Lexical leverage: Category knowledge boosts real-time novel word recognition in two-year- olds

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Abstract

Recent research suggests that infants tend to add words to their vocabulary that are semantically related to other known words, though it is not clear why this pattern emerges. In this paper, we explore whether infants to leverage their existing vocabulary and semantic knowledge when interpreting novel label-object mappings in real-time. We initially identified categorical domains for which individual 24-month-old infants have relatively higher and lower levels of knowledge, irrespective of overall vocabulary size. Next, we taught infants novel words in these higher and lower knowledge domains and then asked if their subsequent real-time recognition of these items varied as a function of their category knowledge. While our participants successfully acquired the novel label -object mappings in our task, there were important differences in the way infants recognized these words in real time. Namely, infants showed more robust recognition of high (vs. low) domain knowledge words. These findings suggest that dense semantic structure facilitates early word learning and real-time novel word recognition.

Keywords

word learning; lexical processing; semantic development; infancy; eye-tracking

The advent of sophisticated graph analytic techniques that probe the structure of semantic networks have led to a number of exciting insights into the nature of early vocabulary growth in infancy. These methods have revealed that typically-developing infant vocabularies can be characterized by semantically structured networks (Beckage et al., 2011; Steyvers & Tenenbaum, 2005), and that this semantic structure can predict which words will next enter a child's vocabulary (Hills et al., 2009). Hills and colleagues (2009) have demonstrated that words that share some semantic relation to other known words are more likely to enter a child's vocabulary than those that are not related. This phenomenon, termed,

"preferential attachment" by network scientists (Barabási & Albert, 1999) provides an explanation as to why semantic networks continue to become more cohesively structured as the child's lexicon grows, though, this pattern, in itself, does not explain the learning mechanisms that give rise to this growth pattern initially.

There are at least two possibilities that explain why children may show particular facility for learning semantically related (v s. unrelated) words. First, children may "leverage" their existing semantic knowledge when acquiring novel words. That is, learning may be facilitated when it is possible to recognize similarities between a novel lexical item and pre-existing concepts. For example, when learning about a novel vehicle, we are likely to expect that the novel item should have some properties (*has wheels, made of metal*), but not others (*not furry, is not edible*). This pre -existing knowledge may enable a learner to infer many aspects of a novel word's meaning immediately. It is also possible that preferential attachment phenomena may be a by-product of semantic structure within the child's individual environment, leading children to learn words in "clusters" that reflect their particular life experiences. It is possible to imagine that if a child is learning about one vehicle (e.g. a car) that they will also experience other vehicles (e.g. truck, ambulance, train, motorcycle) in the same context(s).

While it is uncontroversial that a child's everyday experiences to some extent reflect which words and how many words enter their early vocabulary (e.g. Clark, 1979; Hart & Risley, 1995), there is also empirical evidence to support the former "leverage" account. A number of studies have indicated that the pace of children's vocabulary growth may be tied to their understanding of category structure. For example, the onset of the vocabulary explosion has been linked to the age at which infants begin to spontaneously sort related objects into categories (Gopnik & Choi, 1990; Gopnik et al., 1996; Gopnik & Meltzoff, 1992; Mervis & Bertrand, 1995; Poulin-Dubois et al., 1995 but cf. Gershkoff-Stowe, Thal, Smith & Namy, 1997 and Schafer & Plunkett, 1998 for alternative viewpoints). This association suggests that children who understand that items can be grouped into categories may use this knowledge to boost their vocabulary growth by learning words in already known categories. Semantic structure of 24 -month-old vocabularies have also been tied to the child's success in using a mutual exclusivity strategy to select a novel object(Yurovsky et al., 2012). The semantic microstructure of vocabulary knowledge also appears to facilitate the real-time interpretation of known words, suggesting that lexical items in "denser" semantic networks are easier to understand than more sparsely connected words(Borovsky et al., under review). Together, this prior work suggests that there are important associations between word comprehension and the child's conceptual structure.

However, this prior work has not directly tested a simple prediction that arises out of the leverage account of semantic structure in word learning: words should be learned more effectively in semantic categories that are more densely structured than those in more sparsely structured domains. There is computational and empirical evidence that indirectly support this possibility and highlight how and why the structure of lexical knowledge may influence word learning. Simulations of early word learning have revealed that neural networks that have tightly organized semantic structure in their lexical representations are better able to learn novel words (Borovsky & Elman, 2006). One reason for this effect

appears to be that cohesive semantic structure encourages modeled networks to easily recognize and map similarities from existing items onto new words. This explanation seems consistent with explanations for empirical effects of phonological neighborhood density on word learning in adults (Storkel et al., 2006; Storkel et al., 2014)and in 3-to 6 - year old children(Storkel, 2001 but cf. Gray, Pittman and Weinhold, 2014; Storkel & Hoover, 2011). Similarly, measurement of early word learning through standardized lexical databases indicate that, broadly, children learn words in dense neighborhoods earlier than those in sparser phonological neighborhoods (Storkel, 2004).

Despite these promising findings from the phonological density literature in older children and adults, less empirical work directly explores how phonological structure may influence word learning in infancy. Swingley and Aslin (2007) finds that 18-month-olds fail to learn novel words when they share a similar sounding neighbor that is well -known, but succeed in a word learning task when the novel word has no similar sounding neighbors. Newman, Samuelson and Gupta (2008) present a somewhat different result that indicates that novel word learning is facilitated for novel words that share many phonological neighbors. Together, these findings indicate that phonological density may help to facilitate word learning in some cases, but that at early points in lexical development highly familiar or frequent neighbors may override these effects.

There little work on whether or how categorical structure, or "semantic density" might influence word learning in infancy. Storkel and Adlof (2009b) have investigated how semantic "set size" influences word learning in preschoolers. They found that children were less accurate on a novel-word referent-identification task for items with larger semantic set sizes. The authors suggest that this finding may indicate that semantic neighborhood density (as indexed by semantic set size)may exert an opposite effect than that of phonological neighborhood density on word learning. However, it should be noted that the definition of semantic set size in this research does not necessarily reflect a categorical structure notion of semantic density. Semantic set size was defined as the number of items that adults and children name as related or associated to the novel object images (which are black and white drawings of non-existent objects with no associated label; (Storkel & Adlof, 2009a). This measure therefore takes into account how similar a novel item may seem *on average* to other objects, though it does not take into account how this may interact with the child's pre-existing semantic representations (which may differ significantly across individuals). On the other hand, Yurovsky and colleagues (2012) do calculate individual semantic representational structure and find that it does positively influence the use of a mutual exclusivity strategy to select an unknown referent from an array of objects. However, they did not test whether semantic vocabulary structure led to differences in subsequent retention (i.e. learning) of the selected objects.

Why might network density influence word learning? One proposal, put forth by Storkel and colleagues (Storkel, et al., 2006) posits that denser phonological neighborhoods may facilitate novel word learning by facilitating the formation of connections with existing lexical representations. This account is also consistent with others that suggest that pre-existing knowledge may attune learners to similarities among between novel and known items, and boost learning in domains which share those relevant features (Borovsky &

Elman, 2006; Smith et al., 2002). These accounts suggest a specific prediction regarding learning and recognition of novel objects in semantic domains that vary in density or existing knowledge. Specifically, such a mechanism would predict improved learning and recognition of novel items in semantic domains that have many known neighbors relative to those with fewer known neighbors. We test this hypothesis in the current study by building upon our prior findings that indicate that category structure can influence the real-time recognition of known words, such that children show more efficient and accurate online recognition of known words in categorical domains that they know relatively more about. We test whether this association between category knowledge and lexical processing extends to novel words as well.

Eye-tracking methods that measure gaze towards depicted objects in response to lexical labels have been widely used to measure real-time word recognition of known and novel words in infants (Bergelson & Swingley, 2012; Fernald et al., 1998; Halberda, 2006; Vouloumanos & Werker, 2009; Yu & Smith, 2011). This method capitalizes on infants' natural viewing behaviors in response to language, and does not require an overt manual response from the participant . Prior studies using this type of "looking while listening" method (Fernald et al., 2008)have identified important connections between known word processing and a number of factors, including concurrent vocabulary size (Fernald et al., 2006), future vocabulary growth (Fernald & Marchman, 2012), language experience (Fernald et al., 2013); and category knowledge (Borovsky, et al., under review). This paradigm has also provided useful indices of learning in novel word training studies (Bion et al., 2013; Ellis et al., submitted; Yu & Smith, 2011). Therefore, in this study we use an adaptation of the looking while listening method as vehicle to capture detailed measures of real-time comprehension of recently trained novel words from categories that vary according to child's semantic category knowledge.

We derive category knowledge in several early-acquired semantic domains from measurements of the child's vocabulary according to the MacArthur-Bates Communicative Development Inventory (MBCDI: Fenson, 2007), a parental checklist of infant vocabulary. The Words and Sentences (WS) form of this instrument is designed to capture a highly detailed and standardized snapshot of the child's productive vocabulary knowledge across several early-acquired semantic domains from 16–30 months. The nouns in this inventory have been selected to reflect a comprehensive catalog of words that are common in early infant vocabularies and are organized according to categories that typically appear in infant vocabularies, such as CLOTHES, ANIMALS, FOOD and VEHICLES. Therefore, in addition to capturing a broad measure of toddler's productive vocabulary size, this inventory is potentially useful for characterizing knowledge within early-acquired semantic domains. We take this approach in the current study by calculating a proportion of the total items that infants produce in each of the following domains that are measured by the MBCDI: ANIMALS, BODY-PARTS, CLOTHES, DRINKS, FRUITS and VEHICLES.

The current study

We set out to answer whether and how semantic category knowledge influences the real-time recognition and learning of novel words by training 24-month-old toddlers on items

from six early-acquired semantic domains. Each infant's overall vocabulary was individually measured using the Macarthur-Bates Communicative Development Inventory: Words and Sentences (MBCDI). Next, each child's individual category proficiency in each domain was measured according to the proportion of words they were reported to say. For each child, we individually assigned three categories into a "High" and "Low" knowledge condition, based on their individual category proportions. This procedure therefore yielded a unique combination of categories in High and Low knowledge conditions for each child, while controlling for overall vocabulary across conditions. Next, each infant learned the same words across six category domains, and we assessed their learning and recognition of these items via an adaptation of the "looking while listening" or "visual-word paradigm"(Huettig et al., 2011; Swingley, 2011). Word recognition performance in these paradigms is indexed by the magnitude and timing of looks towards an object in response to a label. This task was therefore designed to shed insight into the reasons why the early vocabularies of young children are learned in semantic "clusters" rather than in an evenly distributed fashion. If children leverage their existing categorical knowledge to facilitate subsequent word learning and comprehension, then we would expect to find differences in the speed and accuracy of comprehension of the recently acquired novel items across High and Low category domains. Otherwise, if learning is simply a by-product of the child's experience, which may itself be clustered or unevenly distributed, then we should not expect to see a difference according to domain knowledge, as words in both conditions will be taught under matched learning conditions.

Method

Participants

Thirty-two 24 -month-old infants (18 F, 14 M) were recruited from a large city in southern California via advertisements posted within the community . There was notable demographic diversity in this sample, with 39% of families indicating membership in an ethnic minority group. These families were also highly educated: all mothers had completed at least a high school degree, and 82% had completed college. Infants were reported to be learning English as their primary language, and to have normal hearing and vision. Parents did not report any other concerns about their child's development. All infants also had normal birth histories, and no history of recent or chronic ear-infections.

Stimuli

Selection of category domains and items—We selected items from categories from the MBCDI checklist that commonly appear in 24-month-old vocabularies, according to the CLEX database. The categories that we identified from these measures served as an indicator of the word categories that children are learning most commonly at this age. These categories are: ANIMALS, CLOTHING, VEHICLES, BODY-PARTS and two food subcategories: FRUITS and DRINKS. Our novel items consisted of rare, and low-frequency exemplars in each of these categories that shared many of recognizable visual features of items within each category . These novel items are illustrated in Figure 1. All of the lexical labels associated with these objects were bi-syllabic and conformed to the phonotactics of

English. We additionally confirmed via parental report that no infants were familiar with any of the lexical labels associated with each of these novel items.

Visual Stimuli—Images of all of the novel items are depicted in Figure 1. For each novel word, a colorful photo realistic representation of the novel item was selected and placed on a square 400x400 pixel white background. Other known objects were presented as additional trials that are analyzed separately as part of a larger project, along with several smaller colorful images that were used to direct the child's attention towards the screen. Other items were also selected to maintain infant interest, such as a large image of the Sesame street character, Elmo.

Auditory Stimuli—The speech that was paired with all items in the study was recorded by a female native speaker of California American English (E.E) in an infant-directed voice. These stimuli were recording on a mono channel at 44100 kHz sampling rate. The length of the novel labels was digitally normalized to the mean duration of all of the originally recorded novel labels using Praat software (Boersma & Weenink, 2012). In addition to the novel labels, the speaker recorded other phrases that were designed to capture and maintain the infant's interest across the study. For example, each novel item was followed by a tag phrase like "Do you like it?" and each novel label was preceded by a carrier, "Look!" Other filler trials that were paired with interesting images were accompanied by encouraging phrases like "You're doing great!" All auditory stimuli in the study were normalized to 70 dB intensity .

Procedure

Vocabulary assessment—Approximately one week before the infant's laboratory visit, parents were mailed a MBCDI:WS form to be completed before their appointment. Parents reported their children saying an average of 405 words (range 171–643, mean percentile: 67%, percentile range: 33%–99%). Parents additionally completed a checklist to indicate whether their infant had heard or used labels that corresponded to the novel items in the study. No parent indicated that his or her child had used or heard any of the novel words that we presented in the study. Parents report that, by and large, infants understood the known words in the study(89% of the time).

Eye-movement calibration and recording—Infants were initially seated in either a car seat or their parents lap in front of a 17" LCD monitor with an attached Eyelink 1000 eye-tracking camera, with 500 Hz sample rate that was mounted directly underneath the monitor . The monitor and camera was positioned by a flexible arm mount to remain within the child's field of view and approximately 600 mm from the child's face. Auditory stimuli were delivered via a loudspeaker placed behind the monitor. Caregivers wore headphones during the experimental procedure that played music unrelated to the task and were asked not to point at or name the pictures located on the monitor.

Next, the eye-tracker was focused and positioned while the infant viewed a short video. The tracker was then calibrated using a 5-point routine with an animated looming bulls -eye image paired with a whistling sound. Most of the participants naturally followed these

images around the screen without any explicit instruction, but in some cases, the experimenter pointed to the screen to direct the child's gaze towards the calibration images.

After the eye-tracker was calibrated, the experimental trials began. Eye movement data were recorded at 500 Hz, and binned into 50 ms intervals offline for plotting and analysis. The eye-tracker's default settings were used to classify eye-movements into fixations, blinks and saccades automatically . Areas of interest were defined as the 400 x 400 region comprising each of the Target and Distractor images.

Novel word training and test task—The experimental task consisted of three blocks of two interleaved tasks: (1) novel word exposure, followed by (2) a test of novel word retention and recognition. During each exposure block, infants were exposed to two novel object-label mappings. Each novel object was individually displayed to the infant for two periods of 12.5 s, during which the novel word was labeled 5 times. As prior evidence indicates that language processing may be assisted by presenting words in sentence frames rather than isolation (Fernald & Hurtado, 2006), all novel words were heard in several simple phrases, which were recorded in an enthusiastic, infant directed voice by EE. For each training phase, infants heard the words repeated five times within the same five phrase sequence: *Look, X! That's a X! Wow, there's a X! Can you see the X? Cool, that's a X!* During each period, one of the two novel objects moved slowly back and forth across the screen to help maintain interest. This resulted in 10 repetitions of the novel label with the object and a total of 25 seconds of exposure to the novel object-label mapping. The toddlers in this study found these stimuli to be engaging and dynamic, and they spent an average of 91% (range: 78.8% to 97.6%, SD = 11.1%) of the training period viewing the interest area over which the novel object travelled.

After the four exposure trials, infants then viewed 12 object recognition trials. Four of these trials consisted of the novel word recognition task, while the remaining eight consisted of other trials containing known objects. The known objects also were derived from the same categories as the novel items, and parental reports corroborated that infants knew the vast majority of the words in these known word trials (89.1%). These known trials are undergoing separate analysis to be submitted for publication as part of a larger project. This ratio of known to novel words was selected to maintain infant interest with fresh stimuli in most trials, and to prevent fussiness and frustration in cases where the object-label mappings may have been hard to identify. Each of the novel object -label trials were presented as follows. First, the infants viewed the two previously trained novel objects in silence for 2000 ms. Next, a small, colorful image (e.g. a picture of a flower) appeared at the center of the screen to direct infant attention to the center of the image along with a verbal label, "Look!" Once the infant had fixated on this center stimulus for 100 ms, the center stimuli disappeared, and the novel label was spoken (e.g. *Boba!*). The goal of this delay was ensure infant attentiveness to the monitor before the onset of the trial label. This procedure therefore resulted in some trial-by-trial variability in silent preview period, though this variability did not differ across across High and Low domain conditions. The mean preview time before label onset was very similar across conditions(M_{high}= 3014.2 ms, SD = high 889; M_{low}= 3013.7 ms, SD = 839, $F(1,31)$ <1). The images remained on the screen for 4000 ms post-label onset.

The six novel objects were always presented in yoked pairs, but the block order of these pairs was counterbalanced across versions. Each novel image appeared four times during the test block, twice as a Target and twice as a Distractor. The side of presentation of each novel image was similarly balanced.

Approach to analysis

Assignment of high and low-category domains—The category domain assignment procedure is as follows: First, each child's category proficiency in each category domain is calculated as a proportion of the number of words that the child says out of total number of words in each category domain. The three categories with the highest calculated proportion were then assigned to the High domain knowledge condition, while the three lowest proportion categories were assigned to the Low domain knowledge condition. Three of the 24-month-olds' category rankings were identical for the third and fourth ranked category proportion, so we assigned both categories to the High domain. The category domain assignment procedure from prior work procedure results in a unique arrangement of items classified as High and Low domain knowledge for each infant based on their individual MBCDI vocabulary report. The distribution of High and Low domain categories, as well as average words known in each domain are reported in Table 1.

Analysis of novel word recognition dataset—Our primary questions involved how domain knowledge would affect novel word learning. We specifically ask whether such differences in knowledge of different semantic categories is reflected in the real-time recognition of a novel object-label mapping involving those categories . Accuracy was calculated with coarse and fine-grained measures. The coarse measures sought to determine whether overall patterns of looking over a large time period varied according to domain knowledge . The finer analyses sought to specify the timing of when fixations towards the Target exceeded those to the Distractor images across the trial period, and whether the magnitude of these finer grained timing differences varied according to Domain knowledge.

We calculated the coarse measure of accuracy as the proportion of fixations towards the Target over total fixations to the Target and Distractor . With this measure, a proportion greater than .5 indicates that looks to the Target represent the majority of total fixations towards the images during the specified time period. We calculated accuracy across a broad time window of analysis, 300–4000 ms. The 300 ms onset represents the time it takes to initiate an eye-movement in response to an auditory stimulus, and the 4000 ms offset represents the end of the trial period . This offset window is longer than typically used for studies of known word processing (e.g. Fernald et. al. 1998). However, it is not uncommon to use relatively longer time windows of analysis in novel word recognition studies(Bion, et al., 2013; Ellis, et al., submitted). Analyses are initially carried out to assess whether there is a significant contribution of the experimental factors on the accuracy measure. These analyses are then followed by planned one-tailed t-test comparisons that indicate whether accuracy significantly exceeds .5 in each experimental condition. Significant results on this latter test indicate that fixations to the Target exceeded those of the Distractor image in the specified time window, while controlling for total gaze to both of the images.

We next carried out two finer-grained analyses of novel word recognition across 50 ms time bins. The first of these finer-grained analyses sought to determine when proportion of fixations to the Target exceeded those of the Distractor in High and Low Knowledge domains separately, while the second analysis compared these fine grained timing differences across domain. We therefore used a dependent measure of interest that yielded an index of the relative advantage of fixations towards the Target vs. Distractor in High and Low knowledge domains as a log-gaze proportion ratio at each 50 ms time bin (Arai et al., 2007; Borovsky, et al., under review; Borovsky et al., 2014; Knoeferle & Kreysa, 2012 for a similar approach). Log-gaze ratios in looking time measures have been used to control for violations of statistical assumptions of linear independence, (e.g. fixations proportions to one item influence fixations towards the other image) and homogeneity of variance (e.g., simple proportion ratios vary between 0 and 1; see Arai et. al. 2007). We calculated the log-gaze proportion ratio in each time bin for the Target vs. Distractor as $\log(P(Target)/P(Distractor)$[1]. Log-gaze ratios vary between positive and negative infinity; a score of zero indicates that looks to the Target and Distractor are equivalent, while positive scores indicate that Target fixations exceed Distractor fixations, and vice versa for negative scores.

In this finer grained analysis we sought to address two questions: (1) Precisely *when* in the time course do infants display a preference for the Target (relative to the Distractor) in High and Low knowledge conditions separately, and (2) Does this relative Target preference vary between High and Low knowledge conditions across time? With respect to the first question, we sought to detect reliable differences while controlling family wise error rate (i.e. correcting for multiple comparisons). We therefore adopted a non-parametric cluster-based permutation test approach that has been applied to FMRI and ERP waveform analyses (Groppe et al., 2011a; Maris & Oostenveld, 2007)and has more recently been applied to adult and infant eye-tracking analyses as well (Barr et al., 2014; Von Holzen & Mani, 2012). We used this test to identify a "cluster t-statistic" by summing across temporally adjacent point-wise t-values that exceed a pre-specified threshold. In this case, the threshold is defined as time points where log-gaze proportions significantly exceed zero, indicating a significant preference for the Target relative Distractor. These comparisons are then compared to a t-statistic distribution that are generated using a permutation procedure (we follow the permutation approach outlined in Barr et. al. 2013, Appendix)to generate a (non - parametric) Monte Carlo p-value. We used 2000 random permutations to estimate the distribution of the null hypothesis, as recommended by Groppe, Urbach and Kutas (2011b) with sufficient precision to control family wise error rate to <.05.

Our second time-based analysis sought to directly text our primary hypothesis, that the magnitude of the fixations to the Target (vs. Distractor) should vary across High and Low domain knowledge conditions, and specifically, this Target preference should be larger for High relative Low domain knowledge items. For this comparison, we applied the same cluster-based permutation technique described above, and directly compared High vs. Low knowledge log -gaze proportion ratios across time.

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[1]We replaced every instance of a zero value in the numerator or denominator with a value of 0.01, because log ratios are undefined at 0.

Finally, we sought to identify trials where children did not respond to the auditory stimuli or were inattentive to the visual stimuli on the screen. Therefore, we removed trials where infants viewed the Target and Distractor collectively for less than 20 % of the 300–4000 ms analytic window. This criteria is within bounds of that used in other studies with young children such as Nordmeyer and Frank (2014), who exclude trials from analysis with more than 30% of samples missing over the entire trial period , or Quam and Swingley (2014), who exclude trials where young children fail to view the pictures for 300 ms out of a 1650 ms analysis window(i.e. 17%). Using this 20% missing sample criterion, we removed 11.7% of trials (45 of 384). Subsequent analyses were performed on the remaining dataset.

Results

The time course of fixation proportions towards the target and distractor images for High and Low domain items is illustrated in Figure 2a. This figure shows a typical rise in fixations within the first 500 ms after the onset of the label that reflects a look away from the (disappearing) gaze-contingent center stimulus during the preview and looks towards both the Target and Distractor images. After this point, looks to the Target appear to diverge from that of the Distractor in both High and Low domain conditions, followed by an apparent secondary divergence in for the High domain condition, but not the Low around 3000 ms post label onset. Our next analyses focused on whether domain differences existing in the amount and timing of fixations to the Target and Distractor across High and Low knowledge conditions by assessing accuracy across relatively coarser and finer-grained time windows.

Accuracy, coarse-grained analysis

We initially carried out a standard calculation of mean accuracy across domain knowledge for the target item using a standard calculation as the proportion of fixations to the Target over total fixation proportions to Target and Distractor, (Table 2a). A repeated measures ANOVA did not yield a significant difference according to Domain 300–4000 ms: $F<1$. Follow- up analyses indicated that infants appeared to learn items in both domains, as they showed a Target preference, with accuracy means exceeding .5 in High and Low Domains (ps<.05; Table 2).

Accuracy, fine-grained analysis

Our initial fine-grained analysis sought to identify *when* fixations to the Target diverged from those of the Distractor across High and Low Knowledge domains . As is visually evident in Figure 2, these statistical analyses indicated that children showed a preference for the Target relative to the Distractor between 3150 to 3900 ms in the High Knowledge domains(cluster t statistic = 44.35, Monte Carlo p =.034), but not in the Low Knowledge domain (cluster t statistic = 17.44, Monte Carlo p = .17).

Our second comparison sought to determine when the apparent differences in divergence between the Target and Distractor reflected true differences across domain knowledge conditions. As described in the approach to analysis section, we compared log-gaze proportions across High and Low knowledge domains in 50 ms time bins starting from label onset, and continuing to the end of the 4000 ms trial period using a cluster based

permutation test approach (Barr, et al., 2014; Maris & Oostenveld, 2007; Von Holzen & Mani, 2012). According to this analysis, log gaze ratios for High knowledge domains exceeded those for Low knowledge domains between 3000 to 3700 ms post label onset (cluster t statistic = 31.24, Monte Carlo p = .04). As illustrated in Figure 2b, these effects appeared relatively late in the time course, well after the offset of the word, potentially reflecting a later conscious selection of the correct target object in the High but not Low knowledge condition after an earlier period of deliberation or switching among the two options.

Further exploration of domain learning effects

The above analyses paint a broad picture that there are overall differences in the real-time recognition and interpretation of novel items as a function of category domain knowledge, though these differences may be subtle and emerge at later points in processing. To deepen our understanding of the relevant factors that contribute to these effects, we extended our analyses to explore several additional factors in our data. Specifically, we conducted exploratory analyses on several variables, including the novel item's category, total vocabulary knowledge, and distractor domain knowledge. We describe the rationale and approach for exploring each of these factors in detail below. In each of the following sections, we analyze the influence of these various factors using coarse-grained measures of accuracy with the identical procedures as above.

Domain effects across individual categories/items—The categories and items that we have included in this paper vary across many dimensions, such as the child's prior experiences and the relative similarity of items within categories. For example, as helpfully noted by an anonymous reviewer, it seems likely that children may have prior experience with the similar items in our BODY-PARTS and DRINK categories, even if the child did not specifically have a label association for the particular objects that were presented in the experiment . On the other hand, items from other categories may be relatively less connected to the child's prior experience. To examine whether learning effects differ as a function of individual categories, we calculated mean fixations to the Target and Distractor in each domain in Table 2b. A one-way repeated measures ANOVA analysis of accuracy as a function of domain indicated that there were accuracy differences by domains, although with a small effect size, $F(5,147.6) = 3.60$, $p = .004$, $\eta^2 = .0\ 22$. Follow-up pairwise Tukey -tests indicated that these differences were driven by accuracy differences between the CLOTHES, FRUITS, and BODY PARTS domains, such that overall accuracy to the novel CLOTHES and FRUITS items were significantly greater than that for the novel BODY PARTS. No other pairwise comparisons were significantly different at $p < .05$. Further analysis revealed that infants showed a target advantage for ANIMALS, CLOTHES and FRUIT, Table 2b. Together, these analyses suggest that some differences in performance do exist among categories, but, the magnitude of these differences are relatively small .

Domain effects as a function of individual vocabulary knowledge—Although domain knowledge was assessed as a within-subject factor to control for the overall impact of vocabulary size on our experimental results, it is nevertheless possible that there could be different learning patterns as a function of domain and vocabulary knowledge. To investigate

this possibility, we compared Accuracy as a function of Domain knowledge in toddlers with Higher and Lower vocabulary, determined by median split (Table 2c). A mixed model ANOVA with between-subjects factor of Vocabulary group (Higher Vocabulary vs . Lower Vocabulary) and a within-subjects factor of Domain Knowledge (Higher Knowledge vs. Lower Knowledge) revealed a marginal main effect of Vocabulary, $F(1,27.93)=3.73$, $p = .06$, $\eta^2= .089$, driven by greater Target accuracy for the Higher (vs. Lower) vocabulary group. No other main effects or interactions were significant. Follow-up analyses in each condition revealed that infants with Higher vocabularies learn items in high and low knowledge domains by showing a target preference for high and low knowledge items $ps<.05$. For the Lower vocabulary group, there was a marginal target preference for High Domain Knowledge items: $t(15) = 1.55$, $p = .07$, $d = .16$, but not for Low Domain Knowledge items. Together, these patterns replicate prior reports that indicate that novel word recognition is associated with vocabulary skill (Bion et al ,. 2013).

The role of distractor domain knowledge—The relationship of the distractor to the target may also influence Domain knowledge effects, so we explored this additional factor in our data by calculating accuracy across the 300–4000 ms time window for each of four conditions: (1) High Knowledge Target – High Knowledge Distractor (HIGH T-HIGHD), (2) High Knowledge Target – Low Knowledge Distractor (HIGHT -LOWD), (3) Low Knowledge Target – High Knowledge Distractor (LOW T– HIGHD), (4) Low Knowledge Target – Low Knowledge Distractor (LOWT – LOWD). We note cautiously that we did not specifically control for this kind of pairing in our experiment, so individual toddlers contributed differently to each of these conditions. We conducted a (2x2) repeated measures ANOVA of Target Domain Knowledge (High Knowledge Target, Low Knowledge Target), and Distractor Domain Knowledge (High Knowledge Distractor, Low Knowledge Distractor). This analysis revealed a no significant main or interaction effects. However, follow up comparisons of condition means did indicate that infants showed a target preference (accuracy exceeded .5)in only the low distractor knowledge conditions (HIGH T –LOW D, and LOW T – LOW D; Table 2d). Therefore, although the main effects of Distractor Domain did not achieve (or approach $p=.31$) significance in our ANOVA, the target preference analysis suggested there may be a greater trend to view the Target when the distractor object was from a lower knowledge domain.

Discussion

In this study, we ask how a crucial language ability – that of recognizing the meaning of a novel word, is influenced by the child's prior knowledge about related items. Prior research had indicated that knowing more words (i.e. having a larger vocabulary) can facilitate the recognition of known words in speech (Fernald, Perfors & Marchman, 2006), and that knowing words that are semantically related to a particular word can also influence this process(Borovsky, et al., submitted). The goal of this study was to explore whether these effects extend to word learning processes as well. Specifically, we asked whether and how the child's knowledge about semantic category domains would influence their ability to learn and recognize novel label -object mappings in real time. With respect to this question,

the results are clear: 2-year-olds recognize novel word meanings more effectively in semantic categories about which they know relatively more words .

Infants successfully recognized novel words in high and low knowledge conditions, although there were important differences across these conditions . Infants' accuracy to the Target over the trial period significantly exceeded chance (.5) for both domain knowledge conditions, indicating that infants had learned and retained the object-label mapping for high and low knowledge domains. Differences in lexical recognition due to domain knowledge were especially salient at later periods of processing, which is most clearly illustrated in the log -gaze difference plots in Figure 2. Infants fixated towards the high (but not low) knowledge targets at later points in processing, long after the label offset, but before image offset.

Although studies of semantic priming as a function of semantic neighborhood size in adults indicate differences in the speed of priming between high and low neighborhood item, the effects in this study were not driven by differences in speed per se. Rather, there was a late-emerging domain knowledge effect. There are several possible mechanisms that may explain this late effect. One possibility is that the late effect might reflect sustained lexical activation for the high (vs. low) knowledge items. For example, if the novel items that were learned in high knowledge (semantically dense) domains have a more robust representation than those in low knowledge domains, this may be reflected by sustained looking or lexical activation for that item in response to a label. Alternatively, the late pattern might arise due to relatively greater uncertainty about the referent of the novel label in low(vs. high) knowledge conditions . In this case, infants would have initially fixated towards a correct item shortly after the word onset for all labels, but then later alternated their fixations between the target and distractor image for items in the low knowledge condition. Although the current paradigm is not designed to distinguish between these two accounts for the late emerging effect, it would be an interesting line for future work, as this could further elucidate the nature of the lexical activation in word learning.

Overall, the domain effects are consistent with a leveraged account of word learning: Word learning proceeds in a non-random, clustered fashion because prior knowledge facilitates the acquisition of meanings that share some similarity with existing lexical items.

These findings also shed light on the reasons why the lexicon's structure is organized according to semantic relationships among words. There is a wealth of evidence to indicate that children seem to recognize semantic links among known words from the earliest moments of language development (Arias-Trejo & Plunkett, 2009, 2013; Rämä et al., 2013; Torkildsen et al., 2006; Torkildsen et al., 2007; Willits et al., 2013). Infants'early recognition of relationships among known words similarly extends to recognition of similarities among novel objects (Wojcik & Saffran, 2013). Additionally infants are more likely to add items to their vocabulary which share semantic similarity to known items, rather than those that are dissimilar, a pattern termed "preferential attachment" by network scientists (Hills, et al., 2009; Steyvers & Tenenbaum, 2005). Our findings seem to suggest that learning these connections among words can pay increasing dividends as language acquisition proceeds .

Novel words belonging to categories with more coherent structure can be learned more effectively than those in less cohesively structured domains.

There has been little work to examine precisely how or why this structure emerges, although a number of possibilities exist. Lexico-semantic structure may emerge as a by-product of experience, where semantically related items are encountered in common events or linguistic frames frequently encountered by the child. However, in our task, we controlled the pairing of the label and objects for all items, so differences in overall exposure to the label-object mapping between the novel items cannot explain our findings. Additionally, we selected items that were relatively uncommon in infant lexicons (and confirmed this via parental report). It was therefore unlikely that infants had prior experience with these particular items in ways that might differentially affect learning performance.

Instead, these results are more consistent with a leveraged learning account, where infants draw upon their prior knowledge to generalize and map their current representation of related items to novel words. In other words, this structure of the lexicon itself may facilitate subsequent word learning for items that share similarities with words in semantically organized categories. Importantly, this effect cannot simply be explained by between-subject differences in word learning proficiency or vocabulary size, as infants' performance varied *within subject* according to individual variation in the infant's knowledge. However, it should be noted that we did find an overall main effect of vocabulary, replicating prior results with known and novel word learning using eye-tracking measures of lexical recognition (Bion, et al., 2013; Fernald, et al., 2006).

The infants in our study were not given any explicit instruction or information about the potential meaning of the novel objects other than the opportunity to view the novel image and listen to its label. The fact that real-time lexical recognition of the novel items varied among high and low domain knowledge categories under these learning conditions additionally suggests that the infant's prior knowledge influenced how they extracted and identified semantic similarities among the novel objects with known words in their vocabulary. Specifically, our findings indicate that the mapping between known and novel items was facilitated when infants knew relatively more items in their categories.

Our pattern of results is also consistent with prior work in the literature that finds that children use their lexical knowledge to facilitate further vocabulary growth (Smith, et al., 2002). In this study, children were trained over the course of eight weeks on novel labels that generalized to object categories that varied by shape, color, or texture. They found that children trained in the shape condition experienced accelerated vocabulary growth for object names (but not other aspects of vocabulary)relative to children in other training conditions . The authors interpret this finding to suggest that the shape condition attuned young children to recognize shape similarities among objects, which then subsequently lead to further gains in object learning for items unrelated to the training condition. Like our own findings, this study suggests that children may use prior knowledge to facilitate lexical learning. Together, this prior study and our own suggests that learning mechanisms that assist children in semantic generalization may be fundamental for early language growth.

We selected items that were likely to provide salient and uniquely identifiable physical cues that strongly suggested membership in a target category. For instance, the novel vehicle, *draisine*, while clearly being an unusual vehicle, had features like wheels that indicated that it was likely to belong in a vehicle category and that it did not belong in other early-acquired domains like body parts or clothing . Our work, however, is not able to comment on precisely what elements of the novel objects could be most useful in generating links with known items. Some theories of early semantic development posit that children may initially prioritize associative (thematic)but not taxonomic relations among items (Markman & Hutchinson, 1984; Smiley & Brown, 1979). But other findings indicate that infants can recognize both taxonomic and associative relations among objects(Arias-Trejo & Plunkett, 2013). There is also significant evidence that infants are more likely to generalize category membership of objects based on certain physical properties, like shape, more than others, such as color or texture(Landau et al., 1988). Future work is needed to investigate whether different information about object relationships is highlighted as the structure of a category transforms along with the child's growing lexicon.

Although we advance a leveraged learning explanation for the learning effects in this experiment, a number of mechanisms are likely to contribute in parallel to the growth of semantic structure in the lexicon. Prior work has indicated that infants recognize semantic association among words according distributional information in language usage (Hills, 2013; Hills et al., 2010), and that they may extract statistical information about known object features to extend to novel items (Lany & Saffran, 2010, 2011). As reviewed in the introduction, the lexicon is also organized along phonological dimensions like neighborhood density and cohort size (Mani & Plunkett, 2011; Storkel, 2004). Similarly, although we discount "clustered" learning experiences as a simple explanation for the effects in the current task, there is evidence that language experience is strongly tied to vocabulary development (Hart & Risley, 1995; Hoff, 2003). Multiple factors must simultaneously contribute to word learning (e.g. Frank et al., 2013). Future work will be necessary to delineate how these learning mechanisms interact across the course of early language development.

We also note several limitations of the current work. First, we only tested retention and real-time recognition of a novel label-object mapping after a very brief delay. However, longer term mapping of novel objects is a key feature in word learning, and there are a number of interesting questions that remain about how prior knowledge might influence the learning process over longer delays that may allow for long-term memory consolidation to interact with the learning process (Williams & Horst, 2014). Our test of word learning is also somewhat different than typical assessments in the infant word learning literature, which often involves asking the child to either name an object or select it from an array. Instead, we rely on gaze measures as an index of word learning. Eye-tracking methods are used with increasing frequency with infants because these paradigms do not require an overt response from the child. However, it is not yet known how recognition of words in these measures translates to other overt behaviors such as object selection and naming, though this would clearly be an important question for future study. Additionally, while we attempted to tightly control the learning conditions for all of the novel items, and we corroborated via parental report that children were not familiar with the object labels, children may have had some

exposure to the novel objects themselves in some domains. For example, it is likely that children may have been exposed to similar looking drink cups such as that which appeared in the "boba" item . Finally, our measure of infant vocabulary, the MBCDI, assesses only productive vocabulary, which we take as an index of the child's knowledge. Future research must address whether semantically structured patterns of early productive vocabulary growth extend to receptive knowledge as well.

In conclusion, while a variety of learning mechanisms contribute to the development of structure in the lexicon, our work indicates that infants can make use of this existing conceptual structure to interpret novel word meanings in real -time. It will be important to characterize how the developmental changes in the lexicon itself may interact with the learning process . Our findings indicate that infants may be best prepared to capitalize on early word learning experiences within semantic domains for which they hold relatively greater knowledge. These results lead to an encouraging hypothesis that we are exploring in ongoing work: that early word learning can be boosted by strategic training of novel items within a limited set of early domains.

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Research Highlights

- We ask how novel word recognition is modulated by semantic domain knowledge in 24-month-old infants.

- Real-time recognition of novel words was facilitated in high knowledge domains

- Children leverage their semantic knowledge to efficiently learn and understand new words.
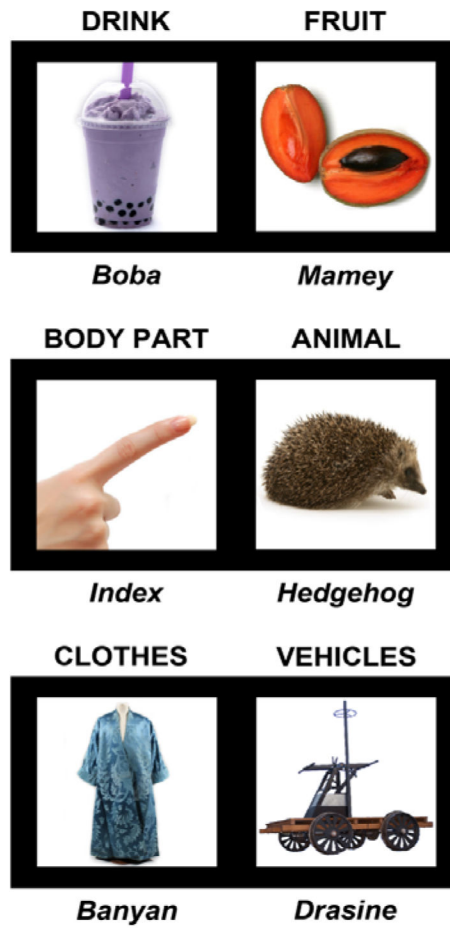
Figure 1.
Illustration of novel word stimuli and categories used in the study.
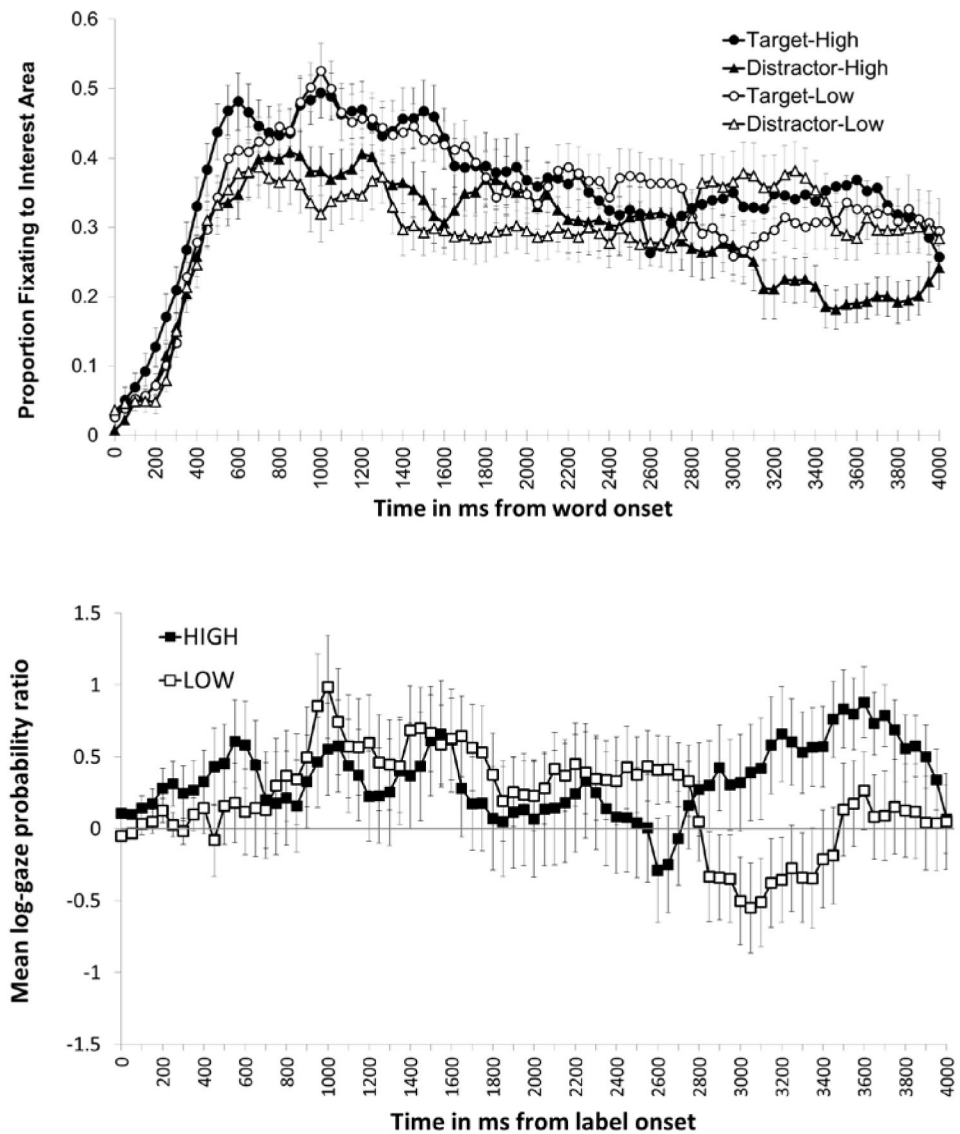
Figure 2.
Time course plots of (A) fixation proportions and (B) log-gaze proportion ratios across the test trial period, starting from label onset until picture offset.

Table 1

Information regarding category assignment, including the distribution of category assignment to High and Low knowledge domains across infants, as well as the mean proportion and standard deviation of words produced in each domain at each age.

	HIGH	LOW	Mean Proportion (Std. Dev.)
ANIMALS	.687	.313	.745 (.225)
BODY-PARTS	.687	.313	.795 (.240)
CLOTHING	.094	.906	.623 (.221)
DRINKS	.281	.719	.664 (.175)
FRUITS	.656	.343	.769 (.220)
VEHICLES	.593	.406	.786 (.148)

Table 2

Mean Accuracy as a function of Domain Target Knowledge, Category Knowledge, Vocabulary group, and Distractor Knowledge. Standard deviations are reported in parentheses.

	Accuracy
A. Target Knowledge	
High Knowledge Domain	.55 (.27) *
Low Knowledge Domain	.54 (.27) *
B. DomainCategory Knowledge	
ANIMALS	.58 (.25) **
BODY-PARTS	.45 (.25)
CLOTHES	.63 (.25) ***
DRINK	.50 (.26)
FRUIT	.61 (.27) **
VEHICLES	.51 (.27)
C. Vocabulary x Domain	
High Voc–High Domain	.57 (.27) *
High Voc–Low Domain	.59(.23) ***
Low Voc–High Domain	.53 (.26)
Low Voc –Low Domain	.49 (.28)
D. Target & Distractor Knowledge	
High T – High D	0.51 (.27)
High T – Low D	0.57 (.26) **
Low T – High D	0.53 (.27)
Low T – Low D	0.55 (.26) *

Symbols indicate whether accuracy means significantly exceed .5

*
-*p* <.05,

**
-p < .01.

***
p <.001