Habituation reflects optimal exploration over noisy perceptual samples

Anonymous CogSci submission

Abstract

From birth, humans constantly make decisions about what to look at and for how long. Yet the mechanism behind such decision-making remains poorly understood. Here we present the "rational action, noisy choice for habituation" (RANCH) model. RANCH is a rational learning model that takes noisy perceptual samples from stimuli and makes sampling decisions based on Expected Information Gain (EIG). The model captures three key patterns of looking time changes well documented in developmental research: habituation and dishabituation. We evaluated the model with adult looking time collected from a paradigm analogous to infant habituation paradigm. We compared RANCH with baseline models (no learning model, no perceptual noise model) and models with alternative linking hypotheses (Surprisal, KL-divergence). We showed that 1) learning and perceptual noise are critical assumptions of the model, and 2) Surprial and KL are good proxies for EIG under the current learning context.

Keywords: decision making; learning; bayesian modeling; cognitive development

Introduction

From trying to find our way through a busy street to swiping through TikTok, we are constantly making the decision of whether to keep looking or to look at something else. Even the youngest infants have to decide whether to keep looking at what is in front of them or move on. How can we explain this decision-making process? Our goal in the current paper is to provide a model of the basic decision whether to keep looking at a stimulus. To do so, we model looking as rational active selection of noisy perceptual samples for learning.

Developmental researchers have long capitalized on infants' ability to control their attention, making inferences about learning and mental representations from changes in looking duration (Aslin, 1991; Sim & Xu, 2019). In a typical experiment, infants decrease their looking duration upon seeing the same stimulus repeatedly (habituation) but recover interest when seeing a novel stimulus (dishabituation). While these phenomena are well-documented, the mechanisms underlying them remain poorly understood, even though assumptions about habituation and dishabituation underpin many other claims about infants' cognitive repertoire (Paulus, 2022; Tafreshi, Thompson, & Racine, 2014).

One classic 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). This theory describes the intersection of exposure, stimulus complexity, and processing difficulty: The more an infant has already been exposed to a stimulus, the less they have yet to learn about it, but the more complicated the stimulus is, the more they have to learn overall. Older infants are assumed to learn faster than younger infants. Although this theory is influential, little work has examined it systematically and it does not make quantitative predictions (For exception, see Hunter & Ames, 1988; Bergmann & Cristia, 2016). Nevertheless, it is often invoked as a post-hoc explanation of observed patterns in infant data.

Recent work has attempted to overcome these limitations by describing infants' looking behaviors quantitatively through computational modeling. Kidd, Piantadosi, & Aslin (2012) developed a look-away paradigm in which infants are shown sequences of events and their lookaways are monitored. They then used a rational learning model to estimate the probabilities of individual events and computed the surprisal (negative log probability) of each event. Infants looked away least from events that were neither too high nor too low in surprisal (a "goldilocks" effect), suggesting that they might be looking longer at stimuli with an optimal level of information content.

In this work, surprisal functioned as a quantitative linking hypothesis, connecting between a learning model and data. But other such linking hypotheses are possible. For example, research on information foraging postulates that human exploratory behaviors are driven by maximizing expected information gain (EIG, Hills et al., 2015; Pirolli & Card, 1999). In this formulation, agents focus on locations or examples where the amount to be learned is on average highest, a conclusion that is ratified by the emerging literature on curiosity in developmental robotics and reinforcement learning (Oudeyer, Kaplan, & Hafner, 2007). Indeed, EIG provides a good model of curiosity-driven learning in human children and adults (e.g., Liquin, Callaway, & Lombrozo, 2021).

Unfortunately, EIG can be difficult to compute. Because EIG is a measure of expected information gain, its computation requires combinatorial search over all future possibilities. As a result, EIG is often approximated by what is termed "learning progress": the amount of information the agent just learned (Haber, Mrowca, Fei-Fei, & Yamins, 2018). Following this intuition, Poli, Serino, Mars, & Hunnius (2020) formalized learning progress as the Kullback-Leibler (KL) divergence between the model's knowledge before and after each stimulus and found that a higher KL divergence (i.e. more learning progress) predicted longer looking time in a look-away paradigm.

These existing models take important steps towards a quantitative model of infant attention, but they have three key limitations. First, conceptually, these prior models are not models of choice. The linking models retrospectively fit infants' overall pattern of attention, without characterizing the decision that infants must make in each moment, whether to keep looking at the current stimulus. Second, and relatedly, these models assume that infants acquire a perfect representation of the stimulus on each exposure. These prior models do not accommodate the noisy nature of perception, and thus cannot explain why infants would have more information to gain from longer looking at the same, already perceived stimulus (Callaway, Rangel, & Griffiths, 2021; Kersten, Mamassian, & Yuille, 2004). Third, because of the first two limitations, the prior models could only directly predict one specific infant looking behavior given an unusual learning problem: looking away from an ongoing stream of stimuli while learning about event probabilities. It is not trivial to use these models to generate quantitative predictions for infant looking behavior in more standard habituation-dishabituation experimental designs.

Here we attempt to overcome these limitations by providing a model 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 accumulating noisy samples and choosing at each moment whether to continue to look at the current stimulus or to look away to the rest of the environment. Critically, RANCH allows us to explore a learning problem closer to the problem faced by infants in a standard habituation experiment: instead of assuming a learner is estimating the probability of event types, the model assumes the learner is encoding perceptual categories. Furthermore, the architecture allows us to investigate different information-theoretic linking hypotheses as informing choice, including surprisal, KL-divergence, and EIG. We make a preliminary evaluation of the RANCH model using adult looking time data collected from a self-paced habituation paradigm that captures habituation, dishabituation, and how these phenomena are modified by stimulus complexity.

Experiment

We developed a stimuli set and an experimental paradigm to reproduce the key looking time patterns in adult participants. We chose a learning context in which participants learn about the content of the stimuli as they look at repeated novel stimuli with no explicit task. This learning context resembles a classic infant habituation-dishabituation experiment, which also assumes that the infants are learning about the stimuli content. This setting is in contrast with previous work, where the behavioral experiment postulates infants are learning about the probabilities of event sequences (e.g., Kidd et al., 2012; Poli et al., 2020)

We decided to start with testing adults for several reasons. First, adult data are suitable for establishing quantitative links between models and human behaviors, since infants' looking time data tend to have small sample sizes and are therefore limited in their quantitative details (Frank et al., 2017). Furthermore, adult data allow us to test the hypothesis that similar rational choice processes underlie infant and adult behavior under similar learning contexts.

Methods

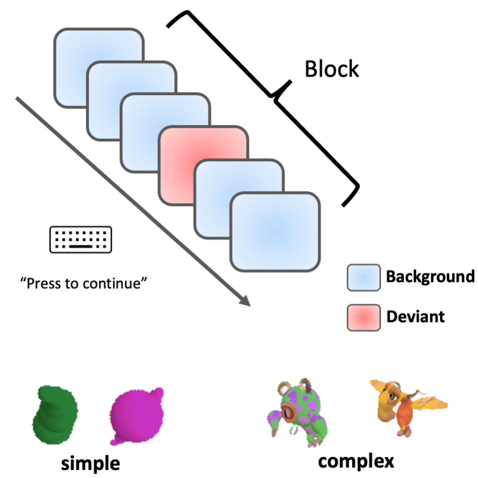

Figure 1: Experimental design and examples of simple and complex stimuli. In each block, a deviant could appear on the second, fourth (as depicted here) or sixth trial or not at all. Stimuli within a block were either all simple or all complex.

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 answer 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 indicated 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]. There were no task effects so we averaged the results across three conditions. We first checked whether 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; $t < 0.001$).

We were interested in whether our paradigm 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, row 1).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: habituation (trial number), dishabituation (the deviant effect), and complexity (the stimulus complexity effect).

Model

(Aalo, 1995) We next tested whether we could capture our behavioral experimental results using our "rational action, noisy choice for habituation" (RANCH) model. RANCH treats the learning problem that participants face in our experiment as a form of Bayesian concept learning (Goodman, Tenenbaum, Feldman, & Griffiths, 2008; Tenenbaum, 1999). In this setting, multiple noisy samples inform the learner's hypothesis about a probabilistic concept represented by a set of binary features (Figure 2).

The formulation of the learner as taking noisy samples from a stimulus allows us to do two things: First, we can explicitly model the learner's decision on when to stop sampling by asking the model to decide, after every sample, whether it wants to continue sampling from the same stimulus or not. This is in contrast to previous models which correlate information-theoretic measures to looking data (Kidd et al., 2012; Poli et al., 2020), but do 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).

Learning

RANCH's goal is to learn a concept θ, which is a set of probabilities over 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 present or absent. The weights on each feature θ_i are sampled from a Beta prior, and individual exemplars y_i are distributed as a binomial with parameter θ_i, forming a conjugate Beta-Bernoulli distribution. Since the features are independent, this relationship holds for the entire concept θ.

To model the timecourse of attention, RANCH does not observe exemplars directly. Instead, it can observe repeated noisy samples $\bar{z}$ from each exemplar. For any sample z from an exemplar y there is a small probability ε that the observation is flipped and the feature is seen to be present when it was actually absent or vice versa. Therefore, by making noisy observations $\bar{z}$, RANCH obtains information about the true identity of the exemplar y, and by extension, about the concept $theta$. By Bayes' rule:

$$P(\theta|\bar{z}) \quad = p(\bar{z}|y)p(y|\theta)p(\theta)/p(\bar{z}) \tag{1}$$

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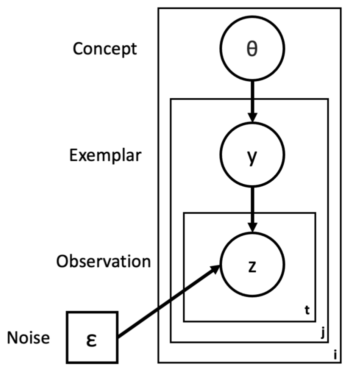

Figure 2: Graphical representation of RANCH. Circles indicate random variables. The square indicates fixed model parameters.

Sampling

Upon observing a sample, RANCH then decides whether to keep sampling or not. We chose as the main linking hypothesis (i.e. the link between learning and sampling) the expected information gain (EIG) from the next sample.

RANCH computes EIG by iterating through each possible next observation and weighing the information gain from each observation by its posterior predictive probability $p(z|\theta)$. We defined information gain as the KL-divergence between the hypothetical posterior after observing a future sample z_{t+1} and the current posterior (Baldi & Itti, 2010):

$$EIG(z_{t+1}) = \sum_{z_{t+1} \in [0,1]} p(z_{t+1}|\theta_t) * D_{KL}(\theta_{t+1}||p(\theta_t)) \tag{2}$$

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 "environmental EIG" from looking away.

$$p(look) = \frac{EIG(z_{t+1})}{EIG(z_{t+1}) + EIG(env)} \tag{3}$$

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

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 $coin = T$
      $continue \leftarrow F$

Model experiment

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 features set to 0. Individual stimuli are then assembled into 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.

Since the model makes stochastic choices about how many samples to take from each stimuli, behavior varies substantially across runs. Thus, we conducted 500 runs for each stimuli sequence and parameter value to obtain a reasonably precise estimate of the model's behavior. 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 environment ($EIG(env)$). The prior over the noise parameter was fixed for all searches (α_ε = 1;β_ε = 10). We selected the parameters that achieved the highest correlation with the behavioral data (EIG: α_θ = 1, β_θ = 4, ε = 0.065, $EIG(env)$ = 0.01; KL: α_θ = 1, β_θ = 5, ε = 0.055, $EIG(env)$ = 0.006; Surprisal: α_θ = 1, β_θ = 3, ε = 0.07, $EIG(env)$ = 8).

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Results

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

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.

RANCH exihibited the main phenomena of interest, showing habituation, dishabituation, and complexity effects (Fig. 3, row 2-4). We also quantitatively explore the model by fitting the model results to the behavioral data (See Table 1, row 1).

Alternative Models

Baseline Comparison

We next wanted to test what aspects of the model are necessary to produce the phenomena. We focused on two assumptions: 1) the model makes decision based on learning and 2) perception is noisy. We implemented two lesioned baseline models corresponding to each assumption.

The first baseline model (No Learning) made random sampling decisions by drawing $p(look)$ from a uniform distribution between 0 and 1 at every time step. The second baseline model (No Noise) omitted the noisy sampling aspect of RANCH. We assumed that learning is free from perceptual noise, i.e. that learners can observe the exemplars y directly. To do so, we set ϵ to 0 and replaced the learner's prior over ϵ with a point mass at 0.000001 for numerical stability. The baseline models used the parameters obtained from fitting the EIG model to the behavioral data.

The baseline models fit the data poorly (Table 1, row 2-3; Fig 3, row 3-4). This suggests that both learning and noisy perception are critical for modeling the phenomena of interests.

Alternative Linking hypotheses

Alternative linking hypotheses We also studied the behavior of RANCH using two other linking hypotheses, surprisal and Kullback-Leibler (KL) divergence. By replacing $EIG(z_{t+1})$ in Equation 2 with surprisal and KL of the current sample z, we can contrast their performance of other information-theoretic linking hypotheses with the rational analysis.

Both linking hypotheses have been used in previous attempts to model infant looking behavior (Kidd et al., 2012; Poli et al., 2020) and to approximate EIG in reinforcement learning literature (Kim, Sano, De Freitas, Haber, & Yamins, 2020). Surprisal, formally described as $-log(p(z|\theta))$, intuitively refers to how surprising an observation z is given the model's beliefs about θ - the intuition that surprising events should result in longer looking times has served as a foundational assumption in developmental psychology (Sim & Xu, 2019). KL-divergence, formally described as $\sum_{x\in X} p(\theta = x|y)\frac{p(\theta_{t-1}=x)}{p(\theta_t=x)}$, measures how much the model changed to accommodate the most recent observation z_t. If an observation causes a large change, a proportionally long looking time might be necessary to integrate the new information.

We showed that under RANCH's model architecture, the performance of surprisal and KL can match that of EIG, a metric that can quantitatively characterize the optimal exploratory behaviors in humans (Table 1, row 4-5, Fig 3, row 5-6; Markant & Gureckis, 2012; Oaksford & Chater, 1994). To calculate EIG one needs to consider all possible combinations of features for the next observation, which becomes computationally expensive and therefore psychologically implausible. The proximity of model fits between EIG, KL, and surprisal suggests that easier-to-compute metrics can be viable heuristics to which to anchor sampling behavior.

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 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.

The current work aimed to provide a computational model that can explain the key phenomena observed in typical infant looking time paradigms: habituation, dishabituation, and how these are modified by stimulus complexity. RANCH assumes

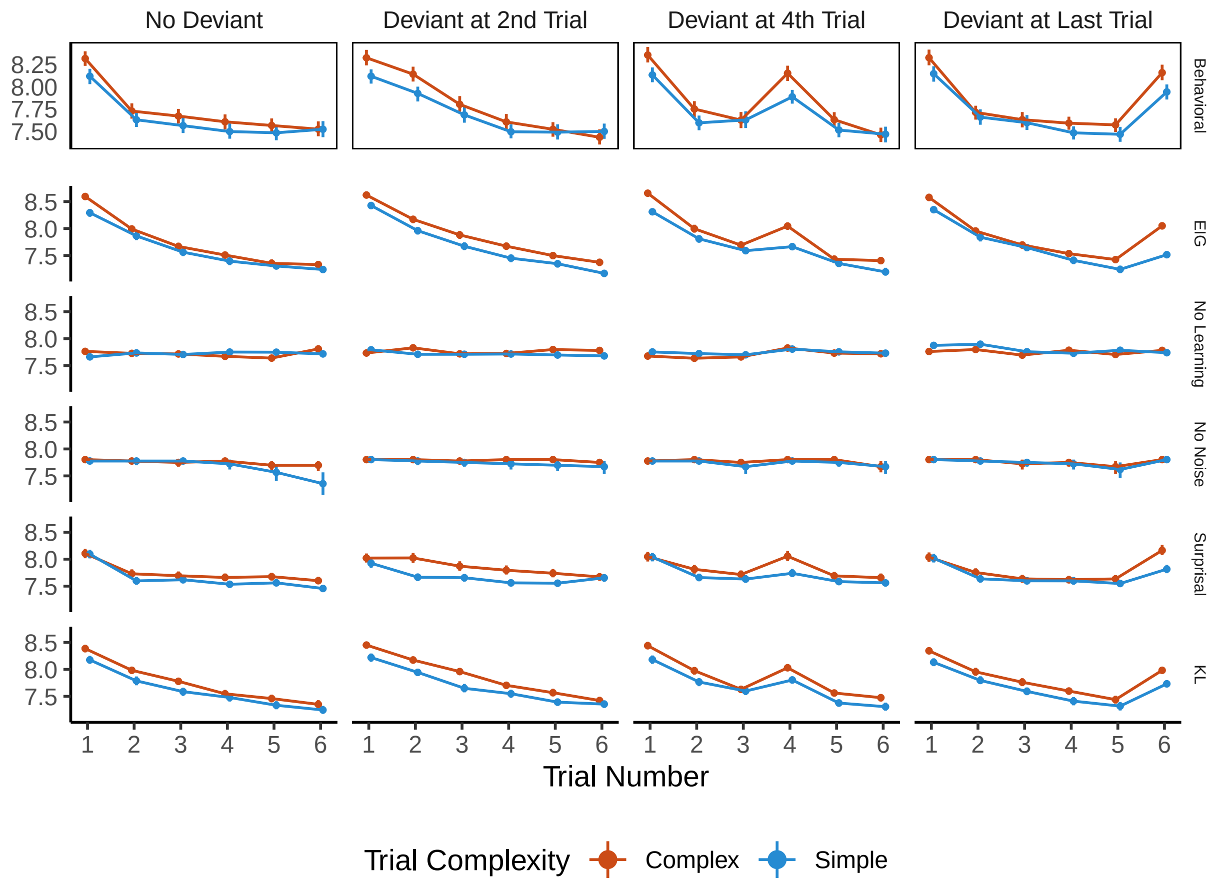

Figure 3: All models' results were adjusted to match behavioral data's scale and intercepts for easier comparisons.Red lines indicated results for complex stimuli, and blue lines indicated results for simple stimuli.

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 from a paradigm that mirrors classic infant looking time paradigms, in which participants are learning about multi-feature concepts. We found that RANCH can successfully reproduce the patterns observed in behavioral data. 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. Moreover, we find that, in the current learning context, other information theoretic quantities (surprisal and KL-divergence) are good proxies for the rational linking hypothesis, EIG.

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 look-away probability and looking time. Our mechanistic account of the sampling process depended on assuming 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 perform the rational analysis of human behavior in the current paradigm by using EIG as the linking hypothesis between learning and sampling.

The similarity between model fits among models with different linking hypotheses highlights the significance of learning contexts. Our results should not be interpreted as evidence showing that the three linking hypotheses are indistinguishable across all learning contexts. Previous work has shown that adopting surprisal as learning policy can lead to undesirable behaviors in artificial agents (e.g. "the white noise problem," Oudeyer et al., 2007). Moreover, the two alternative linking hypotheses are backward-looking metrics that utilize past heuristics to make decisions. This characteristic could lead to them only working when the environment is stable and the cost of sampling is low. Since human exploration is sensitive to environmental complexity, a forward-looking metric like EIG might be particularly suitable to predict behaviors in a more dynamic and realistic learning context (Dubey & Griffiths, 2020; Vogelstein et al., 2022).

There are several limitations to our work. For our behavioral data, one concern is that adult looking time might not be driven by the same process underpinning infant looking time. Adult looking might be driven by task-preparation, rather than intrinsic interests. Nevertheless, across the three conditions with different filler tasks, we found no differences in looking time patterns. This suggests that adult looking time is unlikely to be related to the task. 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, using an unweighted collection of binary features. In addition, RANCH assumes that the EIG from the environment is a constant throughout the experiment, but one can argue that environmental EIG might increase as the experiment progresses (e.g. the longer you haven't attended to the things in your surrounding, the more interesting they become). While implementing more sophisticated assumptions could potentially explain additional variance in the data, our current work suggests that even 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 habituation, dishabituation, and complexity effects. Moving forward, we aim to capture and explain more contentious phenomena documented in the infant looking time literature such as familiarity preferences and age effects (Hunter & Ames, 1988). Our ongoing work with infants will eventually enable us to evaluate our model with developmental data. When combined with adult results, the data and model will provide insights into the general mechanisms through which learners decide what to look at, and when to stop looking.

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