¹ How young children integrate information sources to infer the meaning of words

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Abstract

Before formal education begins, children typically acquire a vocabulary of thousands of words. This learning process requires the use of many different information sources in their social environment, including the context in which they hear words used and their current state of knowledge. How is this information integrated? We specify a developmental model according to which children consider information sources in an age-specific way and integrate them via Bayesian inference. This model accurately predicted 2-to-5 year-old children's word learning across a range of experimental conditions. Model comparison suggests that the central locus of development is an increased sensitivity to individual information sources, rather than changes in integration ability. This work presents a quantitative developmental theory of information integration during language learning, and illustrates how formal models can be used to make a quantitative test of the predictive and explanatory power of competing theories.

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

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Human communicative abilities are unrivaled in the animal kingdom[1–3]. Language – in whatever modality – is the medium that allows humans to collaborate and coordinate in species-unique ways, making it the bedrock of human culture and society.[4] Thus, to absorb the culture around them and become functioning members of society, children need to learn language.[5] A central problem in language learning is referent identification: To acquire the conventional symbolic relation between a word and an object, a child must determine the intended referent of the word. However, there is no unique cue to reference that can be used across all situations.[6] Instead, referents can only be identified inferentially by reasoning about the speaker's intentions.[7–10] That is, the child has to infer what the speaker is communicating about based on information sources in the utterance's social context.

From early in development, children use several different mechanisms to harness social-contextual information sources.[7,9,11] Children expect speakers to use novel words for unknown objects,[12–15] to talk about objects that are relevant,[16,17] new in context,[18,19] or related to the ongoing conversation.[20–22] These different mechanisms, however, have been mainly described and theorized about in isolation. The picture of the learning process that emerges is that of a "bag of tricks": mechanisms that operate (and develop) independently from one another.[11] As such, this view of the learning process does not address the complexity of natural social interaction during which many sources of information are present.[6,23] How do children arbitrate between these sources in order to accurately infer a speaker's intention?

When information integration is studied directly, the focus is mostly on how children interpret an ambiguous referring expression in light of social-contextual information.[24–31] In one classic study,[32] children faced a 2 x 2 display with a ball, a pen and two glasses in it. The speaker, sitting on the opposite side of the display, saw only three of the four compartments: the ball, the pen, and one of the glasses. When the speaker asked for "the

49 glass", children had to integrate the semantics of the utterance with the speaker's

50 perspective to correctly infer which of the glasses the speaker was referring to. This study

51 advanced our understanding by documenting that preschoolers use both information

52 sources, a finding confirmed by a variety of other work.[25,28,30] Yet these studies do not

53 specify – or test – the process by which children integrate different information sources.

54 When interpreting their findings, work in this tradition refers to social-pragmatic theories

55 of language use and learning,[9,10,33–35] all of which assume that information is integrated as

56 part of a social inference process, but none of which clearly defines the process. As a

57 consequence, we have no explicit and quantitative theory of how different information

58 sources (and word learning mechanisms) are integrated.

59 We present a theory of this integration process. Following social-pragmatic theories of

60 language learning,[9,10] our theory is based on the following premises: information sources

61 serve different functional roles but are combined as part of an integrated social inference

62 process.[33–36] Children use all available information to make inferences about the intentions

63 behind a speaker's utterance, which then leads them to correctly identify referents in the

64 world and learn conventional word–object mappings. We formalize the computational steps

65 that underlie this inference process in a cognitive model.[37–39] In the remainder of this

66 paper, we rigorously test this theory by asking how well it serves the two purposes of any

67 psychological theory: prediction and explanation.[40,41] First, we use the model to make

68 quantitative predictions about children's behavior in new situations – predictions we test

69 against new data. This form of model testing has been successfully used with adults[37,42]

70 and here we extend it to children. Next, we quantify how well the model explains the

71 integration process by comparing it to alternative models that make different assumptions

72 about *whether* information is integrated, *how* it is integrated, and how the integration

73 process *develops.*

74 We focus on three information sources that play a central part in theorizing about

75 language use and learning: (1) expectations that speakers communicate in a cooperative

76   and informative manner,[12,16,34] (2) shared common ground about what is being talked

77   about in conversation,[35,43,44] and (3) semantic knowledge about previously learned

78   word–object mappings.[11,45]

79   Our *rational integration model* arbitrates between information sources via Bayesian

80   inference (see Fig. 1f for model formulae). A listener (L_1) reasons about the referent of a

81   speaker's (S_1) utterance. This reasoning is contextualized by the prior probability of each

82   referent ρ – which we take to be a function of the common ground shared between the

83   listener and the speaker. To decide between referents, the listener (L_1) reasons about what

84   a rational speaker (S_1) with informativeness α would say given an intended referent. This

85   speaker is assumed to compute the informativity for each available utterance and then

86   choose the most informative one. The informativity of each utterance is given by imagining

87   which referent a listener, who interprets words according to their literal semantics (what we

88   call a literal listener, L_0), would infer upon hearing the utterance. Naturally, this reasoning

89   depends on what kind of semantic knowledge (for object j) θ_j the speaker ascribes to the

90   (literal) listener.

91   Taken together, this model provides a quantitative theory of information integration

92   during language learning. The three information sources operate on different timescales:

93   speaker informativeness is a momentary expectation about a particular utterance, common

94   ground grows over the course of a conversation, and semantic knowledge is learned across

95   development. This interplay of timescales has been hypothesized to be an important

96   component of word meaning inference,[46,47] and we link these different time-dependent

97   processes together via their hypothesized impact on model components. Furthermore, the

98   model presents an explicit and substantive theory of development. It assumes that, while

99   children's sensitivity to the individual information sources increases with age, the way

100 integration proceeds remains constant.[7,48] In the model, this is accomplished by creating

101 age-dependent parameters capturing developmental changes in sensitivity to speaker

102 informativeness (α_i, Fig. 1d), the common ground (ρ_i, Fig. 1c), and object specific

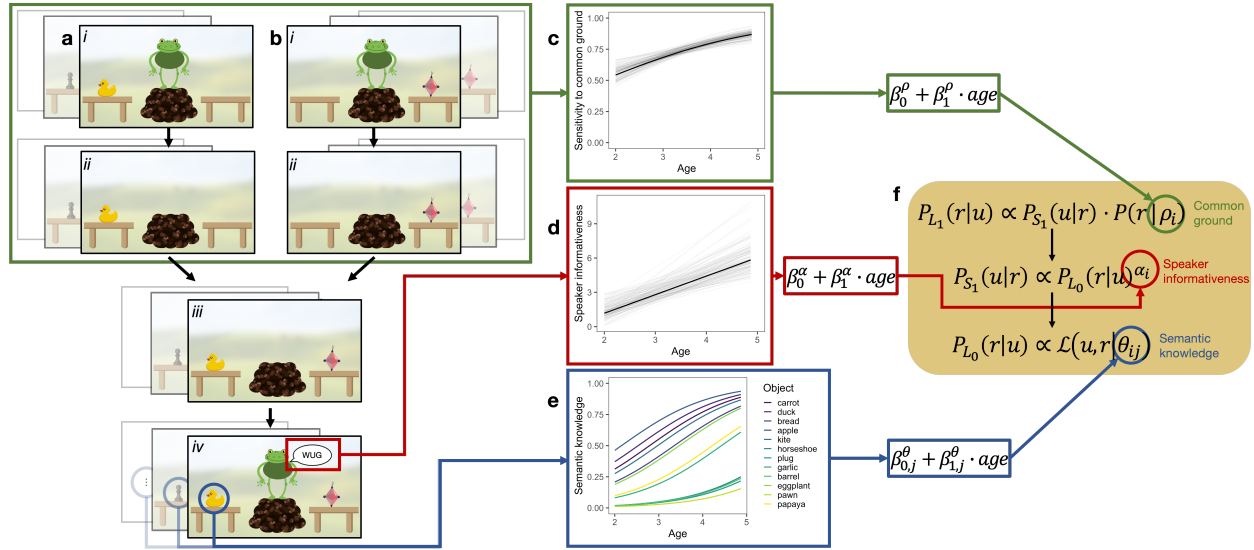103 semantic knowledge ($\theta_{i,j}$, Fig. 1e).

Figure 1. Experimental task and model. (a and b) Screenshots from the experimental task. (i) The speaker encounters one object and then leaves the scene (ii). While the speaker is away, a second object appears (iii), when returning, the speaker uses a novel word to request an object (iv). Sections (i) to (iii) establish common ground between the speaker and the listener, in that one object is new in context (green). The request in (iv) licenses an inference based on expectations about how informative speakers are (red). Listeners' semantic knowledge enters the task because the identity of the known object on one of the tables is varied from well-known objects like a duck to relatively unfamiliar objects like a chess pawn (total of 12 objects – blue). (a) shows the version of the experiment in which common ground information is congruent (i.e., point to the same object) with speaker informativeness and (b) shows the incongruent condition. The congruent and incongruent conditions are each paired with the 12 known objects, resulting in 24 unique conditions. (c to e) show developmental trajectories for each information source, estimated from separate experiments (see supplement). (f) gives the model equation for the rational integration model and links information sources to model parameters.

104 To test the predictive and explanatory power of our model we designed a

105 world-learning experiment in which we jointly manipulated the three information sources

106 (Fig. 1). Children interacted on a tablet computer with a series of storybook speakers.[49]

107 This situation is depicted in Fig. 1a iv, in which a speaker (here, a frog) appears with a

108 known object (a duck, left) and an unfamiliar object (the diamond-shaped object, right).

109 The speakers used a novel word (e.g., "wug") in the context of two potential referents, and

110 then the child was asked to identify a new instance of the novel word, testing their

inference about the speaker's intended referent. To vary the strength of the child's inference, we systematically manipulated the familiarity of the known object (from e.g., the highly familiar "duck" to the relatively unfamiliar "pawn") and whether the familiar or novel object was new to the speaker (meaning that it was not part of common ground).

This paradigm allows us to examine the integration of the three information sources described above. First, the child may infer that a cooperative and informative speaker[12,16] would have used the word "duck" to refer to the known object (the duck); the fact that the speaker did not say "duck" then suggests that the speaker is most likely referring to a different object (the unfamiliar object). This basic inference is oftentimes referred to as a mutual exclusivity inference.[13,15] Second, the child may draw upon what has already been established in the common ground with the speaker. Listeners expect speakers to communicate about things that are new to the common ground.[18,19] Thus, the inference about the novel word referring to the unfamiliar object also depends on which object is new in context (Fig. 1a and b i-iii). Finally, the child may use their previously acquired semantic knowledge, that is, how sure they are that the known object is called "duck". If the known object is something less familiar, such as a chess piece (e.g., a pawn), a 3-year-old child may draw a weaker inference, if they draw any inference at all.[50–52] Taken together, the child has the opportunity to integrate their assumptions about (1) cooperative communication, (2) their understanding of the common ground, and (3) their existing semantic knowledge. In one condition of the experiment, information sources were aligned (Fig. 1a) while in the other they were in conflict (Fig. 1b).

Results

Predicting information integration across development

We tested the model in its ability to predict 2 - 5 year-old children's judgments about word meaning. We estimated children's (N=148) developing sensitivity to individual

information sources in two separate experiments (Experiments 1 and 2; see Fig. 1c-e). We

then generated parameter-free *a priori* model predictions (developmental trajectories)

representing the model's expectations about how children should behave in a new situation

in which all three information sources had to be integrated. We generated predictions for

24 experimental conditions: 12 objects of different familiarities (requiring different levels of

semantic knowledge), with novelty either conflicting or coinciding; Fig. 1. We compared

these predictions to newly collected data from N = 220 children from the same age range

(Experiment 3). All procedures, sample sizes and analysis were pre-registered (see

methods).

The results showed a very close alignment between model predictions and the data

across the entire age range. That is, the average developmental trajectories predicted by

the model resembled the trajectories found in the data (Fig. S6). For a more quantitative

analysis, we binned predictions and data by child age (in years) and correlated the two. We

found a high correlation, with the model explaining 79% of the variance in the data (Fig.

2a). These results support the assumption of the model that children integrate three all

available information sources. However, it is still possible that simpler models might make

equally good – or even better – predictions.

Thus, we formalized the alternative view that children selectively ignore information

sources in the form of three lesioned models (Fig. 2b). These models assume that children

follow the heuristic "ignore x" (with x being one of the information sources) when multiple

information sources are presented together.

The no *word knowledge model* uses the same model architecture as the rational

integration model. It uses expectations about speaker informativeness and common ground

but omits semantic knowledge that is specific to the familiar objects (i.e., uses only general

semantic knowledge). That is, the model assumes a listener whose inference does not vary

depending on the particular familiar object but only depends on the age-specific average

semantic knowledge. The *no common ground model* takes in object-specific semantic

knowledge and speaker informativeness but ignores common ground information. Instead

of assuming that one object has a higher prior probability to be the referent because it is

new in context, the speaker thinks that both objects are equally likely to be the referent.

As a consequence, the listener does not differentiate between situations in which common

ground is aligned or in conflict with the other information sources. Finally, according to

the *no speaker informativeness model*, the listener does not assume that the speaker is

communicating in an informative way and hence ignores the utterance. As a consequence,

the inference is solely based on common ground expectations.

We found little support for these heuristic models (Fig. 2b). When using Bayesian

model comparison via marginal likelihood of the data,[53] we find that the data was several

orders of magnitude more likely under the rational integration model compared to any of

the lesioned models (Fig. 2). Figure 2c exemplifies the differences between the models: all

heuristic models systematically underestimate children's performance in the congruent

condition. Thus, even when the information sources are redundant (i.e. they all point to

the same referent), children's inferences are notably strengthened by each of them. In the

incongruent condition, the no word knowledge model underestimates performance, because

it does not differentiate between the different familiar objects, and in the case of a highly

familiar word such as duck, underestimates the strength of the mutual exclusivity inference

and its compensatory effect. The no speaker informativeness completely ignores this

inferences, which leads to even worse predictions. On the contrary, the no common ground

model overestimates performance because it ignores the dampening effect of common

ground pointing to a different referent. Taken together, we conclude that children

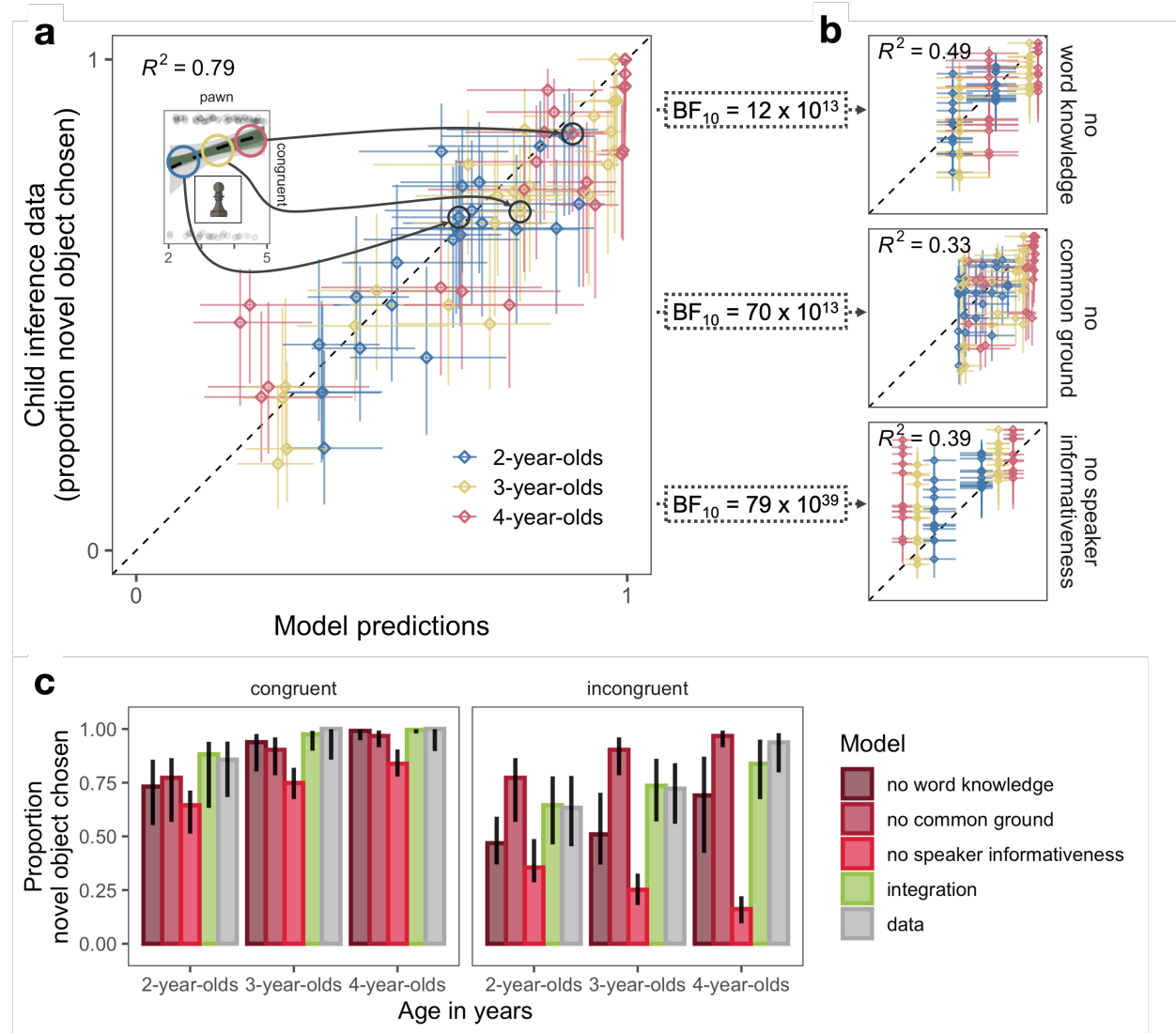considered all available information sources.

Figure 2. **Predicting information integration**. Correlation between model predictions and child inference data for all 24 conditions and for each age group (binned by year) for the rational integration model (a) and the three lesioned models (b). Horizontal and vertical error bars show 95% HDI. Inset shows an example of model predictions as developmental trajectories (see Fig. 3). BF_{10} gives the Bayes Factor in favor of the integration model based on the marginal likelihood of the data under each model. (c) Predictions from all models considered alongside the data (with 95% HDI) for two experimental conditions (familiar word: *duck*).

Explaining the process of information integration

In the previous section, we established that children integrated all available information sources. This result, however, does not speak to the process by which information is assumed to be integrated. Thus, in this section, we ask which integration process best explains children's behavior.

The rational integration model assumes that all information sources enter into a joint inference process, but alternative integration processes are conceivable and might be consistent with the data. For example, the "bag of tricks"[11] hypothesis mentioned in the introduction could be re-phrased as a modular integration process: children might compute independent inferences based on subsets of the available information and then integrate them in a post-hoc manner by weighting them according to some parameter. This view would allow for the possibility that some information sources are considered to be more important than others. In other words, children might be biased towards some information sources. We formalized this alternative view as a *biased integration model.* This model assumes that semantic knowledge and expectations about speaker informativeness enter into one inference (mutual exclusivity inference[12,13,50]) while common ground information enters into a second one. The outcomes of both processes are then weighted according to the parameter ϕ. Like the rational integration model, this model takes in all available information sources in an age-sensitive way and assumes that they are integrated. The only difference lies in the nature of the integration process: the biased integration model privileges some information sources of others in an ad-hoc manner.

The parameter ϕ in the biased integration model is unknown ahead of time and has to be estimated based on the experimental data. That is, in contrast to the rational integration model, the biased integration model has an additional degree of freedom which does not allow us to make *a priori* predictions about new data in the way we describe above. For a fair comparison, we therefore constrained the parameters in the rational

integration model by the data from Experiment 3 as well. As a consequence, both models use all the data available to constrain their parameters (see Fig. S4).

The biased integration model makes reasonable predictions and explains 78% of the variance in the data (Fig. 3b). The parameter ϕ – indicating the bias to one of the inferences – was estimated to favor the mutual exclusivity inference (Maximum A-Posteriori estimate = 0.65; 95% highest density interval (HDI): 0.60 - 0.71, see Fig. 3d). However, the rational integration model presented a much better fit to the data, both in terms of correlation and the marginal likelihood of the data (Fig. 3). Figure 3e exemplifies the difference between the models: the biased integration model puts extra weight on the mutual exclusivity inference and thus fails to capture performance when this inference is weak compared to the common ground inference – such as in the congruent condition for younger children. Thus, a fully integrated – as opposed to a modular and biased – integration process explained the data better.

The rational integration model assumes that the integration process itself does not change with age.[7] That is, while children's sensitivity to each information source develops, the way they relate to one another remains the same. The biased integration model provides an alternative proposal about developmental change, one in which the integration process itself changes with age. That is, children may be biased towards some information sources, and that bias itself may change with age. We formalize such an alternative view as a *developmental bias model* which is structurally identical to the biased integration model but in which the parameter ϕ changes with age. The model assumes that the importance of the different information sources changes with age.

The developmental bias model also explains a substantial portion of the variance in the data: 78% (Fig. 3c). The estimated developmental trajectory for the bias parameter ϕ suggests that younger children put a stronger emphasis on common ground information, while older children rely more on the mutual exclusivity inference (Fig. 3d). The relative

238 importance of the two inferences seems to switch at around age 3. Yet again, when we

239 directly compare the competitor models, we find that the data is several orders of

240 magnitude more likely under the rational integration model (Fig. 3). Looking at Figure 3e,

241 we can see that the developmental bias model tends to underestimate children's

242 performance because the supportive interplay between the different inferences is

243 constrained.

244   Finally, when we compared the rational integration model with its parameters not

245 constrained by the experimental data (i.e. the "pure" prediction model described above), it

246 also outperformed both bias models (see Fig. S10 and Tab. S6). Taken together, these

247 results show that the integration process is best described as fully integrated and stable

248 over time.

Discussion

250   The environment in which children learn language is complex. Children have to

251 integrate different information sources, some of which relate to expectations in the moment,

252 others to the dynamics of the unfolding interactions, and yet others to their previously

253 acquired knowledge. Our findings show that young children can integrate multiple

254 information sources during language learning – even from relatively early in development.

255 To answer the question of how they do so, we presented a formal cognitive model that

256 assumes that information sources are rationally integrated via Bayesian inference.

257   Our work extends the study of information integration during language

258 comprehension[54–58] to pragmatics. Our model is based on classic social-pragmatic theories

259 on language use and comprehension.[10,33–35] As a consequence, instead of assuming that

260 different information sources feed into separate word-learning mechanisms, we assume that

261 all of these information sources play a functional role in an integrated social inference

262 process. Our model goes beyond previous theoretical and empirical work by specifying the
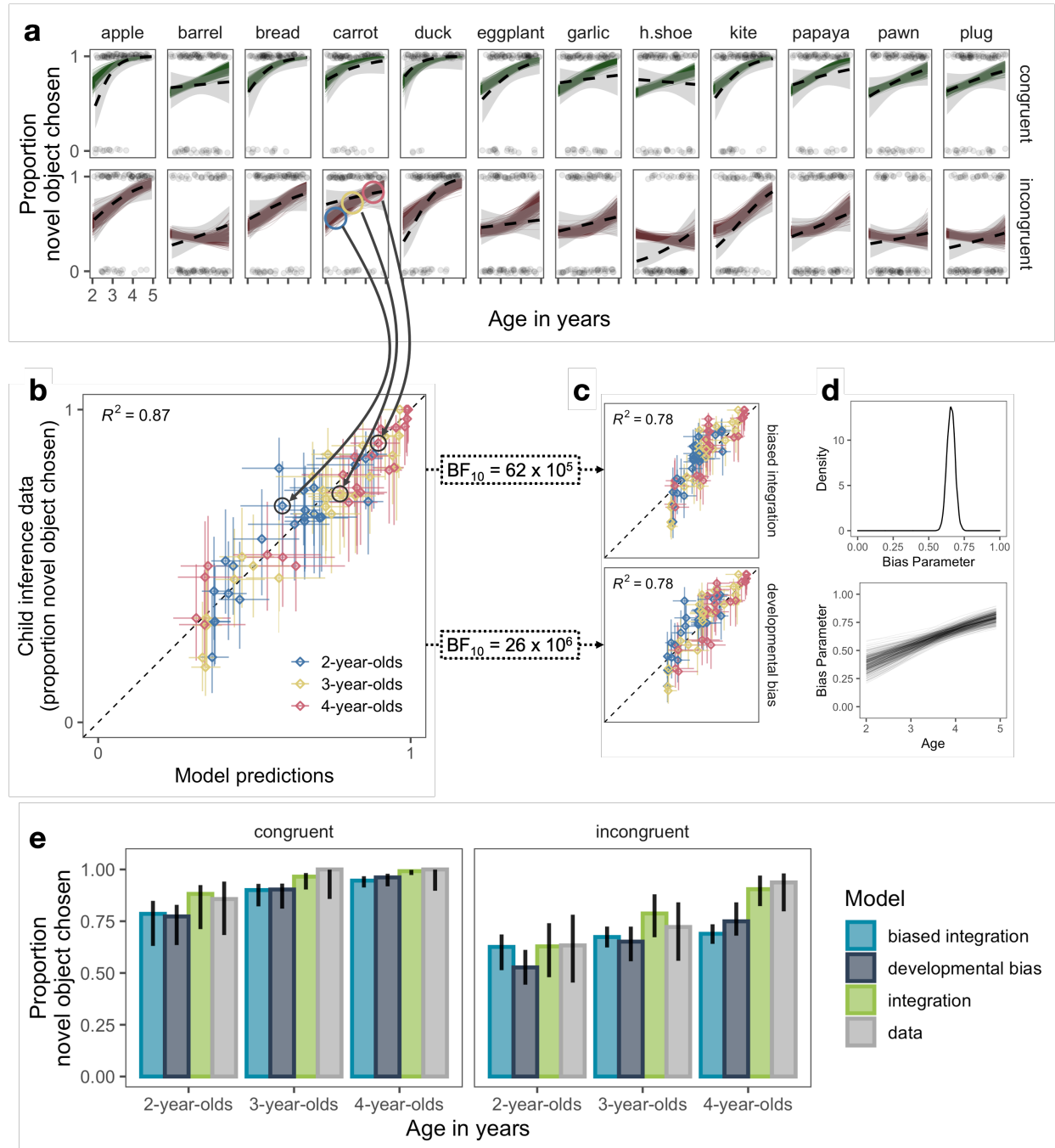
Figure 3. **Explaining information integration across development**. (a) Model predictions from the rational integration model (colored lines) next to the behavioral data (dotted black lines with 95% CI in gray) for all 24 experimental conditions. Top row (blue) shows congruent conditions, bottom row (red) shows incongruent conditions. Familiar objects are ordered based on their rated age of acquisition (left to right). Light dots represent individual data points. (b) Correlations between model predictions binned by age and condition for the integration model and (c) the two biased models. Vertical and horizontal error bars show 95% HDIs. BF_{10} gives the Bayes Factor in favor of the rational integration model based on the marginal likelihood of the data under each model. (d) Posterior distribution of the bias parameter in the biased integration model and developmental trajectories for the bias parameter in the developmental bias model (e) Predictions from all models considered alongside the data (with 95% HDI) for two experimental conditions (familiar word: duck).

computations that underlie this inference process. Furthermore, we present a substantive theory about how this integration process develops: We assume that children become increasingly sensitive to different information sources, but that the way these information sources are integrated remains the same. We used this model to predict and explain children's information integration in a new word learning paradigm in which they had to integrate (1) their assumptions about informative communication, (2) their understanding of the common ground, and (3) their existing semantic knowledge.

We found that this rational integration model made accurate quantitative predictions across a range of experimental conditions both when information sources were aligned and were in conflict. Predictions from the model better explained the data compared to lesioned models which assumed that children ignore one of the information sources, suggesting that children used all available information. To test the explanatory power of the model – how well it explains the process by which information is integrated – we formalized an alternative, modular, view. According to the biased integration model, children use all available information sources but compute separate inferences based on a subset of them. Integration happens by weighing the outcomes of these separate inferences by some parameter. Finally, we tested an alternative view on the development of the integration process. According to the developmental bias model, the importance of the different information sources changed with age. In both cases, the rational integration model provided a much better fit to the data, suggesting that the integration process remains stable over time.

The rational integration model is derived from a more general framework for pragmatic inference, which has been used to explain a wide variety of phenomena in adults' language use and comprehension.[37,38,59–62] Thus, it can be generalized in a natural way to capture word learning in contexts that offer more, fewer, or different types of information. For example, in a recent study with adults and children, we manipulated expectations about informativeness and common ground in a different way. Using a structurally similar

290 model,[48] we also found a close alignment between model predictions and the data. The

291 flexibility of this modeling framework stems from its conceptualization of human

292 communication as a form of rational social action. As such, it connects to computational

293 and empirical work that tries to explain social reasoning by assuming that humans expect

294 each other to behave in a way that maximizes the benefits and minimizes the cost

295 associated with actions.[27,63,64]

296   Our model and empirical paradigm provide a foundation on which to test deeper

297 questions about language development. First, our findings should be replicated in children

298 from different cultural backgrounds, learning different languages.[65] In such studies, we

299 would not expect our results to replicate in a strict sense; that is, we would not expect to

300 see the same developmental trajectories in all cultures and languages. Substantial variation

301 is much more likely. Nevertheless, our model provides a way to think about how to

302 reconcile cross-cultural variation with a shared cognitive architecture: We predict

303 differences in how sensitive children are to the individual information sources at different

304 ages, but similarities in how information is integrated.[7] In computational terms, we assume

305 a universal architecture that specifies the relation between a set of varying parameters. Of

306 course, either confirmation or disconfirmation of this prediction would be informative.

307   Second, it would be useful to flesh out the cognitive processes that underlie reasoning

308 about common ground. In its current form, our model does not specify how the listener

309 arrives at the expectation that some objects are more likely referents because they are new

310 in common ground. We assumed that common ground changes the speaker's expectations

311 about what are likely referents[66] and we measured these expectations to inform the

312 parameter values in our model. But computationally, the model does not differentiate

313 between common ground information and other reasons that might make an object

314 contextually more salient.

315   Finally, our model is a model of referent identification in the moment of the

utterance. At the same time, the constructs made use of by our model are shaped by factors that unfold across multiple time points and contexts: Common ground is built over the course of a conversation, and the lexical knowledge of a child is shaped across a language developmental time-scale. Our model makes use of unidimensional representations of these high-dimensional, structured processes and examines how these representations are integrated. Connecting our model with frameworks that focus on the temporal and cross-situational aspects of word learning would elucidate further these complex, time-dependent processes.[46,47,67]

Taken together, we hope this work advances our understanding of how children navigate the complexity of their learning environment. Methodologically, it illustrates how computational models can be used to test theories; from a theoretical perspective, it adds to broader frameworks that see the onto- and phylogenetic emergence of language as deeply rooted in social cognition.

Methods

A more detailed description of the experiments and the models can be found in the supplementary material. The experimental procedure, sample size, and analysis for each experiment were pre-registered (https://osf.io/7rg9j/registrations). Experimental procedures, model and analysis scripts can be found in an online repository (https://github.com/manuelbohn/spin). Experiments 1 and 2 were designed to estimate children's developing sensitivity to each information source. The results of these experiments determine the parameter values in the model (see Fig. 1 c-f). Experiment 3 was designed to test how children integrate different information sources.

Participants

339   Across the three experiments, a total of 368 children participated. Experiment 1

340 involved 90 children, including 30 2-year-olds (range = 2.03 - 3.00, 15 girls), 30 3-year-olds

341 (range = 3.03 - 3.97, 22 girls) and 30 4-year-olds (range = 4.03 - 4.90, 16 girls). Data from

342 10 additional children were not included because they were either exposed to less than 75%

343 of English at home (5), did not finish at least half of the test trials (2), the technical

344 equipment failed (2) or their parents reported an autism spectrum disorder (1).

345   In Experiment 2, we tested 58 children from the same general population as in

346 Experiment 1, including 18 2-year-olds (range = 2.02 - 2.93, 7 girls), 19 3-year-olds (range

347 = 3.01 - 3.90, 14 girls) and 21 4-year-olds (range = 4.07 - 4.93, 14 girls). Data from 5

348 additional children were not included because they were either exposed to less than 75% of

349 English at home (3) or the technical equipment failed (2).

350   Finally, Experiment 3 involved 220 children, including 76 2-year-olds (range = 2.04 -

351 2.99, 7 girls), 72 3-year-olds (range = 3.00 - 3.98, 14 girls) and 72 4-year-olds (range = 4.00

352 - 4.94, 14 girls). Data from 20 additional children were not included because they were

353 either exposed to less than 75% of English at home (15), did not finish at least half of the

354 test trials (3) or the technical equipment failed (2).

355   All participants were recruited in a children's museum in San José, California, USA.

356 This population is characterized by a diverse ethnic background (predominantly White,

357 Asian, or mixed-ethnicity) and high levels of parental education and socioeconomic status.

358 Parents consented to their children's participation and provided demographic information.

359 All experiments were approved by the Stanford Institutional Review Board (protocol no.

360 19960).

Materials

All experiments were presented as an interactive picture book on a tablet computer. Tablet-based storybooks are commonly used to simulate social interactions in developmental research and interventions.[68] A recent, direct comparison found similar performance with tablet-based and printed storybooks in a word learning paradigm.[49] Furthermore, our results in Experiment 1 and 2 replicate earlier studies on mutual exclusivity and discourse novelty that used live interactions instead of storybooks.[18,19]

Fig. 1a and b show screenshots from the actual experiments. The general setup involved an animal standing on a little hill between two tables. For each animal character, we recorded a set of utterances (one native English speaker per animal) that were used to talk to the child and make requests. Each experiment started with two training trials in which the speaker requested known objects (car and ball).

Procedure

Experiment 1 tested the mutual exclusivity inference.[13,50] On one table, there was a familiar object, on the other table, there was an unfamiliar object (a novel design drawn for the purpose of the study) (Fig. 1a/b iv and Fig. S1a). The speaker requested an object by saying "Oh cool, there is a [non-word] on the table, how neat, can you give me the [non-word]?". Children responded by touching one of the objects. The location of the unfamiliar object (left or right table) and the animal character were counterbalanced. We coded as correct choice if children chose the unfamiliar object as the referent of the novel word. Each child completed 12 trials, each with a different familiar and a different unfamiliar object. We used familiar objects that we expected to vary along the dimension of how likely children were to know the word for it. This set included objects that most 2-year-olds can name (e.g. a duck) as well as objects that only very few 5-year-olds can name (e.g. a pawn [chess piece]). The selection was based on the age of acquisition ratings

386 from Kuperman and colleagues.[69] While these ratings do not capture the absolute age

387 when children acquire these words, they capture the relative order in which words are

388 learned. Fig. S2A in the supplementary material shows the words and objects used in the

389 experiment.

390   Experiment 2 tested children's sensitivity to common ground that is built up over the

391 course of a conversation. In particular, we tested whether children keep track of which

392 object is new to a speaker and which they have encountered previously.[18,19] The general

393 setup was the same as in Experiment 1 (Fig. S1b). The speaker was positioned between

394 the tables. There was an unfamiliar object (drawn for the purpose of the study) on one of

395 the tables while the other table was empty. Next, the speaker turned to one of the tables

396 and either commented on the presence ("Aha, look at that.") or the absence ("Hm, nothing

397 there") of an object. Then the speaker disappeared. While the speaker was away, a second

398 unfamiliar object appeared on the previously empty table. Then the speaker returned and

399 requested an object in the same way as in Experiment 1. The positioning of the unfamiliar

400 object at the beginning of the experiment, the speaker as well as the location the speaker

401 turned to first was counterbalanced. Children completed five trials, each with a different

402 pair of unfamiliar objects. We coded as correct choice if children chose as the referent of

403 the novel word the object that was new to the speaker.

404   Experiment 3 combined the procedures from Experiments 1 and 2. It followed the

405 same procedure as Experiment 2 but involved the same objects as Experiment 1 (Fig. 1

406 i-iv and Fig. S1c). In the beginning, one table was empty while there was an object

407 (unfamiliar or familiar) on the other one. After commenting on the presence or absence of

408 an object on each table, the speaker disappeared and a second object appeared (familiar or

409 unfamiliar). Next, the speaker re-appeared and made the usual request ("Oh cool, there is

410 a [non-word] on the table, how neat, can you give me the [non-word]?"). In the congruent

411 condition, the familiar object was present in the beginning and the unfamiliar object

412 appeared while the speaker was away (Fig. 1a and Fig. S1c – left). In this case, both the

mutual exclusivity and the common ground inference pointed to the novel object as the referent (i.e., it was both novel to the speaker in the context and it was an object that does not have a label in the lexicon). In the incongruent condition, the unfamiliar object was present in the beginning and the familiar object appeared later. In this case, the two inferences pointed to different objects (Fig. 1b and Fig. S1c – right). This resulted in a total of 2 alignments (congruent vs incongruent) x 12 familiar objects = 24 different conditions. Participants received up to 12 test trials, six in each alignment condition, each with a different familiar and unfamiliar object. Familiar objects were the same as in Experiment 1. The positioning of the objects on the tables, the speaker, and the location the speaker first turned to were counterbalanced. Participants could stop the experiment after six trials (three per alignment condition). If a participant stopped after half of the trials, we tested an additional participant to reach the pre-registered number of data points per age group (2-, 3- and 4-year-olds).

Data analysis

To analyze how the manipulations in each experiment affected children's behavior, we used generalized linear mixed models. Since the focus of the paper is on how information sources were integrated, we discuss these models in the supplementary material and focus here on the cognitive models instead. A detailed, mathematical description of the different cognitive models along with details about estimation procedures and priors can be found in the supplementary material. All cognitive models and Bayesian data analytic models were implemented in the probabilistic programming language `WebPPL`.[70] The corresponding model code can be found in the associated online repository. Information about priors for parameter estimation and Markov chain Monte Carlo settings can also be found in the supplementary information and the online repository.

As a first step, we used the data from Experiments 1 and 2 to estimate children's developing sensitivity to each information source. To estimate the parameters for semantic

439 knowledge (θ) and speaker informativeness (α), we adapted the rational integration model

440 to model a situation in which both objects (novel and familiar) have equal prior probability

441 (i.e., no common ground information). We used the data from Experiment 1 to then infer

442 the semantic knowledge and speaker informativeness parameters in an age-sensitive

443 manner. Specifically, we inferred the intercepts and slopes for speaker informativeness via a

444 linear regression submodel and semantic knowledge via a logistic regression submodel, the

445 values of which were then combined in the cognitive model to generate model predictions

446 to predict the responses generated in Experiment 1. To estimate the parameters

447 representing sensitivity to common ground (ρ), we used a simple logistic regression to infer

448 which combination of intercept and slope would generate predictions that corresponded to

449 the average proportion of correct responses measured in Experiment 2. For the

450 "prediction" models, the parameters whose values were inferred by the data from

451 Experiments 1 & 2 were then used to make out-of-sample predictions for Experiment 3.

452 For the "explanation" models, these parameters were additionally constrained by the data

453 from Experiment 3. A more detailed description of how these parameters were estimated

454 (including a graphical model) can be found in the supplementary material.

455   To generate model predictions, we combined the parameters according to the

456 respective model formula. As mentioned above, common ground information could either

457 be aligned or in conflict with the other information sources. In the congruent condition,

458 the unfamiliar object was also new in context and thus had the prior probability ρ. In the

459 incongruent condition, the novel object was the "old" object and thus had the prior

460 probability of $1 - \rho$.

461   The rational integration model is a mapping from an utterance u to a referent r,

462 defined as $P_{L_1}^{int}(r \mid u; \{\rho_i, \alpha_i \, \theta_{ij}\}) \propto P_{S_1}(u \mid r; \{\alpha_i, \theta_{ij}\}) \cdot P(r \mid \rho_i)$ where i represents the age

463 of the participant and the j the familiar object. The three lesioned models that were used

464 to compare how well the model predicts new data are reduced versions of this model. The

465 no word knowledge model uses the same model architecture:

466 $P_{L_1}^{no\_wk}(r \mid u; \{\rho_i, \alpha_i \, \theta_i\}) \propto P_{S_1}(u \mid r; \{\alpha_i, \theta_i\}) \cdot P(r \mid \rho_i)$ and the only difference lies in the

467 parameter θ, which does not vary as a function of j, the object (i.e., θ in this model is

468 analogous to a measure of gross vocabulary development). The object-specific parameters

469 for semantic knowledge are fitted via a hierarchical regression (mixed effects) model. That

470 is, there is an overall developmental trajectory for semantic knowledge (main effect – θ_i)

471 and then there is object-specific variation around this trajectory (random effects – θ_{ij}).

472 Thus, the no word knowledge model takes in the overall trajectory for semantic knowledge

473 (θ_i) but ignores object-specific variation. The no common ground model ignores common

474 ground information (represented by ρ) and is thus defined as

475 $P_{L_1}^{no\_cg}(r \mid u; \{\alpha_i \, \theta_{ij}\}) \propto P_{S_1}(u \mid r; \{\alpha_i, \theta_{ij}\})$. For the no speaker informativeness model, the

476 parameter $\alpha = 0$. As a consequence, the likelihood term in the model is 1 and the model

477 therefore reduces to $P_{L_1}^{no\_si}(r \mid u; \{\rho_i\}) \propto P(r \mid \rho_i)$.

478   As noted above, the explanation models used parameters that were additionally

479 constrained by the data from Experiment 3, but the way these parameters were combined

480 in the rational integration model was the same as above. The biased integration model is

481 defined as $P_{L_1}^{biased}(r \mid u; \{\phi, \rho_i, \alpha_i, \theta_{ij}\}) = \phi \cdot P_{ME}(r \mid u; \{\alpha_i, \theta_{ij}\}) + (1 - \phi) \cdot P(r \mid \rho_i)$ with

482 P_{ME} representing a mutual exclusivity inference which takes in speaker informativeness

483 and object specific semantic knowledge. This inference is then weighted by the parameter ϕ

484 and added to the respective prior probability, which is weighted by $1 - \phi_i$. Thus, ϕ

485 represents the bias in favor of the mutual exclusivity inference. In the developmental bias

486 model the parameter ϕ is made to change with age (ϕ_i) and the model is thus defined as

487 $P_{L_1}^{dev\_bias}(r \mid u; \{\phi_i, \rho_i, \alpha_i, \theta_{ij}\}) = \phi_i \cdot P_{ME}(r \mid u; \{\alpha_i, \theta_{ij}\}) + (1 - \phi_i)$.

488   We compared models in two ways. First, we used Pearson correlations between model

489 predictions and the data. For this analysis, we binned the model predictions and the data

490 by age in years and by the type of familiar object (see Fig. 2 and 3 as well as S7 and S10).

491 Second, we compared models based on the marginal likelihood of the data under each

492 model – the likelihood of the data averaging over ("marginalizing over") the prior

distribution on parameters; the pairwise ratio of marginal likelihoods for two models is known as the Bayes Factor. It is interpreted as how many times more likely the data is under one model compared to the other. Bayes Factors quantify the quality of predictions of a model, averaging over the possible values of the parameters of the models (weighted by the prior probabilities of those parameter values); by averaging over the prior distribution on parameters, Bayes Factors implicitly take into account model complexity because models with more parameters will tend to have a broader prior distribution over parameters, which in effect, can water down the potential gains in predictive accuracy that a model with more parameters can achieve.[53] For this analysis, we treated age continuously.

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