

The Computation of Language: Information processing

One way to think about the computation of language is from an information processing standpoint.

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Natural language processing:

How do people and machines extract information about the world from the language data they encounter?



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The Computation of Language: Information processing

One way to think about the computation of language is from an information processing standpoint.

matter are different between authors vs. between characters by the same author.

Natural language processing:



Another finding: We can use linguistically-sophisticated writeprints to identify who wrote a particular document (Pearl & Steyvers 2012), and even which character written by the same author is currently being voiced in the text (Pearl, Lu, & Haghighi in press) — though the writeprint features that



The Computation of Language: Information processing

One way to think about the computation of language is from an information processing standpoint.

Language acquisition:

How do children extract information about language from the language data they encounter?



Sophisticated framework that makes explicit the different components of the acquisition process.









Language acquisition: Methods of investigation

Computational methods: Strategies for how children acquire knowledge, sophisticated quantitative analysis of children's input & output



Language acquisition: Representation & Development

Language acquisition involves complex knowledge that builds on itself over the course of linguistic development, embedded in a developing cognitive system.

This means there's a natural dependence between theories of knowledge representation and theories of knowledge development.



Language acquisition: Foundational knowledge

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Language acquisition: Foundational knowledge

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Examples of "foundational" processes that children use for building more sophisticated knowledge:

speech segmentation

syntactic categorization



idz & Gagliardi 201

speech segmentation: Pearl, Goldwater and Steyvers 2010, 2011, Phillips and Pearl 2012, 2015b



Language acquisition: Foundational knowledge

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Examples of "foundational" processes that children use for building more sophisticated knowledge:

speech segmentation

syntactic categorization



A recent finding: Developing representations are often "good enough" for scaffolding other acquisition processing even when they don't match adult representations (*Pearl 2014, Pearl & Sprouse 2015, Pearl under review*)

speech segmentation: Phillips and Pearl 2012, 2014a,b, 2015a,b, Pearl and Phillips under review, Phillips and Pearl under revision

syntactic categorization: Bar-Sever and Pearl 2016



Language acquisition: More sophisticated knowledge

Language acquisition involves complex knowledge that builds on itself over the course of linguistic development, embedded in a developing cognitive system.

Examples of more sophisticated knowledge that depends on the foundational knowledge:



Language acquisition: More sophisticated knowledge

Language acquisition involves complex knowledge that builds on itself over the course of linguistic development, embedded in a developing cognitive system.

Examples of more sophisticated knowledge that depends on the foundational knowledge: metrical stress



A current finding: Some linguistic representations may be less acquirable from cognitively plausible child-directed input than previously assumed unless certain learning biases are in place *Pearl 2007, 2008, 2009, 2011, Pearl, Ho, & Detrano 2014, under review, Pearl under review*



metrical stress

Language acquisition: More sophisticated knowledge

Language acquisition involves complex knowledge that builds on itself over the course of linguistic development, embedded in a developing cognitive system.

Examples of more sophisticated knowledge that depends on the foundational knowledge: syntactic islands



English anaphoric one

where arguments appear syntactically

Language acquisition: More sophisticated knowledge

Lidz & Gagliardi 2015

Language acquisition involves complex knowledge that builds on itself over the course of linguistic development, embedded in a developing cognitive system.

Examples of more sophisticated knowledge that depends on the foundational knowledge: syntactic islands

English anaphoric one

where arguments appear syntactically

A current finding: The knowledge needed to create the right acquisitional intake may not necessarily look like we thought it did (e.g., what's in Universal Grammar). syntactic islands: Pearl & Sprouse 2013a, 2013b, Pearl 2014, Pearl & Sprouse 2015, Pearl under rev. English anaphoric one: Pearl 2007, Pearl & Lidz 2009, Pearl & Mis 2011, Pearl 2014, Pearl & Mis in press where arguments appear: Pearl & Sprouse in progress

NSF: "Testing the Universal Grammar Hypothesis", "An Integrated Theory of Syntactic Acquisition"







Motivating Universal Grammar

The argument from acquisition: one explicit motivation that highlights the natural link between linguistic representation and language acquisition.

Universal Grammar (UG) allows children to acquire knowledge about language as effectively and rapidly as they do (Chomsky 1980, Crain 1991, Hornstein & Lightfoot 1981, Lightfoot 1982b, Legate & Yang 2002, among many others).



Motivating Universal Grammar



Motivating Universal Grammar Motivating Universal Grammar If that something is both innate and domain-specific, we consider it part of So if the data themselves don't pick out the right answer (and children all seem to), something internal to children Universal Grammar (UG) (Chomsky 1965, Chomsky 1975, Pearl & Sprouse 2013). must be guiding them. domain-specific vpothesis : hypothesis data derived innate encountere correct domain-general

Motivating the contents of UG

Proposals have traditionally come from characterizing a specific acquisition problem for a particular linguistic phenomenon, and describing the (UG) solution to that specific characterization.

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Syntactic islands: Constraints on long-distance dependencies (Chomsky 1973, Huang 1982, Lasnik & Saito 1984, Pearl & Sprouse 2013a, 2013b, 2015) Where did Jack think Lily bought the necklace from ___? *Where did Jack think the necklace from was too expensive?



Motivating the contents of UG

Proposals have traditionally come from characterizing a specific acquisition problem for a particular linguistic phenomenon, and describing the (UG) solution to that specific characterization. Structure-dependent rules (Chomsky 1980, Anderson & Lightfoot 2000; Fodor & Crowther 2002; Berwick et al. 2011; Anderson 2013) Pirates who can dance can often fight well. Can pirates who can dance __ often fight well?

Motivating the contents of UG

Proposals have traditionally come from characterizing a specific acquisition problem for a particular linguistic phenomenon, and describing the (UG) solution to that specific characterization.

> English anaphoric *one* representation (Baker 1978, Pearl & Mis 2011, 2016) Look – a red bottle! Do you see another *one*?





UG proposals: Generation & evaluation

How to generate a learning theory proposal: Characterize the learning problem precisely and identify a potential solution.

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Characterize the learning problem precisely and identify a potential solution.

How to evaluate a learning theory proposal:

See if it's successful when embedded in a model of the acquisition process for that learning problem.

UG proposals: Generation & evaluation

How to generate a learning theory proposal: Characterize the learning problem precisely and identify a potential solution.

Benefit of computational modeling: We can make sure the learning problem is characterized precisely enough to implement. It's not always obvious what pieces are missing until you try to build a model of the learning process. (Pearl 2014, Pearl & Sprouse 2015)



UG proposals: Generation & evaluation

How to generate a learning theory proposal: Characterize the learning problem precisely and identify a potential solution.

How to evaluate a learning theory proposal:

See if it's successful when embedded in a model of the acquisition process for that learning problem.



Recently, in computational modeling, we've seen the integration of rich hypothesis spaces with probabilistic/statistical learning mechanisms (Sakas & Fodor 2001, Yang 2004, Pearl 2011, Dillon et al. 2013, Pearl & Sprouse 2013, Pearl et al. 2014, Pearl & Mis 2016, among many others).

UG proposals: Generation & evaluation

How to generate a learning theory proposal:

Characterize the learning problem precisely and identify a potential solution.

How to evaluate a learning theory proposal:

See if it's successful when embedded in a model of the acquisition process for that learning problem.

We've also seen the development of more sophisticated acquisition frameworks that highlight the precise role of UG (Lidz & Gagliardi 2015).



Example: UG determines what data from the perceived input are relevant (acquisitional intake)

UG proposals: Generation & evaluation

How to generate a learning theory proposal:

Characterize the learning problem precisely and identify a potential solution.

How to evaluate a learning theory proposal:

See if it's successful when embedded in a model of the acquisition process for that learning problem.

How to decide if any components of the proposal are UG: Examine the components of the successful learning solution.

UG proposals: Generation & evaluation

How to generate a learning theory proposal:

Characterize the learning problem precisely and identify a potential solution.

How to evaluate a learning theory proposal:

See if it's successful when embedded in a model of the acquisition process for that learning problem.

This computational modeling feedback helps us refine our theories about both the knowledge representation the learning theory relies on and the acquisition process that uses that representation.



UG proposals: Generation & evaluation

How to generate a learning theory proposal: Characterize the learning problem precisely and identify a potential solution.

How to evaluate a learning theory proposal:

See if it's successful when embedded in a model of the acquisition process for that learning problem.

How to decide if any components of the proposal are UG: Examine the components of the successful learning solution.

Are they necessarily both domain-specific and innate?

Note: We may use "innate" as a placeholder until we can determine if it's impossible to derive the relevant component (Pearl 2014, Pearl & Mis 2016).



















Characterizing learning problems

Initial state: initial knowledge state + learning biases & capabilities

Data intake: data perceived as relevant for learning

Learning period:

- how long children have to reach the target knowledge state

(when inference & iteration happen)

ex: 3 years, ~1,000,000 data points ex: 4 months, ~36,500 data points



Pearl & Sprouse 2015, Pearl & Mis 2016





Characterizing learning problems

Initial state: initial knowledge state + learning biases & capabilities

Data intake: data perceived as relevant for learning

Learning period: how long children have to learn

Target state: the knowledge children must attain

Once we have all these pieces specified, we should be able to implement an informative model of the learning process.



Pearl & Sprouse 2015, Pearl & Mis 2016

Informing UG (+ acquisition theory)

When we identify a successful learning strategy via modeling, this is an existence proof that children could solve that learning problem using the learning biases, knowledge, and capabilities comprising that strategy.

This identifies useful learning strategy components, which we can then examine to see where they might come from.



Knowledge 1 Knowledge 2 Capability 1 Bias 1 Bias 2 Bias 3 ...







• Why? Central to UG-based syntactic theories.

• What? Dependencies can exist between two non-adjacent items. They do not appear to be constrained by length (Chomsky 1965, Ross 1967), but rather by whether the dependency crosses certain structures (called "syntactic islands").

Some example islands

Complex NP island:

*What did you make [the claim that Jack bought __]?

Subject island:

*What do you think [the joke about __] offended Jack?

Whether island: *What do you wonder [whether Jack bought __]?

Adjunct island: *What do you worry [if Jack buys]?



Pearl & Sprouse 2013a, 2013b, 2015





Syntactic islands: Acquisition target

Adult knowledge as measured by acceptability judgment behavior

Syntactic island = superadditive interaction of the two factors (additional unacceptability that arises when the two factors are combined, above and beyond the independent contribution of each factor).



Syntactic islands: Acquisition target





Lidz & Gagliardi 2015

Superadditivity present for all islands tested = Knowledge that dependencies cannot cross these island structures is part of adult knowledge about syntactic islands

Importance for acquisition: This is one kind of target behavior that we'd like a learner to produce.

Pearl & Sprouse 2013a, 2013b, 2015















This allows the modeled learner to generate judgments about the grammaticality of any dependency.

Higher probability dependencies are more grammatical while lower probability dependencies are less grammatical.



Syntactic islands: Subjacency-ish

Syntactic islands: Subjacency-ish











Recurring themes: Syntactic islands

Informing theories of representation & acquisition

Recurring themes, as seen in syntactic island acquisition: (1) Broadening the set of relevant data in the acquisitional intake to include all *wh*-dependencies





Pearl & Sprouse 2013a, 2013b, 2015

Recurring themes: Syntactic islands

Informing theories of representation & acquisition

Recurring themes, as seen in syntactic island acquisition:

Broadening the set of relevant data in the acquisitional intake to include all *wh*-dependencies
Evaluating output by how useful it is for generating acceptability judgment behavior





Lidz & Gagliardi 2015

Pearl & Sprouse 2013a, 2013b, 2015

Recurring themes: Syntactic islands

Informing theories of representation & acquisition

Recurring themes, as seen in syntactic island acquisition:

Broadening the set of relevant data in the acquisitional intake to include all *wh*-dependencies
Evaluating output by how useful it is for generating acceptability judgment behavior
Not necessarily needing the prior knowledge we thought we did in UG: container nodes rather than bounding nodes, no domain-specific constraint on length





101012013

Pearl & Sprouse 2013a, 2013b, 2015

Open questions

This learning strategy relying on the Subjacency-ish representation for *wh*-dependencies makes some developmental predictions – can we verify these experimentally?

"that-trace" effect prediction:

Children initially disprefer all dependencies containing *that*, even ones adults allow, due to the infrequency of container node trigrams with *CP*_{that} in child-directed speech

Pearl & Sprouse 2013a, 2013b, 2015

Open questions

This learning strategy relying on the Subjacency-ish representation for *wh*-dependencies makes some developmental predictions – can we verify these experimentally?

"that-trace" effect prediction:

Children initially disprefer all dependencies containing *that*, even ones adults allow, due to the infrequency of container node trigrams with CP_{that} in child-directed speech

Subject extraction

*Who do you think *that* ____ read the book? Who do you think read the book?





Open questions

Open questions

How does this learning strategy for wh-dependencies measure up cross-linguistically?

Island effects vary.

Ex: Italian does not have a subject island effect when the *wh*-dependency is part of a relative clause, though it does when the *wh*-dependency is part of a question. (Sprouse et al. in press)

Would the input naturally lead the Subjacency-ish learner to this distinction?



Pearl & Sprouse 2013a, 2013b, 2015



























English anaphoric one: Acquisition target

English anaphoric one: Acquisition target Child knowledge as measured by looking time behavior Look - a red bottle! Now look.. Lidz & Gagliardi 2015 Child behavior at 18 months: Lidz et al. 2003 Control/Noun: Anaphoric/Adjective-Noun: "What do you see now?" "Do you see another one?" "Do you see another bottle?" "Do you see another red bottle?" Prefer to look at novel bottle. Prefer to look at same color bottle. (0.459 to same color) (0.587 to same color)

Now look... Lidz & Gagliardi 2015 Control/Noun: "What do you see now?" "Do you see another bottle?" Prefer to look at novel bottle. (0.459 to same color)

Child knowledge as measured by looking time behavior

Look - a red bottle!

Child behavior at 18 months: Lidz et al. 2003

Anaphoric/Adjective-Noun: "Do you see another one?"

"Do you see another red bottle?" Prefer to look at same color bottle. (0.587 to same color)

Developed knowledge according to Lidz et al. 2003: 18-month-olds interpret one's antecedent as "red bottle" (an N') and its referent as the RED BOTTLE.

Pearl & Mis 2011, Pearl & Mis 2016



Proposed solutions for necessary knowledge & learning biases

Things in common:

 Syntactic categories exist (particularly NP, N', and N 0), and can be recognized.



Pearl & Mis 2011, Pearl & Mis 2016

English anaphoric one: Representations

Proposed solutions for necessary knowledge & learning biases

Things in common:

- Syntactic categories exist (particularly NP, N', and N^0), and can be recognized.
- ✦ Anaphoric elements like one take linguistic antecedents of the same category.



English anaphoric one: Representations

Proposed solutions for necessary knowledge & learning biases

Things that differ:

 Which input is considered relevant from the perceptual intake = acquisitional intake



Lidz & Gagliardi 2015

Pearl & Mis 2011, Pearl & Mis 2016



Proposed solutions for necessary knowledge & learning biases

Things that differ:

 Which input is considered relevant from the perceptual intake = acquisitional intake Lidz & Gagliardi 2015

UG knowledge

Baker (1978): One that could work = DirUnamb + N'

Only utterances directly using one are relevant for learning about anaphoric one.

Only utterances where one's antecedent is unambiguous are relevant.

Children already know that *one* can't be N^0 , so it must be N'.

This solves the problem of one's syntactic category.

Proposed solutions for necessary knowledge & learning biases Things that differ: Which input is considered relevant from the perceptual intake = acquisitional intake Lidz & Gagliardi 2015 Pearl & Lidz 2009: One that doesn't work = DirEO Only utterances directly using one are relevant for learning about anaphoric one. Use probabilistic inference to leverage ambiguous information about one. All ambiguous data are relevant (Equal Opportunity).

English anaphoric one: Representations

Pearl & Mis 2011, Pearl & Mis 2016



Proposed solutions for necessary knowledge & learning biases

Things that differ:

 Which input is considered relevant from the perceptual intake = acquisitional intake



Pearl & Lidz 2009: One that doesn't work = DirEO

Only utterances directly using one are relevant for learning about anaphoric one.

Use probabilistic inference to leverage ambiguous information about one.

All ambiguous data are relevant (Equal Opportunity).

DirSynAmb: Ambiguous about antecedent category (*bottle* = N⁰, N'). "Look – a bottle! Oh, look – another *one*!"



English anaphoric one: Representations

Proposed solutions for necessary knowledge & learning biases

Things that differ:

 Which input is considered relevant from the perceptual intake = acquisitional intake



Pearl & Lidz 2009, Regier & Gahl 2004: One that does work for target knowledge = DirFiltered Only utterances directly using *one* are relevant for learning about anaphoric *one*.

Use probabilistic inference to leverage ambiguous information about one.

Filter out the harmful DirSynAmb data.

DirSynAmb: Ambiguous about antecedent category (*bottle* = N⁰, N'). "Look – a bottle! Oh, look – another *one*!"



Proposed solutions for necessary knowledge & learning biases



 Which input is considered relevant from the perceptual intake = acquisitional intake



Pearl & Mis 2011, 2016: One that could work = IndirPro

Ovy utterances directly using *one* are relevant for learning about anaphoric *one*.

Use probabilistic inference to leverage ambiguous information about one.

Utterances using other pronouns anaphorically are relevant for learning about anaphoric *one*. This is indirect evidence coming from other pronouns.

Pearl & Mis 2011, Pearl & Mis 2016

English anaphoric one: Representations

Proposed solutions for necessary knowledge & learning biases

Things that differ:

 Which input is considered relevant from the perceptual intake = acquisitional intake



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Utterances using other pronouns anaphorically are relevant for learning about anaphoric *one*. This is indirect evidence coming from other pronouns.

IndirUnamb: Relevant because indicates whether antecedent includes the mentioned property (it always does here), which is helpful when choosing between different interpretation options in other contexts.

"Look – a red bottle! I want *one/it.*" a red bottle

8.42% of utterances containing a pronoun in Brown-Eve corpus Pearl & Mis 2011, Pearl & Mis 2016

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English anaphoric one: Representations

Proposed solutions for necessary knowledge & learning biases

Things that differ:

 Which input is considered relevant from the perceptual intake = acquisitional intake



Learning proposal comparisons

						Juccess	nun.
	Unamb	one≠N ⁰	ProbInf	-DirSynAmb	+OtherPro	Representations	Behavior
DirUnamb	1					1 ?	2
DirUnamb + N'	1	1				2	2
					-	· •	۲

Pearl & Mis 2011, Pearl & Mis 2016

Successful?



Proposed solutions for necessary knowledge & learning biases

Things that differ:

 Which input is considered relevant from the perceptual intake = acquisitional intake



Learning proposal comparisons

						Success	itul?
	Unamb	$one \neq N^0$	ProbInf	-DirSynAmb	+OtherPro	Representations	Behavio
DirUnamb	1					?	- ?
DirUnamb + N'	1	1				2	2
DirFiltered			1	1		l 🎸	?
DirEO			1				<u>9</u>

DirUnamo	isn't another one here, though.	Dironamo, Dironamo + N, Dirrinered, DirEO, indirrio
DirRefSynAmb	Look- a red bottle! Oh, look- another one!	DirFiltered, DirEO, IndirPro
DirSynAmb	Look- a bottle! Oh, look- another one!	DirEO, IndirPro
IndirUnamb	Look a red bottle! I want it/one.	IndirPro

Pearl & Mis 2011, Pearl & Mis 2016

English anaphoric one: Representations

Proposed solutions for necessary knowledge & learning biases

Things that differ:

 Which input is considered relevant from the perceptual intake = acquisitional intake



Learning proposal comparisons

	Unamb	one≠N ⁰	ProbInf	-DirSynAmb	+OtherPro	Representations	Behavior
DirUnamb	~					1 7	- ?
DirUnamb + N'	1	1				2	2
DirFiltered			1	1		v	2
DirEO			1				- 2
IndirPro			1		1		-





Engl	ish anaphoric <i>on</i>	e: Target st	ate
Target state: knowle	edge and behavior		
	Look - a red bottle!		Behaver
•	Now look	Particular Particular anomaly Particular processor Consequence representational Consequence representational Building and anomaly Particular	
	Child behavior	Lidz & Gagliardi 2015 at 18 months: L	idz et al. 2003
10 00	Control/Noun:	Anaph	oric/Adjective-Noun:
The -1	"What do you see n	iow?" 🦯 "Do yo	u see another one?"
	"Do you see anothe	er bottle?" "Do yo	u see another red bottle?"
	Prefer to look at nov	vel bottle Prefer	to look at same color bottle
A last of al (Digenous Pr (200) 400 475)	(0.459 to same color	r) (0.587	to same color)
	Developed know 18-month-olds ir bottle (an N') a	ledge according to I nterpret <i>one</i> 's antec id its referent as th	idz et al. 2003: edent as "red RED OTTLE.
		P	eari & Mis 2011, Pearl & Mis 2016







Averages over 1000 simulations, standard deviations in parentheses.

Note: Target p_{beh} = 0.587, all other target p = 1.000

$\rho_{N'}$
p _{incl}
p _{beh}
p _{rep/beh}

Pearl & Mis 2011, Pearl & Mis 2016

English anaphoric one: Learning results

Averages over 1000 simulations, standard deviations in parentheses.

Note: Target $p_{beh} = 0.587$, all other target p = 1.000

	DirUnamb
р _{N'}	0.500 (<0.01)
p _{incl}	0.500 (<0.01)
p _{beh}	0.475 (<0.01)
$p_{_{rep/beh}}$	0.158 (<0.01)

A learner who only looks at direct unambiguous data has no data to learn from, so it learns nothing. (Poverty of the stimulus.)

It's at chance for having the target syntactic and referential knowledge necessary to choose the correct antecedent.

It doesn't generate the observed toddler looking preference, and it's unlikely to have the target representation if it looks at the familiar bottle.



Pearl & Mis 2011, Pearl & Mis 2016

English anaphoric one: Learning results

Averages over 1000 simulations, standard deviations in parentheses.

Note: Target p_{beh} = 0.587, all other target p = 1.000

	DirUnamb
р _{N'}	0.500 (<0.01)
p _{incl}	0.500 (<0.01)
p_{beh}	0.475 (<0.01)
$p_{rep beh}$	0.158 (<0.01)

Implication: Something else is needed. (Baker (1978)'s original observation)



Pearl & Mis 2011, Pearl & Mis 2016

English anaphoric one: Learning results

Averages over 1000 simulations, standard deviations in parentheses.

Note: Target p_{beh} = 0.587, all other target p = 1.000

	DirUnamb	DirUnamb + N'
$p_{N'}$	0.500 (<0.01)	1.000
p _{incl}	0.500 (<0.01)	
p_{beh}	0.475 (<0.01)	
p _{rep beh}	0.158 (<0.01)	

What if the learner also knows that one is category N'? (Baker 1978)

Averages over 1000 simulations, standard deviations in parentheses.

Note: Target $p_{beh} = 0.587$, all other target p = 1.000

	DirUnamb	DirUnamb + N'	
р _{N'}	0.500 (<0.01)	1.000	
p _{incl}	0.500 (<0.01)	0.500 (<0.01)	
p_{beh}	0.475 (<0.01)	0.492 (<0.01)	
$p_{_{rep beh}}$	0.158 (<0.01)	0.306 (<0.01)	

This learner still has no data to learn from, so it learns nothing about the correct referential knowledge necessary to choose the correct antecedent.

This lack of referential knowledge causes it not to generate the observed toddler looking preference in context, and even if it happens to look at the familiar bottle, to be unlikely to have the target representation when doing so.



Pearl & Mis 2011, Pearl & Mis 2016

English anaphoric one: Learning results

Averages over 1000 simulations, standard deviations in parentheses.

Note: Target $p_{beh} = 0.587$, all other target p = 1.000

	DirUnamb	DirUnamb + N'
$p_{N'}$	0.500 (<0.01)	1.000
p _{incl}	0.500 (<0.01)	0.500 (<0.01)
p _{beh}	0.475 (<0.01)	0.492 (<0.01)
$p_{_{rep/beh}}$	0.158 (<0.01)	0.306 (<0.01)

Implication: Knowing *one* is category N' isn't sufficient to generate target behavior if only direct unambiguous data are relevant.



Pearl & Mis 2011, Pearl & Mis 2016

English anaphoric one: Learning results

Averages over 1000 simulations, standard deviations in parentheses.

Note: Target p_{beh} = 0.587, all other target p = 1.000

	DirUnamb	DirUnamb + N'	DirFiltered
p _{N'}	0.500 (<0.01)	1.000	0.991 (<0.01)
p _{incl}	0.500 (<0.01)	0.500 (<0.01)	0.963 (<0.01)
p _{beh}	0.475 (<0.01)	0.492 (<0.01)	0.574 (<0.01)
p _{rep/beh}	0.158 (<0.01)	0.306 (<0.01)	0.918 (<0.01)

The DirFiltered learner (Regier & Gahl 2004, Pearl & Lidz 2009) believes one is N' when it is smaller than NP and a mentioned property should be included in the antecedent, as found previously.

It's also close to generating the observed toddler looking preference, and is likely to have the target representation when looking at the familiar bottle.



English anaphoric one: Learning results

Averages over 1000 simulations, standard deviations in parentheses.

Note: Target $p_{beh} = 0.587$, all other target p = 1.000

	DirUnamb	DirUnamb + N'	DirFiltered
р _{N'}	0.500 (<0.01)	1.000	0.991 (<0.01)
p _{incl}	0.500 (<0.01)	0.500 (<0.01)	0.963 (<0.01)
p _{beh}	0.475 (<0.01)	0.492 (<0.01)	0.574 (<0.01)
p _{rep/beh}	0.158 (<0.01)	0.306 (<0.01)	0.918 (<0.01)

Implication: This new finding suggests this is a pretty successful learning strategy for matching the available behavioral data.



Pearl & Mis 2011, Pearl & Mis 2016

Averages over 1000 simulations, standard deviations in parentheses.

Note: Target $p_{beh} = 0.587$, all other target p = 1.000

	DirUnamb	DirUnamb + N'	DirFiltered	DirEO
р _{N'}	0.500 (<0.01)	1.000	0.991 (<0.01)	0.246 (0.03)
p _{incl}	0.500 (<0.01)	0.500 (<0.01)	0.963 (<0.01)	0.379 (0.05)
p _{beh}	0.475 (<0.01)	0.492 (<0.01)	0.574 (<0.01)	0.464 (<0.01)
$p_{rep/beh}$	0.158 (<0.01)	0.306 (<0.01)	0.918 (<0.01)	0.050 (0.01)

The DirEO learner (explored by Pearl & Lidz 2009) prefers *one* to be N^0 when it is smaller than NP, and does not believe the mentioned property should be included in the antecedent. Neither of these is the target knowledge.

This causes the learner not to generate the observed toddler looking preference, and not to have the target representation if it looks at the familiar bottle.

Pearl & Mis 2011, Pearl & Mis 2016

English anaphoric one: Learning results

Averages over 1000 simulations, standard deviations in parentheses.

Note: Target p_{beh} = 0.587, all other target p = 1.000

	DirUnamb	DirUnamb + N'	DirFiltered	DirEO	
$p_{N'}$	0.500 (<0.01)	1.000	0.991 (<0.01)	0.246 (0.03)	
p _{incl}	0.500 (<0.01)	0.500 (<0.01)	0.963 (<0.01)	0.379 (0.05)	
p_{beh}	0.475 (<0.01)	0.492 (<0.01)	0.574 (<0.01)	0.464 (<0.01)	
p _{rep/beh}	0.158 (<0.01)	0.306 (<0.01)	0.918 (<0.01)	0.050 (0.01)	

Implication: This new finding suggests this isn't a good learning strategy for matching the available behavioral data.



Pearl & Mis 2011, Pearl & Mis 2016

English anaphoric one: Learning results

Averages over 1000 simulations, standard deviations in parentheses.

Note: Target p_{beh} = 0.587, all other target p = 1.000

	DirUnamb	DirUnamb + N'	DirFiltered	DirEO	IndirPro
$p_{N'}$	0.500 (<0.01)	1.000	0.991 (<0.01)	0.246 (0.03)	0.368 (0.04)
p _{incl}	0.500 (<0.01)	0.500 (<0.01)	0.963 (<0.01)	0.379 (0.05)	1.000 (<0.01)
p_{beh}	0.475 (<0.01)	0.492 (<0.01)	0.574 (<0.01)	0.464 (<0.01)	
$p_{_{rep beh}}$	0.158 (<0.01)	0.306 (<0.01)	0.918 (<0.01)	0.050 (0.01)	

The IndirPro learner robustly decides the antecedent should include the mentioned property. However, this learner has a moderate dispreference for believing *one* is N' when it is smaller than NP. This isn't the target representation, w.r.t syntactic category.



English anaphoric one: Learning results

Averages over 1000 simulations, standard deviations in parentheses.

Note: Target p_{beh} = 0.587, all other target p = 1.000

	DirUnamb	DirUnamb + N'	DirFiltered	DirEO	IndirPro
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p _{beh}	0.475 (<0.01)	0.492 (<0.01)	0.574 (<0.01)	0.464 (<0.01)	0.587 (<0.01)
p _{rep/beh}	0.158 (<0.01)	0.306 (<0.01)	0.918 (<0.01)	0.050 (0.01)	0.998 (<0.01)

However...this learner still generates the observed toddler looking preference perfectly, and has the target representation when looking at the familiar bottle.



Why? The learner believes very strongly that the mentioned property must be included in the antecedent.

Only one antecedent allows this: [_{N'} red[_{N'}[_{N0} bottle]]]

Averages over 1000 simulations, standard deviations in parentheses.

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So, because the antecedent includes the mentioned property, it and the pronoun referring to it (*one*) must be N' *in this context* - even if the learner believes *one* is not N' in general.

Only one antecedent allows this: $\left[\frac{1}{N'} \operatorname{red}\left[\frac{1}{N'} \operatorname{bottle}\right]\right]$

Pearl & Mis 2011, Pearl & Mis 2016

English anaphoric one: Learning results

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Implication: A learner viewing other pronoun data as relevant can generate target behavior without necessarily reaching the target knowledge state – instead, this learner has a context-sensitive representation (depending on whether a property was mentioned).



Pearl & Mis 2011, Pearl & Mis 2016

English anaphoric one: Learning results

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$p_{_{rep/beh}}$	0.158 (<0.01)	0.306 (<0.01)	0.918 (<0.01)	0.050 (0.01)	0.998 (<0.01)

Let's look at the strategies that worked and see what the implications are for Universal Grammar, as compared to the original UG proposal by Baker that didn't work.































Recurring themes: English anaphoric one

Informing theories of representation & acquisition

Recurring themes:

(1) Broadening the set of relevant data in the acquisitional intake to include all pronouns





Pearl & Mis 2011, Pearl & Mis 2016

Recurring themes: English anaphoric one

Informing theories of representation & acquisition

Recurring themes:

(1) Broadening the set of relevant data in the acquisitional intake to include all pronouns(2) Evaluating output by how useful it is for generating toddler looking time behavior





Pearl & Mis 2011, Pearl & Mis 2016

Recurring themes: English anaphoric one

Informing theories of representation & acquisition

Recurring themes:

 Broadening the set of relevant data in the acquisitional intake to include all pronouns
Evaluating output by how useful it is for generating toddler looking time behavior
Not necessarily needing the prior knowledge we thought we did in UG: "good enough" derived data filter or derived overhypothesis about pronouns rather than specific knowledge about syntactic category





Lidz & Gagliardi 2015

Pearl & Mis 2011, Pearl & Mis 2016

Big picture: Understanding how children acquire syntactic knowledge

If we precisely define the components of any acquisition task by drawing on the insights from different methodologies, we can make progress on how children solve that acquisition task.

In particular, we can understand the nature of children's language acquisition toolkit — what fundamental building blocks they use are, and what is (or is not) part of Universal Grammar.





	Thank	you!
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UC Irvine	lpearl@uci.edu	determiner x adjective X red XV botic
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