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Using Motor Dynamics to Explore Real-time Competition in Cross-situational Word Learning: Evidence From Two Novel Paradigms

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Abstract

Children and adults can use cross-situational information to identify words' referents. What do learners retain about the potential referents that occur with a word: do they encode multiple referents or a single guess? We tested this question using novel mouse tracking and finger tracking paradigms. Adults were exposed to novel words in a series of ambiguous training trials and then tested on the words' referents. In some test trials, participants saw the target and three referents that had never occurred with the word; other test trials included a high-probability competitor that had repeatedly occurred with the word. Participants' mouse movements were slower, less accurate, and took a more complex path to the selected referent when the competitor was present, indicating that participants were aware that both the target and competitor had previously occurred with the word. This suggests that learners can accrue information about multiple potential referents for a word, and that mouse tracking provides a promising way of assessing this knowledge. However, this knowledge was not evident in participants' finger movements, suggesting that the dynamics of finger movements might not capture real-time competition between referents.

Keywords: cross-situational learning; language acquisition; mouse tracking

Introduction

For any given utterance of a word, the referential scene offers many possible interpretations. Researchers have long assumed that learners cope with such referential ambiguity in part by considering additional referential contexts in which the same word occurs (e.g., Fisher, Hall, Rakowitz, & Gleitman, 1994; Pinker, 1984; Siskind, 1996; Yu & Smith, 2007). Across situations, scene elements that are relevant to a word's meaning should occur more consistently than those that are not relevant. If learners could identify the elements that consistently co-occurred with a word across uses, then this would help them determine the word's likely referent.

Recent evidence suggests that children and adults can use cross-situational information to identify a word's referent (e.g., Scott & Fisher, 2012; Smith & Yu, 2008; Yu & Smith, 2007). For instance, Yu and Smith (2007) presented adults

with a series of training trials in which they saw four novel objects and heard four made-up words. Across trials, each novel label consistently co-occurred with only one object. Following training, participants received a series of test trials in which they heard one novel label and saw its target referent and three distracters. Participants selected the target referent significantly more often than expected by chance.

These findings have raised many questions about the mechanism by which learners exploit cross-situational information in word learning. In particular, how much information do learners retain about the potential referents that occur with a word? Some researchers have proposed that learners simultaneously accrue information about an entire set of potential referents for a word (Fazly, Alishahi, & Stevenson, 2010; Yurovsky, Fricker, Yu, & Smith, 2014). On their first encounter with a word, learners encode whatever referents co-occur with that word. The next time they encounter the word, learners compare the current set of potential referents to the set previously stored in memory, adding new possibilities and updating the co-occurrence probabilities for previously encountered referents.

Other researchers, however, have argued that when learners first encounter a word, they make a guess or conjecture about the word's meaning (e.g., Medina, Snedeker, Trueswell, & Gleitman, 2011; Trueswell, Medina, Hafri, & Gleitman, 2013). Learners retain this hypothesis and discard information about alternative referents. The next time learners encounter the word, they retrieve and evaluate their conjecture. If the hypothesized referent is present, then they strengthen and retain the hypothesis. Otherwise, learners discard the hypothesis and generate a new one based on the current referential scene.

Empirical attempts to test these accounts have yielded mixed results. While some studies suggest that learners accumulate knowledge about multiple competing referents for a word (e.g., Dautriche & Chemla, 2014; Smith, Smith, & Blythe, 2011; Yurovsky & Frank, 2015; Yurovsky et al., 2014), others suggest that participants retain only a single potential referent for a word across observations (Medina et al., 2011; Trueswell et al., 2013). These conflicting findings

are difficult to reconcile because the experiments have differed along many dimensions, including the number of potential referents that occurred on each observation, whether those referents were presented in isolation or in a natural scene, and the interval between observations for a word (see Yurovsky & Frank, 2015; Yurovsky et al., 2014).

Here, however, we focus on a feature that all of these prior studies share: participants' knowledge about the potential referents for a word was inferred from their patterns of explicit guesses across trials. Although the referent that a participant selects provides one index of their knowledge, this measure might nevertheless fail to capture valuable information about the process by which that selection was made. A participant might select the correct referent for a word because that participant had previously guessed that referent and thus confidently selects it again without considering other referents. Alternatively, the participant might consider how often each of the available referents had occurred with the word in the past and select the correct referent because it had the highest co-occurrence probability. In order to distinguish between these two possibilities, one would need to examine the participant's decision-making process as it unfolded in real time.

Mouse tracking provides one way of capturing this decision-making process (e.g., Dale, Kehoe, & Spivey, 2007; Spivey, Grosjean, & Knoblich, 2005). For instance, Spivey et al. (2005) asked participants to click on one of two objects on a computer screen. When the objects were phonological competitors (e.g., *pickle*, *picture*), participants took longer to select the target, achieved maximum velocity later, and exhibited more deviation toward the distracter than they did when the two objects' names were dissimilar. Thus, the velocity, duration, and shape of participants' mouse trajectories revealed real-time competition between alternative referents as they made their selection.

When participants select a referent for a word in a cross-situational learning task, do they experience real-time competition between referents that previously co-occurred with the word? To test this question, we devised novel mouse-tracking (Experiment 1) and finger-tracking (Experiment 2) versions of Yu and Smith's (2007) paradigm. Participants viewed training trials in which multiple novel labels occurred with multiple referents, followed by test trials in which a single label occurred with four objects. On each test trial, participants selected the object that they thought the word referred to, and we tracked their mouse/finger movements as they did so. In half of the test trials (competitor-absent trials), participants saw the target referent and three objects that had not previously occurred with the word. In the remaining test trials (competitor-present trials), one of the three non-target objects had occurred with the word in 50% of the training trials (high-probability competitor). If participants retain co-occurrence information for the set of potential referents for a word, then in the competitor-present trials they should experience online competition between the high-probability competitor and the target as they make their selection. This

competition should impact their response trajectories in the competitor-present trials, resulting in differing patterns of motor dynamics across the two trial types. If, however, the participants track a single conjecture, then the frequency with which the available referents had previously occurred with the word should have no influence and response trajectories should not differ across trial types.

Experiment 1

Method

Participants 208 undergraduates (139 females) completed the experiment for course credit. All the participants used their right hand to perform the task.

Stimuli Referents were high-resolution photos of 18 common objects; each was paired with a 1- or 2-syllable nonsense word. Words were phonotactically probable in English and recorded by a female native English speaker.

Design Participants received 27 training trials and 18 test trials. On each training trial, participants saw four objects, one in each corner of the screen, and heard four labels played over the computer speaker (Figure 1). The objects for each trial were randomly selected with the constraint that each word occurred six times with its target referent, three times with a high-probability competitor referent, and less than three times with all other objects. We randomly generated two unique sets of word-object pairs.

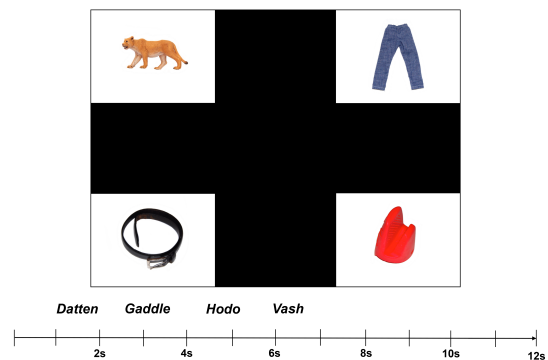


Figure 1: Sample of a single learning trial.

In each test trial, participants saw four objects, one in each corner of the screen, and heard a single label. On competitor-absent trials, objects consisted of the target and three objects that had appeared in training but had never co-occurred with the word. On competitor-present trials, the objects consisted of the target, the high-probability competitor, and two objects that had appeared in training but had never co-occurred with the word. Participants saw one of two randomized test orders. The onscreen positions of the objects were randomly generated with the constraint that on competitor-present trials the target and the high-probability competitor could not be diagonally adjacent.

This ensured a consistent angle between the target and the high-probability competitor relative to the starting position.

Procedure Participants were instructed that they would see a series of objects and hear words and afterwards they would be tested on which word went with which object. Participants then viewed the training trials on a 65 cm by 45 cm computer screen. On each trial, participants saw four objects and heard four consecutively presented audio labels. The first label occurred 1s after the onset of the trial; each subsequent label occurred 1s after the previous label. Each trial lasted 12s; trials were separated by 1s of black screen.

Following training, participants moved to a second identical computer in an adjoining room. Participants were told that they would see sets of objects accompanied by a single word and that after hearing each word, they should drag the green dot that appeared in the center of the screen to the object that they thought matched the word. Participants were told to make their decision as quickly and accurately as possible. At the start of each trial, the objects and the green dot appeared on screen; after 1s, a single audio label was delivered. The green dot was initially locked in place and unlocked at the offset of the audio label. This prevented the participants from making a selection prior to hearing the word. Once the participants released the green dot over one of the objects, the trial ended. Trials were separated by 1s of black screen. During each trial, we recorded the streaming x , y coordinates of the computer mouse as participants dragged the dot from the start position to their chosen referent object (sample rate \approx 71 Hz).

Data Preprocessing On each trial, participants' final x , y coordinates were taken as their referent selection. To examine participants' real-time decision making, trajectories were remapped to orient the target location to the top-right corner by inverting the trajectories along the x -axis and y -axis. All trajectories were lined up to a common x , y starting position (0, 0), then individually normalized by resampling trajectories at 101 equally time-spaced values and computing, by means of linear interpolation, the corresponding mouse-coordinate values (separately for the x and y coordinate vectors).

All data analyses were conducted with R 3.1.2 (2014) and the lme4 package (Bates, Maechler, Bolker, & Walker, 2015). All of the subsequent analysis of variance (ANOVA) models include participant as a random effect.

Results and Discussion

Participants selected the target significantly more often than expected by chance (.25) on both competitor-absent trials ($M = .50$, $SD = .24$), $t(207) = 14.88$, $p < .001$, $d = 2.07$, and competitor-present trials ($M = .41$, $SD = .25$), $t(207) = 9.22$, $p < .001$, $d = 1.28$. However, participants selected the target significantly more often on competitor-absent trials than on competitor-present trials, $t(207) = 5.93$, $p < .001$, $d = .37$.

To determine whether participants experienced real-time competition between potential referents, we examined

participants' mouse trajectories. We identified trials where participants' selected either the target or the high-probability competitor (we did not analyze trials in which participants selected other objects because the angle between the start position and the object varied based on the object selected). We then separated the trajectories into three trajectory types: competitor-absent (795 trajectories), competitor-present correct (target selected; 454 trajectories), and competitor-present incorrect (high-probability competitor selected; 275 trajectories).

We next examined the participants' reaction times (from label offset to mouse-click release). A one-way ANOVA revealed a significant main effect of trajectory type, $F(2, 325) = 6.06$, $p = .003$. Planned comparisons revealed significantly faster reaction times for competitor-absent trajectories ($M = 1618$ ms, $SD = 947$) than for competitor-present correct trajectories ($M = 1767$ ms, $SD = 1030$), $z = -2.74$, $p = .015$, and competitor-present incorrect trajectories ($M = 1802$ ms, $SD = 942$), $z = -2.86$, $p = .01$. The speed of competitor-present correct and competitor-present incorrect trajectories did not differ, $z < 1$. The fact that participants were slower on competitor-present trials suggests that they experienced real-time competition between the target and the high-probability competitor.

To further examine this competition, for each trajectory we computed the maximum deviation (MD): the largest positive x -coordinate deviation from a straight line between the starting position and the selected object. For each participant, we calculated average MD values for each trajectory type. A one-way ANOVA on participants' MD revealed a significant main effect of trajectory type, $F(2, 325) = 5.44$, $p = .005$. Planned comparisons revealed significantly smaller MD values for competitor-absent trajectories ($M = 65.60$, $SD = 68.07$) than competitor-present correct trajectories ($M = 76.23$, $SD = 77.66$), $z = -2.38$, $p = .05$. Competitor-absent trajectories exhibited significantly smaller MD values than competitor-present incorrect trajectories ($M = 82.77$, $SD = 83.89$), $z = -2.91$, $p = .01$. The MD values of competitor-present correct and competitor-present incorrect trajectories did not differ, $z < 1$.

Finally, angle information and sample entropy were computed using the mousetrack R package (Coco & Duran, 2015). Angle information has been used in previous mouse-tracking studies (e.g., Dale et al., 2007) to investigate how initial movements deviated from the point of origin. Angle trajectory of mouse movements is computed as the angle relative to the y -axis for each sample in a trajectory. This provides a single measure that integrates information about x -axis and y -axis movements. A trajectory starting at the origin and moving directly to the participant's final selection would have a constant angle trajectory. If participants experienced competition between referents, then this should result in more complex angle trajectories.

To measure the complexity of angle trajectories, we submitted angle trajectory to an analysis of sample entropy for each trial (Richman & Mooreman, 2000). Sample entropy measures the complexity of a given time series. It is

robust for small time series (Yentes et al., 2013) and has been used to measure the complexity or “disorder” of mouse movement trajectories (Dale et al., 2007; McKinstry, Dale, & Spivey, 2008). Sample entropy is computed for the angle trajectories by counting the number of similar sequences, m and $m+1$ (up to $m=5$), within a similarity tolerance parameter, $0.2 * SD_{\text{angle trajectory}}$ and then taking the negative logarithm of the ratio of similar sequence pair across m and $m + 1$, $-\ln(m/m+1)$. A time series of similar distances between data points across sequence lengths will result in lower sample entropy values. Larger sample entropy values are considered to have higher complexity.

We interpret higher values of sample entropy of angle trajectories as exhibiting competition effects through more disordered movements toward the selected object, whereas lower values of sample entropy indicate more ordered, regular movements toward the selected object. A one-way ANOVA on sample entropy revealed a significant main effect of trajectory type, $F(2, 325) = 6.67, p = .002$. Planned comparisons revealed that trajectories were significantly less complex for competitor-absent trajectories ($M = .13, SD = .06$) than for competitor-present correct trajectories ($M = .14, SD = .07$), $z = -2.63, p = .023$, and competitor-present incorrect trajectories ($M = .15, SD = .08$), $z = -3.23, p = .003$. Within the competitor-present trajectories, the complexity of the trajectories did not differ, $z < 1$.

Participants were slower and their trajectories exhibited greater deflection and complexity when the competitor was present than when it was absent. This suggests that on competitor-present trials, the target and high-probability competitor were partially active as potential response alternatives as participants were making their selection.

These results are inconsistent with what one would expect if learners retained only a single conjecture about a word’s meaning. If participants only recalled their prior guess for a given word, then when that hypothesized referent was present in the test trial, they should have selected it. When that conjecture was absent, participants should have selected a referent at random from the available choices. In either case, their decision-making process should not have been affected by how frequently the available referents had previously co-occurred with the word. Contrary to this prediction, the accuracy, speed, and shape of participants’ response trajectories differed across trial types, suggesting that participants were sensitive to the fact that both high-probability competitor and target previously co-occurred with the word. Thus, our results suggest that under at least some circumstances, learners can accrue information about multiple potential referents for a word.

Experiment 2

The results of Experiment 1 suggest that mouse tracking has the potential to capture learners’ underlying knowledge about alternative referents for a word during cross-situational learning. In Experiment 2, we explored whether we would obtain similar results if we tracked participants’ fingers as they performed our task with a touchscreen

device. If so, this would provide a portable way of assessing cross-situational learning outside of the laboratory. It would also facilitate the assessment of real-time decision-making in young children, who have difficulty interacting with a mouse (e.g., Agudo, Sanchez, & Rico, 2010).

Method

Participants 79 undergraduates (60 females) completed the experiment for course credit (none participated in the previous experiment). All participants used their right hand to perform the task.

Stimuli, Design, and Procedure The stimuli, design, and procedure were identical to Experiment 1 with one exception: participants completed the test phase on a 24 cm by 19 cm touchscreen tablet and we recorded the streaming x, y coordinates of the participants’ finger position as they dragged the dot from the start position to their chosen referent object (sampling rate ≈ 143 Hz). Participants were instructed to not lift their finger as they dragged the dot.

Results and Discussion

Participants selected the target significantly more often than expected by chance (.25) on both competitor-absent trials ($M = .48, SD = .28$), $t(78) = 7.16, p < .001, d = 1.62$, and competitor-present trials ($M = .47, SD = .27$), $t(78) = 7.38, p < .001, d = 1.67$. Unlike in Experiment 1, participants’ accuracy did not differ across trial types, $t < 1$.

We next examined participants’ finger trajectories, separated into three trajectory types: competitor-absent (293 trajectories), competitor-present correct (211 trajectories), and competitor-present incorrect (59 trajectories).

A one-way ANOVA on participants’ reaction times revealed a marginally significant main effect of trajectory type, $F(2, 99) = 2.93, p = .058$. Planned comparisons revealed that competitor-present incorrect trajectories were significantly slower ($M = 540$ ms, $SD = 408$) than competitor-absent trajectories ($M = 395$ ms, $SD = 298$), $z = 2.38, p = .04$, and marginally slower than competitor-present correct trajectories ($M = 392$ ms, $SD = 331$), $z = 2.15, p = .08$. However, competitor-absent and competitor-present correct trajectories did not differ in speed, $z < 1$.

A one-way ANOVA on participants’ MD also revealed a significant main effect of trajectory type, $F(2, 99) = 6.08, p = .003$. Competitor-present incorrect trajectories ($M = 38.70, SD = 50.08$) exhibited significantly larger MD values than did competitor-absent trajectories ($M = 22.48, SD = 29.35$), $z = 3.25, p = .003$, or competitor-present correct trajectories ($M = 21.45, SD = 28.91$), $z = 3.31, p = .003$. MD values for competitor-absent and competitor-present correct trajectories did not differ, $z < 1$.

Finally, a one-way ANOVA on sample entropy revealed a significant main effect of trajectory type, $F(2, 99) = 4.22, p = .02$. Competitor-present incorrect trajectories ($M = .14, SD = .11$) were significantly more complex than competitor-absent trajectories ($M = .11, SD = .10$), $z = 2.76, p = .02$, or competitor-present correct trajectories ($M = .11, SD = .09$), z

= 2.78, $p = .01$. Competitor-absent and competitor-present correct trajectories did not differ in complexity, $z < 1$.

The presence of the high-probability competitor did not impact the accuracy, speed, or shape of participants' finger trajectories. In contrast to the findings of Experiment 1, these results provide no indication that participants' considered the high-probability competitor as a potential response alternative as they made their selection.

General Discussion

Recent studies suggest that adults and children are able to use cross-situational information to identify the referents of novel words under at least some circumstances (e.g., Yu & Smith, 2007). However, it remains unclear how much information learners retain about the potential referents for a given word. The present study attempted to shed light on this question using novel mouse- and finger-tracking paradigms. Adult participants were exposed to novel words in a series of ambiguous learning trials and then tested on their knowledge of the words' referents. In some test trials, participants saw the word's target referent and three alternative referents that had never co-occurred with the word before, while in other trials the target referent was accompanied by a high-probability competitor that had repeatedly occurred with the word during training. In Experiment 1, participants were faster and more accurate when the high-probability competitor was absent than they were when it was present, and their mouse trajectories revealed differing patterns of motor dynamics across the two types of test trials: when the high-probability competitor was present, participants deviated more from a straight line and followed a more complex path to the selected referent. In Experiment 2, however, we observed no differences in accuracy or motor dynamics across trial types.

On the one hand, the results of Experiment 1 demonstrate that continuous measures can provide information about learners' knowledge of potential referents that is not evident in their discrete guesses. For instance, participants' in Experiment 1 were more accurate on competitor-absent than on competitor-present trials. This could reflect the fact that participants were tracking multiple potential referents for each word and the resulting competition increased the difficulty of competitor-present trials. However, unlike competitor-absent trials, competitor-present trials included two referents that had previously co-occurred with the word. These trials therefore afforded the opportunity to confirm an incorrect conjecture: if participants had previously guessed that the word referred to the high-probability competitor, they would select it if present, resulting in lower accuracy on competitor-present trials. Examining participants' mouse trajectories as they made their guesses allowed us to tease apart these two possibilities: the differing patterns of motor dynamics across the two trial types indicated that participants experienced competition between the high-probability competitor and the target. Even when participants ultimately selected the target, the way in which they did so differed when the high-probability competitor

was present. These results thus suggest that assessing the decision-making process in real-time can reveal information not captured by forced-choice measures.

Converging evidence for this conclusion comes from Trueswell et al. (2013), who eye-tracked participants as they performed a cross-situational learning task. Adults viewed a series of trials in which a novel label occurred with two or five everyday objects. On each trial, participants selected the object that they thought the word referred to. Examination of participants' trial-by-trial guesses revealed that when they incorrectly guessed which referent went with a word, they performed at chance on the next encounter with that word. This suggested that participants only remembered their previous conjecture and if that guess was disconfirmed on the next trial, they were unable to remember which alternative referents were present the last time they heard the word. In contrast to their forced-choice responses, however, participants' eye movements suggested that under some conditions, they retained knowledge of multiple referents. Specifically, when participants saw only two referents on each trial, they looked significantly longer at the target than the competitor referent, regardless of whether they had guessed correctly on their previous encounter with a word. Together with the findings of Experiment 1, these results suggest that continuous measures have the potential to capture fine-grained information that learners retain about alternative referents, even when this information does not appear to impact their overt guesses.

More generally, the results of Experiment 1 suggest that mouse tracking offers a promising avenue for exploring the mechanisms behind cross-situational word learning. Incorporating mouse tracking into cross-situational paradigms in which participants select a referent on each exposure to a word (e.g., Smith et al., 2011; Trueswell et al., 2013) could provide new insight into the amount of information participants retain on a given exposure as well as how this information changes across observations. Recent work also suggests that when learners receive similar cross-situational evidence for *two* potential referents for a word, this can disrupt cross-situational learning (e.g., Bunce & Scott, in press; Yurovsky, Yu, & Smith, 2013). Mouse tracking could be used to examine the influence of carefully controlled co-occurring distracters in order to better understand when and how competition between referents leads to breakdowns in cross-situational word learning.

On the other hand, the negative results of Experiment 2 suggest that finger tracking, at least as implemented here, might not capture real-time competition between potential referents. This failure to replicate the results of Experiment 1 could be due in part to the smaller sample size in Experiment 2. However, a power analysis indicated that this sample size should have been more than adequate to detect the difference in accuracy between competitor-absent and competitor-present that we observed in Experiment 1. The fact that we nevertheless failed to observe a difference in accuracy across trial types suggests that the results of Experiment 2 were not merely a product of sample size.

Why then was there no impact of the high-probability competitor on participants' performance in Experiment 2? One possibility is that the shift in context (computer to tablet) interfered with participants' memory of the potential referents for each word, especially those that had occurred with the word less frequently. If so, then perhaps we did not observe real-time competition between the referents because participants' memory for the non-target referents was degraded and thus there was no competition to detect.

Alternatively, it may be that the participants in Experiment 2 did retain knowledge of multiple competing referents, but our finger tracking measure failed to capture that knowledge due to differences in how participants interacted with the touchscreen. Specifically, participants tested on the computer tended to keep their hand on the mouse throughout the test phase, whereas those tested on the tablet only touched the screen while making their selection. As a result, participants tested on the computer may have been more likely to initiate the movement of the dot *during* the decision-making process. Those tested on the tablet may instead have waited to touch the dot until after they had decided which referent they intended to select. Consistent with this possibility, the interval between the audio label and when participants' engaged the dot was longer on average in Experiment 2 than in Experiment 1. This suggests that perhaps we did not detect competition in Experiment 2 because our finger-tracking measure did not capture participants' online decision-making process. Future work will examine whether requiring participants to touch the dot throughout each trial will allow us to detect real-time competition in finger movements.

References

- Agudo, J. E., Sánchez, H., & Rico, M. (2010). Playing games on the screen: Adapting mouse interaction at early ages. In *Proceedings of the IEEE International Conference on Advanced Learning Technologies (ICALT)*, 493-497.
- Bates, D., Maechler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67, 1-48.
- Bunce, J. P. & Scott, R. M. (in press). Finding meaning in a noisy world: Exploring the effects of referential ambiguity and competition on 2.5-year-olds' cross-situational word learning. *Journal of Child Language*.
- Coco, M. I. & Duran, N. D. (2015). mousetrack: Mouse-tracking measures from trajectory data. R package version 1.0.0.
- Dale, R., Kehoe, C. E., & Spivey, M. J. (2007). Graded motor responses in the time course of categorizing atypical exemplars. *Memory & Cognition*, 35, 15-28.
- Dautriche, I. & Chemla, E. (2014). Cross-situational word learning in the right situations. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 40, 892-903.
- Fazly, A., Alishahi, A., & Stevenson, S. (2010). A probabilistic computational model of cross-situational word learning. *Cognitive Science*, 34, 1017-1063.
- Fisher, C., Hall, D. G., Rakowitz, S., & Gleitman, L. R. (1994). When it is better to receive than to give: syntactic and conceptual constraints on vocabulary growth. *Lingua*, 92, 333-375.
- McKinstry, C., Dale, R., & Spivey, M. J. (2008). Action dynamics reveal parallel competition in decision making. *Psychological Science*, 19, 22-24.
- Medina, T. N., Trueswell, J. C., Snedeker, J., & Gleitman, L. R. (2011). How words can and cannot be learned by observation. *PNAS*, 108, 9014-9019.
- Pinker, S. (1984). *Language learnability and language development*. Cambridge, MA: Harvard University Press.
- R Core Team. (2014). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria.
- Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. *American Journal of Physiology: Heart and Circulatory Physiology*, 278, H2039-H2049.
- Scott, R. M. & Fisher, C. (2012). 2.5-year-olds use cross-situational consistency to learn verbs under referential uncertainty. *Cognition*, 122, 163-180.
- Siskind, J. M. (1996). A computational study of cross-situational techniques for learning word-to-meaning mappings. *Cognition*, 61, 39-91.
- Smith, K., Smith, A. D. M., & Blythe, R. A. (2011). Cross-situational learning: an experimental study of word-learning mechanisms. *Cognitive Science*, 35, 480-498.
- Smith, L. B. & Yu, C. (2008). Infants rapidly learn word-referent mappings via cross-situational statistics. *Cognition*, 106, 1558-1568.
- Spivey, M. J., Grosjean, M., & Knoblich, G. (2005). Continuous attraction toward phonological competitors. *PNAS*, 102, 10393-10398.
- Trueswell, J. C., Medina, T. N., Hafri, A., & Gleitman, L. R. (2013). Propose but verify: Fast mapping meets cross-situational word learning. *Cognitive Psychology*, 66, 126-156.
- Yentes, J. M., Hunt, N., Schmid, K. K., Kaipust, J. P., McGrath, D., & Stergiou, N. (2013). The appropriate use of approximate entropy and sample entropy with short data sets. *Annals of Biomedical Engineering*, 41, 349-365.
- Yu, C. & Smith, L. B. (2007). Rapid word learning under uncertainty via cross-situational statistics. *Psychological Science*, 18, 414-420.
- Yurovsky, D. & Frank, M. C. (2015). An integrative account of constraints on cross-situational learning. *Cognition*, 145, 53-62.
- Yurovsky, D., Fricker, D., Yu, C., & Smith, L. B. (2014). The role of partial knowledge in statistical word learning. *Psychonomic Bulletin & Review*, 21, 1-22.
- Yurovsky, D., Yu, C., & Smith, L. B. (2013). Competitive processes in cross-situational word learning. *Cognitive Science*, 37, 891-921.