Necessary Bias in Natural Language Learning

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Natural Language Learning

Theoretical work:
object of acquisition

IP
XP … VP …
Object Verb

Experimental work:
time course of acquisition

worthwhile: mechanism of acquisition
given the boundary conditions provided by
(a) linguistic representation
(b) the trajectory of learning

The Learning Problem

There is often a non-transparent relationship between the observable form of the data and the underlying system that produced it.

Syntactic System
Observable form: word order
Interference: movement rules

Subject Verb $t_{Subject}$ Object t_{Verb}

The Mechanism of Language Learning: Some Bias = Parameters

Premise: learner considers finite range of hypotheses (parameters)

"Assuming that there are *n* binary parameters, there will be 2^n possible core grammars." - Clark (1994)

The Mechanism of Language Learning: Extracting Systematicity Is Hard

"It is unlikely that any example … would show the effect of only a single parameter value; rather, each example is the result of the interaction of several different principles and parameters" - Clark (1994)

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Potential solution: the learner focuses in on a subset of the data perceived as "informative".

Additional Bias = Filter on data intake

Big Questions for Filtering

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(1) Feasibility
Is there a data sparseness problem?

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Can we filter and get correct behavior?

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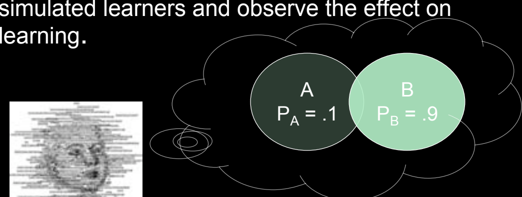
(2) Sufficiency
Can we filter and get correct behavior?

(3) Necessity
Must we filter to get correct behavior?

Computational Modeling of Data Intake Filtering

Why? Can easily (and ethically) restrict data intake to simulated learners and observe the effect on learning.



Recent computational modeling surge: Yang, 2000; Sakas & Fodor, 2001; Yang, 2002; Pearl, 2005; Pearl & Weinberg, 2007

Road Map

Learning Framework Overview

Computational Case Studies:
- Brief Highlights: Old English OV/VO word order
- Details: English Metrical Phonology
- Highlights: English Anaphoric *One*

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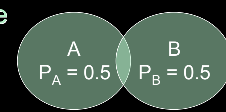
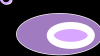
Important Feature: Case studies grounded in empirical data
- searching realistic data space for evidence of underlying system

Learning Framework: 3 Separable Components

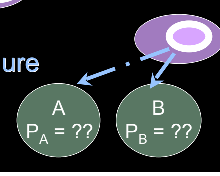
(1) Hypothesis space



(2) Data intake



(3) Update procedure



Benefits of Learning Framework

Components:
(1) hypothesis space (2) data intake (3) update procedure

Application to a wide range of learning problems, provided these three components are defined
- Ex: hypothesis space defined in terms of parameter values (Yang, 2002) or in terms of how much structure is posited for the language (Perfors, Tenenbaum, & Regier, 2006)

Can combine discrete representations (hypothesis space) with probabilistic components (update procedure) to get gradualness and variation found in human language learning

The Hypothesis Space & The Update Procedure

Hypothesis Space: theoretical and experimental work on what hypotheses children entertain (ex: Lidz, Waxman, & Freedman, 2003; Thornton & Crain, 1999; Hamburger & Crain, 1984)

Update Procedure: recent experimental work on probabilistic learning as feasible in adults (Tenenbaum, 2000; Thompson & Newport, 2007) and infants (Newport & Aslin, 2004; Gerken, 2006).

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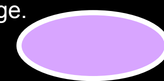
Bayesian updating

Infers likelihood of given hypothesis, given data. Amount of probability shifted depends on layout of hypothesis space.

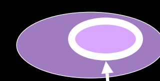
Investigating Data Intake Filtering

Intuition 1: Use all available data to uncover a full range of systematicity, and allow probabilistic model enough data to converge.



input

Intuition 2: Use more “informative” data or more “accessible” data only.



subset of input

Modeling Case Studies of Data Intake Filters

Case One: Old English Syntax

Hypothesis Space: parameters (OV/VO word order)

Proposed Filtering: Degree-0 unambiguous data only

Update Procedure: Bayesian updating

Interesting Feature: target state is a probability distribution

Modeling Case Studies of Data Intake Filters

Case Two: English Metrical Phonology

Hypothesis Space: parameters

Proposed Filtering: unambiguous data only

Update Procedure: Bayesian updating

Interesting Feature: multiple interactive parameters; noisy data

Modeling Case Studies of Data Intake Filters

Case Three: English Anaphoric *One*

Hypothesis Space: structures & associated referents in world

Proposed Filtering: ignore some (pervasive) ambiguous data

Update Procedure: Bayesian updating + hypothesis space layout information

Interesting Feature: multiple sources of information across domains

Big Questions for Filtering

(1) Feasibility
Is there a data sparseness problem?

(2) Sufficiency
Can we filter and get correct behavior?

(3) Necessity
Must we filter to get correct behavior?

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Computational Case Studies:

- Brief Highlights: Old English OV/VO word order
  - unambiguous degree-0 data filtering
  - feasibility
  - sufficiency & necessity
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Old English Filters

Filter 1: Use data perceived as unambiguous (Dresher, 1999; Lightfoot, 1999; Fodor, 1998)

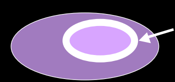
Filter 2: Use structurally "simple" data - matrix clause or "degree-0" data (Lightfoot, 1991)

Jack told his mother that he stole the golden goose.
[----Degree-0-------]
[-------------Degree-1----------]

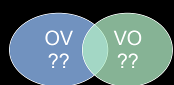
Problems: Feasibility

Potential feasibility problem: data sparseness

degree-0 unambiguous data set is significantly smaller than entire input set



How could a learner find unambiguous data for OV/VO word order?



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Perceived Unambiguous Data: Making "Unambiguous" Feasible

Definitions of data perceived as unambiguous are ***heuristic*** and/or involve only partial knowledge of the adult linguistic system (Lightfoot 1999, Dresher 1999, Fodor 1998)

OV:

$[\ldots]_{XP}$ … Object TensedVerb …

… Object Verb-Marker …

VO:

$[\ldots]_{XP}$ $[\ldots]_{XP}$ … TensedVerb Object …

… Verb-Marker Object …

This allows the learner to identify *some* data points as unambiguous (even if they're actually not for someone with full knowledge of the adult linguistic system)

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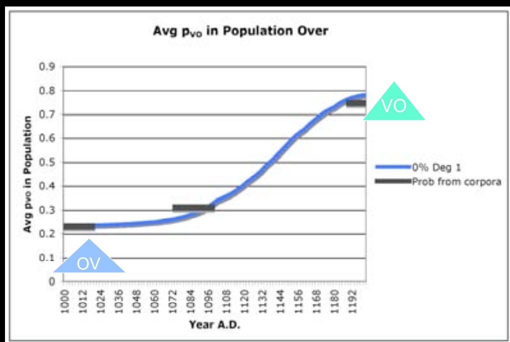
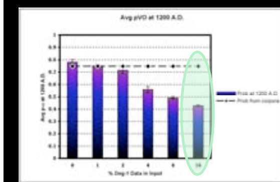
Sufficiency of Filters: Correct Behavior (Population-Level)

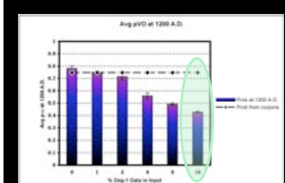


Necessity of Filters: Removal = Incorrect Behavior

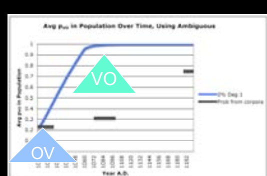


Using degree-1 data

Necessity of Filters: Removal = Incorrect Behavior



Using degree-1 data



Using ambiguous data

Using ambiguous & degree-1 data

Big Questions for Filtering: Old English Syntax

(1) Feasibility
No data sparseness problem.

(2) Sufficiency
Filtering yields the correct behavior.

(3) Necessity
Removing the filters yields incorrect behavior.

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- sufficiency: logical problem of language acquisition

Highlights: English Anaphoric *One*

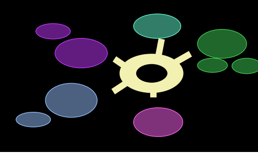
Feasibility

Unambiguous data filter feasibility in a complex system

Data sparseness: are there unambiguous data? (Clark 1992)

How could a learner identify such data?

Metrical phonology (9 interacting parameters)



Interactive Parameters

The order in which parameters are set may determine if they are set correctly (Dresher, 1999): parameter-setting influences what data are identified as "unambiguous".

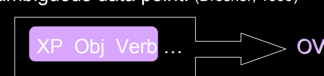
Identifying unambiguous data:

Cues (Dresher, 1999; Lightfoot, 1999)

Parsing (Fodor, 1998; Sakas & Fodor, 2001)

Cues vs. Parsing: Overview

A cue is a local "specific configuration in the input" that corresponds to a specific parameter value. A cue matches an unambiguous data point. (Dresher, 1999)



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XP Obj Verb … → OV

Parsing tries to analyze a data point with "all possible parameter value combinations", conducting an "exhaustive search of all parametric possibilities." (Fodor, 1998)

Subj Verb Obj → OV, +V2 / VO, +V2 / VO, -V2

Cues vs. Parsing: Comparison

	Cues	Parsing
Easy identification of unambiguous data	+	
Can find information in datum sub-part	+	
Can tolerate exceptions	+	
Is not heuristic		+
Does not require additional knowledge		+
Does not use default values		+

Cues vs. Parsing in a Probabilistic Framework

"Both models ... cannot capture the variation in and the gradualness of language development…when a parameter *is* set, it is set in an all-or-none fashion." - Yang (2002)

Benefit of using learning framework to sidestep this problem - separable components used in combination:

(1) cues/parsing to identify unambiguous data

(2) probabilistic framework of gradual updating based on unambiguous data

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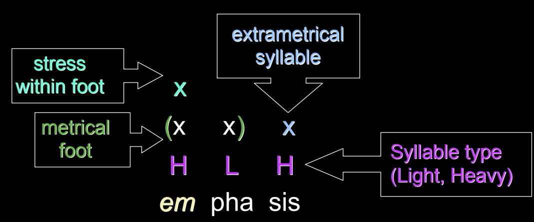
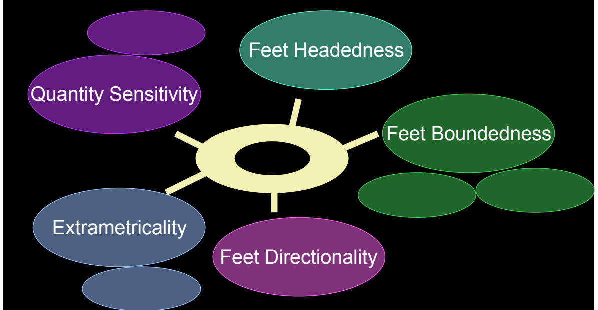
Metrical Phonology

What tells you to put the ***EM***phasis on a particular ***SYL***lable

sample metrical phonology structure



Metrical Phonology Parameters



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Cues for Metrical Phonology Parameters

Recall: Cues match local surface structure (sample cues below)

QS: 2 syllable word with 2 stresses	VV VV
Em-Right: Rightmost syllable is Heavy and unstressed	L H H
Unb: 3+ unstressed S/L syllables in a row	…S S S… … L L L L
Ft Hd Left: Leftmost foot has stress on leftmost syllable	S S S… H L L …

Parsing with Metrical Phonology Parameters

parse data with all available values of all parameters (values cease to be available when one value is chosen as the correct one for the language - the other value(s) is(are) then unavailable)

If all successful parses of a data point share one value of a parameter (e.g. "Extrametrical None"), that data point is considered unambiguous for that parameter value.

Parsing with Metrical Phonology Parameters

Sample data point: VC VC VV ('afternoon')

Parsing with Metrical Phonology Parameters

Sample data point: VC VC VV ('afternoon')

(QS, QSVCL, Em-None, Ft Dir Right,
B, B-2, B-Syl, Ft Hd Right)

(x)	(x	x)
L	L	H)
VC	VC	VV

Parsing with Metrical Phonology Parameters

Sample data point: VC VC VV ('afternoon')

(QS, QSVCL, Em-None, Ft Dir Right,
B, B-2, B-Syl, Ft Hd Right)

(x)	(x	x)
L	L	H)
VC	VC	VV

(QS, QSVCL, Em-None, Ft Dir Left,
Ft Hd Left, B, B-2, B-Syl)

(x	x)	(x)
(L	L	H
VC	VC	VV

Parsing with Metrical Phonology Parameters

Sample data point: VC VC VV ('afternoon')

(QS, QSVCL, Em-None, Ft Dir Right,
B, B-2, B-Syl, Ft Hd Right)

(x) (x x)
L L H)
VC VC VV

(QS, QSVCL, Em-None, Ft Dir Left,
Ft Hd Left, B, B-2, B-Syl)

(x x) (x)
(L L H
VC VC VV

(QI, Em-None, Ft Dir Right,
Ft Hd Right, B, B-2, B-Syl)

(x x) (x)
S S S)
VC VC VV

Parsing with Metrical Phonology Parameters

Values leading to successful parses of data point:
(QI, Em-None, Ft Dir Left, Ft Hd Left, B, B-2, B-Syl)
(QI, Em-None, Ft Dir Right, Ft Hd Right, B, B-2, B-Syl)
(QS, QSVCL, Em-None, Ft Dir Left, Ft Hd Left, UnB)
(QS, QSVCL, Em-None, Ft Dir Left, Ft Hd Left, B, B-2, B-Syl)
(QS, QSVCL, Em-None, Ft Dir Right, Ft Hd Right, B, B-2, B-Syl)

Data point is unambiguous for Em-None.

Parsing with Metrical Phonology Parameters

Values leading to successful parses of data point:
(QI, Em-None, Ft Dir Left, Ft Hd Left, B, B-2, B-Syl)
(QI, Em-None, Ft Dir Right, Ft Hd Right, B, B-2, B-Syl)
(QS, QSVCL, Em-None, Ft Dir Left, Ft Hd Left, UnB)
(QS, QSVCL, Em-None, Ft Dir Left, Ft Hd Left, B, B-2, B-Syl)
(QS, QSVCL, Em-None, Ft Dir Right, Ft Hd Right, B, B-2, B-Syl)

Data point is unambiguous for Em-None.

If QI already set, data point is unambiguous for
Em-None, B, B-2, and B-Syl.

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Finding Unambiguous Data: English Metrical Phonology

Non-trivial system: metrical phonology

Non-trivial language: English (full of exceptions)
- data unambiguous for the *incorrect* value in the adult system

Adult English system values:
- QS, QSVCH, Em-Some, Em-Right, Ft Dir Right, Bounded, B-2, B-Syllabic, Ft Hd Left

Exceptions:
- QI, QSVCL, Em-None, Ft Dir Left, Unbounded, B-3, B-Moraic, Ft Hd Right

Empirical Grounding in Realistic Data: Estimating English Data Distributions

Caretaker speech to children between the ages of 6 months and 2 years (CHILDES: MacWhinney, 2000)

Total Words: 540505
Mean Length of Utterance: 3.5

Words parsed into syllables and assigned stress using the American English CALLHOME database of telephone conversation (Canavan et al., 1997) & the MRC Psycholinguistic database (Wilson, 1988)

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Sufficient Filters: Viable Parameter-Setting Orders

Can learners using unambiguous data (identified by either cues or parsing) learn the English system? What parameter-setting orders are viable?

Viable orders are derived for each method via an exhaustive walk through all possible parameter-setting orders.

Viable Parameter-Setting Orders:
Encapsulating the Knowledge for Acquisition Success

Worst Case: learning with filters produces insufficient behavior

- No orders lead to correct system

Better Cases: learning with filters produces sufficient behavior

- Slightly Better Case: Viable orders available, but fairly random
- Better Case: Viable orders available, can be captured by small number of *order constraints*
- Best Case: All orders lead to correct system

Identifying Viable Parameter-Setting Orders

(a) For all currently unset parameters, determine the unambiguous data distribution in the corpus.

Quantity Sensitivity		Extrametricality	
QI: .00398	QS: 0.0205	None: 0.0294	Some: .0000259
Feet Directionality		**Boundedness**	
Left: 0.000	Right: 0.00000925	Unbounded: 0.00000370	Bounded: 0.00435
Feet Headedness			
Left: 0.00148	Right: 0.000		

Note: Probabilities can be relativized in different ways.

Identifying Viable Parameter-Setting Orders

(a) For all currently unset parameters, determine the unambiguous data distribution in the corpus.

(b) Choose a currently unset parameter to set. The value chosen for this parameter is the value that has a higher probability in the data the learner perceives as unambiguous.

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Left: 0.00148	Right: 0.000		

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(c) Repeat steps (a-b) until all parameters are set.

Identifying Viable Parameter-Setting Orders

(a) For all currently unset parameters, determine the unambiguous data distribution in the corpus…

QS-VC-Heavy/Light		Extrametricality	
Heavy: .00265	Light: 0.00309	None: 0.0240	Some: .0485
Feet Directionality		**Boundedness**	
Left: 0.000	Right: 0.00000555	Unbounded: 0.00000370	Bounded: 0.00125
Feet Headedness			
Left: 0.000588	Right: 0.0000204		

Identifying Viable Parameter-Setting Orders

(a) For all currently unset parameters, determine the unambiguous data distribution in the corpus.

(b) Choose a currently unset parameter to set. The value chosen for this parameter is the value that has a higher probability in the data the learner perceives as unambiguous.

(c) Repeat steps (a-b) until all parameters are set.

(d) Compare final set of values to English set of values. If they match, this is a viable parameter-setting order.

(e) Repeat (a-d) for all parameter-setting orders.

Sufficiency of an Unambiguous Filter

Are there any viable parameter-setting orders for a learner using either method (cues or parsing)? What constraints are there?

Cues: Parameter-Setting Orders

Cues: Sample viable orders

(a) QS, QS-VC-Heavy, Bounded, Bounded-2, Feet Hd Left, Feet Dir Right, Em-Some, Em-Right, Bounded-Syl

(b) Feet Dir Right, QS, Feet Hd Left, Bounded, QS-VC-Heavy, Bounded-2, Em-Some, Em-Right, Bounded-Syl

Cues: Sample failed orders

(a) QS, Bounded, Feet Hd Left, Feet Dir Right, QS-VC-Heavy, Em-Some, Em-Right, Bounded-Syl, Bounded-2

(b) Feet Hd Left, Feet Dir Right, Bounded, Bounded-Syl, Bounded-2, QS, QS-VC-Heavy, Em-Some, Em-Right

…but only for certain assumptions about probability relativization.

Parsing: Parameter-Setting Orders

Parsing: Sample viable orders

(a) Bounded, QS, Feet Hd Left, Feet Dir Right, QS-VC-Heavy, Bounded-Syl, Em-Some, Em-Right, Bounded-2

(b) Feet Hd Left, QS, QS-VC-Heavy, Bounded, Feet Dir Right, Em-Some, Em-Right, Bounded-Syl, Bounded-2

Parsing: Sample failed orders

(a) Feet Dir Right, QS, Feet Hd Left, Bounded, QS-VC-Heavy, Bounded-2, Em-Some, Em-Right, Bounded-Syl

(b) Em-Some, Em-Right, QS, Bounded, Feet Hd Left, Feet Dir Right, QS-VC-Heavy, Bounded-Syl, Bounded-2

…irrespective of what probability relativization assumptions are made.

Cues vs. Parsing: Order Constraints

Cues

(a) QS-VC-Heavy
before Em-Right

(b) Em-Right
before Bounded-Syl

(c) Bounded-2
before Bounded-Syl

The rest of the parameters are freely ordered w.r.t. each other.

Note: Constraints are derivable from properties of the learning system.

Parsing

Group 1:
QS, Ft Head Left, Bounded

Group 2:
Ft Dir Right, QS-VS-Heavy

Group 3:
Em-Some, Em-Right, Bounded-2, Bounded-Syl

The parameters are freely ordered w.r.t. each other within each group.

Note: Most constraints are not derivable from properties of the learning system.

Feasibility & Sufficiency of the Unambiguous Data Filter

Either method of identifying unambiguous data (cues or parsing) is successful. Given the non-trivial system (9 interactive parameters) and the non-trivial data set (English is full of exceptions), this is no small feat.

"It is unlikely that any example … would show the effect of only a single parameter value" - Clark (1994)

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(1) Feasibility & Sufficiency:

- Unambiguous data identified in sufficient quantities
- Correct systematicity can be extracted

(2) This filter is robust across a realistic (highly ambiguous, exception-filled) data set.

Big Questions for Filtering: English Metrical Phonology

(1) Feasibility
No data sparseness problem, even in complex system with multiple interactive parameters.

(2) Sufficiency
Filtering yields the correct behavior.

(3) Necessity
Future investigation

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- interesting problems, adult knowledge, & infant behavior
- available data & filter feasibility considerations
- additional sources of information: hypothesis space layout
- data intake filters: sufficiency & necessity

Anaphoric *One*: Why Is It Interesting?

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

Representations that are linked across domains (syntactic structure & semantic reference)

Available information: linguistic antecedent (*red bottle*) + referent in world

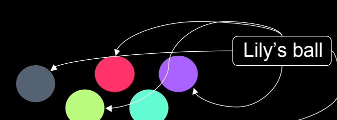
Anaphoric *One*: Adult Knowledge

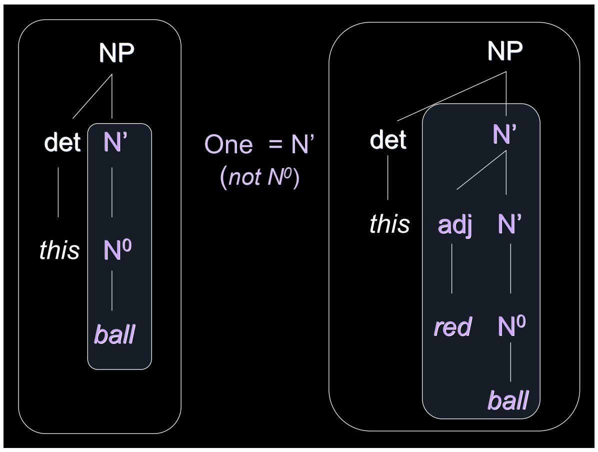
"Jack likes this red ball, and Lily likes that *one*.

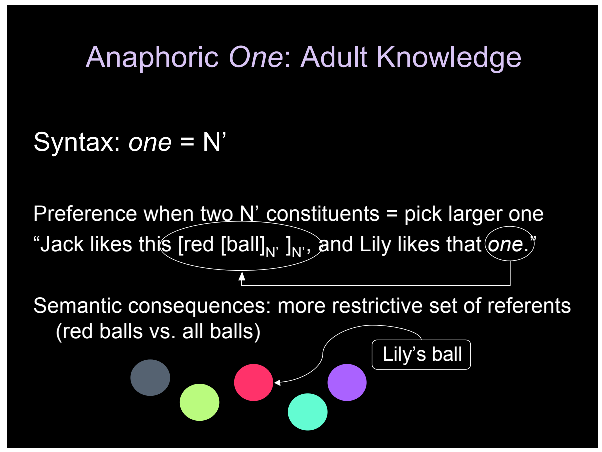
one = red ball

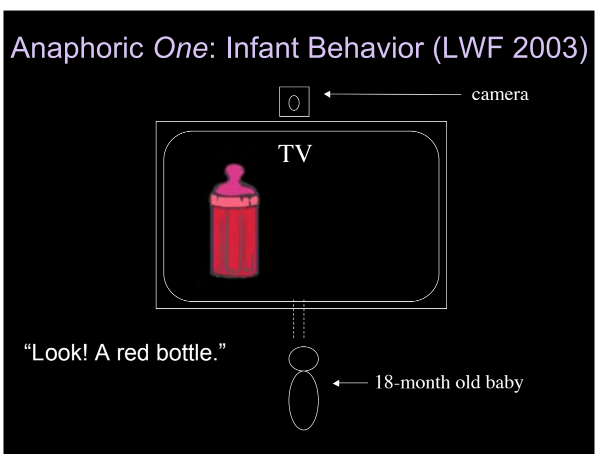
"Jack likes this ball, and Lily likes that *one*.

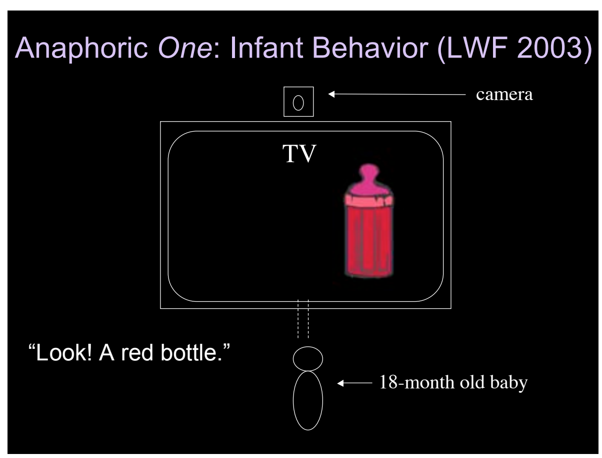
one = ball




NP
det
N'
this
N0
ball
One = N'
(not N0)
NP
det
N'
this
adj
N'
red
N0
ball


Anaphoric One: Adult Knowledge
Syntax: one = N'
Preference when two N' constituents = pick larger one
"Jack likes this [red [ball]N']N', and Lily likes that one."
Semantic consequences: more restrictive set of referents
(red balls vs. all balls)
Lily's ball


Anaphoric One: Infant Behavior (LWF 2003)
camera
TV
"Look! A red bottle."
18-month old baby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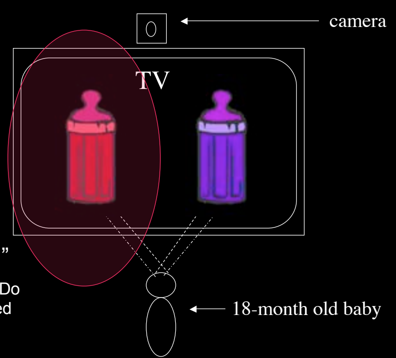


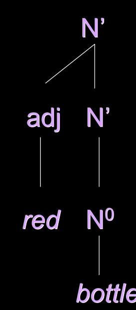
"Do you see another one?"

(Same results as "Do you see another red bottle?")

Anaphoric *One*: Infant Behavior (LWF 2003)

18-month olds have looking preference for red bottle.

LWF (2003) interpretation & conclusion:
Red bottle preference = semantic consequence of syntactic knowledge that *one* = [*red bottle*]$_{N'}$. 18-month olds, like adults, don't think *one* can have an N^0 antecedent.



Road Map

Learning Framework Overview

Computational Case Studies:

Brief Highlights: Old English OV/VO word order

Details: English Metrical Phonology

Highlights: English Anaphoric *One*

- interesting problems, adult knowledge, & infant behavior
- available data & filter feasibility considerations
- additional sources of information: hypothesis space layout
- data intake filters: sufficiency & necessity

Available Anaphoric *One* Data

By 18 months, estimated 4017 anaphoric *one* data points.

But…only 10 of these are unambiguous.

"Jack wants a red ball, but Lily doesn't have another one."

(Situation: Lily doesn't have another *red ball*. She has a red and a purple one, and wants to keep a red ball herself.)

Feasibility problem: data sparseness

Potential Solution: Utilize ambiguous data somehow

Using Ambiguous Data

Type I: 183 data points

"Jack wants a **red ball**, and Lily has another one for him."

(Situation: Lily has another *red ball*. She has two - one for herself, and one for Jack.)

Why ambiguous: She has another *ball*, as well. *One* could refer to *ball,* which is compatible with the N^0 structure.

Using Ambiguous Data

Type I: 183 data points

"Jack wants a **red ball**, and Lily has another one for him."

(Situation: Lily has another *red ball*. She has two - one for herself, and one for Jack.)

Why ambiguous: She has another *ball*, as well. *One* could refer to *ball,* which is compatible with the N^0 structure.

Type II: 3805 data points

"Jack wants a **ball**, and Lily has another one for him."

(Situation: Lily has another *ball*. She has two - one for herself, and one for Jack.)

Why ambiguous: *One* refers to *ball,* which is compatible with the N^0 structure.

Road Map

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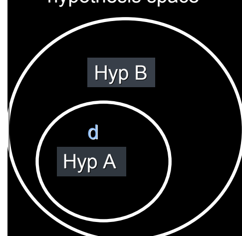
Additional Information Source: Exploiting the Hypothesis Space Layout

Subset-superset hypothesis space

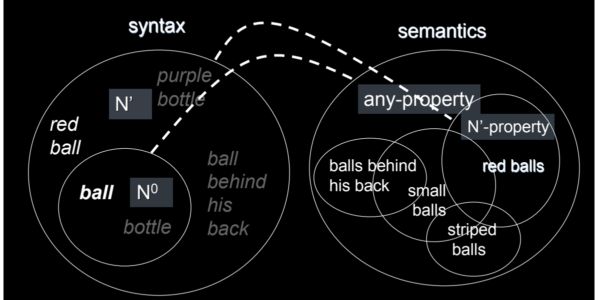


Size principle (Tenenbaum & Griffiths, 2001): favor the subset hypothesis when encountering an ambiguous data point

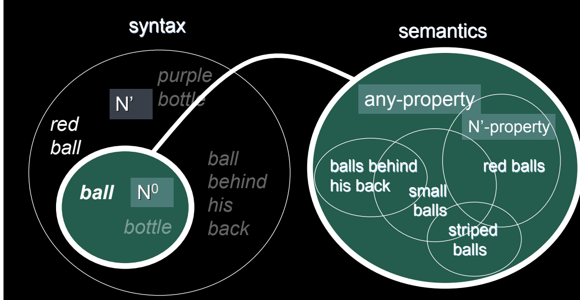
Size principle logic:

- Likelihood of ambiguous data point ***d***
- Learner expectation of set of data points $d_1, d_2, \ldots d_n$

Anaphoric *One*: Hypothesis Space Layout

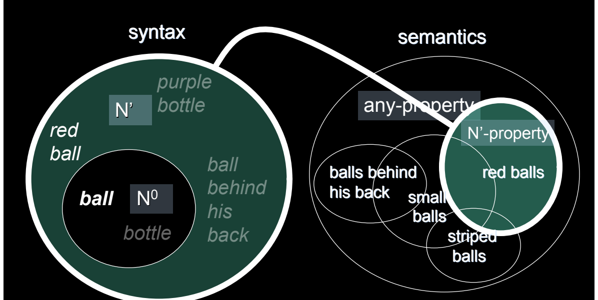


Anaphoric *One*: Hypothesis Space Layout



(Towards the wrong hypothesis) Type II Ambiguous: "…*ball*…*one*…"

Anaphoric *One*: Hypothesis Space Layout



(Towards the right hypothesis) Type I Ambiguous: "…*red ball*…*one*…"

Road Map

Learning Framework Overview

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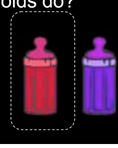
- Brief Highlights: Old English OV/VO word order
- Details: English Metrical Phonology
- Highlights: English Anaphoric *One*
  - interesting problems, adult knowledge, & infant behavior
  - available data & filter feasibility considerations
  - additional sources of information: hypothesis space layout
  - data intake filters: sufficiency & necessity

Data Intake Filtering

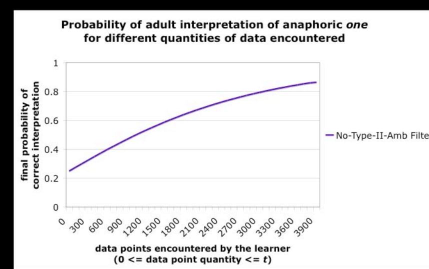
Filter: Use only Unambiguous & Type I Ambiguous data
- less data sparseness (feasibility)
- data will bias learner in the correct direction (Regier & Gahl (2004) insight)
- Note: Use both syntactic & semantic information

Metric of Success: Does learner steadily increase probability of interpreting anaphoric *one* as real 18-month olds do? (sufficiency)

"Look! A red bottle. Do you see another *one*?"



Data Intake Filtering: Sufficiency



Data Intake Filtering

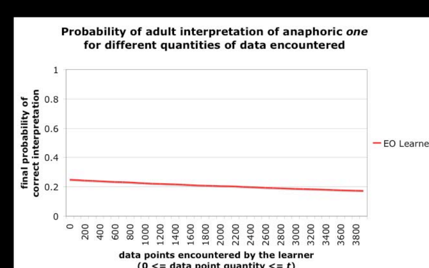
Filter: Use only Unambiguous & Type I Ambiguous data

Feasible: can find sufficient data

Sufficient: produces behavior qualitatively similar to human learners

Necessary?
What happens if we remove the filter and learn from all available data (specifically type II ambiguous, which biases the learner in the wrong direction)?

Equal-Opportunity Learner



Data Intake Filtering

Filter: Use only Unambiguous & Type I Ambiguous data

Feasible: can find sufficient data

Sufficient: produces behavior qualitatively similar to human learners

Necessary: incorrect behavior results when we remove the filtering

Big Picture

Big Picture

(1) Explaining language learning: theory of the mechanism

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(2) Learning framework: separable components that can be explored individually

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Big Picture

(1) Explaining language learning: theory of the mechanism

(2) Learning framework: separable components that can be explored individually

(3) Data intake filtering: feasibility, sufficiency, necessity (perhaps contrary to intuition)

(4) Computational modeling: tool for exploring questions of the learning mechanism & generating testable predictions

Thank You

My Fabulous Thesis Committee:
Amy Weinberg, Jeff Lidz, Bill Idsardi, Charles Yang, Jim Reggia

My Awesome Intellectual/Moral Support:
Norbert Hornstein, Philip Resnik, Colin Phillips, David Poeppel, Peggy Antonisse, Andrea Zukowski, Howard Lasnik, Michelle Hugue, Heather Taylor, Brian Dillon, Yuval Marton, Rachel Shorey, Annie Gagliardi, Raven Alder, Elizabeth Royston, Robert Snyder, Bill Sakas, Cedric Boeckx, Ivano Caponigro, the CNL Lab at UMaryland

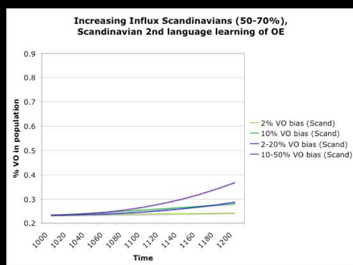
Causes of Language Change

Old Norse influence before 1000 A.D.: VO-biased
- If sole cause of change, requires exponential influx of Old Norse speakers.

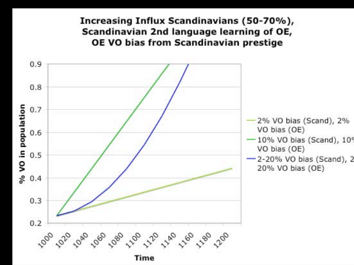
Old French at 1066 A.D.: embedded clauses predominantly OV-biased (Kibler, 1984)
- Matrix clauses often SVO (ambiguous)
- OV-bias would have hindered Old English change to VO-biased system.

Evidence of individual probabilistic usage in Old English
- Historical records likely not the result of subpopulations of speakers who use only one order

Scandinavian Influence, Perfect Learning



Scandinavian Influence, Perfect Learning



Deriving the Bayesian Update Equations for a Hypothesis Space with 2 Hypotheses

$$\mathrm{Max}(\mathrm{Prob}(p_{VO} \mid u)) = \mathrm{Max}\left(\frac{\mathrm{Prob}(u \mid p_{VO}) * \mathrm{Prob}(p_{VO})}{\mathrm{Prob}(u)}\right)$$

Bayes' Rule, find maximum of a posteriori (MAP) probability
Manning & Schütze (1999)

Deriving the Bayesian Update Equations for a Hypothesis Space with 2 Hypotheses

$$\mathrm{Max}(\mathrm{Prob}(p_{VO} \mid u)) = \mathrm{Max}\left(\frac{\mathrm{Prob}(u \mid p_{VO}) * \mathrm{Prob}(p_{VO})}{\mathrm{Prob}(u)}\right)$$

Prob(u | p_{VO}) = probability of seeing unambiguous data point u, given p_{VO}.
= p_{VO}

Prob(p_{VO}) = probability of seeing r out of n data points that are unambiguous for VO, for 0 <= r <= n
= $\binom{n}{r} * p_{VO}^{\,r} * (1 - p_{VO})^{n-r}$

Deriving the Bayesian Update Equations for a Hypothesis Space with 2 Hypotheses

$$\text{Max}(\text{Prob}(\text{pvo} \mid u)) = \text{Max}\left(\frac{\text{pvo} * \binom{n}{r} * \text{pvo}^{r} * (1-\text{pvo})^{n-r}}{\text{Prob}(u)}\right) \quad \text{(for each point } r,\ 0 \le r \le n\text{)}$$

$$\frac{d}{dpvo}\left(\frac{\text{pvo} * \binom{n}{r} * \text{pvo}^{r} * (1-\text{pvo})^{n-r}}{\text{Prob}(u)}\right) = 0$$

$$\frac{d}{dpvo}\left(\frac{\text{pvo} * \binom{n}{r} * \text{pvo}^{r} * (1-\text{pvo})^{n-r}}{\cancel{\text{Prob}(u)}}\right) = 0 \quad \text{(P}(u)\text{ is constant with respect to pvo)}$$

$$\text{pvo} = \frac{r+1}{n+1}$$

Deriving the Bayesian Update Equations for a Hypothesis Space with 2 Hypotheses

$$\text{pvo} = \frac{r+1}{n+1},\ r = \text{pvo}_{\text{Oprev}} * n$$

Replace 1 in numerator and denominator with

$c = \text{pvo}_{\text{Oprev}} * m$ if VO, $c = (1 - \text{pvo}_{\text{Oprev}}) * m$ if OV

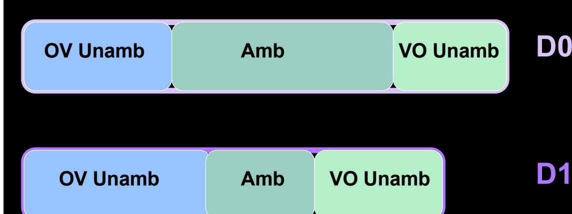
$3.0 \le m \le 5.0$

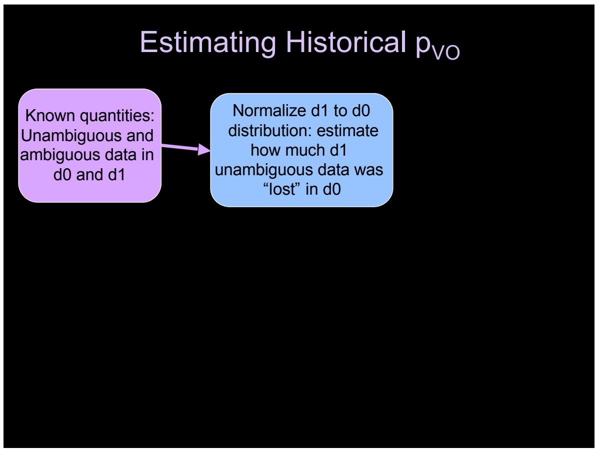
$$\text{pvo} = \frac{\text{pvo}_{\text{Oprev}} * n + c}{n + c}$$

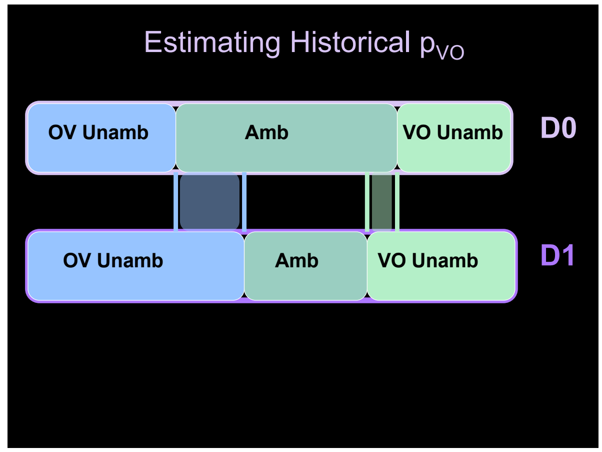
Estimating Historical p_{VO}

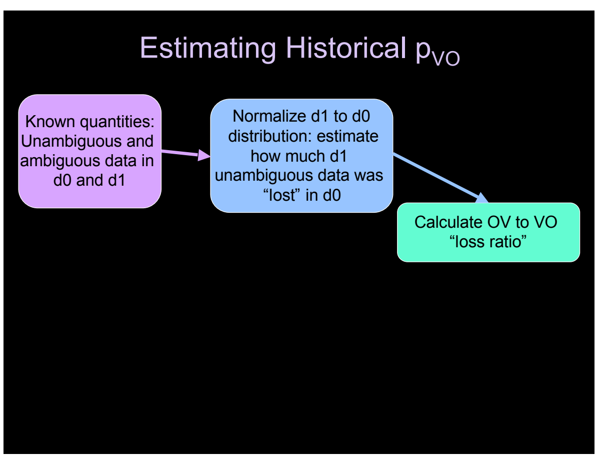
Known quantities: Unambiguous and ambiguous data in d0 and d1

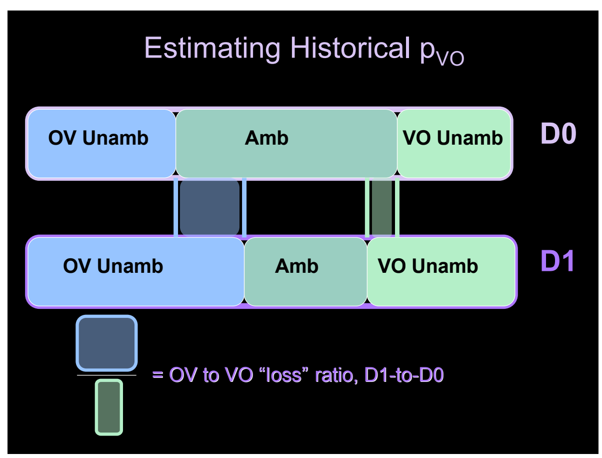
Estimating Historical p_{VO}

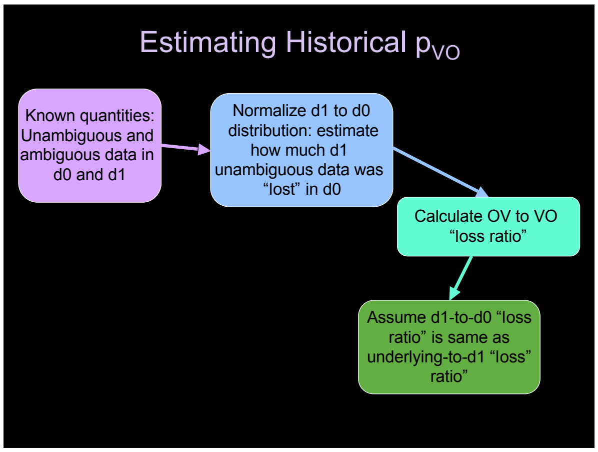


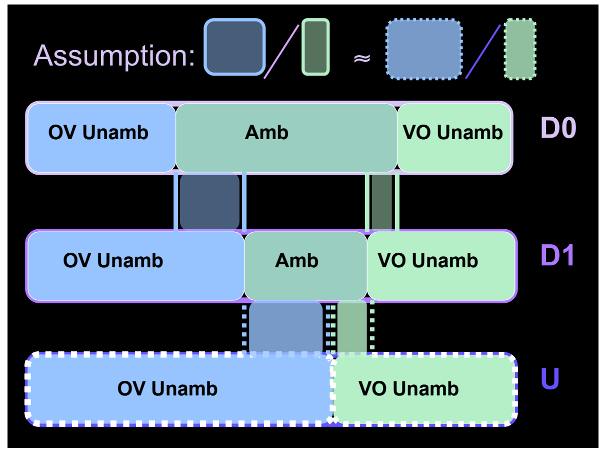

Estimating Historical p_{VO}
Known quantities: Unambiguous and ambiguous data in d0 and d1
Normalize d1 to d0 distribution: estimate how much d1 unambiguous data was "lost" in d0


Estimating Historical p_{VO}
OV Unamb
Amb
VO Unamb
D0
OV Unamb
Amb
VO Unamb
D1


Estimating Historical p_{VO}
Known quantities: Unambiguous and ambiguous data in d0 and d1
Normalize d1 to d0 distribution: estimate how much d1 unambiguous data was "lost" in d0
Calculate OV to VO "loss ratio"


Estimating Historical p_{VO}
OV Unamb
Amb
VO Unamb
D0
OV Unamb
Amb
VO Unamb
D1
= OV to VO "loss" ratio, D1-to-D0


Estimating Historical p_{VO}
Known quantities: Unambiguous and ambiguous data in d0 and d1
Normalize d1 to d0 distribution: estimate how much d1 unambiguous data was "lost" in d0
Calculate OV to VO "loss ratio"
Assume d1-to-d0 "loss ratio" is same as underlying-to-d1 "loss" ratio"


Assumption:
≈
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VO Unamb
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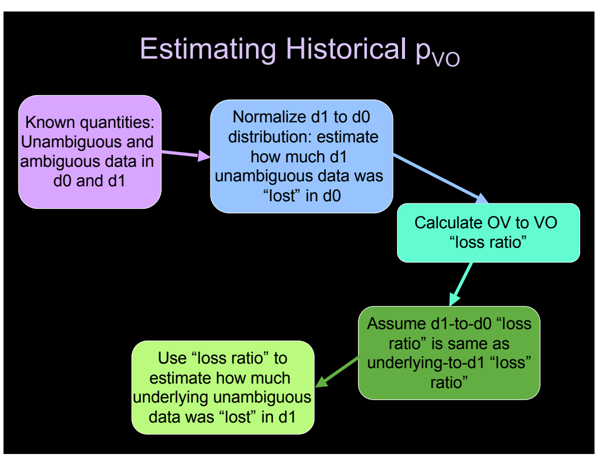
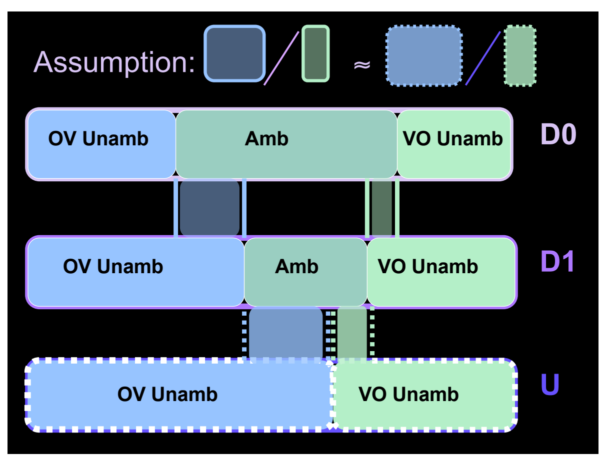

Estimating Historical p_{VO}
Known quantities: Unambiguous and ambiguous data in d0 and d1
Normalize d1 to d0 distribution: estimate how much d1 unambiguous data was "lost" in d0
Calculate OV to VO "loss ratio"
Assume d1-to-d0 "loss ratio" is same as underlying-to-d1 "loss" ratio"
Use "loss ratio" to estimate how much underlying unambiguous data was "lost" in d1


Assumption:
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OV Unamb
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VO Unamb
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OV Unamb
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D1
OV Unamb
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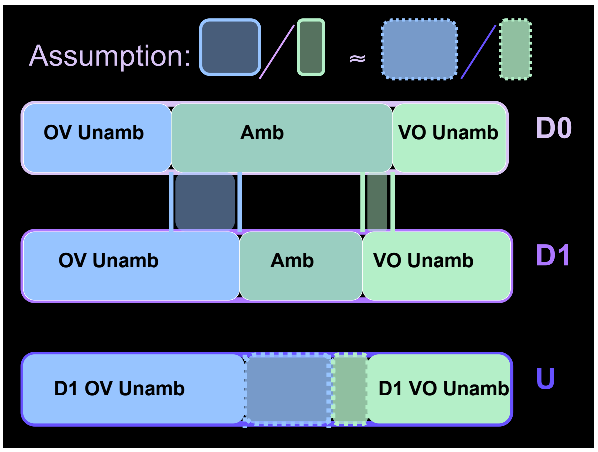
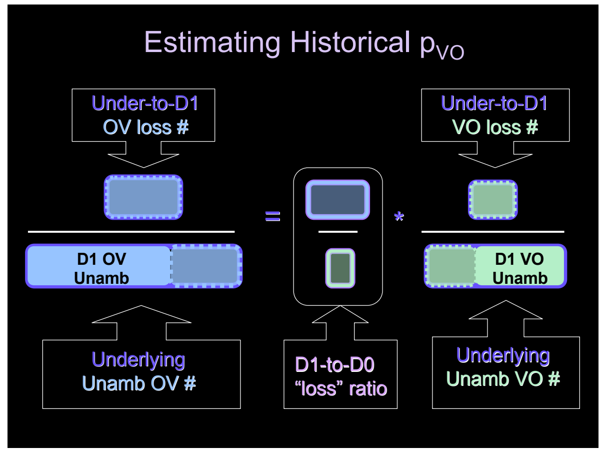
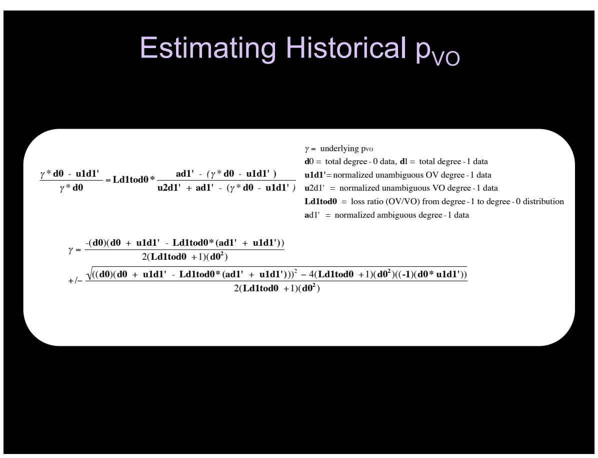
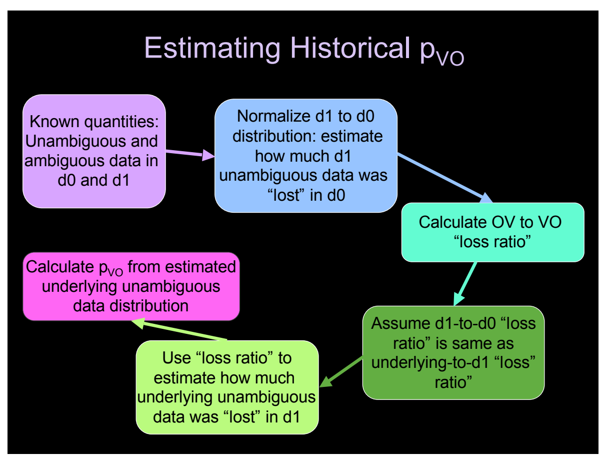




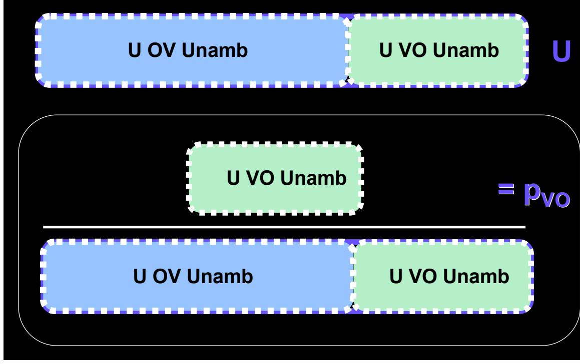


$$\frac{\gamma * \mathbf{d0} - \mathbf{u1d1'}}{\gamma * \mathbf{d0}} = \mathbf{Ld1tod0} * \frac{\mathbf{ad1'} - (\gamma * \mathbf{d0} - \mathbf{u1d1'})}{\mathbf{u2d1'} + \mathbf{ad1'} - (\gamma * \mathbf{d0} - \mathbf{u1d1'})}$$

$$\gamma = \frac{-(\mathbf{d0})(\mathbf{d0} + \mathbf{u1d1'} - \mathbf{Ld1tod0} * (\mathbf{ad1'} + \mathbf{u1d1'}))}{2(\mathbf{Ld1tod0} + 1)(\mathbf{d0}^2)}$$
$$+/- \frac{\sqrt{((\mathbf{d0})(\mathbf{d0} + \mathbf{u1d1'} - \mathbf{Ld1tod0} * (\mathbf{ad1'} + \mathbf{u1d1'})))^2 - 4(\mathbf{Ld1tod0} + 1)(\mathbf{d0}^2)((-1)(\mathbf{d0} * \mathbf{u1d1'}))}}{2(\mathbf{Ld1tod0} + 1)(\mathbf{d0}^2)}$$



Estimating Historical p_{VO}



Why Parameters?

Why posit parameters instead of just associating stress contours with words?

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Why posit parameters instead of just associating stress contours with words?

Arguments from stress change over time (Dresher & Lahiri, 2003):

(1) If word-by-word association, expect piece-meal change over time at the individual word level. Instead, historical linguists posit changes to underlying *systems* to best explain the observed data: many words changing at once.

Why Parameters?

Why posit parameters instead of just associating stress contours with words?

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(1) If word-by-word association, expect piece-meal change over time at the individual word level. Instead, historical linguists posit changes to underlying *systems* to best explain the observed data: many words changing at once.

(2) If stress contours are not composed of pieces (parameters), expect start and end states of change to be near each other. However, examples exist where start & end states are not closely linked from perspective of observable stress contours.

Relativizing Probabilities

Relativize-against-all:

- probability conditioned against entire input set
- relativizing set is constant across methods

Cues or Parsing

	QI	QS
Unambiguous Data Points	2140	11213
Relativizing Set	540505	540505
Relativized Probability	0.00396	0.0207

Relativizing Probabilities

Relativize-against-potential:

- probability conditioned against set of data points that meet preconditions of being an unambiguous data point
- relativizing set is not constant across methods

Cues: have correct syllable structure

	QI	QS
Unambiguous Data Points	2140	11213
Relativizing Set	2755	85268
Relativized Probability	0.777	0.132

Relativizing Probabilities

Relativize-against-potential:

- probability conditioned against set of data points that meet preconditions of being an unambiguous data point
- relativizing set is not constant across methods

Parsing: able to be parsed

	QI	QS
Unambiguous Data Points	2140	11213
Relativizing Set	*p*	*p*
Relativized Probability	2140/*p*	11213/*p*

Cues vs. Parsing Again

Is there any (additional) reason to prefer one method of identifying unambiguous data over the other?

Cues

VV VV L H H

... L L L L

H L L ... ...S S S S...

S S S...

Parsing

(QI, Em-None, Ft Dir Left, Ft Hd Left, B, B-2, B-Syl)
(QI, Em-None, Ft Dir Right, Ft Hd Right, B, B-2, B-Syl)
(QS, QSVCL, Em-None, Ft Dir Left, Ft Hd Left, UnB)
(QS, QSVCL, Em-None, Ft Dir Left, Ft Hd Left, B, B-2, B-Syl)
(QS, QSVCL, Em-None, Ft Dir Right, Ft Hd Right, B, B-2, B-Syl)

Cues vs. Parsing: Success Across Relativization Methods

	Cues	Parsing
Relative-Against-All	Successful	Successful
Relative-Against-Potential	*Unsuccessful*	Successful

…so parsing seems more robust across relativization methods.

Another Consideration: Constraint Derivability

Good: Order constraints exist that will allow the learner to converge on the adult system, provided the learner knows these constraints.

Better: These order constraints can be derived from properties of the learning system, rather than being stipulated.

Deriving Constraints from Properties of the Learning System

Data saliency: presence of stress is more easily noticed than absence of stress, and indicates a likely parametric cause

Data quantity: more unambiguous data available

Default values (cues only): if a value is set by default, order constraints involving it disappear

*Note: **data quantity** and **default values** would be applicable to any system. **Data saliency** is more system-dependent.*

Deriving Constraints: Cues

(a) QS-VC-Heavy
before Em-Right

(b) Em-Right
before Bounded-Syl

(c) Bounded-2
before Bounded-Syl

Deriving Constraints: Cues

(a) QS-VC-Heavy
before Em-Right

Em-Right: absence of stress is less salient (data saliency)

(b) Em-Right
before Bounded-Syl

(c) Bounded-2
before Bounded-Syl

Deriving Constraints: Cues

(a) QS-VC-Heavy
before Em-Right

Em-Right: absence of stress is less salient (data saliency)

(b) Em-Right
before Bounded-Syl

Bounded-Syl as default (default values)

(c) Bounded-2
before Bounded-Syl

Deriving Constraints: Cues

(a) QS-VC-Heavy
before Em-Right

Em-Right: absence of stress is less salient (data saliency)

(b) Em-Right
before Bounded-Syl

Bounded-Syl as default (default values)
Em-Right: more unambiguous data than Bounded-Syl (data quantity)

(c) Bounded-2
before Bounded-Syl

Deriving Constraints: Cues

(a) QS-VC-Heavy
before Em-Right

Em-Right: absence of stress is less salient (data saliency)

(b) Em-Right
before Bounded-Syl

Bounded-Syl as default (default values)
Em-Right: more unambiguous data than Bounded-Syl (data quantity)

(c) Bounded-2
before Bounded-Syl

Bounded-Syl as default (default values)

Deriving Constraints: Cues

(a) QS-VC-Heavy before Em-Right

Em-Right: absence of stress is less salient (data saliency)

(b) Em-Right before Bounded-Syl

Bounded-Syl as default (default values)
Em-Right: more unambiguous data than Bounded-Syl (data quantity)

(c) Bounded-2 before Bounded-Syl

Bounded-Syl as default (default values)
Bounded-2 has more unambiguous data once Em-Right is set; Em-Right has much more than Bounded-2 or Bounded-Syl (data quantity)

Deriving Constraints: Parsing

Group 1:
QS, Ft Head Left, Bounded

Group 2:
Ft Dir Right, QS-VS-Heavy

Group 3:
Em-Some, Em-Right, Bounded-2, Bounded-Syl

Deriving Constraints: Parsing

Group 1:
QS, Ft Head Left, Bounded

Group 2:
Ft Dir Right, QS-VS-Heavy

Group 3:
Em-Some, Em-Right, Bounded-2, Bounded-Syl

Em-Some, Em-Right: absence of stress is less salient (data saliency)

Deriving Constraints: Parsing

Group 1:
QS, Ft Head Left, Bounded

Group 2:
Ft Dir Right, QS-VS-Heavy

Other groupings cannot be derived from data quantity, however…

Group 3:
Em-Some, Em-Right, Bounded-2, Bounded-Syl

Em-Some, Em-Right: absence of stress is less salient (data saliency)

Cues vs. Parsing for Unambiguous Data

The order constraints a learner would need to succeed can be derived in a principled manner for cues but must be mostly stipulated for parsing.

Open Questions

(1) Can we combine the strengths of cues and parsing?

Combining Cues and Parsing

Cues and parsing have a complementary array of strengths and weaknesses

Problem with cues: require prior knowledge
Problem with parsing: requires parse of entire data point

Viable combination of cues & parsing:
parsing of data point subpart = derivation of cues?

Combining Cues and Parsing

Em-Right: Rightmost syllable is Heavy and unstressed …H H

If a syllable is Heavy, it should be stressed.
If an edge syllable is Heavy and unstressed, an immediate solution (given the available parameteric system) is that the syllable is extrametrical.

Combining Cues and Parsing

Viable combination of cues & parsing:
parsing of data point subpart = derivation of cues?

Would partial parsing
(a) derive cues that lead to successful acquisition?
(b) be successful across relativization methods?
(c) have derivable order constraints?
(d) be a more realistic representation of the learning mechanism?

Open Questions

(1) Can we combine the strengths of cues and parsing?

(2) Are order constraints *not* derivable from the learning system consistent cross-linguistically?

Non-derivable Constraints

Parsing Constraints

Group 1:
QS, Ft Head Left, Bounded

Group 2:
Ft Dir Right, QS-VS-Heavy

Group 3:
Em-Some, Em-Right, Bounded-2, Bounded-Syl

Do we find these same groupings if we look at other languages?

Open Questions

(1) Can we combine the strengths of cues and parsing?

(2) Are order constraints *not* derivable from the learning system consistent cross-linguistically?

(3) Are predicted parameter-setting orders observed in real-time learning?

Experimental Predictions for English

Cues

(a) QS-VC-Heavy before Em-Right

(b) Em-Right before Bounded-Syl

(c) Bounded-2 before Bounded-Syl

Parsing

Group 1:
QS, Ft Head Left, Bounded

Group 2:
Ft Dir Right, QS-VS-Heavy

Group 3:
Em-Some, Em-Right, Bounded-2, Bounded-Syl

Open Questions

(1) Can we combine the strengths of cues and parsing?

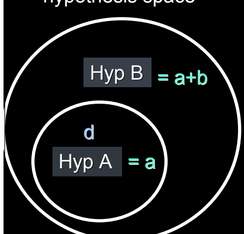
(2) Are order constraints *not* derivable from the learning system consistent cross-linguistically?

(3) Are predicted parameter-setting orders observed in real-time learning?

(4) Is the unambiguous data filter successful for other languages besides English? Other complex linguistic domains?

Additional Information Source: Exploiting the Hypothesis Space Layout

Subset-superset hypothesis space



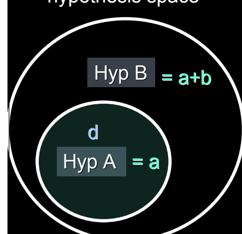
Likelihood of *d* Logic:

Suppose the learner encounters an ambiguous data point *d*

Let the number of examples covered by subset A be *a*. Let the number of examples covered by superset B be *a + b*.

Additional Information Source: Exploiting the Hypothesis Space Layout

Subset-superset hypothesis space



Likelihood of *d* Logic:

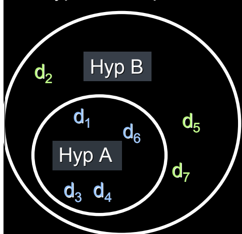
The likelihood that *d* was produced from A is 1/*a*. The likelihood that *d* was produced from B is 1/(*a*+*b*).

1/a > 1/a+b

So, A has a higher probability of having produced *d*. Thus, A is favored when encountering ambiguous data.

Additional Information Source: Exploiting the Hypothesis Space Layout

Subset-superset hypothesis space

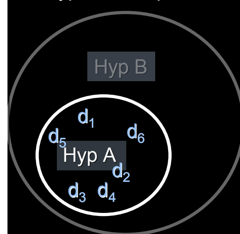


Learner Expectation Logic:

If B were correct, learner should encounter some unambiguous data points for B.

Additional Information Source: Exploiting the Hypothesis Space Layout

Subset-superset hypothesis space



Learner Expectation Logic:

If only subset data points are encountered, a restriction to the subset A becomes more and more likely.

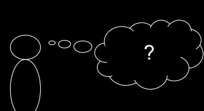
The more subset data points encountered (while not encountering superset B data points), the more the learner is biased towards A.

How does a learner know to use the no-type-II-ambiguous filter?

Want: Filter to ignore type II ambiguous data to result from some principled strategy for learning

Principled strategy: Learn only in cases of uncertainty (Shannon 1948; Gallistel 2001) - that's where information is gained

Jack



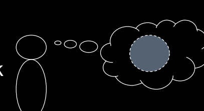
How does a learner know to use this filter?

Want: Filter to ignore type II ambiguous data to result from some principled strategy for learning

Principled strategy: Learn only in cases of uncertainty (Shannon 1948; Gallistel 2001) - that's where information is gained

Need to ignore: data points where potential antecedent has no modifier

Jack

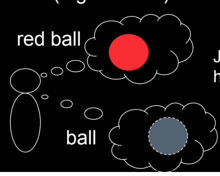


~~Jack wants a ball and Lily has another one for him.~~

How does a learner know to use this filter?

Want: Filter to ignore type II ambiguous data to result from some principled strategy for learning

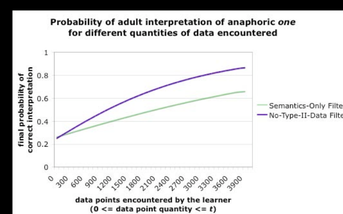
Possibility 1: Look for situations where there is uncertainty in the semantic referent set (e.g. balls vs. red balls) only. This will occur when the utterance has a modifier on the potential antecedent (e.g. *red ball*).



Jack wants a red ball and Lily has/doesn't have another one for him.

Semantic-referents-only filter

Problem: Learner must only care about semantic referents and not about syntactic consequences (N' vs. N^0). Then, only updating domains from semantic information, not semantic & syntactic. Result: lower probability of correct interpretation.

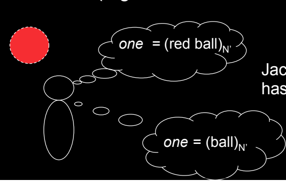


How does a learner know to use this filter?

Want: Filter to ignore type II ambiguous data to result from some principled strategy for learning

Possibility 2: Syntactocentric approach, and solving the problem of *which N' antecedent* is correct when there is more than one.

Only relevant data are those with multiple potential N' antecedents (e.g. nouns with modifiers like *red ball*).



Jack wants a red ball and Lily has/doesn't have another one for him.

Syntactocentric Approach

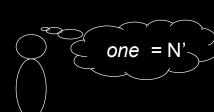
Requirement: Prior knowledge that the antecedent of *one* is N'.

Methods:

-Innate constraints (Hornstein & Lightfoot 1981)

-Syntactocentric filter over distribution of *one* vs. distribution of other nouns w.r.t complements (Foraker et al., in press)

Benefit: learner uses syntactic data to update as well since this is a question of which syntactic antecedent (larger or smaller N') is correct



Jack wants a red ball and Lily has/doesn't have another one for him.

The Simple Variational Model: Subset/Superset

Suppose two grammars, G1 and G2.

For whichever grammar is chosen,
if G1 can parse the sentence (reward):
prob(G1) = old_prob(G1) + ϒ*(1-old_prob(G1))

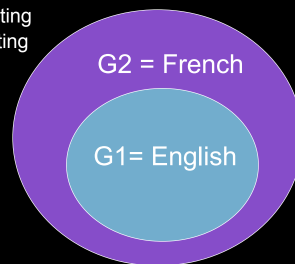
if G1 can't parse the sentence (punish):
prob(G1) = (1-ϒ)*old_prob(G1)
where ϒ is the learning rate

prob(G2) = 1 - prob(G1) since there are only 2 grammars in this world

The Simple Variational Model: Subset/Superset

Subset-Superset: English vs. French wh-questions

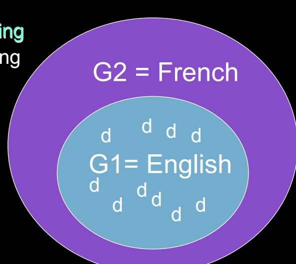
English: wh-fronting
French: wh-fronting
& in-situ



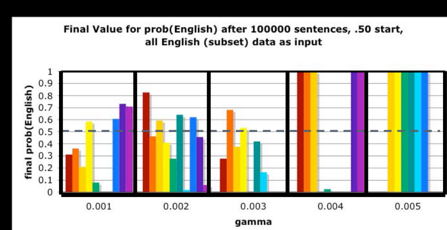
The Simple Variational Model: Subset/Superset

What if only subset data points are encountered (learning English)?

English: wh-fronting
French: wh-fronting
& in-situ



Simple Variational Model: convergence to either grammar



Subset (prob = 1) doesn't win.

Also, learner doesn't stay at 50-50, especially as gamma increases. (Tendency to converge on one grammar)