Role of perceptual similarity in the acquisition of phonological alternations:

A biased maximum entropy learning model

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Role of perceptual similarity in phonological learning

- Does perceptual similarity play a role during phonological learning?
  - If so, what is that role?

- Part of a larger question: Does phonetic substance play a role in phonological learning?
  - Are there substantive biases[1]?

1. Wilson, 2006

Steriade's P-map proposal

- **P-map**: a mental representation of the relative perceptual similarity between speech sounds in a given context.[1]
  - Likely based on an individual's prior perceptual experience.

- Steriade proposed that learners are biased by the P-map when learning phonological patterns.
  - Phonological processes assumed, *a priori*, to involve minimal perceptual modification.

1. Steriade, 2001/2008

Experimental evidence that similarity plays a role

- Alternations involving a 1-feature change easier to learn than those involving a change in 2 or more features.[1]
  - [pamu ~ tamu] easier than [pamu ~ zamu].

- Adults learning /ke/ → [tʃe] are more likely to generalize to /ki/ → [tʃi] than vice versa.
  - [k] and [tʃ] more similar before [i] than before [e].

1. Skoruppa et al., 2011 2. Wilson, 2006

Today's talk

- <u>Goal</u>: Investigate this issue by comparing learning models both with and without a similarity bias.

- <u>Test case</u>: Experimental data showing that adult learners disprefer saltatory alternations (White, in press, *Cognition*).

  = a type of alternation involving not minimal change, but excessive change.

Roadmap

1. Overview of saltatory alternations

2. Overview of experimental results

3. Modeling

1. Saltatory alternation

Saltatory alternation

- Phonological alternation where an intermediate sound is "leaped over".[1]
- Campidanian Sardinian:
  - /p/ ⟶ [β] / V ___V
  - no change for /b/.

[pãi] ⟶ [s:u βãi] 'the bread'

[bĩu] ⟶ [s:u bĩu] 'the wine'

1. White, in press

Saltatory alternation

- Phonological alternation where an intermediate sound is “leaped over”.[1]
- Campidanian Sardinian:

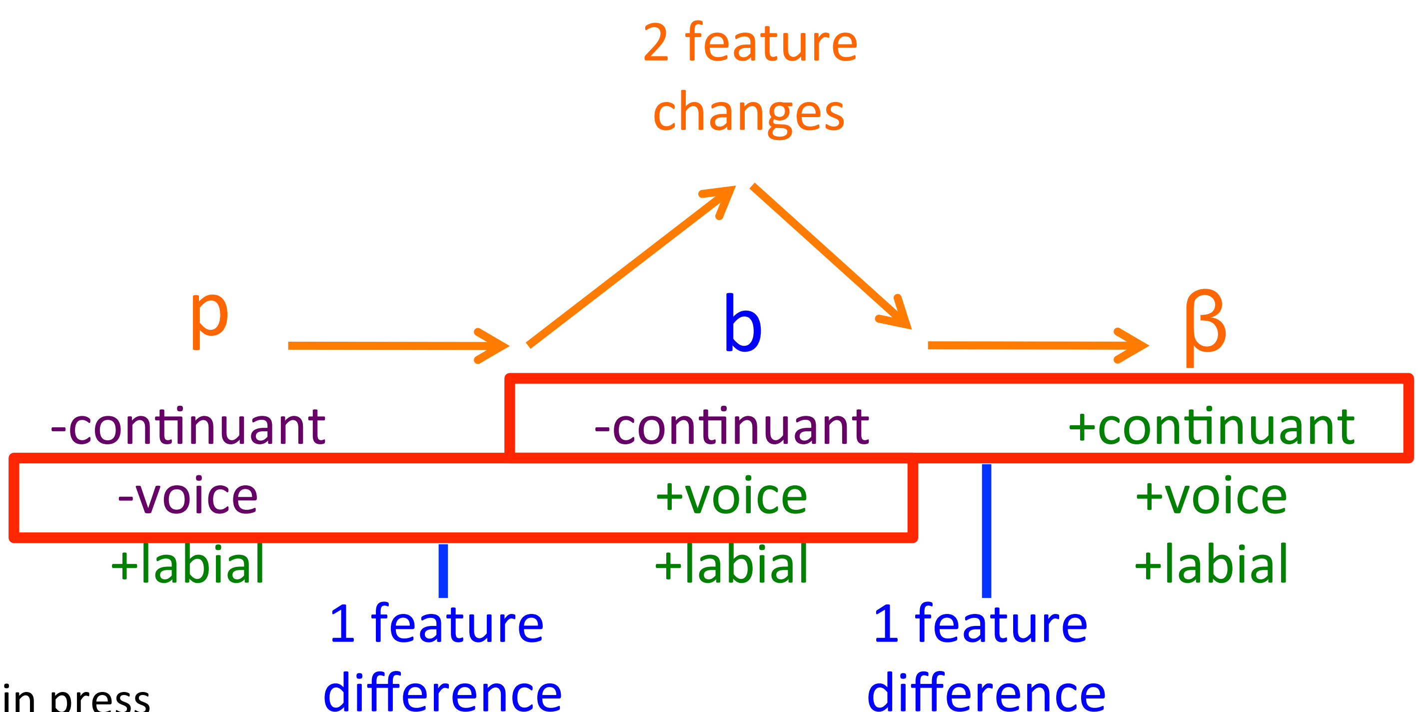
$$p \xrightarrow{\text{2 feature changes}} β$$

p		β
-continuant		+continuant
-voice		+voice
+labial		+labial

1. White, in press

Saltatory alternation

- Phonological alternation where an intermediate sound is "leaped over".[1]
- <u>Campidanian Sardinian</u>:



1. White, in press

2. Experimental results

Learners prefer to avoid saltatory alternations.

Artificial language experiments (adult learners)

1. Exposure phase

 [kamap]

 [kamavi]

Also: non-changing fillers like [luman] ⟶ [lumani]

Artificial language experiments (adult learners)

1. Exposure phase

[kamap]

[kamavi]

2. Verification phase

[kamap]

[kamapi]
or
[kamavi]???

3. Generalization phase

[lunub]

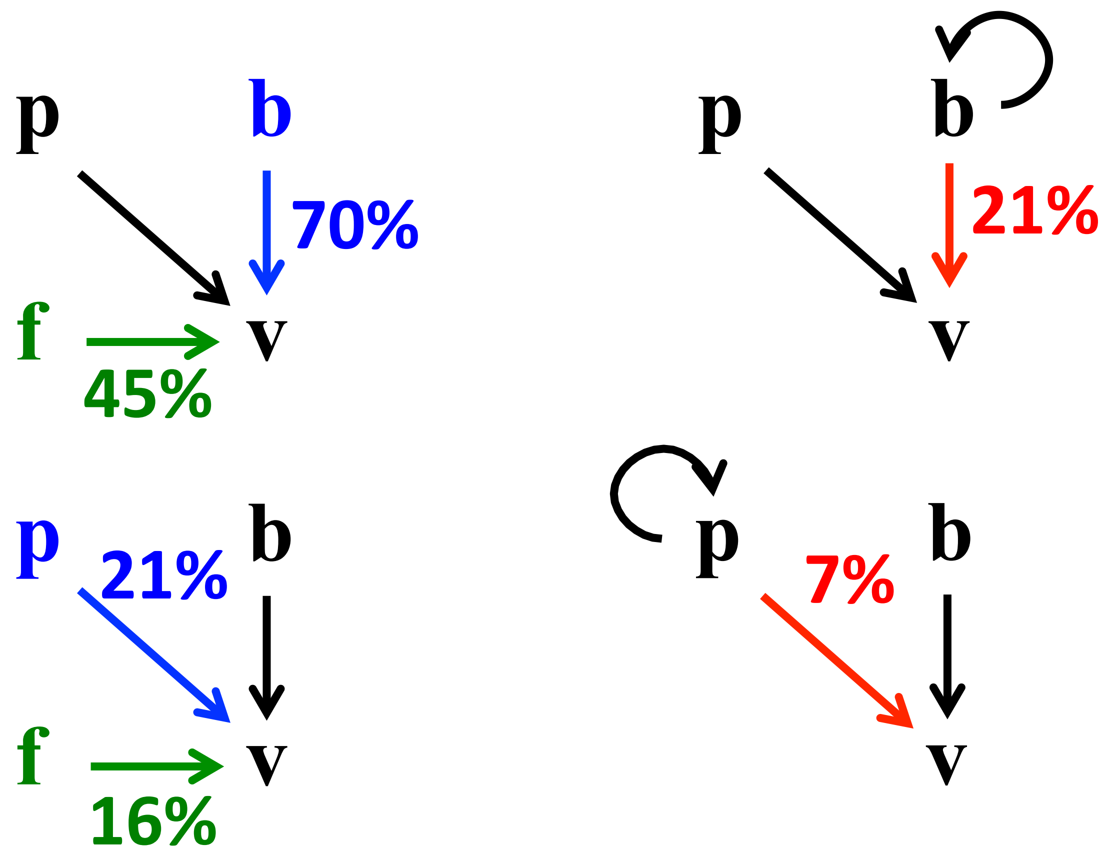
[lunubi]
or
[lunuvi]???

Crucial results to be accounted for

Ambiguous Saltation | Explicit Saltation

Test condition

Control condition



3. Maximum entropy learning model

For previous uses, see Golwater & Johnson, 2003; Wilson, 2006; Hayes & Wilson, 2008; Hayes et al., 2009; Martin, 2012; others.
Implemented using the MaxEnt Grammar Tool (available at Bruce Hayes's webpage).

2 things the learning model should account for

1. Saltatory alternations exist and thus must be <u>learnable</u> for the child.

2. This type of alternation is dispreferred by learners.
   - Can we model the experimental results?

Overview of the model

- Set of OT-style constraints
- Input forms (singular words)
- Candidate output forms (plural words)
- Constraint violations

← **Provide the model**

Training data
(observed input-output pairs)

Prior
(a priori preferred weights)

(Maxent learning)

Grammar
(=weighted constraints)

Predicted probability
of each output

Constraint set

- Feature-based markedness constraints, which motivate alternating.
  - *V [–voice] V
  - *V [–continuant] V

- Correspondence constraints banning alternations between specific pairs of sounds.[1]
  - E.g., *MAP(p,v) = don't have an alternation between [p] and [v].

1. Zuraw, 2007, 2013

Why *MAP constraints?

- Traditional faithfulness constraints (classical OT) cannot generate saltation.[1, 2]
  - True, even with weighted constraints.

- p → v requires two changes, whereas b → v would only require one change.

- Saltation requires a short journeys (b → v) to be banned where long journeys (p → v) are allowed.

1. Lubowicz, 2002 2. Ito & Mester, 2003

Training data

- Same as the training data in the experiments.

- Ambiguous Saltation experiment:

input	possible outputs	# observed
p	v	18
	p	0
	f	0
	b	0

input	possible outputs	# observed
t	ð	18
	t	0
	θ	0
	d	0

Prior (= the bias)

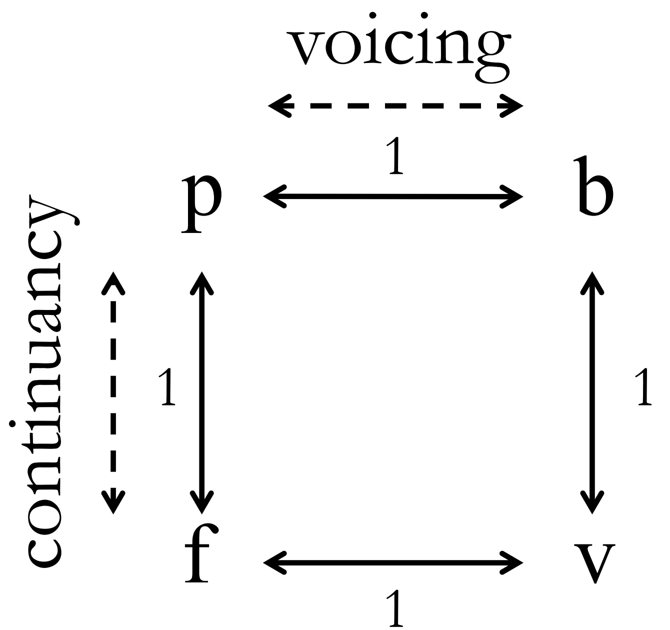
- Biases the learning towards certain outcomes, based on *a priori* assumptions.
  - In this case, based on perceptual similarity.
  - Soft bias, not an absolute restriction.

- The prior is Gaussian. Provide:
  - μ = <u>preferred</u> weight for each constraint.
  - σ^2 = how tightly constraints are held to their preferred weight.

Measure of similarity

- How people judge the similarity of speech sounds is likely complex.[1, 2, 3]
- One possiblity:

Featural similarity

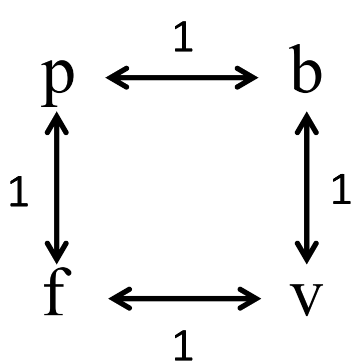


1. Steriade, 2001/2008 2. Mielke, 2008 3. Cristia et al., 2013

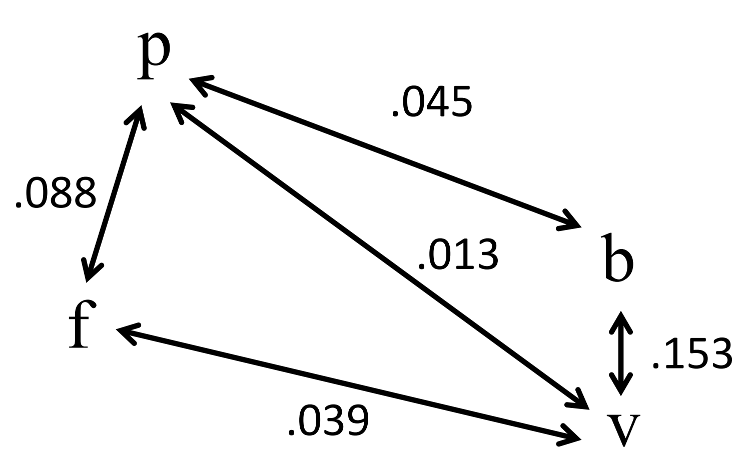
Perceptual similarity

- I use <u>mutual confusability</u> as a simplified measure of perceptual similarity.
  - Data from published confusion experiments with adult English speakers.[1]
- Example:

Features



Mutual confusability



1. Wang & Bilger, 1973

Setting the prior

- <u>Goal</u>: go directly from confusion proportions to prior constraint weights. (No cherry-picking weights).
- <u>Solution</u>: Train up a separate maxent model intended solely to generate prior weights (μ), based on confusion probabilities.

- <u>Intuitively</u>: Represents the listener's perceptual experience, a computational version of the P-map.

Prior weights

Constraints	Substantively Biased
*V [-voice] V	0
*V [-cont] V	0
*MAP(p, f)	1.34
(p, b)	2.44
(p, v)	3.65
(b, v)	1.30
(b, f)	1.96
(f, v)	2.56

2 other models compared

1. **Anti-alternation**: All *MAP constraints start with the same weight.
   - prior weight = average of prior weights in the substantively biased model.
   - *A priori* preference to avoid any alternation equally, regardless of similarity.

2. **Unbiased**: Prior weight of 0 for all constraint.

Prior weights

Constraints	Substantively Biased	Anti-alternation	Unbiased
*V [-voice] V	0	0	0
*V [-cont] V	0	0	0
*MAP(p, f)	1.34	2.27	0
(p, b)	2.44	2.27	0
(p, v)	3.65	2.27	0
(b, v)	1.30	2.27	0
(b, f)	1.96	2.27	0
(f, v)	2.56	2.27	0

Learning procedure

- Find the set of constraint weights that maximizes this function:

$$[\sum_{j=1}^{n} \log \Pr(y_j \mid x_j)] - [\sum_{i=1}^{m} \frac{(w_i - \mu_i)^2}{2\sigma_i^2}]$$

Maximize the likelihood of the training data

with a penalty for weights that vary from the prior

- Model will provably always succeed at finding the "best" grammar by this criterion.[1]

1. Berger et al., 1996

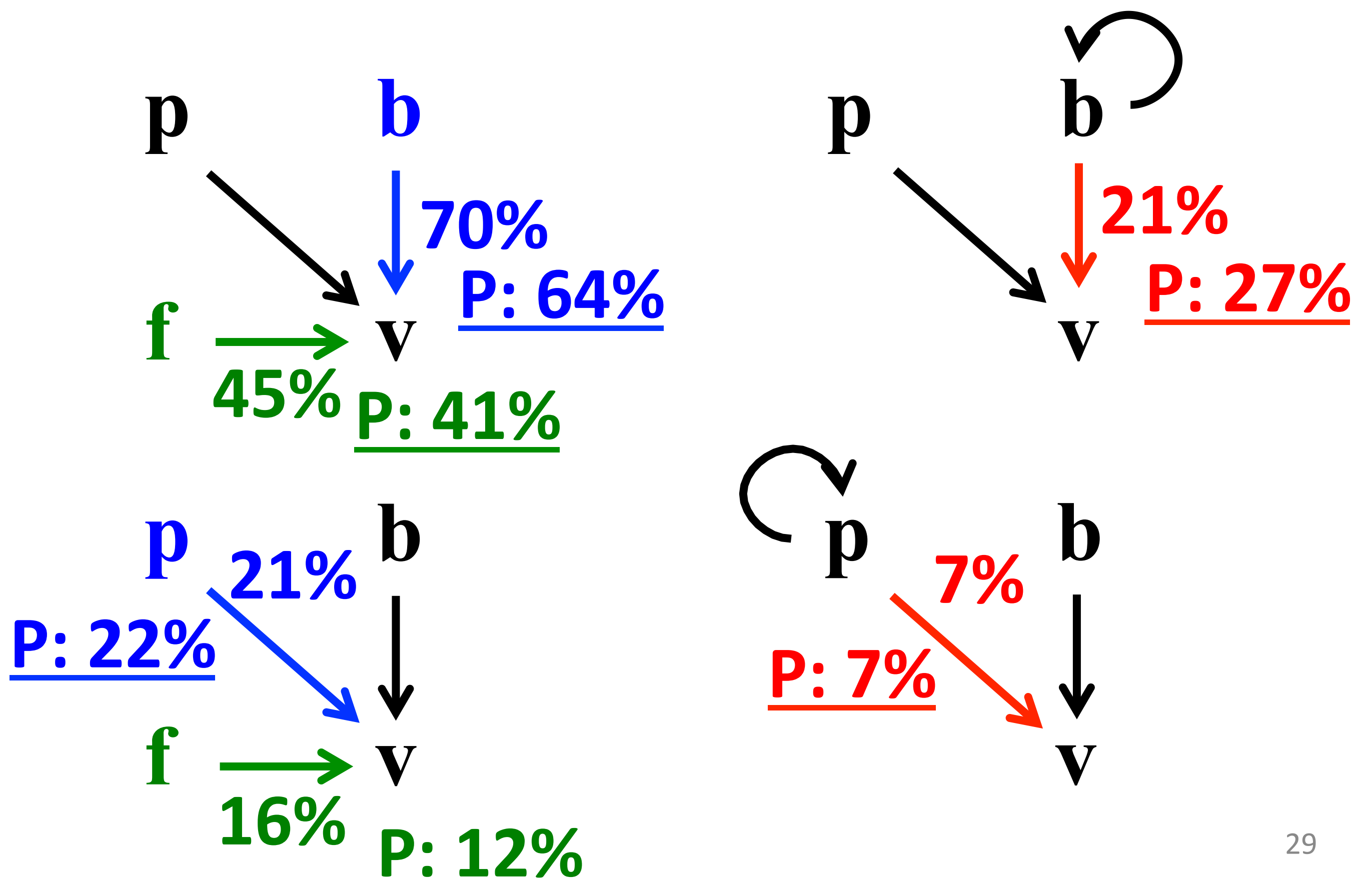
Returning to the crucial experimental results

Ambiguous Saltation

Explicit Saltation

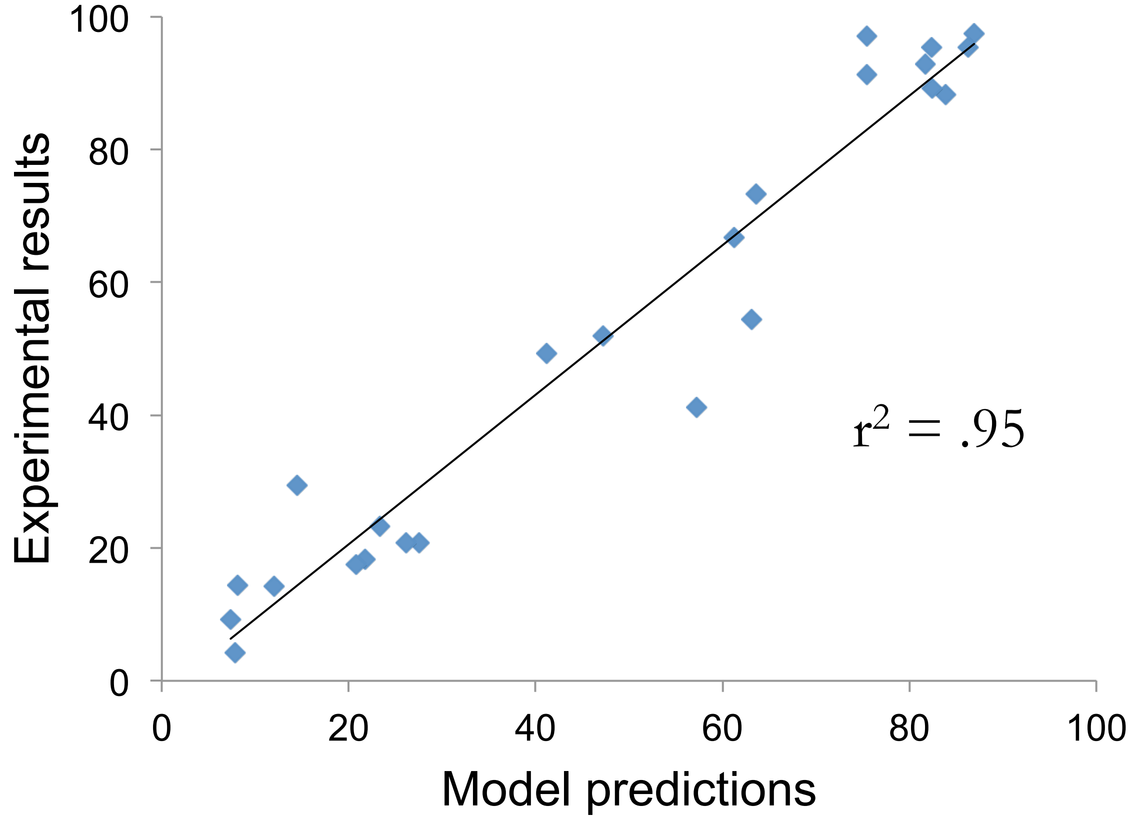
Test condition

Control condition



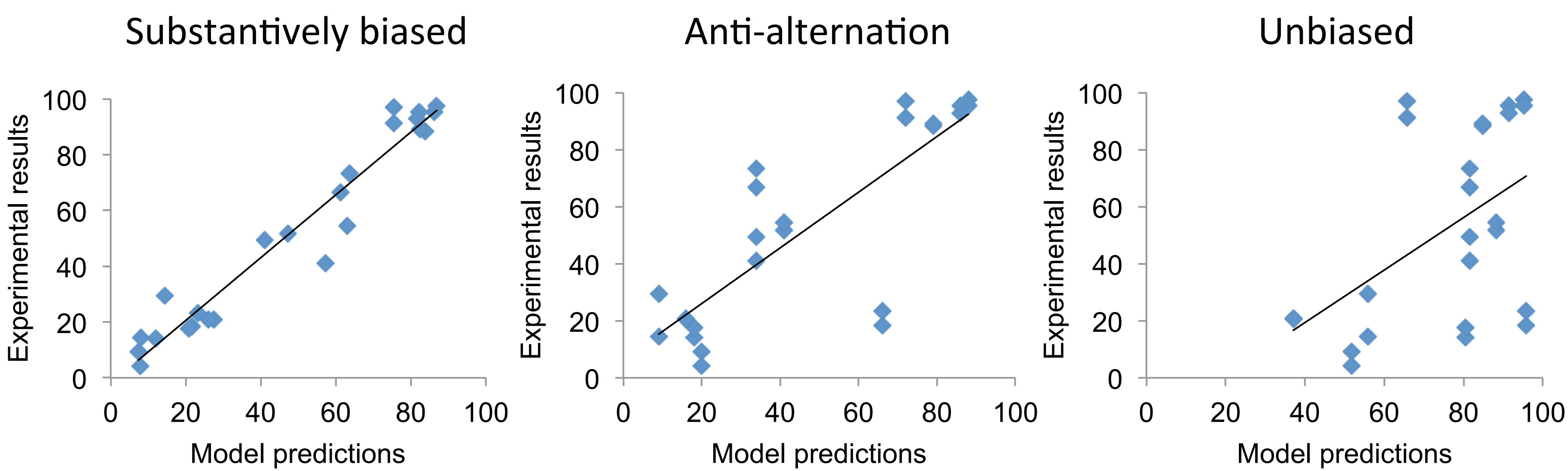
Model performance

Substantively biased model



Recall: No manipulation of prior weights by hand!

Compared to other models



$r^2 = .95$ $r^2 = .67$ $r^2 = .25$

Where do the control models go wrong?

- <u>Unbiased model</u>:
  - In general, predicts too much generalization – no reason to avoid positing new alternations.
- <u>Anti-alternation model</u>:
  - Unable to account for subtler variations between segments (e.g., [b] changed to [v] more often than [f]).
  - Ends up predicting more generalization in the <u>control</u> case than in the saltation case – opposite of the actual results!!

Discussion

- Anti-alternation model outperforms Unbiased model.
  - Consistent with a general preference for avoiding alternations (e.g., OO-Faith set high by default).[1, 2]
- Substantively biased model outperforms Anti-alternation model.
  - Evidence that perceptual similarity plays a role even beyond a general preference to avoid alternations.
- General framework for looking at the role of perceptual similarity in phonological learning.

1. Hayes, 2000   2. Tessier, 2012

Prior as a soft bias

- The prior is crucial to the model's success. It allows the desired learning pattern:
  - Alternations between dissimilar sounds are initially dispreferred.
  - But with enough training data, the prior can be overcome – they are learnable.

- The anti-saltation effect seen in the experiments seems to fall out from a more general similarity bias.

Evidence with infant learners?

- 12-month-olds learning potentially saltatory alternation generalize to intermediate sounds.[1]

- 12-month-old English-learning infants know [d ~ ɾ], but not [t ~ ɾ], despite greater support for [t ~ ɾ] in their input.[2]

1. White & Sundara, 2012, submitted
2. Sundara et al., this conference

Thank you!

- Acknowledgments:
  - For help and discussion, special thanks to Bruce Hayes, Megha Sundara, Kie Zuraw, Robert Daland, Sharon Peperkamp, Adam Albright, and audiences at UCLA and the University of Ottawa.
  - Thanks to my undergraduate research assistants as well as research assistants at the UCLA Langauge Acquisition Lab.

Creating the prior (details)

- Input = identification data from confusion experiments.[1]

E.g.,

Stimulus	Responses p	b	f	v	Stimulus	Responses t	d	θ	ð
p	1844	54	159	26	t	1765	107	92	26
b	206	1331	241	408	d	91	1640	75	193
f	601	161	1202	93	θ	267	118	712	135
v	51	386	127	1428	ð	44	371	125	680

- Each *MAP constraint is weighted according to how likely its sounds are to be confused for each other.
- Output weights → Prior of main model

1. Wang & Bilger 1973

Effect of different confusion data

Source	Table #	Context	In noise?	r^2
WB 1973	2-3	CV and VC	white noise	.95
WB 1973	2	CV	white noise	.93
WB 1973	3	VC	white noise	.92
WB 1973	6-7	CV and VC	none	.93
WB 1973	6	CV	none	.82
WB 1973	7	VC	none	.96
MN 1955	2-6	CV	white noise	.94
C-etal 2004	----	CV and VC	babbled noise	.82
C-etal 2004	----	CV	babbled noise	.79
C-etal 2004	----	VC	babbled noise	.77
Unbiased model (for comparison)				.25

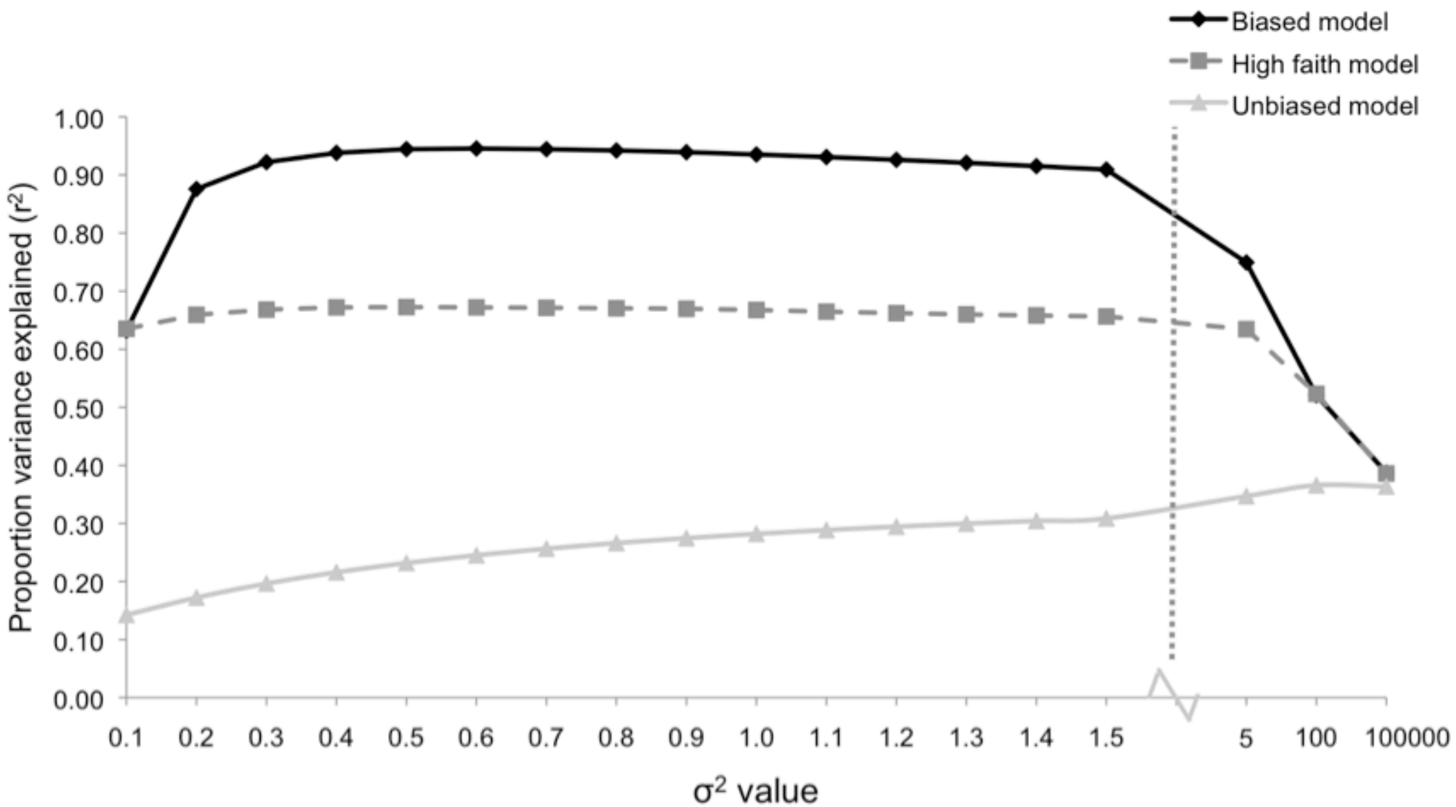
How the weights change during learning

Explicit Saltation experiment

p → v , b → b

Constraints	Prior weight	Post-learning weight
*V [-voice] V	0	2.45
*V [-cont] V	0	1.05
*MAP(p, f)	1.34	1.74
(p, b)	2.44	2.94
(p, v)	**3.65**	**1.96**
(b, v)	**1.30**	**2.02**
(b, f)	1.96	2.02
(f, v)	2.56	2.56

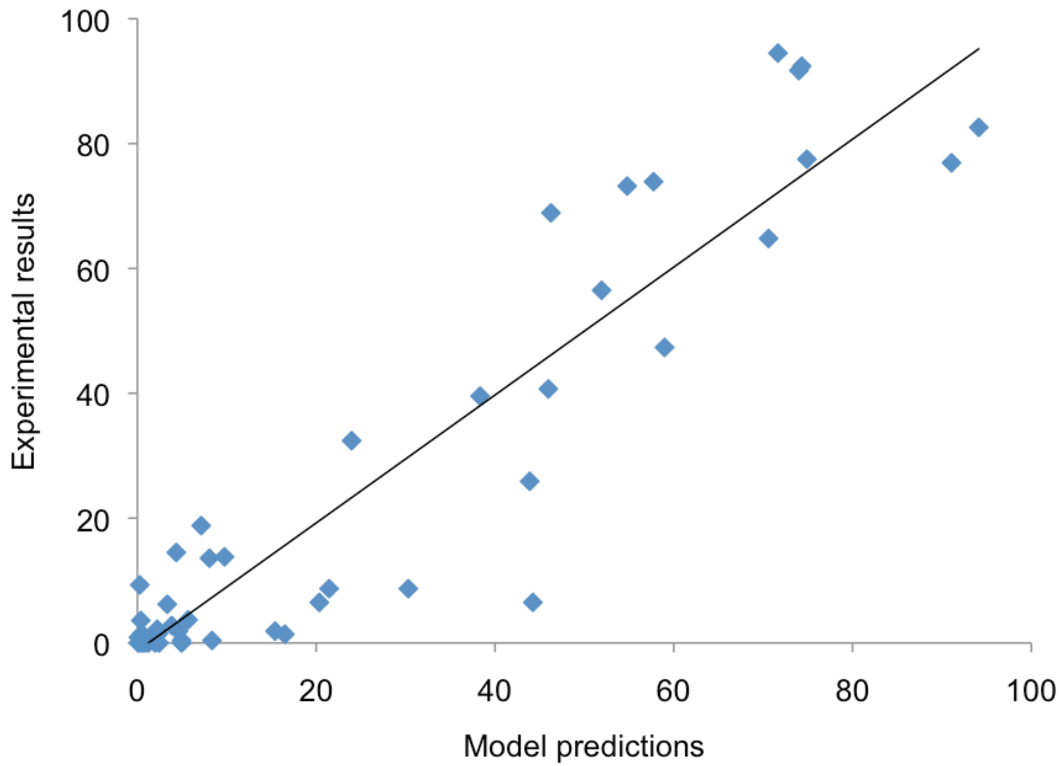
Effect of σ



Biased model
High faith model
Unbiased model
Proportion variance explained (r^2)
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0 1.1 1.2 1.3 1.4 1.5 5 100 100000
σ^2 value

Production study

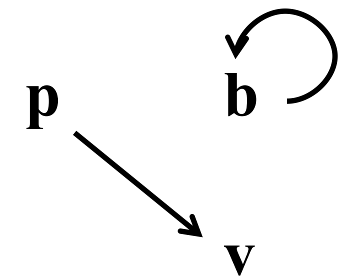
Figure 12. Predictions of the substantively biased model plotted against the experimental results from the production experiment. Overall $r^2 = .87$.



Predicting probabilities from the grammar

Explicit Saltation experiment

Training:



/kama**p**/	*V[-voice]V 2.45	*MAP(b, v) 2.02	*MAP(p, v) 1.96	*V[-cont]V 1.05	Total penalty	Predicted output
kama**v**i			*			
kama**p**i	*			*		

Predicting probabilities from the grammar

Explicit Saltation experiment

<u>Training:</u> **p** **b** **v**

/kamap/	*V[-voice]V 2.45	*MAP(b, v) 2.02	*MAP(p, v) 1.96	*V[-cont]V 1.05	Total penalty	Predicted output
kamavi			*			
kamapi	*			*		

Input form and output candidates

Predicting probabilities from the grammar

Explicit Saltation experiment

Training: p b v

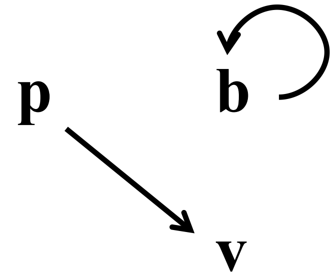
Constraint weights

/kamap/	*V[-voice]V 2.45	*MAP(b, v) 2.02	*MAP(p, v) 1.96	*V[-cont]V 1.05	Total penalty	Predicted output
kamavi			*			
kamapi	*			*		

Predicting probabilities from the grammar

Explicit Saltation experiment

Training:



/kama**p**/	*V[-voice]V 2.45	*MAP(b, v) 2.02	*MAP(p, v) 1.96	*V[-cont]V 1.05	Total penalty	Predicted output
kama**v**i			1.96			
kama**p**i	2.45			1.05		

Predicting probabilities from the grammar

Explicit Saltation experiment

<u>Training:</u> **p** **b**

v

/kama**p**/	*V[-voice]V 2.45	*MAP(b, v) 2.02	*MAP(p, v) 1.96	*V[-cont]V 1.05	**Total penalty**	Predicted output
kama**vi**			1.96		**1.96**	
kama**pi**	2.45			1.05	**3.50**	

Sum

$$\frac{e^{(-\text{penalty})}}{\sum e^{(-\text{penalty})}}$$

Predicting probabilities from the grammar

Explicit Saltation experiment

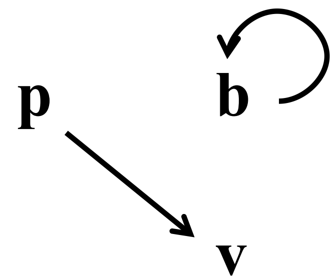
<u>Training:</u> **p** **b** **v**

/kama**p**/	*V[-voice]V 2.45	*MAP(b, v) 2.02	*MAP(p, v) 1.96	*V[-cont]V 1.05	Total penalty	**Predicted output**
kama**vi**			1.96		1.96	**82 %**
kama**pi**	2.45			1.05	3.50	**18 %**

Predicting probabilities from the grammar

Explicit Saltation experiment

Training:



/kama**p**/	*V[-voice]V 2.45	*MAP(b, v) 2.02	*MAP(p, v) 1.96	*V[-cont]V 1.05	Total penalty	**Predicted output**
kama**vi**			1.96		1.96	**82 %**
kama**pi**	2.45			1.05	3.50	**18 %**

/lunu**b**/	*V[-voice]V 2.45	*MAP(b, v) 2.02	*MAP(p, v) 1.96	*V[-cont]V 1.05	Total penalty	Predicted output
lunu**vi**		2.02			2.02	27 %
lunu**bi**				1.05	1.05	73 %

Predicting probabilities from the grammar

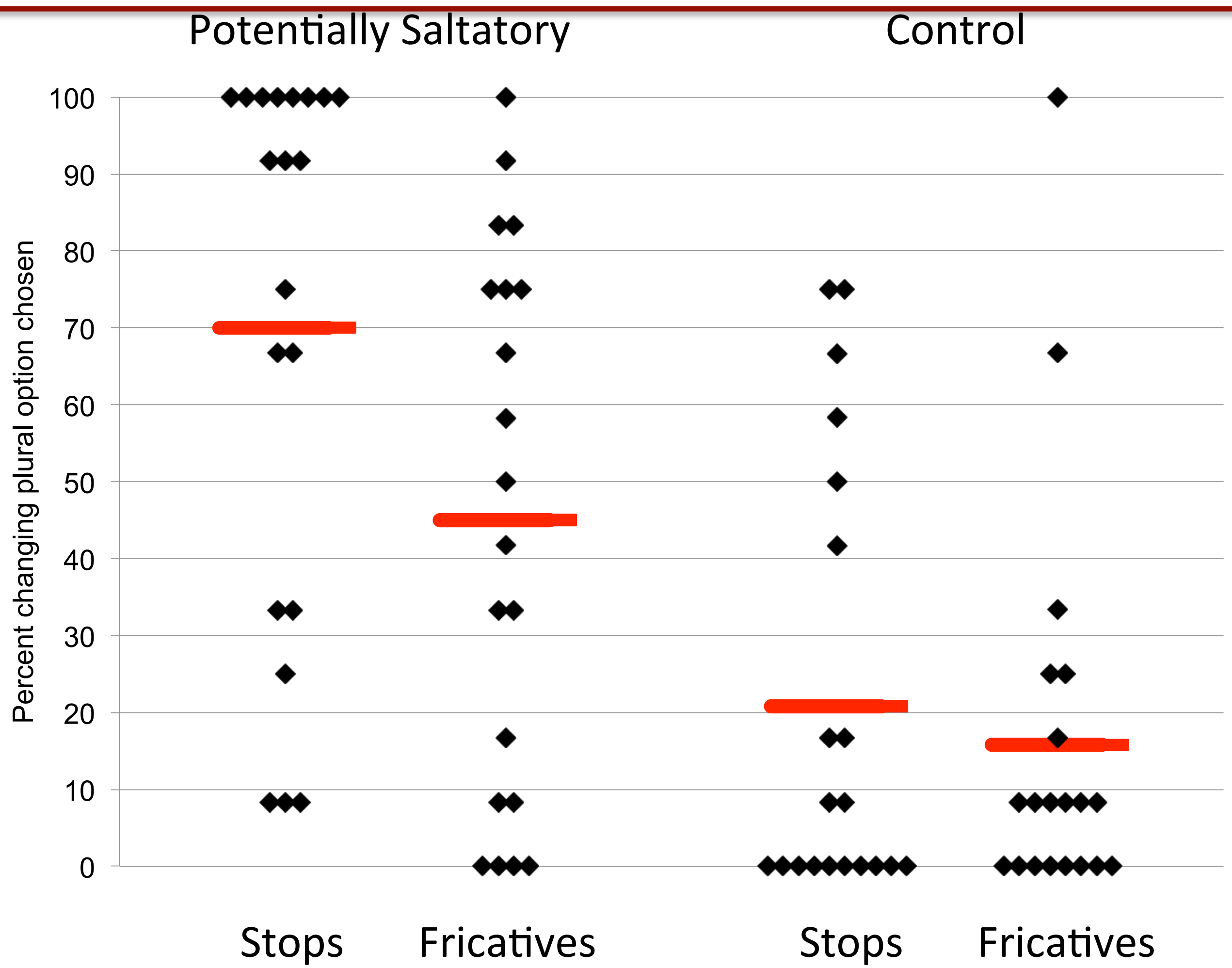
Explicit Saltation experiment

Training: **p** **b** **v**

/kama**p**/	*V[-voice]V 2.45	*MAP(b, v) 2.02	*MAP(p, v) 1.96	*V[-cont]V 1.05	Total penalty	**Predicted output**
kama**vi**			1.96		1.96	**82 %**
kama**pi**	2.45			1.05	3.50	**18 %**

/lunu**b**/	*V[-voice]V 2.45	*MAP(b, v) 2.02	*MAP(p, v) 1.96	*V[-cont]V 1.05	Total penalty	**Predicted output**
lunu**vi**		2.02			2.02	**27 %**
lunu**bi**				1.05	1.05	**73 %**

Exp. 1 Results



Exp. 2 Results