How to Make a Proceedings Paper Submission

Anonymous CogSci submission

Abstract

Include no author information in the initial submission, to facilitate blind review. The abstract should be one paragraph, indented 1/8 inch on both sides, in 9˜point font with single spacing. The heading 'Abstract' should be 10˜point, bold, centered, with one line of space below it. This one-paragraph abstract section is required only for standard six page proceedings papers. Following the abstract should be a blank line, followed by the header 'Keywords' and a list of descriptive keywords separated by semicolons, all in 9˜point font, as shown below.

Keywords: Add your choice of indexing terms or keywords; kindly use a semi-colon; between each term.

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 TikTok. Even young infants are tasked with making the decision on selecting what to look at and for how long. To look or not to look, this decision that infants make constantly has provided developmental researchers an opportunity to investigate infants' mental world. Through the use of looking time paradigms, researchers are able to make inferences about infants' learning and mental representations based on changes in looking time (CITE, CITE, CITE). In a typical experiment, infants increasingly decrease their looking duration upon seeing repeated stimulus (i.e. habituation). When habituated, infants regain their interests when seeing a novel stimulus (i.e. dishabituation). While both phenomena are well-documented, the factors that influence these looking time trajectories remain relatively underexplored. A better understanding of what shapes habituation and dishabituation is critical given their methodological and theoretical significance. The rise and fall in looking time is not only central to understanding infants' mental representation, but also shed light on principles that guide information-seeking behavior in general.

Classical theory of infant looking behavior suggests three factors are crucial to habituation and dishabituation: complexity, familiarization time, and infants' age (Hunter & Ames, 1988). More perceptually complex stimuli take longer time for infants to habituate. Longer familiarization time to one stimulus would make infants more likely to dishabituate to another stimulus. The older infants are, the more efficient they are at information processing, and the faster they are to habituate when other factors are controlled for. Together, these three factors determine how infants' looking time changes during an experiment. Although Hunter & Ames (1988) is influential, the evidence for the theory is weak, with some studies showing mixed results (CITE meta analysis). Furthermore, this verbal theory lacks quantitative details, and therefore unlikely to offer precise predictions on looking time changes based on the different factors.

In contrast to verbal theory, computational models offer quantitative predictions. More recent work has linked infants' looking behaviors with a range of information theoretic measurements derived from models. In pioneering work, KPA (CITE) developed a paradigm in which infants are shown sequences of events. Infants' look-away probabilities toward 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 looking behaviors can be predicted by surprisal. In particular, they pay most attention to event sequences that are neither too high nor too low in surprisal. A recent study with a similar paradigm provides an alternative linking hypothesis. In Poli et al (2020), another information theoretic measurement, Kullback-Leibler divergence, is shown to outperform surprisal in predicting infants' looking time. These attempts on connecting information theoretic measurements to infants' looking time resonate with the emerging literature on curiosity in developmental robotics and reinforcement learning (CITE, CITE, CITE). Curiosity-driven artificial agents' exploratory behaviors are guided by optimizing Expected Information Gain (EIG) (CITE, CITE), a measurement that has been shown to be related to information-seeking in human children and adults as well (CITE).

However, there are several limitations to the existing models. First, the current models did not capture the noisy nature of perceptual learning (CITE noisy perception?). The rational learner models were assumed to acquire perfect representation of each event in the sequence (CITE model). This assumption leads to the second limitation: the lack of explanation in why a learner would choose to learn a stimulus in the first place. Both surprisal and KL-divergence have been presented as potential explanations of infants' looking behaviors, yet neither of the measurements is mechanistically linked to the models' behaviors. They are descriptive in nature, derived from models that track the probabilities of the events. Finally, the behavioral data that the models were evaluated with came from experimental paradigms that were not representatives of infant looking time paradigms. The key phenomena, habituation and dishabituation, were not captured. The extent to which we can extrapolate current behavior-model fits to understand changes in looking time in a typical looking time experiment remains limited.

Here we present a series of models that can explain patterns in looking time. Our Goal is to provide a unifying quantitative account of looking behaviors as arising from optimal decision-making over noisy perceptual representations (CITE C & G; drif diffusion). We begin by instantiating a version of prior learning models in an independent-trial format (where individual stimuli are learned, not sequences of events). We then develop a second model that addresses weakness in previous work by a) assume the model is accumulating noisy samples from the stimulus, and b) assume the model is choosing what to look at depending on the linking hypotheses (surprisal, KL-divergence, and EIG). FInally, we evaluate our model with adult looking time data collected from a paradigm that captures habituation, dishabituation, and complexity effect.

Models

```
#{r child = "02_model.Rmd"} #
```

Experiment

Methods

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 N participants (Curiosity N = 143; Memory: N = 98; Math: N = N = 139).

Procedure This is 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. At the end of the experiment, participants were asked to rate the similarity between pairs of creatures and complexity of creatures they encountered on a 7-point Likert Scale. 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. On each trial, an animated creature showed up on the screen. participants can press the down arrow to go to the next trial whenever they want after a minimum viewing time of 500 ms.

Each block consisted of six trials. A trial can be 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 can appear at either the second (BDBBBB), the fourth (BBBDBB), or the sixth trial (BBBBBD) in the block. Two blocks do not have deviant trials (BBBBBB). The creatures presented in the deviant trials and background trials were matched for complexity.

Participants were randomly assigned to one of the three conditions: Curiosity, Memory, and Math The three conditions only differed in the type of questions asked following each block. In Curiosity condition, participants were asked to rate "How curious are you about the creature?" on a 5-point Likert scale. In 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 Math condition, the participants were asked a simple arithmetic question ("What is 5 + 7?") in multiple-choice format.

Stimuli The animated creatures (Fig 1) were created 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). We used the "animated avatar" function in Spore to capture the creatures in motion.

Results

Analytic Approach The sample size, methods, and main analyses were all pre-registered and are available at [LINK]. Data and analysis scripts are available at [LINK].

Manipulation Check The complex animated creatures were rated as more perceptually complex (M = ; SD =) than the simple animated creatures (M = ; SD =). Pairs of background creature and deviant creature were rated as moderately dissimilar to one another (M = ; SD =).

Evaluating the Paradigm

```
Linear mixed model fit by REML. t-tests use Satterthwaite's
lmerModLmerTest]
Formula: log(trial_looking_time) ~ I(exp(1)^(-trial_number)
    block_type + (1 | subject)
   Data: d

REML criterion at convergence: 37415.2

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.7455 -0.6692 -0.0499  0.5968  5.4843

Random effects:
 Groups   Name        Variance Std.Dev.
 subject  (Intercept) 0.2752   0.5246
```

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 Residual             0.4250   0.6519
Number of obs: 18198, groups:  subject, 380

Fixed effects:

(Intercept)
I(exp(1)^(-trial_number))
trial_typedeviant
block_typesimple_dissimilar
I(exp(1)^(-trial_number)):trial_typedeviant
I(exp(1)^(-trial_number)):block_typesimple_dissimilar
trial_typedeviant:block_typesimple_dissimilar
I(exp(1)^(-trial_number)):trial_typedeviant:block_typesimple_dissimilar

(Intercept)
I(exp(1)^(-trial_number))
trial_typedeviant
block_typesimple_dissimilar
I(exp(1)^(-trial_number)):trial_typedeviant
I(exp(1)^(-trial_number)):block_typesimple_dissimilar
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block_typesimple_dissimilar
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(Intercept)
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block_typesimple_dissimilar
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I(exp(1)^(-trial_number)):block_typesimple_dissimilar
trial_typedeviant:block_typesimple_dissimilar
I(exp(1)^(-trial_number)):trial_typedeviant:block_typesimple_dis

(Intercept)
I(exp(1)^(-trial_number))
trial_typedeviant
block_typesimple_dissimilar
I(exp(1)^(-trial_number)):trial_typedeviant
I(exp(1)^(-trial_number)):block_typesimple_dissimilar
trial_typedeviant:block_typesimple_dissimilar
I(exp(1)^(-trial_number)):trial_typedeviant:block_typesimple_dis

(Intercept)
I(exp(1)^(-trial_number))
trial_typedeviant
block_typesimple_dissimilar
I(exp(1)^(-trial_number)):trial_typedeviant
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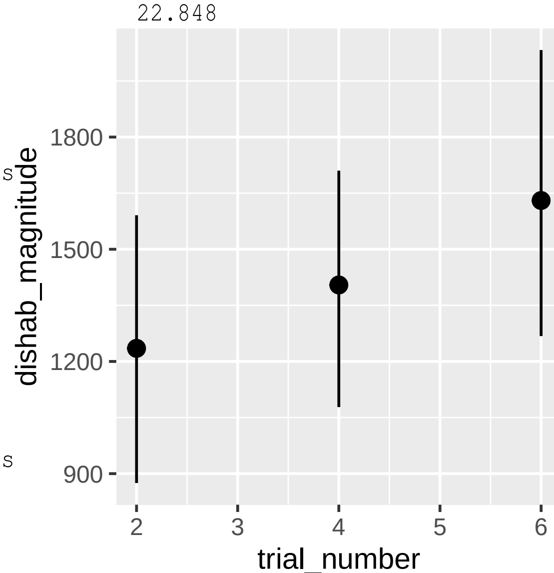
```
I(exp(1)^(-trial_number)):block_typesimple_dissimilar
trial_typedeviant:block_typesimple_dissimilar
I(exp(1)^(-trial_number)):trial_typedeviant:block_typesimpl
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '

Correlation of Fixed Effects:
                  (Intr) I(x(1)^(-_)) trl_ty blck__ I(x(1)^(-_
I(x(1)^(-_))      -0.196
trl_typdvnt       -0.108  0.20
blck_typsm_       -0.228  0.24          0.237
I(x(1)^(-_)):_     0.032 -0.96         -0.647 -0.070
I((1)^(-_)):__     0.138 -0.83         -0.144 -0.606  0.116
trl_typd:__        0.077 -0.14         -0.708 -0.336  0.458
I((1)^(-_)):_:    -0.023  0.01          0.458  0.099 -0.708
                  tr_:__
I(x(1)^(-_))
trl_typdvnt
blck_typsm_
I(x(1)^(-_)):_
I((1)^(-_)):__
trl_typd:__
I((1)^(-_)):_: -0.647
```

```
Estimate
7.531e+00
2.125e+00
1.252e-01
-5.175e-02
-2.226e+00
-4.048e-01
-1.896e-01
-5.378e-01
Std. Error
2.841e-02
5.415e-02
2.737e-02
1.299e-02
3.310e-01
7.652e-02
3.865e-02
4.679e-01
df
4.432e+02
1.781e+04
1.781e+04
1.781e+04
1.781e+04
1.781e+04
1.781e+04
1.781e+04
t value
264.857
39.240
22.848
```

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). To evaluate the phenomenon quantitatively, we ran a linear mixed effects model with maximal random effect structure. [DESCRIBE THE MODEL]. [REPORT THE MODEL RESULTS]



Order Effect

```
***
**
***
Linear mixed model fit by REML. t-tests use Satterthwaite's
lmerModLmerTest]
Formula: dishab_magnitude ~ trial_number + (1 | subject)
```

```
   Data: dishab_d

REML criterion at convergence: 44965.3

Scaled residuals:
    Min      1Q  Median      3Q     Max 
-7.5761 -0.3319 -0.0903  0.2873  7.5993 

Random effects:
 Groups   Name        Variance Std.Dev.
 subject  (Intercept)  2450681 1565    
 Residual             21340805 4620    
Number of obs: 2272, groups:  subject, 380

Fixed effects:
             Estimate Std. Error      df t value Pr(>|t|)    
(Intercept)   1029.26     268.80 2225.33   3.829 0.000132 ***
trial_number    99.05      59.39 1890.38   1.668 0.095529 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr)
trial_numbr -0.884
```

While visualizing the data, we unexpectedly found that the position in which the deviant trial appeared in the sequence had an effect on the shape of the habituation and dishabituation curves. To explore this phenomenon quantitatively, we operationalized the magnitude of dishabituation as the difference between the looking time at the deviant trial minus the background trial at the same position. Then, we fit a mixed effect model with the position of deviant as fixed effect and [???] as a random effect. We found that the position was a significant predictor of the magnitude of dishabituation (looking time at the deviant trial minus the background trial at the same position). Deviant trials that appeared last elicited the strongest dishabituation effect (M = ; SD:,), followed by the deviant trials appeared fourth (M, SD), with the deviant trial on the second showing the smallest amount of dishabituation (M, SD).

Discussion

General Discussion

References

References