Development of word recognition in preschoolers

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Abstract

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Chair of the Supervisory Committee:
Name of my committee chair

Here is my abstract

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Dedication

For Penny

Preface

This book, when finished, will contain my dissertation research.

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PROSPECTUS

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Prospectus Preamble

About This Document

This document outlines the research questions, data, and methods for my dissertation. This proposal started out as a grant-writing project, so it has some of the touchstones of NIH F31 grant (Specific Aims, Significance, Approach), but these sections have been expanded considerably.

Date of oral presentation of dissertation proposal: April 3, 2017.

Dissertation Committee Members

- Jan Edwards, primary mentor and chair, Department of Hearing and Speech Sciences, University of Maryland
- Susan Ellis Weismer, advisor at UW-Madison, Department of Communication Sciences and Disorders
- Margarita Kaushanskaya, Department of Communication Sciences and Disorders
- Audra Sterling, Department of Communication Sciences and Disorders
- David Kaplan, Department of Educational Psychology
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Planned Dissertation Format

Two thematically related manuscripts, one for each specific aim, to be completed by Summer 2018.

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Specific Aims

Individual differences in language ability are apparent as soon as children start talking, but it is difficult to identify children at risk for language delay or disorder. Recent work suggests word recognition efficiency—that is, how well children map incoming speech to words—may help identify early differences in children's language trajectories. Children learn spoken language by listening to caregivers, so children who are faster at recognizing words have an advantage for word learning. This view is borne out by some studies suggesting that children who are faster at processing words show greater vocabulary gains months later (e.g., Weisleder & Fernald, 2013).

We do not know, however, how word recognition itself develops over time within a child. This is an important open question because word recognition may provide a key mechanism for understanding how individual differences emerge in word learning and persist into early language development. Without a developmental account of word recognition, we lack the context for understanding individual differences in lexical processing. Thus, even the big-picture questions are unclear: Do early differences persist over time so that faster processors remain relatively fast later in childhood? Or, is such a question ill-posed because the magnitude of the differences among children shrink with age? I plan to address this gap in knowledge by analyzing three years of word recognition data collected in recently completed longitudinal study of 180 children.

In particular, I will examine the development of *familiar word recognition*, *lexical competition,* and *fast referent selection* (the ability to map novel words to novel objects in the moment). Through these analyses, I will develop a fine-grained description of how the dynamics of word recognition change year over year, and I will study how differences in word recognition performance relate to child-level measures (such as vocabulary and speech perception). I will complement these empirical analyses with computational cognitive models. With these models, I will simulate the word recognition data from each year and study how the models need to change to adapt to children's developing word recognition abilities. These simulations can identify plausible psychological mechanisms that underlie changes in word recognition behavior.

Specific Aim 1 (Familiar Word Recognition and Lexical Competition)

To characterize the development of familiar word recognition and lexical competition, I will analyze data from a visual world paradigm experiment, conducted at age 3, age 4, and age 5.

In these eyetracking experiments, children were presented with four images of familiar objects and heard a prompt to view one of the images. The four images included a target word (e.g., *bell*), a semantically related word (*drum*), a phonologically similar word (*bee*), and an unrelated word (*swing*). I will use a series of growth curve analyses to describe how children's familiar word recognition develop year over year. Of interest is how individual differences at Year 1 persist into Year 3. I will also analyze how expressive vocabulary and lexical processing develop together over time. Lastly, I will examine the children's looks to the distractors to study the developmental course of lexical competition from similar sounding and similar meaning words. Changes in sensitivity to competing words can reveal how lexical competition emerges as a byproduct of learning new words.

Specific Aim 2 (Referent Selection and Mispronunciations)

To characterize how fast referent selection develops longitudinally, I will analyze data from a looking-while-listening mispronunciation experiment, conducted at age 3, age 4, and age 5.

In these eyetracking experiments (Law & Edwards, 2015; based on White & Morgan, 2008), children saw an image of a familiar object and an unfamiliar object, and they heard either a correct production of the familiar object (e.g., *soup*), a one-feature mispronunciation of the familiar object (*shoop*), or a novel word unrelated to either image (*cheem*). The correct productions test familiar word recognition and the non-words test fast referent selection. The mispronunciations test a child's phonological categories (whether the child permits, rejects, or equivocates about mispronunciations).

I will use growth curve analyses to study how children's responses to the three word types change over time. I will examine familiar word recognition and fast referent selection to determine which feature of lexical processing better predicts vocabulary growth. I plan to examine dissociations or asymmetries in these forms of processing within children as a way to empirically assess the claim that "novel word processing (referent selection) is not distinct from familiar word recognition" (McMurray, Horst, & Samuelson, 2012). Finally, I will examine how individual differences in vocabulary and speech perception predict responses to mispronunciations and novel words.

Summary

This project investigates how word recognition develops during the preschool years. There has been no research studying word recognition longitudinally after age two. Findings will show how individual differences in lexical processing change over time and can reveal how low-level mechanisms underlying word recognition mature longitudinally in children. These findings will have translational value by studying processing abilities that subserve word learning and by assessing the predictive relationships between early word recognition ability and later language outcomes.

3 Significance

Public Health Significance

Vocabulary size in preschool is a robust predictor of later language development, and early language skills predict early literacy skills at school entry (P. L. Morgan, Farkas, Hillemeier, Hammer, & Maczuga, 2015). By studying the mechanisms that shape word learning, we can understand how individual differences in language ability arise and identify strategies for closing language gaps between children. Word recognition—the process of mapping incoming speech sounds to known or novel words—has been shown to predict later language outcomes. We do not know how this ability develops over time, and we do not know when word recognition is most predictive of future outcomes. This project will provide an integrated account of how word recognition and its relationship with vocabulary size change from age 3 to age 5.

Scientific Significance

Lexical Processing Dynamics

Mature listeners recognize words by continuously evaluating incoming speech input for possible word matches through lexical competition. The first part of a word activates multiple candidate words in parallel, and these candidates compete so that the best-fitting word is recognized. For example, the onset "bee" might activate the candidates *bee*, *beam*, *beetle*, *beak*, *beaker*, *beginning*, and so on, but an additional "m" would narrow the candidates to just *beam*. Semantic relationships also influence lexical processing, and cascading phonological-semantic effects—e.g., where *castle* activates the phonologically similar *candy* which in turn activates the semantically related *sweet*—have been demonstrated (Marslen-Wilson & Zwitserlood, 1989). Both low-level phonetic cues and high-level grammatical, semantic and pragmatic information can influence this process, but the *continuous processing of multiple competing candidates* is the essential dynamic underlying word recognition (Magnuson, Mirman, & Myers, 2013).

What about young children who know considerably fewer words? Eyetracking studies with toddlers have suggested a developmental continuity between toddlers and adult listeners. Children recognize words incrementally (Swingley, Pinto, & Fernald, 1999), match truncated words to their intended referents (Fernald, Swingley, & Pinto, 2001), and use information from neighboring words in a sentence to facilitate word recognition. This information can be grammatical: Lew-Williams & Fernald (2007) found that Spanish-acquiring preschoolers can use grammatical gender on determiners (*el* or *la*) to anticipate the word named in a two-object word recognition task. The information can also be subcategorical phonetic variation: We found that English-acquiring toddlers look earlier to a named image when the coarticulatory formant cues on word *the* predict the noun of the sentence, compared to tokens with neutral coarticulation (Tristan Mahr, McMillan, Saffran, Ellis Weismer, & Edwards, 2015).

There is some evidence for lexical competition where children are sensitive to phonological and semantic similarities among words. Ellis Weismer, Haebig, Edwards, Saffran, & Venker (2016) showed that toddlers (14–29 months old) looked less reliably to a named image when the onscreen competitor was a semantically related word or perceptually similar image. In Law, Mahr, Schneeberg, & Edwards (2016), preschoolers (28–60 months old) demonstrated sensitivity to semantic and phonological competitors in a four-image eyetracking task. Huang & Snedeker (2011) presented evidence of cascading semantic-phonological activation in five-year-olds such that for a target word like *log*, children looked more to an indirect phonological competitor like *key* (competing through its activation of *lock*) than they looked to an unrelated image like *carrot*. In contrast to these studies which all demonstrate interference from similar words, Mani & Plunkett (2010) demonstrated cross-modal phonological priming effects in 18-month-olds. In this study, a picture of prime word (e.g., cat or teeth) was presented in silence; then two images (e.g., cup and shoe) were presented, one of which was named (*cup*). Children on average looked more to the target word (like *cup*) when it was primed by an image of a phonological neighbor (like *cat*), and the children performed at chance when the prime was not related to the named word. Mani, Durrant, & Floccia (2012) found a similar result for cascading phonological-semantic priming with 24-month-olds: Children looked more to a target *shoe* compared to a distractor *door* when primed by an image of *clock*, assumed to activate *sock* which primed *shoe*.

The above studies involved young children of different ages tested under different procedures, sometimes in different dialects and languages. Averaging these results together, so to speak, the studies suggest that early word recognition demonstrates some hallmarks of adult behavior: Continuous processing of words, integration of information from different levels of representation, and the influence of similar, unspoken words on recognition of a word. Nevertheless, we only have a fragmented view of how familiar word recognition and lexical competition develop within children.

One open question is how lexical competition develops within children. For example, do phonological similar words exert more interference during word recognition as children grow older? As a guiding hypothesis, we can think of word learning as a gradual process where familiarity with a word moves from shallow receptive knowledge to deeper expressive knowledge. In adult listeners, words compete and inhibit one another, so that a word is truly "learned" and integrated into the lexicon when it can influence the processing of other words (a line of reasoning reviewed by Kapnoula, Packard, Gupta, & McMurray, 2015). Increasing sensitivity to similar sounding words over time would reveal that children improve their ability to consider multiple candidates in parallel. By studying how sensitivity to similar-sounding and similar-meaning words develop over time and within ever-growing vocabularies, this project can reveal how children come to process words efficiently.

Another avenue for studying word recognition is to examine how listeners respond to unfamiliar or novel stimuli. A productive line of research has found that children are sensitive to mispronunciations during word recognition (e.g., Swingley & Aslin, 2000, 2002). White & Morgan (2008) presented toddlers with images of a familiar and novel object, and children heard a correct production of the familiar object, mispronunciations of the familiar object of varying severity, or an unrelated nonword. Toddlers looked less to a familiar word when the first segment was mispronounced. Moreover, they demonstrated graded sensitivity such that a 1-feature mispronunciation yielded more looks to an image than a 2-feature mispronunciation, and a 2-feature mispronunciation yielded more looks than a 3-feature one. Finally, in the nonword condition, the children looked more to the novel object than the familiar one, demonstrating *fast referent selection* as they associated novel words to novel objects in the moment. A similar pattern of effects was observed in the mispronunciation study by Law & Edwards (2015) with preschoolers mapping real words to familiar objects, nonwords to novel objects, and equivocating about mispronunciations of familiar words.

As with lexical competition, it is unclear how children's responses to mispronunciations and novel words change over time or how individual differences among children change over time. For example, do children become more forgiving of mispronunciations as they mature and learn more words? We might expect so, as children become more experienced at listening to noisy, degraded, or misspoken speech.

Another open question involves the development of fast referent selection. At face value, we might expect a child's ability to associate new words with unfamiliar objects to be more direct measure of word-learning capacity than a child's ability to process known words. Under this assumption, we would expect individual differences in fast referent selection to be highly correlated with vocabulary growth. But McMurray et al. (2012) propose that the same basic process is at play in both recognition of familiar words and fast association of nonwords. In experiments, the observed behaviors are the same: Children hear a word and direct their attention to an appropriate referent. This project can tackle these questions by describing how mispronunciations are processed as children grow older and by examining whether familiar word recognition and fast referent selection dissociate and which one is a better predictor of vocabulary growth.

Individual Differences in Word Recognition

We have a rough understanding of the development of word recognition, and these gaps in knowledge matter because young children differ in their word recognition abilities. These differences are usually measured using *accuracy* (a probability of recognizing to a word) or *efficiency* (a reaction time or some measure of how quickly accuracy changes over time). These differences are consequential too, as word recognition differences correlate with other language measures concurrently, retrospectively, and prospectively.

The best predictor of lexical processing efficiency is concurrent vocabulary size: Children who know more words look more quickly and reliably to a named word (e.g., Law & Edwards, 2015).

This fact deserves a brief reflection: Suppose the information processing mechanism behind word recognition were just a naïve table search. Then this finding is somewhat puzzling: Children with larger lexicons have to find a needle in a larger haystack—yet this apparent liability is an advantage. That is why the search analogy is naïve. One explanation follows from the earlier described idea about graded word learning: Children become better at recognizing words as they learn more words because they extract regularities and discover similarities among words and develop more efficient lexical representations—the haystack develops regularity and becomes easier to search.

Although it is a robust predictor of word recognition, vocabulary size is nonspecific. For lexical processing dynamics, vocabulary size can be considered an indicator for the organization and efficiency of a child's lexicon, but it also correlates with other (meaningful) differences. Vocabulary is related to differences in speech perception (Cristia, Seidl, Junge, Soderstrom, & Hagoort, 2014) and environmental factors like language input (e.g., Hart & Risley, 1995; Hoff, 2003). For instance, measures of speech perception at 6–8 months predict vocabulary size at 24 months (Kuhl et al., 2008; e.g., Tsao, Liu, & Kuhl, 2004), so processing predicts future vocabulary predicts concurrent processing.

A related complication is the apparent predictive validity of word recognition measures. Marchman & Fernald (2008) found that vocabulary size and lexical processing efficiency at age 2 jointly predicted working memory scores and expressive language scores at age 8. This result would suggest domain-general processing advantages influence word learning. Fernald & Marchman (2012) also found that late talkers who looked more quickly to a named word at 18 months showed larger gains in vocabulary by 30 months compared to late-talkers who looked more slowly at 18 months. Weisleder & Fernald (2013) found that lexical processing and language input at 19 months predict vocabulary size at 25 months and that lexical processing mediated the effect of language input.

Word recognition efficiency and vocabulary size are interconnected measures with concurrent and predictive associations. This project can clarify this relationship by examining the co-development of word recognition, vocabulary size, and speech perception. In particular, I will ask how individual differences in word recognition change over time alongside differences in vocabulary. I can also which features of word recognition (fast referent selection, lexical competition, etc.) are most predictive of vocabulary outcomes at age 5. The additional measures of speech perception can also help clarify the specific effects of vocabulary size on word recognition.

Summary

This project studies word recognition in children over three years, so it will provide the first longitudinal study of word recognition in preschoolers. Children in this cohort cover a range of vocabulary scores at Time 1, and this variability allows one to investigate individual differences in vocabulary and word recognition over time and assess the predictive value of these measures. Furthermore, this project studies word recognition in two experimental tasks that can tap into different aspects of word recognition. Specifically, a four-image experiment with semantic and phonological foils allows me to study how lexical competition develops, and a two-image experiment with nonwords and mispronunciations enables me to study how fast referent selection develops over time as well. I will use mixed effects modeling to study not just gross measures of accuracy or interference from distractors, but the time course and lexical dynamics of word recognition using growth curve analyses.

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Research Hypotheses

In this section, I outline the main hypotheses I plan to study for each specific aim. This section is intended to preregister the main analyses for this project, so I can cleanly separate confirmatory and exploratory results.

Specific Aim 1 (Familiar Word Recognition and Lexical Competition)

- Children's accuracy and efficiency of recognizing words will improve each year.
- There are stable individual differences in lexical processing of familiar words such that children who are relatively fast at age 3 remain relatively fast at age 4 and age 5.

- However, the magnitude of these individual differences diminishes over time, as children converge on a mature level of performance for this paradigm.

- As a consequence, individual differences in word recognition at age 3, for example, will be more discriminating and predictive of age 5 language outcomes than differences at age 4.

- Children will become more sensitive to lexical competitors as they age, based on the hypothesis that children discover similarities among words as a consequence of learning more and more words.

- Children will differ in their sensitivity to lexical competitors, and these individual differences will correlate with other child-level measures.

Specific Aim 2 (Referent Selection and Mispronunciations)

- Children's accuracy and efficiency of recognizing real words and fast-associating nonwords will improve each year.

- Performance in real word recognition and fast association of nonwords will be highly correlated, based on the hypothesis that the same process (referent selection) operates in both situations.

- Under the alternative hypothesis, real word recognition and fast referent selection reflect different skills with different developmental trajectories. Thus, if there is any dissociation between recognition of real words and nonwords, it will be observed in younger children.

- Although these two measures will be correlated, I predict performance in the nonword condition will be a better predict of future vocabulary growth than performance in the real word condition. This hypothesis is based on the idea that fast referent selection is a more relevant skill for learning new words than recognition of known words.

- For the mispronunciations, I predict children with larger vocabularies (that is, older children) will be more likely to tolerate a mispronunciation as a production of familiar word compared to children with smaller vocabularies.

- Mispronunciations that feature later-mastered sounds (e.g., *rice/wice*) will be more likely to be associated to novel objects than earlier-mastered sounds (*duck/guck*).

AIM 1: FAMILIAR WORD RECOGNITION AND LEXICAL COMPETITION

5
Method

Participants

The participants were 28–39 months-old at Time 1, 39–52 at Time 2, and 51–65 at Time 3. Approximately, 180 children participated at Time 1, 170 at Time 2, and 160 at Time 3. Of these children, approximately 20 were identified by their parents as late talkers. Prospective families were interviewed over telephone before participating in the study. Children were not scheduled for testing if a parent reported language problems, vision problems, developmental delays, or an individualized education program for the child. Recruitment and data collection occurred at two Learning to Talk lab sites—one at the University of Wisconsin–Madison and the other at the University of Minnesota.

Table 5.1 summarizes the cohort of children in each year of testing. The numbers and summary statistics here are general, describing children who participated at each year, but whose data may have been excluded from the analyses. Some potential reasons for exclusion include: excessive missing data during eyetracking, experiment or technology error, developmental concerns not identified until later in study, or a failed hearing screening. Final sample sizes will depend on the measures needed for an analysis and the results from data screening checks. For each project aim, I will disclose all measurements and data exclusions following guidelines by the Center for Open Science (Nosek et al., 2014).

Table 5.1: Participant characteristics. Education levels: *Low*: less than high school, or high school; *Middle*: trade school, technical or associates degree, some college, or college degree; and *High*: graduate degree.

	Year 1 (Age 3)	Year 2 (Age 4)	Year 3 (Age 5)
N	184	175	160
Boys, Girls	94, 90	89, 86	82, 78
Maternal education: Low, Middle, High	15, 98, 71	12, 92, 71	6, 90, 64
Dialect: MAE, AAE	171, 13	163, 12	153, 7
Parent-identified late talkers	20	19	16
Age (months): Mean (SD) [Range]	33 (3) [28–39]	45 (4) [39–52]	57 (4) [51–66]
EVT-2 standard score: Mean (SD)	115 (18)	118 (16)	118 (14)
PPVT-4 standard score: Mean (SD)	113 (17)	120 (16)	—
GFTA-2 standard score: Mean (SD)	92 (13)	—	91 (13)

Special case data screening

(*Skip for now.* This is where I review the participant notes and will remove children who have to be excluded for other reasons, like being diagnosed with a language disorder at TimePoint 3.)

Procedure

This experiment used a version of the Visual World Paradigm for word recognition experiments (Law et al., 2016). In eyetracking studies with toddlers, two familiar images are usually presented: a target and a distractor. This experiment is a four-image eyetracking task that was designed to provide a more demanding word recognition task for preschoolers. In this procedure, four familiar images are presented onscreen followed by a prompt to view one of the images (e.g., *find the bell!*). The four images include the target word (e.g., *bell*), a semantically related word (*drum*), a phonologically similar word (*bee*), and an unrelated word (*swing*). Figure 5.1 shows an example of a trial's items. This procedure measures a child's real-time comprehension of words by capturing how the child's gaze location changes over time in response to speech.

Experiment Administration

Children participating in the study were tested over two lab visits (i.e., on different dates). The first portion of each visit involved "watching movies"—that is, performing two blocks of eyetracking experiments. A play break or hearing screening occurred between the two eyetracking blocks, depending on the visit.

Each eyetracking experiment was administered as a block of trials (24 for this experiment and 38 for a two-image task—see chapter X). Children received two different blocks of each experiment. The blocks for an experiment differed in trial ordering and other features. Experiment order and block selection were counterbalanced over children and visits. For example, a child might have received Exp. 1 Block A and Exp. 2 Block B on Visit 1 and next received Exp. 2 Block A and Exp. 1 Block B on Visit 2. The purpose of this presentation was to control possible ordering effects where a particular experiment or block benefited from consistently occurring first or second.

Experiments were administered using E-Prime 2.0 and a Tobii T60XL eyetracker which recorded gaze location at a rate of 60 Hz. The experiments were conducted by two examiners, one "behind the scenes" who controlled the computer running the experiment and another "onstage" who guided the child

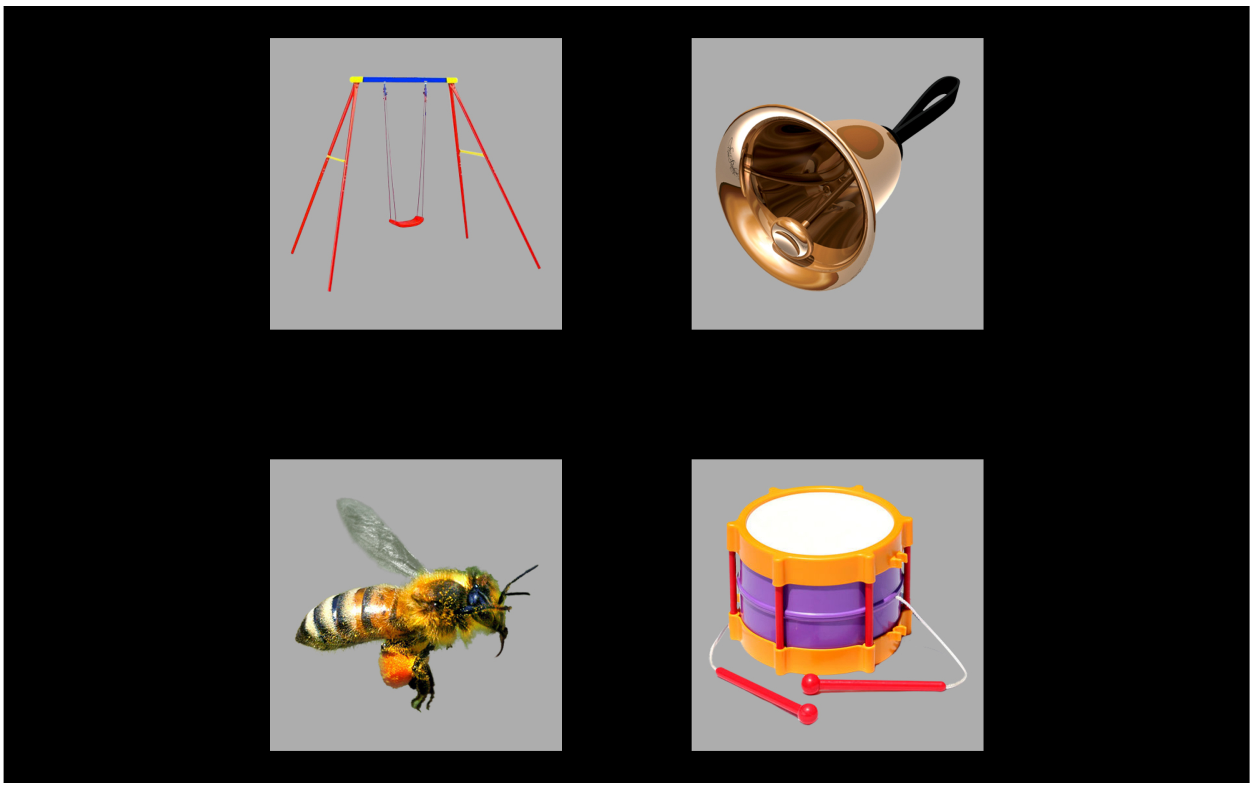


Figure 5.1: Example display for the target *bell* with the semantic foil *drum*, the phonological foil *bee*, and the unrelated *swing*.

through the experiment. At the beginning of each block, the child was positioned so the child's eyes were approximately 60 cm from the screen. The examiners calibrated the eyetracker to the child's eyes using a five-point calibration procedure (center of screen and centers of four screen quadrants). The examiners repeated this calibration procedure if one of the five calibration points for one of the eyes did not calibrate successfully. During the experiment, the behind-the-scenes examiner monitored the child's distance from the screen and whether the eyetracker was capturing the child's gaze. The onstage examiner coached the child to stay fixated on the screen and repositioned the child as needed to ensure the child's eyes were being tracked. Every six or seven trials in a block of an experiment, the experiment briefly paused with a reinforcing animation or activity. During these breaks, the onstage examiner could reposition the child if necessary before resuming the experiment.

We used a gaze-contingent stimulus presentation. First, the images appeared in silence on screen for 2 s as a familiarization period. The experiment then checked whether the child's gaze was being recorded. If the experiment could continuously track the child's gaze for 300 ms, the child's gaze was verified and the trial continued. If the experiment could not verify the gaze after 10 s, the trial continued. This procedure guaranteed that for most trials, the child was looking to the display before presenting the carrier phrase and that the experiment was ready to record the child's response to the carrier. During Year 1 and Year 2, an attention-getter (e.g., *check it out*!) played 1 s following the end of the target noun. These reinforcers were dropped in Year 3 to streamline the experiment for older listeners.

Stimuli

A few sentences to reiterate what the four kinds of images represented. The four images on each trial consisted of a target noun, a phonological foil, a semantic foil, and an unrelated word. A complete list of the items used in the experiment in Appendix B.

The stimuli were recorded in both Mainstream American English (MAE) and African American English (AAE), so that the experiment could accommodate the child's home dialect. Prior to the lab visit, we made a preliminary guess about the child's home dialect, based on the recruitment channel, address, among other factors. If we expected the dialect to be AAE, then the lab visit was led by an examiner who natively spoke AAE and could fluently dialect-shift between AAE and MAE. At the beginning of the lab visit, the examiner listened to the interactions between the child and caregiver in order to confirm the child's home dialect. Prompts to view the target image of a trial (e.g., *find the girl*) used the carrier phrases "find the" and "see the". These carriers were recording in the frame "find/see the egg" and cross-spliced with the target nouns to minimize coarticulatory cues on the determiner "the".

The images used in the experiment consisted of color photographs on gray backgrounds. These images were piloted with 30 children from two preschool classrooms to ensure that children consistently used the same label for familiar objects. The two preschool classrooms differed in their students' SES demographics: One classroom (13 piloting students) was part of a university research center which predominantly serves higher-SES families, and the other classroom (17 piloting students) was part of Head Start center which predominantly serves lower-SES families. The images were tested by presenting four images (a target, a phonological foil, a semantic foil and an unrelated word) and having the student point to the named image. The pictures had to be recognized by at least 80% of students in each classroom.

Data screening

To process the eyetracking data, we first mapped gaze *x-y* coordinates onto the onscreen images. We next performed *deblinking*. We interpolated short runs of missing gaze data (up to 150 ms) if the same image was fixated before and after the missing data run. Put differently, we classified a window of missing data as a blink if the window was brief and the gaze remained on the same image before and after the blink. We interpolated missing data from blinks using the fixated image.

After mapping the gaze coordinates onto the onscreen images, we performed data screening. We considered the time window from 0 to 2000 ms after target noun onset. We identified a trial as *unreliable* if at least 50% of the looks were missing during the time window. We excluded an entire block of trials if it had fewer than 12 reliable trials.

Table 5.2 shows the numbers of participants and trials at each timepoint before and after data screening.

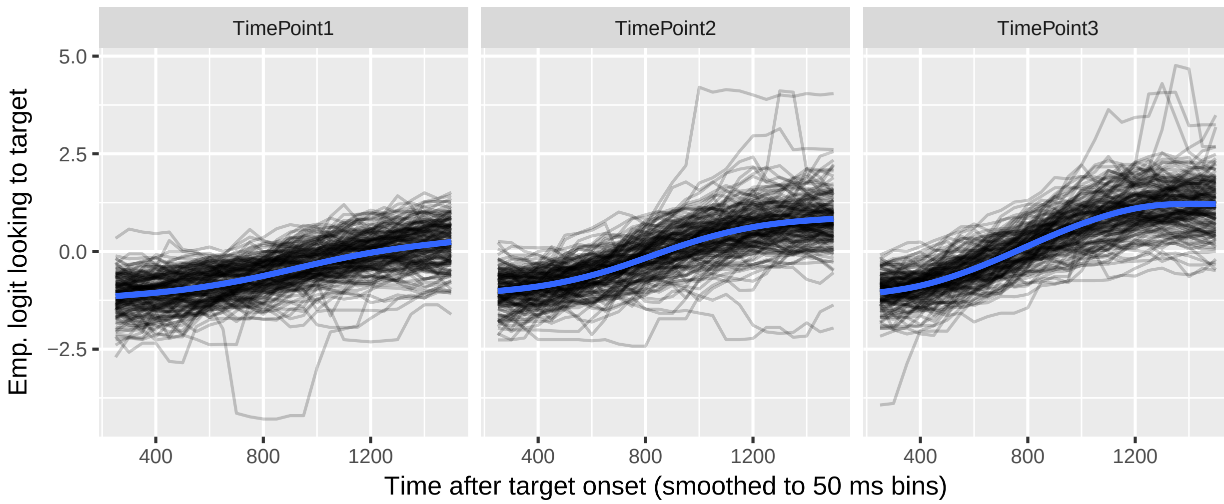
Table 5.2: Eyetracking data before and after data screening. For convenience, the number of exclusions are included as Raw - Screened.

Dataset	Study	N Children	N Blocks	N Trials
Raw	TimePoint1	178	332	7967
	TimePoint2	180	347	8327
	TimePoint3	163	322	7724
Screened	TimePoint1	163	291	5951
	TimePoint2	165	305	6421
	TimePoint3	156	295	6483
NA	TimePoint1	15	41	2016
	TimePoint2	15	42	1906
	TimePoint3	7	27	1241

There were more children in the second timepoint than the first timepoint due to a timing error in the initial version of this experiment, leading to the exclusion of 27 participants from the first timepoint.

Prepare the dataset for modeling

To prepare the data for modeling, we downsampled the data into 50-ms (3-frame) bins, reducing the eyetracker's effective sampling rate to 20 Hz. Eye movements have durations on the order of 100 or 200 ms, so capturing data every 16.67 ms oversamples eye movements and can introduce high-frequency noise into the signal. Binning together data from neighboring frames can smooth out this noise. We modeled the looks from 250 to 1500 ms. Lastly, we aggregated looks by child, study and time, and created orthogonal polynomials to use as time features for the model.



TimePoint1
TimePoint2
TimePoint3
Emp. logit looking to target
5.0
2.5
0.0
−2.5
400
800
1200
Time after target onset (smoothed to 50 ms bins)

6

Analysis of familiar word recognition

Growth curve analysis

Looks to the familiar image were analyzed using Bayesian mixed effects logistic regression. I used *logistic* regression because the outcome measurement is a probability (the log-odds of looking to the target image versus a distractor). I used *mixed-effects* models to estimate a separate growth curve for each child (to measure individual differences in word recognition) but also treat each child's individual growth curve as a draw from a distribution of related curves. I used *Bayesian* techniques to study a generative model of the data. Instead of reporting and describing a single, best-fitting model of some data, Bayesian methods consider an entire distribution of plausible models that are consistent with the data and any prior information we have about the models. By using this approach, one can explicitly quantify uncertainty about statistical effects and draw inferences using estimates of uncertainty (instead of using statistical significance—which is not a straightforward matter for mixed-effects models).[1]

The eyetracking growth curves were fit using an orthogonal cubic polynomial function of time (a now-conventional approach; see Mirman, 2014). Put differently, I modeled the probability of looking to the target during an eyetracking task as:

$$\text{log-odds}(\textit{looking}) = \beta_0 + \beta_1 \text{Time}^1 + \beta_2 \text{Time}^2 + \beta_3 \text{Time}^3$$

That the time terms are *orthogonal* means that Time^1, Time^2 and Time^3 are transformed so that they are uncorrelated. Under this formulation, the parameters β_0 and β_1 have a direct interpretation in terms of lexical processing performance. The intercept, β_0, measures the area under the growth curve—or the probability of fixating on the target word averaged over the whole window. We can think of β_0 as a measure of *word recognition reliability*. The linear time parameter, β_1, estimates the steepness of the growth curve—or how the probability of fixating changes from frame to frame. We can think of β_1 as a measure of *processing efficiency*, because growth curves with stronger linear features exhibit steeper frame-by-frame increases in looking probability.[2]

To study how word recognition changes over time, I modeled how the growth curves change over developmental time. This amounted to studying how the growth curve parameters changes year over year. I included dummy-coded indicators for Age 3, Age 4, and Age 5 and allowed these indicators interact with the growth curve parameters. These year-by-growth-curve terms captured how the shape of the growth

[1] It is tempting to further justify this approach by comparing Bayesian versus classical/frequentist statistics, but my goals in using this method are simple: To estimate statistical effects and quantify uncertainty about those effects. This pragmatic brand of Bayesian statistics is illustrated in texts by Gelman & Hill (2007) and McElreath (2016).

[2] The polynomial other terms are less important—or rather, they have do not map as neatly onto behavioral descriptions as the accuracy and efficiency parameters. The primary purpose of quadratic and cubic terms is to ensure that the estimated growth curve adequately fits the data. In this kind of data, there is a steady baseline at chance probability before the child hears the word, followed a window of increasing probability of fixating on the target as the child recognizes the word, followed by a period of plateauing and then diminishing looks to target. The cubic polynomial allows the growth curve to be fit with two inflection points: the point when the looks to target start to increase from baseline and the point when the looks to target stops increasing.

curves changed each year. The model also included random effects to represent child-by-year effects.

Growth curve features as measures of word recognition performance

As mentioned above, two of the model's growth curve features have straightforward interpretations in terms of lexical processing performance: The model's intercept parameter corresponds to the average proportion or probability of looking to the named image over the trial window, and the linear time parameter corresponds to slope of the growth curve or lexical processing efficiency. I also was interested in *peak* proportion of looks to the target. I derived this value by computing the growth curves from the model and taking the median of the five highest points on the curve. Figure 6.1 shows three simulated growth curves and how each of these growth curve features relate to word recognition performance.

Year over year changes in word recognition performance

The mixed-effects model estimated a population-average growth curve ("fixed" effects) and how individual children deviated from average ("random" effects). Figure 6.2 shows 200 posterior samples of the average growth curves for each study. On average, the growth curves become steeper and achieve higher looking probabilities with each year of the study.

Figure 6.3 depicts uncertainty intervals with the model's average effects of each timepoint on the growth curve features. The intercept and linear time effects increased each year, confirming that children become more reliable and faster at recognizing words as they grow older. The peak accuracy also increased each year. For each effect, the change from age 3 to age 4 is approximately the same as the change from age 4 to age 5, as visible in Figure 6.4.

The average looking probability (intercept feature) was 0.38 [90% UI: 0.37–0.40] at age 3, 0.49 [0.47–0.50] at age 4, and 0.56 [0.54–0.57] at age 5. The averages increased by 0.10 [0.09–0.11] from age 3 to age 4 and by 0.07 [0.06–0.09] from age 4 to age 5. The peak looking probability was 0.55 [0.53–0.57] at age 3, 0.68 [0.67–0.70] at age 4, and 0.77 [0.76–0.78] at age 5. The peak values increased by 0.13 [0.11–0.16] from age 3 to age 4 and by 0.09 [0.07–0.10] from age 4 to age 5. These results numerically confirm the

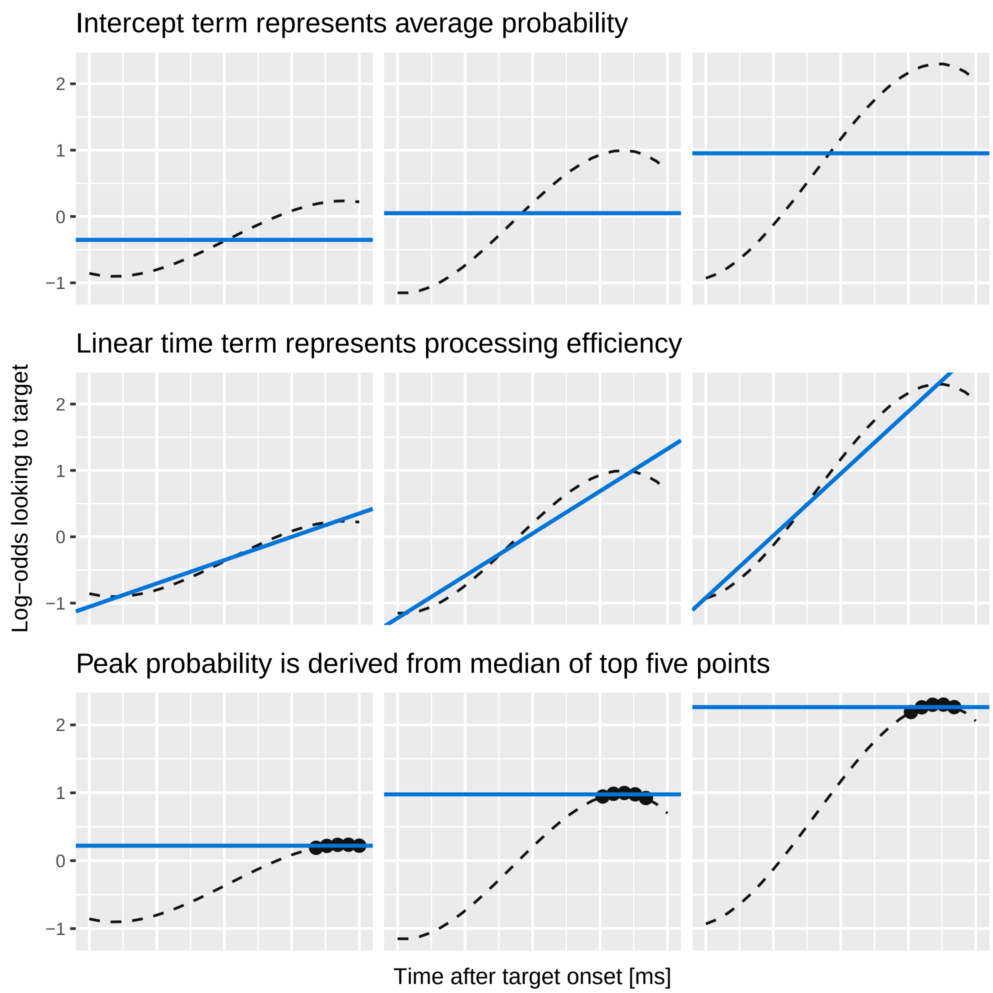


Figure 6.1: Illustration of the three growth curve features and how they describe lexical processing performance. The three curves used are simulations of new participants at Age 4.

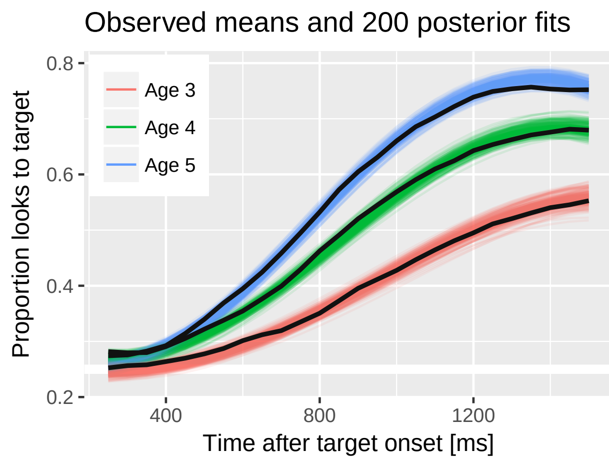


Figure 6.2: The model estimated an average word recognition growth for each study, and the colored lines represent 200 posterior samples of these growth curves. The thick dark lines represent the observed average growth curve in each study.

hypothesis that children would improve in their word recognition reliability, both in terms of average looking and in terms of peak accuracy, each year.

Summary. The average growth curve features increased year over year, so that children looked to the target more quickly and more reliably.

Exploring plausible ranges of performance over time

Bayesian models are generative; they describe how the data could have been generated. This model assumed that each child's growth curve was drawn from a population of related growth curves, and it tried to infer the parameters over that distribution. These two aspects—a generative model and learning about the population of growth curves—allow the model to simulate new samples from that distribution of growth curves. That is, we can predict a set of growth curves for a hypothetical, unobserved child drawn from the same distribution as the 195 observed children. This procedure allows one to explore the plausible degrees of variability in performance at each age.

Figure 6.5 shows the posterior predictions for 1,000 simulated participants, which demonstrates how the

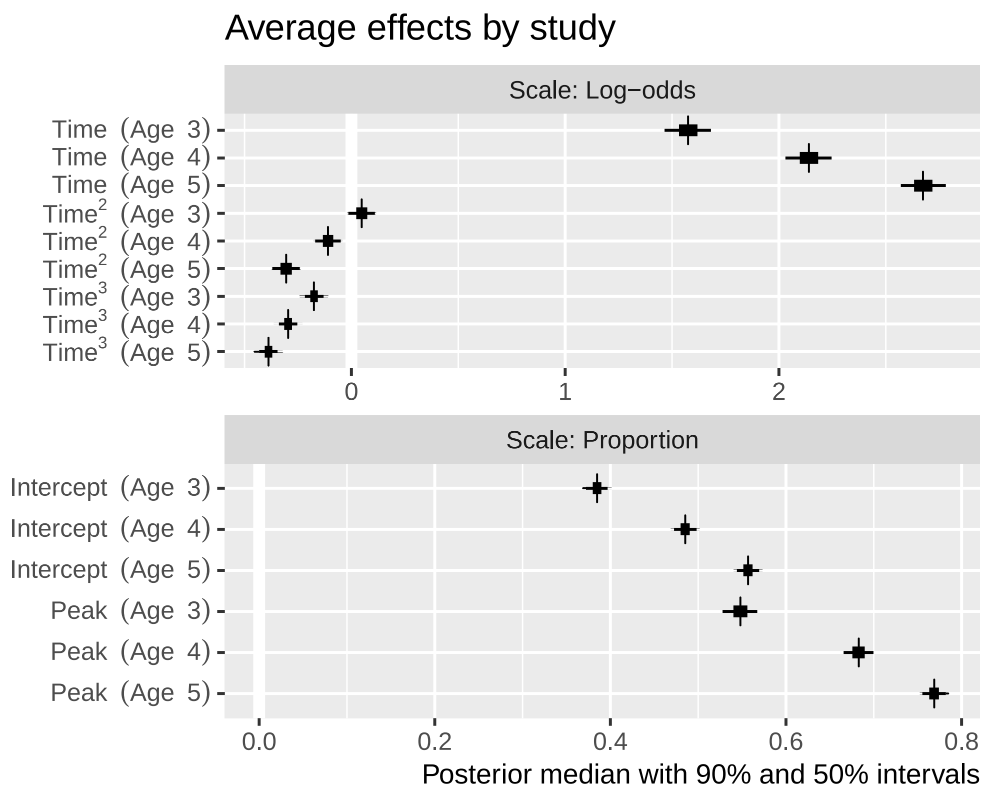


Figure 6.3: Uncertainty intervals for the effects of study years on growth curve features. The intercept and peak features were converted from log-odds to proportions to ease interpretation.

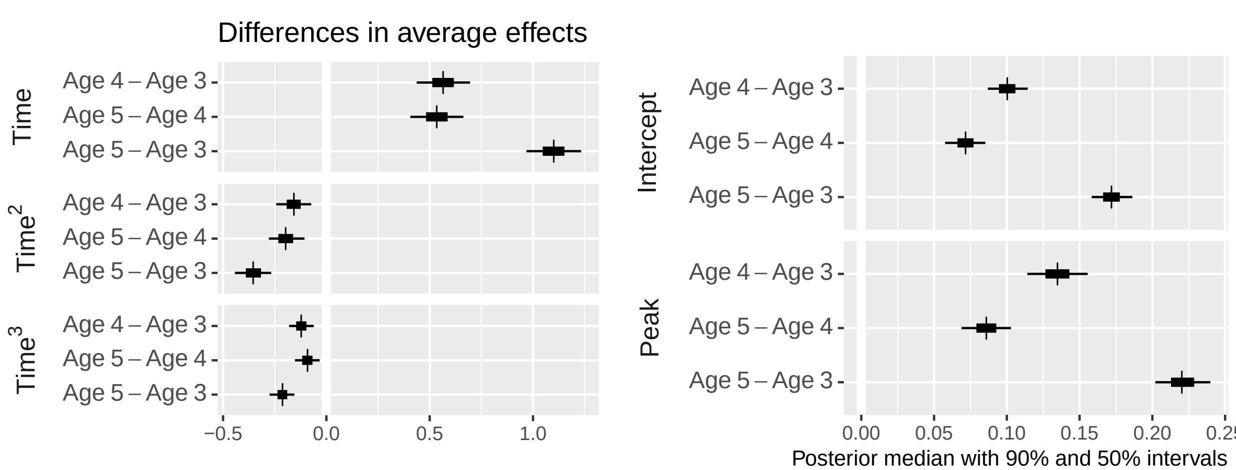


Figure 6.4: Uncertainty intervals for the differences between study timepoints. Again, the intercept and peak features were converted to proportions.

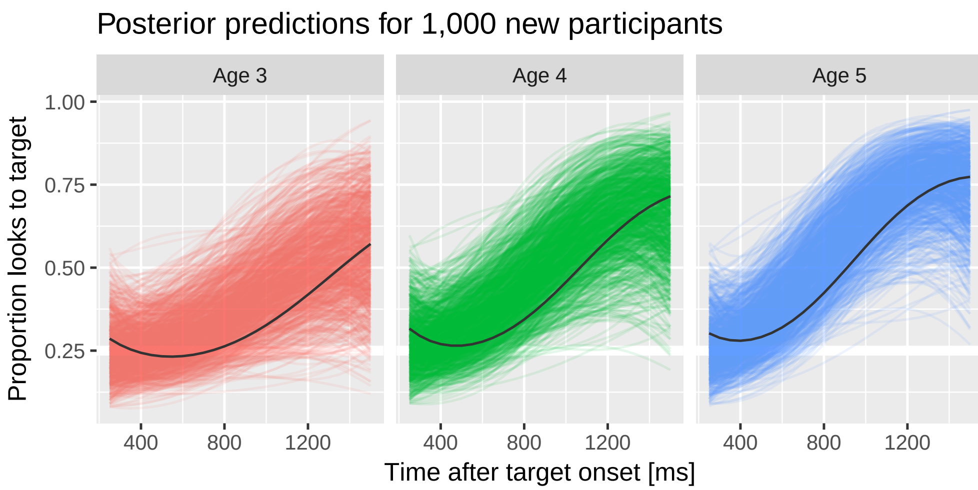


Figure 6.5: Posterior predictions for hypothetical *unobserved* participants. Each line represents the predicted performance for a new participant. The three dark lines highlight predictions from one single simulated participant. The simulated participant shows both longitudinal improvement in word recognition and similar relative performance compared to other simulations each year, indicating that the model would predict new children to improve year over year and show stable individual differences over time.

model expects new participants to improve longitudinally but also exhibit stable individual differences over time. Figure 6.6 shows uncertainty intervals for these simulations. The model learned to predict less accurate and more variable performance at age 3 with improving accuracy and narrowing variability at age 4 and age 5.

I hypothesized that children would become less variable as they grew older and converged on a mature level of performance. I address this question by inspecting the ranges of predictions for the simulated participants. The claim that children become less variable would imply that the range of predictions should be narrower age 5 than for age 4 than age 3. Figure 6.7 depicts the range of the predictions, both in terms of the 90 percentile range (i.e., the range of the middle 90% of the data) and in terms of the 50 percentile (interquartile) range. The ranges of performance decrease from age 3 to age 4 to age 5, consistent with the hypothesized reduction in variability.

The developmental pattern of increasing reliability and decreasing variability was also observed for the growth curve peaks. For the synthetic participants, the model predicted that individual peak probabilities

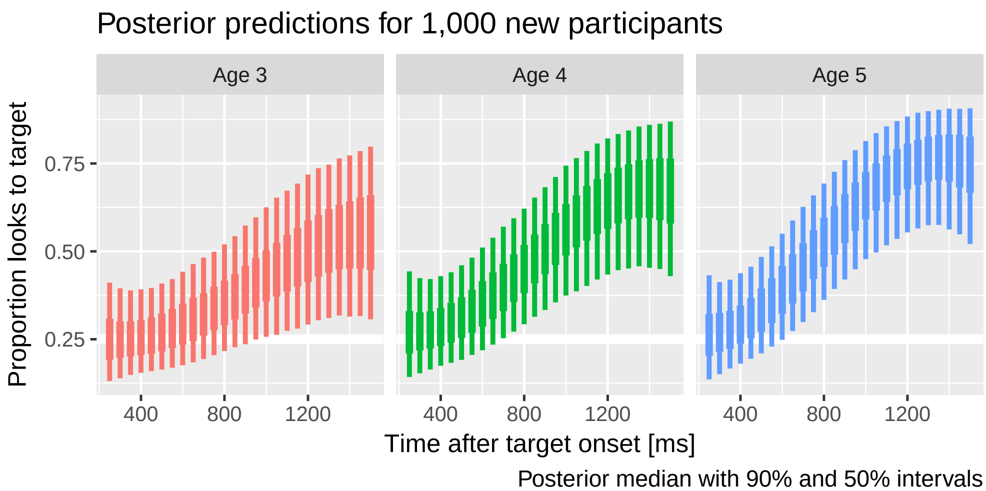


Figure 6.6: Uncertainty intervals for the simulated participants. Variability is widest at age 3 and narrowest at age 5, consistent with the prediction that children become less variable as they grow older.

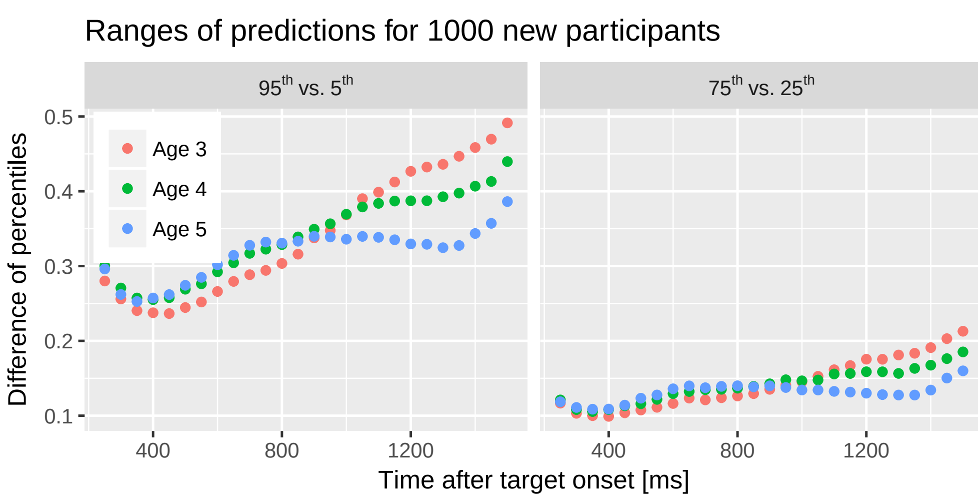


Figure 6.7: Ranges of predictions for simulated participants over the course of a trial. The ranges are most similar during the first half of the trial when participants are at chance performance, and the ranges are most different at the end of the trial as children reliably fixate on the target image. The ranges of performance decreases with each year of the study as children show less variability.

will increase each year, peak3 = 0.55 [90% UI: 0.35–0.77], peak4 = 0.69 [0.48–0.86], peak5 = 0.78 [0.59–0.91]. Moreover, the range of plausible values for the individual peaks narrowed each for the simulated data. For instance, the difference between the 95th and 5th percentiles was 0.43 for age 3, 0.38 for age 4, and 0.32 for age 5.

Summary. I used the model's random effects estimates to simulate growth curves from 1,000 hypothetical, unobserved participants. The simulated dataset showed increasing looking probability and decreasing variability with each year of the study. These simulations confirmed the hypothesis that variability would be diminish as children converge on a mature level of performance on this task.

Are individual differences stable over time?

I predicted that children would show stable individual differences such that children who are faster and more reliable at recognizing words at age 3 remain relatively faster and more reliable at age 5. To evaluate this hypothesis, I used Kendall's W (the coefficient of correspondence or concordance). This nonparametric statistic measures the degree of agreement among J judges who are rating I items. For these purposes, the items are the 123 children who provided reliable eyetracking for all three years of the study. (That is, I excluded children who only had reliable eyetracking data for one or two years.) The judges are the sets of growth curve parameters from each year of study. For example, the intercept term provides three sets of ratings: The participants' intercept terms from year 1 are one set of ratings and the terms from years 2 and 3 provide two more sets of ratings. These three ratings are the "judges" used to compute the intercept's W. Thus, I computed five groups of W coefficients, one for each set of growth curve features: Intercept, Time^1, Time^2, Time^3, and Peak looking probability.

Because I used a Bayesian model, there is a distribution of ratings and thus a distribution of concordance statistics. Each sample of the posterior distribution fits a growth curve for each child in each study, so each posterior sample provides a set of ratings for concordance coefficients. The distribution of W's lets us quantify our uncertainty because we can compute W's for each of the 4000 samples from the posterior distribution.

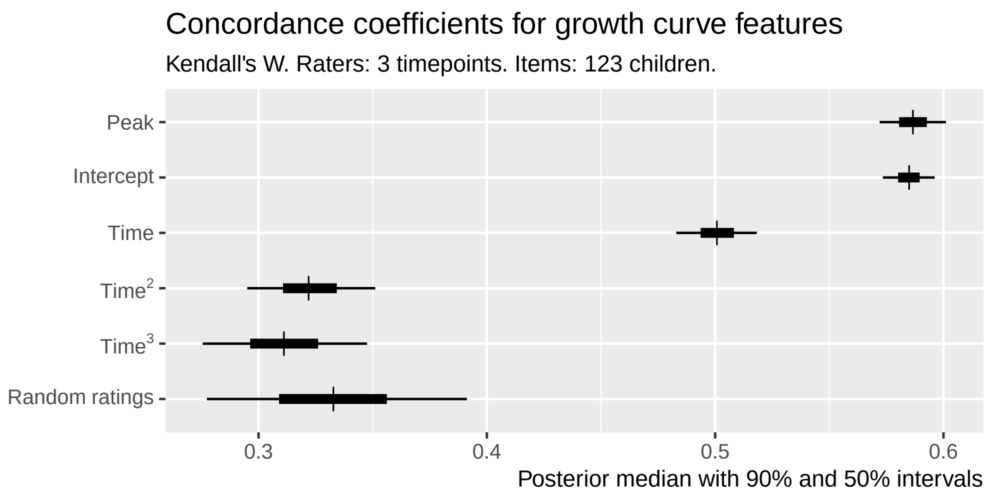


Figure 6.8: Uncertainty intervals for the Kendall's coefficient of concordance. Random ratings provide a baseline of null W statistics. The intercept and linear time features are decisively non-null, indicating a significant degree of correspondence in children's relative word recognition reliability and efficiency over three years of study.

One final matter is how to assess whether a concordance statistic is meaningful. To tackle this question, I also included a "null rater", a fake parameter that assigned each child in each year a random number. I use the distribution of W's generated by randomly rating children as a benchmark for assessing whether the other concordance statistics differ meaningfully from chance.

We used the `kendall()` function in the irr R package (vers. 0.84; Gamer, Lemon, & Singh, 2012) to compute concordance statistics. Figure 6.8 depicts uncertainty intervals for the Kendall W's for these growth curve features. The 90% uncertainty interval of W statistics from random ratings [0.28–0.39] subsumes the intervals for the Time^2 effect [0.30–0.35] and the Time^3 effect [0.28–0.35], indicating that these values do not differentiate children in a longitudinally stable way. That is, the Time^2 and Time^3 features differentiate children across studies as well as random numbers. Earlier, I stated that only the intercept, linear time, and peak features have psychologically meaningful interpretations and that the higher-order features of these models serve to capture the shape of the growth curve data. These concordance statistics support that assertion.

Concordance is strongest for the peak feature, W = 0.59 [0.57–0.60] and the intercept term, W = 0.58 [0.57–0.60], followed by the linear time term, W = 0.50 [0.48–0.52]. Because these values are far removed from the statistics for random ratings, I conclude that there is a credible degree of correspondence across studies when ranking children using their peak looking probability, average look probability (the intercept) or their growth curve slope (linear time).

Summary. Growth curve features reflected individual differences in word recognition performance. By using Kendall's W to measure the degree of concordance among growth curve features over time, I tested whether individual differences in lexical processing persisted over development. I found that the peak looking probability, average looking probability and linear time features were stable over time.

Predicting future vocabulary size

I hypothesized that individual differences in word recognition at age 3 will be more discriminating and predictive future language outcomes than differences at age 4 or age 5. To test this hypothesis, we calculated the correlations of growth curve features with age 5 expressive vocabulary size and age 4 receptive vocabulary. (The receptive test was not administered during the last year of the study for logistical reasons.) As with the concordance analysis, I computed each of the correlations for each sample of the posterior distribution to obtain a distribution of correlations.

Figure 6.9 shows the correlations of the peak looking probability, average looking probability and linear time features with expressive vocabulary size at age 5, and Figure 6.10 shows analogous correlations for the receptive vocabulary at age 4. For all cases, the strongest correlations were found between the growth curve features at age 3.

Growth curve peaks from age 4 correlated with age 5 vocabulary with r = .52, 90% UI [.50–.54], but the concurrent peaks from age 5 showed a correlation of just r = .31, [.29–.33], a difference between age 3 and age 5 of $r3{-}5$ = .21, [.18–.24]. A similar pattern held for lexical processing efficiency values. Linear time features from age 3 correlated with age 5 vocabulary with r = .41, [.39–.44], whereas the concurrent lexical processing values from age 5 only showed a correlation of r = .28, [.26–.31], a difference of $r3{-}5$ = .13,

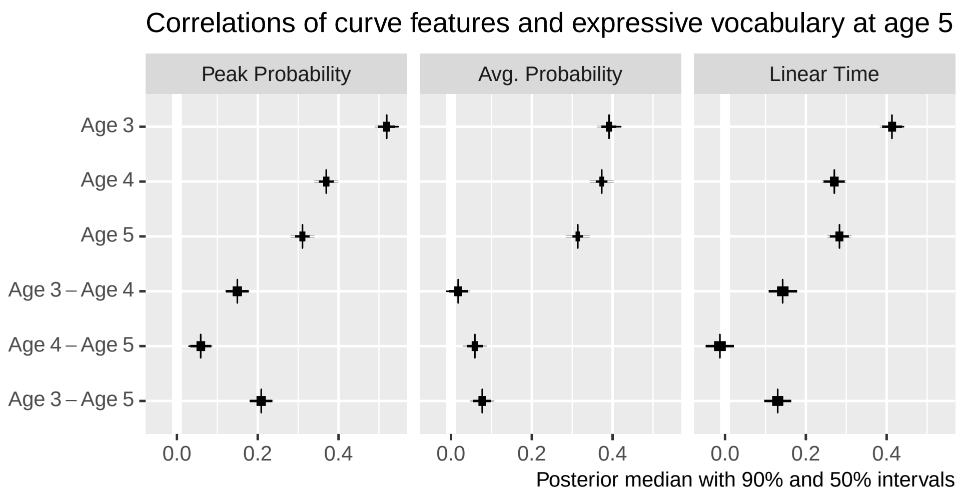


Figure 6.9: Uncertainty intervals for the correlations of growth curve features at each time point with expressive vocabulary (EVT-2 standard scores) at age 5. The bottom rows provide intervals for the pairwise differences in correlations between timepoints.

[.10–.16]. For the average looking probabilities, the correlation for age 3, r = .39, [.39–.44], was probably only slightly greater than the correlation for age 4, r3–4 = .02, [−.01–.04] but considerably greater than the concurrent correlation at age 5, r3–5 = .08, [.05–.10].

Peak looking probabilities from age 3 were strongly correlated with age 4 receptive vocabulary, r = .62, [.61–.64], and this correlation was much greater than the correlation observed for the age 4 growth curve peaks, r3–4 = .26, [.26]. The correlation of age 3 average looking probabilities, r = .45, [.44–.47], was greater than the age 4 correlation, rTP1–TP2 = .08, [.08], and the correlation for age 3 linear time features, r = .51, [.49–.54], was likewise greater, r3–4 = .22, [.19–.26].

Summary. Although individual differences in word recognition were stable over time, early differences were more significant than later ones. The strongest predictors of future vocabulary size were the growth curve features from age 3.

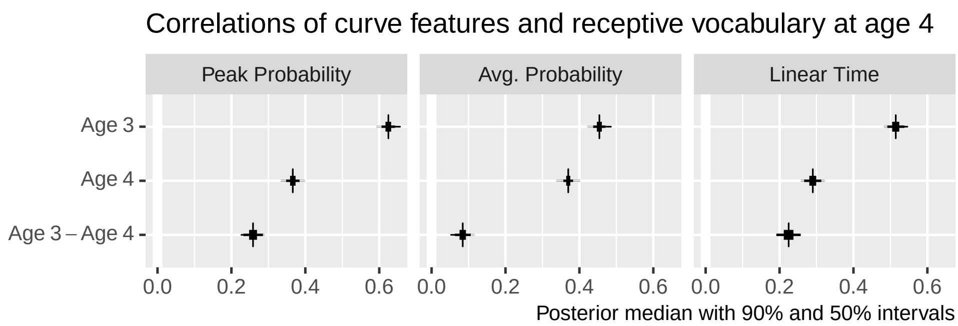


Figure 6.10: Uncertainty intervals for the correlations of growth curve features at each time point with expressive vocabulary (PPVT-4 standard scores) at age 4. The bottom row shows pairwise differences between the correlations from timepoints.

Discussion

In the preceding analyses, I analyzed many aspects of children's recognition of familiar words. First, I examined how children's looking patterns *on average* changed year over year. Children's word recognition improved each year: The growth curves grew steeper, reached higher peaks, and increased in their average value each year. This result was unsurprising, but it was valueable because it confirmed that this word recognition task scaled with development. The task was simple enough that children could recognize words at age 3, but challenging enough for children's performance to improve each year.

After establishing how the averages changed each year, I next asked how variability changed each year. To tackle this question, I used posterior predictive inference to have the model simulate samples of data, and in particular, to simulate new participants. The range of performance narrowed each year, so that children were most variable at age 3 and least variable at age 5. This result is consistent with a model of development children vary widely early on and converge on a more mature level of performance. From this perspective, word recognition as a skill is like articulation where most children grow out of immature speech patterns by grade school. An alternative outcome would have been troubling: Word recognition differences that expanded with age, the emergence of a word recognition "gap".

Although the range of individual differences decreased with age, differences did not disappear over time.

When children at each age were ranked using growth curve features, we found a high degree of correspondence among these ratings. Children who were faster or more accurate at age 3 remained relatively fast or accurate at age 5. Thus, differences in word recognition were longitudinally stable over the preschool years. Extrapolating forwards in time, these differences likely would become smaller and smaller until they are irrelevant. Alternatively, they might matter in more adverse listening conditions. It is conceivable that children's differences would re-emerge in a more difficult word recognition task. [*Study Bob's paper on older children.*]

- the vocabulary results
- Stitch these pieces together
- The shape and structure of words do not change with age. The amount of information needed to identify a word from a closed set is constant with age. So it makes sense that word recognition development follows a trajectory where differences narrow. As a skill, word recognition is a necessary foundation to later more sophisticated degrees of language comprehension. If word recognition is such a foundation, then slow listeners might show challenges in these more difficulty comprehension situations.

Summary. Although individual differences in word recognition are stable over time, early differences are more significant than later ones. The strongest predictors of future vocabulary size were the growth curve features from age 3. That is, word recognition performance from age 3 was more strongly correlated with age 5 expressive vocabulary than word recognition performance at age 5. A similar pattern of results held for predicting receptive vocabulary at age 4.

7

Effects of phonological and semantic competitors

Looks to the phonological competitor

Next, I asked how children's sensitivity to the phonological foils changed over developmental time. Following our approach in (Law et al., 2016), I only examined trials for which the phonological foil and the noun shared the same syllable onset. For example, this criterion included trials with *dress–drum*, *fly–flag*, or *horse–heart*, but it excluded trials *kite–gift* (feature difference), *bear–bread* (onset difference), and *ring–swing* (rimes). I kept 13 of the 24 trials. Appendix B provides a complete list of trials used.

The outcome measure for these analyses was the log-odds of fixating on the phonological foil versus the unrelated image. Because children looked more to the target word with each year of the study, they ne-

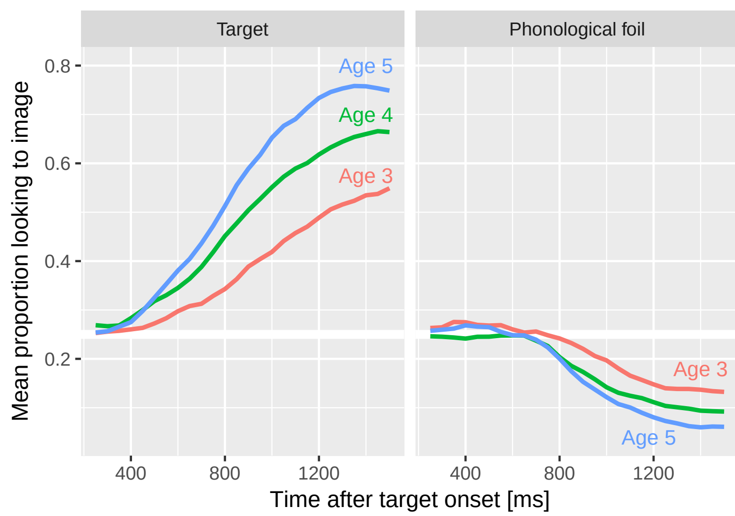


Figure 7.1: Because children looked more to the target as they grew older, they numerically looked less the foils too. This effect is why I evaluated the phonological and semantic foils by comparing them against the unrelated image.

cessarily looked less to the distractors each year. Figure 7.1 illustrates how the proportions of looks to the phonological foils declined each year. Therefore, I examined the effect of the phonological foil in comparison to the unrelated foil. For example, on the trials where the target is *fly*, we can study the effect of the phonological foil *flag* by looking at when and to what to degree the children fixate on *flag* more than the unrelated image *pen*. If a window of time of shows a consistent advantage for the phonological foil over the unrelated image, we can conclude that the children were sensitive to the phonological foil. By studying the time course of fixations to the phonological foil versus the unrelated image, we can identify when the phonological foil affected word recognition most significantly.

As in the previous models, I downsampled the data into 50-ms (3-frame) bins in order to smooth the data. I modeled the looks from to ms. Lastly, I aggregated looks by child, study and time.

To account for the sparseness of the data, I used the empirical log-odds (or empirical logit) transformation (Barr, 2008). This transformation adds .5 to the looking counts. For example, a time-frame with 4 looks to the phonological foil and 1 look to the unrelated image has a conventional log-odds of log(4/1) = 1.39 and empirical log-odds of log(4.5/1.5) = 1.10. This transformation fills in 0 counts, and it dampens the extremeness of some probabilities that arise in sparse count data.

To model these data, I fit a generalized additive model with fast restricted maximum likelihood estimation (Sóskuthy, 2017 for a tutorial for linguists; Wood, 2017). Box 1 provides a brief overview of these models. I used the mgcv R package (vers. 1.8.23; Wood, 2017) with support from the tools in the itsadug R package (vers. 2.3; van Rij, Wieling, Baayen, & van Rijn, 2017).[1]

Box 1: The Intuition Behind Generalized Additive Models.

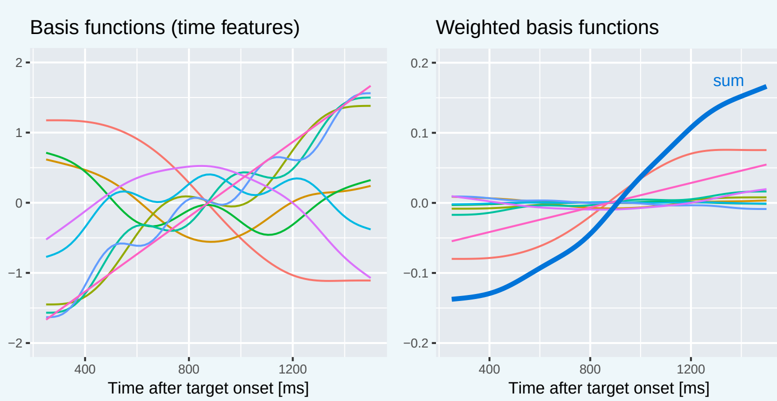
In these analyses, the outcome of interest is a value that changes over time in a nonlinear way. We model these time series by building a set of features to represent time values. In the growth curve analyses of familiar word recognition, I used a set of polynomial features which expressed time as the weighted sum of a linear trend, a quadratic trend and cubic trend. That is:

$$\text{log-odds}(\textit{looking}) = \alpha + \beta_1 * \textit{Time}^1 + \beta_2 * \textit{Time}^2 + \beta_3 * \textit{Time}^3$$

But another way to think about the polynomial terms is as *basis functions*: A set of features that combine to approximate some nonlinear function of time. Under this framework, the model can be expressed as:

$$\text{log-odds}(\textit{looking}) = \alpha + f(\textit{Time})$$

This is the idea behind generalized additive models and their *smooth terms*. These smooths fit nonlinear functions of data by weighting and adding simple functions together. The figures below show 9 basis functions from a "thin-plate spline" and how they can be weighted and summed to fit a growth curve.



Each of these basis functions is weighted by a model coefficient, but the individual basis functions are not a priori meaningful. Rather, it is the whole set of functions that approximate the curvature of the data—

[1] Initially, I tried to use Bayesian polynomial growth curve models, as in the earlier analysis of the looks to the target image. These models however did not converge, even when strong priors were placed on the parameters.

i.e., $f(\text{Time})$)—so we statistically evaluate the whole batch of coefficients simultaneously. This joint testing is similar to how one might test a batch of effects in an ANOVA. If the batch of effects jointly improve model fit, we infer that there is a significant smooth or shape effect.

Smooth terms come with an estimated degrees of freedom (EDF). These values provide a sense of how many degrees of freedom the smooth consumed. An EDF of 1 is a perfectly straight line, indicating no smoothing. Higher EDF values indicate that the smooth term captured more curvature from the data.

The model included main effects of study year. These *parametric* terms work like conventional regression effects and determined the growth curve's average values. The model used age 4 as the reference year, so the intercept represented the average looking probability at age 4. The model's year effects therefore represented differences between age 4 vs. age 3 and age 4 vs. age 5.

The model also included *smooth* terms to represent the time course of the data. As with the parametric effects, age 4 served as the reference year. The model estimated a smooth for age 4 and it estimated *difference smooths* to capture how the curvature at age 3 and age 5 differed from the age-4 curvature. Each of these study-level smooths used 10 knots (9 basis functions). I also included child-level *random smooths* to represent child-level variation in growth curve shapes. Because there is much as less data at the child level than at the study level, these random smooths only included 5 knots (4 basis functions). We can think of these simpler splines as coarse adjustments in growth curve shape to capture child-level variation from limited data. Altogether, the model contained the following terms:

$$
\begin{aligned}
\text{emp. log-odds}(\textit{phon. vs. unrelated}) = \alpha + \beta_1\text{Age3} + \beta_2\text{Age5} + & \quad \text{[growth curve averages]} \\
f_1(\text{Time}, \text{Age4}) + & \quad \text{[reference smooth]} \\
f_2(\text{Time}, \text{Age4} - \text{Age3}) + & \quad \text{[difference smooths]} \\
f_3(\text{Time}, \text{Age4} - \text{Age5}) + & \\
f_i(\text{Time}, \text{Child}_i) & \quad \text{[by-child random smooths]}
\end{aligned}
$$

The model's fitted values are shown in Figure 7.2. These are the average empirical log-odds of fixating on the pho-

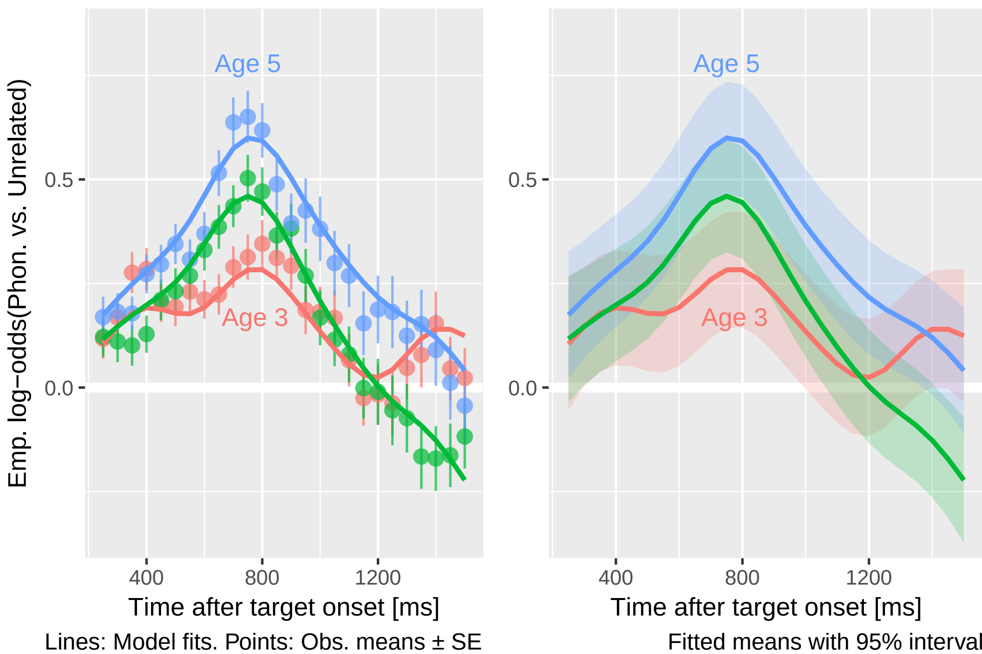


Figure 7.2: With each year of the study, children looked more to the phonological foil, relative to unrelated image, during and after the target noun. the target noun. Both figures show means for each year estimated by the generalized additive model. The left compares model estimates to observed means and standard errors, and the right visualizes estimated means and their 95% confidence intervals.

nological foil versus the unrelated image for each year of the study. The model captured the trend for increased looks to the competitor image with each year of the study. At age 4 and age 5, the shape rises from a baseline to the peak around 800 ms. These curves slope downwards and eventually fall beneath the initial baseline. The shape at age 3 does not have a steady rise from baseline and shows a very small peak around 800 ms.

The average looks to the phonological foil over the unrelated for age 4 was 0.17 emp. log-odds, .54 proportion units. The averages for age 3 and age 4 did not significantly differ, $p = .51$ but the average value was significantly greater at age 5, 0.33 emp. log-odds, .58 proportion units, $p < .001$. Visually, this effect shows up in the almost constant height difference between the age-4 and the age-5 curves.

There was a significant smooth term for time at age 4, estimated degrees of freedom (EDF) = 6.78, $p < .001$. Figure 7.3 visualizes how and when the smooths from other studies differed from the age-4 smooth.

The age-3 and age-4 significantly differed, EDF = 5.45, $p < .001$. In particular, the curves are significantly different

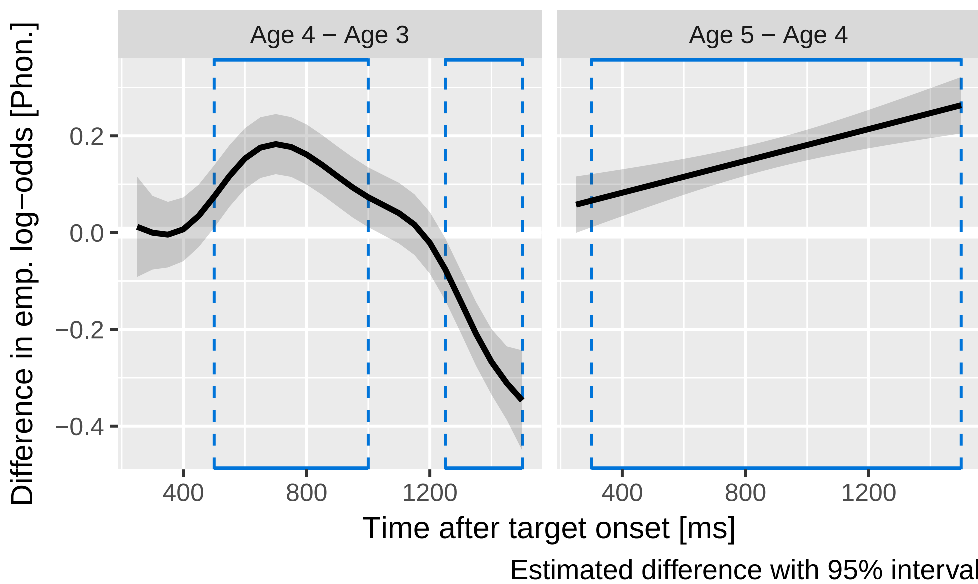


Figure 7.3: Differences in the average looks to the phonological foil versus the unrelated image between age 4 and the other ages. Plotted line is estimated difference and the shaded region is the 95% confidence interval around that difference. Blue boxes highlight regions where the 95% interval excludes zero. From age 3 to age 4, children become more sensitive to the phonological foil during and after the target noun. The curves for age 3 and age 4 have largely the same shape, but they steadily diverge over time.

from 500 to 1050 ms. This result confirms that the looks to the phonological foil increased from age 3 and age 4 during the time window immediately following presentation of the noun. The similarity between the phonological foil and the target occurs early in the trial. Given the 150–300 ms time required to execute an eye movement in response to speech, the time window for these differences indicates that children became more sensitive to the phonological similarities between the foil and the target from age 3 to age 4.

The age-3 and age-4 curves also differed significantly after 1250 ms. The effect reflects how the looks to phonological foil decreased as the trial progresses. After an incorrect look to the foil, the children on average corrected their gaze and looked even less to the phonological foil. We do not observe this degree of correction during age 3, presumably because children at age 3 hardly looked to the phonological foil early on.

The age-4 and age-5 smooths also significantly differed, EDF = 1.00, $p < .001$, although the low EDF values indicates that the shape of the difference was a flat line. Thus, the difference between the age-4 and age-5 smooths is driven primarily by the intercept difference and a linear diverging trend—that is, the distance between the two grows slightly over time. The same general curvature was observed for the two studies, reflecting the same general looking behavior at both time points. Children showed an early increase in looks to the phonological foil relative to the unrelated image but after receiving disqualifying information from the rest of the word, the looks to the phonological foil rapidly decrease. The primary difference between age-4 and age-5 is that the foil effect becomes more pronounced at age 5.

Summary. Children looks more the phonological competitor than unrelated image, demonstrated early looks the phonological competitor, comp

, peaking on average around 800 ms after target onset. These peaks increased in height with each year

Children increased their relative looks to the phonological foil with each year of the study. Although they looked to the target more quickly and more reliably with each of the study, the advantage of the phonological foil over the unrelated image increased with each year. Thus, the children became more sensitive to the phonological cohort words as they grew older.

Talking points:

- There is hardly an effect of the phonological foil during timepoint 1. There are a few ways to interpret this finding. The first may be artefactual. The stimuli were re-recorded at timepoint 2 so the timepoint 1 stimuli were somewhat longer on average (around 800 ms at TP1 vs. 550–800ms later on). However, with slower stimuli, we would still expect an inflection in looks to the foil as children have more time to activate the phonological representations to the cohort. In other words, with more time to respond, there could plausibly be an even greater effect of early phonological information.

- Alternatively, the children in timepoint 1 may not be using the early similarity of words during recognition. That is, instead of immediate incremental activation of lexical cohorts, the children may not be activating the cohorts as reliably. This would imply that further study is required on the evidence for when young children begin to show immediate activation of cohorts.
- The children at timepoint1 may not be incrementally activating the cohorts. The children in timepoint 2 and 3 certainly are.
- Incremental activation and early commitments to partial information goes up with age.

Looks to the semantic competitor

I asked how children's sensitivity to the semantic competitor changed as they grew older. As in (Law et al., 2016), I only examined trials for which the semantic foil and the noun were part of the same category. For example, I included trials with *bee–fly*, *shirt–dress*, and *spoon–pan*, but I excluded trials where the similarity was perceptual (*sword–pen*) or too abstract (*swan–bee*). This criterion kept 13 of the 24 trials. Appendix B provides a complete list of trials used.

For these trials, I used the same modeling technique as the one used for phonological competitor: Generalized additive models with study effects and smooths for time, time by study, and random time by child smooths. I modeled the looks from from 250 to 1800 ms. This window was 300 ms longer than the one used for the phonological competitors in order to capture late-occuring semantic effects.

The model's fitted values are shown in Figure 7.4. The average empirical log-odds of fixating on the semantic foil versus the unrelated image increased with each year of the study. All three years show the same general time course of effects: Looks begin to increase from a baseline around 750 ms and peak around 1300 ms. The peaks of the curves increased as children grew older. The semantic foil shows a clear advantage over the unrelated image at age 3, which was not the case for the phonological foil at age 3.

The average looks to the semantic foil over the unrelated for age 4 was 0.44 emp. log-odds, .61 proportion units.

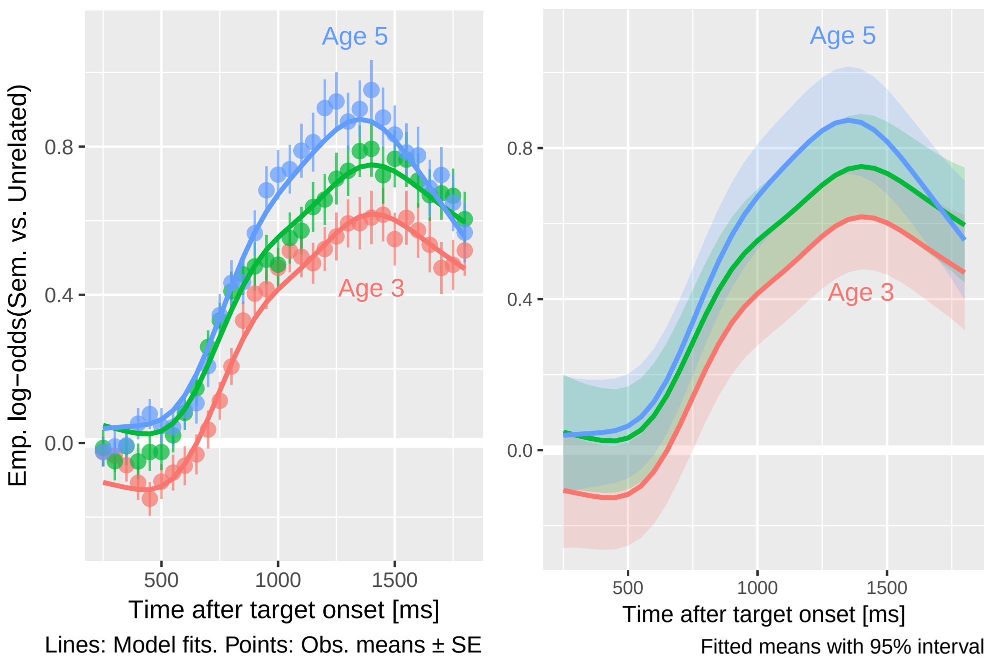


Figure 7.4: With each year of the study, children looked more to the semantic foil, relative to the unrelated image, with peak looking occurring after the target noun. Both figures show means for each year estimated by the generalized additive model. The left compares model estimates to observed means and standard errors, and the right visualizes estimated means and their 95% confidence intervals.

Children looked significantly less to the semantic foil on average at age 3, 0.30 emp. log-odds, .57 proportion units, $p < .001$, and they looked significantly more to the semantic foil at age 5, 0.50 emp. log-odds, .62 proportion units, $p < .001$. The peaks of the growth curves, in proportion units, were .65at age 3, .68 at age 4, and .70.

There was a significant smooth term for time at age 4, estimated degrees of freedom (EDF) = 7.04, $p < .001$. Figure ?? visualizes the time course of the differences between the smooths from each study.

The shapes of the age-3 and age-4 curves did not significantly differ, EDF = 1.00, $p = .535$. The age-3 curve begins to rise about 100 ms later, and it reaches a shallower peak value than the age-4 curve. These two features create a nearly constant height difference between the two curves, and thus, the two curves show the same overall shape.

The age-4 and age-5 smooths significantly differed, EDF = 1.00, $p < .001$. The differences are greatest after the end of the target noun, in the window from 750 to 1500 ms. The two curves start from a similar baseline but quickly diverge as the age-5 curve reaches a higher peak value. After 1500 ms, the age-5 turns downwards to overlap with the age-4 curve. Thus, children look more to the semantic foil relative to the unrelated image, but they are also quicker to correct and look away from it.

Summary. Children became more sensitivity to the semantic foil with each year of the study. Unlike with the phonological foils, the semantic foils clearly influenced looking patterns at age 3. The semantic foil effect occurs when we would expect it too: After the end of the target noun, after activation of the target noun and its neighbors.

- That the effect of the foil increases each year indicates that the semantic representations of words have strengthened.
- Is inhibition coming online at age 5?
- If children were just confused between bear/horse, fly/bee, goat/sheep, etc., they should be confused more at younger ages when they know much less about the world. So if it were confusion or guess, the semantic foil should be stronger at age 3. But they are also slower at word recognition in general at younger ages, so maybe these things cancel each other out?

Differences in competitor sensitivity at age 3

Next, I asked whether children differed reliably in their sensitivity to the phonological and semantic foils based on speech perception and vocabulary measures collected at age 3

As a measure of speech perception, I used scores from a minimal pair discrimination experiment administered during the first year of the study. [citations] The task is essentially an ABX discrimination task: A picture of a familar object is shown and labeled (e.g., "car"), another object is shown and labeled ("jar"), and then both images are shown and one of the two is named. The child then indicated which word they heard by tapping on the image on a touch-screen.

I derived speech perception scores by fitting a hierarchical item-response model. This logistic regression model estimates the probability of child i correctly choosing word j on word-pair k. The equation below provides a term-by-term description of the model. The model's intercept term represents the average participant's probability of correctly answering for an average item. By-child random intercepts capture a child's deviation from the overall average, so they estimate the child's *ability*. By-word and by-word-in-pair random intercepts capture the relative difficulty of particular items on the experiment. The by-word-in-pair effects were necessary because four words appeared in more than one word pair (e.g., *juice–goose* and *juice–moose*). The model also controlled for the children's ages and receptive vocabulary scores (PPVT-4 growth scale values). These predictors were transformed to have mean 0 and standard deviation 1, so the the model's intercept reflected a child of an average age and an average vocabulary level. Put differently, the by-child intercepts reflect a child's ability after controlling for age and receptive vocabulary.

$$
\begin{aligned}
\text{log-odds}(\textit{choosing correct word}) = {} & \alpha\, + & & \text{[average participant ability]} \\
& \alpha_i\, + & & \text{[difference of participant } i\text{'s ability from average]} \\
& \alpha_j\, + & & \text{[word } j\text{'s difficulty]} \\
& \alpha_{j,k}\, + & & \text{[word } j\text{'s difficulty in word-pair } k\text{]} \\
& \beta_1 \text{Age}\, + & & \text{[participant-level predictors]} \\
& \beta_2 \text{Vocabulary} & &
\end{aligned}
$$

I tested whether phonemic discrimination ability at age-3 predicted looks to the phonological foil over the unrelated image by modifying the generalized additive model from earlier. In particular, I included a smooth term for the phonemic discrimination ability score and a "smooth interaction" between the smooth of time and phonemic ability. These smooth interaction terms are analogous to interaction terms in linear models. In this case, the interaction term allows the ability score to change the shape of the time trend. The additive model was therefore:

$$
\begin{aligned}
\text{emp. log-odds}(\textit{phon. vs. unrelated}) = \alpha + & & \text{[growth curve average]} \\
f_1(\text{Time}) + & & \text{[time smooth]} \\
f_2(\text{Ability}) + & & \text{[ability smooth]} \\
f_3(\text{Time} * \text{Ability}) + & & \text{[interaction smooth]} \\
f_i(\text{Time}, \text{Child}_i) & & \text{[by-child random smooths]}
\end{aligned}
$$

The model included data from 144 participants; these were children with eyetracking data, receptive vocabulary and phonological discrimination data at age 3. There was not a significant smooth effect for phonological discrimination ability, EDF = 1.00, p = .742. The interaction smooth between time and ability was significant, EDF = 7.65, p = .029. Model comparison between the model and a reduced model (without the Ability and Ability × Time effects) supported inclusion of the predictor, $\chi 2(5) = 6.84$, p = .018.

To examine the contribution of the interaction term, I visualized model-predicted growth curves for an average participant at different phonological ability scores. Figure 7.5 shows how looks to phonological foil apparently increased with discrimination ability. The left panel shows how the predicted early looks to the phonological foil become more pronounced as phonological discrimination increases. This nonlinear interaction, however, becomes unstable at extreme values. In particular, children with very low phonological discrimination abilities (2 SD below average) showed roughly the same estimated growth curves as children with above average (+1 SD) discrimination scores. For the middle 68% of children, we can observe a sensible and interpretable effect, but this effect term is poorly behaved at very low abilities scores. In particular, children with low phonemic discrimination are predicted to be especially sensitive to the phonological foil. Such a finding contradicts my prior expectation that phonological discrimination would be related to processing of word onsets, so I interpret as a modeling artifact. A conservative conclusion from this model would be that differences in phonological discrimination predicted early looks to the phonological foil, but the direction of this effect was not consistent at low ability scores.

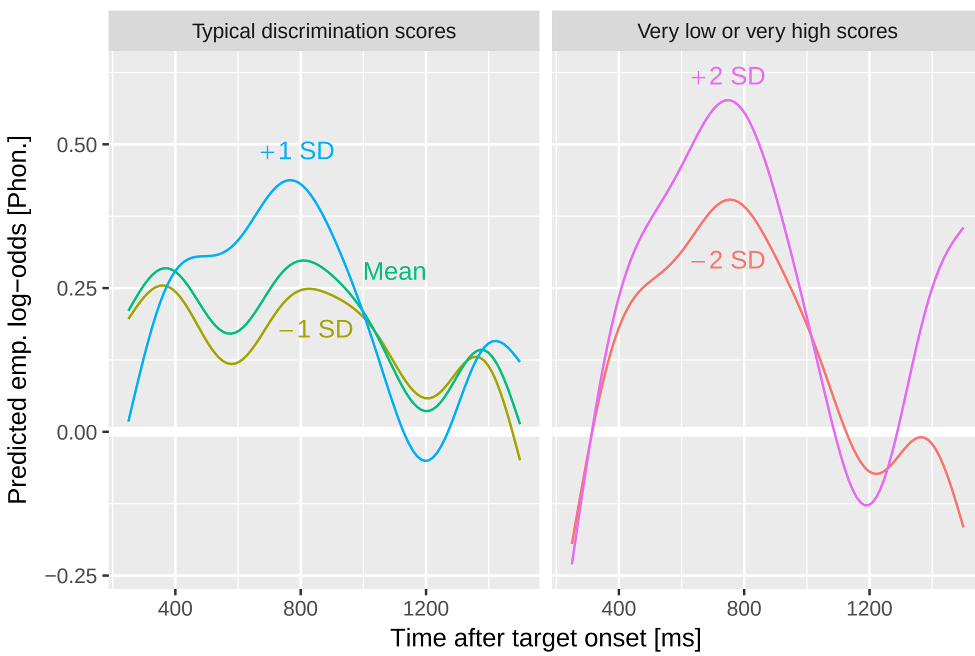


Figure 7.5: Estimated looks the phonological foil relative to the unrelated image at age 3. Lines represent different predictions for an average participant at different levels of performance on a minimal-pair discrimination task. Greater discrimination scores *generally* predicted greater peak looks to the foil at 800 ms, but this trend sharply reversed at very low discrimination scores.

To test the role of receptive vocabulary, I also fit analogous models using growth scale value scores from the PPVT-4, a receptive vocabulary test. I first adjusted these scores in a regression model to control for–that is, to partial out the effects of—age and predicted accuracy on the phonological discrimination task. There was not a significant smooth effect for receptive vocabulary, EDF = 1.00, p = .717, or a significant interaction smooth between time and receptive vocabulary, EDF = 1.00, p = .492. Receptive vocabulary therefore was not related to looks to the phonological foil at age 3.

I tested the same two predictors on looks to the semantic foil at age 3. These child-level factors did not show any significant parametric effects, smooth effects or smooth interactions with time. Thus, children's looks to the semantic foil were not reliably related to phonological discrimination or receptive vocabulary.

Discussion

In the preceding analyses, I examined children's fixation patterns to the phonological and semantic competitors. With each year of the study, children looked more to the target numerically, so these analyses modeled the ratio of looks to the competitors versus the unrelated image used in each trial. Thus, even as the number of looks to the phonological foil decreases with age, the advantage of the foil over the unrelated image would still increase.

Talking points :

- I tested whether two child-level features predicted looks to the competitor image at age 3.
- One a priori expectation was that looks to the phonological foil would relate to phonological discrimination ability, because children who can reliably discriminate one-feature phonetic differences between words would have richer phonological or phonetic representations that supported word recognition.
- The expectation was tenuously supported by a generalized additive model where children with greater discrimination abilities showed more early looks to the phonological foil. However, this model showed an unexpected effect for children with the lowest discrimination scores, so this model is interpreted cautiously.
- The other a prior expectation was that looks to semantic foil would relate to looks to the receptive vocabulary. However, neigther predicted related to looks the semantic foil.

MISCELLANY

8 Scratch paper

This book is made with bookdown, an R package/tool-chain for creating a books in multiple formats. This chapter is just a placeholder section and some scratch-paper so that I have some examples on-hand of how to use bookdown's syntax and features.

This is *a book* written in Markdown. You can use anything that Pandoc's Markdown supports, e.g., a math equation $a^2 + b^2 = c^2$.

For now, you have to install the development versions of bookdown from Github:

```
devtools::install_github("rstudio/bookdown")
```

Code settings:

```
library(methods)
knitr::opts_chunk$set(
  tidy = FALSE,
  collapse = TRUE,
  comment = "#>",
  out.width = 80
)

options(width = 80)
```

Bookdown cheatsheet

Cross-references to sections

The headings above were written with the following markdown:

```
## Bookdown cheatsheet

### Cross-references to sections {#manual-section-label-demo}
```

The first one gets an implicit label. The second one has an explicit section label.

```
I can refer to Section \@ref(bookdown-cheatsheet) and
[link to it](#bookdown-cheatsheet) with its implicit label.

I can refer to Section \@ref(manual-section-label-demo) and
[link to it](#manual-section-label-demo) with its explicit label.
```

I can refer to Section 8 and link to it with its implicit label.

I can refer to Section 8 and link to it with its explicit label.

Cross-references to appendices

The sample principles apply to appendices.

```
This is a reference to [an appendix](#mp-experiment-items)
```

```
The number of that appendix \@ref(mp-experiment-items). I hope.
```

```
Both: See [Appendix \@ref(mp-experiment-items)](#mp-experiment-items)
```

This is a reference to an appendix

The number of that appendix C. I hope.

Both: See Appendix C

Cross-references to tables

```
The chunk label ‘table-single‘ provides an implicit label
for Table \@ref(tab:table-single).

‘‘‘{r table-single, echo = FALSE}
knitr::kable(
  head(mtcars[, 1:5], 5), booktabs = TRUE,
  caption = ’A table of the first 5 rows of the mtcars data.’
)
‘‘‘
```

The chunk label `table-single` provides an implicit label for Table 8.1.

Table 8.1: A table of the first 5 rows of the mtcars data.

	mpg	cyl	disp	hp	drat
Mazda RX4	21.0	6	160	110	3.90
Mazda RX4 Wag	21.0	6	160	110	3.90
Datsun 710	22.8	4	108	93	3.85
Hornet 4 Drive	21.4	6	258	110	3.08
Hornet Sportabout	18.7	8	360	175	3.15

Figure references and using text references as captions

```
The caption for Figure \@ref(fig:cat) is defined as a _text reference_
below and passed to the 'fig.cap' chunk option.

(ref:cat-cap) This is a happy cat.

'''{r cat, fig.cap = "(ref:cat-cap)", out.width = "30%", fig.show = "hold"}
knitr::include_graphics(
  rep("./misc/happy-cat-grooming-itself-vector-file.png", 2)
)
'''
```

The caption for Figure 8.1 is defined as a *text reference* below and passed to the `fig.cap` chunk option.

```
knitr::include_graphics(
  rep("./misc/happy-cat-grooming-itself-vector-file.png", 2)
)
```

Custom blocks

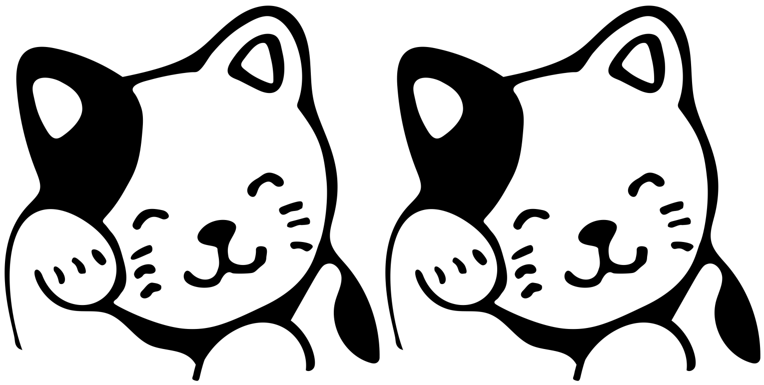


Figure 8.1: This is a happy cat.

Okay. This book is made with bookdown, an R package/tool-chain for creating a books in multiple formats. This chapter is just a placeholder section and some scratch-paper so that I have some examples on-hand of how to use bookdown's syntax and features.

Some text for this block.

- a list item
- another item
- end the list with a blank line

9

Quick testing sandbox

This is a chapter for quickly previewing and testing how content appears

We fit a generalized additive model with fast restricted maximum likelihood estimation [Wood (2017); Sóskuthy (2017) for a tutorial for linguists; see Box 1]. We included main effects of study year. These *parametric* terms work like conventional regression effects and determined the growth curve's average values. We used age-4 as the reference year, so the model's intercept represented the average looking probability at age 4. The model's year effects therefore represented differences between age 4 vs. age 3 and age 4 vs. age 5.

We included a *smooth* term for time. We included a smooth term for trial time to represent a general effect of time following noun onset across all studies, and we also included smooth terms for time for each study. These study-specific smooths estimate how the shape of the data differs in each individual study. As an equation, our model estimated: [Barr (2008);] (vers. 2.3; van Rij et al., 2017)

Box 1: The Intuition Behind Generalized Additive Models.

In these analyses, the outcome of interest is a value that changes over time in a nonlinear way. We model these time series by building a set of features to represent time values. In the growth curve analyses of familiar word recognition, we used a set of polynomial features which expressed time as the weighted sum of a linear trend, a quadratic trend and cubic trend. That is:

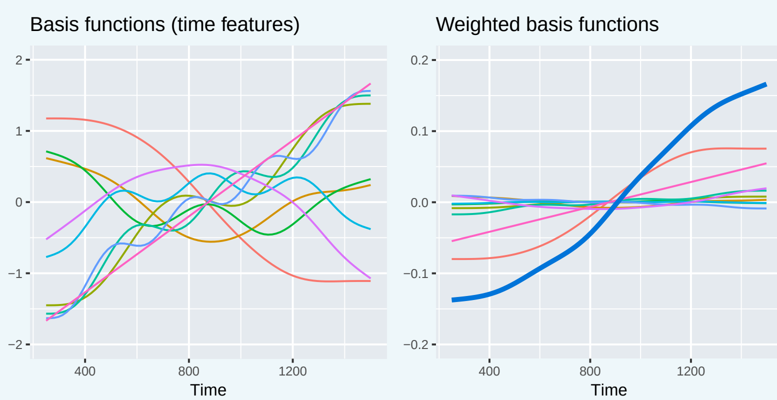
$$\text{log-odds}(\textit{looking}) = \alpha + \beta_1 * \textit{Time}^1 + \beta_2 * \textit{Time}^2 + \beta_3 * \textit{Time}^3$$

But another way to think about the polynomial terms is as *basis functions*: A set of features that combine to approximate some nonlinear function of time. Under this framework, the model can be expressed as:

$$\text{log-odds}(\textit{looking}) = \alpha + f(\textit{Time})$$

This is the idea behind generalized additive models and their *smooth terms*. These smooths fit nonlinear functions of data by weighting and adding simple functions together. The figures below show 9 basis functions from a "thin-plate spline" and how they can be weighted and summed to fit a growth curve.

```
#> Warning: package 'bindrcpp' was built under R version 3.4.4
```



Each of these basis functions is weighted by a model coefficient, but the individual basis functions are not a priori meaningful. Rather, it is the whole set of functions that approximate the curvature of the data—i.e., f(Time))—so we statistically evaluate the whole batch of coefficients simultaneously. This joint testing is similar to how one might test a batch of effects in an ANOVA. If the batch of effects jointly improve model fit, we infer that there is a significant smooth or shape effect. (Not quite sure this is 100% accurate yet.)

Smooth terms come with an estimated degrees of freedom (EDF). These values provide a sense of how many degrees of freedom the smooth consumed. An EDF of 1 is a perfectly straight line, indicating no smoothing. Higher EDF values indicate that the smooth term captured more curvature from the data.

A

Computational Details for Specific Aim 1

Growth Curve Analysis Models

The models were fit in R (version) with RStanARM (version).

When I computed the orthogonal polynomial features for Time, they were rescaled so that the linear feature ranged from $-.5$ to $.5$. Under this scaling a unit change in Time^1 was equal to change from the start to the end of the analysis window. The polynomial features for the Time had the following ranges:

Feature	Min	Max	Range
Time^1^	−0.50	0.50	1.00
Time^2^	−0.33	0.60	0.93
Time^3^	−0.63	0.63	1.26

Here is the code used to fit the model with RStanARM. It took about 24 hours to run the model.

```
library(rstanarm)
options(mc.cores = parallel::detectCores())

m <- stan_glmer(
  cbind(Primary, Others) ~
    (ot1 + ot2 + ot3) * Study +
    (ot1 + ot2 + ot3 | ResearchID/Study),
  family = binomial,
  prior = normal(0, 1, autoscale = FALSE),
  prior_intercept = normal(0, 2),
  prior_covariance = decov(2, 1, 1),
  data = d_m)

readr::write_rds(m, "./data/stan_aim1_cubic_model.rds.gz")
```

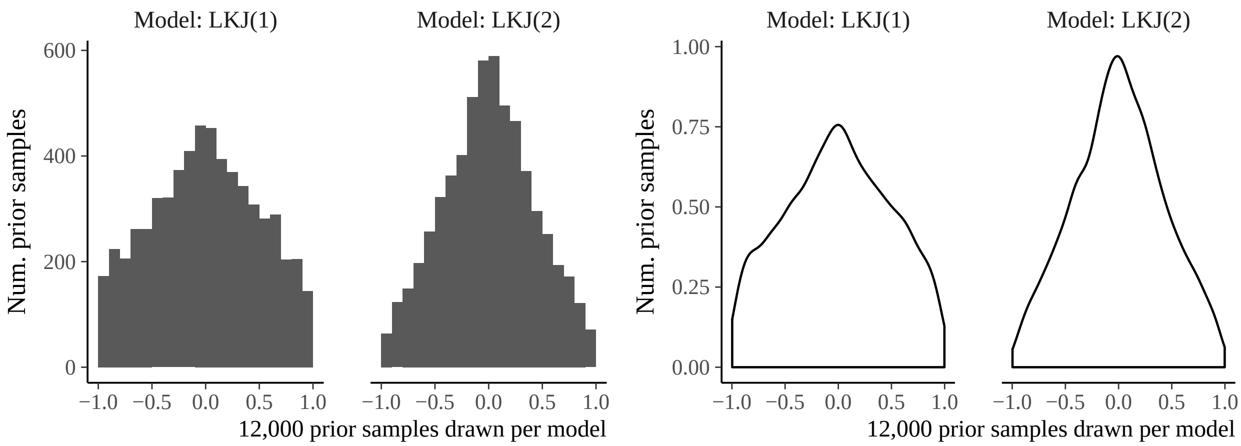
We used moderately informative priors for the main regression effects.

- b ~ Normal(mean = 0, sd = 1)

Under the Normal(0, 1) prior, before seeing any data, we expect 95% of plausible effects to fall in the range ±1.96, which is an adequate range for these growth curve models. For example, consider just the effect of Time^1. If a listener starts at chance performance, 25% or -1.1 logits, and increases to, say, 65% or 0.62, the effect of a unit change in Time^1 would be a change of 1.72 logits. This magnitude of effect is accommodated by our Normal(0, 1) prior.

Here I would have to also describe the random effects structure.

For the hierarchical part of the model, I used RStanARM's `decov()` prior which simultaneously sets a prior of the variances and correlations of the model's random effect terms. For these terms, I used the default prior for the variance terms and used a weakly informative LKJ(2) prior on the random effect correlations. The difference between LKJ(1) and LKJ(2) is that under LKJ(2) extreme correlations are less plausible. In the figure below, we see that the LKJ(2) prior nudges some of the probability mass away from ±1 towards the center. The motivation for this kind of prior was *regularization*: We give the model a small amount of information to nudge it away from extreme, degenerate values.



Box 1: A brief comment about priors.

Bayesian models require prior information ("priors"). Priors are also commonly referred to as "prior beliefs", and Bayesian techniques are criticized or dismissed for smuggling subjectivity into the scientific enterprise. I find this unfortunate on two grounds. First, *belief* overstates things. As George Box said, "all models are wrong, but some are useful" [cite], so no part of a statistical model should be called a "belief" when the whole thing is a convenient fiction. That's why I prefer the term *prior information*. [Hat tip Gelman?] Second, other parts of the statistical model are also subjective: likelihood functions, what kind of ANOVA, what to covary, whether to transform measurements, whether a $p = .07$ is a "marginal" effect or no effect at all, and so on. This subjectivity seems reasonable, provided that we scientists are open about modeling decisions.

For these models, I will use weakly to moderately informative priors. For example, suppose x and y are scaled to mean 0 and standard deviation 1. A weakly informative prior for the effect of x on y might be Normal(0, 5)—a normal distribution with mean 0 and standard deviation 5. If we fit a regression model and observed an effect size of 12 SD units, our first assumption would be that something went wrong with our software. The weakly informative prior captures this level of prior information. A moderately informative prior would be Normal(0, 1). This prior information captures our disciplinary experience that effect sizes greater than ±1 relatively uncommon in child language research. A strongly informative prior for this effect might be something like Normal(.4, .1) which says that our model should be very skeptical of negative effects and of effects larger than .8. For this project, I will default to the first two levels of prior information.

Additional model results

The output below contains the model quick view, a summary of the fixed effect terms, and a summary of the priors used.

```
b
```

```
summary(b, pars = names(fixef(b)))
```

```
prior_summary(b)
```

Plot the intervals for the random effect parameters

These are the parameters governing the random effect distributions. First, we plot the standard deviations. Recall that in our hierarchical model we suppose that each growth curve is drawn from a population of related curves. The model's fixed effects estimate the means of the distribution. These terms estimate the variability around that mean. We did not have any a priori hypotheses about the values of these scales, so do not discuss them any further.

Then the correlations.

Posterior predictive checks

Bayesian models are generative; they describe how the data could have been generated. One way to evaluate the model is to have it simulate new observations. If the simulated data closely resembles the observed data, then we have some confidence that our model has learned an approximation of how the data could have been generated. Figure ?? depicts the density of the observed data from each year of the study versus 200 posterior simulations. Because the simulations closely track the density of the observed data, we can infer that the model has learned how to generate data from each year of the study.

We can ask the model make even more specific posterior predictions. Below we plot the posterior predictions for random participants. This is the model simulating new data for these participants.

```
set.seed(09272017)

ppred <- d_m %>%
  sample_n_of(8, ResearchID) %>%
  tristan::augment_posterior_predict(b, newdata = ., nsamples = 100) %>%
  mutate(trials = Primary + Others)

ggplot(ppred) +
  aes(x = Time, y = Prop, color = Study, group = Study) +
  geom_line(aes(y = .posterior_value / trials,
                group = interaction(.draw, Study)),
            alpha = .20) +
  geom_line(size = 1, color = "grey50") +
  facet_wrap("ResearchID") +
  theme(
    legend.position = c(.95, 0),
    legend.justification = c(1, 0),
    legend.margin = margin(0)) +
  guides(color = guide_legend(title = NULL, override.aes = list(alpha = 1))) +
  labs(
    title = "Observed means and 100 simulations of new data",
    x = "Time after target onset [ms]",
    y = "Proportion looks to target")
```

Or we can plot the linear predictions. These are posterior predictions of the log-odds of looking to target before adding binomial noise.

```
lpred <- d_m %>%
```

```
  sample_n_of(8, ResearchID) %>%
  tristan::augment_posterior_linpred(b, newdata = ., nsamples = 100)

ggplot(lpred) +
  aes(x = Time, y = .posterior_value, color = Study) +
  geom_line(aes(group = interaction(Study, ResearchID, .draw)),
            alpha = .1) +
  facet_wrap("ResearchID") +
  geom_point(aes(y = qlogis(Prop)), shape = 1) +
  theme(
    legend.position = c(.95, 0),
    legend.justification = c(1, 0),
    legend.margin = margin(0)) +
  guides(color = guide_legend(title = NULL, override.aes = list(alpha = 1))) +
  labs(
    title = "Observed data and 100 posterior predictions",
    x = "Time after target onset [ms]",
    y = "Posterior log-odds")
```

B

Items used in the visual world experiment

Each row of the table represents a set of four images used in a trial for the experiment. There were two blocks of trials with different images and trial orderings. For the two unrelated foils with more than one word listed, the first word was used in block one and the second in block two.

Target	Phonological	Semantic	Unrelated
bear	bell	horse	ring
bee	bear	fly	heart
bell	bee	drum	swing
bread	bear	cheese	vase
cheese	shirt	bread	van

Target	Phonological	Semantic	Unrelated
dress	drum	shirt	swing
drum	dress	bell	sword
flag	fly	kite	pear
fly	flag	bee	pen
gift	kite	vase	bread
heart	horse	ring	bread/pan
horse	heart	bear	pan
kite	gift	flag	shirt
pan	pear	spoon	vase
pear	pen	cheese	ring/vase
pen	pear	sword	van
ring	swing	dress	flag
shirt	cheese	dress	fly
spoon	swan	pan	drum
swan	spoon	bee	bell
swing	spoon	kite	heart
sword	swan	pen	gift
van	pan	horse	sword
vase	van	gift	swan

C

Items used in the mispronunciation experiment

The stimuli changed between Year 1 and Year 2 so that dog/tog was replaced with rice/wice.

Time Points	Word Group	Condition	Audio (IPA)	Familiar Object	Unfamiliar Object
1	dog	Correct Production	/dɔg/	dog	wombat
		Mispronunciation	/tɔg/	dog	wombat
		Nonword	/vef/	ball	sextant
1, 2, 3	cake	Correct Production	/kek/	cake	horned melon
		Mispronunciation	/gek/	cake	horned melon
		Nonword	/pʌm/	book	churn
1, 2, 3	duck	Correct Production	/dʌk/	duck	toy creature

Time Points	Word Group	Condition	Audio (IPA)	Familiar Object	Unfamiliar Object
		Mispronunciation	/gʌk/	duck	toy creature
		Nonword	/ʃæn/	cup	reed
1, 2, 3	girl	Correct Production	/gɝl/	girl	marmoset
		Mispronunciation	/dɝl/	girl	marmoset
		Nonword	/nedʒ/	car	work holder
1, 2, 3	shoes	Correct Production	/ʃuz/	shoes	flasks
		Mispronunciation	/suz/	shoes	flasks
		Nonword	/giv/	sock	trolley
1, 2, 3	soup	Correct Production	/sup/	soup	steamer
		Mispronunciation	/ʃup/	soup	steamer
		Nonword	/tʃim/	bed	pastry mixer
2, 3	rice	Correct Production	/ɹaɪs/	rice	anise
		Mispronunciation	/waɪs/	rice	anise
		Nonword	/bep/	ball	sextant

D

Related Work

In this section, I clarify relationships between this project and other word recognition research reported from our lab. In short, our lab has reported results about the two-image and four-image experiments from cross-sectional samples, describing child-level measures that predict performance in these tasks. In contrast, my dissertation 1) focuses on the longitudinal development of word recognition and 2) engages with the fine-grained details of lexical processing.

Law & Edwards (2015) analyzed a different version of the mispronunciation experiment on a different sample of children (n = 34, 30-46 months old). This earlier version included both real word and the mispronunciation of the real word in the same block of trial. For example, a child would hear "dog" and "tog" during the same session of the experiment. This design might subtly temper the effect of mispronounced stimuli by allowing the listener to compare the mispronunciation to its correctly produced counterpart. The version of the experiment in Specific Aim 2 separates the real words and mispronunciations so that a child never hears a familiar word and its mispronunciation during the same block of trials. With this design, there is no explicit point of comparison for the mispronunciation, and the child has to rely on his or her own lexical representations when processing these words.

Law et al. (2016) analyzed data from the four-image experiment in Specific Aim 1. This study featured a diverse cross-sectional sample of 60 children, half of whom received the experiment in African American English and half received it in Mainstream American English. The sample ranged in age from 28 to 60 months. The study "borrowed" data from 23 participants from Year 1 of the longitudinal study to enrich parts of the samples demographics. For this manuscript, we analyzed how vocabulary and maternal education predicted looking patterns, including relative looks to the semantic and phonological foils.

Mahr and Edwards (in press) was the manuscript I originally authored for my preliminary examinations. The paper analyzes the same kinds of relations as Weisleder & Fernald (2013) which showed that lexical processing efficiency mediated the effect of language input on future vocabulary size. In particular, I asked whether word recognition performance on the four-image task of Specific Aim 1, vocabulary size, and home language input data from Year 1 predicted vocabulary size at Year 2. The paper only examined looks to the familiar image from one year of the study, so it did not analyze any lexical competition effects or the development of word recognition within children.

Colophon

Debug info

```
str(list(html = is_html_output(), latex = is_latex_output(),
         word = is_word_output(), width = options("width")[[1]]))
#> List of 4
#>  $ html : logi FALSE
#>  $ latex: logi TRUE
#>  $ word : logi FALSE
#>  $ width: int 80
```

```
devtools::session_info()
#> Session info -------------------------------------------------------------------
#>  setting  value
#>  version  R version 3.4.3 (2017-11-30)
#>  system   x86_64, mingw32
#>  ui       RTerm
#>  language (EN)
#>  collate  English_United States.1252
#>  tz       America/Chicago
#>  date     2018-04-06
```

```
#> Packages ----------------------------------------------------------------------
#>  package    * version date       source
#>  assertthat   0.2.0   2017-04-11 CRAN (R 3.3.2)
#>  backports    1.1.2   2017-12-13 CRAN (R 3.4.3)
#>  base       * 3.4.3   2017-11-30 local
#>  bindr        0.1.1   2018-03-13 CRAN (R 3.4.3)
#>  bindrcpp     0.2.2   2018-03-29 CRAN (R 3.4.4)
#>  bookdown     0.7     2018-02-18 CRAN (R 3.4.3)
#>  colorspace   1.3-2   2016-12-14 CRAN (R 3.3.2)
#>  compiler     3.4.3   2017-11-30 local
#>  datasets   * 3.4.3   2017-11-30 local
#>  devtools     1.13.5  2018-02-18 CRAN (R 3.4.3)
#>  digest       0.6.15  2018-01-28 CRAN (R 3.4.3)
#>  dplyr        0.7.4   2017-09-28 CRAN (R 3.4.2)
#>  evaluate     0.10.1  2017-06-24 CRAN (R 3.4.1)
#>  ggplot2      2.2.1   2016-12-30 CRAN (R 3.4.1)
#>  glue         1.2.0   2017-10-29 CRAN (R 3.4.2)
#>  graphics   * 3.4.3   2017-11-30 local
#>  grDevices  * 3.4.3   2017-11-30 local
#>  grid         3.4.3   2017-11-30 local
#>  gtable       0.2.0   2016-02-26 CRAN (R 3.2.3)
#>  htmltools    0.3.6   2017-04-28 CRAN (R 3.4.0)
#>  huskydown    0.0.4   2018-03-09 local
#>  knitr        1.20    2018-02-20 CRAN (R 3.4.3)
#>  lazyeval     0.2.1   2017-10-29 CRAN (R 3.4.2)
#>  magrittr     1.5     2014-11-22 CRAN (R 3.1.2)
#>  memoise      1.1.0   2017-04-21 CRAN (R 3.3.2)
#>  methods    * 3.4.3   2017-11-30 local
#>  munsell      0.4.3   2016-02-13 CRAN (R 3.2.3)
```

```
#>  parallel      3.4.3   2017-11-30 local
#>  pillar        1.2.1   2018-02-27 CRAN (R 3.4.3)
#>  pkgconfig     2.0.1   2017-03-21 CRAN (R 3.3.3)
#>  plyr          1.8.4   2016-06-08 CRAN (R 3.3.0)
#>  R6            2.2.2   2017-06-17 CRAN (R 3.4.0)
#>  Rcpp          0.12.16 2018-03-13 CRAN (R 3.4.4)
#>  rlang         0.2.0   2018-02-20 CRAN (R 3.4.3)
#>  rmarkdown     1.9     2018-03-01 CRAN (R 3.4.3)
#>  rprojroot     1.3-2   2018-01-03 CRAN (R 3.4.3)
#>  scales        0.5.0   2017-08-24 CRAN (R 3.4.1)
#>  stats       * 3.4.3   2017-11-30 local
#>  stringi       1.1.7   2018-03-12 CRAN (R 3.4.4)
#>  stringr       1.3.0   2018-02-19 CRAN (R 3.4.3)
#>  tibble        1.4.2   2018-01-22 CRAN (R 3.4.3)
#>  tools         3.4.3   2017-11-30 local
#>  utils       * 3.4.3   2017-11-30 local
#>  withr         2.1.2   2018-03-15 CRAN (R 3.4.4)
#>  xfun          0.1     2018-01-22 CRAN (R 3.4.3)
#>  yaml          2.1.18  2018-03-08 CRAN (R 3.4.3)
```

```
last_four_commits <- git2r::commits(git2r::repository("."), n = 4)
msgs <- lapply(last_four_commits, methods::show)
#> [5499d36] 2018-04-05: regenerate site
#> [6e78368] 2018-04-05: work on discussion
#> [eae7fd0] 2018-04-05: clean up output
#> [d2ad7b2] 2018-04-03: regenerate site
```

Built with love using R (Version 3.4.3; R Core Team, 2017) and the R-packages *bayesplot* (Version 1.5.0; Gabry & Mahr, 2018), *bookdown* (Version 0.7; Xie, 2018a), *dplyr* (Version 0.7.4; Wickham, Francois, Henry, & Müller, 2017), *ggplot2* (Version 2.2.1; Wickham & Chang, 2016), *knitr* (Version 1.20; Xie, 2018b), *littlelisteners* (Version 0.0.0.9000;

Tristan Mahr, 2018), *lme4* (Version 1.1.17; Bates, Maechler, Bolker, & Walker, 2018), *rlang* (Version 0.2.0; Henry & Wickham, 2018), *rmarkdown* (Version 1.9; Allaire et al., 2018), *rstanarm* (Version 2.17.3; Gabry & Goodrich, 2018), *tjmisc* (Version 0.0.0.9000; TJ Mahr, 2018a), and *tristan* (Version 0.0.0.9000; TJ Mahr, 2018b).

This is the original colophon from the huskydown package. I need to reword and note my modifications.

> This document is set in EB Garamond, Source Code Pro and Lato. The body text is set at 11pt with *EBGaramond*(3).
>
> It was written in R Markdown and LaTeX, and rendered into PDF using huskydown and bookdown.
>
> This document was typeset using the XeTeX typesetting system, and the University of Washington Thesis class class created by Jim Fox. Under the hood, the University of Washington Thesis LaTeX template is used to ensure that documents conform precisely to submission standards. Other elements of the document formatting source code have been taken from the Latex, Knitr, and RMarkdown templates for UC Berkeley's graduate thesis, and Dissertate: a LaTeX dissertation template to support the production and typesetting of a PhD dissertation at Harvard, Princeton, and NYU
>
> The source files for this thesis, along with all the data files, have been organised into an R package, xxx, which is available at `https://github.com/xxx/xxx`. A hard copy of the thesis can be found in the University of Washington library.

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