Learning-Driven Linguistic Evolution

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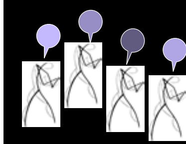
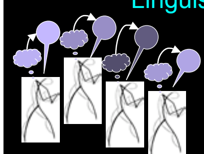
Evolution of Psychological Categories Workshop
Institute for Mathematical Behavioral Sciences
UC Irvine

Linguistic Evolution, In Brief



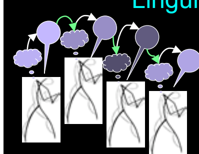
Linguistic knowledge is transmitted in a population via interaction with other speakers in the population.

Linguistic Evolution, In Brief



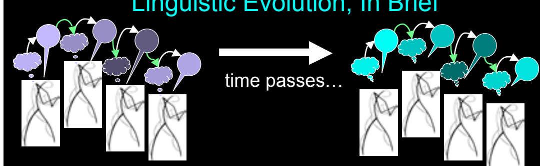
The information speakers transmit (observable data) is based on their own linguistic knowledge.

Linguistic Evolution, In Brief



Speakers adjust their linguistic knowledge based on the observable (and encountered) data from other population members.

Linguistic Evolution, In Brief



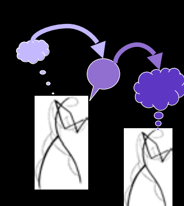
Population-level changes over time depend on what information speakers pass to subsequent generations and how that information is integrated into an individual's linguistic knowledge.

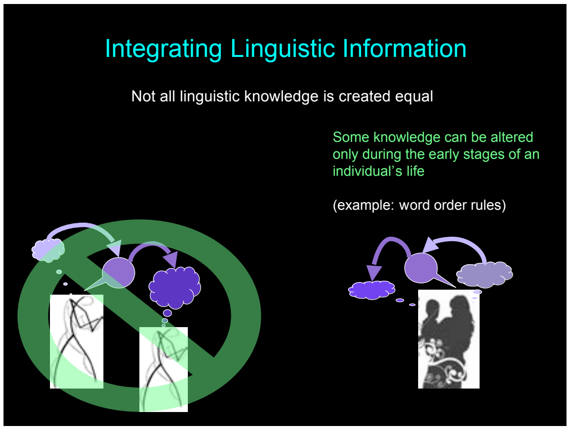
Integrating Linguistic Information

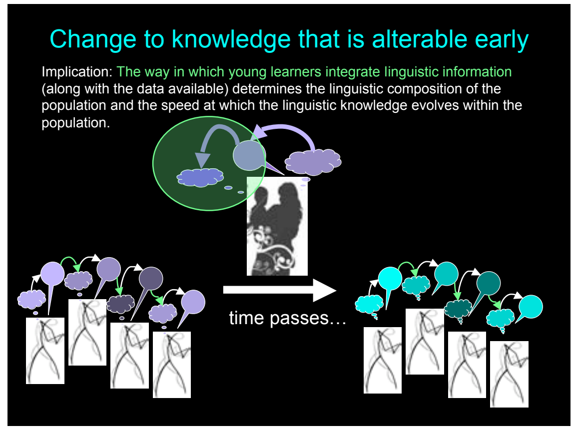
Not all linguistic knowledge is created equal

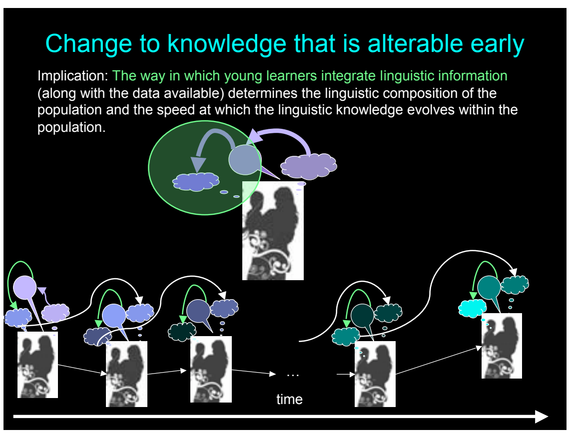
Some knowledge can be altered throughout an individual's life

(example: vocabulary)




Integrating Linguistic Information
Not all linguistic knowledge is created equal
Some knowledge can be altered only during the early stages of an individual's life
(example: word order rules)


Change to knowledge that is alterable early
Implication: The way in which young learners integrate linguistic information (along with the data available) determines the linguistic composition of the population and the speed at which the linguistic knowledge evolves within the population.
time passes…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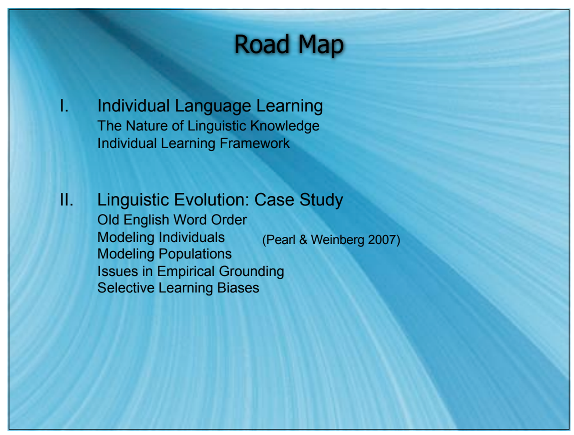
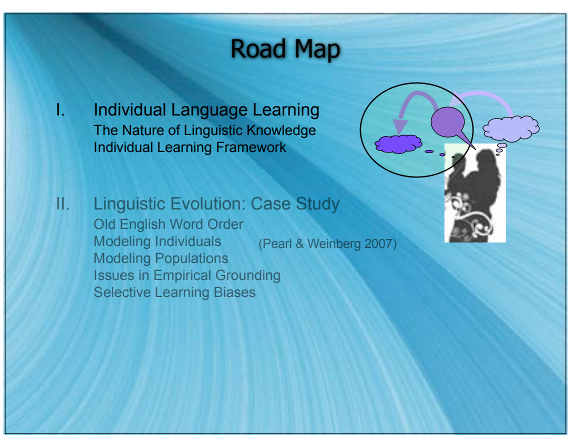

Road Map
I. Individual Language Learning
The Nature of Linguistic Knowledge
Individual Learning Framework
II. Linguistic Evolution: Case Study
Old English Word Order
Modeling Individuals
(Pearl & Weinberg 2007)
Modeling Populations
Issues in Empirical Grounding
Selective Learning Biases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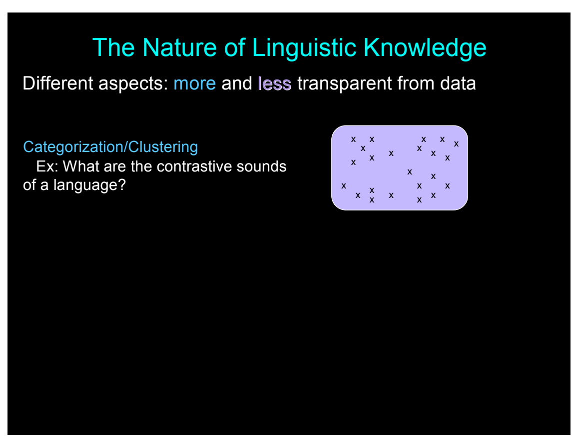
The Nature of Linguistic Knowledge
Different aspects: more and less transparent from data
Categorization/Clustering
Ex: What are the contrastive sounds of a language?

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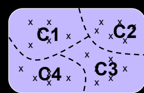

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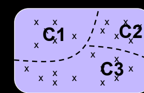

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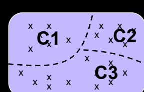

Extraction
Ex: Where are words in fluent speech?

húwzəfréjdəvðəbÍgbæ'dwə'lf

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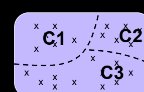

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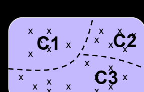

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Mapping
What are the word affixes that signal meaning (e.g. past tense in English)?

blink~blinked confide~confided

drink~drank

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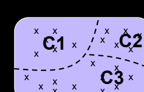

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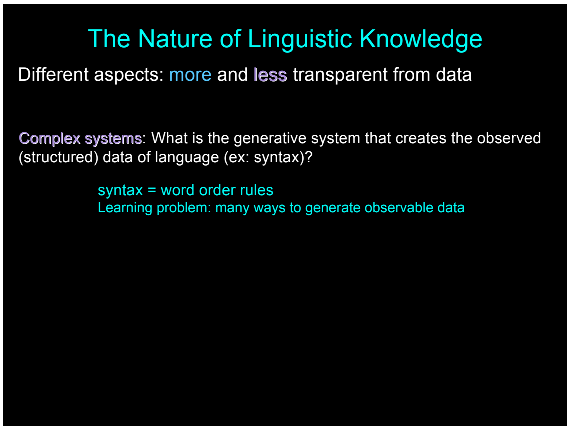
blɪŋk blɪŋkt kənfajd kənfajdəd

drink~drank
drɪŋk drejŋk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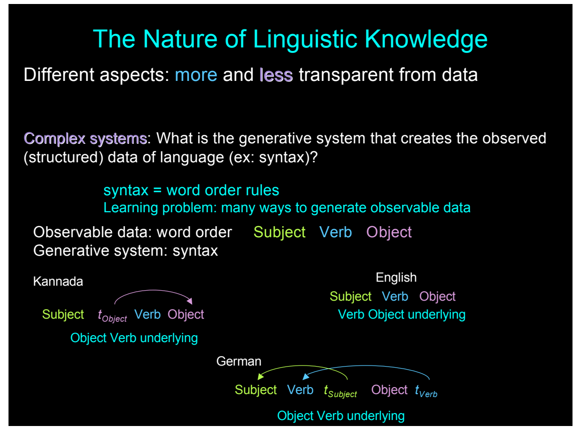
Complex systems: What is the generative system that creates the observed (structured) data of language (ex: syntax)?
syntax = word order rules
Learning problem: many ways to generate observable data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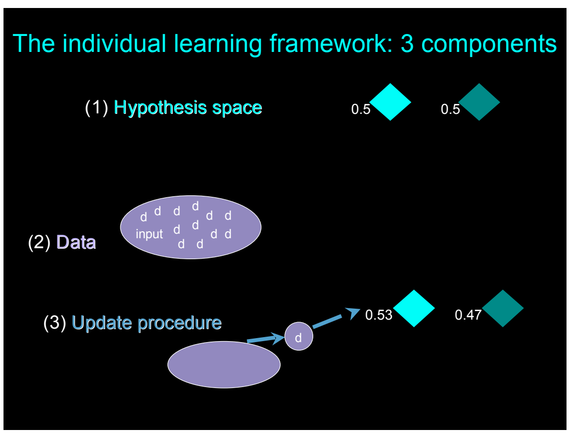
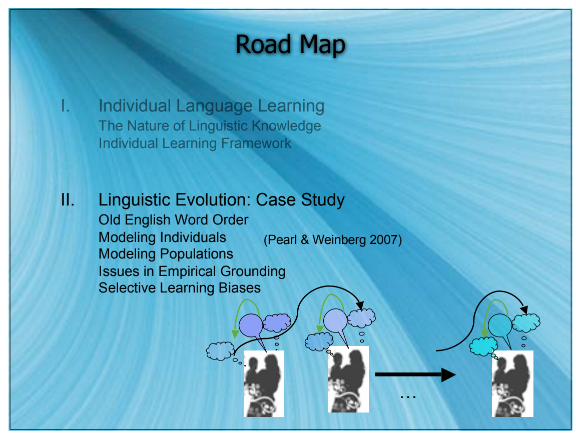
Learning problem: many ways to generate observable data
Observable data: word order Subject Verb Object
Generative system: syntax
Kannada
Subject t_{Object} Verb Object
Object Verb underlying
English
Subject Verb Object
Verb Object underlying
German
Subject Verb $t_{Subject}$ Object t_{Verb}
Object Verb underlying


The individual learning framework: 3 components
(1) Hypothesis space
0.5
0.5
(2) Data
input
d
(3) Update procedure
d
0.53
0.47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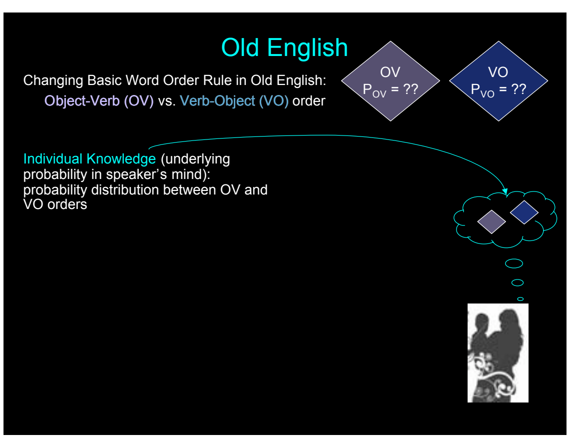
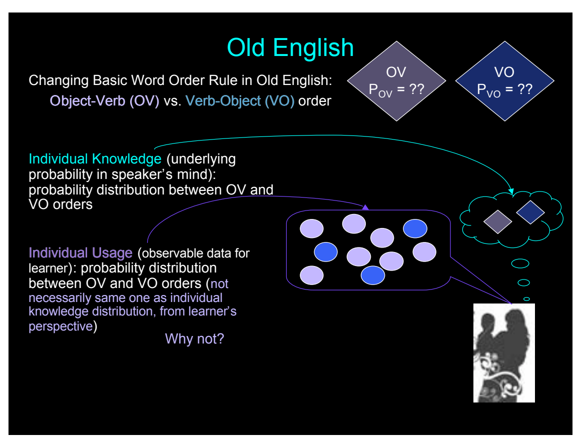

Old English
Changing Basic Word Order Rule in Old English:
Object-Verb (OV) vs. Verb-Object (VO) order
OV
P_{OV} = ??
VO
P_{VO} = ??
Individual Knowledge (underlying probability in speaker's mind): probability distribution between OV and VO orders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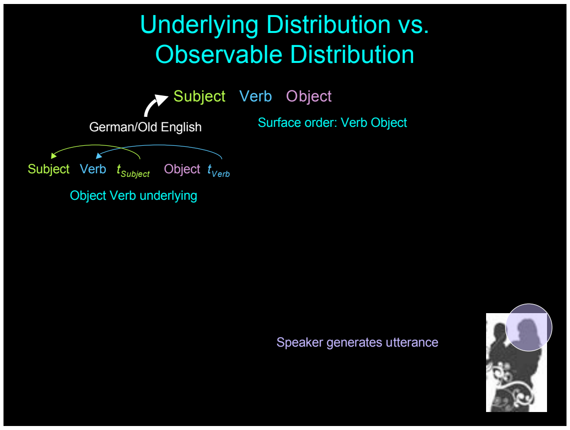
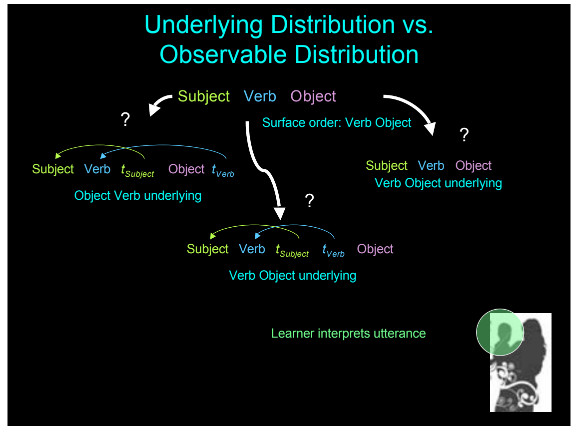
Why not?


Underlying Distribution vs. Observable Distribution
Subject Verb Object
German/Old English
Surface order: Verb Object
Subject Verb t Subject Object t Verb
Object Verb underlying
Speaker generates utterance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?
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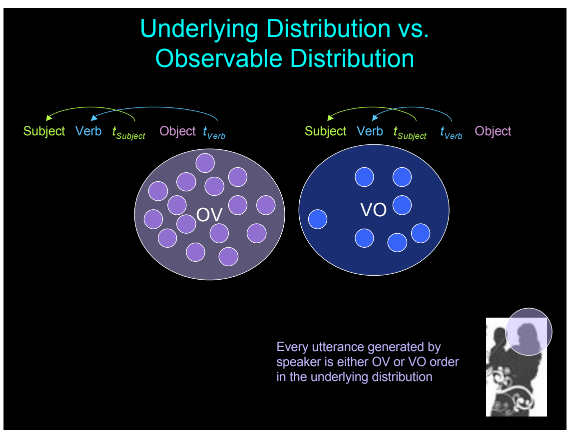
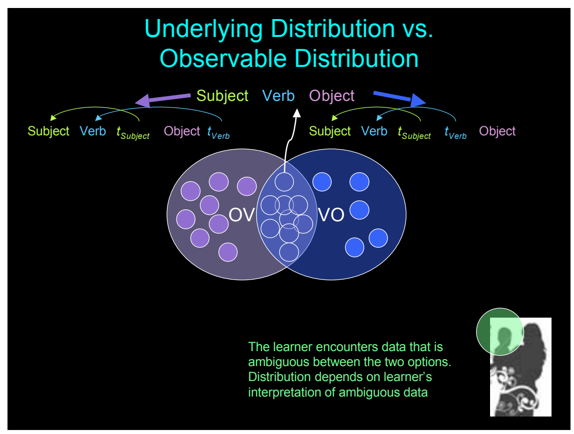
Verb Object underlying
Learner interprets utterance


Underlying Distribution vs. Observable Distribution
Subject Verb t Subject Object t Verb
Subject Verb t Subject t Verb Object
OV
VO
Every utterance generated by speaker is either OV or VO order in the underlying distribution


Underlying Distribution vs. Observable Distribution
Subject Verb Object
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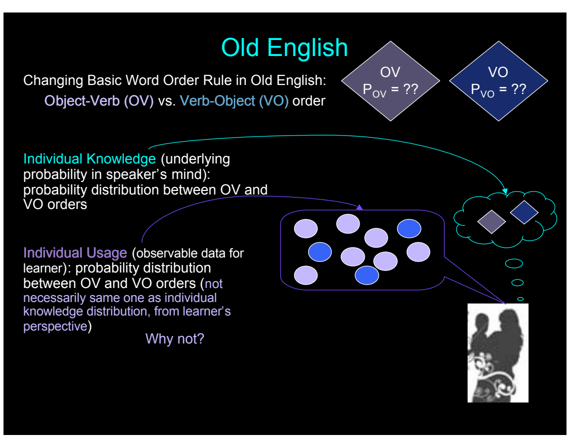
OV
VO
The learner encounters data that is ambiguous between the two options. Distribution depends on learner's interpretation of ambiguous data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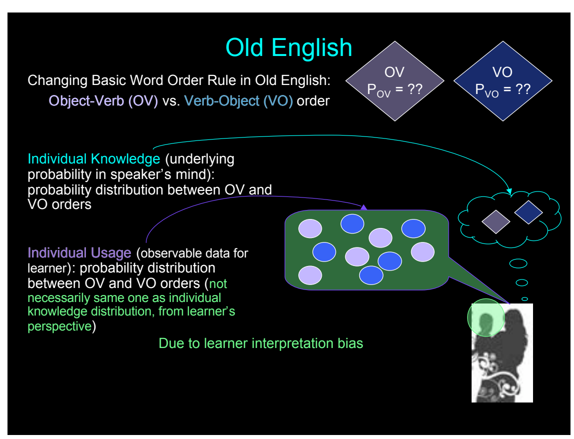
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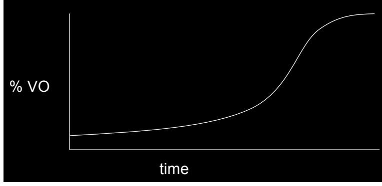
Due to learner interpretation bias

Old English

Estimates of average individual usage from historical corpora:
YCOE Corpus 2003; PPCME2 Corpus 2000

~1000 A.D.-1150 A.D.: OV-biased → ~1200 A.D.: VO-biased

OV P_{OV} = ?? | VO P_{VO} = ?? → OV P_{OV} = ?? | VO P_{VO} = ??



To get this rate of change, young individual learners at each time step must change their probability distribution the exact right amount from the previous population members' distribution

Modeling Individuals: Learning Biases

d d d d d d intake input d

Interpretation Bias: Use only data perceived as most informative (Fodor 1998, Lightfoot 1999, Dresher 1999).

Interpretation Bias: Use only data that is more accessible (perhaps for language processing reasons) (Lightfoot 1991).

Modeling Individuals: Learning Biases

d d d d d d intake input d

Interpretation Bias : Use only data perceived as most informative: unambiguous data (Fodor 1998, Lightfoot 1999, Dresher 1999).

Learner has heuristics for identifying unambiguous OV/VO data, based on partial knowledge of possible adult system rules (Fodor 1998, Lightfoot 1999, Dresher 1999)

Knowledge of tensed verb movement to 2nd phrasal position of sentence

OV unambiguous data:
$[\ldots]_{XP}$ … Object TensedVerb …
…TensedVerb … Object Verb-Marker …

VO unambiguous data:
$[\ldots]_{XP}$ $[\ldots]_{XP}$ … TensedVerb Object …
…TensedVerb … Verb-Marker Object …

Interpretation Bias: Use only data that is more accessible (perhaps for language processing reasons) (Lightfoot 1991).

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

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

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VO unambiguous data:
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…TensedVerb … Verb-Marker Object …

Interpretation Bias: Use only structurally simple (degree-0) data (Lightfoot 1991).

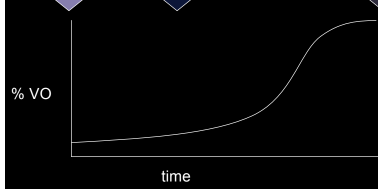
Jack told his mother that the giant was easy to fool.
[----Degree-0-------]
[-------------Degree-1----------]

Modeling Individuals: Learning Biases

The point of interpretation biases: Unambiguous degree-0 data distribution may differ the right amount from population's underlying distribution to change at the right rate.

~1000 A.D.-1150 A.D.: OV-biased → ~1200 A.D.: VO-biased

OV P_{OV} = ?? | VO P_{VO} = ?? → OV P_{OV} = ?? | VO P_{VO} = ??



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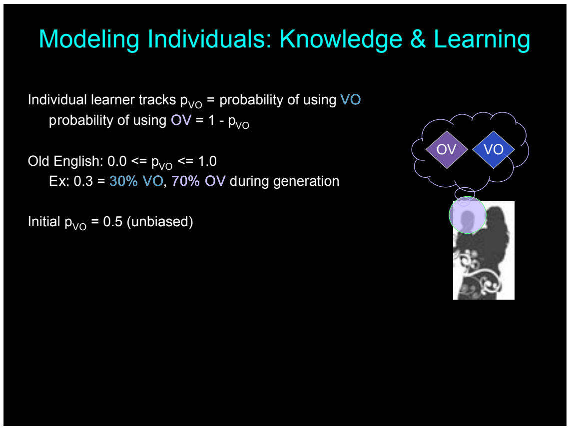
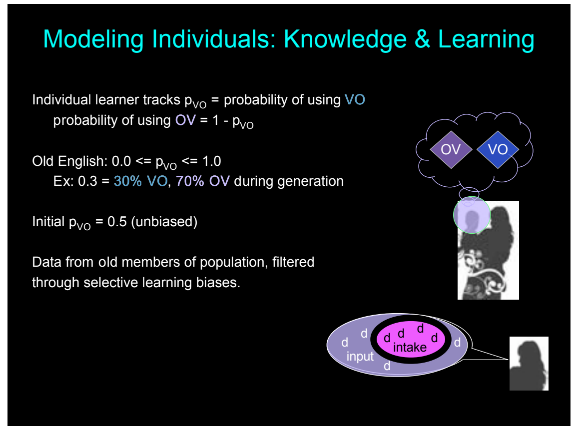

Modeling Individuals: Knowledge & Learning
Individual learner tracks p_{VO} = probability of using VO
probability of using OV = 1 - p_{VO}
Old English: 0.0 <= p_{VO} <= 1.0
Ex: 0.3 = 30% VO, 70% OV during generation
Initial p_{VO} = 0.5 (unbiased)
OV
VO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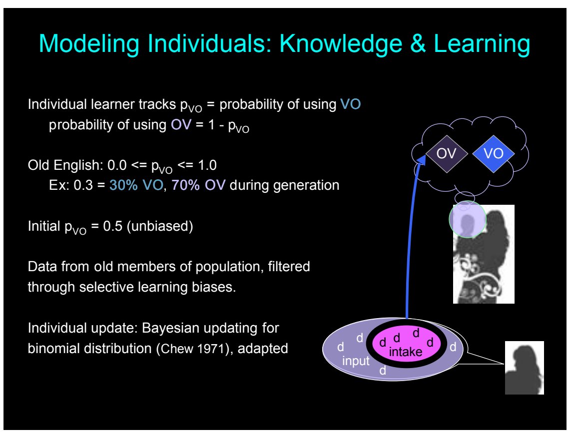
Data from old members of population, filtered through selective learning biases.
OV
VO
input
intake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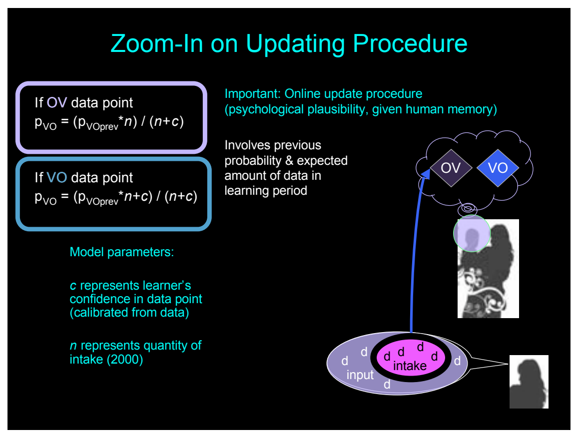
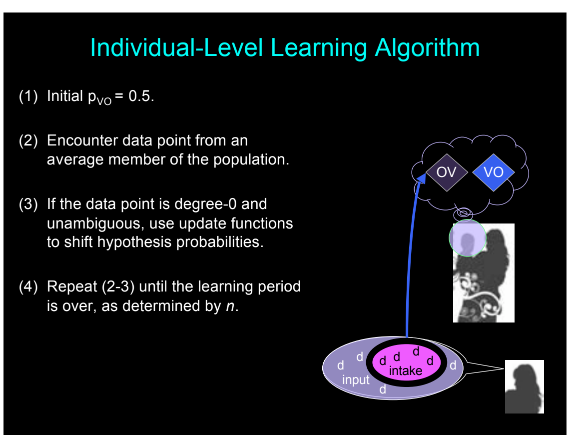
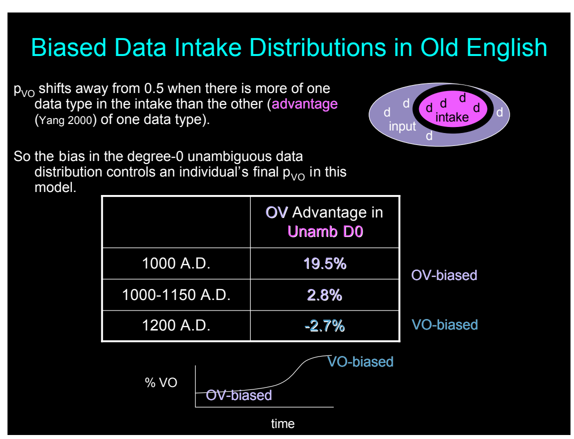
Individual update: Bayesian updating for binomial distribution (Chew 1971), adapted
OV
VO
input
intake


Zoom-In on Updating Procedure
If OV data point
$p_{VO} = (p_{VOprev}*n) / (n+c)$
If VO data point
$p_{VO} = (p_{VOprev}*n+c) / (n+c)$
Important: Online update procedure (psychological plausibility, given human memory)
Involves previous probability & expected amount of data in learning period
Model parameters:
c represents learner's confidence in data point (calibrated from data)
n represents quantity of intake (2000)
OV
VO
input
intake


Individual-Level Learning Algorithm
(1) Initial p_{VO} = 0.5.
(2) Encounter data point from an average member of the population.
(3) If the data point is degree-0 and unambiguous, use update functions to shift hypothesis probabilities.
(4) Repeat (2-3) until the learning period is over, as determined by n.
OV
VO
input
intake


Biased Data Intake Distributions in Old English
p_{VO} shifts away from 0.5 when there is more of one data type in the intake than the other (advantage (Yang 2000) of one data type).
So the bias in the degree-0 unambiguous data distribution controls an individual's final p_{VO} in this model.
OV Advantage in Unamb D0
1000 A.D. 19.5%
1000-1150 A.D. 2.8%
1200 A.D. -2.7%
OV-biased
VO-biased
% VO
time
input
intake

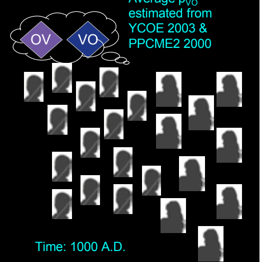
Population-Level Model

(1) Set the age range of the population from 0 to 60 years old and create 18,000 population members.

(2) Initialize the members of the population to the average p_{VO} at 1000 A.D. Set the time to 1000 A.D.

Population size estimated from population statistics of the time period (Koenigsberger & Briggs 1987)

Average p_{VO} estimated from YCOE 2003 & PPCME2 2000



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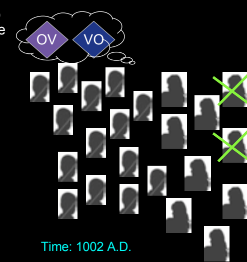
(3) Move forward 2 years.

(4) Members age 59-60 die off.



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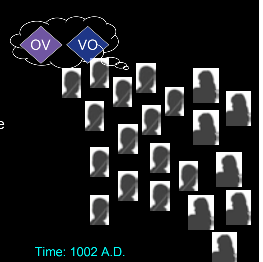
(2) Initialize the members of the population to the average p_{VO} at 1000 A.D. Set the time to 1000 A.D.

(3) Move forward 2 years.

(4) Members age 59-60 die off. The rest of the population ages 2 years.



Population-Level Model

(1) Set the age range of the population from 0 to 60 years old and create 18,000 population members.

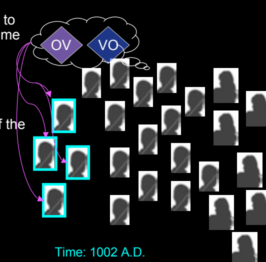
(2) Initialize the members of the population to the average p_{VO} at 1000 A.D. Set the time to 1000 A.D.

(3) Move forward 2 years.

(4) Members age 59-60 die off. The rest of the population ages 2 years.

(5) New members are born. These new members use the individual acquisition algorithm to set their p_{VO}.

Population growth rate estimated from population statistics of the time period (Koenigsberger & Briggs 1987)



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(1) Set the age range of the population from 0 to 60 years old and create 18,000 population members.

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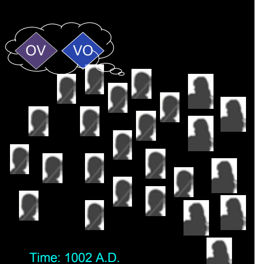


Population-Level Model

(1) Set the age range of the population from 0 to 60 years old and create 18,000 population members.

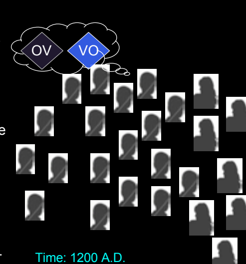
(2) Initialize the members of the population to the average p_{VO} at 1000 A.D. Set the time to 1000 A.D.

(3) Move forward 2 years.

(4) Members age 59-60 die off. The rest of the population ages 2 years.

(5) New members are born. These new members use the individual acquisition algorithm to set their p_{VO}.

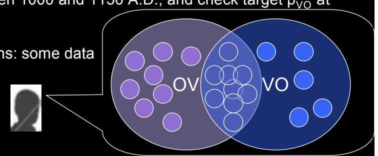
(6) Repeat steps (3-5) until the year 1200 A.D.



Empirical Grounding Issues: What exactly is the underlying distribution?

Historical data used to initialize population's p_{VO} at 1000 A.D., calibrate population's p_{VO} between 1000 and 1150 A.D., and check target p_{VO} at 1200 A.D.

Historical data distributions: some data are ambiguous



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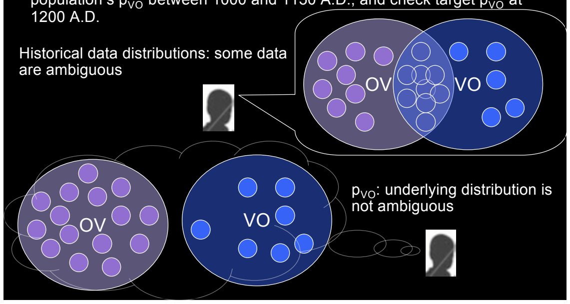

p_{VO}: underlying distribution is not ambiguous

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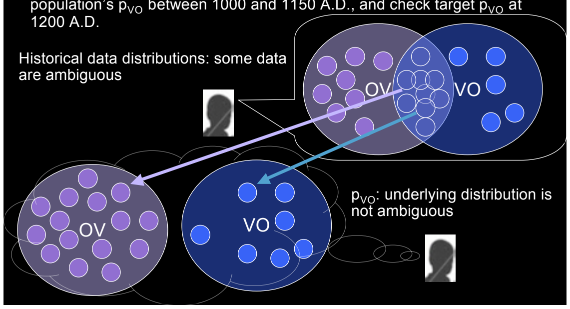


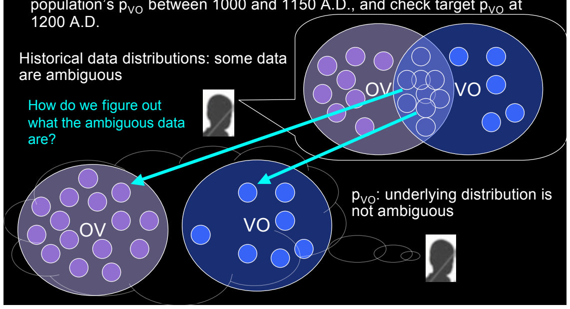
p_{VO}: underlying distribution is not ambiguous

Empirical Grounding Issues: What exactly is the underlying distribution?

Historical data used to initialize population's p_{VO} at 1000 A.D., calibrate population's p_{VO} between 1000 and 1150 A.D., and check target p_{VO} at 1200 A.D.

Historical data distributions: some data are ambiguous

How do we figure out what the ambiguous data are?



p_{VO}: underlying distribution is not ambiguous

Empirical Grounding Issues: What exactly is the underlying distribution?

(YCOE and PPCME2 Corpora)
% Ambiguous Utterances

	Degree-0 % Ambiguous	Degree-1 % Ambiguous
1000 A.D.	76%	28%
1000 - 1150 A.D.	80%	25%
1200 A.D.	71%	10%

Observations:
(1) Degree-1 data less ambiguous than degree-0 data.

Empirical Grounding Issues: What exactly is the underlying distribution?

(YCOE and PPCME2 Corpora)
% Advantage

	OV Advantage in Unamb D0	OV Advantage in Unamb D1
1000 A.D.	19.5%	41.7%
1000-1150 A.D.	2.8%	28.7%
1200 A.D.	-2.7%	-45.2%

Observations:
(1) Degree-1 data less ambiguous than degree-0 data.
(2) Advantage is magnified in degree-1.

Empirical Grounding Issues: What exactly is the underlying distribution?

Observations:
(1) Degree-1 data less ambiguous than degree-0 data.
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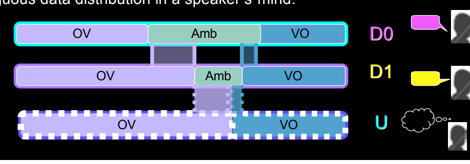
Assumption: Ambiguous data distorts underlying distribution.
Assumption: degree-1 distribution less distorted from underlying distribution.

Empirical Grounding Issues: What exactly is the underlying distribution?

Observations:
(1) Degree-1 data less ambiguous than degree-0 data.
(2) Advantage is magnified in degree-1.

Assumption: Ambiguous data distorts underlying distribution.
Assumption: degree-1 distribution less distorted from underlying distribution.

Plan of Action: Use the difference in distortion between the **degree-0** and **degree-1** unambiguous data distributions to estimate the difference in distortion between the **degree-1** distribution and the **underlying** unambiguous data distribution in a speaker's mind.



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known quantities

γ = underlying p_{VO}

d0 = total degree-0 data, **d1** = total degree-1 data

u1d1' = normalized unambiguous OV degree-1 data
u2d1' = normalized unambiguous VO degree-1 data
Ld1tod0 = loss ratio (OV/VO) from degree-1 to degree-0 distribution
ad1' = normalized ambiguous degree-1 data

derived quantities

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

$$= \frac{-(d0)(d0 + u1d1' - Ld1tod0 * (ad1' + u1d1'))}{2(Ld1tod0 + 1)(d0^2)}$$

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

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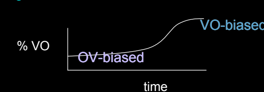

	(Initialization) 1000 A.D.	(Calibration) 1000-1150 A.D.	(Termination) 1200 A.D.
Average p_{VO}	0.234	0.310	0.747

OV-biased VO-biased

Empirical Grounding Issues: What exactly is the underlying distribution?

Observations:
(1) Degree-1 data less ambiguous than degree-0 data.
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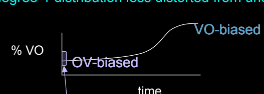

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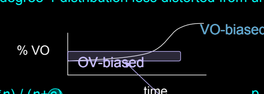

$p_{VO} = (p_{VOprev} * n) / (n + c)$

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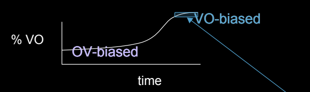

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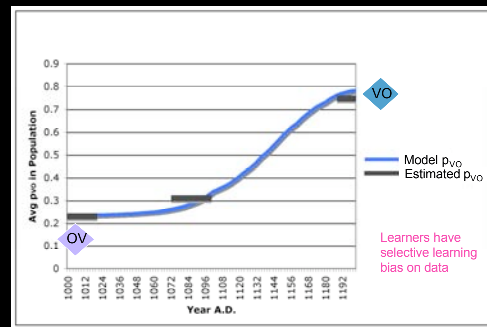
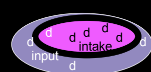
OV-biased VO-biased

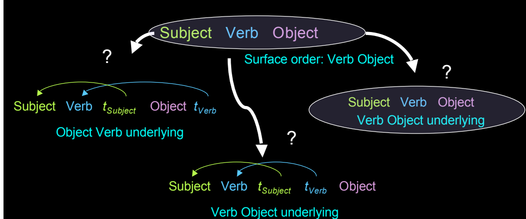
Linguistic Evolution: Change at the Historically-Attested Rate



Linguistic Evolution: Different Individual-Level Learning

Learner uses ambiguous data. Strategy for learning: assume surface order is actual order. (Fodor 1998)





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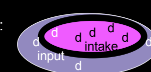
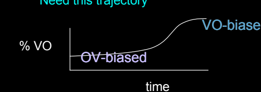


Advantage in intake determines learner's ending distribution between OV and VO order.

Need this trajectory



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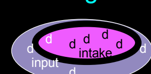

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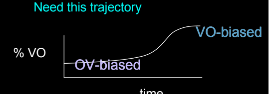

	Degree-0 OV Advantage
1000 A.D.	-21.0%
1000 - 1150 A.D.	-26.9%
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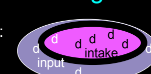

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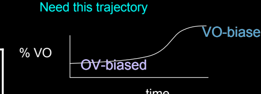

	Degree-0 OV Advantage
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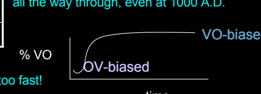
Problem: VO-biased all the way through, even at 1000 A.D.



Change is too fast!

Linguistic Evolution: Different Individual-Level Learning

Learner uses degree-0 and degree-1 unambiguous data.

(YCOE and PPCME2 Corpora)
% Advantage

	OV Advantage in Unamb D0	OV Advantage in Unamb D1
1000 A.D.	19.5%	41.7%
1000-1150 A.D.	2.8%	28.7%
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Very strongly OV-biased before 1150 A.D.

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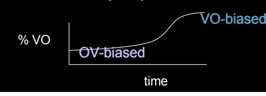
Very strongly OV-biased before 1150 A.D.

Need this trajectory

But population must become VO-biased.



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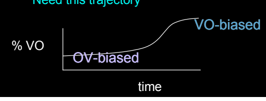
Very strongly OV-biased before 1150 A.D.

Need this trajectory

Can a population learning from degree-1 data make the change to VO-biased?



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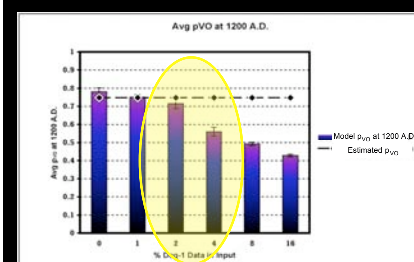
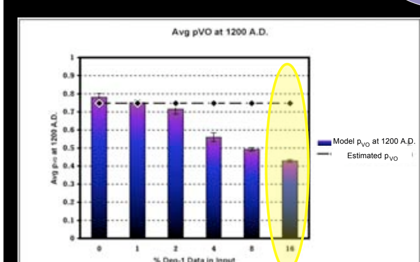


Modeled population can change at the right rate only if input contains less than 4% degree-1 data - otherwise, change is too slow for learners not using a degree-0 bias.

Linguistic Evolution: Different Individual-Level Learning

Learner uses degree-0 and degree-1 unambiguous data.



Estimates from modern English child-directed speech: Input consists of ~16% degree-1 data.

Prognosis: Change would be too slow without a degree-0 bias for individual learners.

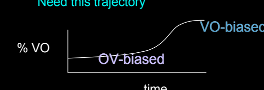
Linguistic Evolution: Different Individual-Level Learning

Learner uses degree-0 and degree-1 data, and learns from ambiguous data.

(YCOE and PPCME2 Corpora)
% Advantage

	OV Advantage in D0	OV Advantage in D1
1000 A.D.	-21.0%	28.1%

Need this trajectory



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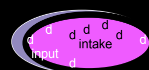
Learner uses degree-0 and degree-1 data, and learns from ambiguous data.

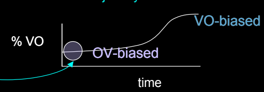


(YCOE and PPCME2 Corpora)
% Advantage

	OV Advantage in D0	OV Advantage in D1
1000 A.D.	-21.0%	28.1%

Need this trajectory

Population must remain OV-biased at 1000 A.D.



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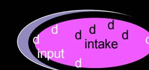

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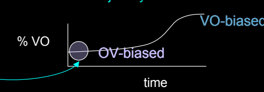

To do this, advantage in intake must be for OV order at 1000 A.D.
Otherwise, population changes too quickly to VO-biased distribution.

Linguistic Evolution: Different Individual-Level Learning

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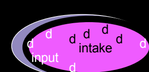

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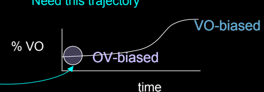
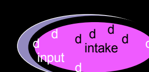


Requirement for OV advantage at 1000 A.D.: 43% of input is degree-1 data

Linguistic Evolution: Different Individual-Level Learning

Learner uses degree-0 and degree-1 data, and learns from ambiguous data.



(YCOE and PPCME2 Corpora)
% Advantage

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Need this trajectory

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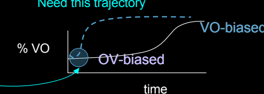


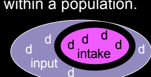
Requirement for OV advantage at 1000 A.D.: 43% of input is degree-1 data
…but estimates show only ~16% of it is. Change will be too fast.

Linguistic Evolution: Summary

Some cases where linguistic evolution is driven by individual-level learning. Suggested example: Old English word order.

Individual-level learning: can involve selective learning biases, with strong effects on rate of linguistic change within a population.

Individual-Level Selective Learning:
(1) unambiguous data
(2) degree-0 data



Additional point: linguistic evolution can inform us about the nature of individual learning.

Linguistic Evolution: Open Questions

(1) If we add social complexity to the population model, do we still need these individual-level selective learning biases?
Weight data points in individual intake using various factors:
(a) spatial location of speaker with respect to learner
(b) social status of speaker
(c) speaker's relation to learner (family, friend, stranger)
(d) context of data point (social context, linguistic context)

(2) Are these learning biases necessary if we look at other language changes where individual-level learning is thought to be the main factor driving change at the population-level?

Learning-Driven Linguistic Evolution: Take-Home Messages

(1) Correct population-level behavior can result from correct individual-level learning behavior in some cases (small discrepancies compounded over time).

Learning-Driven Linguistic Evolution: Take-Home Messages

(1) Correct population-level behavior can result from correct individual-level learning behavior in some cases (small discrepancies compounded over time).

(2) In the case study examined here, linguistic evolution occurs at the correct rate only when learners employ selective learning biases that cause them to use only a subset of the available data.

Learning-Driven Linguistic Evolution: Take-Home Messages

(1) Correct population-level behavior can result from correct individual-level learning behavior in some cases (small discrepancies compounded over time).

(2) In the case study examined here, linguistic evolution occurs at the correct rate only when learners employ selective learning biases that cause them to use only a subset of the available data.

(3) Models of linguistic evolution can be empirically grounded and then more easily manipulated to fit the available data (less parameters of variation).

Individual-level: learning period, data distribution, linguistic representation, probabilistic learning

Population-level: population size, population growth rate, time period of change, rate of change

Thank You

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Individual Framework Applicability

Benefit: Can combine discrete representations, selective learning biases, and probabilistic learning for many types of linguistic knowledge.

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Discrete Representation: How much structure is posited for language?

A = linear structure

IP
Subject Verb Object

B = hierarchical structure

IP
Subject VP
Verb Object

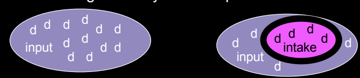
Discrete Representation : Is the basic word order Object Verb or Verb Object?

A = Object Verb

B = Verb Object

Framework Applicability

Benefit: Can combine discrete representations, selective learning biases, and probabilistic learning for many different problems.



Learning Bias: Use all available data. (Good for probabilistic learner - no data sparseness problem.)

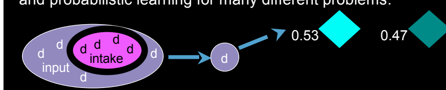
Selective Learning Bias: Use only data perceived as most informative (Fodor 1998, Lightfoot 1999, Dresher 1999).

Selective Learning Bias: Use only data that is more accessible (perhaps for language processing reasons) (Lightfoot 1991).

Selective Learning Bias: Use only data that is perceived as more systematic (Yang 2005).

Framework Applicability

Benefit: Can combine discrete representations, selective learning biases, and probabilistic learning for many different problems.



This can be instantiated as Bayesian updating, a Linear reward-penalty scheme, or any other probabilistic learning procedure.

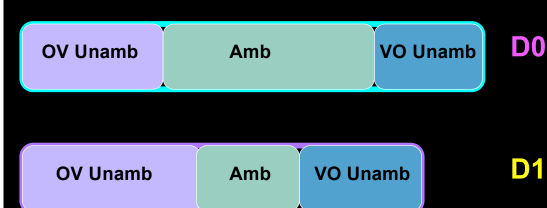
$$\text{Max}(\text{Prob}(p_{VO} \mid u)) = \text{Max}\left(\frac{\text{Prob}(u \mid p_{VO}) * \text{Prob}(p_{VO})}{\text{Prob}(u)}\right)$$

$$p_{OV} = p_{OV} + \gamma(1 - p_{VO})$$
$$p_{VO} = 1 - p_{OV}$$

Estimating Historical p_{VO}

Known quantities: Unambiguous and ambiguous data in d0 and d1

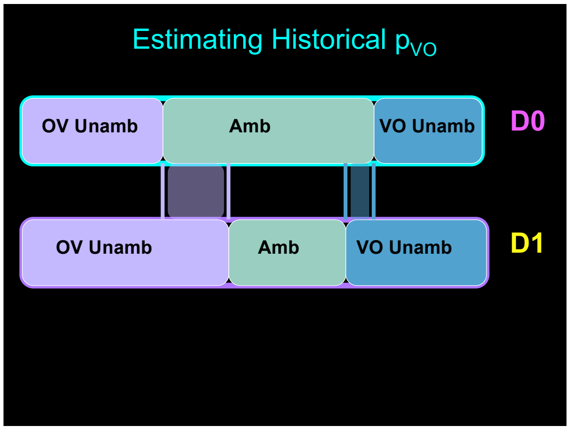
Estimating Historical p_{VO}

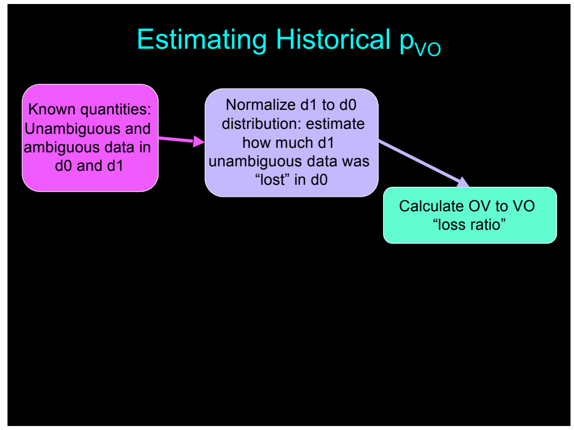


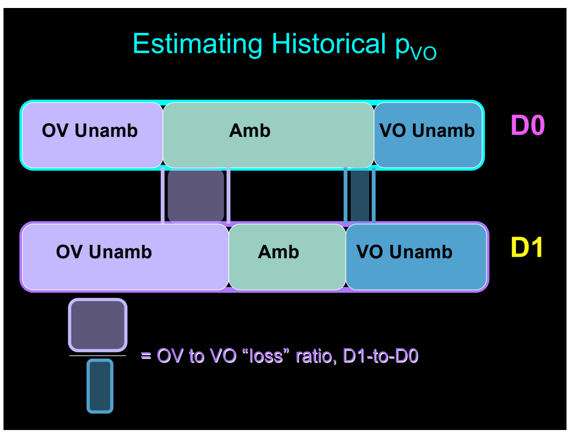
Estimating Historical p_{VO}

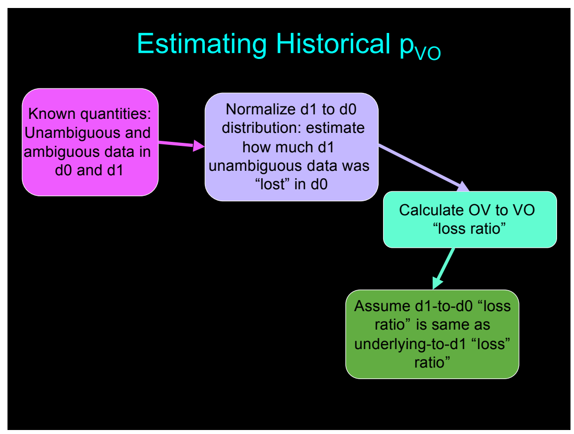
Known quantities: Unambiguous and ambiguous data in d0 and d1

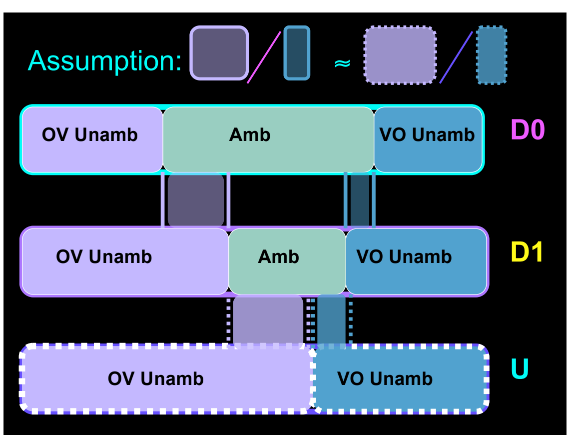
→ Normalize d1 to d0 distribution: estimate how much d1 unambiguous data was "lost" in d0

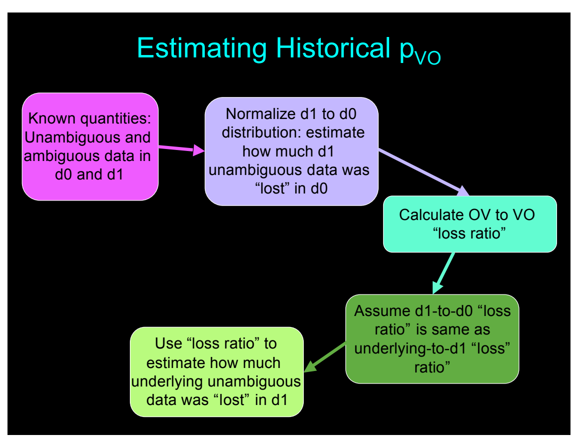

Estimating Historical p_{VO}
OV Unamb
Amb
VO Unamb
D0
OV Unamb
Amb
VO Unamb
D1

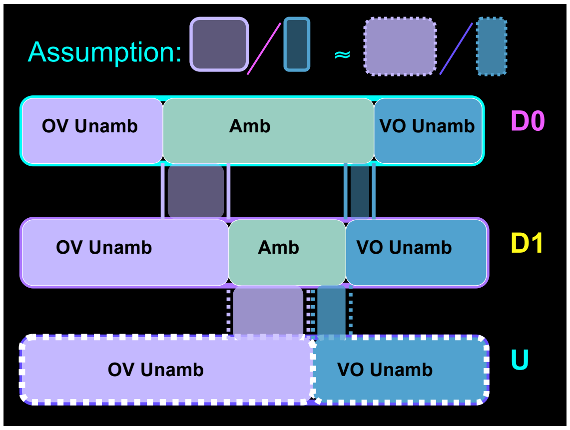

Estimating Historical p_{VO}
Known quantities: Unambiguous and ambiguous data in d0 and d1
Normalize d1 to d0 distribution: estimate how much d1 unambiguous data was "lost" in d0
Calculate OV to VO "loss ratio"

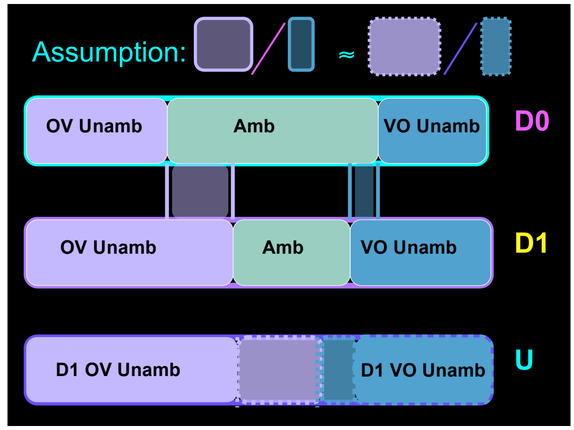

Estimating Historical p_{VO}
OV Unamb
Amb
VO Unamb
D0
OV Unamb
Amb
VO Unamb
D1
= OV to VO "loss" ratio, D1-to-D0

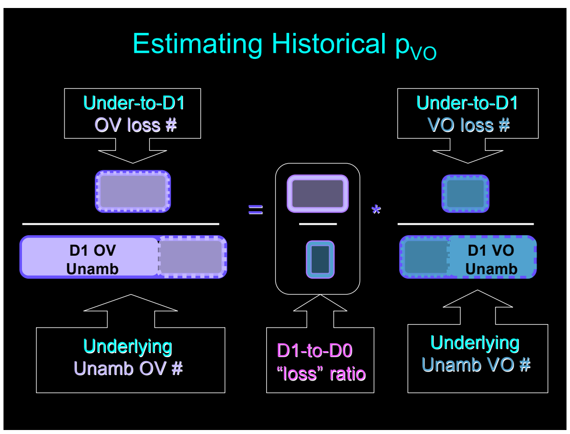

Estimating Historical p_{VO}
Known quantities: Unambiguous and ambiguous data in d0 and d1
Normalize d1 to d0 distribution: estimate how much d1 unambiguous data was "lost" in d0
Calculate OV to VO "loss ratio"
Assume d1-to-d0 "loss ratio" is same as underlying-to-d1 "loss" ratio"

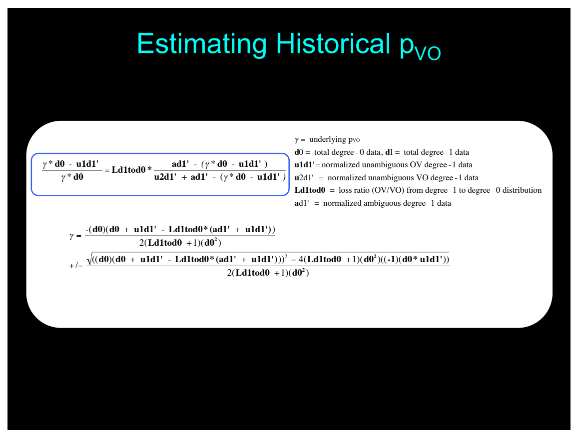

Assumption:
≈
OV Unamb
Amb
VO Unamb
D0
OV Unamb
Amb
VO Unamb
D1
OV Unamb
VO Unamb
U

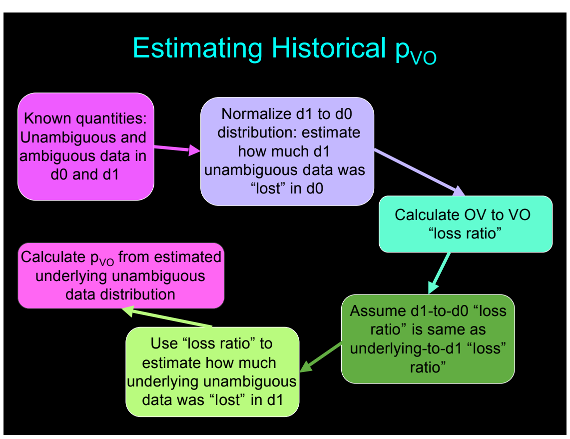

Estimating Historical p_{VO}
Known quantities: Unambiguous and ambiguous data in d0 and d1
Normalize d1 to d0 distribution: estimate how much d1 unambiguous data was "lost" in d0
Calculate OV to VO "loss ratio"
Assume d1-to-d0 "loss ratio" is same as underlying-to-d1 "loss" ratio"
Use "loss ratio" to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

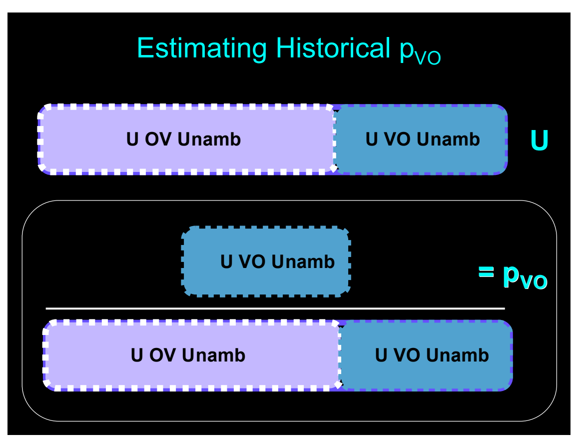

Assumption:
≈
OV Unamb
Amb
VO Unamb
D0
OV Unamb
Amb
VO Unamb
D1
OV Unamb
VO Unamb
U


Assumption:
≈
OV Unamb
Amb
VO Unamb
D0
OV Unamb
Amb
VO Unamb
D1
D1 OV Unamb
D1 VO Unamb
U


Estimating Historical p_{VO}
Under-to-D1 OV loss #
Under-to-D1 VO loss #
=
*
D1 OV Unamb
D1 VO Unamb
Underlying Unamb OV #
D1-to-D0 "loss" ratio
Underlying Unamb VO #


Estimating Historical p_{VO}
$\frac{\gamma * d0 - u1d1'}{\gamma * d0} = Ld1tod0 * \frac{ad1' - (\gamma * d0 - u1d1')}{u2d1' + ad1' - (\gamma * d0 - u1d1')}$
γ = underlying p_{VO}
d0 = total degree-0 data, d1 = total degree-1 data
u1d1' = normalized unambiguous OV degree-1 data
u2d1' = normalized unambiguous VO degree-1 data
Ld1tod0 = loss ratio (OV/VO) from degree-1 to degree-0 distribution
ad1' = normalized ambiguous degree-1 data
$\gamma = \frac{-(d0)(d0 + u1d1' - Ld1tod0*(ad1' + u1d1'))}{2(Ld1tod0 + 1)(d0^2)} +/- \frac{\sqrt{((d0)(d0 + u1d1' - Ld1tod0*(ad1' + u1d1')))^2 - 4(Ld1tod0 + 1)(d0^2)((-1)(d0*u1d1'))}}{2(Ld1tod0 + 1)(d0^2)}$


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
Calculate p_{VO} from estimated underlying unambiguous data distribution


Estimating Historical p_{VO}
U OV Unamb
U VO Unamb
U
U VO Unamb
U OV Unamb
U VO Unamb
= p_{VO}

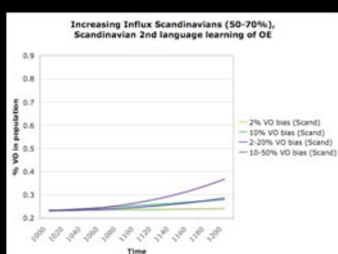
Potential Causes of Language Change

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

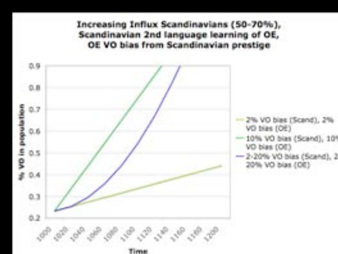
Old French at 1066 A.D.: embedded clauses predominantly OV-biased
- (Kibler, 1984)
- Matrix clauses often SVO (ambiguous)
- OV-bias would have hindered Old English change to VO-biased system.

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

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

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

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

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

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

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

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

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

$$p_{VO} = \frac{r+1}{n+1}$$

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

$$p_{VO} = \frac{r+1}{n+1}, \quad r = p_{VOprev} * n$$

Replace 1 in numerator and denominator with

$c = p_{VOprev} * m$ if VO, $c = (1 - p_{VOprev}) * m$ if OV

$3.0 \le m \le 5.0$

$$p_{VO} = \frac{p_{VOprev} * n + c}{n + c}$$

Other Ways to Interpret Ambiguous Data

Strategies for assessing ambiguous data

(1) assume base-generation
- attempted and failed
- system-dependent (syntax)

(2) weight based on level of ambiguity (Pearl & Lidz, in submission)
- unambiguous = highest weight
- moderately ambiguous = lower weight
- fully ambiguous = lowest weight (ignore)

(3) randomly assign to one hypothesis (Yang 2002)

Perceived Unambiguous Data: OV

Unambiguous OV data

(1) Tensed Verb is immediately post-Object

he$_{Subj}$ **hyne**$_{Obj}$ **gebidde**$_{TensedVerb}$
He him may-pray
'He may pray (to) him'
(*Ælfric's Letter to Wulfsige,* 87.107, ~1075 A.D.)

(2) Verb-Marker is immediately post-Object

we$_{Subj}$ sculen$_{TensedVerb}$ **[ure yfele þeawes]**$_{Obj}$ **forlæten**$_{Verb\text{-}Marker}$
we should our evil practices abandon
'We should abandon our evil practices.'
(*Alcuin's De Virtutibus et Vitiis,* 70.52, ~1150 A.D.)

Perceived Unambiguous Data: VO

Unambiguous VO data

(1) Tensed Verb is immediately pre-Object, **2+ phrases** precede (due to **interaction of V2 movement**)

& [mid his stefne]$_{PP}$ **he**$_{Subj}$ **awecð**$_{TensedVerb}$ **deade**$_{Obj}$ [to life]$_{PP}$
& with his stem he awakened the-dead to life
'And with his stem, he awakened the dead to life.'
(*James the Greater,* 30.31, ~1150 A.D.)

(2) Verb-Marker is immediately pre-Object

þa$_{Adv}$ ahof$_{TensedVerb}$ Paulus$_{Subj}$ **up**$_{Verb\text{-}Marker}$ **[his heafod]**$_{Obj}$
then lifted Paul up his head
'Then Paul lifted his head up.'
(*Blickling Homilies,* 187.35, between 900 and 1000 A.D.)

Verb-Markers

Sub-piece of the verbal complex that is semantically associated with a Verb, used to determine original position of Verb

Examples: particle ('up', 'out'), a non-tensed complement to tensed Verbs, a closed-class adverbial ('never'), or a negative ('not') (Lightfoot, 1991).

þa$_{Adv}$ ahof$_{TensedVerb}$ Paulus$_{Subj}$ **up**$_{Verb\text{-}Marker}$ **[his heafod]**$_{Obj}$
then lifted Paul up his head
'Then Paul lifted his head up.'

we$_{Subj}$ sculen$_{TensedVerb}$ **[ure yfele þeawes]**$_{Obj}$ **forlæten**$_{Verb\text{-}Marker}$
we should our evil practices abandon
'We should abandon our evil practices.'

Unreliable Verb-Markers

Sometimes the Verb-Marker would not remain adjacent to the Object.

ne$_{Negative}$ geseah$_{TensedVerb}$ ic$_{Subj}$ **næfre**$_{Adverbial}$ **[ða burh]**$_{Obj}$
NEG saw I never the city
'Never did I see the city.'
(Ælfric, *Homilies.* I.572.3, between 900 and 1000 A.D.)