1   **Communicative pressure on caregivers leads to language input that supports**

2   **children's word learning**

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Abstract

Children do not learn language from passive observation of the world, but from interaction with caregivers motivated to communicate with them. Does this communicative pressure on caregivers lead them to structure children's linguistic input in a way that facilitates learning? As a case study, we analyze a canonical pedagogical behavior in caregivers: use of ostensive labeling to teach children new words. Using a multi-method approach, we show that this pedagogically supportive behavior can emerge from communicative pressure alone, without any explicit pedagogical goals. First, in a corpus study, we show that caregivers communicate by ostensive labeling precisely when children are likely to learn a new word. In an iterated reference game, we experimentally show that this strategy can arise from pressure to communicate successfully with a less knowledgeable partner. Then, we show that speaker behavior in our experiment can be explained by a rational communication model that includes planning, without any explicit teaching goal. Finally, in a series of simulations, we explore the language learning consequences of having a communicatively-motivated caregiver. We show that under many parameterizations, simple learning mechanisms interacting with a communicatively-motivated partner outperform more powerful learning mechanisms. This perspective offers a first step toward a unifying, formal account of both how linguistic input is structured and how children learn from it.

Keywords: communication; child-directed speech; language learning; computational modeling

Word count: X

Communicative pressure on caregivers leads to language input that supports children's word learning

One of the most striking aspects of children's language learning is just how quickly they master the complex system of their natural language (Bloom, 2000). In just a few short years, children go from complete ignorance to conversational fluency in a way that is the envy of second-language learners attempting the same feat later in life (Newport, 1990). What accounts for this remarkable transition?

Distributional learning presents a unifying account of early language learning: Infants come to language acquisition with a powerful ability to learn the latent structure of language from the statistical properties of speech in their ambient environment (Saffran, 2003). Distributional learning mechanisms can be seen in accounts across levels of language, including phonemic discrimination (Maye et al., 2002), word segmentation (Saffran, 2003), learning the meanings of both nouns (L. B. Smith & Yu, 2008) and verbs (Scott & Fischer, 2012), learning the meanings of words at multiple semantic levels (Xu & Tenenbaum, 2007), and perhaps even the grammatical categories to which a word belongs (Mintz, 2003). A number of experiments have confirmed both the early availability of distributional learning mechanisms, and their potential utility across these diverse language phenomena (DeCasper & Fifer, 1980; DeCasper & Spence, 1986; Estes et al., 2007; Gomez & Gerken, 1999; Maye et al., 2002; Saffran et al., 1996; L. B. Smith & Yu, 2008; Xu & Tenenbaum, 2007).

However, there is reason to be suspicious about just how precocious statistical learning abilities are in early development. Although these abilities are available early, they are highly constrained by limits on other developing cognitive capacities. For example, infants' ability to track the co-occurrence information connecting words to their referents is constrained significantly by their developing memory and attention systems (L. B. Smith & Yu, 2013; Vlach & Johnson, 2013). In addition, computational models of statistical learning show that the rate of acquisition is highly sensitive to variation in environmental statistics.

53 For example, the Zipfian distribution of word frequencies and word meanings in the real

54 world can lead to very long learning times for rare words (Vogt, 2012). Further, a great deal

55 of empirical work demonstrates that cross-situational learning even in adults drops off

56 rapidly when participants are asked to track more referents, and also when the number of

57 intervening trials is increased–features likely typical of the naturalistic learning environment

58 (e.g., Yurovsky & Frank, 2015). Thus, precocious unsupervised statistical learning appears to

59 fall short of a complete explanation for rapid early language learning.

60   Even relatively constrained statistical learning could be rescued, however, if

61 caregivers structured their language in a way that simplified children's learning problem.

62 Caregivers do adjust many aspects of their communication when conversing with young

63 children, in both their language (infant directed speech, Snow, 1977) and actions (motionese,

64 Brand et al., 2002)-and such modifications have been shown to yield learning benefits across

65 a number of language phenomena. For example, in phoneme learning, infant-directed speech

66 provides examples that seem to facilitate the acquisition of phonemic categories (Eaves Jr et

67 al., 2016). In word segmentation tasks, infant-directed speech facilitates infant learning more

68 than matched adult-directed speech (Thiessen et al., 2005). In word learning scenarios,

69 caregivers produce more speech during episodes of joint attention with young infants, which

70 uniquely predicts later vocabulary (Tomasello & Farrar, 1986). Child-directed speech even

71 seems to support learning at multiple levels in parallel–e.g., simultaneous speech

72 segmentation and word learning (Yurovsky et al., 2012). For each of these language problems

73 faced by the developing learner, caregiver speech exhibits structure that seems uniquely

74 beneficial for learning.

75   Under distributional learning accounts, the existence of this kind of structure is a

76 theory-external feature of the world that does not have an independently motivated

77 explanation. Such accounts view the explaining the process that generates structure in the

78 language environment as a problem separate from explaining language learning. However,

79 across a number of language phenomena, the language environment is not merely supportive,

80 but seems calibrated to children's changing learning mechanisms (Yurovsky, 2018). For

81 example, across development, caregivers engage in more multimodal naming of novel objects

82 than familiar objects, and rely on this temporal synchrony between verbal labels and gesture

83 most with young children (Gogate et al., 2000). The prevalence of such synchrony in

84 child-directed speech parallels infant learning mechanisms: young infants appear to rely more

85 on synchrony as a cue for word learning than older infants, and language input mirrors this

86 developmental shift (Gogate et al., 2000). Beyond age-related changes, caregiver speech may

87 also support learning through more local calibration to a child's knowledge. Caregivers have

88 been shown to provide more language about referents that are unknown to their child, and

89 adapt their language in-the-moment to the knowledge their child displays during a referential

90 communication game (Leung et al., 2021). The calibration of caregivers' production to the

91 child's learning and knowledge suggests a co-evolution such that these processes should not

92 be considered in isolation.

93   What then gives rise to the structure in early language input that mirrors children's

94 learning mechanisms? Because of widespread agreement that caregivers' speech is not

95 usually motivated by explicit pedagogical goals (Newport et al., 1977), the calibration of

96 speech to learning mechanisms seems a happy accident; caregivers' speech just happens to be

97 calibrated to children's learning needs. If caregivers' speech was pedagogically-motivated,

98 extant formal frameworks of teaching could be used to derive predictions and expectations

99 (e.g., Shafto et al., 2014). This framework–in which caregivers choose what they say in order

100 to maximize their children's learning–has seen some success in explaining children's

101 developing phoneme discrimination (Eaves Jr et al., 2016). Even here, however, the

102 statistical structure of phonemes in caregivers' input also contains features that are not well

103 explained by a pedagogical goal (McMurray et al., 2013).

104   Instead, the recent outpouring of work exploring optimal communication (the

105 Rational Speech Act model, see Frank & Goodman, 2012) provides a different framework for

106 understanding caregivers' production. Under optimal communication accounts, speakers and

107 listeners engage in recursive reasoning to produce and interpret speech cues by making

108 inferences over one another's intentions (Frank & Goodman, 2012). These accounts have

109 made room for advances in our understanding of a range of language phenomena previously

110 uncaptured by formal modeling, most notably a range of pragmatic inferences (Bohn &

111 Frank, 2019; e.g., Frank & Goodman, 2012; Goodman & Frank, 2016). In this work, we

112 consider the communicative structure that emerges from an optimal communication system

113 across a series of interactions where one partner has immature linguistic knowledge. This

114 perspective offers the first steps toward a unifying account of both the child's learning and

115 the caregiver's production: Both are driven by a pressure to communicate successfully.

116 Early, influential functionalist accounts of language learning focused on the

117 importance of communicative goals (e.g., Brown, 1977). Recent work has demonstrated that

118 many structural aspects of natural language may have arisen from pressure to communicate

119 efficiently (Gibson et al., 2019). Our goal in this work is to formalize the intuitions in these

120 accounts in a computational model of language input, and to test this model against

121 experimental data. We take as the caregiver's goal the desire to communicate with the child,

122 not about language itself, but instead about the world in front of them. To succeed, the

123 caregiver must produce the kinds of communicative signals that the child can understand and

124 respond contingently, potentially leading caregivers to tune the complexity of their speech as

125 a byproduct of this in-the-moment pressure to communicate successfully (Yurovsky, 2018).

126 To examine this hypothesis, we draw on evidence from naturalistic data, a reference

127 game experiment, a formal model, and learning simulations. We focus on ostensive labeling

128 (i.e. using both gesture and speech in the same referential expression) as a case-study

129 phenomenon of information-rich structure in the language learning environment. We first

130 analyze naturalistic caregiver communicative behavior in a longitudinal corpus of

parent-child interaction in the home (Goldin-Meadow et al., 2014). We investigate the extent to which caregivers tune their ostensive labeling across their child's development to align to their child's developing linguistic knowledge (Yurovsky et al., 2016).

We then experimentally induce this form of structured language input in a simple model system: an iterated reference game in which two players earn points for communicating successfully with each other. Modeled after our corpus data, participants are asked to make choices about which communicative strategy to use (akin to modality choice). In an experiment on Mechanical Turk using this model system, we show that pedagogically-supportive input can arise from a pressure to communicate. We then show that participants' behavior in our game conforms to a model of communication as rational planning: People seek to maximize their communicative success while minimizing their communicative cost over expected future interactions. Finally, we demonstrate potential benefits for the learner through a series of simulations to show that communicative pressure on caregivers' speech facilitates learning. Under a variety of parameter settings, simple learners interacting with communicative partners outperform more complex statistical learners.

In sum, our goal in this work is to argue that the fundamental unit of analysis for understanding children's language learning is not the child alone, but rather the caregiver-child dyad. To provide converging evidence for this claim, we use apply a multi-method approach to a case study of one pedagogically-supportive behavior. We use observational data to understand the contexts in which ostensive labeling happens, and then experimentally manipulate these contexts in a model system in order to demonstrate that the observed relationships are causal. We develop a formal model that quantitatively accounts for this experimental data, and then simulate the long-term learning outcomes of this model for children's language learning. Together, these different methods show that rapid language learning can emerge from even highly-constrained child learners working

157   together with communicative-motivated caregivers.

Corpus Analysis

159   We first investigate parents' use of ostensive labeling in referential communication in

160   a longitudinal corpus of parent-child interaction. Ostensive labeling–the behavior pointing to

161   and labeling an object with its name–is a powerful source of information for word learning

162   because it reduces the ambiguity about the possible meanings of the word the child is

163   hearing. The word could of course still have many possible meanings–it could refer to a part

164   of the object, or something about it's state for instance, but it is unlikely to refer to one of

165   the other objects in the room (Quine, 1960). Prior work has shown that parents tend to use

166   ostensive labeling when referring to objects with basic level words Ninio (1980), and that

167   ostensive labeling is a particularly powerful source of data for young children (e.g., Baldwin,

168   2000; Gogate et al., 2000). We take the ostensive labeling with multi-modal cues to be a

169   case-study phenomenon of pedagogically supportive language input. While our account

170   should hold for other language phenomena, by focusing on one phenomenon we attempt to

171   specify the dynamics involved in the production of such input.

172   In this analysis of naturalistic communication, we examine the prevalence of ostensive

173   labeling in children's language environment at different ages. We find that this

174   pedagogically-supportive form of input shows a key hallmark of adaptive tuning: caregivers

175   using this information-rich cue more for young children and infrequent objects. Thus,

176   parents' production of ostensive labeling is tuned to children's developing linguistic

177   knowledge (Yurovsky et al., 2016).

Methods

179   We used data from the Language Development Project–a large-scale, longitudinal

180   corpus of naturalistic parent child-interaction in the home (Goldin-Meadow et al., 2014).

181   The Language Development Project corpus contains transcription of all speech and

communicative gestures produced by children and their caregivers over the course of the 90-minute home recordings. We coded each of these communicative instances to identify each time a concrete noun was referenced using speech, gesture, or both in the same referential expression (so called ostensive labeling). In these analyses, we focus on caregivers' productions of ostensive labeling in the form of a multi-modal reference.

Participants

The Language Development Project aimed to recruit a sample of families who are representative of the Chicago community in socio-economic and racial diversity (Goldin-Meadow et al., 2014). These data are drawn from a subsample of 10 families from the larger corpus. Our subsample contains data taken in the home every 4-months from when the child was 14-months-old until they were 34-months-old, resulting in 6 timepoints (missing one family at the 30-month timepoint). Recordings were 90 minute sessions, and participants were given no instructions.

Of the ten target children, five were girls, three were Black and two were Mixed-Race. Families spanned a broad range of incomes, with two families earning $15,000 to $34,999 and 1 family earning greater than $100,000. The median family income was $50,000 to $74,999.

Procedure

From the extant transcription and gesture coding, we specifically coded all concrete noun referents produced in either the spoken or gestural modality (or both). Spoken reference was coded only when a specific noun form was used (e.g., "ball"), to exclude pronouns and anaphoric usages (e.g., "it"). Gesture reference was coded only for deictic gestures (e.g., pointing to or holding an object up for view) to minimize ambiguity in determining the intended referent. In order to fairly compare rates of communication across modalities, we need to examine concepts that can be referred to in either gesture or speech (or both) with similar ease. Because abstract entities are difficult to gesture about using

207 deictic gestures, we coded only references to concrete nouns.

Reliability

209   To establish the reliability of the referent coding, 25% of the transcripts were

210 double-coded. Inter-rater reliability was sufficiently high (Cohen's $\kappa = 0.76$). Disagreements

211 in coding decisions were discussed and resolved by hand.

212   To ensure that our each referent could potentially be referred to in gesture or speech,

213 we focused on concrete nouns. We further wanted to ensure that the referents were physically

214 present in the scene (and thus available for deictic gestures). Using the transcripts, a human

215 rater judged whether the referent was likely to be present, primarily relying on discourse

216 context (e.g., a referent was coded as present if the deictic gesture is used or used at another

217 timepoint for the reference, or if the utterance included demonstratives such as "This is an

218 X"). A full description of the coding criteria can be found in the Supporting Materials.

219   To ensure our transcript-based coding of referent presence was sufficiently accurate, a

220 subset of the transcripts (5%) were directly compared to corresponding video data

221 observation. Reliability across the video data and the transcript coding was sufficiently high

222 ($\kappa = 0.72$). Based on transcript coding of all the referential communication about concrete

223 nouns, 90% of the references were judged to be about referents that were likely present. All

224 references are available in the open access dataset for further analysis.

Results

226   Corpus data were analyzed using a mixed effects regression to predict parents' use of

227 ostensive labeling for a given referent. The model included fixed effects of age in months,

228 frequency of the referent, and the interaction between the two. The model included a

229 random intercept and random slope of frequency by subject and a random intercept for each

230 unique referent. Frequency and age were both log-scaled and then centered both because age

231 and frequency tend to have log-linear effects and to help with model convergence. The model

232 showed that parents use ostensive labeling less with older children ($\beta = -0.84$, $p < .001$) and

233 less for more frequent referents ($\beta = -0.09$, $p = .045$). In addition, the interaction between

234 the two was significant, indicating that for parents ostensively label more for younger

235 children when referents are infrequent ($\beta = 0.18$, $p = .001$). Thus, in these data, we evidence

236 that parents provide more pedagogically-supportive input about rarer things in the world for

237 their younger children (Figure 1).
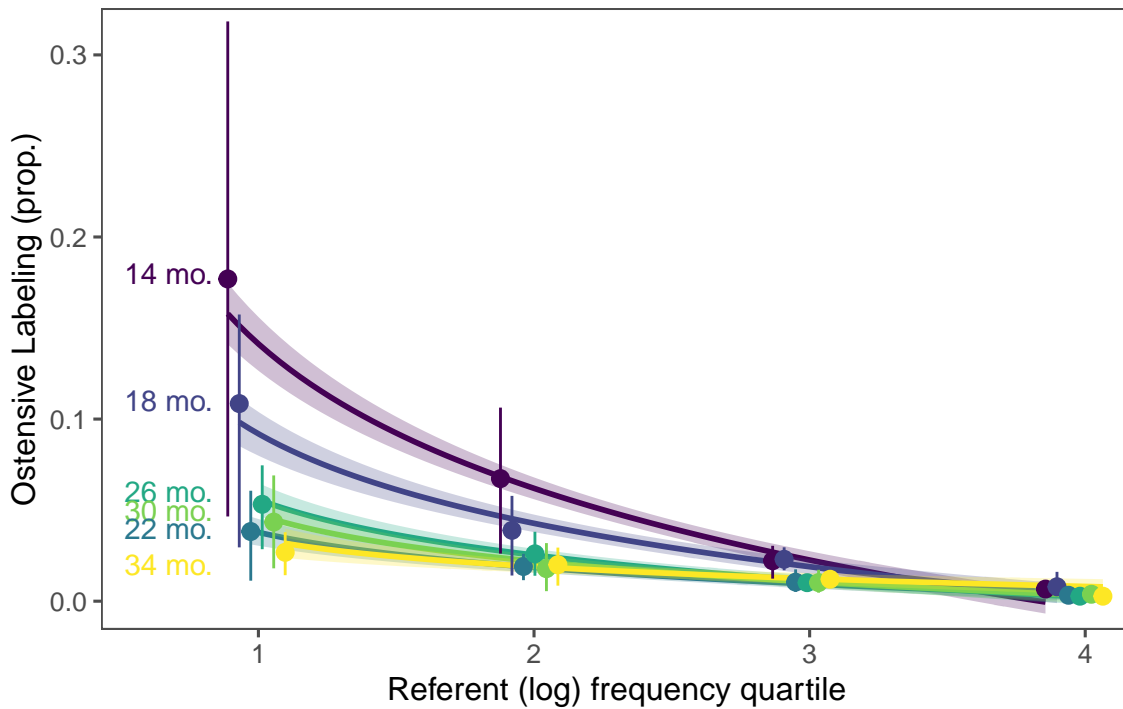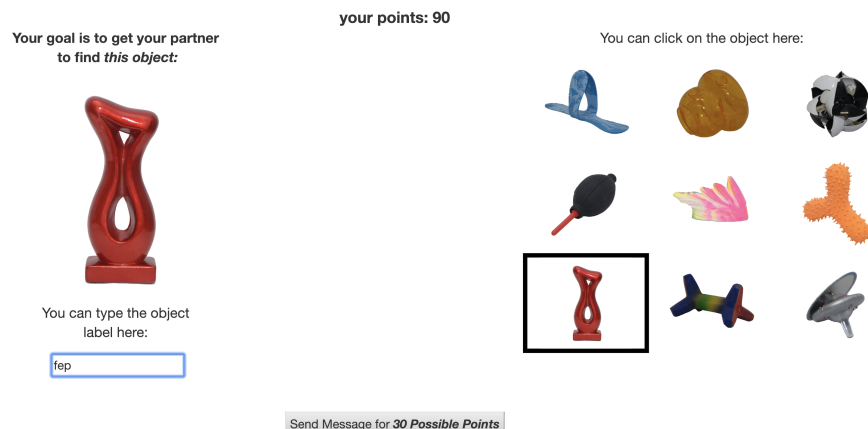

Figure 1

Parents' rate of ostensive labelling via multi-modal reference for referents of varying frequency.
Log frequences were binned into quartiles for visualization. Points show empirical frequencies
along with 95% confidence intervals computed by non-parametric bootstrapping. Lines show
estimates from a logisitic regression along with ribbons indicating one standard error. Parents
used ostensive labeling more for younger children and infrequent referents.

Discussion

Caregivers are not indiscriminate in their use of ostensive labeling; in these data, they provided more of this support when their child was younger and when discussing less familiar objects. These longitudinal corpus findings are consistent with an account of caregiver alignment: parents are sensitive to their child's linguistic knowledge and adjust their communication accordingly (Yurovsky et al., 2016).

This caregiver alignment is straightforwardly predicted from a dyadic perspective that privileges communicative goals, yet wholly missing from learner-centric accounts of language learning (Yurovsky, 2018) . While some early accounts of language learning suggested a important role for caregiver tuning of linguistic input (e.g., Snow, 1972), these accounts fell out of favor in light of influential investigations that did not find tuning of syntactic structure (Newport et al., 1977). However, this work, along with other recent papers, shows that caregivers may be well calibrated to their children's semantic knowledge and this tuning may be quite relevant for language problems like word learning where communicative success is central Leung et al. (2021).

While language input that is tuned to the child's linguistic competence could undoubtedly aid in language learning, the presence of such input does not necessarily imply pedagogical goals. These data could potentially be explained by a simpler, less altruistic goal: to communicate successfully. Because we do not have access to parents' goals, we these data alone cannot distinguish between these competing accounts not can they determine whether word frequency and children's linguistic knowledge are *causally* related to the use of ostensive labeling. To demonstrate that communicative pressure alone is sufficient to explain these patterns in ostensive labeling, we next developed an experimental paradigm to study these and other factors in a controllable model system.

Figure 2

Screenshot showing the participant view during gameplay.

²⁶² **Experiment**

²⁶³   To study the emergence of pedagogically supportive input from communicative

²⁶⁴ pressure, we developed a simple reference game in which participants would be motivated to

²⁶⁵ communicate successfully. After giving people varying amounts of training on novel names

²⁶⁶ for nine novel objects, we asked them to play a communicative game in which they were

²⁶⁷ given one of the objects as their referential goal, and they were rewarded if their partner

²⁶⁸ successfully selected this referent from among the set of competitors (Figure 2). Although we

²⁶⁹ told participants that their partner would be played by another human, all partners were

²⁷⁰ actually pre-programmed bots.

²⁷¹   Participants could choose to refer either using the novel labels they had been exposed

²⁷² to, or they could use a deictic gesture (i.e. point) to indicate the referent to their partner.

²⁷³ The point was unambiguous, and thus would always succeed. However, in order for language

²⁷⁴ to be effective, the participant and their partner would have to know the correct novel label

²⁷⁵ for the referent.

276   In choosing a communicative signal, participants should try to maximize their

277 likelihood of success while minimizing their communicative cost (see e.g. Frank & Goodman,

278 2012). This cost should be related to the energy required to produce the signal. Though it

279 need not be the case for all gestures and contexts, our task compares simple lexical labeling

280 and unambiguous deictic gestures, which are likely are slower and more effortful to produce

281 (e.g., see Yurovsky et al., 2018). We thus assumed that pointing should be more costly than

282 speaking. Nonetheless, because we do not have a way of estimating the costs of pointing and

283 speaking from the observational data, we manipulated them experimentally across conditions

284 to understand how they impact peoples' behavior.

285   Critically, participants were told that they would play this game repeatedly with their

286 partner. In these repeated interactions, participants are able to learn about an interlocutor

287 and potentially influence their learning. Thus, there is a third type of signal participants

288 could send: using both pointing and speech within a single trial to effectively teach the

289 listener through ostensive labeling. This strategy necessitates making inferences about their

290 partner's knowledge state, so we induced knowledge asymmetries between the participant

291 and their partner. To do so, we manipulated how much training they thought their partner

292 had received.

293   Our communicative game was designed to reward in-the-moment communication, and

294 thus teaching required the participant pay a high cost upfront. However, rational

295 communicators may understand that if one is accounting for future trials, paying the cost

296 upfront to teach their partner allows them to use a less costly message strategy on

297 subsequent trials (namely, speech). Manipulating the partner's knowledge and the utility of

298 communicative strategies, we aimed to experimentally determine the circumstances under

299 which richly-structured input emerges, without an explicit pedagogical goal.

300   While our reference game setting has limited ecological validity, this setup allows us

301 to explicitly manipulate the crucial features of the communicative setting (e.g.,

communicative cost, strategy, and partner knowledge). In this controlled task, we can look for the emergence of structure that parallels the naturalistic input described in our corpus evidence, while also experimentally testing for possible drivers of such structure. This experimental setup further allows us to straightforwardly test and compare key predictions using a formal model to explain participant behavior.

Method

In this experiment, participants were recruited to play our reference game via Amazon Mechanical Turk, an online platform that allows workers to complete surveys and short tasks for payment. In this study, all participants were placed in the role of speaker and listener responses were programmed.

Transparency and Openness

This sample size, experimental design, and analysis plan were pre-registered at https://osf.io/63qdg. Sample size was determined based on prior pilot experiments. All data, analysis code, and research materials are available at https://osf.io/d9gkw/. Data were analyzed using R version 4.1.1 (R Core Team, 2021). Models were estimated using version 1.1-27.1 of the lme4 package (Bates et al., 2015).

Participants

480 participants were recruited though Amazon Mechanical Turk and received $1 for their participation. Data from 51 participants were excluded from subsequent analysis for failing the critical manipulation check (accurately reporting their partners knowledge prior to gameplay) and a further 28 for producing pseudo-English labels (e.g., "pricklyyone"). The analyses reported here exclude the data from those participants, but all analyses were also conducted without excluding any participants and all patterns hold ($ps < 0.05$).

Design and Procedure

Participants were told they would be introduced to novel object-label pairs and then asked to play a communication game with a partner wherein they would have to refer to a particular target object. Participants were exposed to nine novel objects, each with a randomly assigned pseudo-word label. We manipulated the exposure rate within-subjects: during training participants saw three of the nine object-label mappings four times, three of them two times, and three of them just one time, yielding a total of 21 training trials. Participants were then given a simple recall task to establish their knowledge of the novel lexicon (pretest).

During gameplay, participants saw the target object in addition to an array of all nine objects. Participants had the option of either directly selecting the target object from the array (pointing)–a higher cost, but unambiguous cue–or typing a label for the object (speech)–a lower cost cue contingent on their partner's knowledge. After sending the message, participants were shown which object their partner selected.

We also manipulated participants' expectations about their partner's knowledge to explore the role of knowledge asymmetries. Prior to beginning the game, participants were told how much exposure their partner had to the lexicon. Across three between-subjects conditions, participants were told that their partner had either no experience with the lexicon, had the same experience as them, or had twice their experience. As a manipulation check, participants were then asked to report their partner's level of exposure, and were corrected if they answered incorrectly. Participants were then told that they would be asked to refer to each object three times during the game.

Partners were programmed with starting knowledge states initialized according to the partner knowledge condition. Partners with no exposure began the game with knowledge of 0 object-label pairs. Partners with the same exposure as the participant began with

knowledge of five object-label pairs (three high-frequency, on mid-frequency, one

low-frequency), based on the learning we observed from participants in a pilot experiment.

Lastly, partners with twice as much exposure as the participant began with knowledge of all

nine object-label pairs.

To simulate knowledgeable behavior, when the participant typed an object label, the

partner was programmed to consult their own knowledge. Messages were evaluated by taking

the Levenshtein distance (LD) between the typed label and each possible label in the

partner's vocabulary. Partners then selected the candidate with the smallest edit distance

(e.g., if a participant typed the message "tomi," the programmed partner would select the

referent corresponding to "toma," provided toma was found in its vocabulary). If the

participant's message was more than two edits away from all of the words in the partner's

vocabulary, the partner selected an object whose label they did not know. If the participant

clicked on an object (pointing), the partner was programmed to always select that referent.

Participants could win up to 100 points per trial if their partner correctly selected the

target referent based on their message. If the partner failed to identify the target object,

participants received no points. We manipulated the relative utility of the speech cue

between subjects across two conditions: Higher Speech Efficiency and Lower Speech

Efficiency. In the *Higher Speech Efficiency* condition, participants received 30 points for

gesturing and 100 points for labeling, and thus speech had very little cost relative to pointing

and participants should be highly incentivized to speak. In the *Lower Speech Efficiency*

condition, participants received 50 points for gesturing and 80 points for labeling, and thus

gesturing is still costly relative to speech, but the difference between them is smaller lowering

the incentivize to speak.

Participants were told about a third type of possible message: using both pointing

and speech within a single trial to effectively teach their partner an object-label mapping.

This action directly mirrors the ostensive labeling behavior parents produced in the corpus

376 data–it yields an information-rich, pedagogically-supportive learning moment. In order to

377 produce this teaching behavior, participants had to pay the cost of producing both cues

378 (i.e. both pointing and speech). Note that, in all utility conditions, teaching yielded

379 participants 30 points (compared with the much more beneficial strategy of speaking which

380 yielded 100 points or 80 points across our two utility manipulations). Partners were

381 programmed to integrate new taught words into their knowledge of the lexicon, and check

382 those taught labels on subsequent trials when evaluating participants' messages.

383   Crossing our 2 between-subjects manipulations yielded 6 conditions (2 utility

384 manipulations: Higher Speech Efficiency and Lower Speech Efficiency; and 3 levels of

385 partner's exposure: None, Same, Twice), with 80 participants in each condition. We

386 expected to find results that mirrored our corpus findings such that rates of teaching would

387 be higher when there was an asymmetry in knowledge where the participant knew more

388 (None manipulation) compared with when there was equal knowledge (Same manipulation)

389 or when the partner was more familiar with the language (Twice manipulation). We

390 expected that participants would also be sensitive to our utility manipulation, such that

391 rates of labeling and teaching would be higher in the Higher Speech Efficiency conditions

392 than the other conditions.

Results

394   In each trial, participants could choose one of 3 communicative strategies: pointing,

395 speech, or teaching. We expected participants to flexibly use communicative strategies in

396 response to their relative utilities, their partner's knowledge of the lexicon, and participants'

397 own lexical knowledge. To test our predictions about each communicative behavior (pointing,

398 speech, and teaching), we fit separate logistic mixed effects models for each behavior,

399 reported below. It should be noted that these three behaviors are mutually exhaustive. First,

400 we report how well participants learned our novel lexicon during training.

Learning

As an initial check of our exposure manipulation, we first fit a logistic regression predicting accuracy at test from a fixed effect of exposure rate and random intercepts and slopes of exposure rate by participant as well as random intercepts by item. We found a reliable effect of exposure rate, indicating that participants were better able to learn items that appeared more frequently in training ($\beta = 1.08$, $p < .001$, see Figure 3). On average, participants knew approximately 6 of the 9 words in the lexicon ($M(sd) = 6.28$ (2.26)). An analysis of variance confirmed that learning did not differ systematically across participants by partner's exposure, utility manipulation, or their interaction ($ps > 0.05$).
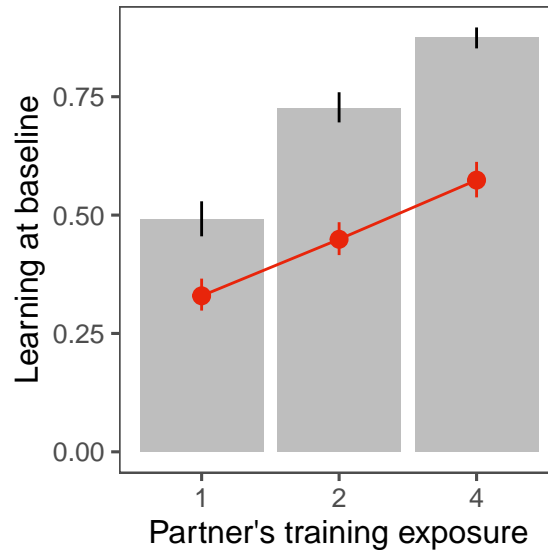

Figure 3

Participants' performance on the baseline recall task for the lexicon, as function of amount of exposure during training (grey bars). The red line shows the propotion of trials during gameplay in which participants used the learned labels, excluding teaching behaviors. Error bars show 95% confidence intervals computed by non-parametric bootstrapping.

Pointing

When should we expect participants to rely on pointing? Pointing has the highest utility for words you failed to learn during training, words you think your partner is unlikely
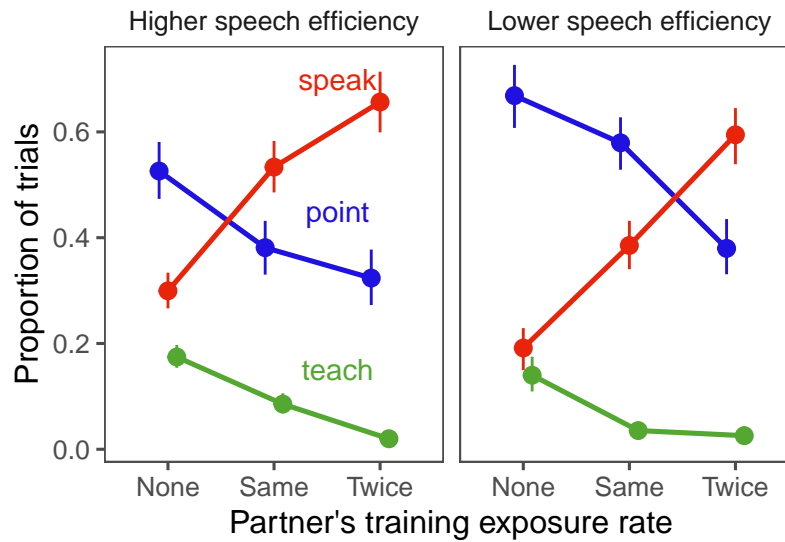
Figure 4

Participants' communicative method choice as a function of exposure and the utility manipulation. Error bars indicate 95% confidence intervals computed by non-parameteric bootstrapping

to know (i.e., for lower partner knowledge conditions), and when the utility scheme is relatively biased toward pointing (i.e., the Lower Speech Efficiency condition). To test these predictions, we ran a mixed effects logistic regression to predict whether participants chose to point during a given trial as a function of the target object's exposure rate during training, object instance in the game (first, second, or third), utility manipulation, and partner manipulation. Random effects terms for subject and object were included in the model.

Consistent with our predictions, exposure rate during training was a significant negative predictor of pointing during the game, such that participants were less likely to rely on pointing for well trained (and thus well learned) objects ($\beta = $ -0.50, $p < .001$). Additionally, participants were significantly more likely to point in the Lower Speech Efficiency condition where pointing is relatively less costly, compared with the Higher Speech Efficiency condition ($\beta = 1.20$, $p < .001$; see Figure 4). We also found a significant negative effect of partner's knowledge, such that participants pointed more for partners with less knowledge of the lexicon ($\beta = $ -0.81, $p < .001$).

427   Note that these effects cannot be explained by solely participants' knowledge; all

428 patterns above hold when looking *only* at words known by the participant at pretest (*ps <*

429 *0.01*). Further, these patterns mirror previous corpus analyses demonstrating parents' use of

430 pointing in naturalistic parental communicative behaviors, and parents likely have lexical

431 knowledge of even the least frequent referent (see Yurovsky et al., 2018).

432 ### *Speech*

433   When should we expect participants to use speech? Speech has the highest utility for

434 words you learned during training, words you think your partner is likely to know (i.e., for

435 higher partner knowledge conditions), and when utility scheme is relatively biased toward

436 speech (i.e., the Higher Speech Efficiency condition). To test these predictions, we ran a

437 mixed effects logistic regression to predict whether participants chose to speak during a given

438 trial as a function of the target object's exposure rate during training, object instance in the

439 game (first, second, or third), utility manipulation, and partner manipulation. Random

440 effects terms for subjects and object were included in the model.

441   Consistent with our predictions, speech seemed to largely trade off with gesture.

442 Exposure rate during training was a significant positive predictor of speaking during the

443 game, such that participants were more likely to use speech for well trained (and thus well

444 learned) objects ($\beta = 0.35$, $p < .001$). Additionally, participants were significantly less likely

445 to speak in the Lower Speech Efficiency condition where speech is relatively more costly,

446 compared with the Higher Speech Efficiency condition ($\beta = $ -0.87, $p = .001$). We also found

447 a significant positive effect of partner's knowledge, such that participants used speech more

448 for partners with more knowledge of the lexicon ($\beta = 1.95$, $p < .001$). Unlike for gesture,

449 there was a significant effect of object instance in the game (i.e., first, second, or third trial

450 with this target object) on the rate of speaking, such that later trials were more likely to

451 elicit speech ($\beta = 0.72$, $p < .001$). This effect of order likely stems from a trade-off with the

452 effects we see in teaching (described below); after a participant teaches a word on the first or

second trial, the utility of speech is much higher on subsequent trials.

Emergence of Teaching.

Thus far, we have focused on relatively straightforward scenarios to demonstrate that a pressure to communicate successfully in the moment can lead participants to trade off between gesture and speech sensibly. Next, we turn to the emergence of teaching behavior.

When should we expect participants to teach? Teaching has the highest utility for words you learned during training, words you think your partner is unlikely to know (i.e., for lower partner knowledge conditions), and when utility scheme is relatively biased toward speech (i.e., the Higher Speech Efficiency condition). In this utility scheme, it is more valuable to pay the cost of teaching early because of the increased benefit of using speech later. To test these predictions, we ran a mixed effects logistic regression to predict whether participants chose to teach during a given trial as a function of the target object's exposure rate during training, object instance in the game (first, second, or third), utility manipulation, and partner manipulation. Random effects terms for subjects and object were included in the model.

Consistent with our predictions, rates of teaching were higher for more highly trained words, less knowledgeable partners, and when speech had the highest utility. Exposure rate during training was a significant positive predictor of teaching during the game, such that participants were more likely to teach for well trained (and thus well learned) objects ($\beta = 0.14$, $p = .001$). While costly in the moment, teaching can be a beneficial strategy in our reference game because it subsequently allows for lower cost strategy (i.e. speaking), thus when speaking has a lower cost, participants should be more incentivized to teach. Indeed, participants were significantly less likely to teach in the Lower Speech Efficiency condition where speech is relatively more costly, compared with the Higher Speech Efficiency condition ($\beta = -0.96$, $p = .001$). We also found a significant negative effect of partner's knowledge, such
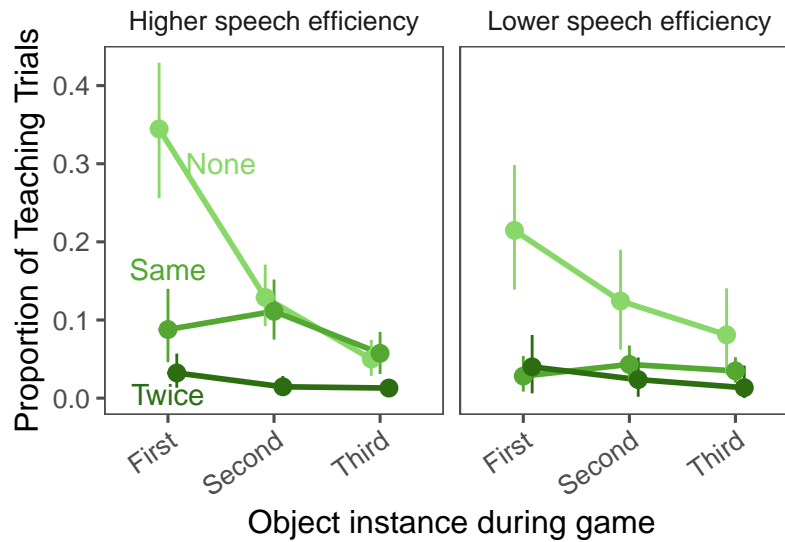
Figure 5

Rates of teaching across the six utility and partner knowledge conditions as a function of how many times the current target referent object had previously been the target. Error bars show 95% confidence intervals computed by non-parametric bootstrapping.

that participants taught more with partners that had less knowledge of the lexicon ($\beta =$ -2.23, $p < .001$). There was also a significant effect of object instance in the game (i.e., whether this is the first, second, or third trial with this target object) on the rate of teaching. The planned utility of teaching comes from using another, cheaper strategy (speech) on later trials, thus the expected utility of teaching should decrease when there are fewer subsequent trials for that object, predicting that teaching rates should drop dramatically across trials for a given object. Participants were significantly less likely to teach on the later appearances of the target object ($\beta =$ -1.09, $p < .001$).

Discussion

As predicted, the results of this experiment corroborate our findings from the corpus analysis, demonstrating that pedagogically supportive behavior emerges despite the initial cost when there is an asymmetry in knowledge and when speech is less costly than other

modes of communication. While this paradigm has stripped away much of the interactive environment of the naturalistic corpus data, it provides important proof of concept that the structured and tuned language input we see in those data could arise from a pressure to communicate. The paradigm's clear, quantitative trends also allow us to build a formal model to predict our empirical results.

The results from this experiment are qualitatively consistent with a model in which participants make their communicative choices to maximize their expected utility from the reference game. We next formalize this model to determine if these results are predicted quantitatively as well.

Model: Communication as planning

In order to model when people should speak, point, or teach, we begin from the problem of what goal people are trying to solve (Marr, 1982). Following a long history of work in philosophy of language, we take the goal of communication to be causing an action in the world by transmitting some piece of information to one's conversational partner (Austin, 1975; e.g., Wittgenstein, 1953). If people are near-optimal communicators, they should choose communicative signals that maximize the probability of being understood while minimizing the cost of producing the signal (Clark, 1996; Grice, 1975). In the special case of reference, solving this problem amounts to producing the least costly signal that correctly specifies one's intended target referent in such a way that one's conversational partner can select it from the set of alternative referents.

Recently, Frank and Goodman (2012) developed the Rational Speech Act framework– a formal instantiation of these ideas. In this model, speakers choose from a set of potential referential expressions in accordance to a utility function that maximizes the probability that a listener will correctly infer their intended meaning while minimizing the number of words produced. This framework has been succesfully applied to a variety of linguistic phenomena

515 such as scalar implicature, conventional pact formation, and production and interpretation of

516 hyperbole (Goodman & Frank, 2016; see also related work from Franke, 2013). These models

517 leverage recursive reasoning–speakers reasoning about listeners who are reasoning about

518 speakers–in order to capture cases in which the literal meaning and the intended meaning of

519 sentences diverge.

520   To date, this framework has been applied primarily in cases where both

521 communicative partners share the same linguistic repertoire, and thus communicators know

522 their probability of communicating successfully having chosen a particular signal. This is a

523 reasonable assumption for pairs of adults in contexts with shared common ground. But what

524 if partners do not share the same linguistic repertoire, and in fact do not know the places

525 where their knowledge diverges? In this case, communicators must solve two problems

526 jointly: (1) Figure out what their communicative partner knows, and (2) produce the best

527 communicative signal they can given their estimates of their partner's knowledge. If

528 communicative partners interact repeatedly, these problems become deeply intertwined:

529 Communicators can learn about each-other's knowledge by observing whether their attempts

530 to communicate succeed. For instance, if a communicator produces a word that they believe

531 identifies their intended referent, but their partner fails to select that referent, the

532 communicator can infer that their partner must not share their understanding of that word.

533 They might then choose not to use language to refer to this object in the future, but choose

534 to point to it instead.

535   Critically, communicators can also change each-other's knowledge. When a

536 communicator both points to an object and produces a linguistic label, they are in effect

537 teaching their partner the word that they use to refer to this object. While this behavior is

538 costly in the moment, and no more referentially effective than pointing alone, it can lead to

539 more efficient communication in the future–instead of pointing to this referent forever more,

540 communicators can now use the linguistic label they both know that they share. This

behavior naturally emerges from a conception of communication as planning: Communicators' goal is to choose a communicative signal today that will lead to efficient communication not just in the present moment, but in future communications as well. If they are likely to need to refer to this object, it is worth it to be inefficient in this one exchange in order to be more efficient future. In this way, pedagogically supportive behavior can emerge naturally from a model with no separate pedagogical goal. In the following section, we present a formal instantiation of this intuitive description of communication as planning and show that it accounts for the behavior we observed in our experiments.

Alternatively, pedagogically-supportive input could emerge from an explicit pedagogical goal. Shafto et al. (2014) have developed an framework of rational pedagogy built on the same recursive reasoning principles as in the Rational Speech Act Framework: Teachers aim to teach a concept by choosing a set of examples that would maximize learning for students who reason about the teachers choices as attempting to maximize their learning. Rafferty et al. (2016) et al. expanded this framework to sequential teaching, in which teachers use students in order to infer what they have learned and choose the subsequent example. In this case, teaching can be seen as a kind of planning where teachers should choose a series of examples that will maximize students learning but can change plans if an example they thought would be too hard turns out too easy–or vice-versa. In the case of our reference game, this model is indistinguishable from a communicator who seeks to maximize communicative success but is indifferent to communicative cost. A cost-indifferent model makes poor predictions about caregivers' behavior in our corpus, and also adults' behavior in our experiments, but we return to it in the subsequent section to consider how differences in caregivers' goals and differences in children's learning contribute to changes in the rate of language acquisition.

Formal Model

We take as inspiration the idea that communication is a kind of action–e.g., talking is a speech act (Austin, 1975). Consequently, we can understand the choice of *which communicative act* a speaker should take as a question of which act would maximize their utility: achieving successful communication while minimizing their cost (Frank & Goodman, 2012). In this game, speakers can take three actions: talking, pointing, or teaching. The Utilities (U) are given directly by the rules of this game. Because communication is a repeated game, people should take actions that maximize their Expected Utility (EU) not just for the current round, but for all future communicative acts with the same conversational partner. We can think of communication, then as a case of recursive planning. However, people do not have perfect knowledge of each-other's vocabularies (v). Instead, they only have uncertain beliefs (b) about these vocabularies that combine their expectations about what kinds of words people with as much linguistic experience as their partner are likely to know with their observations of their partner's behavior in past communicative interactions. This makes communication a kind of planning under uncertainty well modeled as a Partially Observable Markov Decision Process (POMDP, Kaelbling et al., 1998).

Optimal planning in a Partially Observable Markov Decision Process involves a cycle of three phases: (1) Plan, (2) Act, and (3) Update beliefs. On each trial of the referential game, the model first makes a plan–reasoning about which action it should take on this trial and on subsequent trials to come. To help build intuition for the model, we first describe how it might operate in a series of example trials. We then give a formal description of the model's learning and behavior.

At the start of each trial, the model makes a plan consider the actions it will take on this trial and future trials. If the model speaks–producing the label for the target object, two outcomes are possible. First, its partner could select the correct referent. This would give maximal utility on the current trial, and also cause the model to know that its partner
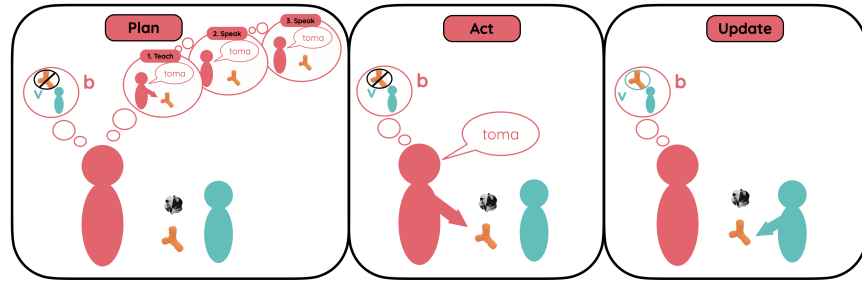
Figure 6

A schematic of the plan-act-update cycle of communication as a partially observable Markov decision process (POMDP). The red figure correponds to caregivers in the world, or participants in the experiment. The blue figure corresponds to children or experimental partners. The caregiver is using their beliefs (b) about their child's true vocabulary (v) to plan their next communicative act. Teaching by ostensive labeling is costly in the moment, but has utility because it enables a plan to speak in the future.

knows the right label for this object. In that case, the model could speak again on future trials and expect to succeed and be rewarded. On the other hand, its partner could select the wrong referent. This could happen either because the model itself does not know the right label, or because its partner does not. In that case, the model would get low utility on this round, and would likely teach or point for this referent on subsequent trials. Alternatively the model could point. This would give some utility on the current trial, and would leave the model in the same state of uncertainty about whether its partner knows the correct label for the referent on subsequent trials. Finally the model could teach. This would lead to very little utility on the current trial, but would cause the model to know that it can speak to refer to this referent on future trials (as in Figure 6). Reasoning forward about

601 however many trials are left to play for this referent, the model makes a plan with the

602 appropriate number of steps. At the start of the game, the model knows it will play three

603 times for each referent so it might make a plan like {*speak*, *speak*, *speak*}

604   After formulating this plan, the model will take the first action in the plan sequence

605 (e.g. *speak*). It will then observe its partner's behavior. In this case, suppose that its partner

606 selects the incorrect referent. The model will then update its beliefs–its partner must not

607 know the correct label for the target object. The next time it needs to communicate about

608 the same object, it will be very unlikely to plan to speak, even though its previous plan was

609 to do so. This is because the model's belief about the world has changed and now it will be

610 more likely to {*point*, *point*} or to {*teach*, *speak*}.

611   We next formally specify each step in the cycle and finally define how people form

612 initial beliefs about their partner's language. All code for implementing the model is

613 available on the Open Science Foundation project page associated with this paper.

614 *Plan*

615   When people plan, they compute the expected utility of each possible action (a) by

616 combining the expected utility of that action now with the Discounted Expected Utility they

617 will get in all future actions. The amount of discounting (γ) reflects how much people care

618 about success now compared to success in the future. Because utilities depend on the

619 communicative partner's vocabulary, people should integrate over all possible vocabularies in

620 proportion to the probability that their belief assigns to that vocabulary ($\mathbb{E}_{v \sim b}$).

$$EU\left[a \,|\, b\right] = \mathbb{E}_{v \sim b}\left(U(a|v) + \gamma\,\mathbb{E}_{v',o',a'}\left(EU\left[a'|b'\right]\right)\right) \tag{1}$$

Act

Next, people take an action as a function of its expected utility. Following other models in the Rational Speech Act framework, we use the Luce Choice Axiom, in which each choice is taken in probability proportional to its exponentiated utility (Frank & Goodman, 2012; Luce, 1959). This choice rule has a single parameter α that controls the noise in this choice–as α approaches 0, choice is random and as α approaches infinity, choice is optimal.

$$P\left(a|b\right) \propto \alpha \, e^{EU[a|b]}$$

Update beliefs

After taking an action, people observe (o) their partner's choice–sometimes they correctly select the intended object, and sometimes they do not. People then update their beliefs about the partner's vocabulary based on this observation. For simplicity, we assume that people think their partner should always select the correct target if they point to it, or if they teach, and similarly should always select the correct target if they produce its label and the label is in their partner's vocabulary. Otherwise, they assume that their partner will select the wrong object. People could of course have more complex inferential rules, e.g., assuming that if their partner does know a word they will choose among the set of objects whose labels they do not know (mutual exclusivity, Markman & Wachtel, 1988). Empirically, however, our simple model appears to accord well with people's behavior.

$$b'(v') \propto P\left(o|v', a\right) \sum_{v \in V} P\left(v'|v, a\right) b\left(v\right)$$

The critical feature of a repeated communication game is that people can change their partner's vocabulary. In teaching, people pay the cost of both talking and pointing together, but can leverage their partner's new knowledge on future trials. Note here that teaching has an upfront cost and the only benefit to be gained comes from using less costly communication modes later. There is no pedagogical goal–the model treats speakers as

selfish agents aiming to maximize their own utilities by communicating successfully. We

assume for simplicity that teaching is always successful in this very short game, that

communicative partners do not forget words once they have learned them, and that no

learning happens by inference from mutual exclusivity.

$$P\left(v'|v,a\right) = \begin{cases} 1 & \text{if } v_w \in v \& v' \mid a = \text{point+talk} \\ 0 & otherwise \end{cases}$$

Initial Beliefs

The final detail is to specify how people estimate their partner's learning rate (p) and

initial vocabulary (v). We propose that people begin by estimating their own learning rate

by reasoning about the words they learned at the start of the task: Their learning rate (p) is

the rate that maximizes the probability of them having learned their initial vocabularies

from the trials they observed. People can then expect their partner to have a similar p (per

the "like me" hypothesis, Meltzoff, 2005). Having an estimate of their partner's p, they can

estimate their vocabulary by simulating their learning from the amount of prior exposure to

language their partner had before the game. In our experiments, we explicitly manipulated

this expectation by telling participants how much exposure their partner had relative to their

own exposure.

Method

We implemented the planning model using `WebPPL`–a programming language designed

for specifying probabilistic models (Goodman & Stuhlmüller, 2014). We began with the

POMDP specification developed by Evans et al. (2017). To derive predictions from the

model, we exposed it to the same trial-by-trial stimuli as the participants in our experiment,

and used the probabilistic equations defined above to determine the likelihood of choosing

each behavior (i.e., *speak*, *point*, or *teach*) on every trial. Separate predictions were made

665 for each trial for each participant on the basis of all of the information available to each

666 participant at that point in time (e.g., how many words they had learned, their partner's

667 observed behavior previously, etc).

668   The model's behavior is contingent on two parameters–discounting (γ), and its

669 rationality (α). In order to determine the values of these parameters that best characterize

670 human participants, we used empirical Bayesian inference to estimate the posterior means of

671 both. Using posterior mean estimates rather than the maximum likelihood estimates

672 naturally penalizes models for their ability to predict patterns of data that were not

673 observed, applying a kind of Bayesian Occam's razor (MacKay, 1992). Because of we found

674 substantial variability in the best parameter estimates across individual participants, we

675 estimated parameters hierarchically, with group-level hyper-parameters forming the priors for

676 individual participants' parameters. This hierarchical estimation process achieves the same

677 partial pooling as as subject-level random effects in mixed-effects models, giving estimates of

678 the group-level parameters (Gelman & Hill, 2006). Details of the estimation procedure can

679 be found in the Supplemental Materials.

Model Results

681   In line with previous work on rational speech act models, and decision making, we

682 expected rationality (α) to be around 1 or 2 (Frank & Goodman, 2012, 2014). We estimated

683 the posterior mean rationality (α) to be 1.33 with a 95% credible interval of [1.24, 1.42]. We

684 did not have strong expectations for the value of the discounting parameter (γ), but

685 estimated it to be 0.42 [0.39, 0.44], suggesting that on average participants weighed the next

686 occurrence of a referent as slightly less than half as important as the current occurrence.

687   To derive predictions from the model, we ran 100 simulations of the model's choices

688 participant-by-participant and trial-by-trial using our posterior estimates of the

689 hyper-parameters α and γ. Because we did not use our participant-level parameter estimates,
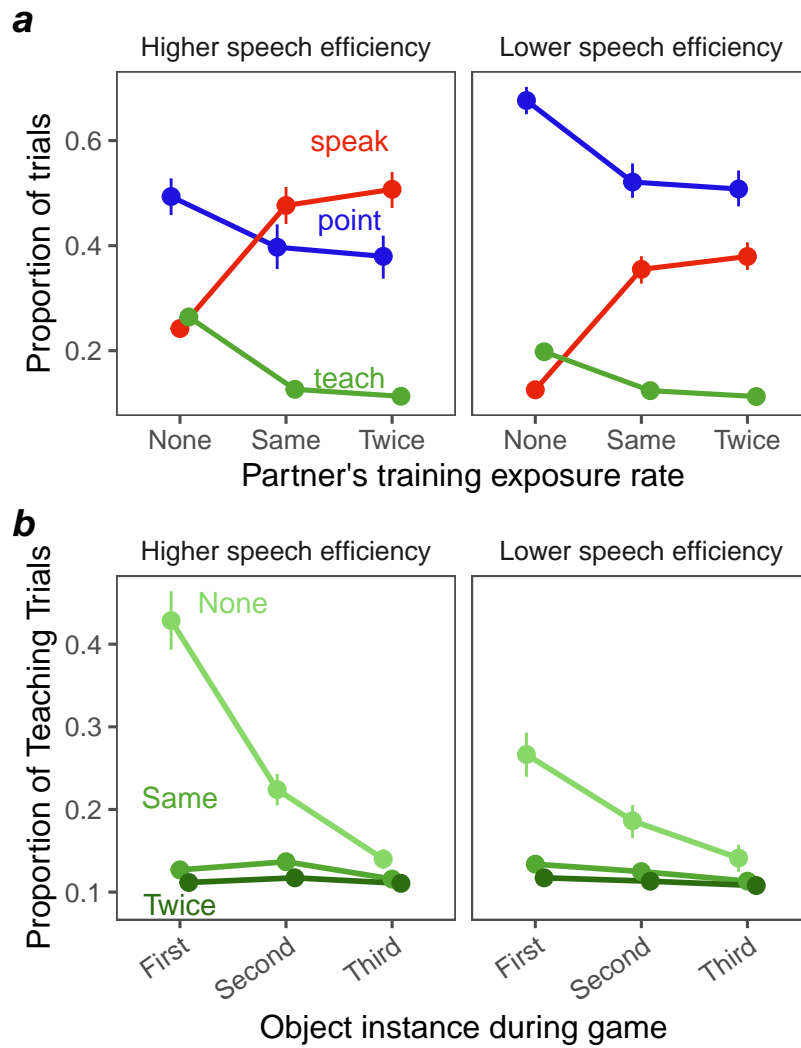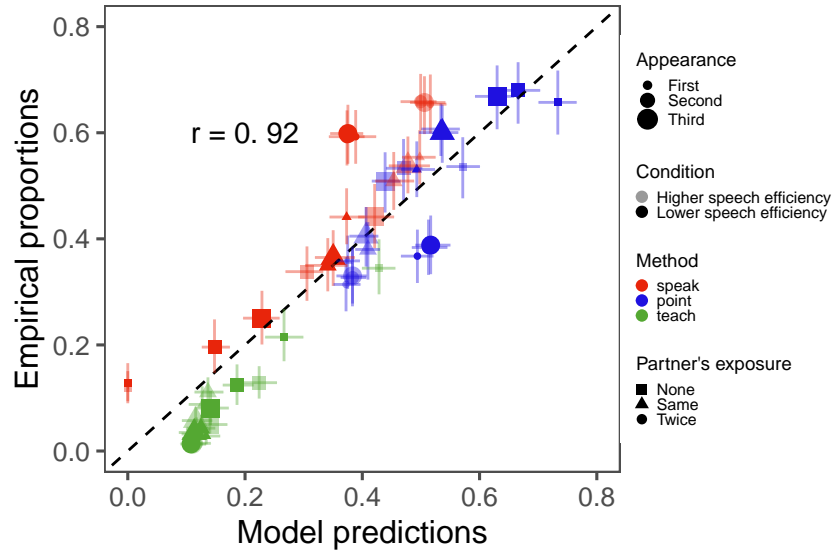
Figure 7

(a) Model prediction choice of communicative method choice as a function of exposure and the utility manipulation. (b) Model predicted probability of teaching by Partner's language knowledge and exposure rate.

690 this underestimates the correlations between model predictions and empirical data (as it

691 ignores variability across participants). Instead, it reflects the model's best predictions about

692 the results of a replication of our experiment, where individual participants' parameters will

693 not be known apriori. Figure 7a shows the predictions from the model in analogous format

694 to the empirical data in Figure 4. The model correctly captures the qualitative trends in

695 participants' behavior: It speaks more and points less in the Higher speech efficiency

696 condition. Figure 7b shows the model's predicted teaching behavior in detail in an analogous

697 format to the empirical data in Figure 5. The model again captures the qualitative trends

698 apparent in participants' behavior. The model teaches less knowledgeable partners,

699 especially those who it believes have no language knowledge at all. The model teaches more

700 when speech is relatively more efficient, and thus the future utility of teach a partner is

701 higher. And finally the model teaches most on the first occurrence of each object, and

702 becomes less likely to teach on future occurrences when (1) partners should be more likely to

703 know object labels, and (2) the expected future rewards of teaching are smaller.

704   To estimate the quantitative fit between model predictions and empirical data, we

705 compute the Pearson correlation between the model's probability of using each action and

706 participants' probability of using that same action as a function of appearance, condition,

707 and partner's exposure. Across experimental manipulations, the model's predictions were

708 highly correlated with participant behavior ($r = 0.92$ [0.86, 0.95], $t(52) = 16.67$, $p < .001$;

709 Figure 8).

710   Finally, we compare this model to two simpler alternative models: (1) A no-cost

711 model in which people are indifferent to the costs of communication, and (2) a myopic model

712 in which people do not plan for future interactions, and instead only care about the utility of

713 their communicative choices on the immediate communicative event. We estimated

714 parameters for these two simpler models using the same procedure as the full model: We

715 first fit individual participant-level parameters and then estimated the posterior mean

Figure 8

Fit between model predictions and empirical data.

parameters for the population of participants. To compare these reduced models to our full model, we computed the log likelihood of observing the experimental data if participants behaved according to each of the three models. These likelihoods combine both the probability of observing the empirical the data under the model, and the probability of the model parameters under the model priors. This prior probability implements a kind of Bayesian Occam's razor, penalizing the two models which involve planning and thus fit a discounting parameter (full, no-cost) relative to the no-planning model which has only a rationality parameter. For the full model, the average likelihood across 100 runs of the model was -15,771.93. By comparison, the likelihoods for the no-cost model and myopic model were -21,016.96 and -17,257.91 respectively. Thus, the probability of observing the empirical data was thousands of times more likely under the full model than either of the simpler alternatives.

Discussion

In both qualitative and quantitative analyses, participants' behavior in our communication task was well explained by a model of communication as rational planning under uncertainty. The key intuition formalized by this model is that the value of a communicative acts derives from (1) the immediate effect on resolving the current communicative need, and (2) the potential benefit of the act for communication with this conversational partner in the future. Crucially, this model is able to predict a putatively altruistic behavior–teaching by ostensive labeling–without any altruistic goals at all. Because ostensive labeling can increase the efficiency of future communication, it can be beneficial even under a purely self-interested utility function. What's more, the model correctly predicts the circumstances under which participants will engage in teaching behavior: early interactions with linguistically naive communicative partners in circumstances where language is a relatively efficient communicative modality.

Importantly, this model does not rule out the possibility that participants in our experiment–and more broadly people in the real world–may teach because of other more altruistic mechanisms or pressures. The model simply shows that appealing to such mechanisms is not necessary to explain the ostensive labeling observed in caregivers' conversations with their children, and by extension other behaviors that may at first blush appear to be pedagogically motivated. By the same logic, the model predicts that there should be other pedagogically supportive behaviors in the interactions between caregivers and their children, and likely in the interactions between any two communicative partners who have some expectation that they will communicate again in the future. This framework thus provides a potential explanation for the occurrence of these behaviors and a framework for understanding their impact on language learning.

Of course, not all potentially pedagogically-supportive behaviors will yield an immediate or future communicative benefit. For instance, correcting children's syntactic

754 errors could be helpful for their language development, but unless it resolves a

755 communicative ambiguity, it will have little impact on communicative success. Our

756 framework would predict that these behaviors should be rare, and indeed such behaviors

757 appear to be generally absent in children's input (Marcus, 1993). We return this issue at

758 greater length in the General Discussion. Before turning to that, however, we first consider

759 the consequences of this model of communication for children's language. In the next section,

760 we use simulation methods to ask how caregivers' communicative motivation may impact

761 their children's learning, and how this impact changes as a function of the complexity of the

762 world and the efficacy of children's learning mechanisms.

Consequences for Learning

764 In the model and experiments above, we asked whether the pressure to communicate

765 successfully with a linguistically-naive partner would lead to pedagogically supportive input.

766 These results confirmed its sufficiency: As long as linguistic communication is less costly

767 than deictic gesture, people should be motivated to teach in order to reduce future

768 communicative costs. Further, the strength of this motivation is modulated by predictable

769 factors (speakers' linguistic knowledge, listeners' linguistic knowledge, relative cost of speech

770 and pointing, learning rate, etc.), this modulation is quantitatively well predicted by a

771 rational model of planning under uncertainty about a partner's vocabulary.

772 In this final section, we take up the consequences of communicatively-motivated

773 linguistic input for a child learning language. To do this, we adapt a framework used by

774 Blythe et al. (2010) to estimate the learning times for an idealized child learning language

775 under different models of the child and their careviver We derive estimates by simulating

776 exposure to successive communicative events, and measuring the probability that successful

777 learning happens after each event. The question of how different caregiver goals during

778 caregiver-child impact children's learning can then be formalized as a question of how much

779 more quickly learning happens under one simulation of child and caregiver model than

another.

We consider children's word learning in three different simulated language
environments:

1. *Teaching* - The caregiver's goal in each interaction is to maximize their child's learning
   (by teaching on every trial). This goal is equivalent to a model in which the goal is to
   maximize communicative success without minimizing communicative cost. In this case,
   we model the child's learning with the same simple binomial model we proposed for
   participants in the experiment. After every teaching event, if the child has not yet
   learned the label, they do so with a probability defined by their learning rate.

2. *Communication* - The caregiver's goal in each interaction with their child is to
   maximize their communicative success while minimizing their communicative cost.
   This the model described in the Model section above. In this case, we model the child's
   learning with the same simple binomial model whenever the caregiver produces a
   teaching event. If the caregiver instead points or speaks, the child cannot learn at all.
   We make this assumption for simplicity–a fairer simulation would also include the
   child's learning from co-occurrence statistics of speaking events as in the model above.
   However, simultaneously simulating the child's learning from ambiguous input and the
   caregivers' reasoning about their child's likelihood of having learned from ambiguous
   input is computationally challenging. This model thus underestimates the rate at which
   children would learn from communication and should be considered a lower bound.

3. *Talking* - The caregiver's goal in each interaction is to refer to their intended referent
   so that a knowledgeable listener would understand them, without accounting for the
   child's language knowledge. This goal is equivalent to minimizing communicative cost
   without maximizing communicative success. Because the caregiver never teaches under
   this model, the child must learn from the co-occurrence statistics of the words they hear

805   and objects they see. That is, the child needs to solve the cross-situational learning

806   problem (Yu & Smith, 2007). In this case, the child's learning is affected not only by

807   their own ability to remember words and track statistics, but also by the ambiguity of

808   the learning environment (i.e. how many objects are around when they hear a word).

809   Formalizing these models allows us to ask three questions: (1) What is the lower

810   bound on time to learn if caregivers are motivated to teach and always engage in ostensive

811   labeling? (2) If caregivers have a less altruistic goal–communication–how much longer would

812   it take to learn? (3) If the child instead had to rely on learning from co-occurrence statistics,

813   how powerful a statistical learner would a child have to be in order to match the rate of

814   learning of a very simple learner in the context of goal-motivated caregivers?

815   One important point to note is that we are modeling the learning of a single word

816   rather than the entirety of a multi-word lexicon (as in Blythe et al., 2010). Although

817   learning times for each word could be independent, an important feature of many models of

818   word learning is that they are not (Frank et al., 2009; Yu, 2008; Yurovsky et al., 2014;

819   although c.f. McMurray, 2007). Indeed, positive synergies across words are predicted by the

820   majority of models and the impact of these synergies can be quite large under some

821   assumptions about the frequency with which different words are encountered (Reisenauer et

822   al., 2013). We assume independence primarily for pragmatic reasons here–it makes the

823   simulations significantly more tractable (although it is also what our experimental

824   participants appear to assume about learners). Nonetheless, it is an important issue for

825   future consideration. Of course, synergies that support learning under a cross-situational

826   scheme must also support learning from communicators and teachers (Frank et al., 2009;

827   Markman & Wachtel, 1988; Yurovsky et al., 2013). Thus, the ordering across conditions

828   should remain unchanged. However, the magnitude of the difference across conditions could

829   potentially increase or decrease.

830 **Method**

831   In each of the sections below, we describe the join models of caregivers'

832 communication and children's learning that predict learning times under each of the three

833 models of caregivers' goals.

834 *Teaching.*

835   Because the teaching caregiver is indifferent to communicative cost, they in ostensive

836 labeling (pointing + speaking) on each communicative event. Consequently, learning on each

837 trial occurs with a probability that depends entirely on the learner's learning rate ($P_k = p$).

838 Because we assume that the learner does not forget, the probability that a learner has failed

839 to successfully learn after n trials is equal to the probability that they have failed to learn on

840 each of n successive independent trials (The probability of zero successes on n trials of a

841 Binomial random variable with parameter p). The probability of learning after n trials is

842 thus:

$$P_k(n) = 1 - (1 - p)^n$$

843   The expected probability of learning after n trials was thus defined analytically and

844 required no simulation. For comparison to the other models, we computed P_k for values of p

845 that ranged from .1 to 1 in increments of .1.

846 *Communication.*

847   To test learner under the communication model, we implemented the same model

848 described in the Model section. However, because our interest was in understanding the

849 relationship between parameter values and learning outcomes rather than inferring the

850 parameters that best describe people's behavior, we made a few simplifying assumptions to

851 allow many runs of the model to complete in a more practical amount of time. First, in the

852 full model above, speakers begin by inferring their own learning parameters (p_s) from their

853 observations of their own learning, and subsequently use their maximum likelihood estimate

854 as a stand-in for their child's learning parameter (p_l). Because this estimate will converge to

855 the true value in expectation, we omit these steps and simply stipulate that the speaker

856 correctly estimates the listener's learning parameter.

857   Second, unless the speaker knows a priori how many times they will need to refer to a

858 particular referent, the planning process is an infinite recursion. However, each future step in

859 the plan is less impactful than the previous step (because of exponential discounting). This

860 infinite process is in practice well approximated by a relatively small number of recursive

861 steps. In our explorations we found that predictions made from models which planned over

862 three future events were indistinguishable from models that planned over four or more, so we

863 simulated three steps of recursion[1]. Finally, to increase the speed of the simulations we

864 re-implemented them in the `R` programming language. All other aspects of the model were

865 identical.

866   In our simulations, we varied the children's learning rate (p) from .1 to 1 in steps of .1

867 as in the Teaching simulation, caregivers' future-weighting (γ) from .1 to 1 in steps of .1, the

868 caregivers' rationality (α) from .5 to 3 in steps of .5, and considered three values each of the

869 cost of speaking ($S = (0, 10, 20)$) and pointing ($P = (50, 60, 70)$). The utility of

870 communicating successfully was always 100.

871 ***Talking.***

872   When caregivers are are producing a label for one of the objects in the environment,

873 but the child does not know which one, learning requires tracking how often that words

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[1] It is an interesting empirical question to determine how the level of depth to which that people plan in this and similar games (see e.g. bounded rationality in Simon, 1991; resource-rationality in Griffiths et al., 2015). This future work is outside the scope of the current project.

occurs with each potential object. This learning problem has been studied extensively in the language acquisition literature under the guise of "cross-situational learning" (Yu & Smith, 2007). Models of cross-situational learning have taken a variety of forms in order to instantiate different theoretical positions about the mechanisms involved in learning, most centrally whether learning is hypothesis-driven or associative (see Yu & Smith, 2012 for a review). In our analyses, we do not attempt to distinguish among these classes of models as has been done in other learning-time simulations (e.g. K. Smith et al., 2011). Because of its natural alignment with the learning models we use in the Teaching and Communication simulations, we implemented a simple positive hypothesis testing model. Our choice to focus on hypothesis testing rather than other learning frameworks is purely a pragmatic choice–the learning parameter p in this model maps cleanly onto the learning parameter in our other models. We encourage other researchers to adapt the code we have provided to estimate the long-term learning for other models.

In this model, learners begin with no hypotheses and add new ones to their store as they encounter data. Upon first encountering a word and a set of objects, the model encodes up to h hypothesized word-object pairs each with probability p. On subsequent trials, the model checks whether any of the existing hypotheses are consistent with the current data, and prunes any that are not. If no current hypotheses are consistent, it adds up to h new hypotheses each with probability p. The model has converged when it has pruned all but the one correct hypothesis for the meaning of a word. This model is most similar to the Propose but Verify model proposed in Trueswell et al. (2013), with the exception that it allows for multiple hypotheses. Because of the data generating process, storing prior disconfirmed hypotheses (as in Stevens et al., 2017), or incrementing hypotheses consistent with some but not all of the data (as in Yu & Smith, 2012) has no impact on learner and so we do not implement it here. We note also that, as described in Yu and Smith (2012), hypothesis testing models can mimic the behavior of associative learning models given the right parameter settings (Townsend, 1990).

901   In contrast to the Teaching and Communication simulations, the behavior of the

902 Talking model depends on which particular non-target objects are present on each naming

903 event. We thus began each simulation by generating a corpus of 100 naming events. On each

904 event, we sampled the correct target as well as (C-1) competitors from a total set of M

905 objects. We then simulated learning over this set of events as described above, and recorded

906 the first trial on which the learner converged (having only the single correct hypothesized

907 mapping between the target word and target object). We repeated this process 1000 times

908 for each simulated combination of $M = (8, 16, 32, 64, 128)$ total objects, $C = (1, 2, 4, 8)$

909 objects per trial, $h = (1, 2, 3, 4)$ concurrent hypotheses, as the child's learning rate p varied

910 from .1 to 1 in increments of .1.

Results

912   In order to understand how learning rates vary with model parameters, we first

913 discuss the dependence of each of the three tested models on its parameters, and then

914 discuss relationships between the models. For clarity of exposition, we analyze the number of

915 events required for 75% of simulated learners to acquire the target word, and plot a

916 representative subset of parameter values.

917   In addition the results reported here, we have made the full set of simulated results

918 available in an interactive web application at dyurovsky.shinyapps.io/ref-sims. We encourage

919 readers to fully explore the relationships among the models beyond the summary we provide.

Teaching.

921   Because the Teaching model behaves identically on each trial regardless of the learner,

922 the rate of learning under this model depends entirely on the learner's learning rate p. If the

923 learning rate was high (e.g. .8), more than 75% of learners acquired the word after a single

924 learning instance. If the learning rate was medium, closer to the range we estimated for

925 adult learners (.6), more than 75% of learners acquired the word after only 2 instances.

926 Finally, if the learning rate was very low (.2), the same threshold was reached after 7

927 instances. Thus, the model is predictably sensitive to learning rate, but even very slow

928 learners are expected to acquire words after a small number of communicative events.
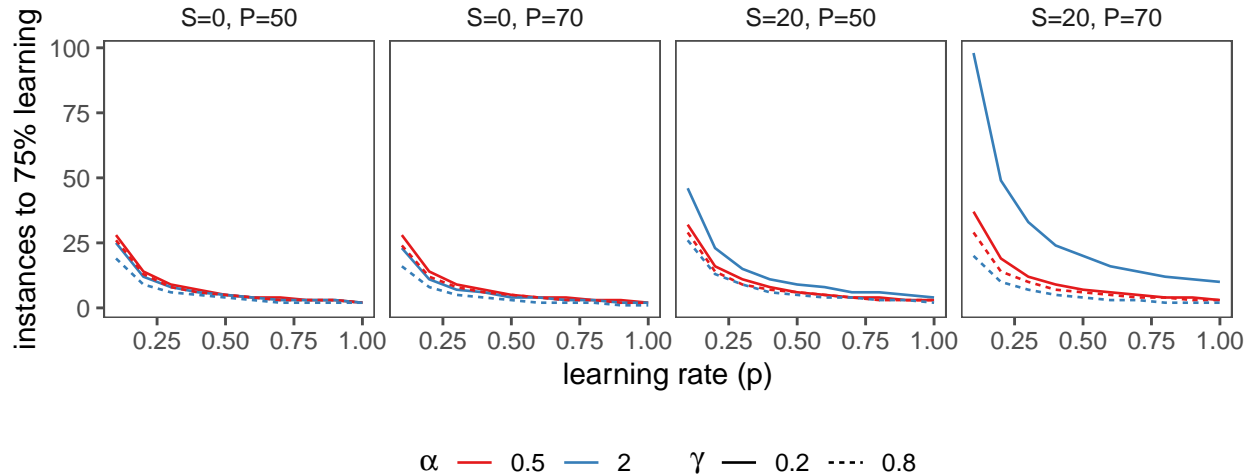
929 *Communication*

Figure 9

Number of exposures required for 75% of children to learn a word under the Communication model as parameters vary. Color shows rationality (α), Linetype shows future weighting (γ), facets indicate the the cost of speaking (S) and pointing (P). The middle two facets corresponds to Higher Speech Efficiency and Lower Speech efficiency conditions of the experiment.

930   The Communication model's behavior depends on parameters of both the child

931 learner and the caregiver communicator. In general, parameters of both participants had

932 predictable effects on learning: Children learned faster when they had higher learning rates,

933 when caregivers were more rational, and when caregivers gave greater weight to the future.

934 Further, the effects of caregivers' parameters were more pronounced at the lowest learning

935 rates. However, as the cost of speaking increased relative to pointing, the effects of

936 caregivers' parameters changed. In particular, highly rational caregivers who heavily

937 discounted the future lead to significantly slower learning. At these parameter settings, the

938 caregiver becomes very likely to point on any given trial in order to maximize the local

utility at the expense of discounted future utility gained from teaching. In addition, as the cost of both modalities increases, the utility of communicating successfully (here defined as 100 points) becomes less motivating. Thus, caregivers become less discriminating among their communicative choices. Figure 9 shows the number of trials required for 75% of learners to acquire a word as a function of parameters in the Communication model.

Talking.

Finally, when caregivers spoke on each trial and children had to learn from cross-situational statistics, learning was controlled by the the child's learning rate, the number of hypotheses the child could entertain, the number of objects per event, and to a small extent the total vocabulary size. In general, children learned faster when they had a higher learning rate, and could entertain more hypotheses. Learning was also predictably slower when there were more objects on each event and thus ambiguity was higher. Finally, as the total vocabulary size increased, the rate of learning increased slightly, as it does with human cross-situational learners (Yu & Smith, 2007). This counter-intuitive outcome occurs because the rate of spurious co-occurrences, in which the target word consistently co-occurs with an object that is not its referent, decreases as the set of potential foils expands. The the effect of context size (C) and number of hypotheses can be seen along with the learning rates of the other two models in Figure 10.

Comparing the Models

Because the real-world parameters appropriate for each model are difficult to determine, we consider the relationship between the models over the range of their possible parameters. Figure 10 shows the time for 75% of learners to acquire a word in each of the three models. Across all possible child learning rates (p), the Teaching model lead to the fastest learning as expected. We can treat this model as a lower bound how quickly learning could possibly happen.

⁹⁶⁴   For the Communication model, we considered the range of all possible rates of

⁹⁶⁵ learning that could unfold as the parameters of both child and caregiver varied. The range

⁹⁶⁶ was substantial. If caregivers weigh the future near equally to the present, and are highly

⁹⁶⁷ rational, the child's resultant rate of learning is nearly identical to the rate of learning under

⁹⁶⁸ the Teaching model: Children required 1.07 times as many learning instances under the

⁹⁶⁹ Communication model as the Teaching model when averaging over all child learning rates.

⁹⁷⁰ In contrast, if the caregiver weighs the future much less than the present, and is relatively

⁹⁷¹ irrational about maximizing utility, the rate of learning can be quite slow–in the worst case

⁹⁷² requiring children to have 24.30 as many learning instances as under the Teaching model.

⁹⁷³ Despite this bad worst case scenario, if caregivers' parameters are close to the ones we

⁹⁷⁴ estimated in our experiment, Communication would require only 1.75 as many instances as

⁹⁷⁵ Teaching if speech is high efficiency relative to pointing, and 3.12 as many instances if speech

⁹⁷⁶ is lower efficiency.

⁹⁷⁷   For the Talking model, we also observed a wide range of learning times as a function

⁹⁷⁸ of both the ambiguity of the learning environment and the number of simultaneous

⁹⁷⁹ hypotheses that the child can maintain. When the environment was unambiguous–only 2

⁹⁸⁰ objects were present at a time–and the child could encode both, learning under Talking took

⁹⁸¹ only 2.03 times as many instances as Teaching. In contrast, if ambiguity was high, and

⁹⁸² learners could only track a single hypothesis, learning was significantly slower under Talking

⁹⁸³ than Teaching, (requiring 10.05 times as many instances).

⁹⁸⁴   Comparing Communication and Talking to each-other, we find that that Talking can

⁹⁸⁵ lead to faster learning under some parameter settings. In particular, if events are low in

⁹⁸⁶ ambiguity, or children can maintain a very large number of hypotheses about the meaning of

⁹⁸⁷ a word relative the number of objects in each event, children can learn rapidly even if

⁹⁸⁸ caregivers are just Talking. This learning can be faster than simpler child models learning

⁹⁸⁹ from highly myopic or relatively irrational caregivers Communicating, especially if speech is

high-cost. At medium levels of ambiguity, Communication and Talking are similar and their ordering depends on other parameters. At high levels of ambiguity Communication is the clear winner.

Together, these results suggest that if the set of possible candidate referents is small, even simple cross-situational learners can cope just fine even if their caregiver is just Talking; they learn roughly two to three times more slowly than if their caregiver was Teaching them. However, if the set of possible referents is four, or, eight, or even more on average, cross-situational learners need to have very high bandwidth or their rates of learning will be an order of magnitude slower than if their caregiver were Teaching them. In these cases, even the simplest learner–who can encode a single hypothesis about the meaning of a word and gets no information from co-occurrence statistics–can learn quite rapidly if they are learning from a caregiver that Communicates with them.

Discussion

Most of the language that children hear from their caregivers is unlikely to be designed to teach them language. However, the language that caregivers direct to them *is* designed to communicate successfully. Here we consider the learning consequences of these differences in design. How different are the learning consequences of language designed for teaching, language designed for communication, and ambient language not designed for the child at all?

If input is not communicatively motivated, the rate of learning depends entirely on what the learner brings to the table. In line with prior analyses of cross-situational learning, we find that learning can be quite rapid if environments are low in ambiguity or the learner has very high bandwidth for storing candidate hypotheses (K. Smith et al., 2011; Yu & Smith, 2012). However, the child's environment is neither guaranteed to be unambiguous nor are young children likely to have high bandwidth for statistical information (Medina et al.,
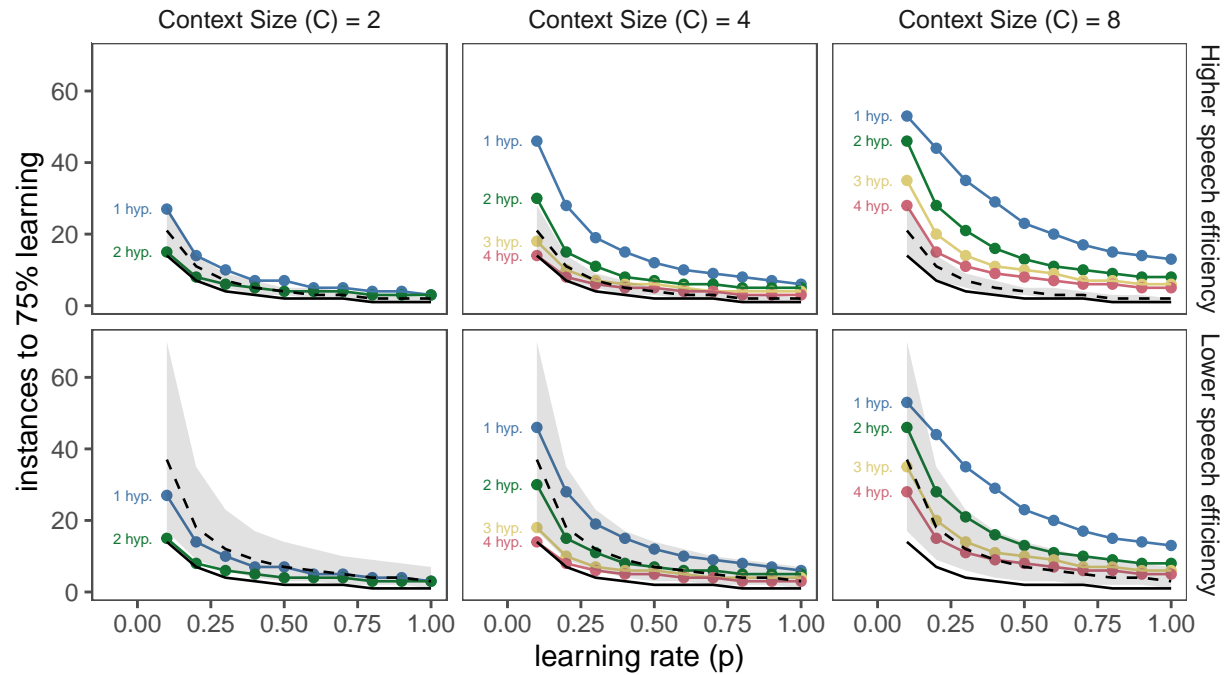
Figure 10

Comparing the number of exposures required for 75% of children to learn a word under all three models as parameters vary. Columns show variation in context size (C), a parameter of the Talking model. Rows show the two variations in the costs of Speech and Pointing for the Communication model used in our experiments. In each facet, the solid black line shows learning under the Teaching model, the light gray region shows an envelope of learning times corresponding to all variations in Communication model parameters, and the black dotted line shows learning time under the Communication model with parameters equal to the empirical estimates from experiments. Colored lines show learning times under the Talking model with varying numbers of hypotheses. Because there was little effect of the total number of objects (M) in the Talking model, all panels show results for 128 objects. Note that Communication model parameters vary across rows, while Talking model parameters vary across columns.

2011; Vlach & Johnson, 2013; Woodard et al., 2016). In fact, when the set of candidate referents is small, it is quite likely to be small in part because caregivers have designed the context to support communication (Tomasello & Farrar, 1986).

Learning from communication consistently outperforms learning from ambient language for all but the most precocious learners. If we take learning from teaching as an upperbound, we see that the rate of learning from communication is almost as fast under many possible parameter settings we explored. On average, across all possible parameter values, learning from communication is only 2.5 times slower than learning from teaching. Further, in this model, the learner gets no information from co-occurrence statistics at all. Combining learning from communication with low-bandwidth cross-situational learning could bring the expected rate of learning down to very close to learning from teaching (MacDonald et al., 2017). We thus might make significant progress on understanding how children learn language so quickly not just by studying children, but also by understanding how caregivers design the language they produce in order to support successful communication (Leung et al., 2021).

General Discussion

Across naturalistic corpus data, experimental data, and model predictions and simulation, we see evidence that pressure to communicate successfully with a linguistically immature partner could fundamentally structure caregiver production and shape child learning. In our experiment, we showed that people tune their communicative choices to varying cost and reward structures, and also critically to their partner's linguistic knowledge– providing richer cues when partners are unlikely to know the language and many more rounds remain. These data are consistent with the patterns shown in our corpus analysis of caregiver referential communication and demonstrate that such pedagogically supportive input could arise from a motivation to maximize communicative success while minimizing communicative cost—no additional motivation to teach is necessary. In simulation, we

1041 demonstrate that simple learners whose caregivers want to communicate with them out-learn

1042 more powerful statistical learners whose caregivers do not have a communicative goal.

1043   Accounts of language learning often aim to explain its striking speed in light of the

1044 sheer complexity of the language learning problem itself. Many such accounts argue that

1045 simple (associative) learning mechanisms alone seem insufficient to explain the rapid growth

1046 of language skills and appeal instead to additional explanatory factors, such as the so-called

1047 language acquisition device, working memory limitations, word learning biases, and many

1048 more (e.g., Chomsky, 1965; Goldowsky & Newport, 1993; Markman, 1990). While some have

1049 argued for the simplifying role of language distributions (e.g., McMurray, 2007), these

1050 accounts largely focus on learner-internal explanations. For example, Elman (1993) simulates

1051 language learning under two possible explanations to intractability of the language learning

1052 problem: one environmental, and one internal. He first demonstrates that learning is

1053 significantly improved if the language input data is given incrementally, rather than

1054 all-at-once. He then demonstrates that similar benefits can arise from learning under limited

1055 working memory, consistent with the "less-is-more" proposal (Elman, 1993; Goldowsky &

1056 Newport, 1993). Elman dismisses the first account arguing that ordered input is implausible,

1057 while shifts in cognitive maturation are well-documented in the learner; our account's

1058 emphasis on calibration to such learning mechanisms suggests the role of ordered or

1059 incremental input from the environment may be crucial. Our findings support the idea that

1060 rapid language learning may be facilitated by the *combination* of the learner's limited

1061 statistical learning skills combined with communicatively (but not pedagogically) motivated

1062 caregiver input. Such results emphasize the importance of a dyadic learning approach,

1063 whereby considering the joint contributions of learner and caregiver can yield new insights

1064 (Yurovsky, 2018).

1065   This account is consonant with work in other areas of development, such as recent

1066 demonstrations that the infant's visual learning environment has surprising consistency and

incrementality, which could be a powerful tool for visual learning. Notably, research using head mounted cameras has found that infant's visual perspective privileges certain scenes and that these scenes change across development. In early infancy, the child's egocentric visual environment is dominated by faces, but shifts across infancy to become more hand and hand-object oriented in later infancy (Fausey et al., 2016). This observed shift in environmental statistics mirrors learning problems solved by infants at those ages, namely face recognition and object-related goal attribution respectively. These changing environmental statistics have clear implications for learning and demonstrate that the environment itself is a key element to be captured by formal efforts to evaluate statistical learning (L. B. Smith et al., 2018). Frameworks of visual learning must incorporate both the relevant learning abilities and this motivated, contingent structure in the environment.

By analogy, the work we have presented here aims to draw a similar argument for the language environment, which is also demonstrably beneficial for learning and changes across development. In the case of language, the contingencies between learner and environment are even clearer than visual learning. Functional pressures to communicate and be understood make successful caregiver speech highly dependent on the learner. Any structure in the language environment that is continually adapting to changing learning mechanisms must come in large part from caregivers themselves. Thus, a comprehensive account of language learning that can successfully grapple with the infant curriculum must explain caregiver production as well as learning itself. Recent work has shown that many aspects of the the structure of natural languages, both in semantics and in syntax, can be explained by evolutionary optimization of language to be more efficient for communication (see Gibson et al., 2019 for a review). Further, people talking with other native language speakers make in-the-moment word choices that are well predicted by models of optimal communication (e.g., Mahowald et al., 2013). Here we extend these ideas to asymmetric communications between speakers and less knowledgeable listeners, and show that they can predict how caregivers modify their communicative acts when talking with their children.

1094   Explaining caregiver modification is a necessary condition for building a complete

1095 theory of language learning, but modification is certainly not a sufficient condition for

1096 language learning. No matter how calibrated the language input, non-human primates are

1097 unable to acquire language. Indeed, caregiver modification need not even be a necessary

1098 condition for language learning. Young children are able to learn novel words from

1099 (unmodified) overheard speech between adults (Foushee et al., 2016; although c.f. Shneidman

1100 & Goldin-Meadow, 2012). Our argument is that the rate and ultimate attainment of

1101 language learners will vary substantially as a function of caregiver modification, and that

1102 describing the cause of this variability is a necessary feature of models of language learning.

1103   Our account aims to explain caregivers' production and child learning in the same

1104 system, putting these processes into explicit dialogue. While we have focused on ostensive

1105 labeling as a case-study phenomenon, our account should reasonably extend to the changing

1106 structure found in other aspects of child-directed speech. Some such phenomena will be

1107 easily accounted for; aspects of language that shape communicative efficiency should shift in

1108 predictable patterns across development. For example, the exaggerated pitch contours seen

1109 in infant-directed speech serve to draw infants' attention and facilitate phoneme learning.

1110 These language modifications are well-explained by our proposed framework, though

1111 incorporating them will likely require altering aspects of our account and decisions about

1112 which alterations are most appropriate. In the example of exaggerated pitch, one could

1113 expand the definition of communicative success to include the goal of maintaining attention,

1114 or accomplish the same goal by altering the cost structure to penalize loss of engagement.

1115 Thus, while this account should generalize to other modifications found in child-directed

1116 speech, such generalizations will likely require alterations to the extant structure of the

1117 framework.

1118   Of course, not all aspects of language should be calibrated to the child's language

1119 development. Our account also provides an initial framework for explaining aspects of

communication that would not be modified in child-directed speech: aspects of communication that minimally affect communicative efficiency. In other words, communication goals and learning goals are not always aligned. For example, young children sometimes overregularize past and plural forms, producing incorrect forms such as "runned" or "foots" (rather than the irregular verb "ran" or irregular plural "feet," Marcus et al., 1992). Mastering the proper tense endings (i.e. the learning goal) might be aided by feedback from caregivers; however, adults rarely provide explicit corrective feedback for these errors (Marcus, 1993). This is perhaps because incorrect grammatical forms nonetheless successfully communicate their intended meaning, and thus do not prevent the successful completion of the communicative goal of language (Chouinard & Clark, 2003). The degree of alignment between communication and learning goals should predict the extent to which a linguistic phenomenon is modified in child-directed speech.

Some aspects of caregiver production are unrepresented in our framework, such as aspects of production driven by speaker-side constraints. Furthermore, our account is formulated primarily around concrete noun learning and future work must address its viability in other aspects of language learning. We chose to focus on ostensive labeling as a case-study phenomenon because it is an undeniably information-rich cue for young language learners, however ostensive labeling varies substantially across socio-economic, linguistic, and cultural groups (Hoff, 2003). This is to be expected to the extent that caregiver-child interaction is driven by different goals (or goals given different weights) across these populations–variability in goals could give rise to variability in the degree of modification. Indeed, child-directed speech itself varies cross-linguistically, both in its features (Fernald et al., 1989) and quantity (e.g., Shneidman & Goldin-Meadow, 2012)–although, there is some evidence that child-directed speech predicts learning even in cultures where it is qualitatively different and less prevalent than in American samples (Shneidman & Goldin-Meadow, 2012). Future work is needed to establish the generalizability of our account beyond the western samples studied here.

1147   We see this account as building on established, crucial statistical learning skills–

1148 distributional information writ large and (unmodified) language data from overheard speech

1149 are undoubtedly helpful for some learning problems (e.g., phoneme learning). There is likely

1150 large variability in the extent to which statistical learning skills drive learning for a given

1151 learning problem, which could derive from domain or cultural differences. Understanding

1152 generalizability of this sort and the limits of statistical learning will likely require a full

1153 account spanning both caregiver production and child learning. A full account that explains

1154 variability in modification across aspects of language will rely on a fully specified model of

1155 optimal communication. Such a model will allow us to determine both which structures are

1156 predictably unmodified, and which structures must be modified for other reasons.

1157 Nonetheless, this work is an important first step in validating the hypothesis that language

1158 input that is structured to support language learning could arise from a single unifying goal:

1159 The desire to communicate effectively.

Conclusion

1161   Building on early functional accounts of language learning, our perspective considers

1162 the caregiver-child dyad as the fundamental unit of analysis and emphasizes the importance

1163 of communicative success in shaping language input and language learning. We have

1164 developed an initial formal account for jointly considering caregiver productions and child

1165 language learning within the same system.

1166   Such an account helps to explain caregivers' increased production of ostensive labeling

1167 in naturalistic communication for infrequent referents and when children are very young. In

1168 an experimental context, pressure to with a less knowledgeable partner results in analogous

1169 behavior from participants in an iterated reference game. A rational communication model

1170 that includes planning can explain these behaviors without an explicit teaching goal, and

1171 such a model produces learning outcomes that outperform all but the best cross-situational

1172 learners in simulations. In sum, this work demonstrates that the pressure to communicate

successfully across knowledge asymmetries may help create a learning environment that fosters language learning. Rapid language learning in early childhood may be best explained by considering that the child's powerful, though not precocious, learning mechanisms are met with a language environment specifically designed to communicate successfully with them.

Acknowledgement

References

Austin, J. L. (1975). *How to do things with words* (Vol. 88). Oxford university press.

Baldwin, D. (2000). Interpersonal understanding fuels knowledge acquisition. *Current Directions in Psychological Science, 9*, 40–45.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Bloom, P. (2000). *How children learn the meanings of words.* MIT press: Cambridge, MA.

Blythe, R. A., Smith, K., & Smith, A. D. M. (2010). Learning times for large lexicons through cross-situational learning. *Cognitive Science, 34*, 620–642.

Bohn, M., & Frank, M. C. (2019). The pervasive role of pragmatics in early language. *Annual Review of Developmental Psychology, 1*, 223–249.

Brand, R. J., Baldwin, D. A., & Ashburn, L. A. (2002). Evidence for 'motionese': Modifications in mothers' infant-directed action. *Developmental Science, 5*(1), 72–83.

Brown, R. (1977). Introduction. In C. E. Snow & C. A. Ferguson (Eds.), *Talking to children: Language input and interaction.* Cambridge, MA.: MIT Press.

Callanan, M. A. (1985). How parents label objects for young children: The role of input in the acquisition of category hierarchies. *Child Development*, 508–523.

Chomsky, N. (1965). *Aspects of the theory of syntax.* MA: MIT Press.

Chouinard, M. M., & Clark, E. V. (2003). Adult reformulations of child errors as negative evidence. *Journal of Child Language, 30*, 637–669.

Clark, H. H. (1996). Using language. In *Journal of Linguistics* (pp. 167–222). Cambridge Univ Press.

DeCasper, A. J., & Fifer, W. P. (1980). Of human bonding: Newborns prefer their mothers' voices. *Science, 208*(4448), 1174–1176.

DeCasper, A. J., & Spence, M. J. (1986). Prenatal maternal speech influences newborns' perception of speech sounds. *Infant Behavior and Development*, *9*(2), 133–150.

Eaves Jr, B. S., Feldman, N. H., Griffiths, T. L., & Shafto, P. (2016). Infant-directed speech is consistent with teaching. *Psychological Review*, *123*(6), 758.

Elman, J. L. (1993). Learning and development in neural networks: The importance of starting small. *Cognition*, *48*(1), 71–99.

Estes, K. G., Evans, J. L., Alibali, M. W., & Saffran, J. R. (2007). Can infants map meaning to newly segmented words? Statistical segmentation and word learning. *Psychological Science*, *18*(3), 254–260.

Evans, O., Stuhlmüller, A., Salvatier, J., & Filan, D. (2017). *Modeling Agents with Probabilistic Programs*. http://agentmodels.org.

Fausey, C. M., Jayaraman, S., & Smith, L. B. (2016). From faces to hands: Changing visual input in the first two years. *Cognition*, *152*, 101–107.

Fernald, A., Taeschner, T., Dunn, J., Papousek, M., Boysson-Bardies, B. de, & Fukui, I. (1989). A cross-language study of prosodic modifications in mothers' and fathers' speech to preverbal infants. *Journal of Child Language*, *16*(3), 477–501.

Foushee, R., Griffiths, T. L., & Srinivasan, M. (2016). *Lexical complexity of child-directed and overheard speech: Implications for learning.*

Frank, M. C., & Goodman, N. D. (2012). Predicting pragmatic reasoning in language games. *Science*, *336*, 998–998.

Frank, M. C., & Goodman, N. D. (2014). Inferring word meanings by assuming that speakers are informative. *Cognitive Psychology*, *75*, 80–96.

Frank, M. C., Goodman, N., & Tenenbaum, J. (2009). Using speakers' referential intentions to model early cross-situational word learning. *Psychological Science*, *20*, 578–585.

Franke, M. (2013). Game theoretic pragmatics. *Philosophy Compass*, *8*(3), 269–284.

Gelman, A., & Hill, J. (2006). *Data analysis using regression and multilevel/hierarchical models.* Cambridge university press.

Gibson, E., Futrell, R., Piantadosi, S. P., Dautriche, I., Mahowald, K., Bergen, L., & Levy, R. (2019). How efficiency shapes human language. *Trends in Cognitive Sciences, 23*(5), 389–407.

Gogate, L. J., Bahrick, L. E., & Watson, J. D. (2000). A study of multimodal motherese: The role of temporal synchrony between verbal labels and gestures. *Child Development, 71*(4), 878–894.

Goldin-Meadow, S., Levine, S. C., Hedges, L. V., Huttenlocher, J., Raudenbush, S. W., & Small, S. L. (2014). New evidence about language and cognitive development based on a longitudinal study: Hypotheses for intervention. *American Psychologist, 69*(6), 588–599.

Goldowsky, B. N., & Newport, E. L. (1993). Limitations on the acquisition of morphology: The less is more hypothesis. *The Proceedings of the Twenty-Fourth Annual Child Language Research Forum*, 124.

Gomez, R. L., & Gerken, L. (1999). Artificial grammar learning by 1-year-olds leads to specific and abstract knowledge. *Cognition, 70*(2), 109–135.

Goodman, N. D., & Frank, M. C. (2016). Pragmatic language interpretation as probabilistic inference. *Trends in Cognitive Sciences, 20*(11), 818–829.

Goodman, N. D., & Stuhlmüller, A. (2014). *The Design and Implementation of Probabilistic Programming Languages.* http://dippl.org.

Grice, H. P. (1975). Logic and conversation. In P. Cole & J. L. Morgan (Eds.), *Syntax and semantics: Vol. 3: Speech acts* (pp. 41–58). New York, NY: Academic Press.

Griffiths, T. L., Lieder, F., & Goodman, N. D. (2015). Rational use of cognitive resources: Levels of analysis between the computational and the algorithmic. *Topics in Cognitive Science, 7*(2), 217–229.

Hoff, E. (2003). The specificity of environmental influence: Socioeconomic status

affects early vocabulary development via maternal speech. *Child Development*, *74*(5), 1368–1378.

Kaelbling, L. P., Littman, M. L., & Cassandra, A. R. (1998). Planning and acting in partially observable stochastic domains. *Artificial Intelligence*, *101*, 99–134.

Leung, A., Tunkel, A., & Yurovsky, D. (2021). Parents fine-tune their speech to children's vocabulary knowledge. *Psychological Science*, *32*(7), 975–984.

Luce, R. D. (1959). *Individual choice behavior*.

MacDonald, K., Yurovsky, D., & Frank, M. C. (2017). Social cues modulate the representations underlying cross-situational learning. *Cognitive Psychology*, *94*, 67–84.

MacKay, D. J. (1992). Bayesian interpolation. *Neural Computation*, *4*(3), 415–447.

Mahowald, K., Fedorenko, E., Piantadosi, S. T., & Gibson, E. (2013). Info/information theory: Speakers choose shorter words in predictive contexts. *Cognition*, *126*(2), 313–318.

Marcus, G. F. (1993). Negative evidence in language acquisition. *Cognition*, *46*(1), 53–85.

Marcus, G. F., Pinker, S., Ullman, M., Hollander, M., Rosen, T. J., Xu, F., & Clahsen, H. (1992). Overregularization in language acquisition. *Monographs of the Society for Research in Child Development*, i–178.

Markman, E. M. (1990). Constraints children place on word meanings. *Cognitive Science*, *14*(1), 57–77.

Markman, E. M., & Wachtel, G. F. (1988). Children's use of mutual exclusivity to constrain the meanings of words. *Cognitive Psychology*, *20*(2), 121–157.

Marr, D. (1982). *Vision: A Computational Investigation into the Human Representation and Processing of Visual Information*. New York, NY: W. H. Freeman.

Maye, J., Werker, J. F., & Gerken, L. (2002). Infant sensitivity to distributional

information can affect phonetic discrimination. *Cognition*, *82*(3), B101–B111.

McMurray, B. (2007). Defusing the childhood vocabulary explosion. *Science*, *317*(5838), 631–631.

McMurray, B., Kovack-Lesh, K. A., Goodwin, D., & McEchron, W. (2013). Infant directed speech and the development of speech perception: Enhancing development or an unintended consequence? *Cognition*, *129*(2), 362–378.

Medina, T. N., Snedeker, J., Trueswell, J. C., & Gleitman, L. R. (2011). How words can and cannot be learned by observation. *Proceedings of the National Academy of Sciences*, *108*(22), 9014–9019.

Meltzoff, A. N. (2005). Imitation and other minds: The "like me" hypothesis. *Perspectives on Imitation: From Neuroscience to Social Science*, *2*, 55–77.

Mintz, T. H. (2003). Frequent frames as a cue for grammatical categories in child directed speech. *Cognition*, *90*(1), 91–117.

Newport, E. L. (1990). Maturational constraints on language learning. *Cognitive Science*, *14*(1), 11–28.

Newport, E. L., Gleitman, H., & Gleitman, L. R. (1977). Mother, I'd rather do it myself: Some effects and non-effects of maternal speech style. In C. A. Ferguson (Ed.), *Talking to children language input and interaction* (pp. 109–149). Cambridge University Press.

Ninio, A. (1980). Ostensive definition in vocabulary teaching. *Journal of Child Language*, *7*(3), 565–573.

Quine, W. V. O. (1960). Word and object. In *Cambridge, Mass.* Cambridge, Mass.: MIT Press.

R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Rafferty, A. N., Brunskill, E., Griffiths, T. L., & Shafto, P. (2016). Faster teaching via pomdp planning. *Cognitive Science*, *40*(6), 1290–1332.

Reisenauer, R., Smith, K., & Blythe, R. A. (2013). Stochastic dynamics of lexicon
    learning in an uncertain and nonuniform world. *Physical Review Letters*, *110*(25),
    258701.

Saffran, J. R. (2003). Statistical language learning: Mechanisms and constraints.
    Current Directions in Psychological Science, *12*(4), 110–114.

Saffran, J. R., Aslin, R. N., & Newport, E. L. (1996). Statistical learning by
    8-month-old infants. *Science*, *274*, 1926–1928.

Scott, R. M., & Fischer, C. (2012). 2.5-year-olds use cross-situational consistency to
    learn verbs under referential uncertainty. *Cognition*, *122*, 163–180.

Shafto, P., Goodman, N. D., & Griffiths, T. L. (2014). A rational account of
    pedagogical reasoning: Teaching by, and learning from, examples. *Cognitive
    Psychology*, *71*, 55–89.

Shneidman, L. A., & Goldin-Meadow, S. (2012). Language input and acquisition in a
    mayan village: How important is directed speech? *Developmental Science*, *15*(5),
    659–673.

Simon, H. A. (1991). Bounded rationality and organizational learning. *Organization
    Science*, *2*(1), 125–134.

Smith, K., Smith, A. D., & Blythe, R. A. (2011). Cross-situational learning: An
    experimental study of word-learning mechanisms. *Cognitive Science*, *35*(3),
    480–498.

Smith, L. B., Jayaraman, S., Clerkin, E., & Yu, C. (2018). The developing infant
    creates a curriculum for statistical learning. *Trends in Cognitive Sciences*, *22*(4),
    325–336.

Smith, L. B., & Yu, C. (2008). Infants rapidly learn word-referent mappings via
    cross-situational statistics. *Cognition*, *106*, 1558–1568.

Smith, L. B., & Yu, C. (2013). Visual attention is not enough: Individual differences
    in statistical word-referent learning in infants. *Language Learning and*

Development, *9*, 25–49.

Snow, C. E. (1972). Mothers' speech to children learning language. *Child Development*, *43*, 549–565.

Snow, C. E. (1977). Mothers' speech research: From input to interaction. *Talking to Children: Language Input and Acquisition*, *3149*.

Stevens, J. S., Gleitman, L. R., Trueswell, J. C., & Yang, C. (2017). The pursuit of word meanings. *Cognitive Science*, *41*, 638–676.

Thiessen, E., Hill, E. A., & Saffran, J. R. (2005). Infant-directed speech facilitates word segmentation. *Infancy*, *7*, 53–71.

Tomasello, M., & Farrar, M. J. (1986). Joint attention and early language. *Child Development*, *57*, 1454–1463.

Townsend, J. T. (1990). Serial vs. Parallel processing: Sometimes they look like tweedledum and tweedledee but they can (and should) be distinguished. *Psychological Science*, *1*(1), 46–54.

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*(1), 126–156.

Vlach, H. A., & Johnson, S. P. (2013). Memory constraints on infants' cross-situational statistical learning. *Cognition*, *127*(3), 375–382.

Vogt, P. (2012). Exploring the robustness of cross-situational learning under zipfian distributions. *Cognitive Science*, *36*(4), 726–739.

Wittgenstein, L. (1953). *Philosophical investigations*. Oxford, UK: Basil Blackwell.

Woodard, K., Gleitman, L. R., & Trueswell, J. C. (2016). Two-and three-year-olds track a single meaning during word learning: Evidence for propose-but-verify. *Language Learning and Development*, *12*(3), 252–261.

Xu, F., & Tenenbaum, J. B. (2007). Word learning as Bayesian inference. *Psychological Review*, *114*(2), 245–272.

1371 Yu, C. (2008). A statistical associative account of vocabulary growth in early word
1372   learning. *Language Learning and Development*, *4*(1), 32–62.

1373 Yu, C., & Smith, L. B. (2007). Rapid word learning under uncertainty via
1374   cross-situational statistics. *Psychological Science*, *18*, 414–420.

1375 Yu, C., & Smith, L. B. (2012). Modeling cross-situational word-referent learning:
1376   Prior questions. *Psychological Review*, *119*, 21–39.

1377 Yurovsky, D. (2018). A communicative approach to early word learning. *New Ideas in*
1378   *Psychology*, *50*, 73–79.

1379 Yurovsky, D., Doyle, G., & Frank, M. C. (2016). Linguistic input is tuned to
1380   children's developmental level. *Proceedings of the Annual Meeting of the Cognitive*
1381   *Science Society*, 2093–2098.

1382 Yurovsky, D., & Frank, M. C. (2015). An integrative account of constraints on
1383   cross-situational learning. *Cognition*, *145*, 53–62.

1384 Yurovsky, D., Fricker, D. C., Yu, C., & Smith, L. B. (2014). The role of partial
1385   knowledge in statistical word learning. *Psychonomic Bulletin & Review*, *21*, 1–22.

1386 Yurovsky, D., Meyers, M., Burke, N., & Goldin-Meadow, S. (2018). Children gesture
1387   when speech is slow to come. In J. Z. Chuck Kalish Martina Rau & T. Rogers
1388   (Eds.), *Proceedings of the 40th annual meeting of the cognitive science society* (pp.
1389   2765–2770).

1390 Yurovsky, D., Yu, C., & Smith, L. B. (2012). Statistical speech segmentation and
1391   word learning in parallel: Scaffolding from child-directed speech. *Frontiers in*
1392   *Psychology*, *3*, 374.

1393 Yurovsky, D., Yu, C., & Smith, L. B. (2013). Competitive processes in
1394   cross-situational word learning. *Cognitive Science*, *37*, 891–921.