

1 Predicting pragmatic cue integration in adults' and children's inferences about novel word
2 meanings

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11

Abstract

12 Language is learned in complex social settings where listeners must reconstruct speakers'
13 intended meanings from context. To navigate this challenge, children can use pragmatic
14 reasoning to learn the meaning of unfamiliar words. One important challenge for pragmatic
15 reasoning is that it requires integrating multiple information sources. Here we study this
16 integration process. We isolate two sources of pragmatic information and, using a
17 probabilistic model of conversational reasoning, formalize both how they should be combined
18 and how this process might develop. We use this model to generate quantitative predictions,
19 which we test against new behavioral data from three- to five-year-old children ($N = 243$)
20 and adults ($N = 694$). Results show close numerical alignment between model predictions
21 and data. This work integrates distinct sets of findings regarding early language and
22 suggests that pragmatic reasoning models can provide a quantitative framework for
23 understanding developmental changes in language learning.

24 *Keywords:* language acquisition, social cognition, pragmatics, Bayesian modeling,
25 common ground

26 Predicting pragmatic cue integration in adults' and children's inferences about novel word
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28 **Introduction**

29 What someone means by an utterance is oftentimes not reducible to the words they
30 used. It takes pragmatic inference – context-sensitive reasoning about the speaker's
31 intentions - to recover the intended meaning (Grice, 1991; Levinson, 2000; Sperber & Wilson,
32 2001). Contextual information comes in many forms. On the one hand, there is information
33 provided by the utterance¹ itself. Competent language users expect each other to
34 communicate in a cooperative way such that speakers produce utterances that are relevant
35 and informative. Thus, semantic ambiguity can be resolved by reasoning about why the
36 speaker produced this particular utterance (H. H. Clark, 1996; Grice, 1991; Sperber &
37 Wilson, 2001; Tomasello, 2008). On the other hand, there is information provided by
38 common ground (the body of knowledge and beliefs shared between interlocutors)(Bohn &
39 Koymen, 2018; E. V. Clark, 2015; H. H. Clark, 1996). Because utterances are embedded in
40 common ground, pragmatic reasoning in context always requires information integration.
41 But how does integration proceed? And how does it develop? Verbal theories assume that
42 information is integrated and that this process develops but do not specify how. We bridge
43 this gap by formalizing information integration and development in a probabilistic model of
44 pragmatic reasoning.

45 Children learning their first language make inferences about intended meanings based
46 on utterance-level and common-ground information both for language understanding and
47 language learning (Bohn & Frank, 2019; E. V. Clark, 2009; Tomasello, 2008). Starting very

¹We use the terms utterance, utterance-level information or utterance-level cues to capture all cues that the speaker provides for their intended meaning. This includes direct referential information in the form of pointing or gazing, semantic information in the form of conventional word meanings as well as pragmatic inferences that are licenced by the particular choice of words or actions.

48 early, infants expect adults to produce utterances in a cooperative way (Behne, Carpenter, &
49 Tomasello, 2005), and expect language to be carrying information (Vouloumanos, Onishi, &
50 Pogue, 2012). By age two, children are sensitive to the informativeness of communication
51 (O'Neill & Topolovec, 2001). By age three children can use this expectation to make
52 pragmatic inferences (Stiller, Goodman, & Frank, 2015; Yoon & Frank, 2019) and to infer
53 novel word meanings (Frank & Goodman, 2014). And although older children continue to
54 struggle with some complex pragmatic inferences until age five and beyond (Noveck, 2001),
55 an emerging consensus identifies these difficulties as stemming from difficulties reasoning
56 about linguistic alternatives rather than pragmatic deficits (Barner, Brooks, & Bale, 2011;
57 Horowitz, Schneider, & Frank, 2018; Skordos & Papafragou, 2016). Thus, children's ability
58 to reason about utterance-level pragmatics is present at least by ages three to five, and
59 possibly substantially younger.

60 Evidence for the use of common ground information by young children is even stronger:
61 Common ground information guides how infants produce non-verbal gestures and interpret
62 ambiguous utterances (Bohn, Zimmermann, Call, & Tomasello, 2018; Saylor, Ganea, &
63 Vázquez, 2011). For slightly older children, common ground – in the form of knowledge
64 about discourse novelty, preferences, and even discourse expectations – also facilitates word
65 learning (Akhtar, Carpenter, & Tomasello, 1996; Saylor, Sabbagh, Fortuna, & Troseth, 2009;
66 Sullivan, Boucher, Kiefer, Williams, & Barner, 2019).

67 All of these examples, however, highlight children's use of a single pragmatic
68 information source or cue. Harnessing multiple – potentially competing – cues poses a
69 separate challenge. One aspect of this integration problem is how to balance common ground
70 information that is built up over the course of an interaction against information gleaned
71 from the current utterance. Much less is known about whether and how children – or even
72 adults – combine these types of information. While many theories of pragmatic reasoning
73 presuppose that both information sources are integrated, the nature of their relationship has

74 typically not been specified.

75 Recent innovations in probabilistic models of pragmatic reasoning provide a
76 quantitative method for addressing the problem of integrating multiple sources of contextual
77 information. This class of computational models, which are referred to as Rational Speech
78 Act (RSA) models (Frank & Goodman, 2012; Goodman & Frank, 2016) formalize the
79 problem of language understanding as a special case of Bayesian social reasoning. A listener
80 interprets an utterance by assuming it was produced by a cooperative speaker who had the
81 goal to be informative. Being informative is defined as providing a message that would
82 increase the probability of the listener recovering the speaker’s intended meaning in context.
83 This notion of contextual informativeness captures the Gricean idea of cooperation between
84 speaker and listener, and provides a first approximation to what we have described above as
85 utterance-level pragmatic information.

86 RSA models capture common ground information as a shared prior distribution over
87 possible intended meanings. Thus, a natural locus for information integration within
88 probabilistic models of pragmatic reasoning is the trade off between the prior probability of a
89 meaning and the informativeness of the utterance. This trade off between contextual factors
90 during word learning is a unique aspect that is not addressed by other computational models
91 of word learning, which have focused on learning from cross-situational, co-occurrence
92 statistics (Fazly, Alishahi, & Stevenson, 2010; Frank, Goodman, & Tenenbaum, 2009) or
93 describing generalizations about word meaning (Xu & Tenenbaum, 2007).

94 We make use of this framework to study pragmatic cue integration across development.
95 To this end, we adapt a method used in perceptual cue integration studies (Ernst & Banks,
96 2002): we make independent measurements of each cue’s strength and then combine them
97 using the RSA model described above to make independent predictions about conditions in
98 which they either coincide or conflict. Finally, we pre-register these quantitative predictions
99 and test them against new data from adults and children.

100 We start by replicating previous findings with adults showing that listeners make
101 pragmatic inferences based on non-linguistic properties of utterances in isolation (experiment
102 1). Then we show that adults make inferences based on common ground information
103 (experiment 2A and 2B). We use data from these experiments as parameters to generate a
104 priori predictions from RSA models about how utterance and common ground information
105 should be integrated. We consider three models that make different assumptions about the
106 integration process: In the *integration model*, the two information sources are integrated with
107 one another. The other two models are lesion models that assume that participants focus on
108 one type of information and disregard the other whenever they are presented together.
109 According to the *no common ground* model, participants focus only on the utterance
110 information and in the *no informativeness* model, only common ground information is
111 considered. We compare predictions from these models to new empirical data from
112 experiments in which utterance and common ground information are manipulated
113 simultaneously (Experiment 3 and 4).

114 After successfully validating this approach with adults in study 1, we apply the same
115 model-driven experimental procedure to children (study 2): We first show that they make
116 pragmatic inferences based on utterance and common ground information separately
117 (experiment 5 and 6). Then we generate a priori model predictions and compare them to data
118 from an experiment in which both information sources have to be integrated (experiment 7).

119 Taken together, this work makes two primary contributions: first, it shows that both
120 adults and children integrate utterance-level and common-ground information flexibly.
121 Second, it uses Bayesian data analysis within the RSA framework to provide a model for
122 understanding the multiple loci for developmental change in complex behaviors like
123 contextual communication.

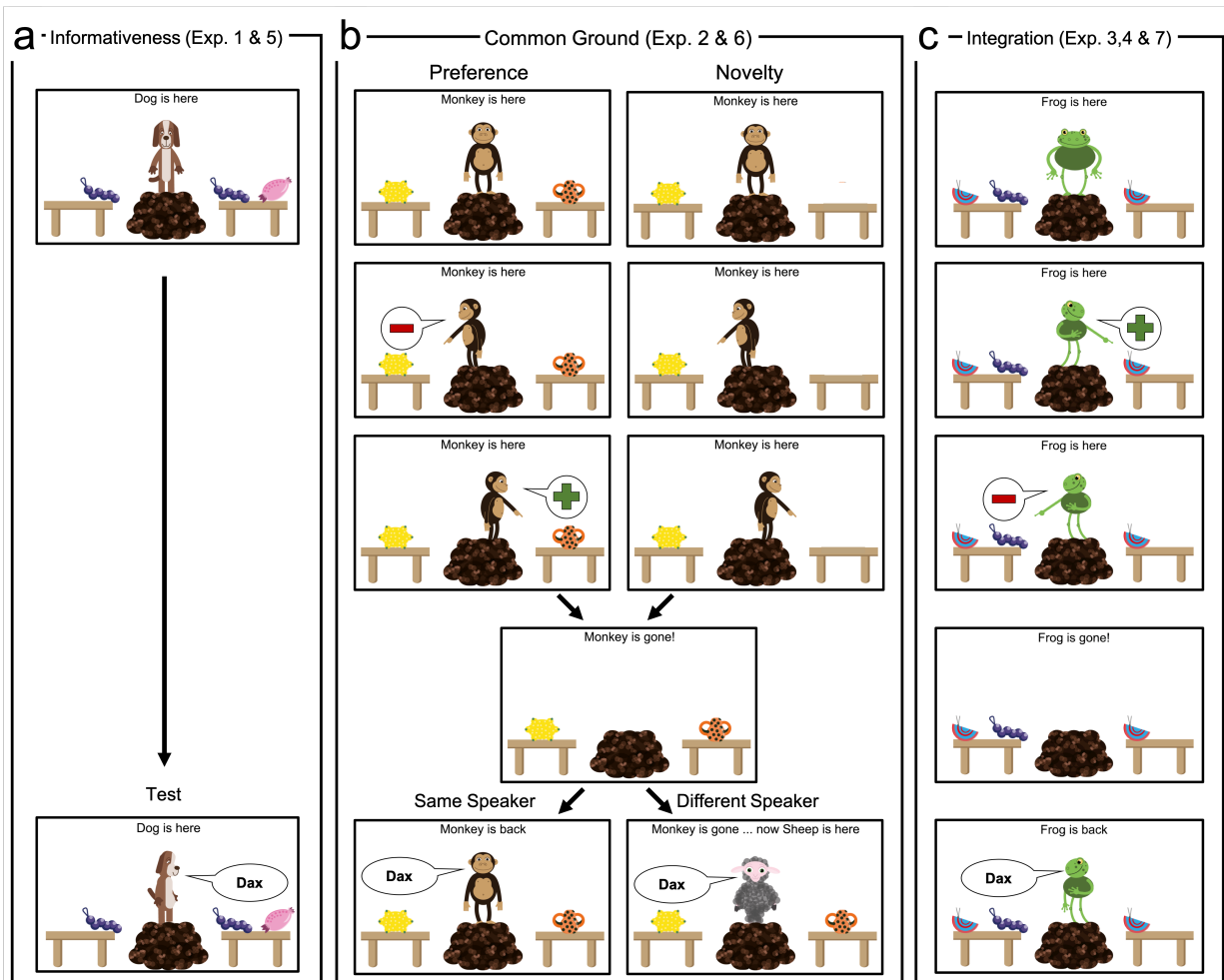


Figure 1. Schematic experimental procedure with screenshots from the adult experiments. In all conditions, at test (bottom), the speaker ambiguously requested an object using a non-word (e.g. “dax”). Participants clicked on the object they thought the speaker referred to. Speech bubbles represent pre-recorded utterances. Informativeness (a) translated to making one object less frequent in context. Common ground (b) was manipulated by making one object preferred by or new to the speaker. Green plus signs represent utterances that expressed preference and red minus signs represent utterances that expressed dispreference (see main text for details). Integration (c) combined informativeness and common ground manipulations. One integration condition is shown here: preference - same speaker - incongruent.

Study 1: Adults

124

125 **Participants**

126 Adult participants were recruited via Amazon Mechanical Turk (MTurk) and received
127 payment equivalent to an hourly wage of ~ \$9. Each participant contributed data to only
128 one experiment. Experiment 1 and each manipulation of experiment 2 had $N = 40$
129 participants. Sample size in experiment 3 was $N = 121$. $N = 167$ participated in the
130 experiments to measure the strong, medium and weak preference and novelty manipulations
131 that went into experiment 4. Finally, experiment 4 had $N = 286$ participants. Sample sizes
132 in all adult experiments were chosen to yield at least 120 data points per cell. All studies
133 were approved by the Stanford Institutional Review Board (protocol no. 19960).

134 **Materials**

135 All experimental procedures were pre-registered (see
136 <https://osf.io/u7kxe/registrations>). Experimental stimuli are freely available in the following
137 online repository: <https://github.com/manuelbohn/mcc>. All experiments were framed as
138 games in which participants would learn words from animals. They were implemented in
139 HTML/JavaScript as a website. Adults were directed to the website via MTurk and
140 responded by clicking objects. For each animal character, we recorded a set of utterances
141 (one native English speaker per animal) that were used to provide information and make
142 requests. All experiments started with an introduction to the animals and two training trials
143 in which familiar objects were requested (car and ball). Subsequent test trials in each
144 condition were presented in a random order.

145 **Analytic approach**

146 We preregistered sample sizes, inferential statistical analysis and computational models
147 for all experiments. All deviations from the registered analysis plan are explicitly mentioned.
148 All analyses were run in R (R Core Team, 2018). All p-values are based on two sided
149 analysis. Cohen’s d (computed via the function `cohensD`) was used as effect size for t-tests.
150 Frequentist logistic GLMMs were fit via the function `glmer` from the package `lme4` (Bates,
151 Mächler, Bolker, & Walker, 2015) and had a maximal random effect structure conditional on
152 model convergence. Details about GLMMs including model formulas for each experiment
153 can be found in the Supplementary Material available online. Probabilistic models and
154 model comparisons were implemented in WebPPL (Goodman & Stuhlmüller, 2014) using the
155 R package `rwebppl` (Braginsky, Tessler, & Hawkins, 2019). In experiment 3, 4 and 7, we
156 compared probabilistic models based on Bayes Factors which were calculated from the
157 marginal likelihoods of each model given the data. Details on models, including information
158 about priors for parameter estimation and Markov chain Monte Carlo settings can be found
159 in the Supplementary Material available online. Code to run the models is available in the
160 associated online repository.

161 **Experiment 1**

162 **Methods.** In experiment 1, participants could learn which object a novel word
163 referred to by assuming that the speaker communicated in an informative way (Frank &
164 Goodman, 2014). The speaker was located between two tables, one with two novel objects, A
165 and B, and the other with only object A (Fig 1a). At test, the speaker turned and pointed
166 to the table with the two objects (A and B) and used a novel word to request one of them.
167 The same utterance was used to make a request in all adult studies (“Oh cool, there is a
168 [non-word] on the table, how neat, can you give me the [non-word]?”). Participants could
169 infer that the word referred to object B via the counter-factual inferences that, if the

170 (informative) speaker had wanted to refer to object A, they would have pointed to the table
171 with the single object (this being the least ambiguous way to refer to that object). In the
172 control condition, both tables contained both objects and no inference could be made based
173 on the speaker’s behavior. Participants received six trials, three per condition.

174 **Results.** Participants selected object B above chance in the test condition (mean =
175 0.74, 95% CI of mean = [0.65; 0.83], $t(39) = 5.51$, $p < .001$, $d = 0.87$) and more often
176 compared to the control condition ($\beta = 1.28$, $se = 0.29$, $p < .001$, see Fig 2). This finding
177 replicates earlier work showing that adult listeners expect speakers to communicate in an
178 informative way.

179 Experiment 2

180 **Methods.** In experiments 2A and 2B, we tested if participants use common ground
181 information that is specific to a speaker to identify the referent of a novel word (Akhtar et
182 al., 1996; Diesendruck, Markson, Akhtar, & Reudor, 2004; Saylor et al., 2009). In experiment
183 2A, the speaker expressed a preference for one of two objects (Fig 1b, left). The animal
184 introduced themselves, then turned to one of the tables and expressed either that they liked
185 (“Oh wow, I really like that one”) or disliked (“Oh bleh, I really don’t like that one”) the
186 object before turning to the other side and expressing the respective other attitude. Next the
187 animal disappeared and, after a short pause, either the same or a different animal returned
188 and requested an object while facing straight ahead. Participants could use the speakers
189 preference to identify the referent when the same speaker returned but not when a different
190 speaker appeared whose preferences were unknown.

191 In experiment 2B, common ground information came in the form of novelty (Fig 1b,
192 right). The animal turned to one of the sides and commented either on the presence (“Aha,
193 look at that”) or the absence (“Hm... , nothing there”) of an object before turning to the

194 other side and commenting in a complementary way. Later, a second object appeared on the
 195 previously empty table. Then the speaker used a novel word to request one of the objects.
 196 The referent of the novel word could be identified by assuming that the speaker uses it to
 197 refer to the object that is new to them. This inference was not licensed when a different
 198 speaker returned to whom both objects were equally new. For both novelty and preference,
 199 participants received six trials, three with the same and three with the different speaker.

200 **Results.** In experiment 2A, participants selected the preferred object above chance
 201 (mean = 0.97, 95% CI of mean = [0.93; 1], $t(39) = 29.14$, $p < .001$, $d = 4.61$) and more so
 202 than in the speaker change control condition ($\beta = 2.92$, $se = 0.57$, $p < .001$).

203 In experiment 2B, participants selected the novel object above chance (mean = 0.83,
 204 95% CI of mean = [0.73; 0.93], $t(39) = 6.77$, $p < .001$, $d = 1.07$) when the same speaker
 205 made the request and more often compared to when a different speaker made the request (β
 206 = 6.27, $se = 1.96$, $p = .001$, see Fig 2).

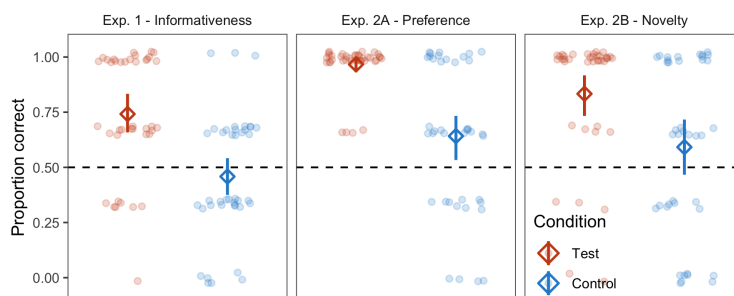


Figure 2. Results from experiments 1, 2A, and 2B for adults. For preference and novelty, control refers to a different speaker (see Fig 1b). Transparent dots show data from individual participants, diamonds represent condition means, error bars are 95% CIs. Dashed line indicates performance expected by chance.

207 **Modelling information integration**

208 Experiments 1 and 2 confirmed that adults make pragmatic inferences based on
 209 information provided by the utterance as well as by common ground and provided
 210 quantitative estimates of the strength of these inferences for use in our model. We modeled
 211 the integration of utterance informativity and common ground as a process of socially-guided
 212 probabilistic inference, using the results of experiments 1 and 2 to inform key parameters of
 213 a computational model. The Rational Speech Act (RSA) model architecture introduced by
 214 Frank and Goodman (2012) encodes conversational reasoning through the perspective of a
 215 listener (“he” pronoun) who is trying to decide on the intended meaning of the utterance he
 216 heard from the speaker (“she” pronoun). The basic idea is that the listener combines his
 217 uncertainty about the speaker’s intended meaning - a prior distribution over referents $P(r)$ -
 218 with his generative model of how the utterance was produced: a speaker trying to convey
 219 information to him. To adapt this model to the word learning context, we enrich this basic
 220 architecture with a mechanism for expressing uncertainty about the meanings of words
 221 (lexical uncertainty) - a prior distribution over lexica $P(L)$ (Bergen, Levy, & Goodman, 2016).

$$P_L(r, \mathcal{L}|u) \propto P_S(u|r, \mathcal{L}) \cdot P(\mathcal{L}) \cdot P(r)$$

222 In the above equation, the listener is trying to jointly resolve the speaker’s intended
 223 referent r and the meaning of words (thus learning the lexicon \mathcal{L}). He does this by imagining
 224 what a rational speaker would say, given the referent they are trying to communicate and a
 225 lexicon. The speaker is an approximately rational Bayesian actor (with degree of rationality
 226 α), who produces utterances as a function of their informativity. The space of utterances
 227 the speaker could produce depends upon the lexicon $P(u|\mathcal{L})$; simply put, the speaker labels
 228 objects with the true labels under a given lexicon L (see Supplementary Material available
 229 online for details):

$$P_S(u|r, \mathcal{L}) \propto \text{Informativity}(u; r)^\alpha \cdot P(u|\mathcal{L})$$

230 The informativity of an utterance for a referent is taken to be the probability with
 231 which a naive listener, who only interprets utterances according to their literal semantics,
 232 would select a particular referent given an utterance.

$$\text{Informativity}(u; r) = P(r|u) \propto P(r) \cdot \mathcal{L}_{point}$$

233 The speaker’s possible utterances are pairs of linguistic and non-linguistic signals,
 234 namely labels and points. Because the listener does not know the lexicon, the informativity
 235 of an utterance comes from the speaker’s point, the meaning of which is encoded in \mathcal{L}_{point}
 236 and is simply a truth-function checking whether or not the referent is at the location picked
 237 out by the speaker’s point. Though the speaker makes their communicative decision
 238 assuming the listener does not know the meaning of the labels, we assume that in addition to
 239 a point, the speaker produces a label consistent with their own lexicon \mathcal{L} , described by
 240 $P(u|\mathcal{L})$ (see Supplementary Material available online for modeling details).

241 This computational model provides a natural avenue to formalize quantitatively how
 242 informativeness and common ground trade-off during word learning. As mentioned above,
 243 the common ground shared between speaker and listener plays the role of the listener’s prior
 244 distribution over meanings, or types of referents, that the speaker might be referring to and
 245 which we posit depends on prior interactions around the referents in the present context
 246 (e.g., preference or novelty; experiment 2A and B). We use the results from experiment 2 to
 247 specify this distribution. The in-the-moment, contextual informativeness of the utterance is
 248 captured in the likelihood term, whose value depends on the rationality parameter α .
 249 Assumptions about rationality may change depending on context and we therefore used the
 250 data from experiment 1 to specify α (see Supplementary Material available online for details

251 about these parameters).

252 The model generates predictions for situations in which utterance and common ground
253 expectations are jointly manipulated (Fig 1c - see Supplementary Material available online
254 for additional details and a worked example of how predictions were generated). In addition
255 to the parameters fit to the data from previous experiments, we include an additional noise
256 parameter, which can be thought of as reflecting the cost that comes with handling and
257 integrating multiple information sources. Technically it estimates the proportion of responses
258 better explained by a process of random guessing than by pragmatics; we estimate this
259 parameter from the observed data (experiment 3). Including the noise parameter greatly
260 improved the model fit to the data (see Supplementary Material available online for details).
261 We did not pre-register the inclusion of a noise parameter for experiment 3 but did so for all
262 subsequent experiments.

263 **Experiment 3**

264 **Methods.** In experiment 3, we combined the procedures of experiment 1 and 2A or
265 2B. The test setup was identical to experiment 1, however, before making a request, the
266 speaker interacted with the objects so that some of them were preferred by or new to them
267 (Fig 1c). This combination resulted in two ways in which the two information sources could
268 be aligned with one another. In the congruent condition, the object that was the more
269 informative referent was also the one that was preferred by or new to the speaker. In the
270 incongruent condition, the other object was the one that was preferred by or new to the
271 speaker. Taken together, there were 2 (novelty or preference) x 2 (same or different speaker)
272 x 2 (congruent or incongruent) = 8 conditions in experiment 3. For each of these eight
273 conditions, we generated model predictions using the modelling framework introduced above.
274 The test hypothesis about how information is integrated we compared the three models
275 introduced in the introduction: The *integration model* in which both information sources are

276 flexibly combined, the *no common ground model* that focused only on utterance-level
277 information and the the *no informativeness model* that focused only on common ground
278 information.

279 Participants completed eight trials for one of the common ground manipulations with
280 two trials per condition (same/different speaker x congruent/incongruent). Conditions were
281 presented in a random order. We discuss and visualize the results as the proportion with
282 which participants chose the more informative object (i.e., the object that would be the more
283 informative referent when only utterance information is considered).

284 **Results.** As a first step, we used a GLMM to test whether participants were
285 sensitive to the different ways in which information could be aligned. We found that
286 participants distinguished between congruent and incongruent trials when the speaker
287 remained the same (model term: **alignment x speaker**; $\beta = -2.64$, $se = 0.48$, $p < .001$).
288 Thus, participants were sensitive to the different combinations of manipulations.

289 As a second step, we compared the model predictions to the data. Participants'
290 average responses were highly correlated with the predictions from the *integration model* in
291 each condition (Fig 3b). When comparing model, we found that model fit was considerably
292 better for the* *integration model** compared to the *no common ground model* (Bayes Factor
293 (BF) = $4.2e+53$) or the *no informativeness model* (BF = $2.5e+34$), suggesting that
294 participants considered and integrated both sources of information.

295 Finally, we examined the noise parameter for each model. The estimated proportion of
296 random responses according to the *integration model* was 0.30 (95% Highest Density Interval
297 (HDI): 0.23 - 0.36). This parameter was substantially lower for the *integration model*
298 compared to the alternative models (*no common ground model*: 0.60 [0.46 - 0.72]; *no*
299 *informativeness model*: 0.41 [0.33 - 0.51]), lending additional support to the conclusion that
300 the *integration model* better captured the behavioral data. Rather than explaining

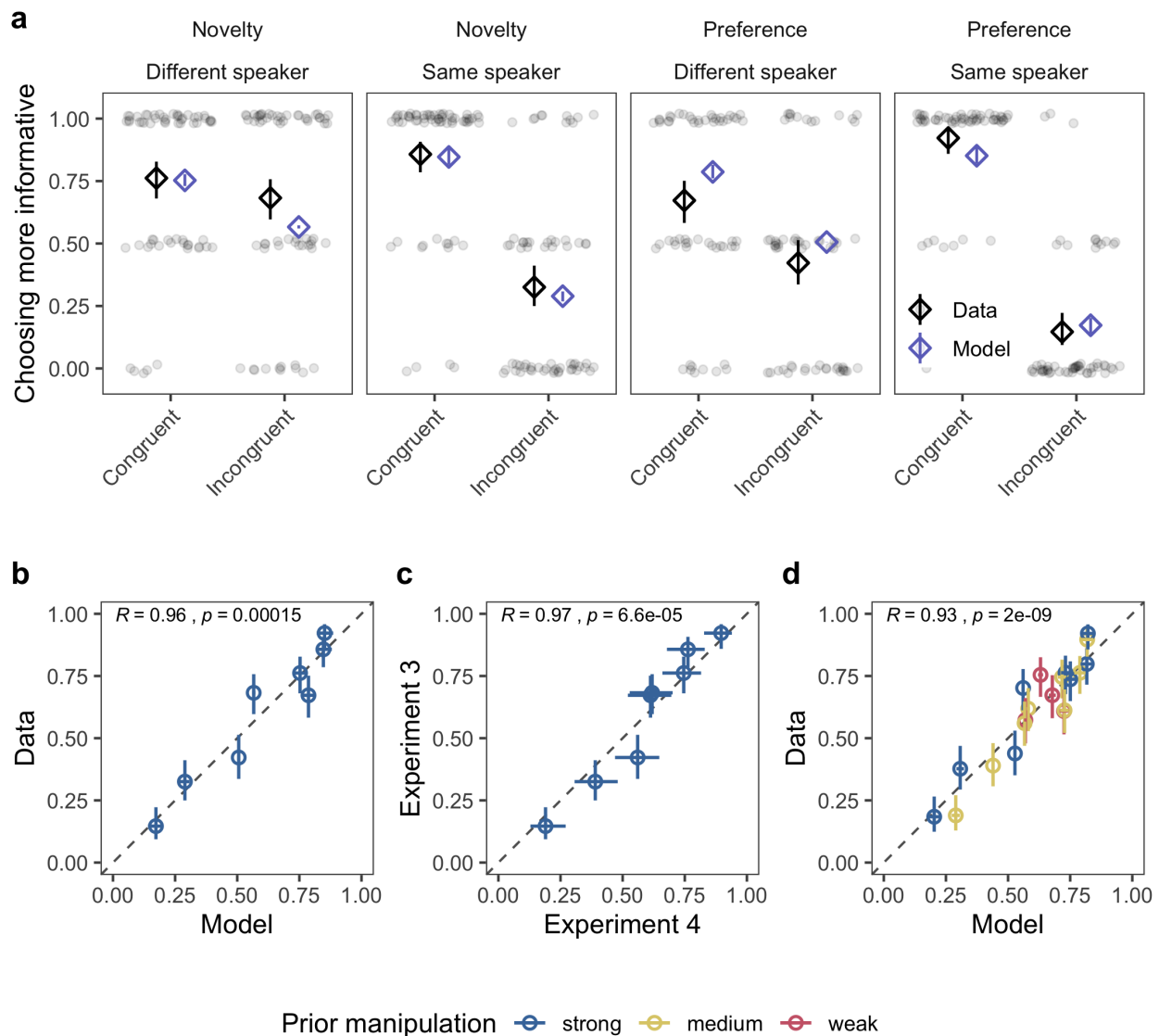


Figure 3. Results from experiment 3 and 4 for adults. Data and model predictions by condition for experiment 3 (a). Transparent dots show data from individual participants, diamonds represent condition means. Correlation between model predictions and data in Experiment 3 (b), between data in Experiment 3 and the direct replication in experiment 4 (c) and between model predictions and data in experiment 4 (d). Coefficients and p-values are based on Pearson correlation statistics. Error bars represent 95% HDIs.

301 systematic structure in the data, the alternative models achieved their best fit only by
 302 assuming a very high level of noise.

303 **Experiment 4**

304 **Methods.** To test if the *integration model* makes accurate predictions for different
305 combinations, we first replicated and then extended the results of experiment 3 to a broader
306 range of experimental conditions. Specifically, we manipulated the strength of the common
307 ground information (3 levels - strong, medium and weak - for preference and 2 levels - strong
308 and medium - for novelty) by changing the way the speaker interacted with the objects prior
309 to the request. The procedural details and statistical analysis for these these manipulations
310 are described in the Supplementary Material available online. For experiment 4, we paired
311 each level of prior strength manipulation with the informativeness inference in the same way
312 as in experiment 3. This resulted in a total of 20 conditions, for which we generated a priori
313 model predictions in the same way as in experiment 3. The strong prior manipulation in
314 experiment 4 was a direct replication of experiment 3 (see Fig 3c). Each participant was
315 randomly assigned to a common ground manipulation and a level of prior strength and
316 completed eight trials in total, two in each unique condition in that combination.

317 **Results.** The direct replication of experiment 3 within experiment 4 showed a very
318 close correspondence between the two rounds of data collection (see Fig 3c). GLMM results
319 for experiment 4 can be found in the Supplementary Material available online. Here we focus
320 on the analysis based on the probabilistic models. Model predictions from the *integration*
321 *model* were again highly correlated with the average response in each condition (see Fig 3d).
322 We evaluated model fit for the same models as in experiment 3 and found again that the
323 *integration model* fit the data much better compared to the *no common ground* (BF =
324 4.7e+71) or the *no informativeness model* (BF = 8.9e+82). The inferred level of noise based
325 on the data for the *integration model* was 0.36 (95% HDI: 0.31 - 0.41), which was similar to
326 experiment 3 and again lower compared to the alternative models (*no common ground model*:
327 0.53 [0.46 - 0.62]; *no informativeness model*: 0.67 [0.59 - 0.74]).

Study 2: Children

328

329 The previous section showed that competent language users flexibly integrate
330 information during pragmatic word learning. Do children make use of multiple information
331 sources during word learning as well? When does this integration emerge developmentally?
332 While many verbal theories of language learning imply that this integration takes place, the
333 actual process has neither been described nor tested in detail. Here we provide an
334 explanation in the form of our *integration model* and test if it is able to capture children's
335 word learning. Embedded in the assumptions of the model is the idea that developmental
336 change is change in the strength of the individual inferences, leading to a change in the
337 strength of the integrated inference. As a starting point, our model assumes developmental
338 continuity in the integration process itself (Bohn & Frank, 2019), though this assumption
339 could be called into question by a poor model fit. The study for children followed the same
340 general pattern as the one for adults. We generated model predictions for how information
341 should be integrated by first measuring children's ability to use utterance (informativeness)
342 and common ground (preference) information in isolation when making pragmatic inferences.
343 We then adapted our model to study developmental change: We sampled children
344 continuously between 3.0 and 5.0 years of age – a time in which children have been found to
345 make the kind of pragmatic inferences we studied here (Bohn & Frank, 2019; Frank &
346 Goodman, 2014) - and generated model predictions for the average developmental trajectory
347 in each condition.

348 Participants

349 Children were recruited from the floor of the Children's Discovery Museum in San Jose,
350 California, USA. Parents gave informed consent and provided demographic information.
351 Each child contributed data to only one experiment. We collected data from a total of 243
352 children between 3.0 and 5.0 years of age. We excluded 15 children due to less than 75% of

353 reported exposure to English, five because they responded incorrectly on 2/2 training trials,
354 three because of equipment malfunction, and two because they quit before half of the test
355 trials were completed. The final sample size in each experiment was as follows: $N = 62$ (41
356 girls, mean age = 4) in experiment 5, $N = 61$ (28 girls, mean age = 3.99) in experiment 6
357 and $N = 96$ (54 girls, mean age = 3.96) in experiment 7. For experiment 5 and 6, we also
358 tested two-year-olds but did not find sufficient evidence that they use utterance and/or
359 common ground information in the tasks we used to justify investigating their ability to
360 integrate the two. Sample sizes in all experiments were chosen to yield at least 80 data
361 points in each cell for each age group.

362 **Materials**

363 Experiments were implemented in the same general way as for adults. Children were
364 guided through the games by an experimenter and responded by touching objects on the
365 screen of an iPad tablet (Frank, Sugarman, Horowitz, Lewis, & Yurovsky, 2016).

366 **Experiment 5**

367 **Methods.** Experiment 5 for children was modeled after Frank and Goodman (2014).
368 Instead of on tables, objects were presented as hanging in trees (to facilitate showing points
369 to distinct locations). After introducing themselves, the animal turned to the tree with two
370 objects and said: “This is a tree with a [non-word], how neat, a tree with a [non-word]”).
371 Next, the trees and the objects in them disappeared and new trees replaced them. The two
372 objects from the tree the animal turned to previously were now spread across the two trees
373 (one object per tree, position counterbalanced). While facing straight, the animal first said
374 “Here are some more trees” and then asked the child to pick the tree with the object that
375 corresponded to the novel word (“Which of these trees has a [non-word]?”). Children
376 received six trials in a single test condition.

377 **Results.** To compare children’s performance to chance level, we binned age by year.
 378 Four-year-olds selected the more informative object (i.e. the object that was unique to the
 379 location the speaker turned to) above chance (mean = 0.62, 95% CI of mean = [0.53; 0.71],
 380 $t(29) = 2.80$, $p = .009$, $d = 0.51$). Three-year-olds, on the other hand, did not (mean = 0.46,
 381 95% CI of mean = [0.41; 0.52], $t(31) = -1.31$, $p = .198$, $d = 0.23$). Consequently, when we fit
 382 a GLMM to the data with age as a continuous predictor, performance increased with age (β
 383 = 0.38, $se = 0.11$, $p < .001$, see Fig 4). Thus, children’s ability to use utterance information
 384 in a word learning context increased with age.

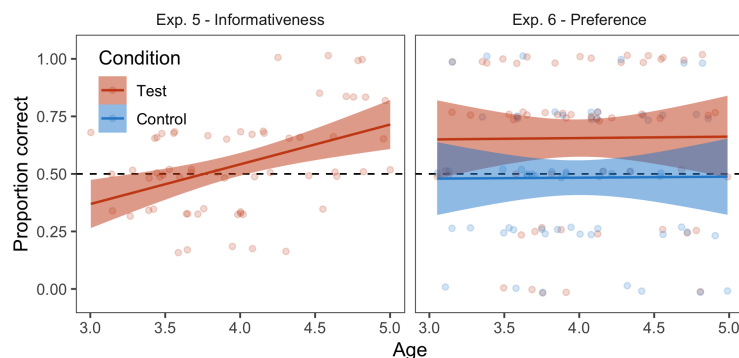


Figure 4. Results from experiment 5 and 6 for children. For preference, control refers to to the different speaker condition (see Fig. 1B). Transparent dots show data from individual participants, regression lines show fitted linear models with 95% CIs. Dashed line indicates performance expected by chance.

385 Experiment 6

386 **Methods.** In experiment 6, we assessed whether children use common ground
 387 information to identify the referent of a novel word. We tested children only with the
 388 preference manipulation². The procedure for children was identical to the preference

²We initially tested children with the novelty as well as the preference manipulation. We found that children made the basic inference in that they selected the object that was preferred by or new to the speaker, but found little evidence that children distinguished between requests made by the same speaker or a different

389 manipulation for adults. Children received eight trials, four with the same and four with a
390 different speaker.

391 **Results.** Four-year-olds selected the preferred object above chance when the same
392 speaker made the request (mean = 0.71, 95% CI of mean = [0.61; 0.81], $t(30) = 4.14$, $p <$
393 $.001$, $d = 0.74$), whereas three-year-olds did not (mean = 0.60, 95% CI of mean = [0.47;
394 0.73], $t(29) = 1.62$, $p = .117$, $d = 0.30$). However, when we fit a GLMM to the data with age
395 as a continuous predictor, we found an effect of speaker identity ($\beta = 0.89$, $se = 0.24$, $p <$
396 $.001$) but no effect of age ($\beta = 0.02$, $se = 0.16$, $p = .92$) or interaction between speaker
397 identity and age ($\beta = -0.01$, $se = 0.23$, $p = .97$, see Fig 4). Thus, children across the age
398 range used common ground information to infer the referent of a novel word.

399 **Modelling information integration in children**

400 Model predictions for children were generated using the same model described above
401 for adults. However, to incorporate developmental change in the model, we allowed the
402 rationality parameter α and the prior distribution over objects to change with age. That is,
403 instead of a single value, we inferred the intercept and slope for each parameter that best
404 described the developmental trajectory in the data of experiment 5 and 6. These parameter
405 settings were then used to generate age sensitive model predictions in 2 (same or different
406 speaker) x 2 (congruent or incongruent) = 4 conditions. As for adults, all models included a
407 noise parameter, which was estimated based on the data of experiment 7.

408 **Experiment 7**

speaker in the case of novelty. This finding contrasts with earlier work (Diesendruck et al., 2004). However, since our focus was on how children integrate informativeness and common ground, we did not follow up on this finding but dropped the novelty manipulation and focused on preference for the remainder of the study

409 **Methods.** In experiment 7, we combined the procedures of experiment 5 and 6 and
410 collected new data from children between 3.0 and 5.0 years of age in each of the four
411 conditions (Fig 1c). We again inserted the preference manipulation into the setup of
412 experiment 5. After greeting the child, the animal turned to one of the trees, pointed to an
413 object (object was temporarily enlarged and moved closer to the animal) and expressed
414 liking or disliking. Then the animal turned to the other tree and expressed the other
415 attitude for the other kind of object. Next, the animal disappeared and either the same or a
416 different animal returned. The rest of the trial was identical to the request phase of
417 experiment 5. Children received eight trials, two per condition (same/different speaker x
418 congruent/incongruent) in a randomized order.

419 **Results.** As a first step, we used a GLMM to test whether children were sensitive to
420 the different ways in which information could be aligned. Children’s propensity to
421 differentiate between congruent and incongruent trials for the same or a different speaker
422 increased with age (model term: `age x alignment x speaker`; $\beta = -0.89$, $se = 0.36$, $p =$
423 $.013$).

424 Analyses comparing the model predictions from the probabilistic models to the data
425 suggest that children flexibly integrate both common ground and informativity information.
426 Furthermore, this integration process is accurately captured by the *integration model* at least
427 for four-year-olds. For the correlational analysis, we binned model predictions and data by
428 year. There was a substantial correlation between the predicted and measured average
429 response for four-year-olds, but less so for three-year-olds (Fig 5b). One of the reasons for
430 the latter was the low variation between conditions. For the model comparison, we treated
431 age continuously. As with adults, we found a much better model fit for the *integration model*
432 compared to the *no common ground* (BF = 577) or the *no informativeness model* (BF =
433 10560).

434 The inferred level of noise based on the data for the integration model was 0.51 (95%

435 HDI: 0.26 - 0.77), which was lower compared to the alternative models considered (*no*
436 *common ground model*: 0.81 [0.44 - 1.00]; *no informativeness model*: 0.99 [0.88 - 1.00]) but
437 numerically higher than that of adults.

438 The high level of inferred noise moved the model predictions for children in all
439 conditions close to chance level. We therefore compared two additional sets of models with
440 different parameterizations of the noise parameter that emphasized differences between
441 conditions in the model predictions more (see Supplementary Material available online and
442 Fig 5a). This analysis was not pre-registered. Parameter free models did not include a noise
443 parameter and developmental noise models allowed the noise parameter to change with age.
444 In each case, the *integration model* provided a better fit compared to the alternative models
445 (*no common ground*: parameter free BF = 334, developmental noise BF = 16361; *no*
446 *informativeness*: parameter free BF = 20, developmental noise BF = 1e+06). The
447 developmental noise parameter for the integration model decreased with age, suggesting that
448 older children behaved more in line with model predictions compared to younger children
449 (see Fig. S13 in Supplementary Material available online).

450

Discussion

451 Integrating multiple sources of information is an integral part of human communication
452 (Tanenhaus, Spivey-Knowlton, Eberhard, & Sedivy, 1995). To infer the intended meaning of
453 an utterance, listeners must combine their knowledge of communicative conventions
454 (semantics and syntax) with social expectations about their interlocutor. This integration is
455 especially vital in early language learning, and the different varieties of pragmatic
456 information are among the most important sources (Bohn & Frank, 2019). But how are
457 pragmatic cues integrated during word learning? Here we used a Bayesian cognitive model to
458 formalize this integration process. We studied how utterance-level (Gricean) expectations
459 about informative communication are integrated with common ground information. Adults'

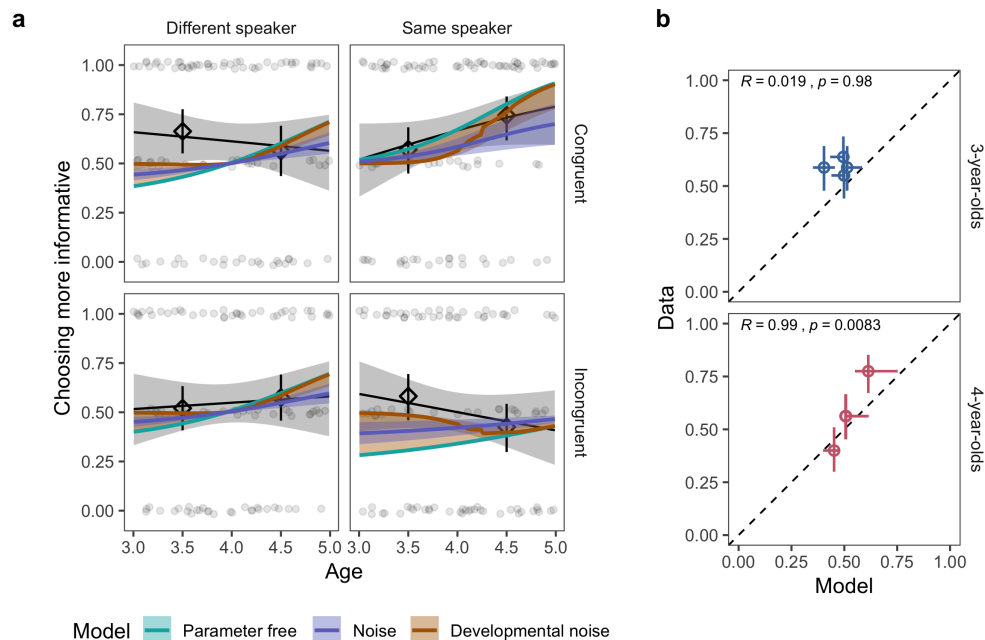


Figure 5. Results from experiment 7 for children. Model predictions and data across age in the four conditions (a). Transparent black dots show data from individual participants and black lines show conditional means of the data with 95% CI. Black diamonds show the mean of the data for age bins by year and error bars show 95% CIs. Correlation between model predictions (with noise parameter) and condition means binned by year (b). Coefficients and p-values are based on Pearson correlation statistic. Error bars and shaded regions represent 95% HDIs. For 4-year-olds, two conditions yielded the same data means and model predictions and are thus plotted on top of each other.

460 and children’s learning was best predicted by a model in which both sources of information
 461 traded-off flexibly. Alternative models that considered only one source of information made
 462 substantially worse predictions.

463 All of the models we compared here integrated some explicit structure, rather than (for
 464 example) simply weighing information sources by some ratio. We made this decision because
 465 we wanted to make predictions within a framework in which the models were models of the
 466 task, rather than simply models of the data. That is, inferences are not computed separately

467 by the modeler and specified as inputs to a regression model, but instead are the results of
468 an integrated process that operates over a (schematic) representation of the experimental
469 stimuli. Further, our models are variants derived from the broader RSA framework, which
470 has been integrated into larger systems for language learning in context (Cohn-Gordon,
471 Goodman, & Potts, 2018; Monroe, Hawkins, Goodman, & Potts, 2017; Wang, Liang, &
472 Manning, 2016).

473 How is information integrated in this context in this context? The *integration model*
474 assumes that the informativeness of an utterance depends on the common ground shared
475 between interlocutors. That is, the listener assumes that the speaker takes the common
476 ground shared between the speaker and the (naive) listener as a starting point when
477 computing the effect of each utterance. As a consequence, when prior interactions strongly
478 implicate one object as the more likely referent (for example in the preference - same speaker
479 conditions in experiment 3, 4 and 7), the speaker reasons that this object will be the inferred
480 referent of any semantically plausible utterance, even when the same utterance would point
481 to a different object in the absence of common ground. Taken together, this model provides
482 an explicit and formal description of the integration process, thereby offering an answer to
483 the question of *how* information may be integrated during pragmatic word learning.
484 Predictions generated based on this process accurately captured adults' inferences across a
485 wide range of conditions.

486 The *integration model* also predicted information integration in four-year-olds.
487 However, the model did not successfully describe three-year-olds' inferences; thus, it is
488 possible that they were not able to integrate information sources. But our findings are also
489 consistent with a simpler explanation, namely that the overall weaker responses we observed
490 in the independent measurement experiments (experiments 5 and 6), combined with some
491 noise in responding, led the younger children to appear relatively random in their responses.
492 As a consequence, there was not much variation in three-year-old's responses for the model

493 to explain.

494 The primary source of developmental change in our model is age related changes in the
495 propensity to make the individual inferences. As they get older, children expect speakers to
496 be more informative and to be more likely to follow common ground, but the process by
497 which the two information sources are integrated at any given age is assumed to be the same.
498 Other developmental models are also worth exploring in future work; one possible candidate
499 would be a model in which the integration process itself changes with age.

500 The developmental noise model reported for experiment 7 offers another way to
501 address the question of what changes with development. This model estimates a
502 developmental trajectory for the proportion of responses that are better explained by
503 random guessing than by the model structure. If such a model would find that model fit is
504 comparable for younger and older children but that the noise parameter through which this
505 fit is achieved decreases with age, we might conclude that cognitive abilities that have to do
506 with task demands are the major locus of change rather than abilities that have to do with
507 integrating information. In the developmental noise model in experiment 7, we found that
508 noise decreased with age but, at the same time, that the resulting model fit was substantially
509 worse for younger children. However, rather than a difference in how information is
510 integrated, we think that a lack of variation in children's responses is the reason for this poor
511 model fit. The strongest evidence for developmental changes in integration would come in a
512 case where younger children showed evidence of above/below-chance judgment in the
513 combined task that was distinct from that predicted by the two above/below-chance
514 component tasks. Such a comparison would require more precision (either via more trials or
515 more participants) than our current experiment affords, however.

516 Studying how multiple types of pragmatic cues are balanced contributes to a more
517 comprehensive understanding of word learning. In the current study, participants inferred
518 the referent by integrating non-linguistic cues (speakers pointing to a table) with

519 assumptions about speaker informativeness and common ground information, going beyond
520 previous experimental work in measuring how these information sources were combined. The
521 real learning environment is far richer than what we captured in our experimental design,
522 however. For example, in addition to multiple layers of social information, children can rely
523 on semantic and syntactic features of the utterances as cues to meaning (E. V. Clark, 1973;
524 Gleitman, 1990). Across development, children learn to recruit these different sources of
525 information and integrate them. RSA models allow for the inclusion of semantic information
526 as part of the utterance (Bergen et al., 2016) and it will be a fruitful avenue for future
527 research to model the integration of linguistic and pragmatic information across development.
528 To conclude, our work here shows how computational models of language comprehension can
529 be used as powerful tools to explicate and test hypotheses about information integration
530 across development.

References

- 531
- 532 Akhtar, N., Carpenter, M., & Tomasello, M. (1996). The role of discourse novelty in early
533 word learning. *Child Development*, *67*(2), 635–645.
- 534 Barner, D., Brooks, N., & Bale, A. (2011). Accessing the unsaid: The role of scalar
535 alternatives in children’s pragmatic inference. *Cognition*, *118*(1), 84–93.
- 536 Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models
537 using lme4. *Journal of Statistical Software*, *67*(1), 1–48. doi:10.18637/jss.v067.i01
- 538 Behne, T., Carpenter, M., & Tomasello, M. (2005). One-year-olds comprehend the
539 communicative intentions behind gestures in a hiding game. *Developmental Science*,
540 *8*(6), 492–499.
- 541 Bergen, L., Levy, R., & Goodman, N. (2016). Pragmatic reasoning through semantic
542 inference. *Semantics and Pragmatics*, *9*.
- 543 Bohn, M., & Frank, M. C. (2019). The pervasive role of pragmatics in early language.
544 *Annual Review of Developmental Psychology*, *1*(1), 223–249.
- 545 Bohn, M., & Koymen, B. (2018). Common ground and development. *Child Development*
546 *Perspectives*, *12*(2), 104–108.
- 547 Bohn, M., Zimmermann, L., Call, J., & Tomasello, M. (2018). The social-cognitive basis of
548 infants’ reference to absent entities. *Cognition*, *177*, 41–48.
- 549 Braginsky, M., Tessler, M. H., & Hawkins, R. (2019). *Rwebppl: R interface to webppl*.
550 Retrieved from <https://github.com/mhtess/rwebppl>
- 551 Clark, E. V. (1973). What’s in a word? On the child’s acquisition of semantics in his first
552 language. In T. Moore (Ed.), *Cognitive development and acquisition of language* (pp.

- 553 65–110). New York: Academic Press.
- 554 Clark, E. V. (2009). *First language acquisition*. Cambridge: Cambridge University Press.
- 555 Clark, E. V. (2015). Common ground. In B. MacWhinney & W. O’Grady (Eds.), *The*
556 *handbook of language emergence* (Vol. 87, pp. 328–353). John Wiley & Sons.
- 557 Clark, H. H. (1996). *Using language*. Cambridge: Cambridge University Press.
- 558 Cohn-Gordon, R., Goodman, N., & Potts, C. (2018). Pragmatically informative image
559 captioning with character-level inference. *arXiv Preprint arXiv:1804.05417*.
- 560 Diesendruck, G., Markson, L., Akhtar, N., & Reudor, A. (2004). Two-year-olds’ sensitivity
561 to speakers’ intent: An alternative account of samuelson and smith. *Developmental*
562 *Science*, 7(1), 33–41.
- 563 Ernst, M. O., & Banks, M. S. (2002). Humans integrate visual and haptic information in a
564 statistically optimal fashion. *Nature*, 415(6870), 429.
- 565 Fazly, A., Alishahi, A., & Stevenson, S. (2010). A probabilistic computational model of
566 cross-situational word learning. *Cognitive Science*, 34(6), 1017–1063.
- 567 Frank, M. C., & Goodman, N. D. (2012). Predicting pragmatic reasoning in language games.
568 *Science*, 336(6084), 998–998.
- 569 Frank, M. C., & Goodman, N. D. (2014). Inferring word meanings by assuming that
570 speakers are informative. *Cognitive Psychology*, 75, 80–96.
- 571 Frank, M. C., Goodman, N. D., & Tenenbaum, J. B. (2009). Using speakers’ referential
572 intentions to model early cross-situational word learning. *Psychological Science*,
573 20(5), 578–585.
- 574 Frank, M. C., Sugarman, E., Horowitz, A. C., Lewis, M. L., & Yurovsky, D. (2016). Using

- 575 tablets to collect data from young children. *Journal of Cognition and Development*,
576 *17*(1), 1–17.
- 577 Gleitman, L. (1990). The structural sources of verb meanings. *Language Acquisition*, *1*(1),
578 3–55.
- 579 Goodman, N. D., & Frank, M. C. (2016). Pragmatic language interpretation as probabilistic
580 inference. *Trends in Cognitive Sciences*, *20*(11), 818–829.
- 581 Goodman, N. D., & Stuhlmüller, A. (2014). The design and implementation of probabilistic
582 programming languages. <http://dippl.org>.
- 583 Grice, H. P. (1991). *Studies in the way of words*. Cambridge, MA: Harvard University Press.
- 584 Horowitz, A. C., Schneider, R. M., & Frank, M. C. (2018). The trouble with quantifiers:
585 Exploring children’s deficits in scalar implicature. *Child Development*, *89*(6),
586 e572–e593.
- 587 Levinson, S. C. (2000). *Presumptive meanings: The theory of generalized conversational*
588 *implicature*. Cambridge, MA: MIT press.
- 589 Monroe, W., Hawkins, R. X., Goodman, N. D., & Potts, C. (2017). Colors in context: A
590 pragmatic neural model for grounded language understanding. *Transactions of the*
591 *Association for Computational Linguistics*, *5*, 325–338.
- 592 Noveck, I. A. (2001). When children are more logical than adults: Experimental
593 investigations of scalar implicature. *Cognition*, *78*(2), 165–188.
- 594 O’Neill, D. K., & Topolovec, J. C. (2001). Two-year-old children’s sensitivity to the
595 referential (in) efficacy of their own pointing gestures. *Journal of Child Language*,

- 596 28(1), 1–28.
- 597 R Core Team. (2018). *R: A language and environment for statistical computing*. Vienna,
598 Austria: R Foundation for Statistical Computing.
- 599 Saylor, M. M., Ganea, P. A., & Vázquez, M. D. (2011). What’s mine is mine:
600 Twelve-month-olds use possessive pronouns to identify referents. *Developmental*
601 *Science*, 14(4), 859–864.
- 602 Saylor, M. M., Sabbagh, M. A., Fortuna, A., & Troseth, G. (2009). Preschoolers use
603 speakers’ preferences to learn words. *Cognitive Development*, 24(2), 125–132.
- 604 Skordos, D., & Papafragou, A. (2016). Children’s derivation of scalar implicatures:
605 Alternatives and relevance. *Cognition*, 153, 6–18.
- 606 Sperber, D., & Wilson, D. (2001). *Relevance: Communication and cognition* (2nd ed.).
607 Cambridge, MA: Blackwell Publishers.
- 608 Stiller, A. J., Goodman, N. D., & Frank, M. C. (2015). Ad-hoc implicature in preschool
609 children. *Language Learning and Development*, 11(2), 176–190.
- 610 Sullivan, J., Boucher, J., Kiefer, R. J., Williams, K., & Barner, D. (2019). Discourse
611 coherence as a cue to reference in word learning: Evidence for discourse
612 bootstrapping. *Cognitive Science*, 43(1), e12702.
- 613 Tanenhaus, M. K., Spivey-Knowlton, M. J., Eberhard, K. M., & Sedivy, J. C. (1995).
614 Integration of visual and linguistic information in spoken language comprehension.
615 *Science*, 268(5217), 1632–1634.
- 616 Tomasello, M. (2008). *Origins of human communication*. Cambridge, MA: MIT press.
- 617 Vouloumanos, A., Onishi, K. H., & Pogue, A. (2012). Twelve-month-old infants recognize

618 that speech can communicate unobservable intentions. *Proceedings of the National*
619 *Academy of Sciences*, 109(32), 12933–12937.

620 Wang, S., Liang, P., & Manning, C. D. (2016). Learning language games through interaction.
621 In *54th annual meeting of the association for computational linguistics, acl 2016* (pp.
622 2368–2378). Association for Computational Linguistics (ACL).

623 Xu, F., & Tenenbaum, J. B. (2007). Word learning as bayesian inference. *Psychological*
624 *Review*, 114(2), 245.

625 Yoon, E. J., & Frank, M. C. (2019). The role of salience in young children’s processing of ad
626 hoc implicatures. *Journal of Experimental Child Psychology*, 186, 99–116.

Declarations of interest

627

628 None.

628

Author Contributions

629

630 M. Bohn and M.C. Frank conceptualized the study, M. Merrick collected the data, M.
631 Bohn and M.H. Tessler analyzed the data, M. Bohn, M. H. Tessler and M.C. Frank wrote
632 the manuscript, all authors approved the final version of the manuscript.

Acknowledgments

633

634 We thank Jacqueline Quirke and Sabina Zacco for help with the data collection and
635 Bria Long and Gregor Kachel for comments on an earlier version of the paper.

Funding

636

637 M. Bohn received funding from the European Union's Horizon 2020 research and
638 innovation programme under the Marie Skłodowska-Curie grant agreement no. 749229. M.
639 C. Frank was supported by a Jacobs Foundation Advanced Research Fellowship and the
640 Zhou Fund for Language and Cognition.