A rational model of syntactic bootstrapping

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Introduction

How do children learn the meanings of words like verbs, which make reference to abstract relations?

Any observation of the use of such words largely underdetermines their meaning [2].

Syntactic bootstrapping solution: the syntactic frame(s) in which a word appears hint at the word's meaning.

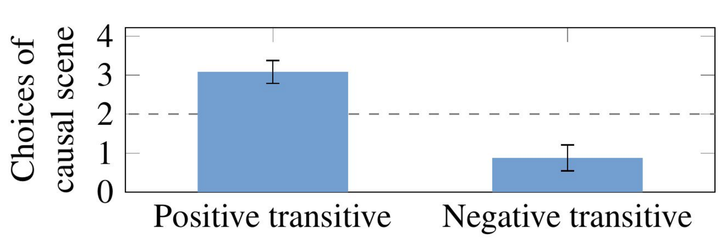
Are existing computational frameworks set up to test this idea?

	Cognitive models (aimed to explain developmental phenomena)	**Complex meanings** (easily scalable to things like verb meanings)
Computational models of word learning [3, 4, 5]	✓	✗
Semantic parsing [6]	✗	✓

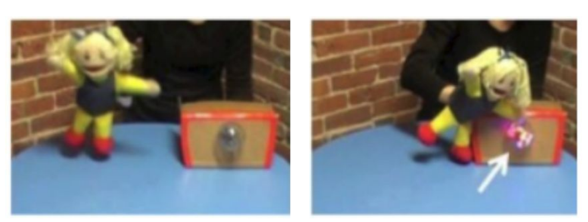
We design a **computational word learning model** which deals in abstract, LoT-like representations. It replicates the phenomenon of syntactic bootstrapping after **unsupervised learning from scratch** on a dataset of utterances paired with their contexts.

Syntactic bootstrapping

Experimental result [1]
Positive transitive query:
"Point where the girl *wugged* the toy."
Negative transitive query:
"Point where the girl *didn't wug* the toy."



"Causal" scene



"Non-causal" scene (gap in time + space)

[1] Melissa Kline et al. (2017). Linking language and events: spatiotemporal cues drive children's expectations about the meanings of novel transitive verbs.
[2] Lila R Gleitman (2005). Hard words.
[3] Stevens et al. (2016). The pursuit of word meanings.
[4] Frank et al. (2009). Using speakers' referential intentions to model early cross-situational word learning.
[5] Yu and Smith (2007). Rapid word learning under uncertainty via cross-situational statistics.
[6] Zettlemoyer & Collins (2006). Online learning of relaxed CCG grammars for parsing to logical form.

Relevant prior art:
Kwiatkowski et al. (2012). A probabilistic model of syntactic and semantic acquisition from child-directed utterances and their meanings.
Abend et al. (2017). Bootstrapping language acquisition.

For technical details, please see our papers:
Gauthier et al. (2018). Word learning and the acquisition of syntactic–semantic overhypotheses.
Gauthier et al. (2019). A rational model of syntactic bootstrapping.

Model

Step 1: commit to *representations* which can (1) distinguish complex meanings and (2) support bootstrapping inferences.

Syntactic types: $\{S, N\}$
Semantic predicates: $\{\textsc{Become}(\cdot,\cdot), \textsc{Cause}(\cdot,\cdot), \textsc{Contact}(\cdot,\cdot), \textsc{Move}(\cdot), \ldots\}$

Lexicon Λ

Form w	Syntax s_w	Meaning m_w
push	$S\backslash N/N$	$\lambda y\, x.\, \textsc{Cause}(x, \textsc{Move}(y))$
activate	$S\backslash N/N$	$\lambda y\, x.\, \textsc{Cause}(x, \textsc{Become}(y, \textsc{Active}))$
touch	$S\backslash N/N$	$\lambda y\, x.\, \textsc{Contact}(x, y)$
go	$S\backslash N$	$\lambda x. \textsc{Move}(x)$
sneeze	$S\backslash N$	$\lambda x. \textsc{Sneeze}(x)$
the	N/N	$\lambda x. \iota(x)$
girl	N	$\lambda x. \textsc{Female}(x)$
toy	N	$\lambda x. \textsc{Toy}(x)$
toy	N	$\lambda x. \textsc{Dog}(x)$

CCG Ruleset R

Forward application: $\dfrac{X/Y : m_1 \quad Y : m_2}{X : m_1(m_2)}>$

Backward application: $\dfrac{Y : m_2 \quad X\backslash Y : m_1}{X : m_1(m_2)}<$

Analysis A

the	girl	pushes	the	toy
$s_w = N/N$	N	$S\backslash N/N$	N/N	N
$: m_w = \iota$	$: \lambda x.\, \textsc{Female}(x)$	$: \lambda y\, x.\, F(x, y)$	$: \iota$	$: \lambda x. \textsc{Toy}(x)$

$N : \iota(\lambda x.\, \textsc{Female}(x))$ (>)

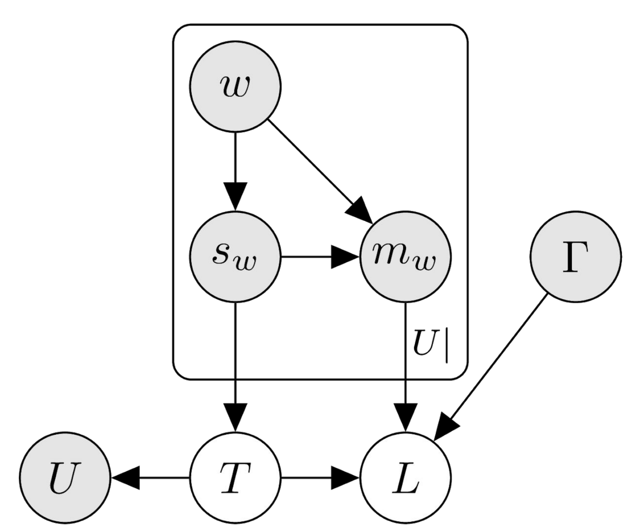
$N : \iota(\lambda x.\, \textsc{Toy}(x))$ (>)

$S\backslash N : \lambda x.\, F(x, \iota(\lambda x.\, \textsc{Toy}(x)))$ (>)

$S : F(\iota(\lambda x.\, \textsc{Female}(x)), \iota(\lambda x.\, \textsc{Toy}(x)))$ (<)

Step 2: design a probabilistic model which can power inference over these representations.

The model incorporates a crucial link between a word's syntactic type s_w and its meaning m_w.



w	Wordform
s_w	Syntactic type of w
m_w	Meaning of w
Γ	Scene/context
U	Utterance (word sequence)
T	Derivation (syntactic analysis)
L	Logical form (semantic analysis)

Bootstrapping simulation

Utterance *u*:
"the girl *gorps* the toy"
Novel word *w*: *gorps*

Scene	Events
Γ_1	$\textsc{Cause}(girl, \textsc{Become}(toy, active))$
	$\textsc{Contact}(girl, toy)$; $\textsc{Move}(girl)$
Γ_2	$\textsc{Become}(toy, active)$;
	$\textsc{Move}(girl)$

The model explains childrens' ability to make zero-shot syntactic bootstrapping inferences.

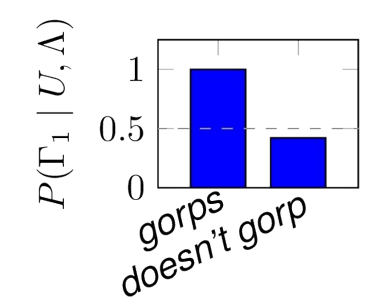
Meaning of *gorps* given transitive syntax: $P(m_w \mid s_w = S\backslash N/N)$

Word meaning m_w	Mass
$\lambda y.\lambda x.\, \textsc{Become}(x, y)$	0.0091
$\lambda y.\lambda x.\, \textsc{Contact}(x, y)$	0.0091
$\lambda y.\lambda x.\, \textsc{Cause}(x, \textsc{Move}(y))$	0.0079
$\ldots$	

Full sentence meanings $P(L \mid m_w)$

Logical form L	Mass
$\textsc{Contact}(girl, toy)$	0.869
$\textsc{Cause}(girl, \textsc{Become}(toy, active))$	0.131

2AFC choice $P(\Gamma \mid L)$



Learning from scratch

We presented a learner with **utterances** in **noisy** contexts:

Entities

Entity	Properties
s	$\textsc{Agent}, \textsc{Female}$
r	$\textsc{Agent}$
t	$\textsc{Toy}$

Events

$\textsc{Move}(r)$
$\textsc{Contact}(s, t)$
$\textsc{Cause}(s, \textsc{Become}(t, \textsc{Active}))$

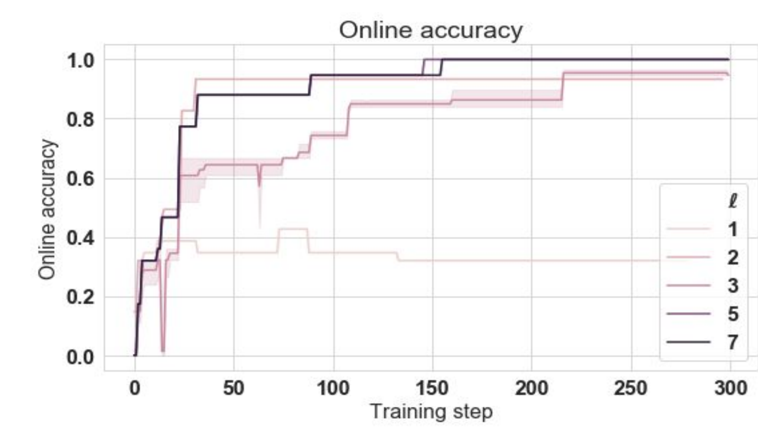
Utterance

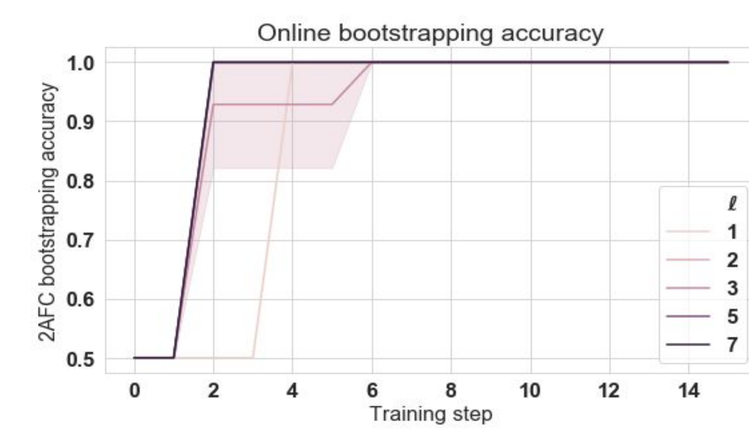
"fa torp pilk fa norp"

Task: acquire a lexicon and accurately predict sentence meanings.

Unsupervised learning: Utterance–meaning / word–meaning relations are *never* directly observed.

Evaluation: (1) held-out parsing test set; (2) syntactic bootstrapping test





The model learns syntax–semantics biases without direct word-level or sentence-level supervision.

Conclusion

We provide a **formal account of syntactic bootstrapping**, capturing qualitative experimental results, and unifying research in computational models of word learning and semantic parsing.

Our framework promises to

1. Scale to naturalistic corpora
2. Make predictions about novel bootstrapping phenomena