Mind the Gap: Learning the Surface Forms of Movement

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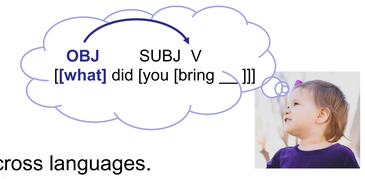
How do Learners Identify Movement Dependencies?

Learners need to identify both **local** and **non-local** syntactic dependencies:

(1) You **brought some toys**.
(2) a. *Wh-question:* **What** did you **bring** __?
b. *Relative clause:* I like **the toys** that you **brought** __.
c. *Passive:* **Those toys** were **brought** __.



► Different types of argument movement take different forms across languages. How do learners identify these forms in their target language?

Empirical Background

Wh-Dependency Development in Infancy

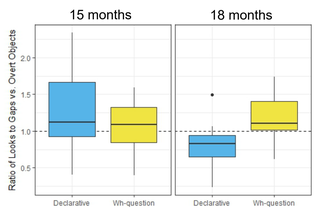
15- to 16-month-olds:
- Recognize local argument relations, sensitive to verb transitivity [1, 2, 3]
- May use verb knowledge to cheat at interpreting *wh*-dependencies [4, 5]

18- to 20-month-olds:
- Know that a moved *wh*-phrase is an argument in a *wh*-question [3]
- Reliably produce and comprehend *wh*-questions [4, 6, 7]

Fig. 1 Listening time preferences for sentences without post-verbal objects

**A dog! The cat should bump.*	*Which dog should the cat bump?*
A dog! The cat should bump him.	**Which dog should the cat bump him?*

Perkins (2019)

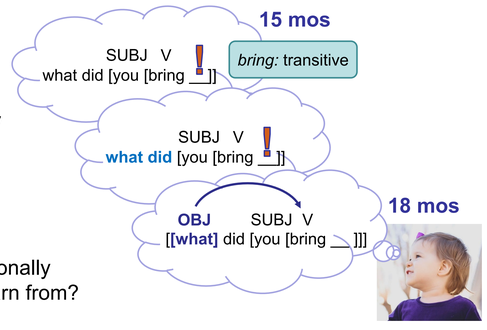


► Infants represent argument movement after learning verb argument structure

Hypothesis: Gap-Driven Learning

Learners may use verb argument structure knowledge to identify different types of movement dependencies [3, 4, 5, 7]:

- Notice when expected argument of a verb is missing in its canonical position (**gap**)
- Identify what **forms** co-occur with unexpectedly missing arguments
- Infer what underlying **dependencies** are responsible for those forms



► **Current question:** Is this hypothesis computationally feasible, given the data that children have to learn from?

Prior Model: Acquiring Argument Structure

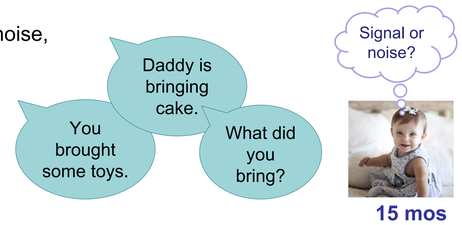
It is computationally possible for learners to identify verb argument structure even before they can recognize moved arguments [8, 9]

- **Input filtering**: assume data has both signal and noise, and learn to filter noise

Fig. 2 Proportions of verbs categorized correctly

Transitive	Intransitive	Alternating	Total
0.67	0.83	0.63	0.66

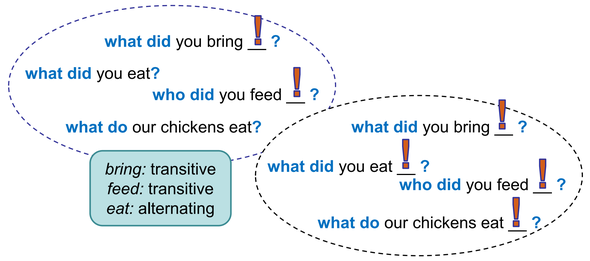
Perkins, Feldman, & Lidz (2017; under revision)



Current Model

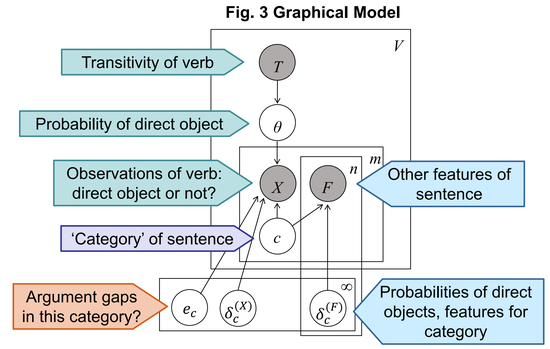
Syntactically-Informed Distributional Analysis

Learners might combine verb argument structure knowledge with distributional learning to identify which forms characterize movement in English



Joint Inference:
- Categorize sentences according to their surface **forms**
- Use verb transitivity knowledge to infer which sentence '**categories**' contain object **gaps**

Fig. 3 Graphical Model



Data

18,503 sentences of child-directed speech from the CHILDES Treebank [10]

- 50 frequent transitive, intransitive, and alternating verbs learned by prior model [8, 9]
- Coded for presence of overt direct object and other morphosyntactic features
- For evaluation, also coded for underlying clause type (basic, *wh*-question, passive, etc.)

Fig. 4 Observed Morphosyntactic Sentence Features (*F*)

Subject	subject is overt; sentence-initial; preceded by an auxiliary; preceded by another noun
Verb	verb is first verb in sentence; followed by a preposition or particle; has *-ed*, *-en*, *-ing*, *-s*, or irregular morphology
Tense, Auxiliaries	verb is preceded by *to*, *be*, *have*, *get*, or *do*
Other	question; unknown function word* in sentence-initial, medial, or final position

*Includes *wh*-words, complementizers, focus particles, quantifiers, conjunctions

Results

Accuracy on Identifying Movement

Model inferred 35 total sentence categories, 15 containing argument gaps

- High overall cluster purity (0.76) compared to actual underlying clause types
- Above-chance accuracy on identifying sentences with movement, higher accuracy on object movement
- Similar accuracy across verb classes

► Joint inference enabled learner to identify movement even for verbs that do not require objects

Fig. 5 Overall Accuracy: All Movement

Measure	Precision	Recall	F1 Score
Our Model	0.51	0.62	0.56
No-Category Baseline	0.25	0.37	0.30
Distributional Baseline	0.15	1.00	0.27
Chance	0.15	0.50	0.25

Fig. 6 Accuracy on Object Movement: % Correctly Identified

Verb Class	Transitive	Intransitive	Alternating	Total
Our Model	0.81	0.93	0.86	0.85
No-Category	0.76	0.36	0.50	0.55

No-Category Baseline:
- Identified object gaps using verb transitivity knowledge, without categorizing sentences by their surface features

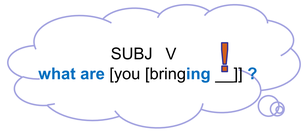
► Helpful to generalize across sentences with similar forms

Distributional Baseline:
- Categorized sentences by their surface features, without using verb transitivity knowledge
- All categories would be identified as having gaps

► Important for verb knowledge to guide distributional learning

Features of Argument-Gap Categories

Distinctive **features** of argument-gap categories included **forms that characterize movement** in English, but also included **irrelevant forms**



► How do learners ignore spurious correlations in their data?

Fig. 7 Features with Significantly Higher Odds Ratios in Two Sample Argument-Gap Categories

Clause Type	Distinctive Features
Wh-question	subject is overt, preceded by an auxiliary; verb is first in sentence, **has *–ing*, preceded by *be***; **sentence-initial function word; question**
Passive	subject is overt, sentence-initial; verb is first in sentence, **has *–en*, preceded by *be*** or ***have***

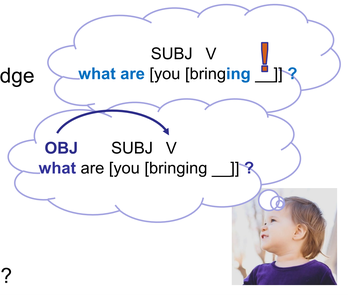
Discussion

It is possible for a learner to perform distributional learning in order to identify forms that characterize movement dependencies in English
- Doing so incrementally requires prior verb argument structure knowledge

► Provides a computational account for the observed developmental trajectory of argument structure and argument movement acquisition

Distributional learning only goes so far: model identified forms that characterize movement, but also irrelevant forms

► How do learners infer the different dependencies that are responsible?



Acknowledgments

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