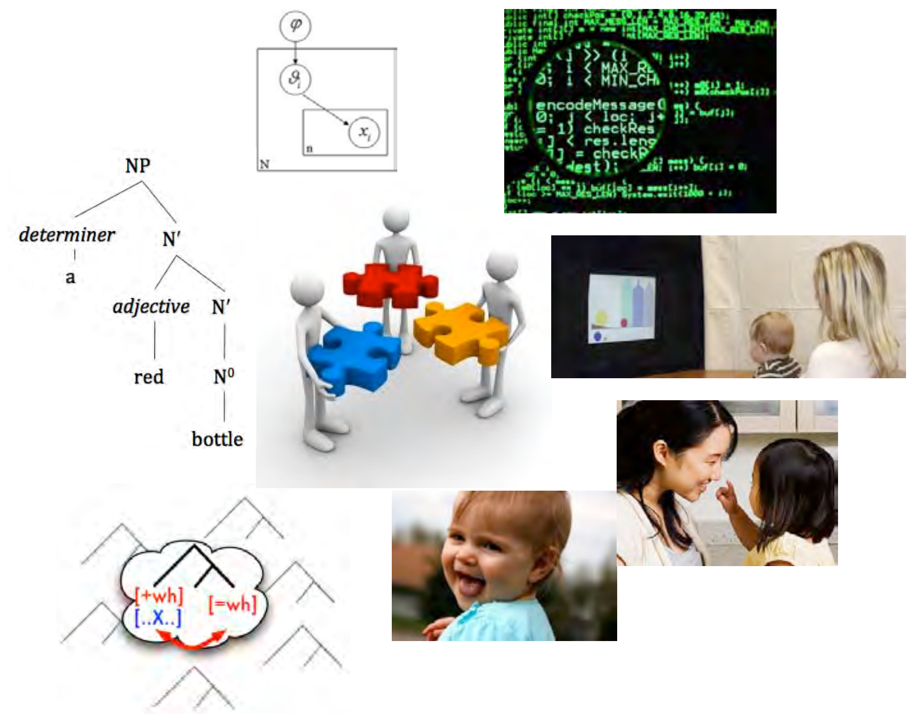
Empirically investigating the Universal Grammar hypothesis

Lisa Pearl

University of California, Irvine

Computation of Language Laboratory

UC Irvine



Nov 16, 2012: Department of Linguistics Colloquium

New York University

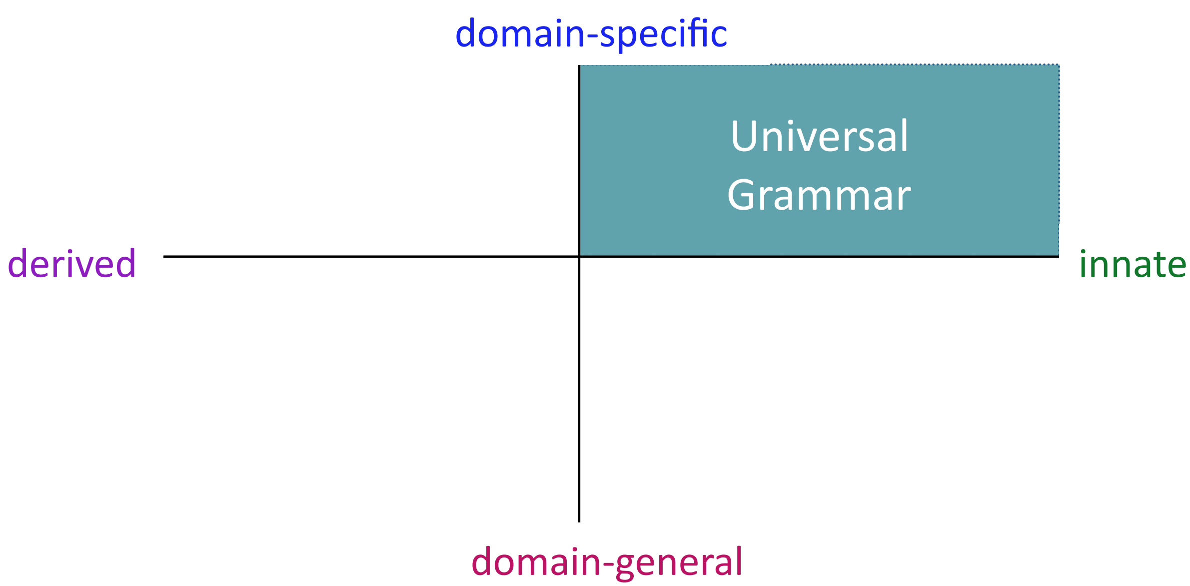
Motivating Universal Grammar

One explicit motivation: The argument from 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

Specifically, Universal Grammar consists of the necessary learning biases that are both innate and domain-specific (Chomsky 1965, Chomsky 1975).

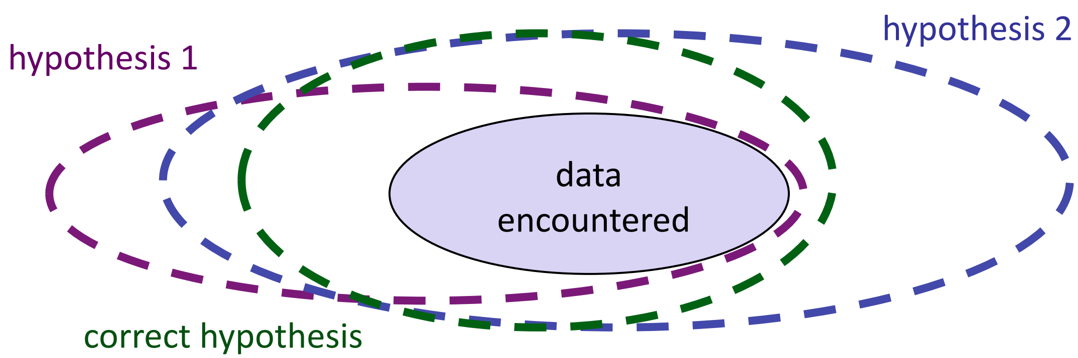


Motivating Universal Grammar

What's so hard about acquiring language?

There seem to be induction problems, given the available data.

(Poverty of the Stimulus, Logical Problem of Language Acquisition, Plato's Problem)



Motivating the contents of UG

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

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- Structure-dependent rules (Chomsky 1980)

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 induction problem pertaining to a particular linguistic phenomenon, and describing the (UG) solution to that specific characterization.

- Constraints on long-distance dependencies (Chomsky 1973)

  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 induction problem pertaining to a particular linguistic phenomenon, and describing the (UG) solution to that specific characterization.

- English anaphoric *one* representation (Baker 1978)

  Look – a red bottle! Do you see another *one*?

one =  ?

Motivating the contents of UG

Benefits of a specific characterization of an induction problem:

- Precisely describe a potential solution
- Explicitly test that solution & compare it to other potential solutions

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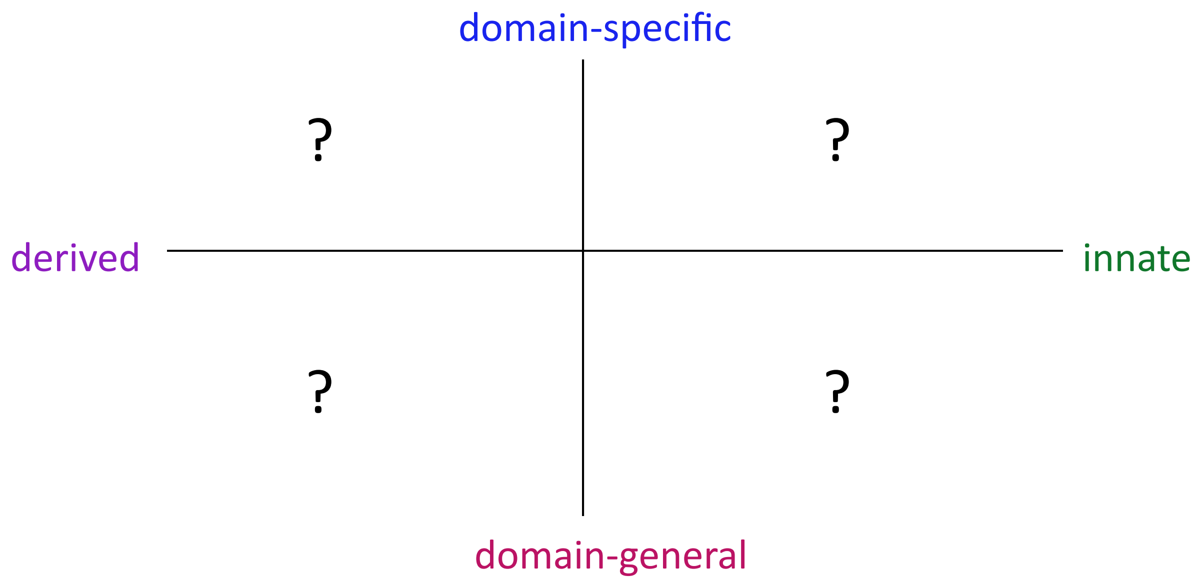
- Explicitly test that solution & compare it to other potential solutions

When we find a potential solution, we can examine the nature of the learning biases it involves.



Motivating the contents of UG

Benefits of a specific characterization of an induction problem:

- Precisely describe a potential solution
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Benefits for investigating UG:

- If *all* the solutions involve UG biases:
  - supports the existence of UG
  - provides specific proposals for its contents

Motivating the contents of UG

Benefits of a specific characterization of an induction problem:

- Precisely describe a potential solution
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Benefits for investigating UG:

- If *all* the solutions involve UG biases:
  - supports the existence of UG
  - provides specific proposals for its contents
- If some solutions do not involve UG biases
  - takes away the support for UG that comes from that characterization of the induction problem

Characterizing induction problems

Initial state:

Pearl & Mis submitted

Characterizing induction problems

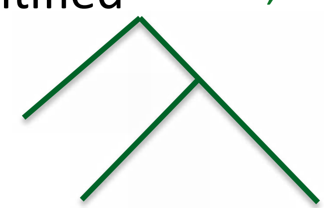
Initial state:

- initial knowledge state

ex: grammatical categories exist and can be identified

N^0, N', NP, DP, …

ex: phrase structure exists and can be identified



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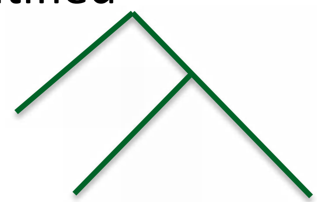
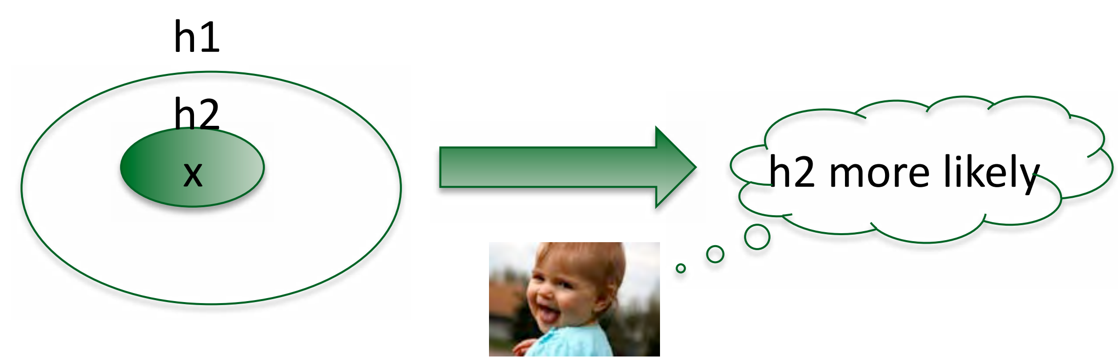


- learning biases & capabilities

ex: frequency information can be tracked $N^0 = N^0 + 1$

ex: distributional information can be leveraged



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Characterizing induction problems

Initial state: initial knowledge state + learning biases & capabilities

Data intake:

Pearl & Mis submitted

Characterizing induction problems

Initial state: initial knowledge state + learning biases & capabilities

Data intake:

- data perceived as relevant for learning (Fodor 1998)

ex: all *wh*-utterances for learning about *wh*-dependencies

ex: syntactic data for learning syntactic knowledge

[defined by knowledge & biases/capabilities in the initial state]

Pearl & Mis submitted

Characterizing induction problems

Initial state: initial knowledge state + learning biases & capabilities

Data intake: data perceived as relevant for learning

Learning period:

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Characterizing induction 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

ex: 3 years, ~1,000,000 data points

ex: 4 months, ~36,500 data points

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Characterizing induction 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:

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Characterizing induction problems

Initial state: initial knowledge state + learning biases & capabilities

Data intake: data perceived as relevant for learning

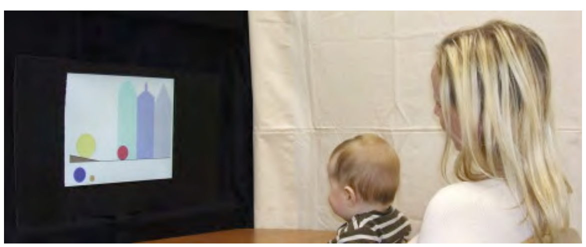
Learning period: how long children have to learn

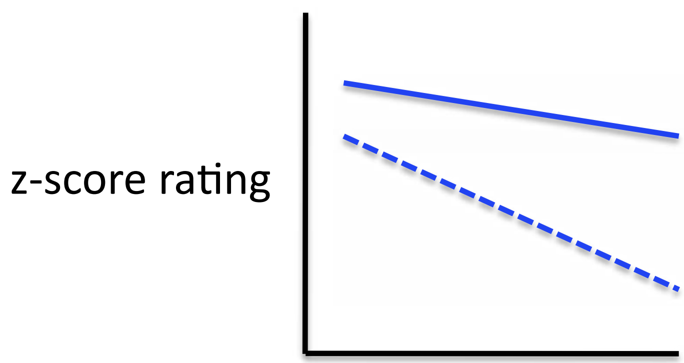
Target state:

- the knowledge children are trying to attain

ex: *Where did Jack think the necklace from __ was too expensive?

ex: *one* is category N' when it is not NP





Pearl & Mis submitted

Characterizing induction 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

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Characterizing induction problems

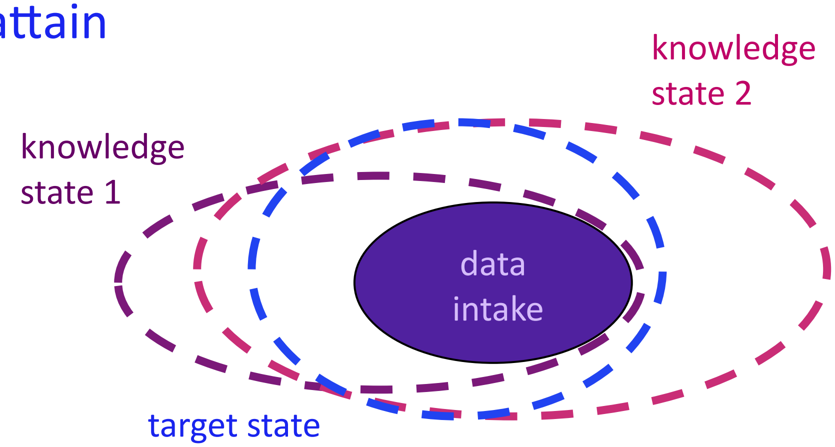
Initial state: initial knowledge state + learning biases & capabilities

Data intake: data perceived as relevant for learning

Learning period: how long children have to learn

Target state: the knowledge children must attain

Induction problem:
Given a specific initial state, data intake, and learning period, the target state is not the only knowledge state that could be reached.



Pearl & Mis submitted

To characterize potential induction problems, we need to draw on a variety of research methods.

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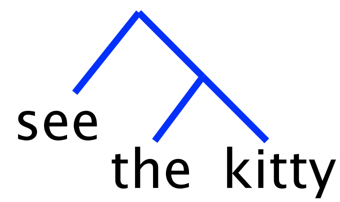
Theoretical methods:

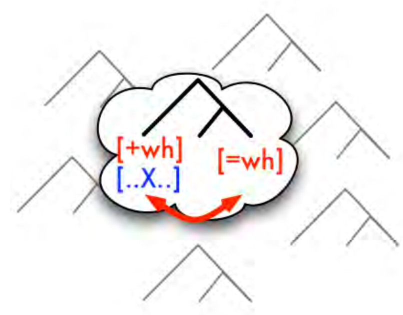
What knowledge of language is (and what children have to learn)

[initial state, target state]

SEE the KItty



si ðə kiɾi



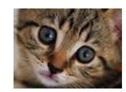
$$\begin{bmatrix}+\text{stop}\\+\text{consonant}\\+\text{alveolar}\end{bmatrix} \rightarrow [\text{ɾ}] \;/\; \begin{bmatrix}+\text{vowel}\\+\text{stressed}\end{bmatrix} \text{—} \begin{bmatrix}+\text{vowel}\\-\text{stressed}\end{bmatrix}$$

see'(the kitty)($x_{listener}$)

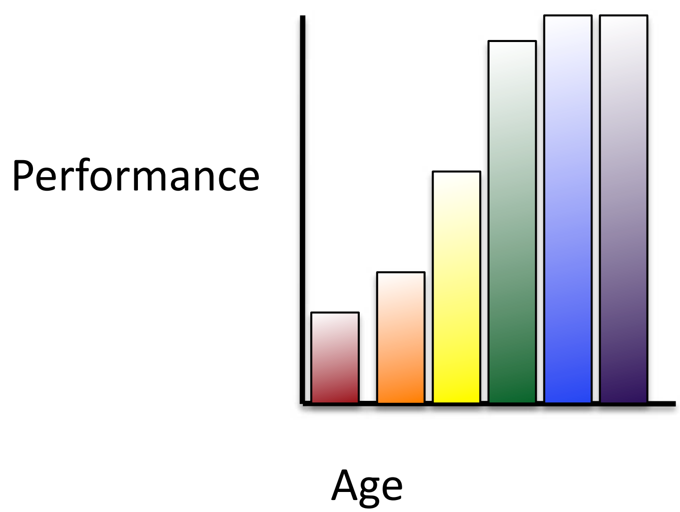
To characterize potential induction problems, we need to draw on a variety of research methods.

Experimental methods:
When knowledge is acquired, what the **input** looks like, & plausible capabilities underlying **how** acquisition works
[initial state, data intake, learning period]

$$\frac{p(ki\ \ tty)}{p(ki)}$$

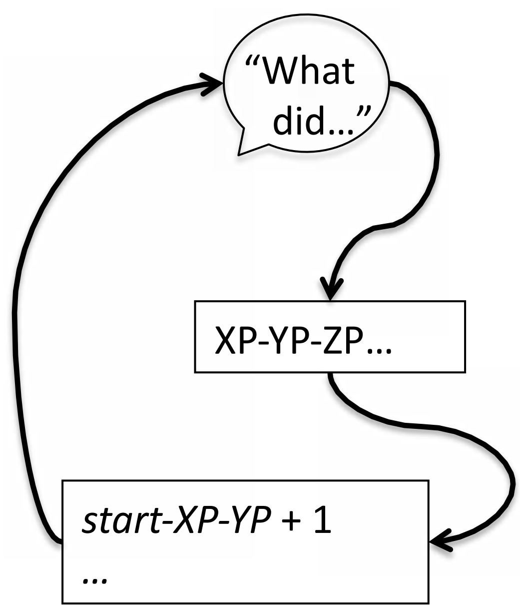
$p(\mathrm{H1} \mid$  $)$

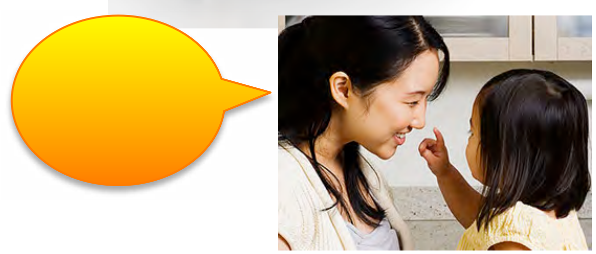
$\propto p($  $\mid \mathrm{H1})\, p(\mathrm{H1})$

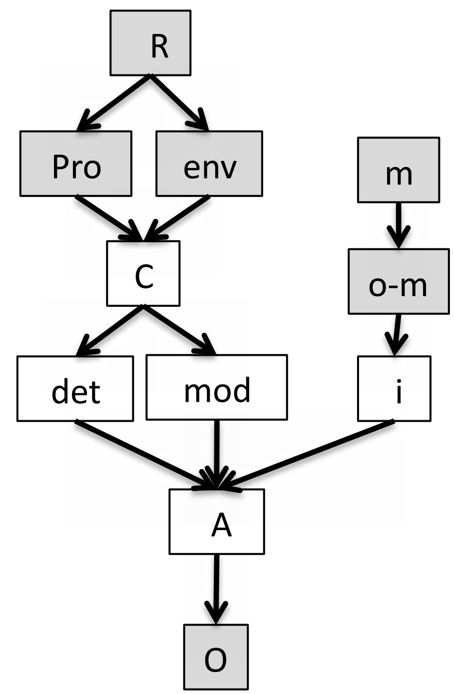


To characterize potential induction problems, we need to draw on a variety of research methods.

Computational methods:
Strategies that are both useful and useable for **how** children acquire knowledge + quantitative analysis of input
[initial state, data intake]



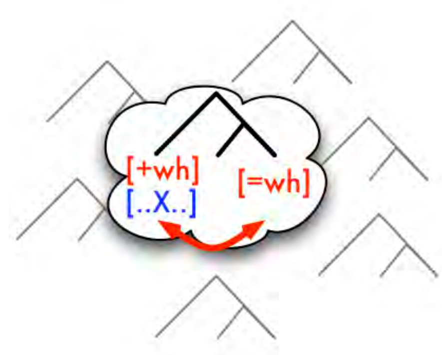




Road Map

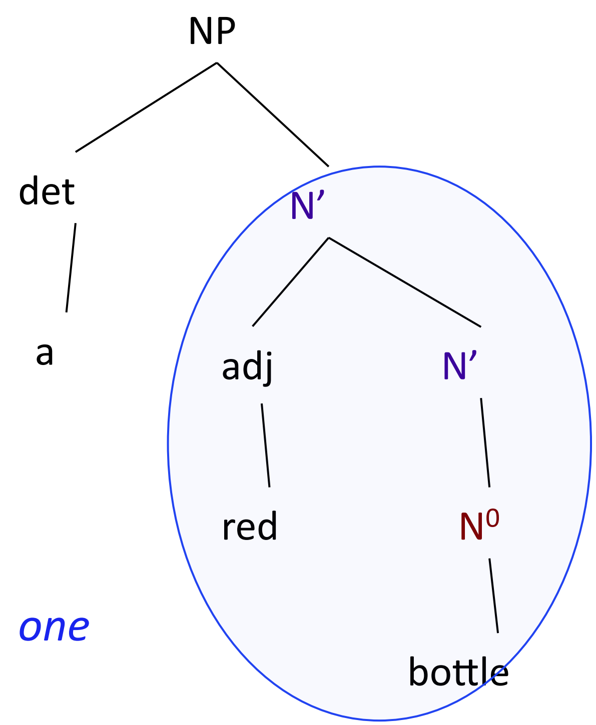
I. Potential induction problem:

Learning constraints on long-distance dependencies



II. Potential induction problem:

Learning English anaphoric *one*



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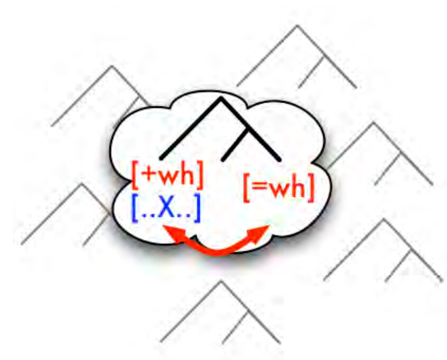
Learning constraints on long-distance dependencies



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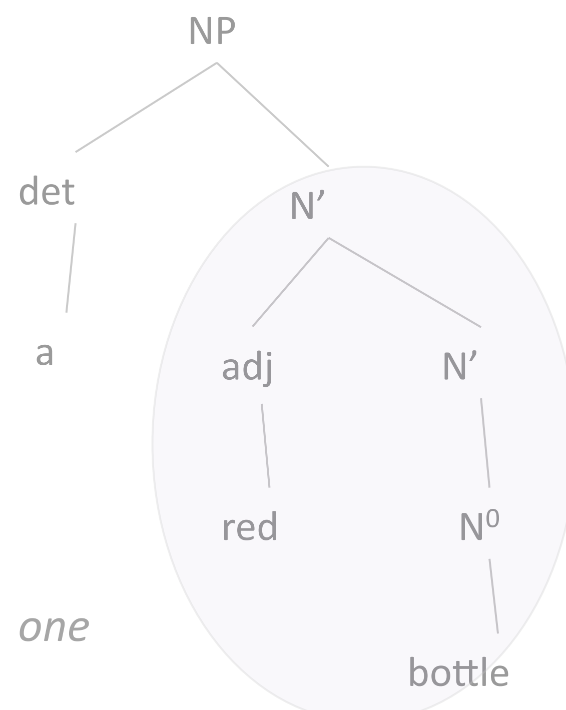

Syntactic islands

- **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").

Pearl & Sprouse forthcoming

Syntactic islands

- **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").

What does Jack think __?

What does Jack think that Lily said that Sarah heard that Jareth believed __?

Pearl & Sprouse forthcoming

Syntactic islands

- **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").

<u>Some example islands</u>

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 __]?

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Syntactic islands

- **Predominant theory in generative syntax:**
  syntactic islands require innate, domain-specific learning biases

Example: Subjacency (Chomsky 1973, Huang 1982, Lasnik & Saito 1984)
(1) A dependency cannot cross two or more bounding nodes.

Wh … $[_{BN2}$ … $[_{BN1}$ … ___]]

Pearl & Sprouse forthcoming

Syntactic islands

- **Predominant theory in generative syntax:**
  syntactic islands require innate, domain-specific learning biases

Example: Subjacency (Chomsky 1973, Huang 1982, Lasnik & Saito 1984)
(1) A dependency cannot cross two or more bounding nodes.

(2) Bounding nodes: language-specific
(CP, IP, and/or NP – must learn which ones are relevant for language)

Wh … [$_{BN2}$ … [$_{BN1}$ … __]]

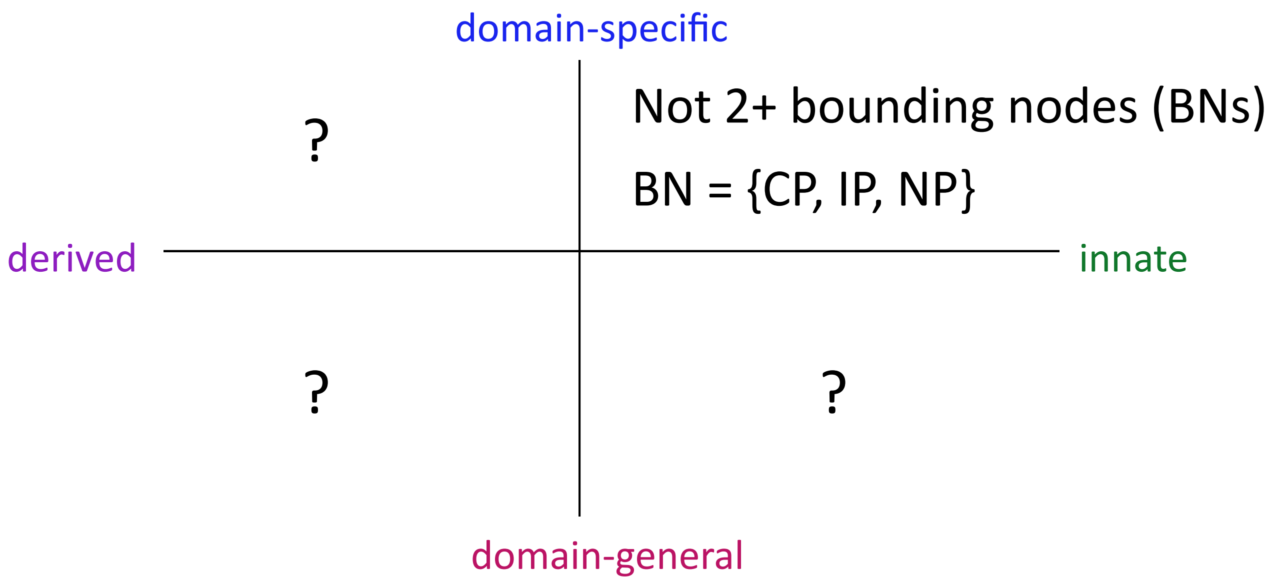
{CP, IP, NP}?

Pearl & Sprouse forthcoming

Syntactic islands

- **Predominant theory in generative syntax:**

  syntactic islands require innate, domain-specific learning biases…in addition to whatever else they might require.



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Syntactic islands

- **How do we test this?**

(1) Explicitly define the target knowledge state, using adult acceptability judgments.

(2) Identify the data available in the input, using realistic samples. (Is there an induction problem, given what we think children's data intake is?)

(3) Implement a probabilistic learner that can learn about syntactic islands and see what kind of learning biases it requires. This requires making the initial state and learning period explicit.

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The target state:
Adult knowledge of syntactic islands

Sprouse et al. (2012) collected magnitude estimation judgments for four different islands, using a factorial definition that controlled for two salient properties of island-crossing dependencies:

- length of dependency (matrix vs. embedded)
- presence of an island structure (non-island vs. island)

Pearl & Sprouse forthcoming

The target state: Adult knowledge of syntactic islands

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- presence of an island structure (non-island vs. island)

Complex NP islands

Who __ claimed that Lily forgot the necklace?	matrix | non-island
What did the teacher claim that Lily forgot __?	embedded | non-island
Who __ made the claim that Lily forgot the necklace?	matrix | island
*What did the teacher make the claim that Lily forgot __?	embedded | island

Pearl & Sprouse forthcoming

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Subject islands

Who __ thinks the necklace is expensive?	matrix | non-island
What does Jack think __ is expensive?	embedded | non-island
Who __ thinks the necklace for Lily is expensive?	matrix | island
*Who does Jack think the necklace for __ is expensive?	embedded | island

Pearl & Sprouse forthcoming

The target state: Adult knowledge of syntactic islands

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Whether islands

Who __ thinks that Jack stole the necklace?	matrix | non-island
What does the teacher think that Jack stole __ ?	embedded | non-island
Who __ wonders whether Jack stole the necklace?	matrix | island
*What does the teacher wonder whether Jack stole __ ?	embedded | island

Pearl & Sprouse forthcoming

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Adjunct islands

Who __ thinks that Lily forgot the necklace?	matrix | non-island
What does the teacher think that Lily forgot __ ?	embedded | non-island
Who __ worries if Lily forgot the necklace?	matrix | island
*What does the teacher worry if Lily forgot __ ?	embedded | island

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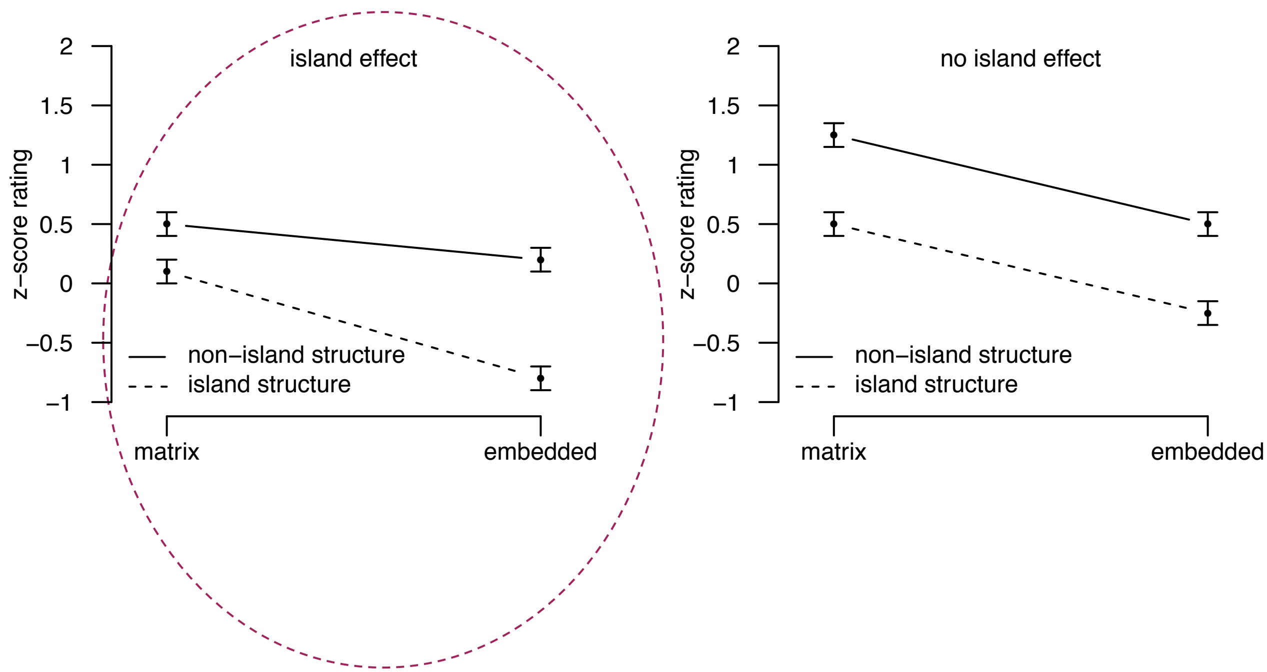
The target state: Adult knowledge of syntactic islands

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).



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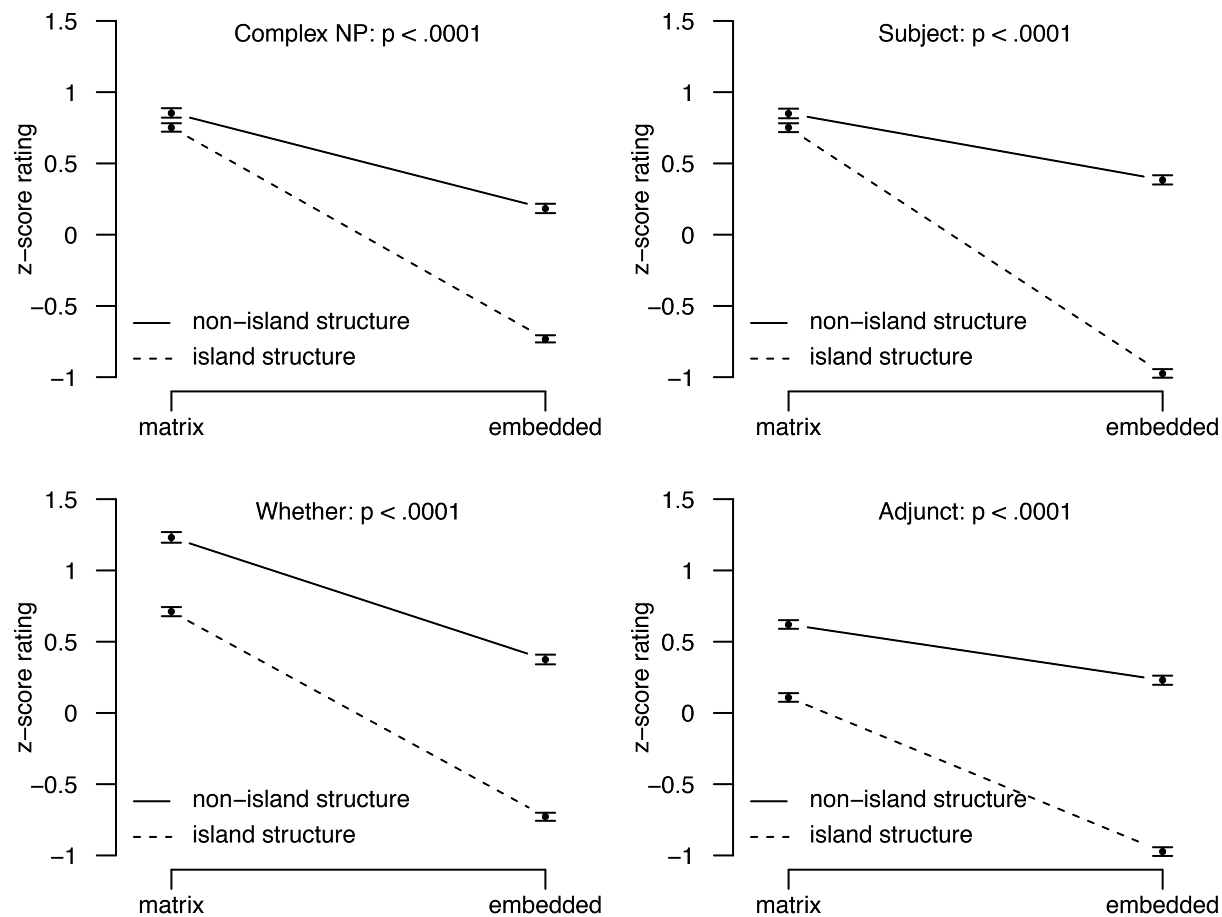
The target state:
Adult knowledge of syntactic islands

Sprouse et al. (2012)'s data on the four island types (173 subjects)

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



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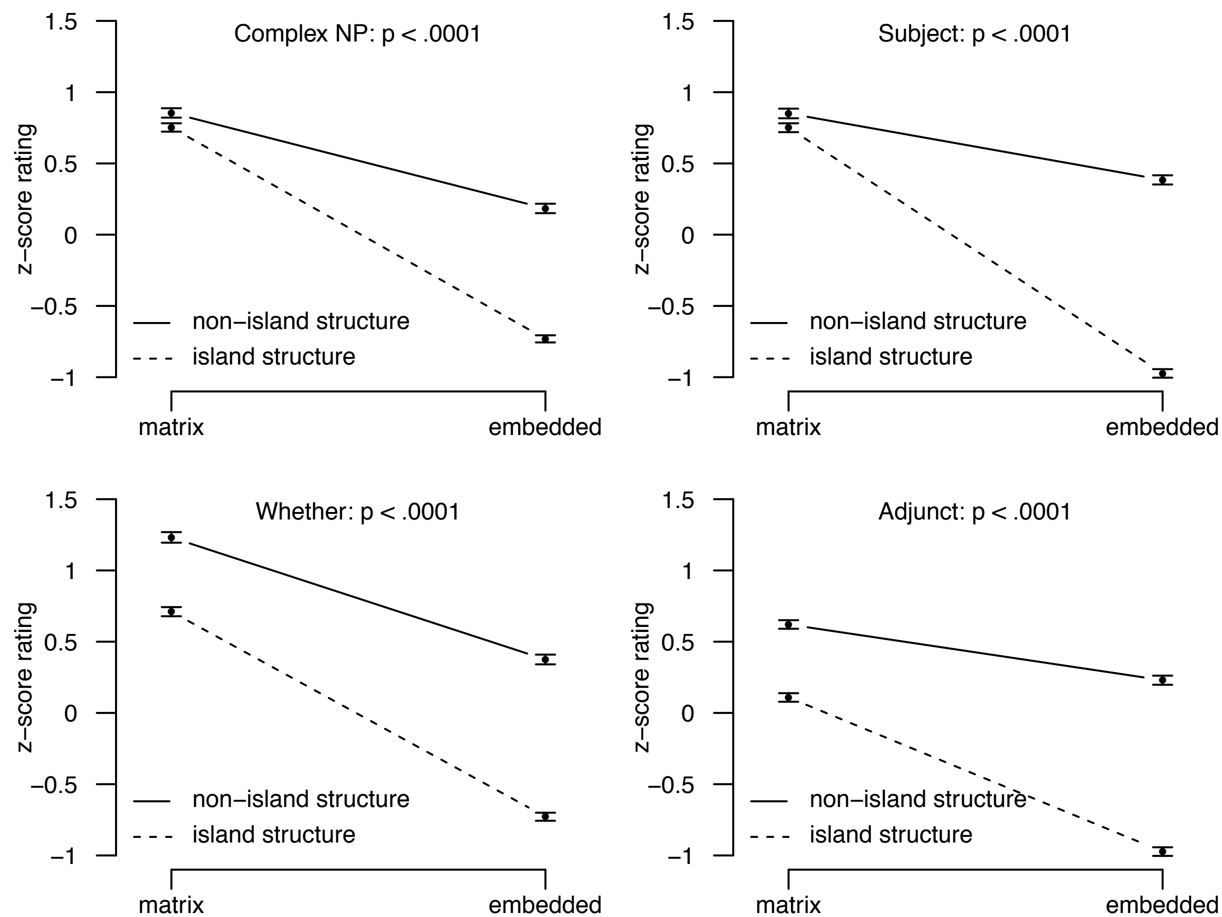
Characterizing the induction problem: Syntactic islands

target state: knowledge of grammatical and ungrammatical dependencies, as indicated by Sprouse et al. (2012) judgment data



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The data in the input

Data from five corpora of child-directed speech (Brown-Adam, Brown-Eve, Brown-Sarah, Suppes, Valian) from CHILDES (MacWhinney 2000): speech to 25 children between the ages of one and five years old.

Total words: 813,036

Utterances containing a *wh*-dependency: 31,247

Sprouse et al. (2012) stimuli types:

ungrammatical

	MATRIX + NON-ISLAND	EMBEDDED + NON-ISLAND	MATRIX + ISLAND	*EMBEDDED + ISLAND*
Complex NP	7	295	0	0
Subject	7	29	0	0
Whether	7	295	0	0
Adjunct	7	295	15	0

Pearl & Sprouse forthcoming

The data in the input

wh-dependency rarity

These kinds of utterances are fairly rare in general - the most frequent appears about 0.9% of the time (295 of 31,247).

Sprouse et al. (2012) stimuli types (**out of 31,247**):

ungrammatical

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Complex NP	7	295	0	0
Subject	7	29	0	0
Whether	7	295	0	0
Adjunct	7	295	15	0

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The data in the input

Being grammatical doesn't necessarily mean an utterance will appear in the input at all.

Sprouse et al. (2012) stimuli types (**out of 31,247**):

ungrammatical

	MATRIX + NON-ISLAND	EMBEDDED + NON-ISLAND	MATRIX + ISLAND	*EMBEDDED + ISLAND*
Complex NP	7	295	0	0
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Whether	7	295	0	0
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Pearl & Sprouse forthcoming

The data in the input

Unless the child is sensitive to very small frequencies, it's difficult to tell the difference between grammatical and ungrammatical dependencies sometimes…

Sprouse et al. (2012) stimuli types (**out of 31,247**):

ungrammatical

	MATRIX + NON-ISLAND	EMBEDDED + NON-ISLAND	MATRIX + ISLAND	*EMBEDDED + ISLAND*
Complex NP	7	295	0	0
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Pearl & Sprouse forthcoming

The data in the input

…and impossible to tell no matter what the rest of the time.

Sprouse et al. (2012) stimuli types (**out of 31,247**):

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Complex NP	7	295	0	0
Subject	7	29	0	0
Whether	7	295	0	0
Adjunct	7	295	15	0

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The data in the input

If children are relying only on direct evidence and keying grammaticality directly to frequency, this looks like an induction problem.

Sprouse et al. (2012) stimuli types (**out of 31,247**):

ungrammatical

	MATRIX + NON-ISLAND	EMBEDDED + NON-ISLAND	MATRIX + ISLAND	*EMBEDDED + ISLAND*
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Characterizing the induction problem: Syntactic islands

initial state:

Bias: Learn only from direct evidence.

data intake: examples of specific *wh*-dependencies in the input

target state: knowledge of grammatical and ungrammatical dependencies, as indicated by Sprouse et al. (2012) judgment data

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Building a computational learner

Idea: Use indirect positive evidence, too.

Similar in spirit to linguistic parameters: Data are deemed informative, even if they are not data about the specific phenomenon of interest.

Here: Dependencies other than the ones of interest (the Sprouse et al. 2012 stimuli) are useful to learn from.

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Characterizing the induction problem: Syntactic islands

initial state:

-Bias: Learn only from direct evidence.

+Bias: Learn from both direct and indirect evidence coming from *wh*-dependencies.

data intake: all *wh*-dependencies in the input

target state: knowledge of grammatical and ungrammatical dependencies, as indicated by Sprouse et al. (2012) judgment data

Pearl & Sprouse forthcoming

Building a computational learner

Learning Bias: Children track the occurrence of structures that can be derived from phrase structure trees during parsing - container nodes.

$[_{CP}$ Who did $[_{IP}$ she $[_{VP}$ like ___]]]?

IP VP

Container node sequence: IP-VP

$[_{CP}$ Who did $[_{IP}$ she $[_{VP}$ think $[_{CP}$ $[_{IP}$ $[_{NP}$ the gift] $[_{VP}$ was $[_{PP}$ from ___]]]]]]]]?

IP VP CP IP VP PP

Container node sequence: IP-VP-CP-IP-VP-PP

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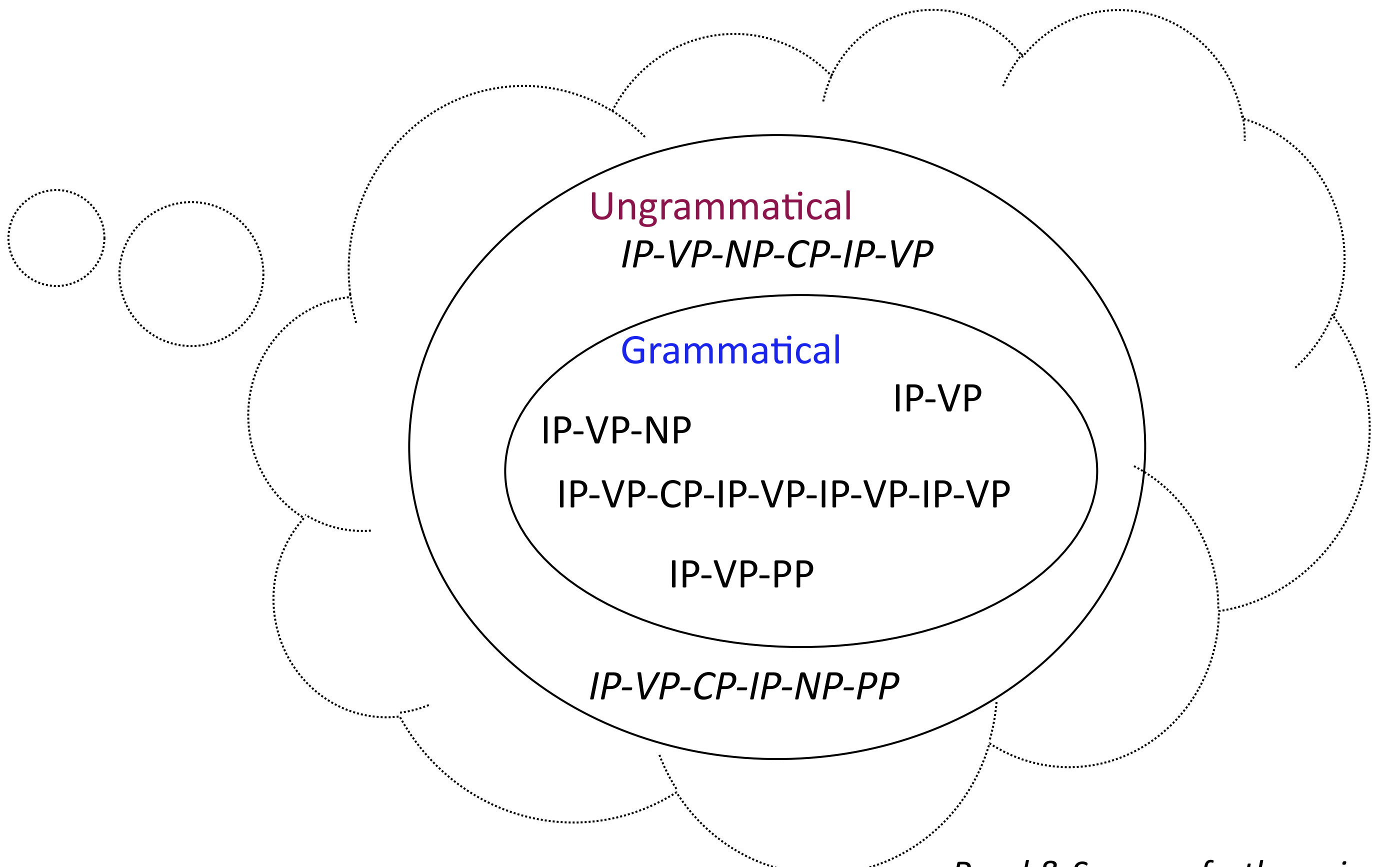
Building a computational learner

Children's hypotheses are about what container node sequences are grammatical for dependencies in the language.



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Characterizing the induction problem: Syntactic islands

initial state:

Bias: Learn from both direct and indirect evidence coming from *wh*-dependencies.

+Capability: Be able to parse data in the input into phrase structure trees.

+Bias: Characterize dependencies as sequences of container nodes.

data intake: all *wh*-dependencies in the input

target state: knowledge of grammatical and ungrammatical dependencies, as indicated by Sprouse et al. (2012) judgment data

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What does the target knowledge look like?

Sprouse et al. (2012) stimuli:

Complex NP islands		**Subject islands**
IP	matrix | non-island	IP
IP-VP-CP-IP-VP	embedded | non-island	IP-VP-CP-IP
IP	matrix | island	IP
*IP-VP-NP-CP-IP-VP	embedded | island	*IP-VP-CP-IP-NP-PP

All the ungrammatical dependencies are distinct from all the grammatical dependencies for these syntactic islands.

Pearl & Sprouse forthcoming

What does the target knowledge look like?

Sprouse et al. (2012) stimuli:

Whether islands

IP	matrix | non-island	
IP-VP-CP-IP-VP	embedded | non-island	
IP	matrix | island	
*IP-VP-CP-IP-VP	embedded | island	

Adjunct islands

IP
IP-VP-CP-IP-VP
IP
*IP-VP-CP-IP-VP

Pearl & Sprouse forthcoming

What does the target knowledge look like?

Sprouse et al. (2012) stimuli:

Whether islands		**Adjunct islands**
IP	matrix | non-island	IP
IP-VP-CP-IP-VP	embedded | non-island	IP-VP-CP-IP-VP
IP	matrix | island	IP
*IP-VP-CP-IP-VP	embedded | island	*IP-VP-CP-IP-VP

Uh oh - the ungrammatical dependencies look identical to some of the grammatical dependencies for these syntactic islands.

Pearl & Sprouse forthcoming

Building a computational learner

Learning bias solution:
Have CP container nodes be more specified for the learner:
Use the lexical head to subcategorize the CP container node.

CP_{null}, CP_{that}, $CP_{whether}$, CP_{if}, etc.

The learner can then distinguish between these structures:

IP-VP-$CP_{null/that}$-IP-VP
IP-VP-$CP_{whether/if}$-IP-VP

Pearl & Sprouse forthcoming

What does the target knowledge look like?

Sprouse et al. (2012) stimuli:

Complex NP islands

IP	matrix	non-island
IP-VP-CP$_{that}$-IP-VP	embedded	non-island
IP	matrix	island
*IP-VP-NP-CP$_{that}$-IP-VP	embedded	island

Subject islands

IP
IP-VP-CP$_{null}$-IP
IP
*IP-VP-CP$_{null}$-IP-NP-PP

All the ungrammatical dependencies are still distinct from all the grammatical dependencies for these syntactic islands.

Pearl & Sprouse forthcoming

What does the target knowledge look like?

Sprouse et al. (2012) stimuli:

Whether islands

IP	matrix	non-island
IP-VP-CP_{that}-IP-VP	embedded	non-island
IP	matrix	island
*IP-VP-$CP_{whether}$-IP-VP	embedded	island

Adjunct islands

IP
IP-VP-CP_{that}-IP-VP
IP
*IP-VP-CP_{if}-IP-VP

Now the ungrammatical dependencies are distinct from all the grammatical dependencies for these syntactic islands, too.

Pearl & Sprouse forthcoming

Characterizing the induction problem: Syntactic islands

initial state:

Bias: Learn from both direct and indirect evidence coming from *wh*-dependencies.

Capability: Be able to parse data in the input into phrase structure trees.

Bias: Characterize dependencies as sequences of container nodes.

+Bias: Subcategorize container nodes by CP lexical content.

data intake: all *wh*-dependencies in the input

target state: knowledge of grammatical and ungrammatical dependencies, as indicated by Sprouse et al. (2012) judgment data

Pearl & Sprouse forthcoming

Building a computational learner

Learning Bias: Implicitly assign a probability to a container node sequence by tracking trigrams of container nodes. A sequence's probability is the smoothed product of its trigrams.

Pearl & Sprouse forthcoming

Building a computational learner

Learning Bias: Implicitly assign a probability to a container node sequence by tracking trigrams of container nodes. A sequence's probability is the smoothed product of its trigrams.

$[_{CP}$ Who did $[_{IP}$ she $[_{VP}$ think $[_{CP}$ $[_{IP}$ $[_{NP}$ the gift] $[_{VP}$ was $[_{PP}$ from __]]]]]]]]?

IP VP CP_{null} IP VP PP

start-IP-VP-CP_{null}-IP-VP-PP-end =

start-IP-VP

IP-VP-CP_{null}

VP-CP_{null}-IP

CP_{null}-IP-VP

IP-VP-PP

VP-PP-end

Pearl & Sprouse forthcoming

Building a computational learner

Learning Bias: Implicitly assign a probability to a container node sequence by tracking trigrams of container nodes. A sequence's probability is the smoothed product of its trigrams.

[$_{CP}$ Who did [$_{IP}$ she [$_{VP}$ think [$_{CP}$ [$_{IP}$ [$_{NP}$ the gift] [$_{VP}$ was [$_{PP}$ from __]]]]]]]]?

IP VP CP_{null} IP VP PP

start-IP-VP-CP_{null}-IP-VP-PP-end =

start-IP-VP

IP-VP-CP_{null}

VP-CP_{null}-IP

CP_{null}-IP-VP

IP-VP-PP

VP-PP-end

Probability(IP-VP-CP_{null}-IP-VP-PP) = p(start-IP-VP-CP_{null}-IP-VP-PP-end)

= p(start-IP-VP) * p(IP-VP-CP_{null})*p(VP-CP_{null}-IP)*p(CP_{null}-IP-VP)

*p(IP-VP-PP)*p(VP-PP-end)

Pearl & Sprouse forthcoming

Building a computational learner

Learning Bias: Implicitly assign a probability to a container node sequence by tracking trigrams of container nodes. A sequence's probability is the smoothed product of its trigrams.

What this does:

• longer dependencies are less probable than shorter dependencies, all other things being equal

• individual trigram frequency matters: short dependencies made of infrequent trigrams will be less probable than longer dependencies made of frequent trigrams

Effect: the frequencies observed in the input can temper the detrimental effect of dependency length.

Pearl & Sprouse forthcoming

Characterizing the induction problem: Syntactic islands

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Capability: Be able to parse data in the input into phrase structure trees.

Bias: Characterize dependencies as sequences of container nodes.

Bias: Subcategorize container nodes by CP lexical content.

+Bias: Track trigrams of container nodes in the input.

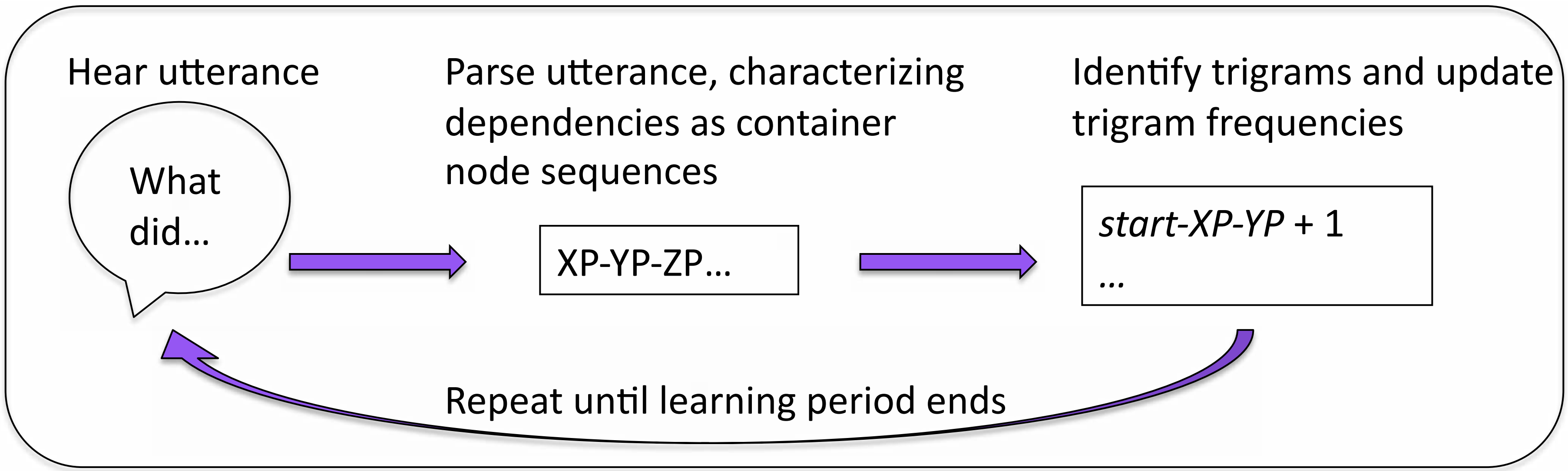
+Capability: Generate probability of *wh*-dependency from trigrams of container nodes characterizing it.

data intake: all *wh*-dependencies in the input

target state: knowledge of grammatical and ungrammatical dependencies, as indicated by Sprouse et al. (2012) judgment data

Pearl & Sprouse forthcoming

Learning process



Pearl & Sprouse forthcoming

Generating grammaticality preferences

Parse structure, characterizing dependencies as container node sequences

XP-YP-ZP…

Identify trigrams

start-XP-YP
XP-YP-ZP
…

Calculate probability of container node sequence from trigrams

Probability =
p(start-XP-YP) *
p(XP-YP-ZP) *
…

Pearl & Sprouse forthcoming

Building a computational learner: Empirical grounding

Child-directed speech (Brown-Adam, Brown-Eve, Suppes, Valian) from CHILDES:

What kind of dependencies are present?

76.7%	IP-VP	*What did you see __?*
12.8%	IP	*What __ happened?*
5.6%	IP-VP-IP-VP	*What did she want to do __?*
2.5%	IP-VP-PP	*What did she read from __?*
1.1%	IP-VP-CP_{null}-IP-VP	*What did she think he said __?*

…

Pearl & Sprouse forthcoming

Characterizing the induction problem: Syntactic islands

initial state:

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Capability: Be able to parse data in the input into phrase structure trees.

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data intake: all *wh*-dependencies in the input

target state: knowledge of grammatical and ungrammatical dependencies, as indicated by Sprouse et al. (2012) judgment data

Pearl & Sprouse forthcoming

Building a computational learner: Empirical grounding

Hart & Risley 1995: Children hear approximately one million utterances in their first three years.

Assumption: learning period for modeled learners is 3 years (ex: between 2 and 5 years old for modeling children's acquisition), so they would hear one million utterances.

Total learning period: 200,000 *wh*-dependency data points (*wh*-dependencies make up approximately 20% of the input)

Pearl & Sprouse forthcoming

Characterizing the induction problem: Syntactic islands

initial state:

Bias: Learn from both direct and indirect evidence coming from *wh*-dependencies.

Capability: Be able to parse data in the input into phrase structure trees.

Bias: Characterize dependencies as sequences of container nodes.

Bias: Subcategorize container nodes by CP lexical content.

Bias: Track trigrams of container nodes in the input.

Capability: Generate probability of *wh*-dependency from trigrams of container nodes characterizing it.

data intake: all *wh*-dependencies in the input

learning period: ~3 years = ~200,000 *wh*-dependency data points

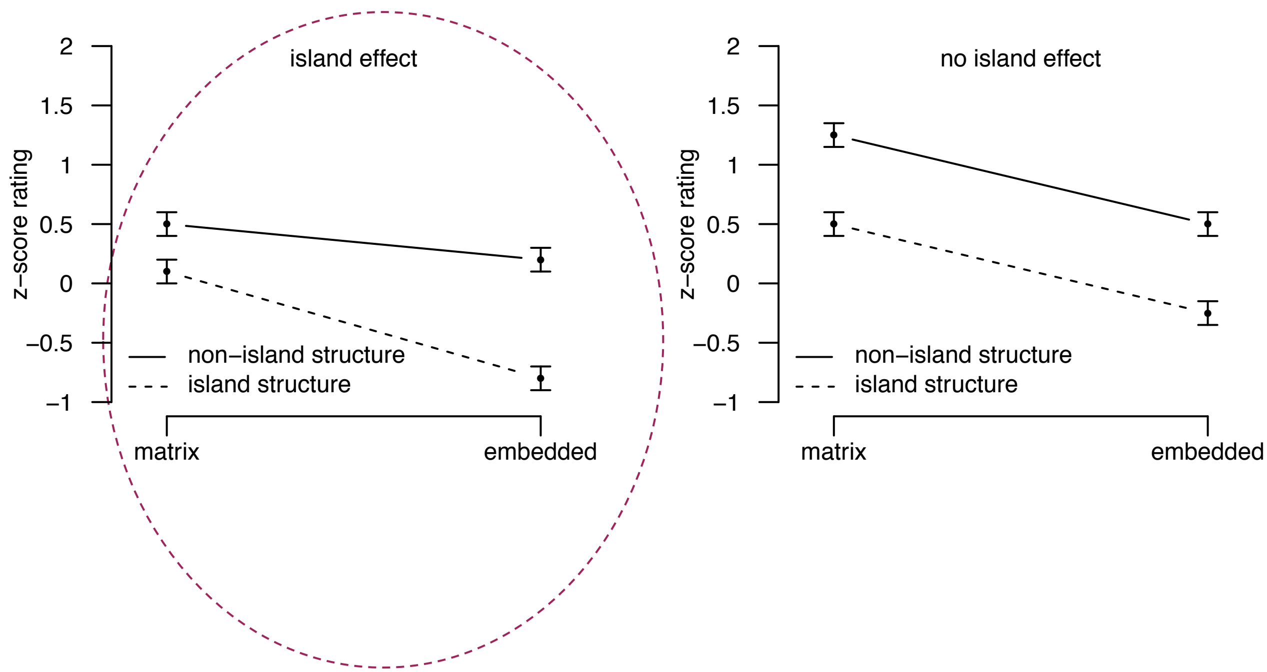
target state: knowledge of grammatical and ungrammatical dependencies, as indicated by Sprouse et al. (2012) judgment data

Pearl & Sprouse forthcoming

Success metrics

Compare learned grammaticality preferences to Sprouse et al. (2012) judgment data.

Then, for each island, we plot the predicted grammaticality preferences from the modeled learner on an interaction plot, using log probability of the dependency on the y-axis. Non-parallel lines indicate knowledge of islands.



Pearl & Sprouse forthcoming

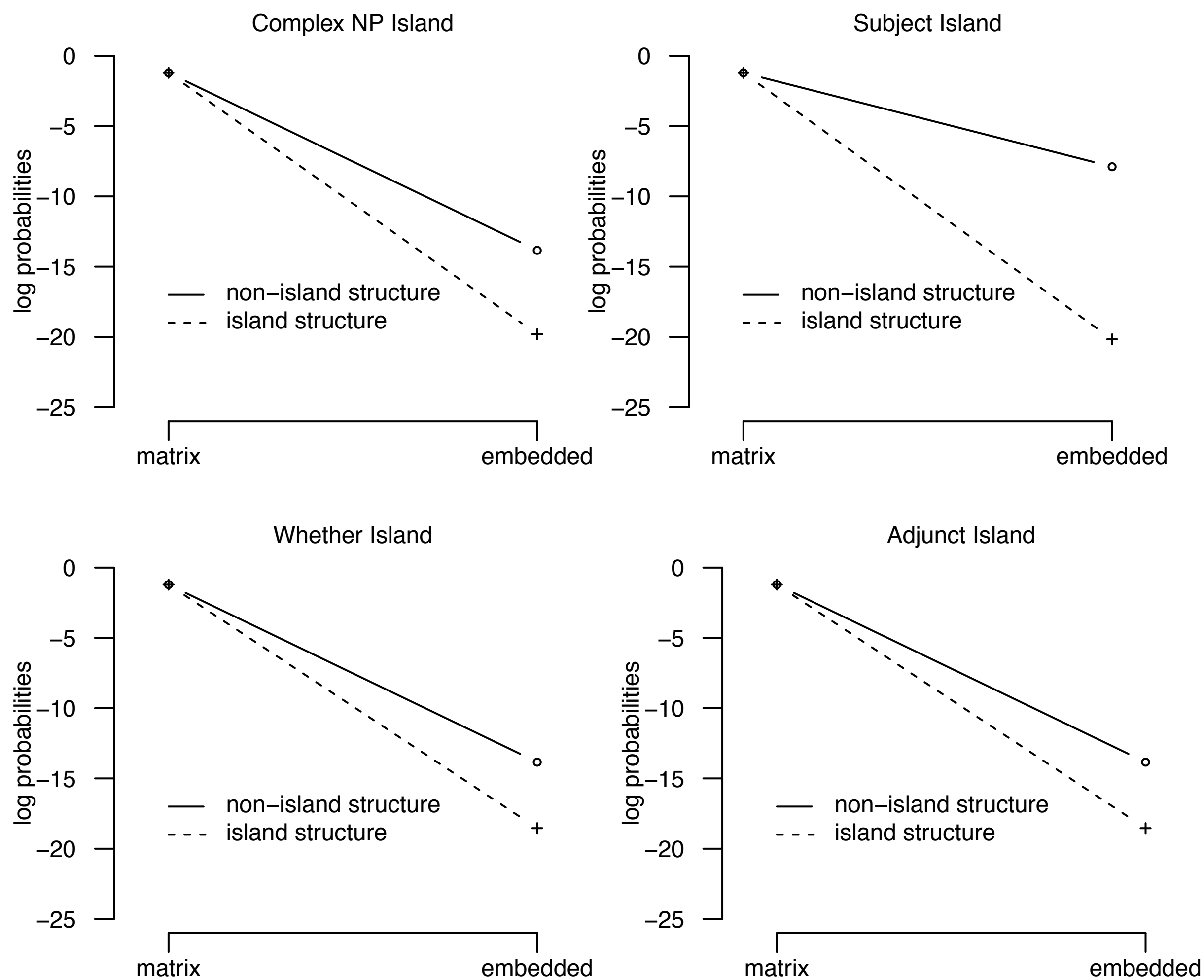
Learning results

Superadditivity observed for all four islands:

This learner has knowledge of these syntactic islands!

That means this learner can solve this induction problem.

Now…what did it need to do so?



Pearl & Sprouse forthcoming

Proposed learning biases/capabilities

Several learning biases/capabilities are potentially both innate and domain-specific.

	Innate	Derived	Domain-specific	Domain-general
Learn from all *wh*-dependencies	?	?	*	
Parse data into phrase structure trees	?	?	*	
Attend to container nodes & subcategorize by CP	?	?	*	
Extract & track container node trigrams	*			*
Calculate dependency probability from trigrams	*			*

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Learn from all *wh*-dependencies	?	?	*	

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Learn from all *wh*-dependencies	?	?	*	

Clearly domain-specific, since this is language data.

May seem reasonable to attend to *wh*-dependency data when learning about *wh*-dependencies (and so this would be derived)

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Learn from all *wh*-dependencies	?	?	*	

Clearly domain-specific, since this is language data.

May seem reasonable to attend to *wh*-dependency data when learning about *wh*-dependencies (and so this would be derived)

…but then why not attend to *all* dependencies (ex: relative clause dependencies, binding dependencies) since *wh*-dependencies are a kind of dependency?

Empirical necessity of just using *wh*-dependency data:
There are different island effects for relative clauses (Sprouse et al. submitted) and no island effects for binding dependencies, so the learner needs to know to pay attention just to *wh*-dependencies.

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Parse data into phrase structure trees	?	?	*	

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Parse data into phrase structure trees	?	?	*	

Clearly domain-specific, since the structure is specific to language.

May be possible to bootstrap this information (acquiring syntactic categories: Mintz 2003, 2006; acquisition of hierarchical structure given syntactic categories as input: Klein & Manning 2002). If so, this would be derived…

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Parse data into phrase structure trees	?	?	*	

Clearly domain-specific, since the structure is specific to language.

May be possible to bootstrap this information (acquiring syntactic categories: Mintz 2003, 2006; acquisition of hierarchical structure given syntactic categories as input: Klein & Manning 2002). If so, this would be derived…

…but it's currently unclear if all the necessary phrase structure knowledge can be bootstrapped.

Important:
The need for this capability is not specific to learning islands – it's (presumably) needed for learning any kind of syntactic knowledge.

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Attend to container nodes & subcategorize by CP	?	?	*	

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Attend to container nodes & subcategorize by CP	?	?	*	

Identifying container nodes

- applies to language data: domain-specific
- derived from ability to parse utterances

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Attend to container nodes & subcategorize by CP	?	?	*	

Identifying container nodes

- applies to language data: domain-specific
- derived from ability to parse utterances

Attending to container nodes (among all the other data out there)

- applies to language data: domain-specific
- innate vs. derived?
  - could be specified innately (like bounding nodes)
  - could be derived from a bias to use representations that are already being used for parsing

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Attend to container nodes & **subcategorize by CP**	?	?	*	

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Attend to container nodes & **subcategorize by CP**	?	?	*	

About a linguistic representation: domain-specific

Innate vs. derived?

- Could be specified innately

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Attend to container nodes & **subcategorize by CP**	?	?	*	

About a linguistic representation: domain-specific

Innate vs. derived?

- Could be specified innately

- Could be derived from prior linguistic experience:

    - Uncontroversial to assume children learn to distinguish different types of CPs since the lexical content of CPs has substantial consequences for the semantics of a sentence.

    - Also, adult speakers are sensitive to the distribution of *that* versus null complementizers (Jaeger 2010).

…but still have to know this is the right thing to subcategorize.

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Extract & track container node trigrams	*			*

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Extract & track container node trigrams	*			*

Applied in different cognitive domains: domain-general

Likely innate – learning with sequences of three units (transitional probabilities: Saffran et al. 1996, Aslin et al. 1998, Graf Estes et al. 2007, Pelucchi et al. 2009a, Pelucchi et al. 2009b; frequent frames for grammatical categorization: Mintz 2006, Wang & Mintz 2008)

…though why trigrams instead of some other n-gram?

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Calculate dependency probability from trigrams	*			*

Pearl & Sprouse forthcoming

	Innate	Derived	Domain-specific	Domain-general
Calculate dependency probability from trigrams	*			*

Applied in different cognitive domains: domain-general

Likely innate

Pearl & Sprouse forthcoming

Main implications of this learner

(1) Even though there is an induction problem for these syntactic islands, it may not require Universal Grammar learning biases to solve it.

	Innate	Derived	Domain-specific	Domain-general
Learn from all *wh*-dependencies	?	?	*	
Parse data into phrase structure trees	*?*	*?*	***	
Attend to container nodes & subcategorize by CP	?	?	*	
Extract & track container node trigrams	*			*
Calculate dependency probability from trigrams	*			*

Pearl & Sprouse forthcoming

Main implications of this learner

(2) Even if Universal Grammar learning biases are required, they are different from (and less specific than) the biases previously proposed.

In particular, while one bias also specifies a particular linguistic representation, there is no bias defining the "constraint". This falls out from the other non-UG learning biases.

	Innate	Derived	Domain-specific	Domain-general
Learn from all *wh*-dependencies	?	?	*	
Attend to container nodes & subcategorize by CP	?	?	*	
vs.				
Attend to bounding nodes (BNs)	*			*
Dependencies crossing 2+ BNs are not allowed	*			*

Pearl & Sprouse forthcoming

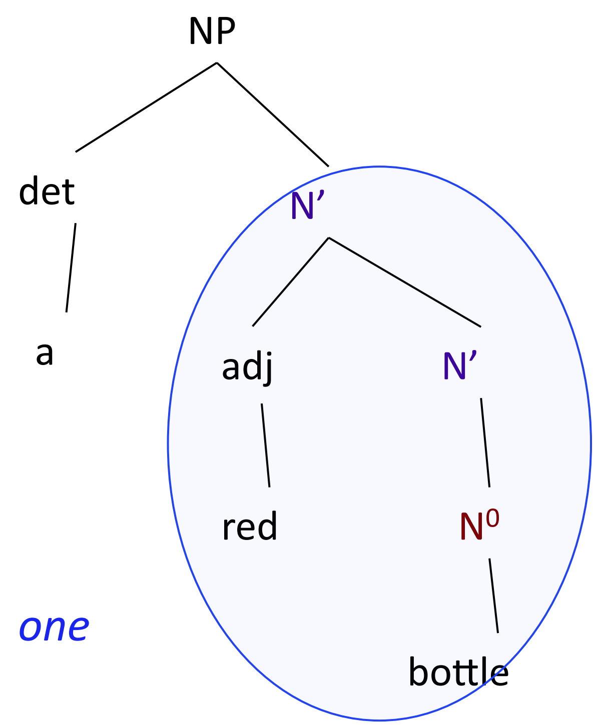
Road Map

I. Potential induction problem:

✓ Learning constraints on long-distance dependencies

II. Potential induction problem:

Learning English anaphoric *one*



English anaphoric *one*

Look - a red bottle!

Pearl & Mis submitted

English anaphoric *one*

Look - a red bottle!

Do you see another *one*?

Pearl & Mis submitted

English anaphoric *one*

Look - a red bottle!

red bottle

Do you see another *one*?

Process: First determine the antecedent of *one* (what string *one* is referring to).
→"red bottle"

Pearl & Mis submitted

English anaphoric *one*

Look - a red bottle!

red bottle

Do you see another *one*?

Process: Because the antecedent ("red bottle") includes the modifier "red", the property RED is important for the referent of *one* to have.

→ referent of *one* = RED BOTTLE

Pearl & Mis submitted

English anaphoric *one*

Look - a red bottle!

Do you see another *one*?

Two steps:

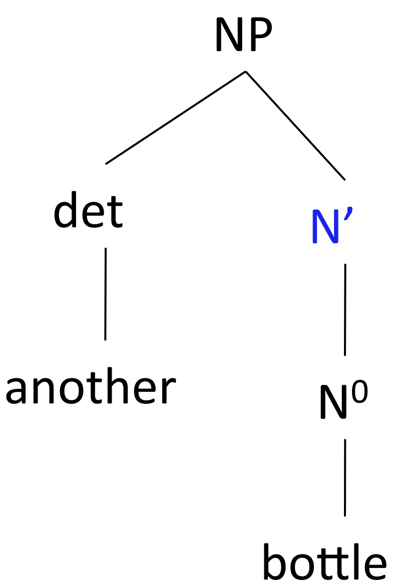
(1) Identify syntactic antecedent

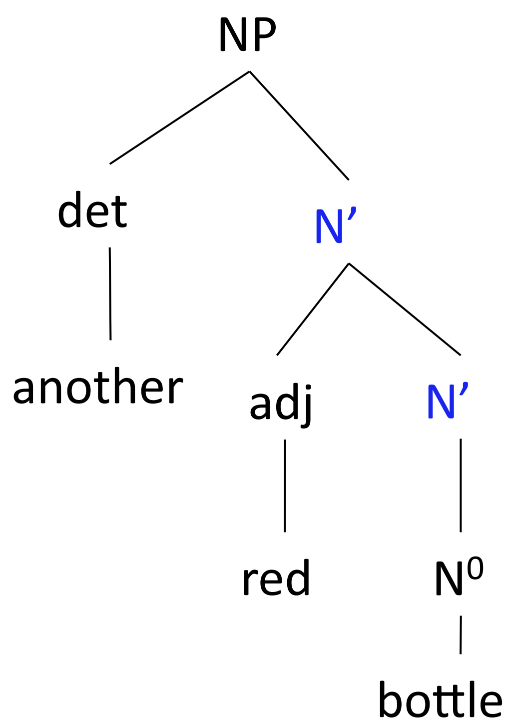
(2) Identify semantic referent (based on syntactic antecedent)

Pearl & Mis submitted

Anaphoric *one*: Syntactic category

Standard linguistic theory (Chomsky 1970, Jackendoff 1977) posits that *one* in these kind of utterances is a syntactic category smaller than an entire noun phrase (NP), but larger than just a noun (N^0). This category is N'. This category includes strings like "bottle" and "red bottle".





$[_{NP}\text{ another }[_{N'}\,[_{N0}\text{ bottle}]]]$

$[_{NP}\text{ another }[_{N'}\text{ red }[_{N'}\,[_{N0}\text{ bottle}]]]]$

Pearl & Mis submitted

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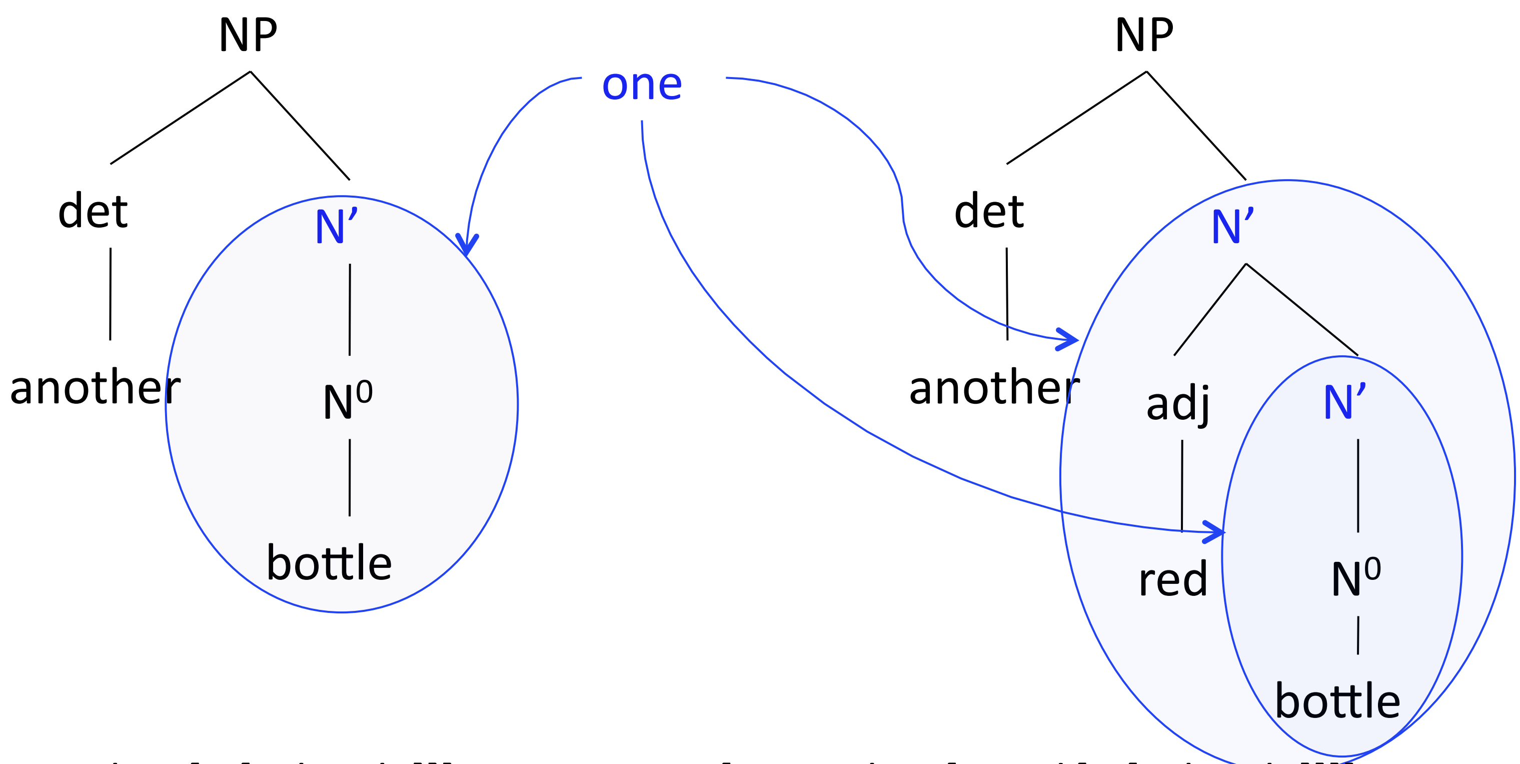


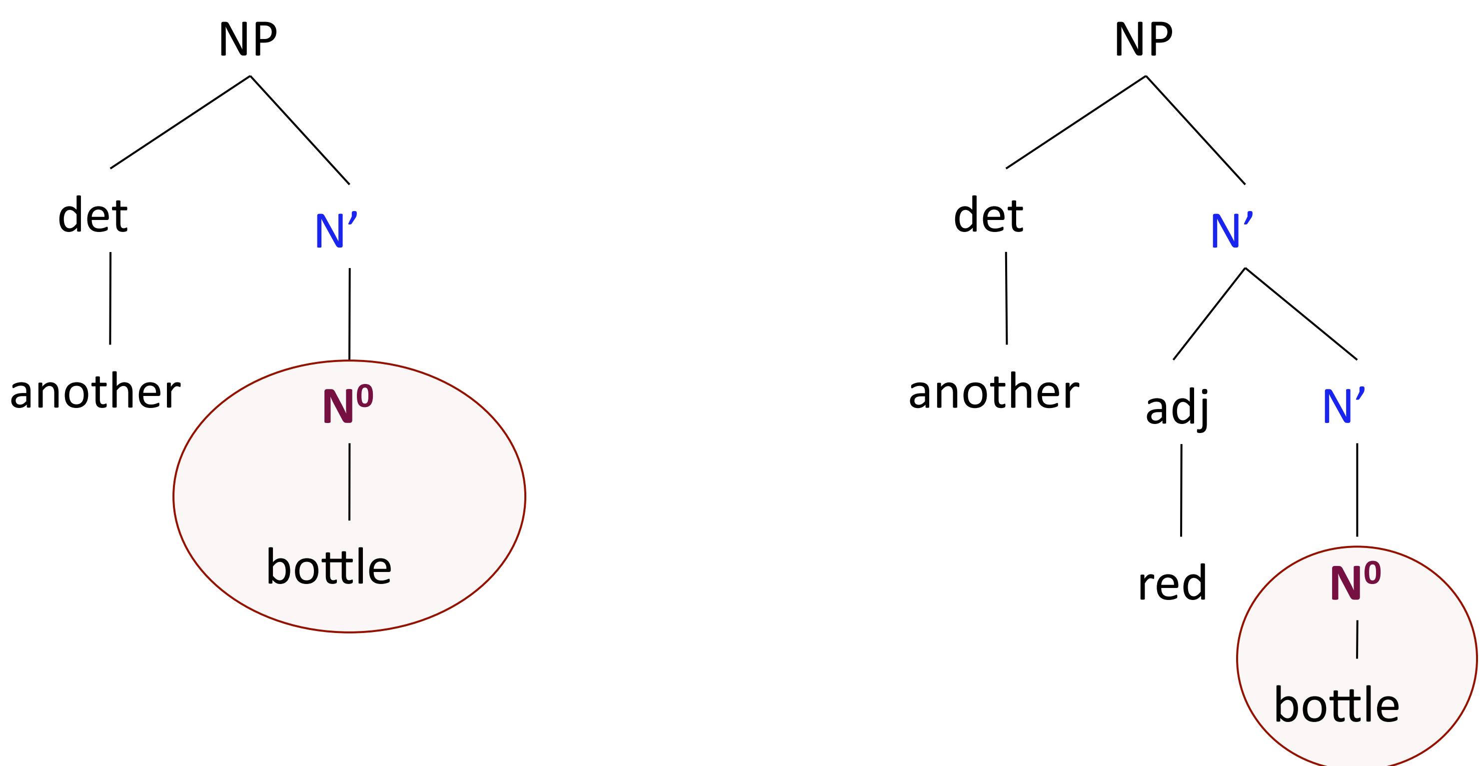
$[_{NP}$ another $[_{N'}$ $[_{N0}$ bottle]]]

$[_{NP}$ another $[_{N'}$ red $[_{N'}$ $[_{N0}$ bottle]]]]

Pearl & Mis submitted

Anaphoric *one*: Syntactic category

Importantly, *one* is not N^0. If it was, it could only have strings like "bottle" as its antecedent, and could never have strings like "red bottle" as its antecedent.



$[_{NP}$ another $[_{N'}$ $[_{N0}$ bottle$]]]$

$[_{NP}$ another $[_{N'}$ red $[_{N'}$ $[_{N0}$ bottle$]]]]$

Pearl & Mis submitted

Anaphoric *one*: Interpretations based on syntactic category

If *one* was N^0, we would have a different interpretation of

"Look – a red bottle!  Do you see another one?"  

Because *one*'s antecedent could only be "bottle", we would have to interpret the second part as "Do you see another *bottle*?" and the purple bottle would be a fine referent for *one*.

Since *one*'s antecedent is "red bottle", and "red bottle" cannot be N^0, *one* must not be N^0.

Pearl & Mis submitted

Anaphoric *one*: Adult knowledge

"Look – a red bottle! Look, there's another one!"

≈ "Look – a red bottle! Look, there's another red bottle!"

Target state:

Syntactic knowledge: category N'

Semantic knowledge: mentioned property ("red") is included in the linguistic antecedent (antecedent = "red bottle")

Pearl & Mis submitted

Anaphoric *one*: Children's knowledge

Lidz, Waxman, & Freedman (2003) [LWF] found that 18-month-olds have a preference for the red bottle in the same situation.

"Look – a red bottle! Do you see another one?"

LWF interpretation & conclusion:

Preference for the RED BOTTLE means the preferred syntactic antecedent is "red bottle".

Pearl & Mis submitted

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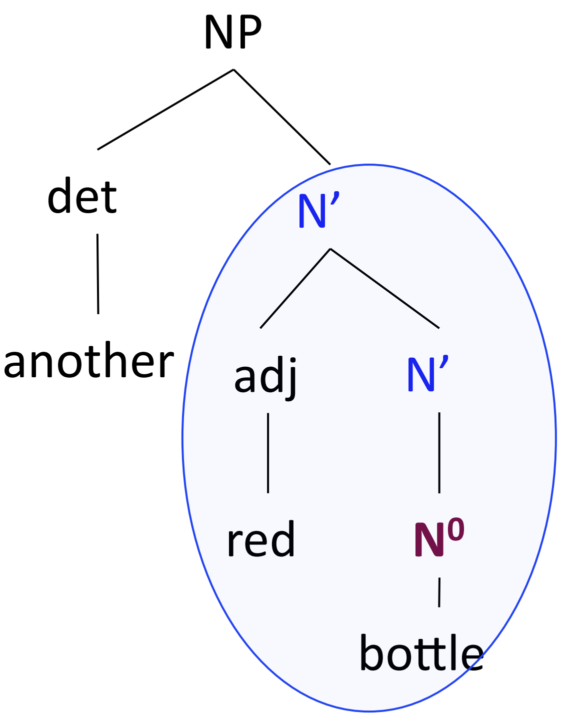


LWF concluded that 18-month-old knowledge =

syntactic category of *one* = N'

syntactic antecedent when modifier is present (i.e., property is mentioned) includes modifier (e.g., "red") = referent has modifier property

Learning period = completed by 18 months

Pearl & Mis submitted

Characterizing the induction problem: English anaphoric *one*

initial state:

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

Bias: Only direct evidence of *one* is useful.

Bias: Only unambiguous evidence of *one* is useful (Baker 1978).

data intake:

All unambiguous *one* evidence in the input.

learning period:

Completed by 18 months (LWF 2003)

target state:

One is category N' and its antecedent includes the mentioned modifier when present.

Behavior signal: Generate adult interpretation in utterances with mentioned modifier ("Look – a red bottle. Do you see another one?")

Pearl & Mis submitted

Anaphoric *one*: The available data

Acquisition: Children must learn the right syntactic category for *one*, and the right interpretation preference for *one* in situations with more than one option.

Pearl & Mis submitted

Anaphoric *one*: The available data

Acquisition: Children must learn the right syntactic category for *one*, and the right interpretation preference for *one* in situations with more than one option.

Problem: Unambiguous data are rare (<0.25%: LWF 2003, 0.00%: Pearl & Mis submitted)

Unambiguous (UNAMB) data:

"Look – a red bottle! Hmmm - there doesn't seem to be another one here, though."

one's referent = BOTTLE? If so, *one*'s antecedent = "bottle".

But it's strange to claim there's not another *bottle* here.

So, *one*'s referent must be RED BOTTLE, and *one*'s antecedent = $[_{N'}$ red$[_{N'}[_{N0}$ bottle$]]]$.

Pearl & Mis submitted

Anaphoric *one*: The available data

Acquisition: Children must learn the right syntactic category for *one*, and the right interpretation preference for *one* in situations with more than one option.

Problem: Most data children encounter are ambiguous.

Syntactically (SYN) ambiguous data:

"Look – a bottle! Oh, look – another one."

one's referent = BOTTLE

one's antecedent = $[_{N'}[_{N0}$ bottle$]]$ or $[_{N0}$ bottle$]$?

Pearl & Mis submitted

Anaphoric *one*: The available data

Acquisition: Children must learn the right syntactic category for *one*, and the right interpretation preference for *one* in situations with more than one option.

Problem: Most data children encounter are ambiguous.

Semantically and syntactically (SEM-SYN) ambiguous:

"Look – a red bottle! Oh, look – another one."

one's referent = RED BOTTLE or BOTTLE?

one's antecedent = $[_{N'}\text{ red}[_{N'}[_{N0}\text{ bottle}]]]$ or $[_{N'}[_{N0}\text{ bottle}]]$ or $[_{N0}\text{ bottle}]$?

Pearl & Mis submitted

Previous learning strategies

Update the initial state

Baker (1978) (also Hornstein & Lightfoot 1981, Lightfoot 1982, Hamburger & Crain 1984, Crain 1991): Only unambiguous data are informative. Because they're so rare, they can't be responsible for the acquisition of *one*.

How then?

Children have innate, domain-specific knowledge restricting the hypotheses about *one*: *one* cannot be syntactic category N^0.

What about when there are multiple N' antecedents?

$[_{N'}$ red$[_{N'}[_{N0}$ bottle$]]]$ or $[_{N'}[_{N0}$ bottle$]]$?

(No specific proposal for this.)

Pearl & Mis submitted

Previous learning strategies

Update the initial state

Baker (1978) [**DirectUnamb**]

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

Bias: Only direct evidence of *one* is useful.

Bias: Only unambiguous evidence of *one* is useful (Baker 1978).

+ (UG) Knowledge: *one* is not N^0.

Successful at solving induction problem w.r.t syntactic category.

Pearl & Mis submitted

Previous learning strategies

Update the initial state

Regier & Gahl 2004 [**R&G**]: Sem-Syn ambiguous data can be leveraged, in addition to using unambiguous data.

"Look – a red bottle! Oh, look – another one!"

How?

Use innate domain-general statistical learning abilities (Bayesian inference) to track how often *one*'s referent has the mentioned property (e.g. *red*). If the referent often has the property (RED BOTTLE), this is a **suspicious coincidence** unless the antecedent really does include the modifier ("red bottle") and *one*'s category is N'.

$[_{N'}$ red$[_{N'}[_{N0}$ bottle$]]]$

Pearl & Mis submitted

Previous learning strategies

Update the initial state

Regier & Gahl 2004 [**R&G**]

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

Bias: Only direct evidence of *one* is useful.

- Bias: Only unambiguous evidence of one is useful (Baker 1978).

+ Bias: Use Bayesian inference.

Successful at solving induction problem.

Pearl & Mis submitted

Previous learning strategies

Update the initial state

Pearl & Lidz 2009 [**P&L**]: Syn ambiguous data must not be leveraged, even if Sem-Syn and unambiguous data are used.

"Look – a bottle! Oh, look – another one!'

Why?

These data cause an "equal-opportunity" (EO) probabilistic learner to think *one*'s category is N^0.

$[_{N0}$ bottle$]$

How?

P&L propose a domain-specific learning bias to ignore just these ambiguous data, though they speculate how this bias could be derived from an innate domain-general preference for learning when there is local uncertainty.

Pearl & Mis submitted

Previous learning strategies

Update the initial state

Pearl & Lidz 2009 [**R&G in practice, Equal Opportunity = DirectEO**]

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

Bias: Only direct evidence of *one* is useful.

- *Bias: Only unambiguous evidence of one is useful (Baker 1978).*

+ Bias: Use Bayesian inference.

Not successful at solving induction problem.

Pearl & Mis submitted

Previous learning strategies

Update the initial state

Pearl & Lidz 2009 [**R&G intended, P&L filtered = DirectFiltered**]

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

Bias: Only direct evidence of *one* is useful.

- *Bias: Only unambiguous evidence of one is useful (Baker 1978).*

+ Bias: Use Bayesian inference.

+ (UG?) Bias: Ignore Syn ambiguous data.

Successful at solving induction problem.

Pearl & Mis submitted

A new strategy: Using indirect positive evidence

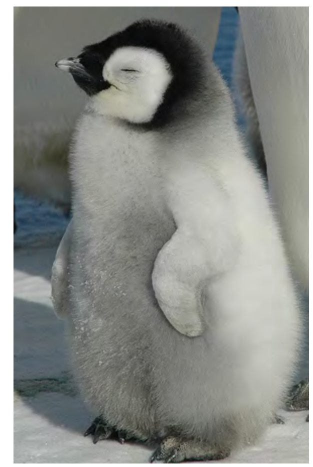
Pearl & Mis (2011, submitted) [**+OtherPro**]: Other words in the language can also be used anaphorically: *him, her, it, …*

Look at the cute penguin. I want to hug it.

$[_{NP}$ the $[_{N'}$ cute $[_{N'}$ $[_{N0}$ penguin$]]]]$ → $[_{NP}$ it$]$

Look! A cute penguin. I want one.

$[_{NP}$ a $[_{N'}$ cute $[_{N'}$ $[_{N0}$ penguin$]]]]$ → $[_{NP}$ one$]$



Note: The issue of *one*'s category only occurs when *one* is used in a syntactic environment that indicates it is smaller than an NP (<NP).

Pearl & Mis submitted

A new strategy: Using indirect positive evidence

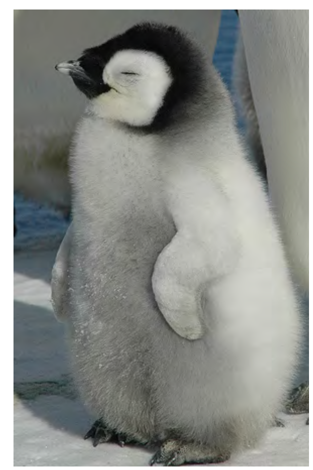
Pearl & Mis (2011, submitted) [**+OtherPro**]: Track how often the referent of the anaphoric element *(one, him, her, it*, etc.) has the property mentioned in the potential antecedent, using innate domain-general statistical learning abilities (Bayesian inference).

Important: This applies, even when the syntactic category is known.

Look at the cute penguin. I want to hug it.

Look! A cute penguin. I want one.

Is the referent cute? Yes!
So the antecedent includes the modifier "cute".



Pearl & Mis submitted

A new strategy:
Using indirect positive evidence

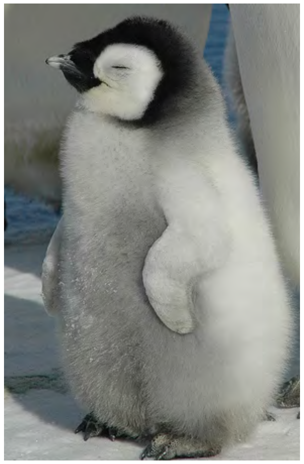
Pearl & Mis (2011, submitted) [**+OtherPro**]: Track how often the referent of the anaphoric element *(one, him, her, it*, etc.) has the property mentioned in the potential antecedent, using innate domain-general statistical learning abilities (Bayesian inference).

Important: This applies, even when the syntactic category is known.

Look at the cute penguin. I want to hug it.

Look! A cute penguin. I want one.

These kind of data points will always include the modifier in the antecedent, since the category of the pronoun is NP and so the antecedent is the entire NP. These data are unambiguous: The referent must have the mentioned property & the antecedent must include the modifier corresponding to that property.



Pearl & Mis submitted

A new strategy:
Using indirect positive evidence

Pearl & Mis (2011, submitted) [**+OtherPro**]

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

- *Bias: Only direct evidence of one is useful.*
- *Bias: Only unambiguous evidence of one is useful (Baker 1978).*

+ Bias: Use Bayesian inference.

+ (UG?) Bias: Learn from other pronoun data.

Successful at solving induction problem?

Pearl & Mis submitted

Data set comparisons

Unamb <NP
"Look – a red bottle! Hmmm - there doesn't seem to be another *one* here, though."

Learners: DirectUnamb, DirectFiltered, DirectEO, +OtherPro

Sem-Syn Amb
"Look – a red bottle! Oh, look – another *one*!"

Learners: DirectFiltered, DirectEO, +OtherPro

Syn Amb
"Look – a bottle! Oh, look – another *one*!"

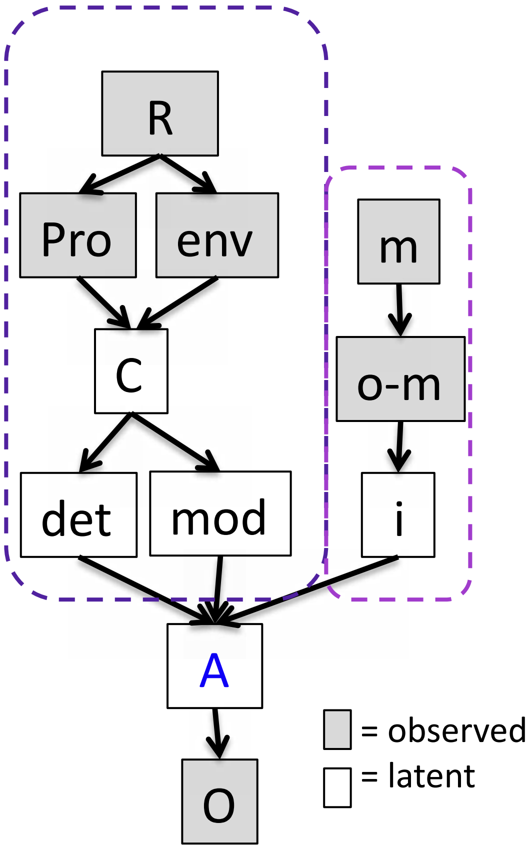
Learners: DirectEO, +OtherPro

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

Learners: +OtherPro

Pearl & Mis submitted

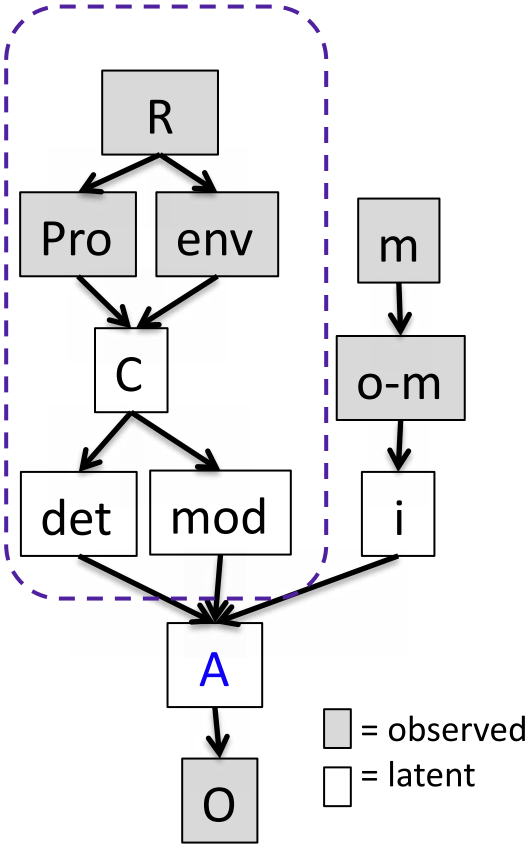
Information in the data



Understanding a referential expression

Includes both syntactic and semantic/referential information, since both are used to determine the linguistic antecedent.

Pearl & Mis submitted



Information in the data

“Look, a red bottle! Look, another one!”

Syntactic information

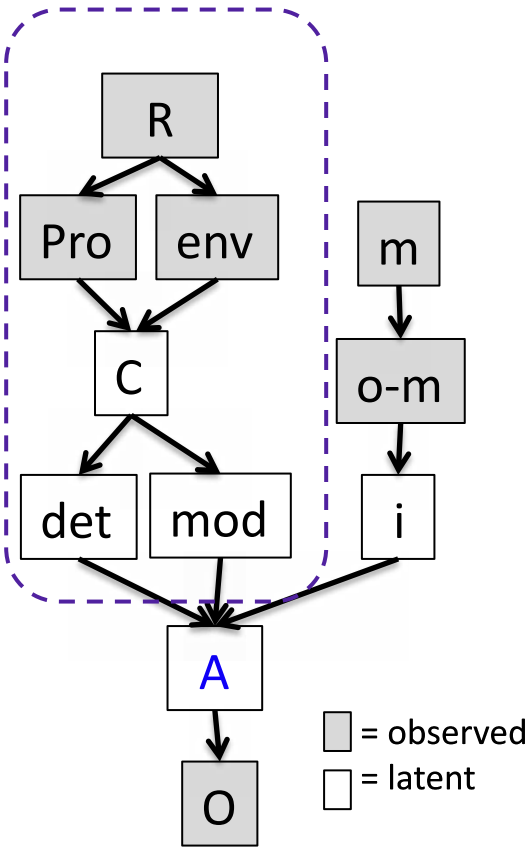
R = referential expression used
ex: “another one”

Pro = pronoun used in referential expression
ex: “one”

env = smaller than NP?
ex: yes

Pearl & Mis submitted

Information in the data



"Look, a red bottle! Look, another one!"

Syntactic information

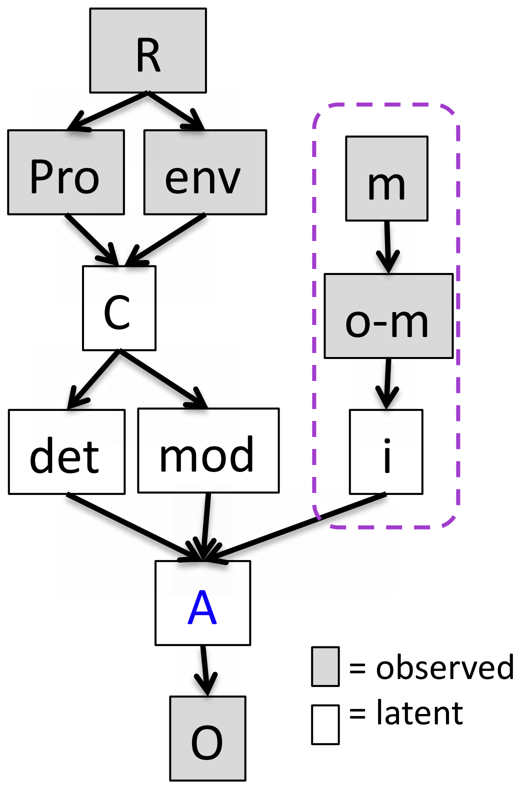
C = syntactic category of pronoun used (= syntactic category of linguistic antecedent)
ex: N'

det = antecedent includes determiner?
ex: no

mod = antecedent includes modifier?
ex: yes

Pearl & Mis submitted

Information in the data



"Look, a red bottle! Look, another one!"

Semantic/referential information

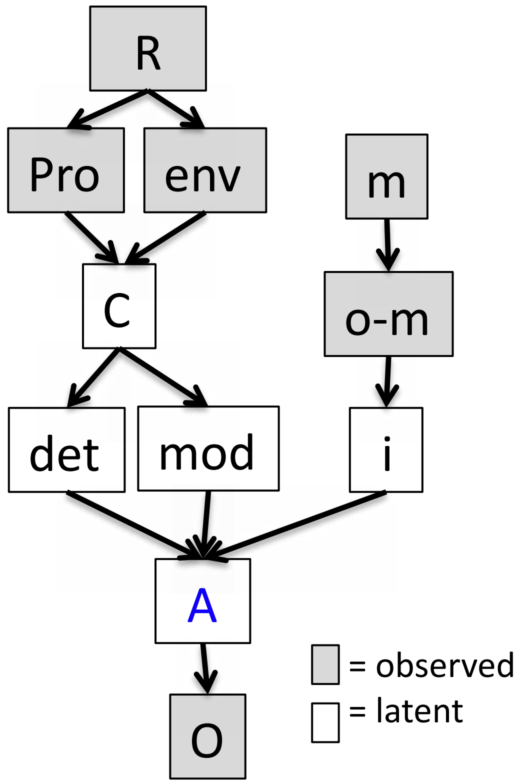
m = property mentioned in previous linguistic context
ex: yes

o-m = referent (object) in current context has mentioned property
ex: yes

i = mentioned property is included in antecedent?
ex: yes

Pearl & Mis submitted

Information in the data



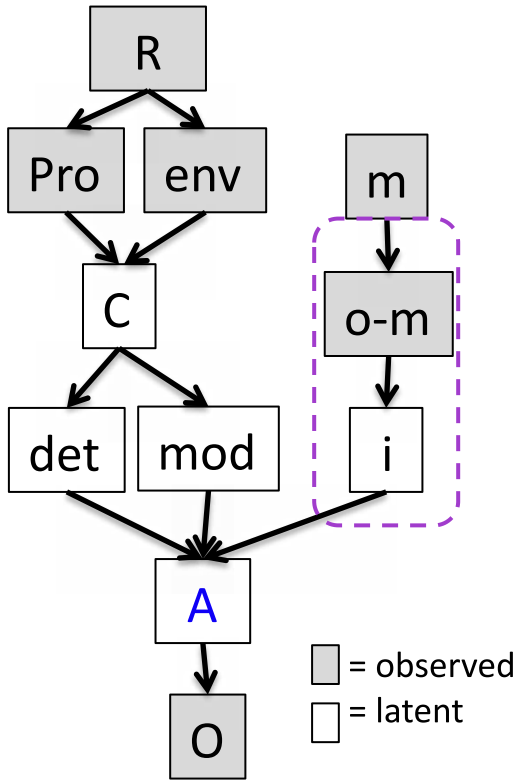
"Look, a red bottle! Look, another one!"

A = antecedent
ex: "red bottle"
(depends on both syntactic information of det and mod, and semantic/referential information from i.)

O = intended object (learner can usually observe this)
ex: RED BOTTLE

Pearl & Mis submitted

The online probabilistic learning framework



semantic/referential knowledge

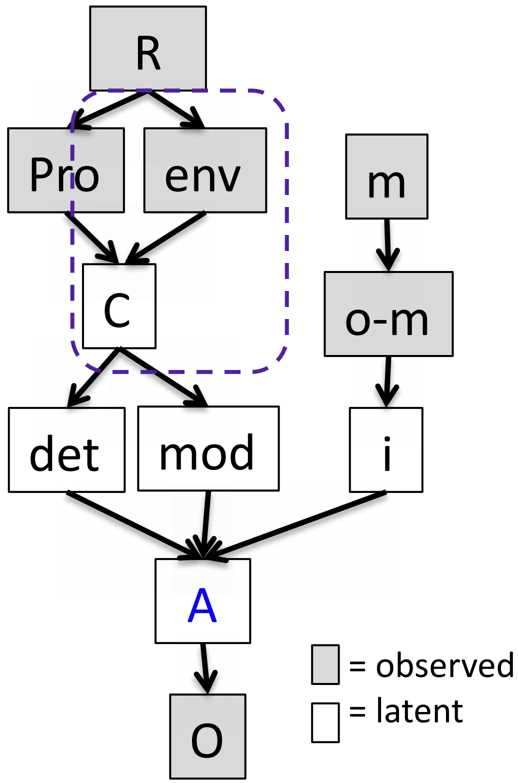
When an object has the property mentioned in the potential antecedent (o-m=yes), track the probability that the property is included in the antecedent (i=yes):

p_{incl} = p(i=yes | o-m=yes)

Two values: (i=yes or i=no)

Pearl & Mis submitted

The online probabilistic learning framework



syntactic knowledge

When the syntactic environment indicates the category is smaller than NP (env=<NP), track the probability that the syntactic category is N' (C=N'):

$p_{N'}$ = p(C=N' | env=<NP)

Two values: (C=N' or C=N^0)

Pearl & Mis submitted

The online probabilistic learning framework

General form of online update equations for p_x (adapted from Chew 1971):

data seen suggesting x is true

$$p_x = \frac{\alpha + data_x}{\alpha + \beta + totaldata_x}, \alpha = \beta = 1$$

A very weak prior

total informative data seen w.r.t x

After every informative data point encountered:

$$data_x = data_x + \phi_x$$

Incremented by probability that data point suggests x is true

$$totaldata_x = totaldata_x + 1$$

One informative data point seen

Pearl & Mis submitted

Corpus analysis & learner input

Brown/Eve corpus (CHILDES: MacWhinney 2000)

17,521 utterances of child-directed speech, 2874 referential pronoun utterances

Unamb <NP	0.00%
Sem-Syn Amb	0.66%
Syn Amb	7.52%
Unamb NP	8.42%
Uninformative	83.4%

Pearl & Lidz 2009: Children learn *one*'s representation between 14 and 18 months.

Based on estimates of the number of utterances children hear from birth until 18 months (Akhtar et al., 2004), we can calculate the data distribution in their input (36,500 referential pronoun utterances total).

Pearl & Mis submitted

Corpus analysis & learner input

Brown/Eve corpus (CHILDES: MacWhinney 2000)

17,521 utterances of child-directed speech, 2874 referential pronoun utterances

		DirectUnamb	DirectFiltered	DirectEO	+OtherPro
Unamb <NP	0.00%	0	0	0	0
Sem-Syn Amb	0.66%	0	242	242	242
Syn Amb	7.52%	0	0	2743	2743
Unamb NP	8.42%	0	0	0	3073
Uninformative	83.4%	36500	36258	33515	30442

Pearl & Lidz 2009: Children learn *one*'s representation between 14 and 18 months.

Based on estimates of the number of utterances children hear from birth until 18 months (Akhtar et al., 2004), we can calculate the data distribution in their input (36,500 referential pronoun utterances total).

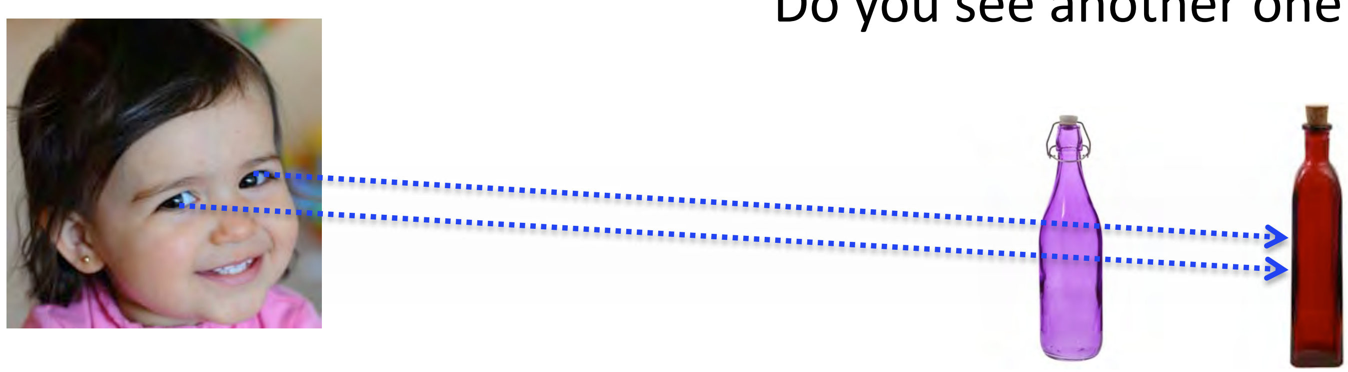
Pearl & Mis submitted

Measures of success: Children's behavior

In addition to directly assessing p_{incl} and $p_{N'}$, we can measure how often a learner would reproduce the behavior in the LWF experiment (p_{beh}).

Look – a red bottle!

Do you see another one?



Pearl & Mis submitted

Testing assumptions about what behavior means

Does target behavior in the LWF experiment mean the learner has the target representation for *one* in general (as measured by p_{incl} and $p_{N'}$)?

Signal: p_{beh} is high only when p_{incl} and $p_{N'}$ are both high.

Does the target behavior in the LWF experiment mean the learner has the target representation for *one* at the time the behavior is being produced?

$\mathrm{p}_{\mathrm{rep|beh}}$: Given that the learner has looked at the red bottle, what is the probability that the learner has the target knowledge representation (N', "red bottle") while doing so?

Signal: $p_{rep|beh}$ is high (irrespective of p_{incl} and $p_{N'}$).

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

	DirectUnamb
p_{incl}	0.50 (<0.01)
$p_{N'}$	0.50 (<0.01)
p_{beh}	0.56 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)

Since the input data include no Unambiguous <NP data, and those are the only data the DirectUnamb learner learns from, it learns nothing.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

	DirectUnamb
p_{incl}	0.50 (<0.01)
$p_{N'}$	0.50 (<0.01)
p_{beh}	0.56 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)

It is at chance for having the target syntactic and semantic representation.

It is only slightly above chance at producing the observed toddler behavior, and when it does, it is unlikely to have the target representation when doing so.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

	DirectUnamb
p_{incl}	0.50 (<0.01)
$p_{N'}$	0.50 (<0.01)
p_{beh}	0.56 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)

Implication:
This is an induction problem if only unambiguous <NP data are relevant.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

	DirectUnamb	DirectFiltered
p_{incl}	0.50 (<0.01)	0.91 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.98 (<0.01)
p_{beh}	0.56 (<0.01)	0.88 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.87 (<0.01)

Other learning strategies: DirectFiltered learner (R&G, P&L's filtered)

This learner believes a mentioned property should be included in the antecedent and *one* is N' when it is smaller than NP, which is similar to previous findings by R&G & P&L.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

	DirectUnamb	DirectFiltered
p_{incl}	0.50 (<0.01)	0.91 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.98 (<0.01)
p_{beh}	0.56 (<0.01)	0.88 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.87 (<0.01)

Other learning strategies: DirectFiltered learner (R&G, P&L's filtered)

In addition, it is likely to generate the observed toddler behavior, and have the target representation when doing so.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

	DirectUnamb	DirectFiltered	DirectEO
p_{incl}	0.50 (<0.01)	0.91 (<0.01)	0.10 (0.05)
$p_{N'}$	0.50 (<0.01)	0.98 (<0.01)	0.18 (0.03)
p_{beh}	0.56 (<0.01)	0.88 (<0.01)	0.50 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.87 (<0.01)	0.01 (0.01)

Other learning strategies: DirectEO learner (P&L's EO)

The learner does not believe the mentioned property should be included in the antecedent, and prefers *one* to be N^0 when it is smaller than NP.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

	DirectUnamb	DirectFiltered	DirectEO
p_{incl}	0.50 (<0.01)	0.91 (<0.01)	0.10 (0.05)
$p_{N'}$	0.50 (<0.01)	0.98 (<0.01)	0.18 (0.03)
p_{beh}	0.56 (<0.01)	0.88 (<0.01)	0.50 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.87 (<0.01)	0.01 (0.01)

Other learning strategies: DirectEO learner (P&L's EO)

This causes the learner to be at chance at generating the observed toddler behavior, and unlikely to have the target representation when generating that behavior.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

	DirectUnamb	DirectFiltered	DirectEO	+OtherPro
p_{incl}	0.50 (<0.01)	0.91 (<0.01)	0.10 (0.05)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.98 (<0.01)	0.18 (0.03)	0.37 (0.04)
p_{beh}	0.56 (<0.01)	0.88 (<0.01)	0.50 (<0.01)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.87 (<0.01)	0.01 (0.01)	>0.99 (<0.01)

The +OtherPro learner robustly decides the antecedent should include the mentioned property.

However, the learner has a moderate dispreference for believing *one* is N' when it is smaller than NP.

This is therefore not the target representation.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

	DirectUnamb	DirectFiltered	DirectEO	+OtherPro
p_{incl}	0.50 (<0.01)	0.91 (<0.01)	0.10 (0.05)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.98 (<0.01)	0.18 (0.03)	0.37 (0.04)
p_{beh}	0.56 (<0.01)	0.88 (<0.01)	0.50 (<0.01)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.87 (<0.01)	0.01 (0.01)	>0.99 (<0.01)

However…this learner still generates the observed toddler behavior with high probability, and has the target representation when doing so.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

	DirectUnamb	DirectFiltered	DirectEO	+OtherPro
p_{incl}	0.50 (<0.01)	0.91 (<0.01)	0.10 (0.05)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.98 (<0.01)	0.18 (0.03)	0.37 (0.04)
p_{beh}	0.56 (<0.01)	0.88 (<0.01)	0.50 (<0.01)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.87 (<0.01)	0.01 (0.01)	>0.99 (<0.01)

Why?

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

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

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

	DirectUnamb	DirectFiltered	DirectEO	+OtherPro
p_{incl}	0.50 (<0.01)	0.91 (<0.01)	0.10 (0.05)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.98 (<0.01)	0.18 (0.03)	0.37 (0.04)
p_{beh}	0.56 (<0.01)	0.88 (<0.01)	0.50 (<0.01)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.87 (<0.01)	0.01 (0.01)	>0.99 (<0.01)

Why?

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

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

	DirectUnamb	DirectFiltered	DirectEO	+OtherPro
p_{incl}	0.50 (<0.01)	0.91 (<0.01)	0.10 (0.05)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.98 (<0.01)	0.18 (0.03)	0.37 (0.04)
p_{beh}	0.56 (<0.01)	0.88 (<0.01)	0.50 (<0.01)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.87 (<0.01)	0.01 (0.01)	>0.99 (<0.01)

Take away point:

A learner using an indirect positive evidence strategy can generate target behavior without reaching the target state – instead, this learner has a context-sensitive representation (depending on whether a property was mentioned).

Pearl & Mis submitted

Learning strategies & induction problems

Using indirect positive evidence:
Generate observed target behavior without having target state knowledge

What does this mean for the induction problem?

target state:

One is category N' and its antecedent includes the mentioned modifier when present.

Behavior signal: Generate adult interpretation in utterances with mentioned modifier
(“Look – a red bottle. Do you see another one?”) **????**

The link between observed behavior and underlying knowledge representation may not be so clearcut.

Pearl & Mis submitted

Learning strategies & induction problems

Using indirect positive evidence:
Generate observed target behavior without having target state knowledge

What does this mean for the induction problem?

target state:

One is category N' and its antecedent includes the mentioned modifier when present.

Behavior signal: Generate adult interpretation in utterances with mentioned modifier ("Look – a red bottle. Do you see another one?")

+Behavior signal: Recognize ungrammaticality of utterances where *one* is used as an N^0, like *"Jack sat by the side of the road and Lily sat by the one of the river."

Children may achieve this later than 18 months.

Pearl & Mis submitted

Learning strategies & induction problems

Using indirect positive evidence:
Generate observed target behavior without having target state knowledge

What does this mean for the induction problem?

target state:

One is category N' and its antecedent includes the mentioned modifier when present.

[Stage 1] Behavior signal: Generate adult interpretation in utterances with mentioned modifier ("Look – a red bottle. Do you see another one?")

[Stage 2] Behavior signal: Recognize ungrammaticality of utterances like

*"Jack sat by the side of the road and Lily sat by the one of the river."

Maybe there are (at least) two stages of acquisition?

Pearl & Mis submitted

Motivating UG

What kind of biases does the +OtherPro learner use, if we want to achieve stage 1?

initial state: Two new biases

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

+ Bias: Use Bayesian inference.

+ Bias: Learn from other pronoun data.

Pearl & Mis submitted

Motivating UG

What kind of biases does the +OtherPro learner use, if we want to achieve stage 1?

Bias to use Bayesian inference:

innate, domain-general statistical learning ability (not UG)

Pearl & Mis submitted

Motivating UG

What kind of biases does the +OtherPro learner use, if we want to achieve stage 1?

Bias to learn from other pronoun data:

concerns language data, so clearly domain-specific

innate or derived?

Pearl & Mis submitted

Motivating UG

What kind of biases does the +OtherPro learner use, if we want to achieve stage 1?

Bias to learn from other pronoun data:

concerns language data, so clearly domain-specific

innate or derived?

If innate, then this is a UG bias.

If so, this is a specific proposal for the contents of UG that is less specific than Baker's proposal and doesn't involve limiting the data intake like the DirectFiltered strategy.

Pearl & Mis submitted

Motivating UG

What kind of biases does the +OtherPro learner use, if we want to achieve stage 1?

Bias to learn from other pronoun data:

concerns language data, so clearly domain-specific

innate or derived?

Could be derived from prior linguistic experience with pronouns (and noticing overlapping syntactic environments for "one" and other referential pronouns.)

If so, this is a non-UG learning strategy that will produce the desired behavior. This then takes away support for UG that comes from this induction problem characterization.

Pearl & Mis submitted

The big picture: Making an argument from acquisition for UG

Universal Grammar: a theory of linguistic knowledge that is explicitly motivated by the existence of induction problems during acquisition and the solutions to those problems.

Existence

Requires a specific characterization that defines initial state, data intake, learning period, and target state

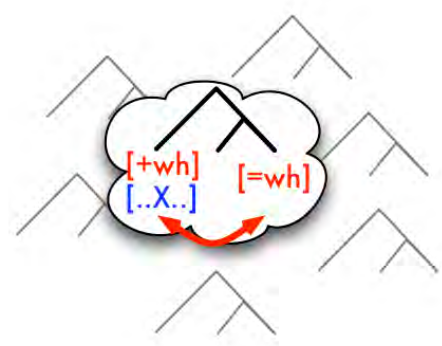
Solutions

Here: Exploring an indirect positive evidence learning strategy as a general approach, and applying it to two different induction problems. We can then examine the biases involved.

Making progress on UG

I. Potential induction problem:

Learning constraints on long-distance dependencies



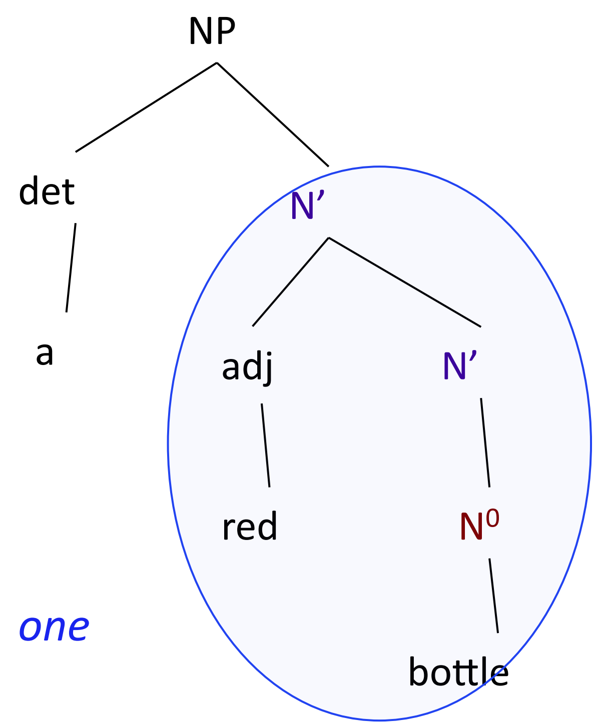
- Target state knowledge indicated by adult judgment behavior.
- Indirect positive evidence strategy can generate this behavior.
- Strategy may involve UG biases, but if so, they're much less specific than those previously proposed.

Making progress on UG

- Target state knowledge thought to be indicated by 18-month-old behavior… but may not actually be (potential recharacterization of induction problem).
- Indirect positive evidence strategy can generate this behavior, though.
- Strategy may involve a UG bias, but if so, it's much less specific than what was previously proposed.
- May mean there are two stages of knowledge acquisition.

II. Potential induction problem:

Learning English anaphoric *one*



Empirically investigating UG

Empirical investigation of UG involves drawing on multiple research methods to

(1) make sure we're all worried about the same problem, and

(2) make headway on the UG debate by providing a formal mechanism for evaluating induction problem solutions

Thank you!

Jon Sprouse | Benjamin Mis

Diogo Almeida	Max Bane	Misha Becker	Bob Berwick
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Virginia Valian	Ming Xiang	Charles Yang	

Computational Models of Language Learning seminar, UC Irvine 2010

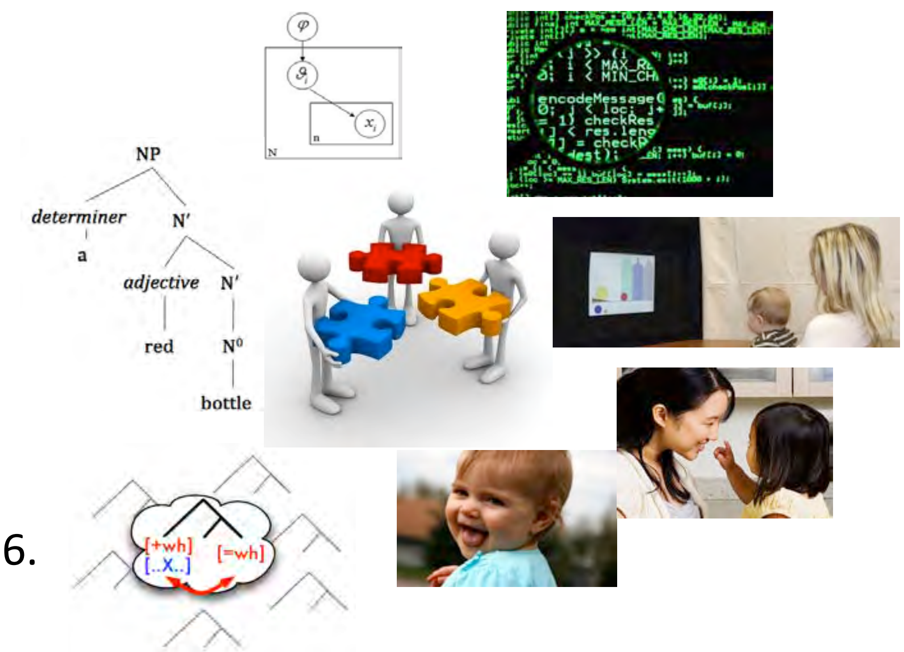
Audiences at:

CogSci 2011

UChicago 2011 workshops on

Language, Cognition, and Computation &

Language, Variation, and Change



Computation of Language Laboratory

UC Irvine

This work was supported in part by NSF grant BCS-0843896.

Extra Material

Why learning from container node trigrams works

For each island-spanning dependency, there is at least one extremely low probability container node trigram in the dependency.

Complex NP island
start-IP-VP-NP-CP_{that}-IP-VP-*end*

Subject island
start-IP-VP-CP_{null}-IP-NP-PP-*end*

Whether island
start-IP-VP-$CP_{whether}$-IP-VP-*end*

Adjunct island
start-IP-VP-CP_{if}-IP-VP-*end*

These trigrams are never observed in the input – which is crucially different than being observed rarely. Thus, these islands are worse than dependencies involving trigrams that are rarely seen (e.g., dependencies with CP_{that}) and even longer dependencies that involve more frequent trigrams (e.g., triply embedded object dependencies using CP_{null}).

Pearl & Sprouse forthcoming

The empirical necessity of trigrams

Not unigrams

A unigram model will successfully learn Whether and Adjunct islands, as there are container nodes in these dependencies that never appear in grammatical dependencies ($CP_{whether}$ and CP_{if})….but it will fail to learn Complex NP and Subject islands, as all of the container nodes in these islands are shared with grammatical dependencies.

Complex NP:	*IP-VP-NP-CP_{that}-IP-VP
Subject:	*IP-VP-CP_{null}-IP-NP-PP
Whether:	IP-VP-$CP_{whether}$-IP-VP
Adjunct:	IP-VP-CP_{if}-IP-VP

Pearl & Sprouse forthcoming

The empirical necessity of trigrams

Not bigrams

At least for Subject islands, there is no bigram that occurs in a Subject island violation but not in any grammatical dependencies. The most likely candidate for such a bigram is IP-NP…However, sentences such as *What, again, about Jack impresses you?* or *What did you say about the movie scared you?* suggest that a gap can arise inside of NPs, as long as the extraction is of the head noun (what), not of the noun complement of the preposition.

Complex NP:	IP-VP-NP-CP_{that}-IP-VP
Subject:	*IP-VP-CP_{null}-IP-NP-PP
Whether:	IP-VP-$CP_{whether}$-IP-VP
Adjunct:	IP-VP-CP_{if}-IP-VP

Pearl & Sprouse forthcoming

Parasitic gaps

The learner can't handle parasitic gaps, which are dependencies that span an island (and so should be ungrammatical) but which are somehow rescued by another dependency in the utterance.

*Which book did you laugh [before reading __]?
Which book did you judge $\_\_{}_{\text{true}}$ [before reading $\_\_{}_{\text{parasitic}}$]?

Adjunct island

*What did [the attempt to repair __] ultimately damage the car?
What did [the attempt to repair $\_\_{}_{\text{parasitic}}$] ultimately damage $\_\_{}_{\text{true}}$?

Complex NP island

Pearl & Sprouse forthcoming

Parasitic gaps

Why not? The current learner would judge the parasitic gap as ungrammatical since it is inside an island, irrespective of what other dependencies are in the utterance.

*Which book did you laugh [before reading __]?
 Which book did you judge $\_\__{\text{true}}$ [before reading $\_\__{\text{parasitic}}$]?

Adjunct island

*What did [the attempt to repair __] ultimately damage the car?
 What did [the attempt to repair $\_\__{\text{parasitic}}$] ultimately damage $\_\__{\text{true}}$?

Complex NP island

This may be able to be addressed in a learner that is able to combine information from multiple dependencies in an utterance (perhaps because the learner has observed multiple dependencies resolved in utterances in the input).

Pearl & Sprouse forthcoming

Across-the-board constrcutions

A similar problem occurs for across-the-board constructions.

Which book did you [[read __] and [then review __]]?
dependency for both gaps: IP-VP-VP

*Which book did you [[read the paper] and [then review __]]?
dependency for gap: IP-VP-VP

*Which book did you [[read __] and [then review the paper]]?
dependency for gap: IP-VP-VP

Again, this may be able to be addressed in a learner that is able to combine information from multiple dependencies in an utterance (perhaps because the learner has observed multiple dependencies resolved in utterances in the input).

Pearl & Sprouse forthcoming

Some cross-linguistic issues

High probability trigrams that may be ungrammatical

Rizzi (1982): reports situations in Italian where simply doubling a grammatical sequence of trigrams leads to ungrammaticality…

IP-VP-CP_{wh}-IP-VP
but
*IP-VP-CP_{wh}-IP-VP-CP_{wh}-IP-VP-IP-VP

But these involve the same trigrams, so the learner in Pearl & Sprouse (forthcoming) will treat both the same (either grammatical or ungrammatical). If humans do have different judgments of these, then this cannot be accounted for by this learning algorithm.

Pearl & Sprouse forthcoming

Complementizer *that*

That-trace effects

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

The current learning strategy captures this distinction.

Pearl & Sprouse forthcoming

Complementizer *that*

That-trace effects

…but the current learning strategy will also generate a preference for object gaps without *that* compared to object gaps with *that.* (object *that*-trace effect)

What do you think that he read __ ? [prefers this one]
What do you think he read __ ?

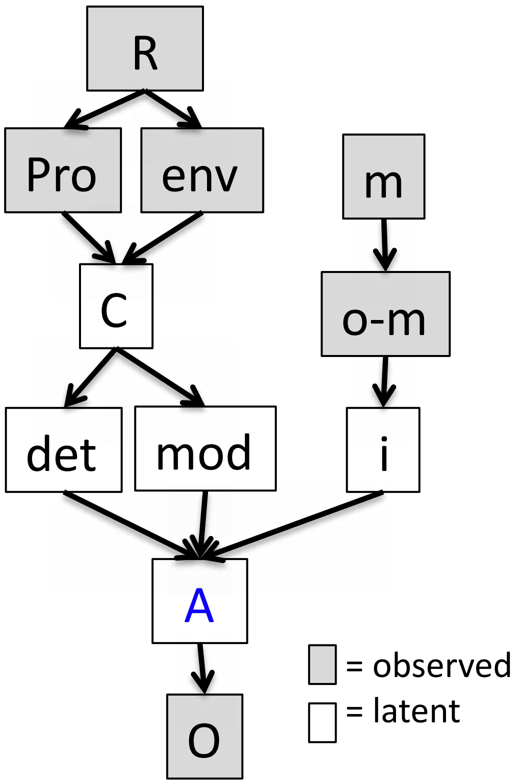
Interestingly, Cowart 1997 finds an object *that-trace* effect, but it is much smaller than the subject *that-trace* effect

The model generates an asymmetrical dispreference when using adult-directed corpora, which contain more instances of *that* (5.40 versus 2.81). This could be taken to be a developmental prediction of the current algorithm: Children may disprefer object gaps in embedded *that-CP* clauses more than adults, and this dispreference will weaken as they are exposed to additional tokens of *that* in utterances containing dependencies.

Pearl & Sprouse forthcoming

English anaphoric *one*

Information in the data: Unamb <NP



"Look, a red bottle! Hmm – there isn't another *one* here though!"

R = "another one"
Pro = "one"
env = <NP

m = yes
o-m = yes

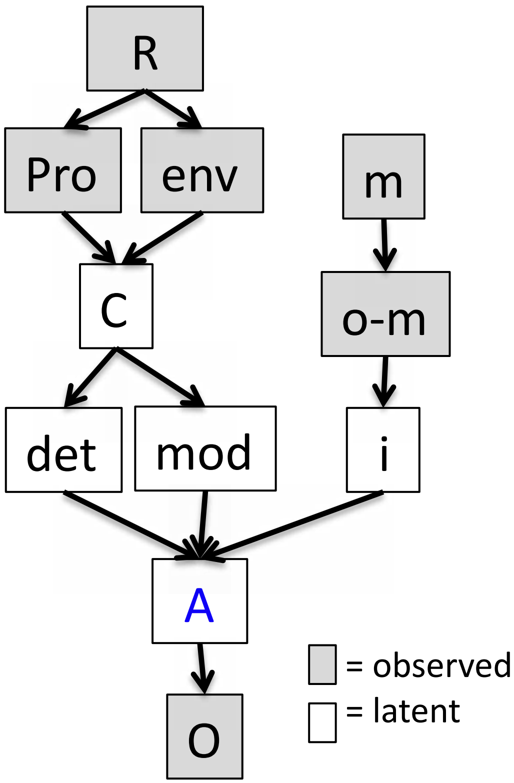
C = N'
det = no
mod = yes

i = yes

A = "red bottle"
O = RED BOTTLE

Pearl & Mis submitted

Information in the data: Sem-Syn ambiguous



"Look, a red bottle! Look – another one!"

R = "another one"
Pro = "one"
env = <NP

m = yes
o-m = yes

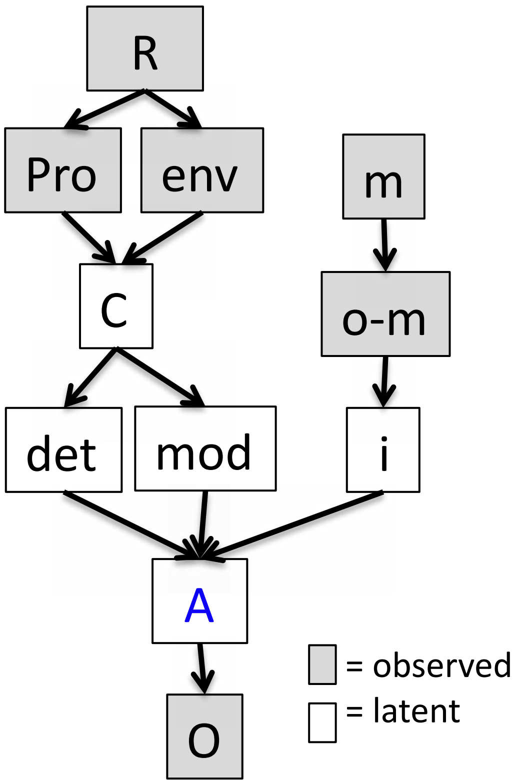
C = N' or N^0?
det = no
mod = yes or no?

i = yes or no?

A = "red bottle" or "bottle"?
O = RED BOTTLE

Pearl & Mis submitted

Information in the data: Syn ambiguous



"Look, a bottle! Look – another one!"

R = "another one"
Pro = "one"
env = <NP

m = no
o-m = N/A

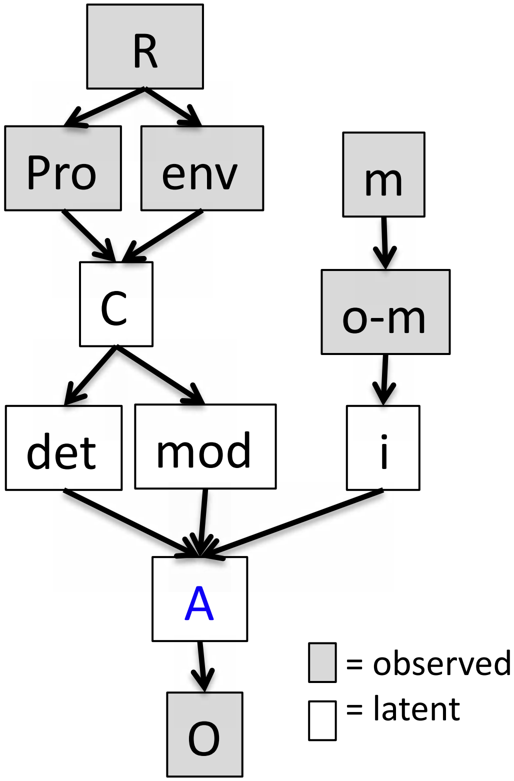
C = N' or N^0?
det = no
mod = no

i = N/A

A = "bottle"
O = BOTTLE

Pearl & Mis submitted

Information in the data: Unamb NP



"Look, a red bottle! I want it."

R = "it"
Pro = "it"
env = NP

m = yes
o-m = yes

C = NP
det = yes
mod = yes

i = yes

A = "a red bottle"
O = RED BOTTLE

Pearl & Mis submitted

The online probabilistic framework: Updating p_{incl}

	ϕ_{incl}	Explanation
Unamb <NP	1	Property definitely included
Unamb NP	1	Property definitely included
Syn Amb	N/A	Not informative for p_{incl}
Sem-Syn Amb	$\frac{rep_1}{rep_1 + rep_2 + rep_3}$	Probability property is included

$$rep_1 = p_{N'} * \frac{m}{m+n} * p_I$$

Category = N', choose N' with modifier, property is included

$$rep_2 = p_{N'} * \frac{n}{m+n} * (1 - p_{incl}) * \frac{1}{s}$$

Category = N', choose N' without modifier, property is not included, choose object with property by chance

$$rep_3 = (1 - p_{N'}) * (1 - p_{incl}) * \frac{1}{s}$$

Category = N^0, property is not included, choose object with property by chance

Pearl & Mis submitted

The online probabilistic framework: Updating $p_{N'}$

	$\phi_{N'}$	Explanation
Unamb <NP	1	Category definitely N'
Unamb NP	N/A	Not informative for $p_{N'}$
Syn Amb	$\frac{rep_4}{rep_4 + rep_5}$	Probability category is N'
Sem-Syn Amb	$\frac{rep_1 + rep_2}{rep_1 + rep_2 + rep_3}$	Probability category is N'

$rep_1 = p_{N'} * \frac{m}{m+n} * p_I$ Category = N', choose N' with modifier, property is included

$rep_2 = p_{N'} * \frac{n}{m+n} * (1 - p_{incl}) * \frac{1}{s}$ Category = N', choose N' without modifier, property is not included, choose object with property by chance

$rep_3 = (1 - p_{N'}) * (1 - p_{incl}) * \frac{1}{s}$ Category = N^0, property is not included, choose object with property by chance

Pearl & Mis submitted

The online probabilistic framework: Updating $p_{N'}$

	$\phi_{N'}$	Explanation
Unamb <NP	1	Category definitely N’
Unamb NP	N/A	Not informative for $p_{N'}$
Syn Amb	$\frac{rep_4}{rep_4 + rep_5}$	Probability category is N’
Sem-Syn Amb	$\frac{rep_1 + rep_2}{rep_1 + rep_2 + rep_3}$	Probability category is N’

$rep_4 = p_{N'} * \frac{n}{m+n}$ Category = N’, choose N’ without modifier

$rep_5 = 1 - p_{N'}$ Category = N^0

Pearl & Mis submitted

Example updates

Start with $p_{N'} = p_{incl} = 0.50$, m = 1, n = 2.9, s = 10

[from Pearl & Lidz 2009]

One Unamb <NP data point: $p_{N'} = 0.67$, $p_{incl} = 0.67$

One Unamb NP data point: $p_{N'} = 0.50$, $p_{incl} = 0.67$

One Sem-Syn Amb data point: $p_{N'} = 0.59$, $p_{incl} = 0.53$

One Syn Amb data point: $p_{N'} = 0.48$, $p_{incl} = 0.50$

Pearl & Mis submitted

Corpus analysis & learner input

Brown/Eve corpus (CHILDES: MacWhinney 2000): starting at 18 months

17,521 utterances of child-directed speech, 2874 referential pronoun utterances

		Baker	**DirectFiltered**	**DirectEO**	**+OtherPro**
Unamb <NP	0.00%	0	0	0	0
Sem-Syn Amb	0.66%	0	242	242	242
Syn Amb	7.52%	0	0	2743	2743
Unamb NP	8.42%	0	0	0	3073
Uninformative	83.4%	36500	36258	33515	30442

Free parameters:
m=1, n=2.9 (from corpus estimates done by P&L)

s (concerns number of salient properties learner is considering):
Child may only be aware of a few salient properties or may consider all known properties (# of adjectives known by 16 months ≈ 49 (MacArthur CDI: Dale & Fenson 1996). Use range from 2 to 49.

Pearl & Mis submitted

Measures of success:
LWF children's behavior

In addition to directly assessing p_{incl} and $p_{N'}$, we can measure how often a learner would reproduce the behavior in the LWF experiment (p_{beh}).

2 choices
s = 2

$$p_{beh} = \frac{rep_1 + rep_2 + rep_3}{rep_1 + 2 * rep_2 + 2 * rep_3}$$

Any outcome where learner looks at red bottle

Additional two outcomes where learner looks at other bottle

$$rep_1 = p_{N'} * \frac{m}{m+n} * p_{incl}$$ Category = N', antecedent = "red bottle"

$$rep_2 = p_{N'} * \frac{n}{m+n} * (1 - p_{incl}) * \frac{1}{s}$$ Category = N', antecedent = "bottle"

$$rep_3 = (1 - p_{N'}) * (1 - p_{incl}) * \frac{1}{s}$$ Category = N^0, antecedent = "bottle"

Pearl & Mis submitted

Testing LWF's assumption about what behavior means

In addition to directly assessing the learner's behavior, we can assess LWF's assumption that target behavior indicates the children have the target representation for *one*.

Is it possible to get target behavior in the LWF experiment without having the target representation for *one* in general (as measured by p_{incl} and $p_{N'}$)?

Is it possible to get target behavior in the LWF experiment without having the target representation for *one* at the time the behavior is being produced?

$$p_{rep|beh} = \frac{rep_1}{rep_1 + rep_2 + rep_3}$$

the probability the look to the red bottle is because the learner has the target representation (N', "red bottle")

given that the learner looks at the red bottle

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

s = 2, 5, 7, 10, 20, 49

	DirectUnamb
p_{incl}	0.50 (<0.01)
$p_{N'}$	0.50 (<0.01)
p_{beh}	0.56 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)

Since the input data include no Unambiguous <NP data, and those are the only data the Baker learner learns from, it learns nothing.

It is at chance for having the target syntactic and semantic representation.

It is only slightly above chance at producing the observed toddler behavior, and when it does, it unlikely to have the target representation when doing so.

Implication: This is an induction problem if only unambiguous <NP data are relevant.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

s = 2, 5, 7, 10, 20, 49

	DirectUnamb	+OtherPro
p_{incl}	0.50 (<0.01)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.34-0.38 (0.03-0.05)
p_{beh}	0.56 (<0.01)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	>0.99 (<0.01)

The learner robustly decides the antecedent should include the mentioned property.

However, the learner has a moderate dispreference for believing *one* is N' when it is smaller than NP.

This is therefore not the target representation.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

s = 2, 5, 7, 10, 20, 49

	DirectUnamb	+OtherPro
p_{incl}	0.50 (<0.01)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.34-0.38 (0.03-0.05)
p_{beh}	0.56 (<0.01)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	>0.99 (<0.01)

However…this learner still generates the observed toddler behavior (not what LWF would expect) with high probability, and has the target representation when doing so (is what LWF would expect).

Why? Because the learner believes so strongly that a mentioned property must be included in the antecedent, the only representation that allows this (e.g., $[_{N'}$ red$[_{N'}[_{N0}$ bottle$]]]$) overpowers the other potential representations' probabilities. Thus, the +OtherPro learner will conclude the antecedent includes the mentioned property, and so it and the referential pronoun referring to it (one) must be N' *in this context* - even if the learner believes *one* is not N' in general.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

s = 7, 10, 20, 49

	DirectUnamb	DirectFiltered	+OtherPro
p_{incl}	0.50 (<0.01)	0.91-0.99 (<0.01)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.98-0.99 (<0.01)	0.37-0.38 (0.04-0.05)
p_{beh}	0.56 (<0.01)	0.88-0.99 (<0.01)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.87-0.99 (<0.01)	>0.99 (<0.01)

Other learning strategies: DirectFiltered learner (R&G, P&L's filtered)
Variability, depending on the value of s, which determines how suspicious a coincidence it is that the intended object just happens to have the mentioned property.

When s =7 or above, this learner believes a mentioned property should be included in the antecedent and *one* is N' when it is smaller than NP, which is similar to previous findings by R&G & P&L. In addition, it is likely to generate the observed toddler behavior, and have the target representation when doing so.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

s = 5

	DirectUnamb	DirectFiltered	+OtherPro
p_{incl}	0.50 (<0.01)	0.68 (<0.01)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.94 (<0.01)	0.36 (0.04)
p_{beh}	0.56 (<0.01)	0.70 (<0.01)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.58 (<0.01)	>0.99 (<0.01)

Other learning strategies: DirectFiltered learner (R&G, P&L's filtered)
Variability, depending on the value of s, which determines how suspicious a coincidence it is that the intended object just happens to have the mentioned property.

However, when s=5, the learner is less sure the mentioned property should be included in the antecedent, which causes the learner to be less likely to generate the observed toddler behavior, and only slightly above chance at having the target representation when generating that behavior.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

s = 2

	DirectUnamb	DirectFiltered	+OtherPro
p_{incl}	0.50 (<0.01)	0.02 (<0.01)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.34 (<0.01)	0.34 (0.03)
p_{beh}	0.56 (<0.01)	0.50 (<0.01)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	<0.01 (<0.01)	>0.99 (<0.01)

Other learning strategies: DirectFiltered learner (R&G, P&L's filtered)
Variability, depending on the value of s, which determines how suspicious a coincidence it is that the intended object just happens to have the mentioned property.

When s=2, the learner is sure the mentioned property should *not* be included in the antecedent, and prefer *one* to be N^0 when it is smaller than NP. This causes the learner to be at chance for generating the observed toddler behavior, and very unlikely to have the target representation when generating that behavior.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

s = 2, 5

	DirectUnamb	DirectFiltered	+OtherPro
p_{incl}	0.50 (<0.01)	0.02, 0.68 (<0.01)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.34, 0.94 (<0.01)	0.34-0.36 (0.03-0.04)
p_{beh}	0.56 (<0.01)	0.50, 0.70 (<0.01)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	<0.01, 0.58 (<0.01)	>0.99 (<0.01)

What's going on?

If the suspicious coincidence isn't strong enough, Sem-Syn ambiguous data don't help the learner increase p_{incl} – in fact, they cause p_{incl} to drop. Because both p_{incl} and $p_{N'}$ are used to calculate ϕ_{incl} and $\phi_{N'}$, a very low p_{incl} can eventually drag $p_{N'}$ down.

Ex: s=2

If the first 20 data points are Sem-Syn ambiguous data points, p_{incl} = 0.12 and $p_{N'}$ = 0.48.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

s = 2, 5, 7, 10

	DirectUnamb	DirectFiltered	DirectEO	+OtherPro
p_{incl}	0.50 (<0.01)	0.02-0.96 (<0.01)	<0.01-0.38 (<0.01-0.18)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.34-0.99 (<0.01)	0.14-0.25 (<0.01-0.06)	0.34-0.37 (0.03-0.04)
p_{beh}	0.56 (<0.01)	0.50-0.98 (<0.01)	0.50-0.53 (<0.01-0.04)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	<0.01-0.95 (<0.01)	<0.01-0.11 (<0.01-0.11)	>0.99 (<0.01)

Other learning strategies: DirectEO learner (P&L's EO)
Variability, depending on the value of s, which determines how suspicious a coincidence it is that the intended object just happens to have the mentioned property.

When s is less than 10, the learner does not believe the mentioned property should be included in the antecedent, and prefers *one* to be N^0 when it is smaller than NP.
This causes the learner to be at chance at generating the observed toddler behavior, and unlikely to have the target representation when generating that behavior.

This is similar to what P&L previously found.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

s = 20, 49

	DirectUnamb	DirectFiltered	DirectEO	+OtherPro
p_{incl}	0.50 (<0.01)	0.99 (<0.01)	0.93-0.99 (<0.01-0.03)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.99 (<0.01)	0.34-0.37 (0.05)	0.37-0.38 (0.04-0.05)
p_{beh}	0.56 (<0.01)	0.98-0.99 (<0.01)	0.79-0.94 (0.02-0.07)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.98-0.99 (<0.01)	0.72-0.94 (0.02-0.11)	>0.99 (<0.01)

Other learning strategies: DirectEO learner (P&L's EO)
Variability, depending on the value of s, which determines how suspicious a coincidence it is that the intended object just happens to have the mentioned property.

However, when s is 20 or 49, the learner strongly believes the mentioned property should be included in the antecedent, though it still prefers *one* to be N^0 when it is smaller than NP. This causes the learner to be likely to generate the observed toddler behavior, and likely to have the target representation when generating that behavior.

This is different from what P&L found, and more like the +OtherPro learner results.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

s = 20, 49

	DirectUnamb	DirectFiltered	DirectEO	+OtherPro
p_{incl}	0.50 (<0.01)	0.99 (<0.01)	0.93-0.99 (<0.01-0.03)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.99 (<0.01)	0.34-0.37 (0.05)	0.37-0.38 (0.04-0.05)
p_{beh}	0.56 (<0.01)	0.98-0.99 (<0.01)	0.79-0.94 (0.02-0.07)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	0.98-0.99 (<0.01)	0.72-0.94 (0.02-0.11)	>0.99 (<0.01)

What's going on?

The flip side of what we saw with the R&G learner. If the suspicious coincidence is very strong, Sem-Syn ambiguous data help the learner increase p_{incl} (and $p_{N'}$) – in fact, they become almost as powerful as Unambiguous <NP data. Because both p_{incl} and $p_{N'}$ are used to calculate ϕ_{incl} and $\phi_{N'}$, a very high p_{incl} can bolster $p_{N'}$, and overpower the effect of the troublesome Syn ambiguous data.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

s = 2, 5, 7, 10, 20, 49

	DirectUnamb	DirectFiltered	DirectEO	+OtherPro
p_{incl}	0.50 (<0.01)	0.02-0.99 (<0.01)	<0.01-0.99 (<0.01-0.18)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.34-0.99 (<0.01)	0.14-0.37 (<0.01-0.06)	0.34-0.38 (0.03-0.05)
p_{beh}	0.56 (<0.01)	0.50-0.99 (<0.01)	0.50-0.94 (<0.01-0.07)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	<0.01-0.95 (<0.01)	<0.01-0.94 (<0.01-0.11)	>0.99 (<0.01)

Why isn't the +OtherPro learner as succeptible to changing s values?

Unambiguous NP data only ever increase p_{incl}, no matter what the value of s. So, because there are so many of them, they can overwhelm the effect of Sem-Syn ambiguous data on p_{incl} (whether s is low or high). This helps keep $p_{N'}$ from plummetting, though it still drops due to the troublesome Syn ambiguous data in the learner's intake.

Pearl & Mis submitted

Learner results: Strategy comparison

Averages over 1000 simulations, standard deviations in parentheses.

s = 2, 5, 7, 10, 20, 49

	DirectUnamb	DirectFiltered	DirectEO	+OtherPro
p_{incl}	0.50 (<0.01)	0.02-0.99 (<0.01)	<0.01-0.99 (<0.01-0.18)	>0.99 (<0.01)
$p_{N'}$	0.50 (<0.01)	0.34-0.99 (<0.01)	0.14-0.37 (<0.01-0.06)	0.34-0.38 (0.03-0.05)
p_{beh}	0.56 (<0.01)	0.50-0.99 (<0.01)	0.50-0.94 (<0.01-0.07)	>0.99 (<0.01)
$p_{rep\|beh}$	0.23 (<0.01)	<0.01-0.95 (<0.01)	<0.01-0.94 (<0.01-0.11)	>0.99 (<0.01)

Take away points:.

An indirect positive evidence learning strategy has a beneficial impact on learning anaphoric *one* – it makes the learner's behavior robust, no matter how suspicious a coincidence the Sem-Syn ambiguous data are (or aren't).

A learner using an indirect positive evidence strategy can generate target behavior without reaching the target state – instead, this learner has a context-sensitive representation (depending on whether a property was mentioned).

Pearl & Mis submitted

Other induction problem characterizations

A different target state

Baker 1978 & Foraker et al. 2009

target state

One is category N' *and its antecedent includes the modifier*.

Just learning about the syntactic representation of *one* when it is smaller than NP.

Baker's original proposal:
initial state includes UG knowledge that *one* is not N^0.

Pearl & Mis submitted

Other induction problem characterizations

A different target state

Baker 1978 & Foraker et al. 2009

target state

One is category N' *and its antecedent includes the modifier*.

Just learning about the syntactic representation of *one* when it is smaller than NP.

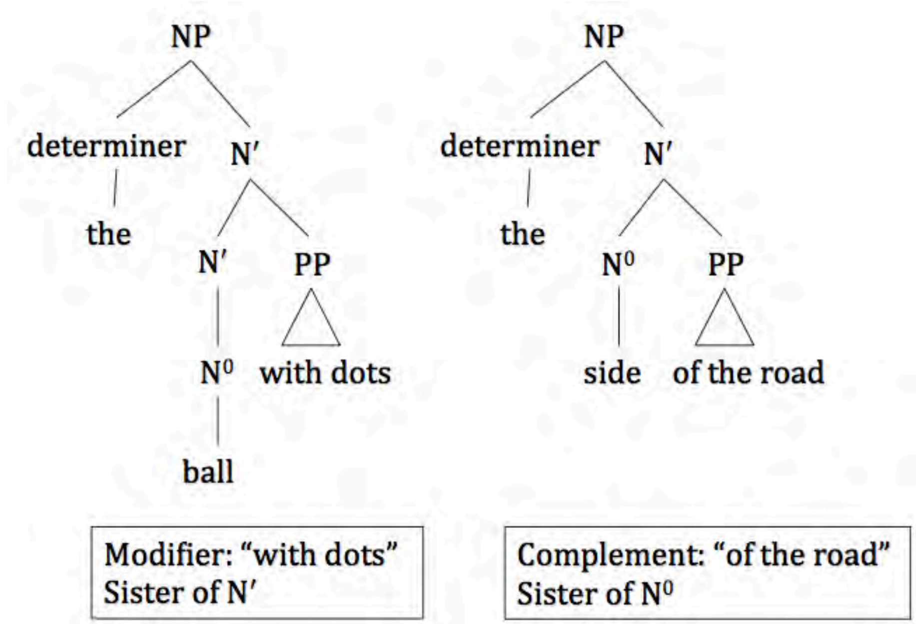
Foraker et al.'s proposal:
Use Bayesian inference on the available syntactic data only, given domain-specific knowledge of complements and modifiers.

Pearl & Mis submitted

Modifiers & complements

Syntactic modifier: not "conceptually evoked by its head noun", indicates noun string is N'
Ex: "the ball with dots" (I like the one with dots.)

Syntactic complement: "conceptually evoked by its head noun", indicates noun string is N^0
Ex: "the side of the road" (*I waited by the one of the road.)



Pearl & Mis submitted

The Foraker et al. learning strategy

Foraker et al. 2009

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

+ Bias: Only syntactic data are useful.

+ Bias: Use Bayesian inference.

+ Bias: Learn from all linguistic elements that take complements or modifiers.

+ Knowledge: Complements conceptually evoke their head noun while modifiers do not.

+ Knowledge: Syntactic category N^0 is sister to a complement, not a modifier.

This strategy was successful at learning *one* is category N' (not N^0) from child-directed speech data.

Pearl & Mis submitted

Foraker et al. bias types

Foraker et al. 2009

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

+ Bias: Only syntactic data are useful.

This bias could be derived from the target knowledge only pertaining to the syntactic representation.

Pearl & Mis submitted

Foraker et al. bias types

Foraker et al. 2009

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

+ (non-UG) Bias: Only syntactic data are useful.

+ Bias: Use Bayesian inference.

This bias is likely innate and domain-general.

Pearl & Mis submitted

Foraker et al. bias types

Foraker et al. 2009

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

+ (non-UG) Bias: Only syntactic data are useful.

+ (non-UG) Bias: Use Bayesian inference.

+ Bias: Learn from all linguistic elements that take complements or modifiers.

This indirect positive evidence bias is clearly domain-specific. It could be specified innately, though it could possibly be derived by noticing salient properties of nominal phrases.

Pearl & Mis submitted

Foraker et al. bias types

Foraker et al. 2009

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

+ (non-UG) Bias: Only syntactic data are useful.

+ (non-UG) Bias: Use Bayesian inference.

+ (UG?) Bias: Learn from all linguistic elements that take complements or modifiers.

+ Knowledge: Complements conceptually evoke their head noun while modifiers do not.

Knowing complements evoke their head nouns while modifiers do not is domain-specific knowledge that is not obviously derivable.

Pearl & Mis submitted

Foraker et al. bias types

Foraker et al. 2009

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

+ (non-UG) Bias: Only syntactic data are useful.

+ (non-UG) Bias: Use Bayesian inference.

+ (UG?) Bias: Learn from all linguistic elements that take complements or modifiers.

+ (UG) Knowledge: Complements conceptually evoke their head noun while modifiers do not.

+ Knowledge: Syntactic category N^0 is sister to a complement, not a modifier.

Knowing N^0 is sister to complement is also domain-specific knowledge that is not obviously derivable.

Pearl & Mis submitted

Foraker et al. bias types

Foraker et al. 2009

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', and NP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

+ (non-UG) Bias: Only syntactic data are useful.

+ (non-UG) Bias: Use Bayesian inference.

+ (UG?) Bias: Learn from all linguistic elements that take complements or modifiers.

+ (UG) Knowledge: Complements conceptually evoke their head noun while modifiers do not.

+ (UG) Knowledge: Syntactic category N^0 is sister to a complement, not a modifier.

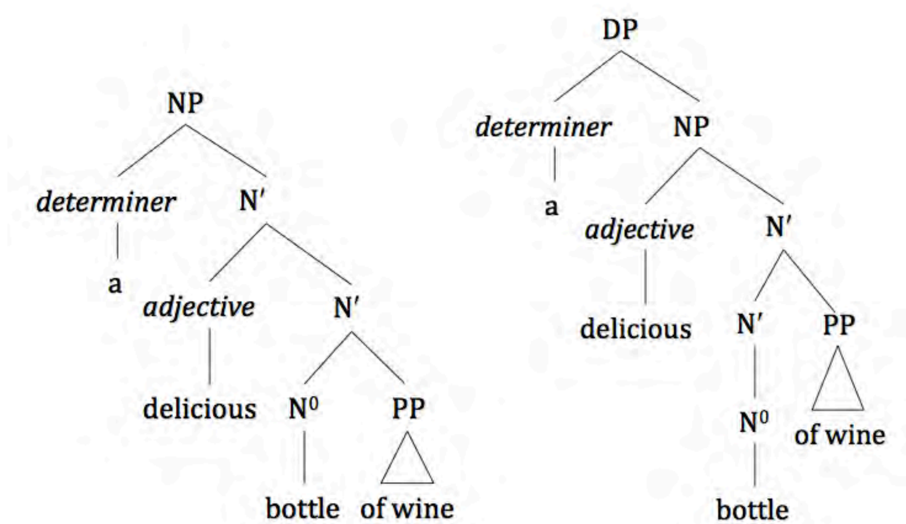
Upshot: This form of the induction problem leads to a different proposal for the contents of UG, even when Bayesian inference is used.

Pearl & Mis submitted

Other induction problem characterizations

A different initial & target state: Alternate theoretical representations

N^0, N', and NP vs. N^0, N', NP, and DP



Other induction problem characterizations

A different initial & target state: Syntactic categories N^0, N', NP, DP

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', NP, and DP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

Bias: Only direct evidence of *one* is useful.

Bias: Only unambiguous evidence of *one* is useful.

target state

Knowledge: In utterances like "Look, a red bottle! Look, another one!", ***one* is category NP** and so its antecedent includes the modifier ("red").

Other induction problem characterizations

A different initial & target state: Syntactic categories N^0, N', NP, DP

What an indirect positive evidence strategy like +OtherPro would do

initial state

Knowledge: Syntactic categories exist, in particular N^0, N', NP, and DP.

Knowledge: Anaphoric elements like *one* take linguistic antecedents of the same category.

- *Bias: Only direct evidence of one is useful.*

- *Bias: Only unambiguous evidence of one is useful.*

+ (non-UG) Bias: Use Bayesian inference

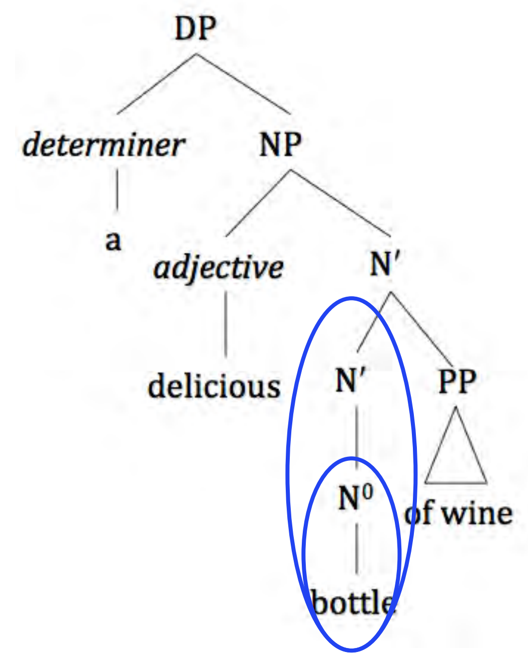
+ (UG?) Bias: Learn from other pronoun data.

Other induction problem characterizations

A different initial & target state: Syntactic categories N^0, N', NP, DP

What an indirect positive evidence strategy like +OtherPro would do

(1) Syn ambiguous data still ambiguous between two categories (N^0 and N'), and Bayesian inference causes learner to prefer the hypotheses that includes fewer strings, which is still the N^0 category. (N' includes noun +complement strings)



Syn ambiguous data still cause $p_{N'}$ to drop, though perhaps not as fast.

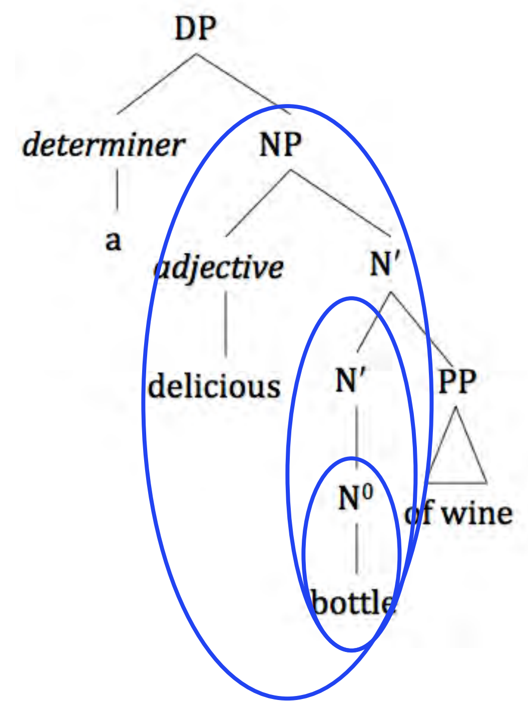
Other induction problem characterizations

A different initial & target state: Syntactic categories N^0, N', NP, DP

What an indirect positive evidence strategy like +OtherPro would do

(2) Sem-Syn ambiguous data still ambiguous between three antecedents. When *s* is high enough (>5), the suspicious coincidence still causes the learner to increase p_{incl}.

Sem-Syn ambiguous data still cause p_{incl} to increase when the suspicious coincidence is strong enough.



Other induction problem characterizations

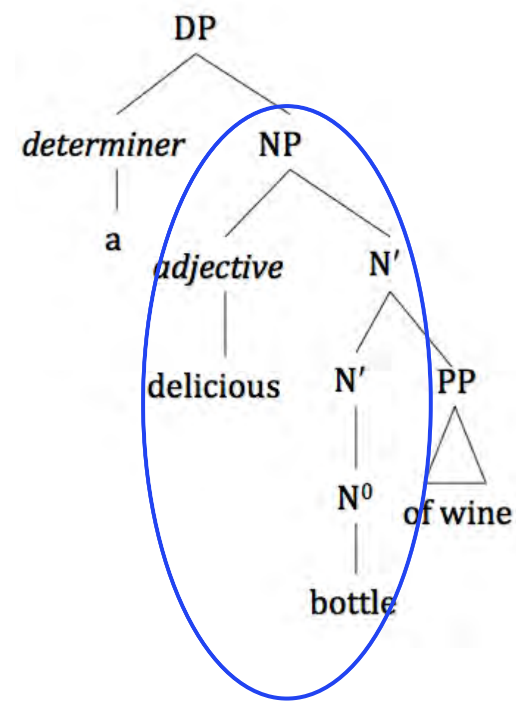
A different initial & target state: Syntactic categories N^0, N', NP, DP

What an indirect positive evidence strategy like +OtherPro would do

(3) Unmbiguous <NP data still indicate antecedent that includes modifier – it's just that the category label is NP (rather than N').

p_{incl} and p_{NP} both increase.

Unambiguous <NP data still cause p_{incl} and the category that includes the modifier (NP) to increase.



Other induction problem characterizations

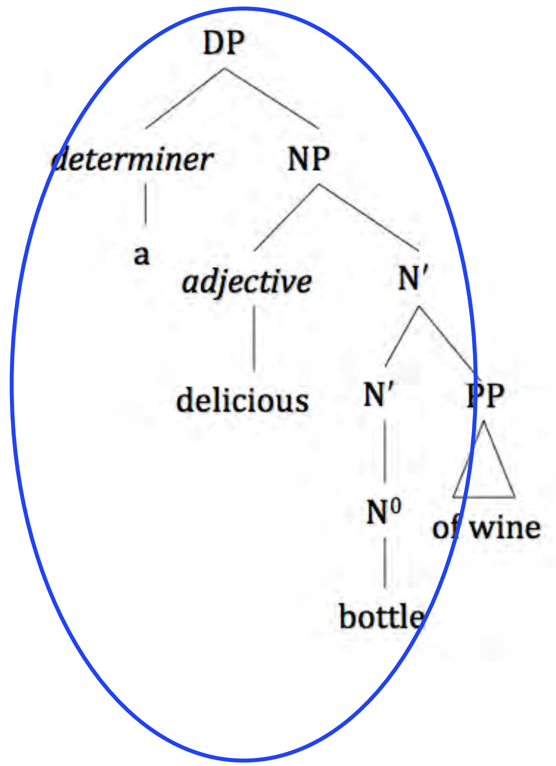
A different initial & target state: Syntactic categories N^0, N’, NP, DP

What an indirect positive evidence strategy like +OtherPro would do

(4) Unambiguous NP data still indicate antecedent that includes modifier – it’s just that the category label is DP (rather than NP).

p_{incl} still increases.

Unambiguous NP data still cause p_{incl} to increase.



Other induction problem characterizations

A different initial & target state: Syntactic categories N^0, N', NP, DP

What an indirect positive evidence strategy like +OtherPro would do

Given that the updates from the different data types are effectively the same, the overall outcome should be similar: p_{incl} should be high while p_{NP} should be low.
(Note: $p_{N'}$ should also be very low, since no data cause it to increase.)

Non-target context-dependent representation.
p_{incl} = high, p_{NP} = low

LWF experiment: target behavior (and target representation when displaying that behavior) because of p_{incl}.