

Psych 215L: Language Acquisition

Lecture 13 Poverty of the Stimulus: Anaphoric One

An induction problem by any other name...

One of the most controversial claims in linguistics is that children face an **induction problem**:

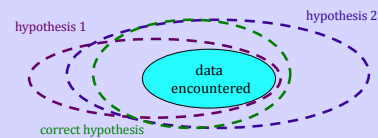
“**Poverty of the Stimulus**” (Chomsky 1980, Crain 1991, Lightfoot 1989, Valian 2009)

“**Logical Problem of Language Acquisition**” (Baker 1981, Hornstein & Lightfoot 1981)

“**Plato’s Problem**” (Chomsky 1988, Dresher 2003)

Basic claim:

The data encountered are **compatible with multiple hypotheses**.

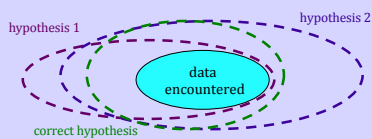


The induction problem

Extended claim:

Given this, the data are insufficient for identifying the correct hypothesis as quickly as children do (Legate & Yang 2002) – or at all.

Big question: **How do children do it, then?**



One answer: Children come prepared

- Children are not unbiased learners.



- But if children come equipped with helpful learning biases, then what is the nature of these necessary biases?

- Are they **innate** or **derived** from the input somehow?
- Are they **domain-specific** or **domain-general**?
- Are they about **what’s being learned** or about **how to learn**?

The Universal Grammar (**UG**) hypothesis (Chomsky 1965, Chomsky 1975):

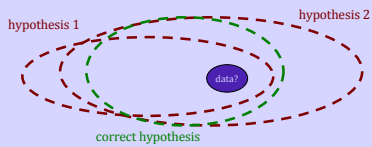
These biases are **innate** and **domain-specific**.

Induction problems, UG, and informative data

Traditional Idea

Induction problems → Universal Grammar (UG)

Traditional assumption:
Only directly related data are informative data. These data are often rare, and that's why induction problems occur.



The direct evidence assumption

If you want to learn linguistic knowledge L, you learn it by observing examples of L in your input (and possibly by also being sensitive to indirect negative evidence about what examples are missing from the input.)

Learning complex yes/no questions

Direct evidence L:
"Is the boy who is in the corner t_{is} happy?"

Possible indirect negative evidence:
**"Is the boy who t_{is} in the corner is happy?"

The direct evidence assumption

If you want to learn linguistic knowledge L, you learn it by observing examples of L in your input (and possibly by also being sensitive to indirect negative evidence about what examples are missing from the input.)

Learning the representation of English anaphoric one

Situation



Direct evidence L:
"I see a red bottle... but there isn't another one around."

Possible indirect negative evidence:
**"I like the student of linguistics and he likes the one of computer science."

The direct evidence assumption

If you want to learn linguistic knowledge L, you learn it by observing examples of L in your input (and possibly by also being sensitive to indirect negative evidence about what examples are missing from the input.)

Learning syntactic islands

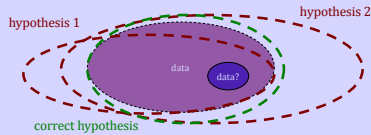
Direct evidence L:
"What did the teacher think t_{what} inspired the students?"
"Who did the teacher think the letter from the soldier inspired t_{who} ?"
"Who t_{who} thought the letter from the soldier inspired the students?"

Possible indirect negative evidence:
**"Who did the teacher think [[the letter from t_{who}] inspired the students]?"

←—————→
island

A broader set of informative data

Indirect evidence: other kinds of data that may also be relevant, thereby broadening the set of **informative data**



Recent computational models have been exploring this:

- Complex yes/no questions (Pefors, Tenenbaum, & Regier 2006, 2011)
- Anaphoric one (Regier & Gahl 2004, Pearl & Lidz 2009, Foraker et al. 2009)

Mapping out UG & the acquisition process

Big questions:

- When induction problems exist, what does it take to solve them?
 - What **indirect evidence** is available? How might a child leverage this evidence?
 - What learning biases can get the job done, given the available data? Are they necessarily **innate** and **domain-specific** (UG)?
- How can the necessary learning biases inform us about how the acquisition process works?



Anaphoric One

Look - a red bottle!



Do you see another *one*?



Anaphoric One

Look - a red bottle!




Do you see another *one*?





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

Anaphoric One

Look - a red bottle!




Do you see another ^{red bottle} *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

Anaphoric One

Look - a red bottle!



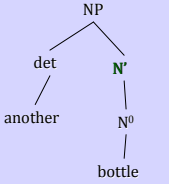
Do you see another *one*?

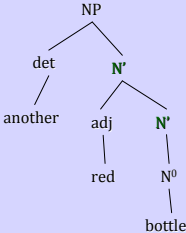
Two steps:
 (1) Identify *syntactic* antecedent (based on syntactic category of *one*)
 (2) Identify *semantic* referent (based on syntactic antecedent)

Anaphoric One: Syntactic Category

Standard linguistic theory claims that *one* in these kind of utterances is a syntactic category smaller than an entire noun phrase, but larger than just a noun (N⁰). This category is sometimes called N'. This category includes strings like "bottle" and "red bottle".



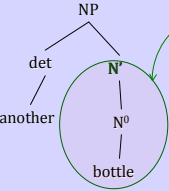
[_{NP} another [_{N'} [_{N⁰} bottle]]]



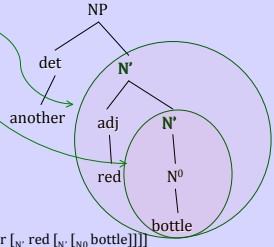
[_{NP} another [_{N'} red [_{N'} [_{N⁰} bottle]]]]

Anaphoric One: Syntactic Category

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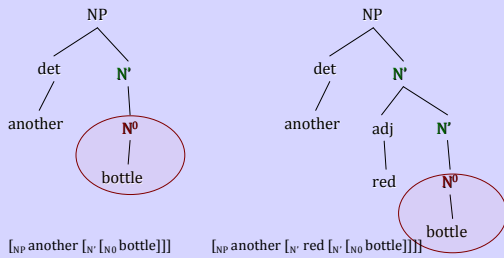
[_{NP} another [_{N'} [_{N⁰} bottle]]]



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

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.



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 .

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:

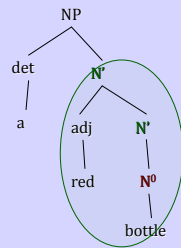
Preference for the RED BOTTLE means the preferred syntactic antecedent is "red bottle".

LWF conclude that 18-month-old knowledge =

syntactic category of *one* = N'

syntactic antecedent when modifier is present includes

modifier (e.g., red) = referent has modifier property



Anaphoric *One*: The induction problem

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

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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]?

Anaphoric *One*: The induction problem

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 = [_Nred[_N[_{N0}bottle]]] or [_N[_{N0}bottle]] or [_{N0}bottle]?

Anaphoric *One*: The induction problem

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%, based on LWF's analysis)

Unambiguous (UNAMB) data:

"Look - a red bottle! Hmm - 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 =

[_Nred[_N[_{N0}bottle]]].

Previous proposals for learning about *one*

Baker (1978) [Baker] (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 N⁰.

What about when there are multiple N' antecedents?

[_Nred[_N[_{N0}bottle]]] or [_N[_{N0}bottle]]?

(No specific proposal for this.)

Previous proposals for learning about *one*

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 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'.

$[_{N'} \text{red}[_{N^0} \text{bottle}]]$

Previous proposals for learning about *one*

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 N⁰.

$[_{N^0} \text{bottle}]$

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.

Previous proposals for learning about *one*

Foraker et al. 2009 [F&al]: Leverage the syntactic distribution of *one* with innate domain-general statistical learning, by using subtle domain-specific semantic distinctions that indicate syntactic category.

"ball with stripes" "side of the road"

"one with dots" *"*one of the river*"

[modifiers] [complements = conceptually evoked by head noun]
[head noun = N'] [head noun = N⁰]

How?

Indirect negative evidence (never seeing *one* with a complement, even though other nouns take complements) indicates *one* is not N⁰.

A new proposal: Broadening the data set

Pearl & Mis, submitted [P&M]: Other pronouns in the language can also be used anaphorically: *him, her, it, ...*

Look at the cute penguin. I want to hug *him/her/it*.

$[_{NP} \text{the } [_{N'} \text{cute } [_{N^0} \text{penguin}]]]] \longrightarrow [_{NP} \text{him/her/it}]$



Look! A cute penguin. I want *one*.

$[_{NP} \text{a } [_{N'} \text{cute } [_{N^0} \text{penguin}]]]] \longrightarrow [_{NP} \text{one}]$

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).

A new proposal: Broadening the data set

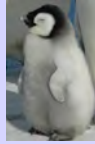
Pearl & Mis, submitted [P&M]: Track how often the referent of the anaphoric element (*one, him, her, it, etc.*) has the property mentioned in the potential antecedent, using innate domain-general statistical learning abilities.

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

Look at the cute penguin. I want to hug *him/her/it*.

Look! A cute penguin. I want *one*.

Is the referent cute? Yes!
So it's important that the antecedent include the modifier "cute".



A new proposal: Broadening the data set

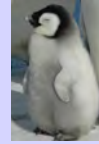
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Important: This applies, even when the syntactic category is known.

Look at the cute penguin. I want to hug *him/her/it*.

Look! A cute penguin. I want *one*.

Data points like those above 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.



Data set comparisons: Learners using syntactic and semantic information

Unamb <NP

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



Learners: Baker, R&G, P&L's EO, P&M

Sem-Syn Amb

"Look - a red bottle! Oh, look - another *one*!"



Learners: R&G, P&L's EO, P&M

Syn Amb

"Look - a bottle! Oh, look - another *one*!"



Learners: P&L's EO, P&M

Unamb NP

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

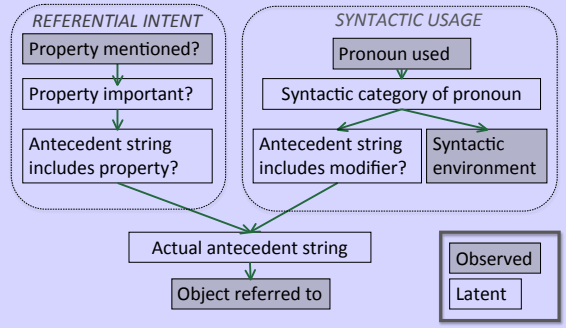


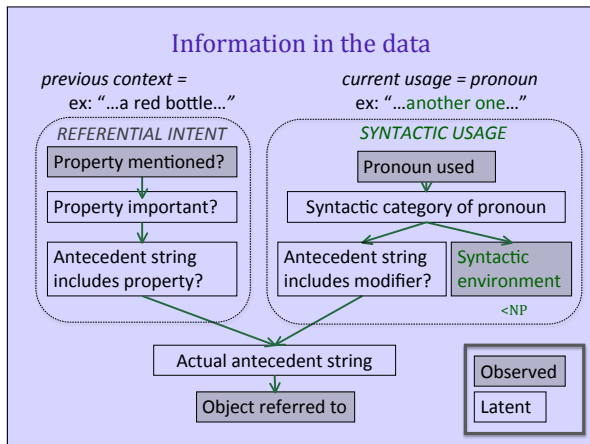
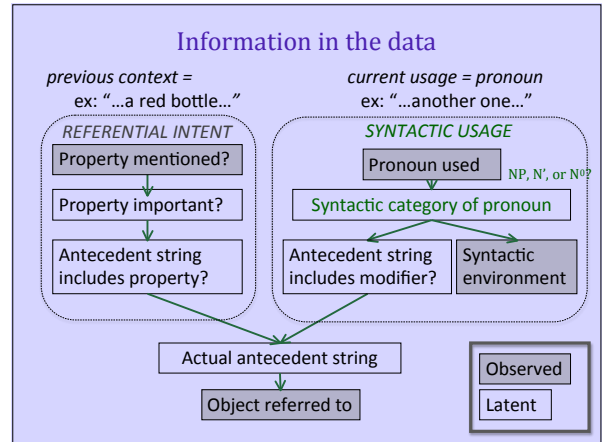
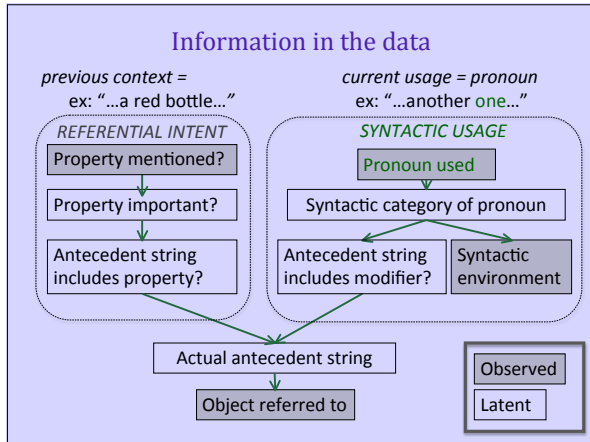
Learners: P&M

Information in the data

previous context =
ex: "...a red bottle..."

current usage = pronoun
ex: "...another one..."



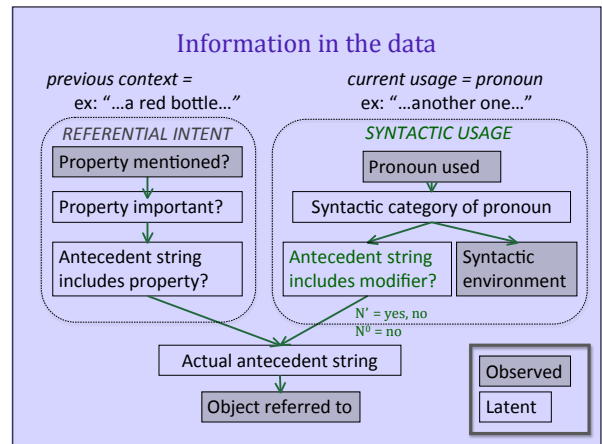


Actual antecedent string

Object referred to

Observed

Latent

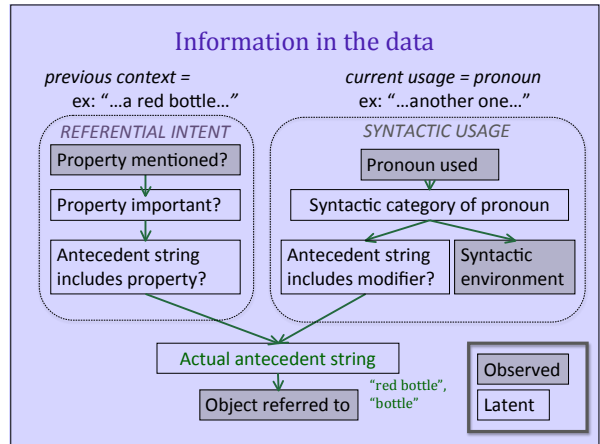
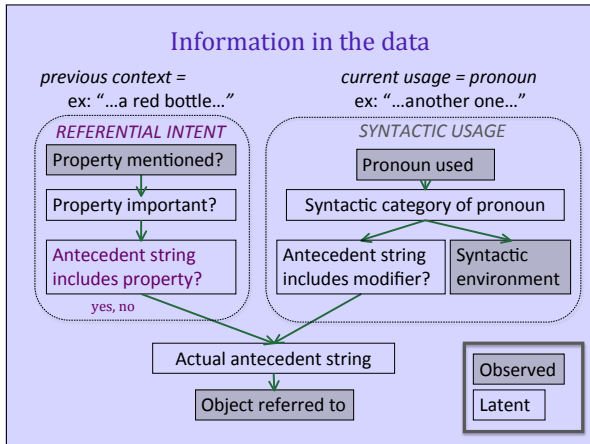
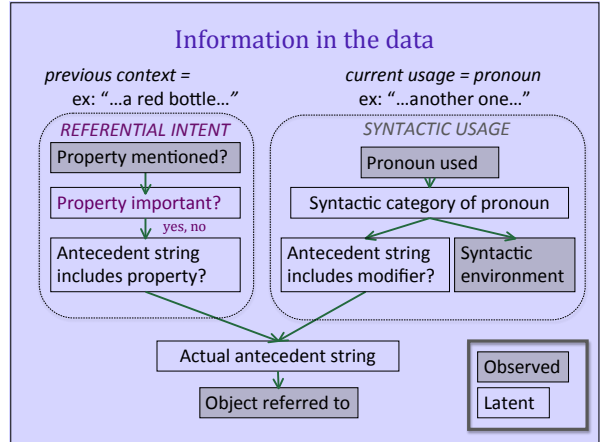
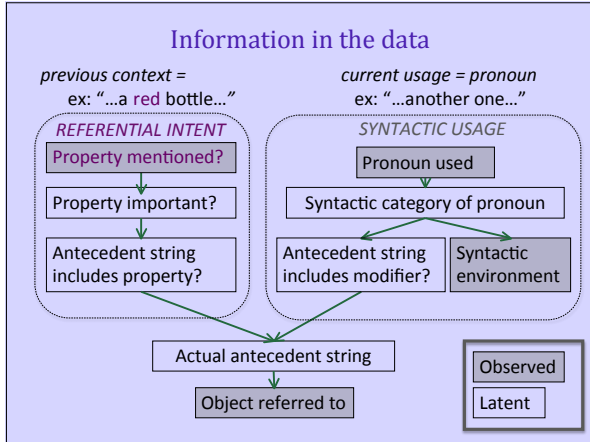


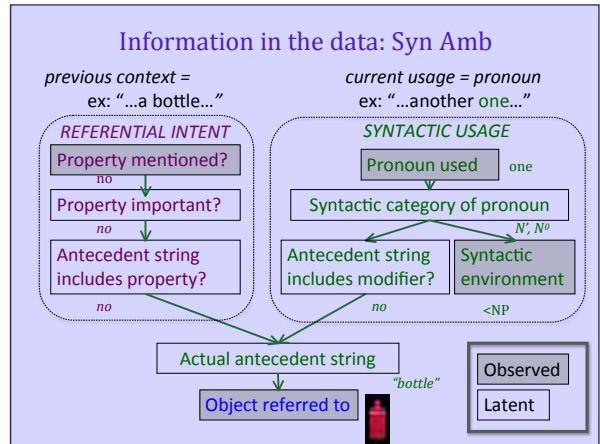
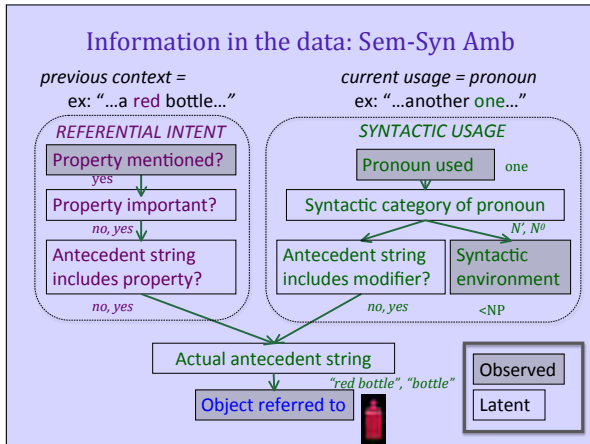
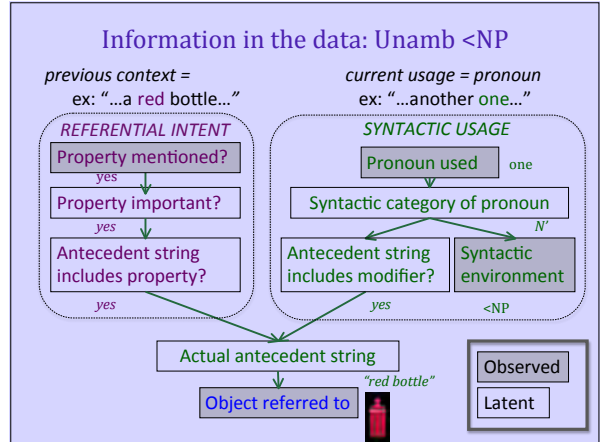
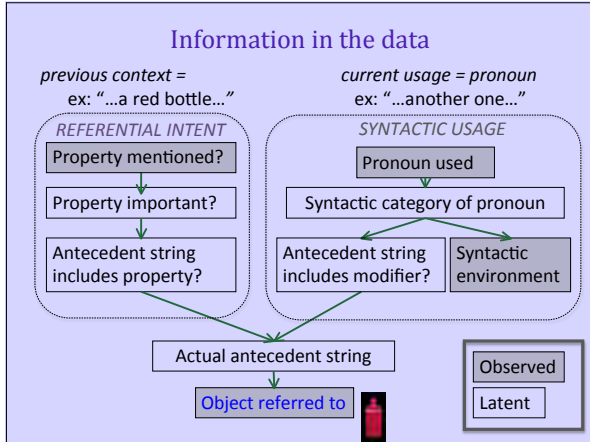
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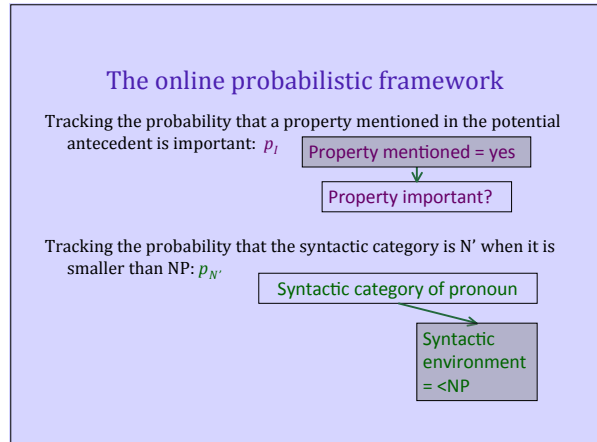
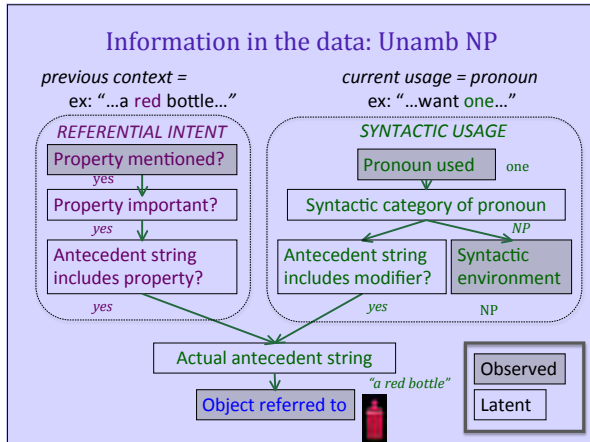
Object referred to

Observed

Latent







The online probabilistic framework

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

data seen suggesting x is true

$$p_x = \frac{\alpha + \text{data}_x}{\alpha + \beta + \text{totaldata}_x} \quad (\alpha = \beta = 1) \text{ A very weak prior}$$

total informative data seen w.r.t x

After every informative data point encountered:

$\text{data}_x = \text{data}_x + \phi_x$ Incremented by probability that data point suggests x is true

$\text{totaldata}_x = \text{totaldata}_x + 1$ One informative data point seen

The online probabilistic framework: Updating p_i

	ϕ_i	Explanation
Unamb <NP	1	Property definitely important
Unamb NP	1	Property definitely important
Syn Amb	N/A	Not informative for p_i
Sem-Syn Amb	$\frac{\rho_1}{\rho_1 + \rho_2 + \rho_3}$	Probability property is important

$\rho_1 = p_N * \frac{m}{m+n} * p_i$ Category = N', choose N' with modifier, property is important

$\rho_2 = p_N * \frac{n}{m+n} * (1-p_i) * \frac{1}{t}$ Category = N', choose N' without modifier, property is not important, choose object with property by chance

$\rho_3 = (1-p_N) * (1-p_i) * \frac{1}{t}$ Category = N⁰, property is not important, choose object with property by chance

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	$\frac{\rho^4}{\rho^4 + \rho^5}$	Probability category is N'
Sem-Syn Amb	$\frac{\rho^1 + \rho^2}{\rho^1 + \rho^2 + \rho^3}$	Probability category is N'

$\rho^1 = p_{N'} * \frac{m}{m+n} * p_I$ Category = N', choose N' with modifier, property is important
 $\rho^2 = p_{N'} * \frac{n}{m+n} * (1-p_I) * \frac{1}{t}$ Category = N', choose N' without modifier, property is not important, choose object with property by chance
 $\rho^3 = (1-p_{N'}) * (1-p_I) * \frac{1}{t}$ Category = N⁰, property is not important, choose object with property by chance

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

	$\Phi_{N'}$	Explanation
Unamb <NP	1	Category definitely N'
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Syn Amb	$\frac{\rho^4}{\rho^4 + \rho^5}$	Probability category is N'
Sem-Syn Amb	$\frac{\rho^1 + \rho^2}{\rho^1 + \rho^2 + \rho^3}$	Probability category is N'

$\rho^4 = p_{N'} * \frac{n}{m+n}$ Category = N', choose N' without modifier
 $\rho^5 = 1 - p_{N'}$ Category = N⁰

Example updates

Start with $p_{N'} = p_I = 0.50$

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

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

One Sem-Syn Amb data point: $p_{N'} = 0.56, p_I = 0.47$
m=1, n=3, t=5 [from P&L]

If m=1, n=3, t=20 $p_{N'} = 0.58, p_I = 0.62$

One Syn Amb data point: $p_{N'} = 0.48, p_I = 0.50$
m=1, n=3, t=5 [from P&L]

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

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).

Corpus Analysis & Learner Input

Learner Input based on Brown/Eve corpus distributions

		Baker	R&G	P&L's EO	P&M
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.

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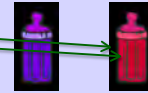
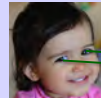
Measures of Success: LWF children's behavior

In addition to directly assessing p_1 and p_{N^0} , we can measure how often a learner would reproduce the behavior in the LWF experiment.

Look – a red bottle!



Do you see another one?



Measures of Success: LWF children's behavior

In addition to directly assessing p_1 and p_{N^0} , we can measure how often a learner would reproduce the behavior in the LWF experiment.

2 choices
 $t = 2$



$\rho_1 + \rho_2 + \rho_3$ Any outcome where learner looks at red bottle
 $\rho_1 + 2 * \rho_2 + 2 * \rho_3$ Additional two outcomes where learner looks at other bottle

$$\rho_1 = p_{N^0} * \frac{m}{m+n} * p_1 \quad \text{Category} = N^0, \text{ antecedent} = \text{"red bottle"}$$

$$\rho_2 = p_{N^0} * \frac{n}{m+n} * (1-p_1) * \frac{1}{t} \quad \text{Category} = N^1, \text{ antecedent} = \text{"bottle"}$$

$$\rho_3 = (1-p_{N^0}) * (1-p_1) * \frac{1}{t} \quad \text{Category} = N^0, \text{ antecedent} = \text{"bottle"}$$

Testing LWF's assumption about what behavior means

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

Is it possible to get correct behavior in the LWF experiment without having the correct representation for *one* in general (as measured by p_1 and p_{N^0})?

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

$$\frac{\rho_1}{\rho_1 + \rho_2 + \rho_3} \quad \text{the probability the look to the red bottle is because the learner has the correct representation (N^0, "red bottle") given that the learner looks at the red bottle}$$

Learner Results

Averages over 1000 simulations, standard deviations in parentheses.

	Baker	R&G	P&L's EO	P&M
p_I	0.50 (<.01)	0.95 (<.01)	0.02 (<.01)	>0.99 (<.01)
p_N	0.50 (<.01)	0.97 (<.01)	0.17 (.02)	0.37 (.04)
$p(\text{LWF behavior})$				
$p(\text{correct representation when producing LWF behavior})$				

As previous studies found:

- Traditional unambiguous data alone fails (Baker).
- Leveraging Sem-Syn ambiguous data succeeds (R&G, P&L).
- Leveraging Syn ambiguous data in addition fails (P&L's EO).

New result: Leveraging Unamb NP data (P&M) does not yield the correct representation in general (p_N is low), but...

Learner Results

Averages over 1000 simulations, standard deviations in parentheses.

	Baker	R&G	P&L's EO	P&M
p_I	0.50 (<.01)	0.95 (<.01)	0.02 (<.01)	>0.99 (<.01)
p_N	0.50 (<.01)	0.97 (<.01)	0.17 (.02)	0.37 (.04)
$p(\text{LWF behavior})$	0.53 (<.01)	0.93 (<.01)	0.50 (<.01)	>0.99 (<.01)
$p(\text{correct representation when producing LWF behavior})$				

New result:

The probability of producing the LWF behavior with this incorrect representation is high.

How does this work?

If p_I is high, then when a property is mentioned (like "red"), the learner believes that property is relevant – which means the referent must include that property (RED BOTTLE).

Learner Results

Averages over 1000 simulations, standard deviations in parentheses.

	Baker	R&G	P&L's EO	P&M
p_I	0.50 (<.01)	0.95 (<.01)	0.02 (<.01)	>0.99 (<.01)
p_N	0.50 (<.01)	0.97 (<.01)	0.17 (.02)	0.37 (.04)
$p(\text{LWF behavior})$	0.53 (<.01)	0.93 (<.01)	0.50 (<.01)	>0.99 (<.01)
$p(\text{correct representation when producing LWF behavior})$				

What this means:

LWF's assumption that correct behavior indicates the child has the correct representation does not seem to hold.

Learner Results

Averages over 1000 simulations, standard deviations in parentheses.

	Baker	R&G	P&L's EO	P&M
p_I	0.50 (<.01)	0.95 (<.01)	0.02 (<.01)	>0.99 (<.01)
p_N	0.50 (<.01)	0.97 (<.01)	0.17 (.02)	0.37 (.04)
$p(\text{LWF behavior})$	0.53 (<.01)	0.93 (<.01)	0.50 (<.01)	>0.99 (<.01)
$p(\text{correct representation when producing LWF behavior})$	0.22 (<.01)	0.92 (<.01)	<0.01 (<.01)	>0.99 (<.01)

Or does it?

When the child produces the correct behavior in the LWF experiment, the probability that the child has the correct representation *when making that interpretation* is very high, even if the probability for the correct representation *in general* (e.g., when there is no modifier present) is very low.

Upshot: LWF were not wrong about children's representation when interpreting utterances like those in their experiment.

Learner Results

Averages over 1000 simulations, standard deviations in parentheses.

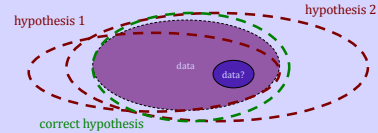
	Baker	R&G	P&L's EO	P&M
p_I	0.50 (<.01)	0.95 (<.01)	0.02 (<.01)	>0.99 (<.01)
$p_{N'}$	0.50 (<.01)	0.97 (<.01)	0.17 (.02)	0.37 (.04)
$p(\text{LWF behavior})$	0.53 (<.01)	0.93 (<.01)	0.50 (<.01)	>0.99 (<.01)
$p(\text{correct representation when producing LWF behavior})$	0.22 (<.01)	0.92 (<.01)	<0.01 (<.01)	>0.99 (<.01)

Also, the other learners behave as LWF expect:

When they show the **correct** behavior, they have the **correct** representation.
When they show **incorrect** behavior, they have the **incorrect** representation.

Recap & Implications

• Children may be able to learn the correct interpretation for *one* in certain situations (such as the LWF experiment) by broadening the set of data they consider relevant.



• Just because children demonstrate that they have the correct **interpretation** some of the time does not mean they have the correct **representation** all of the time.

Recap & Implications

• While children must eventually learn the correct representation of *one*, they do not necessarily need to do so by 18 months.

• Instead, they may realize that *one's* category is N' (rather than N⁰) at some later point.



One possibility:

[F&al] Leverage the syntactic distribution of *one* with innate domain-general statistical learning, by using subtle domain-specific semantic distinctions that indicate syntactic category.

"ball with stripes"

"side of the road"

"one with dots"

*"one of the river"

[modifiers]

[complements = conceptually evoked by head noun]

[head noun = N']

[head noun = N⁰]

The Acquisition Trajectory

I want *it*.
I want *one*.

Another *one*!

Do you see *him*?
Do you see *one*?



Before 18 months:


Need **domain-specific** knowledge

Recognize that *one* is similar to other anaphoric elements (*it*, *him*, etc.).



How to get it?

Derive it by using innate domain-general statistical learning abilities to observe the distribution of *one* compared to these other elements.

The Acquisition Trajectory






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

Before 18 months:
Track how often a mentioned property is important for a referent to have.

How to get it?
Use **innate domain-general statistical learning** abilities to track this.


The Acquisition Trajectory


18 months:
Be able to assign the correct interpretation to utterances like those in the LWF experiment. (Know that *one* is N' in these cases.)

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

The Acquisition Trajectory



"ball with stripes"
"side of the road"
"one with dots"
*"one of the river"

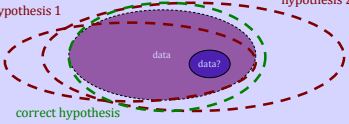


After 18 months:
Need **domain-specific knowledge** about subtle semantic distinctions that indicate syntactic category in order to leverage the syntactic distribution of *one* with **innate domain-general statistical learning**.

How?
May come from **innate domain-specific knowledge (UG)** about language.

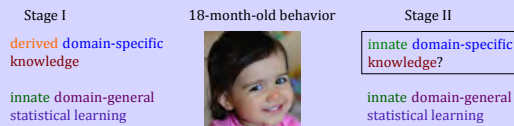
Back to the bigger questions

- When induction problems exist, what does it take to solve them?
 - What **indirect evidence** is available? How might a child leverage this evidence?
- Broader data sets that are identifiable via innate domain-general learning abilities may be additional sources of useful information.



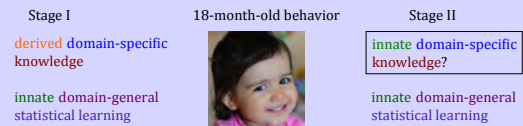
Back to the bigger questions

- When induction problems exist, what does it take to solve them?
 - What learning biases can get the job done, given the available data? Are they necessarily **innate** and **domain-specific** (UG)?
- In this case study, the first step may not involve this kind of knowledge, although achieving the final adult knowledge state may.



Back to the bigger questions

- How can the necessary learning biases inform us about how the acquisition process works?
 - identify learning biases needed to achieve 18-month-old behavior
 - identify knowledge state those biases suggest
 - suggest a **two stage acquisition process** for learning anaphoric *one*



The big picture

- Indirect evidence does **not necessarily mean** indirect **negative** evidence – it can come from considering a broader pool of informative data
- Indirect evidence does **not necessarily negate** the need for learning biases (of whatever kind)
- Considering indirect evidence and its impact on acquisition can help **define concrete proposals** about what is necessarily innate and domain-specific, and thus **what is in Universal Grammar**
- Knowing the impact of the necessary learning biases on acquisition may also inform us about the **acquisition trajectory**