of the deviant: The sequence could either be a pure habituation sequence with six background stimuli, or a deviant deviant appeared at positions 2, 4 or 6. For a particular sequence, we constructed the deviant stimulus based on the background stimulus to make sure that they were always maximally different and had the same number of features present.

The model then chose how to sample based on the three information-theoretic linking hypotheses (EIG, surprisal and KL), as well as the baseline linking hypotheses (random looking and no noise).

We let the model run 500 times for each sequence to obtain a reasonably precise estimate of the model's behavior.

Parameter estimation

We performed an iterative grid search in parameter space for each linking hypothesis. We a priori constrained our parameter space on the prior beta distribution to have shape parameters $\alpha_\theta > \beta_\theta$, which describe the prior beliefs as "more likely to see the absence of a feature than the presence of a feature". We then searched for the priors over the concept (θ), the noise parameter that decides how likely a feature would be misperceived (ε), and the constant EIG from the world ($EIG(world)$). The prior over the noise parameter was fixed for all searches ($\alpha_\varepsilon = 1; \beta_\varepsilon = 10$). We selected the parameters that achieved the highest correlation with the behavioral data (EIG: $\alpha_\theta = 1$, $\beta_\theta = 4$, $\varepsilon = 0.065$, $EIG(world) = 0.01$; KL: $\alpha_\theta = 1$, $\beta_\theta = 5$, $\varepsilon = 0.055$, $EIG(world) = 0.006$; Surprisal: $\alpha_\theta = 1$, $\beta_\theta = 3$, $\varepsilon = 0.07$, $EIG(world) = 8$).

Results and Discussion

Alternative Models

Baseline Comparison

Alternative Linking hypotheses

General discussion

The current work aimed to provide a computational model that can explain the three key phenomena observed in typical infant looking time paradigms: habituation, dishabituation, and complexity effect. RANCH assumes a rational learner that takes noisy perceptual samples from stimuli and makes sampling decisions based on expected information gain. We evaluated the model with adult looking time data collected
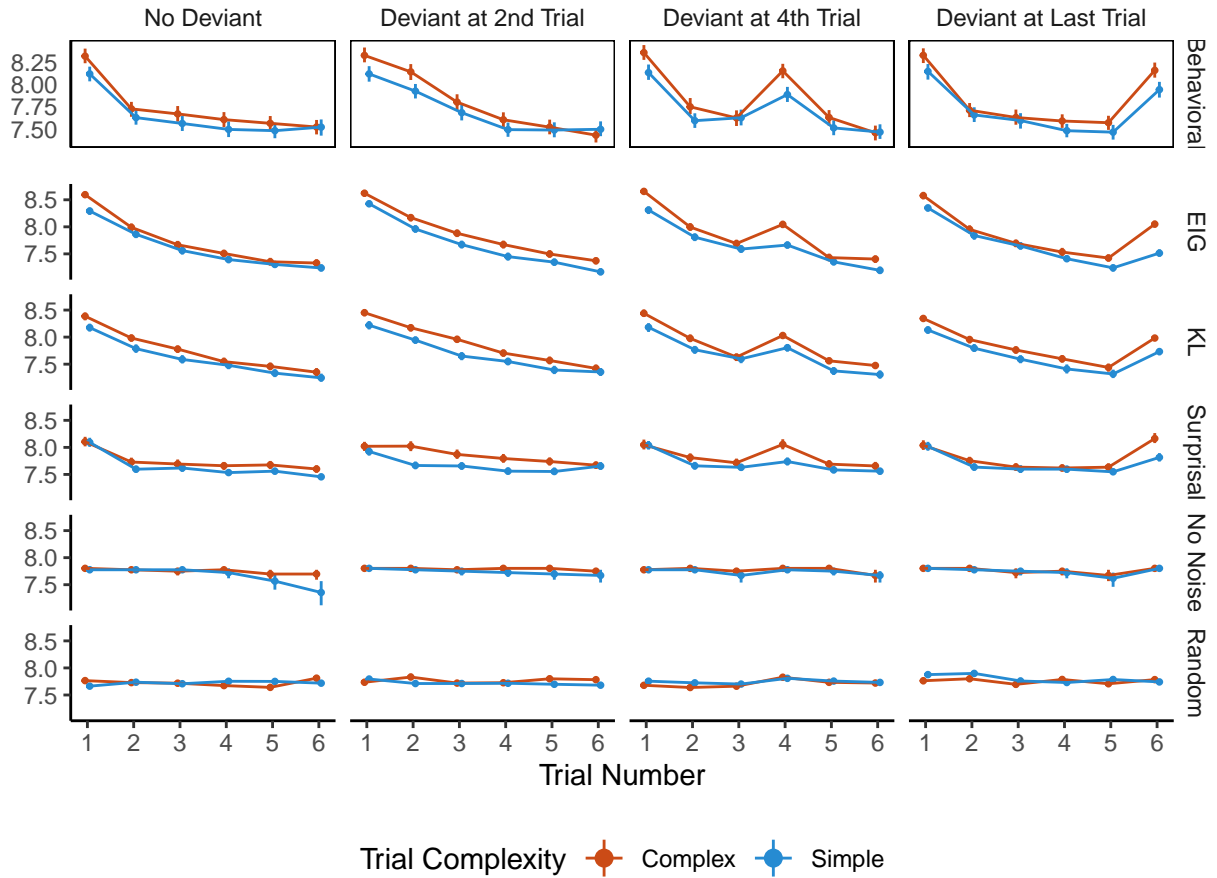
Figure 3: Continuous time model using different linking hypotheses provide qualitatively indistinguishable fits to the behavioral data. All model results are log-transformed and adjusted to be at the same scale and intercepts as the log-transformed behavioral data. The solid lines represent human data, and the dotted lines represent the model's results. Red lines indicated results for complex stimuli, and blue lines indicated results for simple stimuli.

Model Type (Linking Hypothesis)	Pearson's r	RMSE
RANCH (EIG)	0.92	0.19
RANCH (KL-divergence)	0.93	0.12
RANCH (Surprisal)	0.92	0.13
Baseline: No Noise	0.50	0.25
Baseline: No Learning	0.21	0.27

Table 1: This table shows the correlations between the log-transformed model results and the log-transformed looking time data. RANCH model implemented with the three different linking hypotheses showed similar performance with slight numerical differences and outperomed the baseline models.

from a paradigm that mirrors classic infant looking time paradigms. We found that RANCH can successfully reproduce the patterns observed in behavioral data. We find that other information theoretic quantities (e.g. KL-divergence

and Surprisal) are good proxies for the rational learning policy. Moreover, by contrasting the model results with our baseline models, we showed that habituation, dishabituation, and complexity effects only arise in a learning model that takes into account the noisy nature of perception.

RANCH constitutes a significant step forward in the modeling of looking time in that it models the moment-to-moment decision making process of whether to keep sampling or look away. This is in contrast to previous approaches, which incremented time in steps of whole stimuli, and therefore can merely correlate information-theoretic variability in the stimulus sequence to looking time. Our mechanistic account of the sampling process depended on the assumption that perception is noisy, which made it necessary to take multiple samples from a stimulus until the information content of the stimulus has been learned. The moment-to-moment increments in which RANCH operates also enabled us to use EIG as a linking hypothesis between learning and sampling. Using EIG allowed us to perform the rational analysis of hu-

man behavior in our paradigm, and contrast it with easier-to-compute and psychologically plausible linking hypothesis, surprisal and KL.

There are several limitations to our work. For our behavioral data, one concern is that our self-paced visual presentation task might not be capturing participants' intrinsic interests in exploring the stimuli. Adults may be viewing the stimuli in preparation for tasks, which deviates from the infant looking duration primarily driven by intrinsic motivation. However, across our three conditions with different filler tasks, we found no differences in looking time patterns. This suggests that the recorded behaviors are independent of task demand and are likely tapping into the same processes that produce infants' looking time patterns.

In regards to the model, a few concerns can be raised about the current implementation. First of all, the current stimulus representation is rather oversimplified. The stimuli are represented as a collection of binary features. We did not take into consideration how perceptual features can be processed with different priorities. Our complex stimuli are different from simple stimuli not only in the number of perceptual features but also in the kinds of features, such as eyes. There are studies showing that features like eyes might be particularly interesting to viewers because they convey potential social information and serve as strong cues for animacy (Anderson, Meagher, Welder, & Graham, 2018; Birmingham, Bischof, & Kingstone, 2009). Properly representing different cognitive consequences of different types of features could be an interesting next step for the model. In addition, RANCH assumes that looking duration is determined by the decision between "continue looking" and "look away". However, one can argue that in the behavioral experiment the participants were deciding between "continuing looking at the current stimulus" and "looking at the next stimulus". Building in these more sophisticated assumptions into the model would certainly help us better understand looking time under a rational analysis framework. But as a first step, our current work suggests that a simple rational learner that takes noisy samples from a set of independent binary features is capable of explaining key phenomena in looking time change.

Our ultimate goal is to provide a rational learner model that can account for information seeking behaviors through the lens of infants' looking time. Here we have shown that such a model can reproduce adults' looking time changes. As we further elaborate on our modeling approach, our ongoing work with infants will eventually help address the developmental trajectories of the mechanisms through which learners decide what to look at, and when to stop looking.

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