

Logistic regression, the binomial construction, and a hierarchical regression model

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9.19: Computational Psycholinguistics

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Probing binomial ordering preferences

- In each pair, which phrase sounds more natural?

hit and run

run and hit

gold and silver

silver and gold

deer and trees

trees and deer

drink and food

food and drink

bacteria and candy

candy and bacteria

radio and television

television and radio

shares and stocks

stocks and shares

chanting and enchanting

enchanting and chanting

quails and felines

felines and quails

Ordering preferences in binomials

- Every occurring binomial is result of a *speaker's choice* about *binomial ordering*

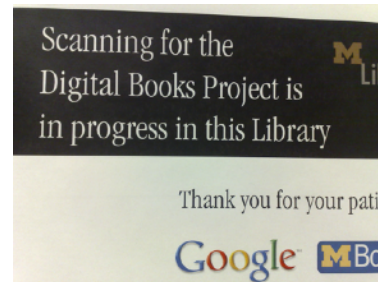
(US Google Books ngram counts, 1960–2012; ~340B words)	Count	Count(Rev)
salt and pepper	568,951	32,082
cat and mouse	26,774	367
skirts and sweaters	1,763	1,707
bishops and seamstresses	<40	<40
few and unfavorable	<40	<40
principal and interest	120,034	50,032

- What is the representation of these ordering preferences?
- Are these preferences also *productive*?

An n -grams dataset from millions of books



(image credit Top of the List)



RESEARCH ARTICLE

Quantitative Analysis of Culture Using Millions of Digitized Books

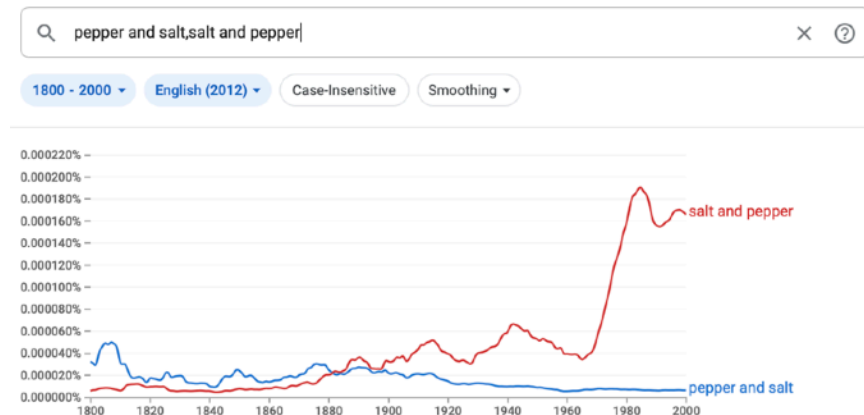
Jean-Baptiste Michel,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} Yuan Kui Shen,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} Aviva Presser Aiden,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} Adrian Veres,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} Matthew K. Gray,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} The Google Books Team,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} Joseph P. Pickett,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} Dale Hoiberg,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} Dan Clancy,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} Peter Norvig,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} Jon Orwant,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} Steven Pinker,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} Martin A. Nowak,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100} Erez Lieberman Aiden,^{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,60,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77,78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96,97,98,99,100}

We constructed a corpus of digitized texts containing about 4% of all books ever printed. Analysis of this corpus enables us to investigate cultural trends quantitatively. We survey the vast terrain of 'culturalomics,' focusing on linguistic and cultural phenomena that were reflected in the English language between 1800 and 2000. We show how this approach can provide insights about fields as diverse as lexicography, the evolution of grammar, collective memory, the adoption of technology, the pursuit of fame, censorship, and historical epidemiology. Culturalomics extends the boundaries of rigorous quantitative inquiry to a wide array of new phenomena spanning the social sciences and the humanities.

pages of 1208 books. The corpus contains 386,434,758 words from 1861; thus, the frequency is 5.5×10^{-5} . The use of "slavery" peaked during the Civil War (early 1860s) and then again during the civil rights movement (1955–1968) (Fig. 1B).

In contrast, we compare the frequency of "the Great War" to the frequencies of "World War I" and "World War II". References to "the Great War" peak between 1915 and 1941. But although its frequency drops thereafter, interest in the underlying events had not disappeared; instead, they are referred to as "World War I" (Fig. 1C).

These examples highlight two central factors that contribute to cultural trends. Cultural change guides the concepts we discuss (such as "slavery"). Linguistic change, which, of course, has cultural roots, affects the words we use for those concepts ("the Great War" versus "World War I"). In this paper, we examine both linguistic changes, such as changes in the lexicon and grammar, and cul-



(Michel et al., 2011; the Google Books project)

Testing some more intuitions

boof and kaboof

kaboof and boof

glagy and gligy

gligy and glagy

swirp and swirr

swirr and swirp

smates and smats

smats and smates

rasby and dasby

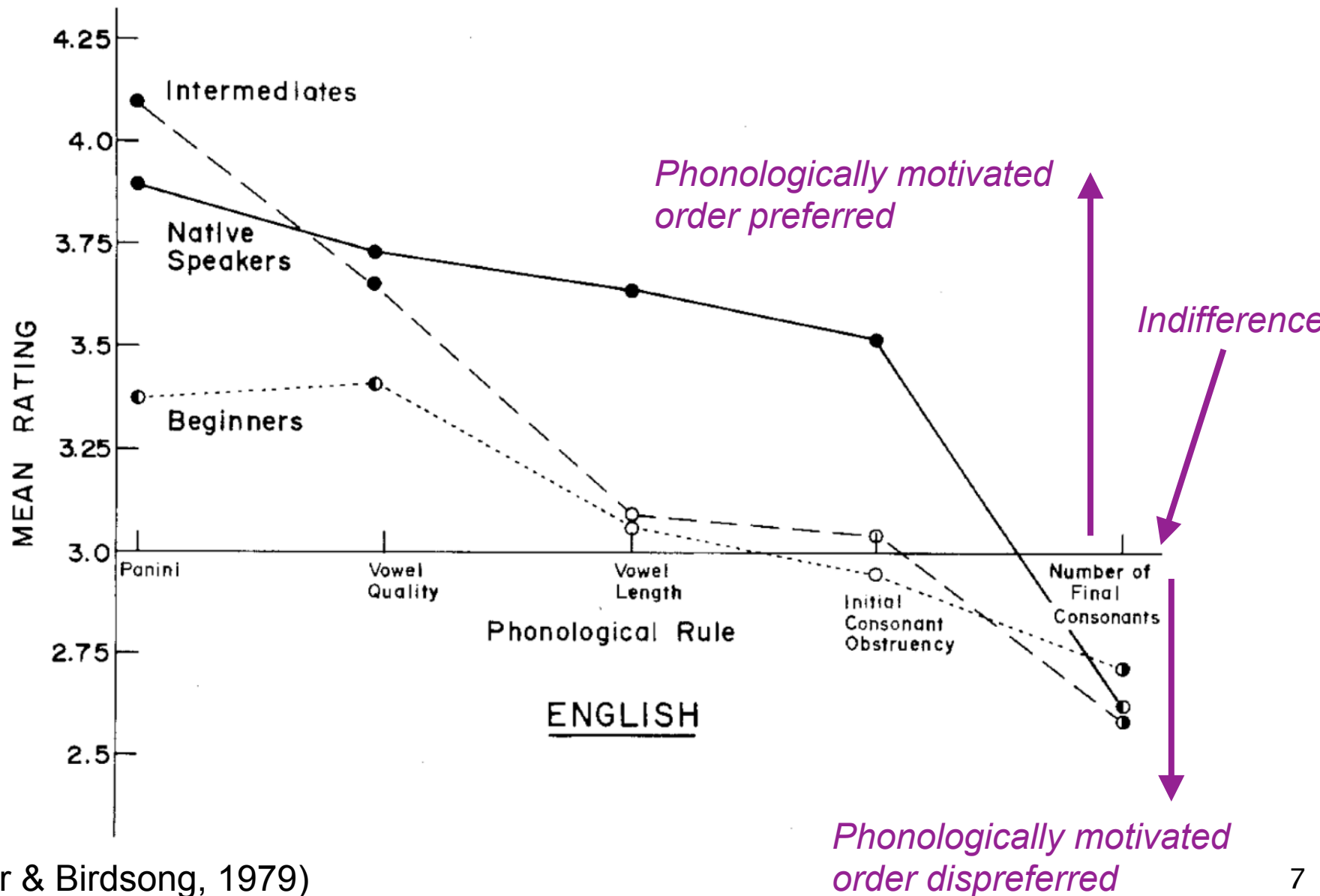
dasby and rasby

Testing some more intuitions

fim - *fum*
begroast *and* *begroat*
spladilk *or* *dilk*
waf - *paf*
frinning *and* *freening*

fum - *fim*
begroat *and* *begroast*
dilk *or* *spladilk*
paf - *waf*
freening *and* *grinning*

Ordering preferences for nonce words



Previous work: *novel* binomials

- Pinker & Birdsong (1979) used *nonce-word* binomials to test phonological constraints in offline judgments:
 - ✓ Length (*boof and kaboo*; **dadabig and dabig*)
 - ✓ Vowel Quality: high<low (*gligy and glagy*; **roppo and reppo*)
 - ✓ Vowel Length: long<short (*smats and smates*)
 - ✓ Initial Consonant: sonorant<obstruent (*haipo and daipo*)
 - ✗ # Final Consonants (*skalk and skull*; **flar and flard*)
- McDonald, Bock, and Kelly (1993) tested (mostly) *novel* binomials in offline judgments and production:
 - ✓ Animacy
 - ✗ Length in production
 - ✓ Length in offline judgments

Ordering preferences: productive knowledge

What constraints predict relative preference for *X and Y* versus *Y and X* has been extensively investigated (Malkiel 1959, Bolinger 1962, Cooper & Ross 1975, Gustafsson 1976, Fenk-Oczlon 1989, Benor & Levy 2006)

- Iconic/scalar sequencing
 - what comes first happens first
 - *open and read* (a book); *hit and run* (auto); **hit and run* (baseball)
- Perceptual Markedness
 - animate, concrete, positive, ... < inanimate, abstract, negative, ...
 - *deer and trees*; *honest and stupid*; **flora and fauna*
- Power
 - More culturally prioritized or “powerful” word comes first
 - *clergymen and parishioners*; *food and drinks*;
**clerks and postmasters*

Attested but violates constraint



The condiment rule
(Cooper & Ross 1975)

Ordering preferences: productive knowledge

- Formal Markedness
 - Words with more general or broader meaning distributions come first
 - *sewing and quilting; changing and improving; *roses and flowers*
- No final stress
 - The final syllable of *Y* in *X and Y* must not be stressed
 - *abused and neglected; skirts and sweaters; *manufacture and install*
- Frequency
 - The more frequent word comes first
 - *bride and groom; smile and wink; *psychiatrists and patients*
- Length (“Panini’s Law”)
 - The shorter word comes first (we count in syllables)
 - *ask and answer; tense and irritable; *family and friends*

Formalizing ordering preferences

- Varieties of *probabilistic grammar* for forms F and meanings M :
 - Grammars over *forms*: $P(F)$ (word strings, syntax trees, ...)
 - Grammar over *possible forms given a meaning to be expressed*: $P(F | M)$
 - Interpretive grammars of possible meanings given a form: $P(M | F)$

$$P(\text{"X and Y"} | \{X, Y\})$$

$$\text{e.g., } P(\text{"pepper and salt"} | \{\text{salt, pepper}\})$$

A dataset of binomial expressions

Binomials are all over in naturalistic use→easy to sample:

ask and answer	right and good
knew and admired	sit-ups and push-ups
medicines and yeast	fits and starts
surprised and dubious	anxiously and eagerly
rank and file	congressional and presidential
thick and brown	toe and fronts
understand and share	startling and skillful
consider and rate	carefully and prudently
commoners and kings	WordPerfect and Lotus
always and everywhere	milk and honey
stained and waxed	improperly and unfairly
officially and publicly	business and government
tear and inflame	playbacks and study
By and large	cold and wet
linguistic and paralinguistic	softly and triumphantly
further and unnecessarily	register and vote
pie and bar	proposed and accepted
anger and anxiety	geographical and socio-economic
follow and understand	welcomed and approved
crime and sports	dwindling and diminishing
poetry and non-poetry	tough and dirty
immediately and directly	eighth and ninth

Probabilistic models of binomial ordering preferences

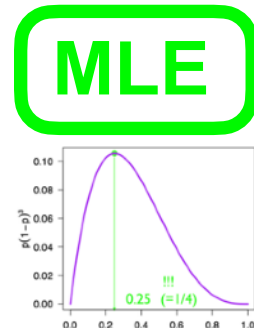
- One-constraint model, e.g.,

$$P([\text{SHORT}] \text{ and } [\text{LONG}] | \{[\text{short}], [\text{long}]\}) = p$$

- In our dataset, 65% preference when conjuncts differ in number of syllables
 - We set the relative-frequency estimate of p to 0.65
 - Remember: this is the **maximum likelihood estimate!**

abused and neglected ✓
bold and entertaining ✓
coughed and chattered ✓
medicines and yeast ✗

people and soils ✗
surprised and dubious ✓
sought and received ✓
sharp and rapid ✓



From earlier in
the semester!

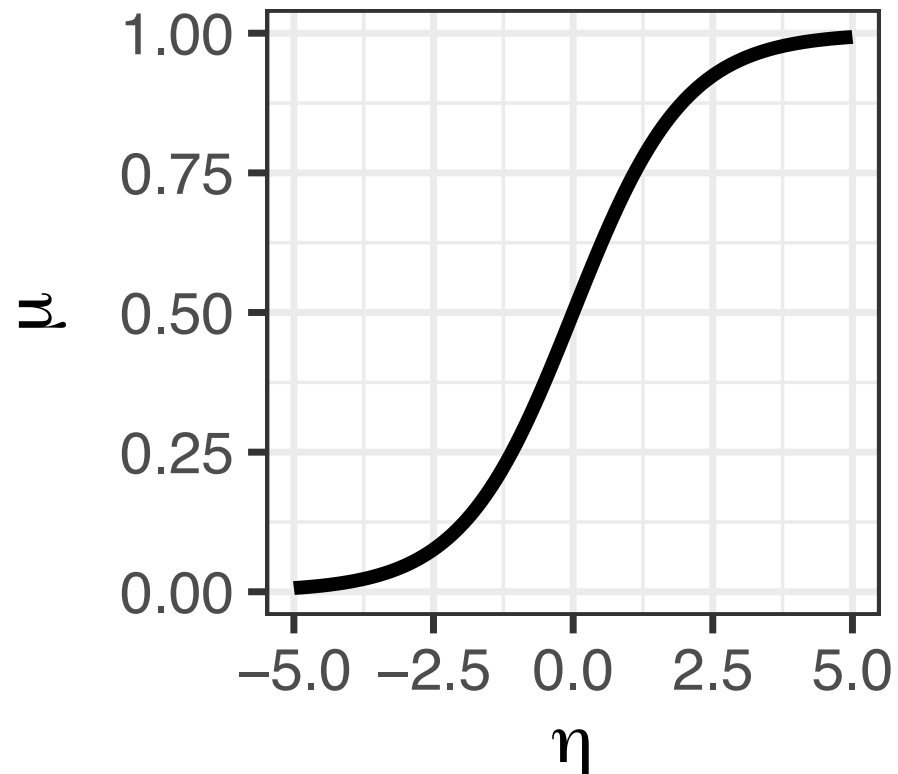
Multiple, cross-cutting constraints

- When we have more constraints, we use **logistic regression**

$$\underbrace{P(\text{“success”})}_{\text{a.k.a. mean } \mu} = \frac{e^{\eta}}{1 + e^{\eta}}$$

$$\eta = \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_N X_N$$

a “goodness score”



Logistic (sigmoid)
activation function

Fitting logistic regression via MLE

- With multiple model parameters, we get a likelihood *surface* on which we want to find the maximum
- 2-constraint example: word **length** and word **frequency**

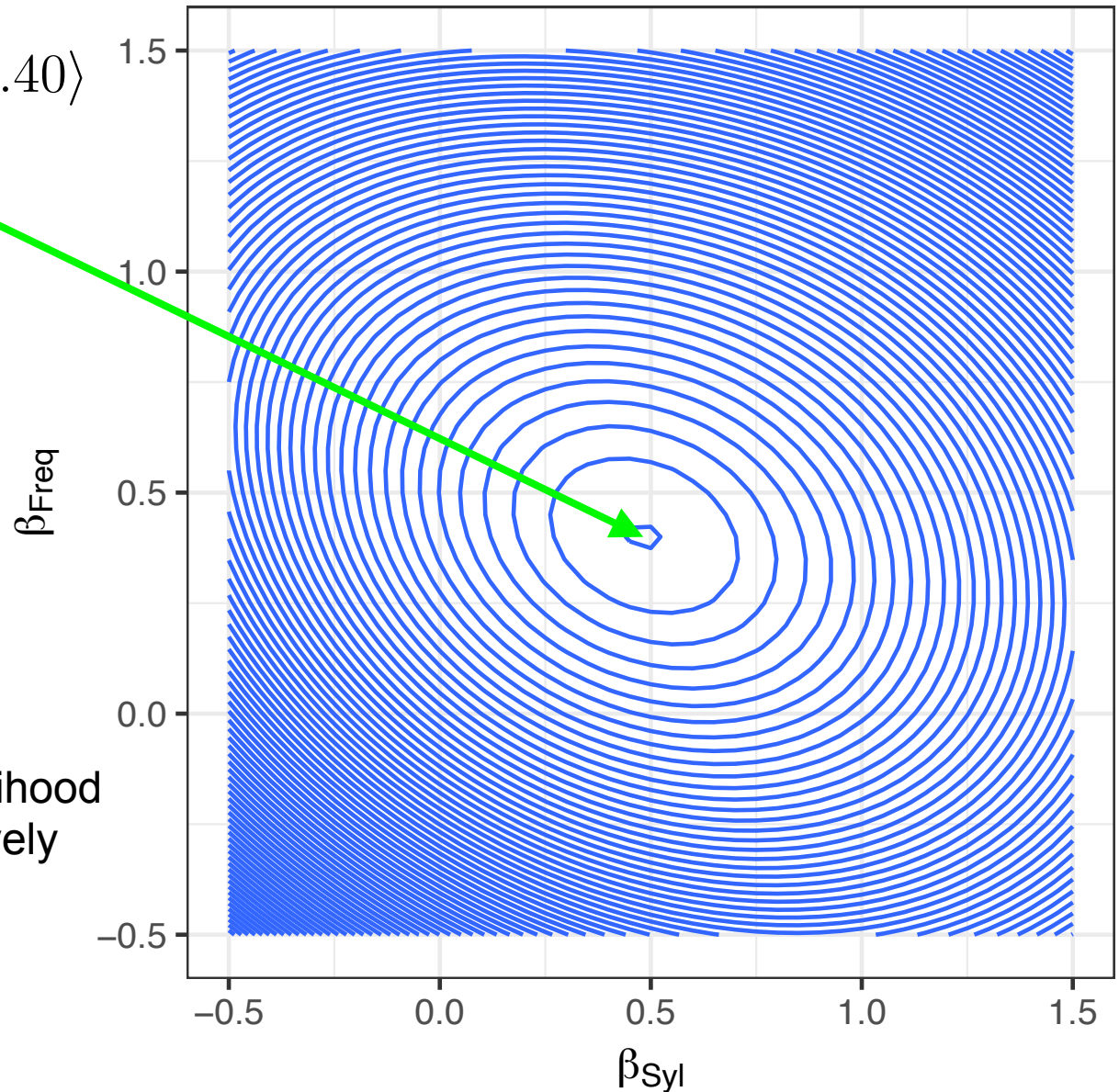
	Short < Long?	Freq < Infreq?
<i>new and modern</i>	✓	✓
<i>correct and acute</i>	n/a	✓
<i>down and out</i>	n/a	✗
<i>cruel and unusual</i>	✓	✗
<i>anger and spite</i>	✗	✓
<i>crochet and knit</i>	✗	✗

$$\eta = \beta_{\text{Syl}} X_{\text{Syl}} + \beta_{\text{Freq}} X_{\text{Freq}}$$

$$P(A \text{ and } B | \{A, B\}) = \frac{e^{\eta}}{1 + e^{\eta}}$$

Maximum of the likelihood surface

$$\langle \hat{\beta}_{Syl}, \hat{\beta}_{Freq} \rangle = \langle 0.48, 0.40 \rangle$$



For logistic regression, likelihood surface is **convex** — relatively easy to find optimum

Model predictions from fitted parameters

Logistic Regression Model Structure

$$\eta = \beta_{Syl} X_{Syl} + \beta_{Freq} X_{Freq}$$

$$P(A \text{ and } B | \{A, B\}) = \frac{e^\eta}{1 + e^\eta}$$

a.k.a. **mean μ**

Fitted model parameters

$$\langle \hat{\beta}_{Syl}, \hat{\beta}_{Freq} \rangle = \langle 0.48, 0.40 \rangle$$

Model predictions

	Short < Long	Freq < Infreq?
<i>new and modern</i>	✓	✓
<i>correct and acute</i>	n/a	✓
<i>down and out</i>	n/a	✗
<i>cruel and unusual</i>	✓	✗
<i>anger and spite</i>	✗	✓
<i>crochet and knit</i>	✗	✗

Multiple, cross-cutting constraints

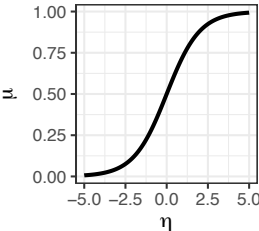
{ X_i }	Constraint	Example	Strength	{ β_i }
	Iconic/scalar sequencing	<i>open and read</i>	20	
	Perceptual markedness	<i>deer and trees</i>	1.7	
	Formal markedness	<i>change and improve</i>	1.4	
	Power	<i>food and drink</i>	1	
	Avoid final stress	<i>confuse and disorient</i>	0.5	
	Short<Long	<i>cruel and unusual</i>	0.4	
	Frequent<Infrequent	<i>neatly and sweetly</i>	0.3	

As a Bayes Net:

Freq Power

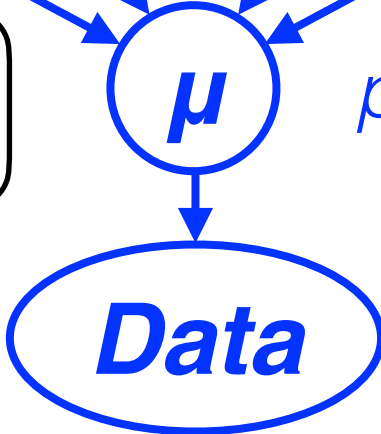
Lapse Length

$X_{1...N}$



$$\eta = \sum_i \beta_i X_i \quad \mu = \frac{e^\eta}{1 + e^\eta}$$

μ | Constraints is deterministic

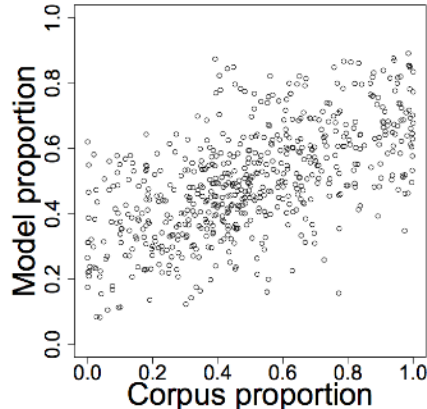


productive preference

$$P(\text{order} | \mu) = \mu$$

Bernoulli (coin-flip) distribution

predictive distribution



Another source of knowledge

~~seamstress potatoes~~ ~~meat shops~~

OR

~~bishop potatoes~~ ~~seamstress~~

?

corpus prob | {meat, potatoes} ≈ 0.95

corpus prob | {meat, potatoes} ≈ 0.05

You may prefer this because you're biased toward:

- culturally more powerful/central before less powerful/central
- short before long
- frequent before infrequent
- minimizing # consecutive unstressed syllables

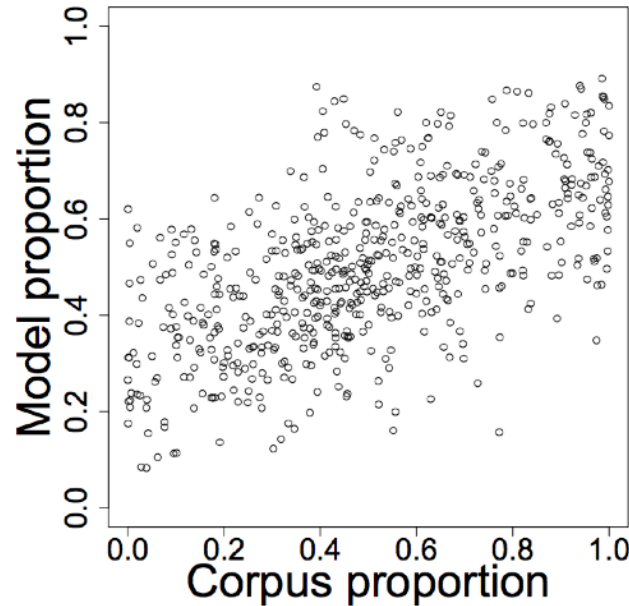
Productive knowledge

OR, you may prefer it before you've heard it far more often!

Direct experience

Productive knowledge and direct experience

- Our logistic regression model isn't perfectly predictive



- Part of this is that it fails to capture idiosyncrasy from direct experience
- A rational learner should...
 - ...apply productive knowledge in novel expressions
 - ...rely more on direct experience when it's plentiful

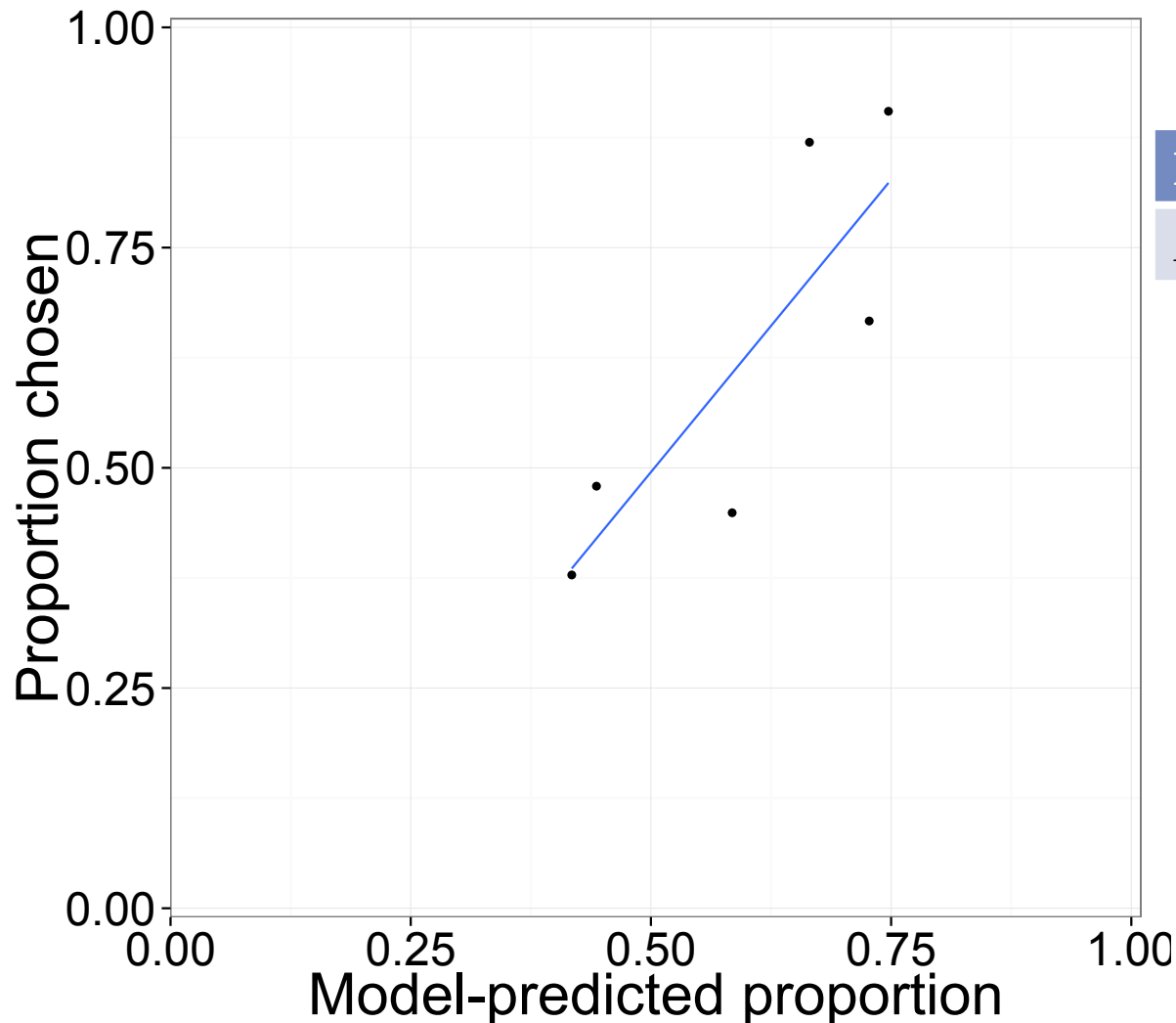
Binary forced-choice experiment

“Which sounds better?”

There were many **bishops and seamstresses** in the small town where I grew up.

There were many **seamstresses and bishops** in the small town where I grew up.

Results: novel binomials



Predictor	Estimate	<i>p</i>
Abs know	6.18	0.003**

Predictor = statistically significant (reliably non-zero)

Predictor	Estimate
<i>Direct experience</i>	6.71***
<i>Gen. knowledge</i>	-0.61



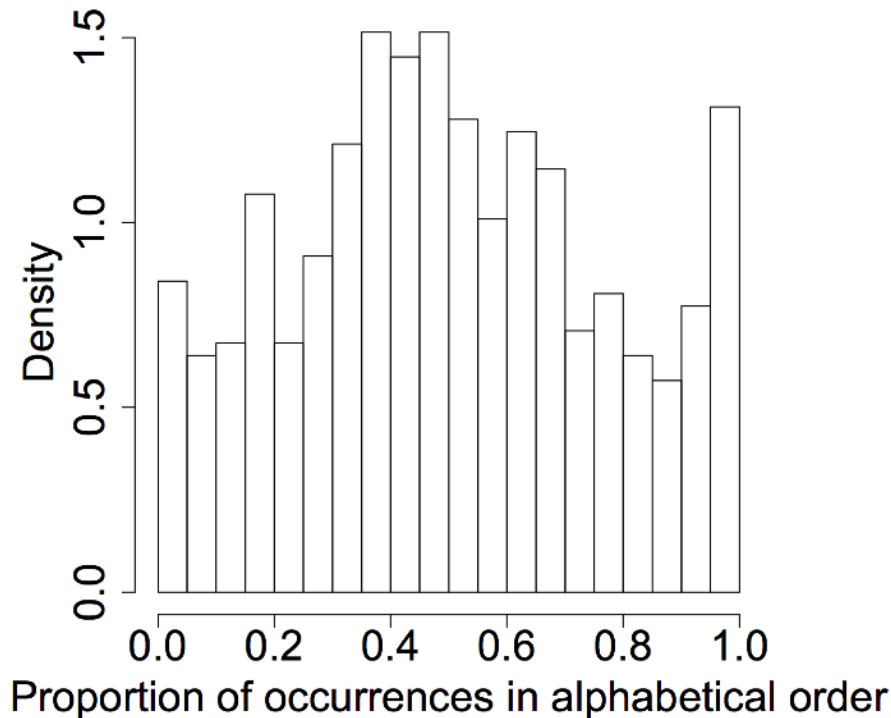
The idiosyncratic and the general

- We've seen evidence that binomial-specific ordering preferences have cognitive reality for speakers
- How dramatically do these preferences depart from the overall generative knowledge?
- How can we model both the generative knowledge and the idiosyncratic preferences simultaneously?

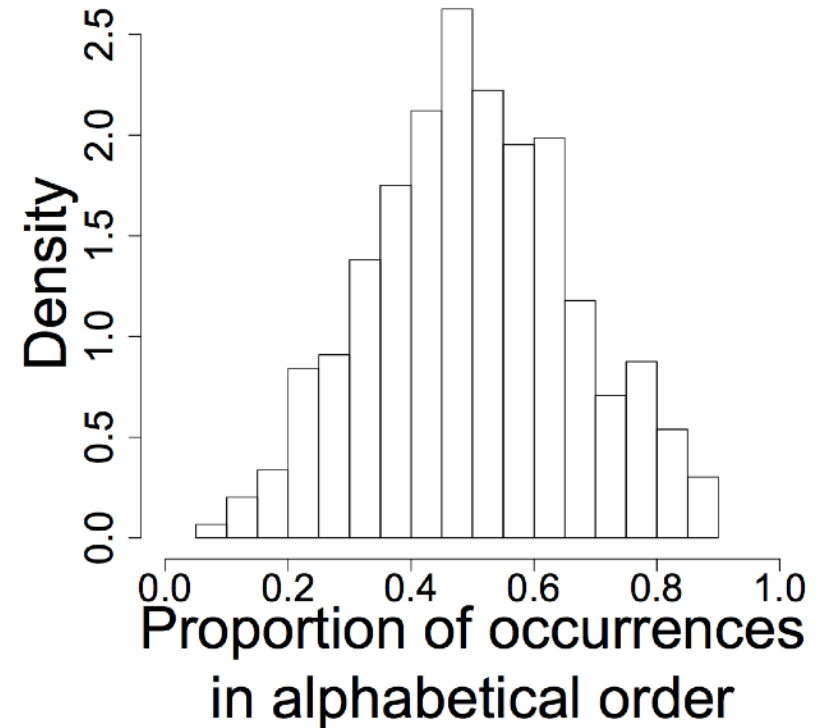
Distribution of ordering preference

Reality

Histogram of binomial types



Our model



Ordering preferences depart dramatically from generative knowledge!

Modeling idiosyncrasy

- Here was logistic regression:

$$P(\text{“success”}) = \frac{e^{\eta}}{1 + e^{\eta}}$$

$$\eta = \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_N X_N$$

- We revise it to include a ***beta-binomial*** component


$$P(\text{“success”}) = p$$

$$p \sim \text{Beta} \left(\frac{e^{\eta}}{1 + e^{\eta}}, \nu \right)$$

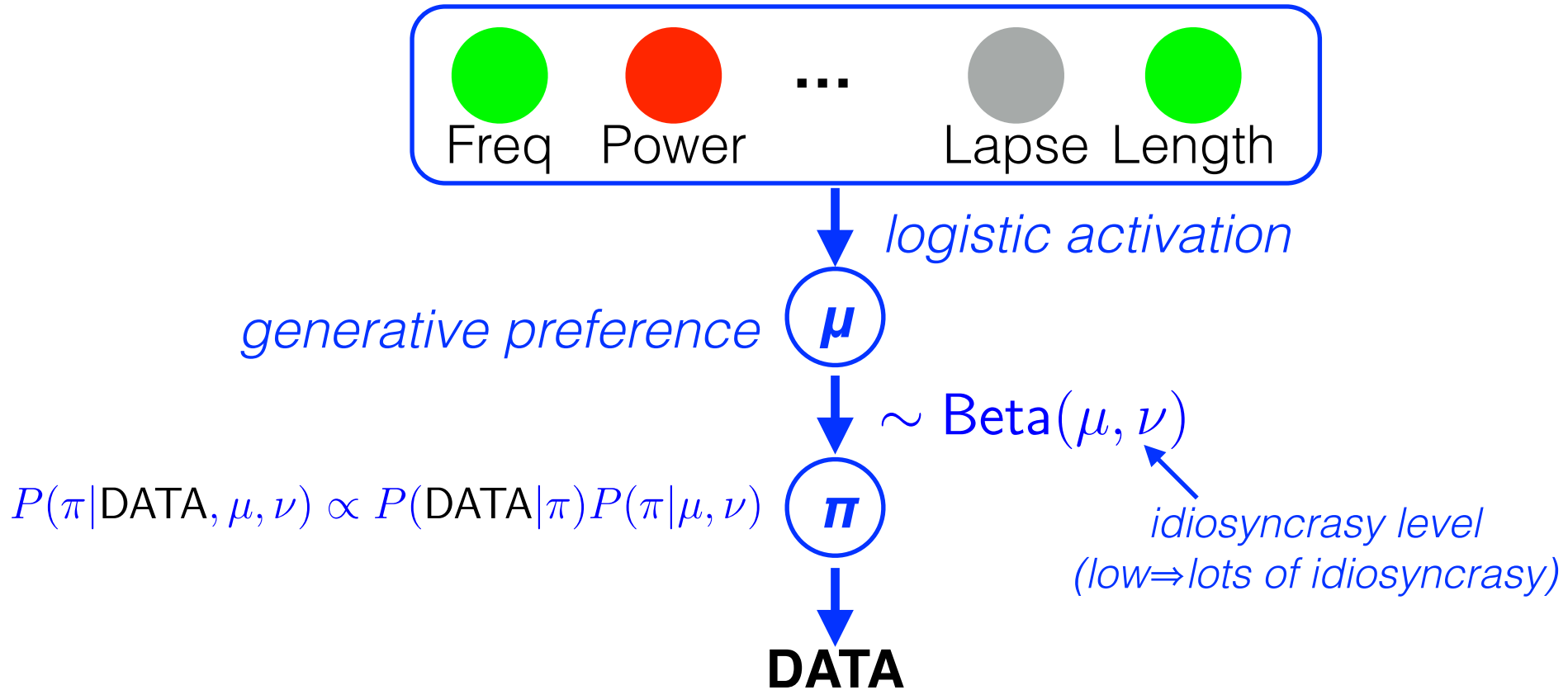
$$\eta = \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_N X_N$$

Frequency-sensitivity of binomial idiosyncrasy

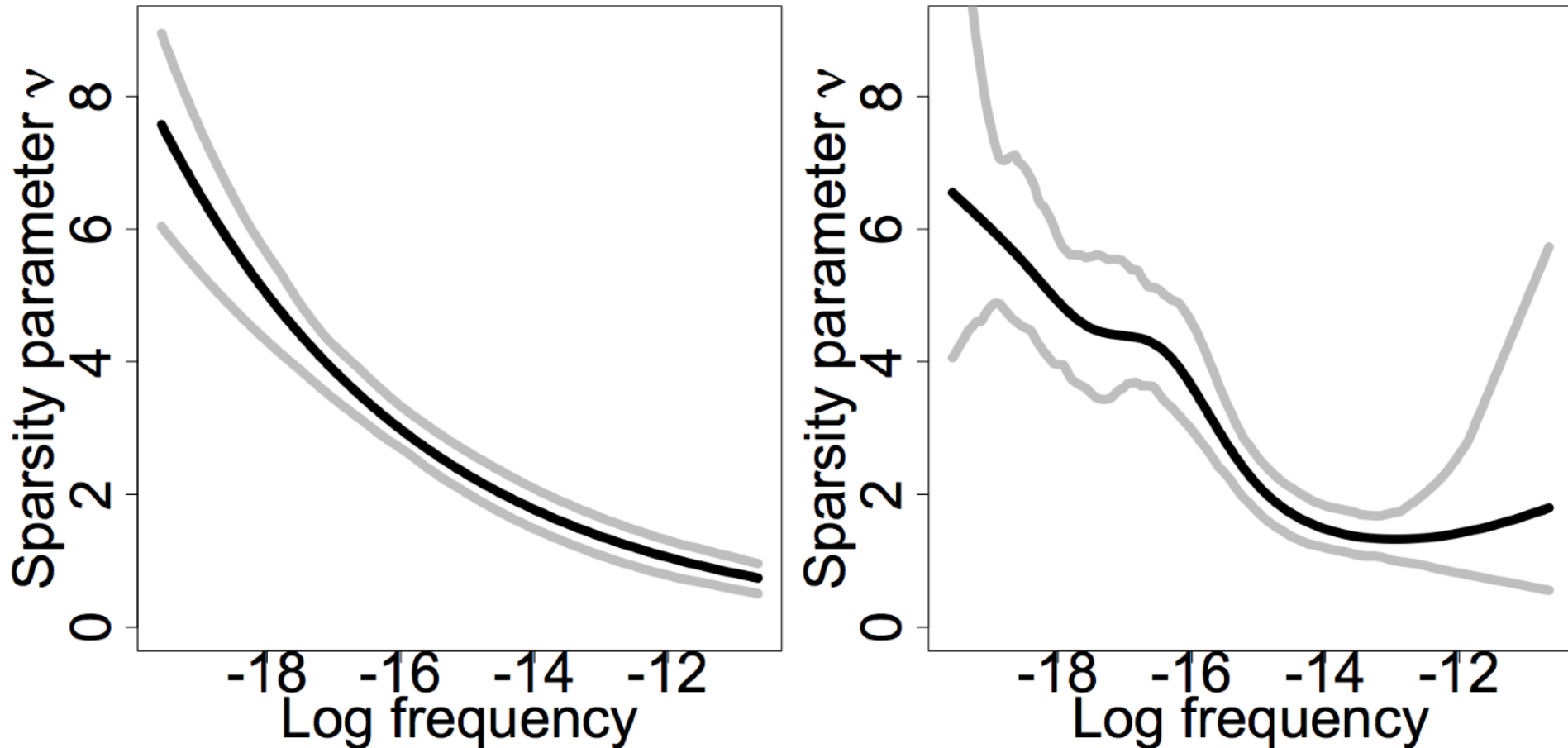
Overall unordered frequency


$$v = \exp(\alpha + \beta \cdot \log(M_n))$$

Our complete model



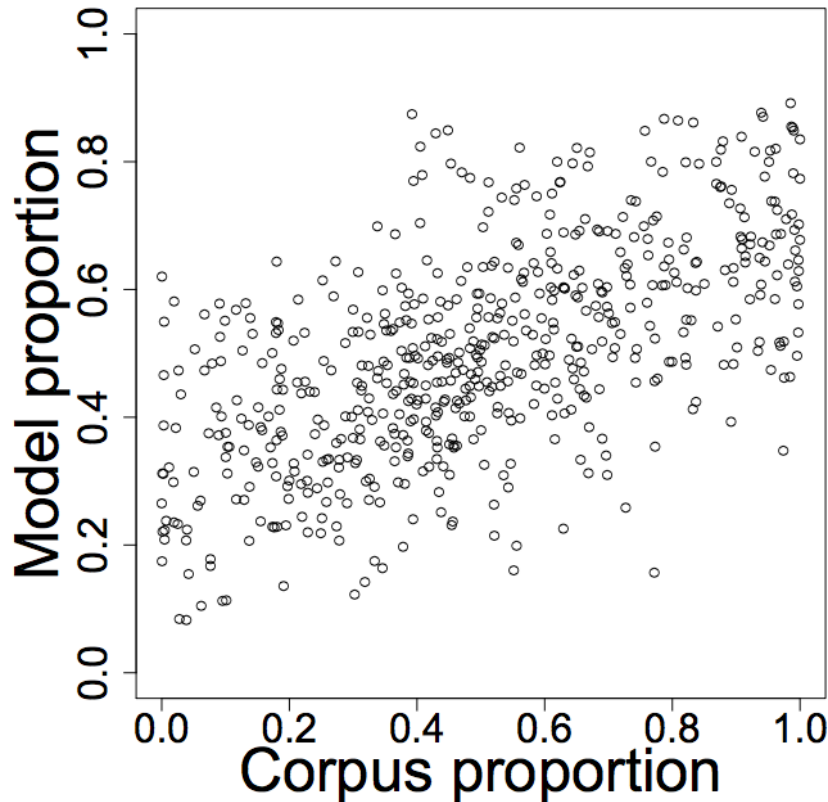
Results: frequency sensitivity of ν



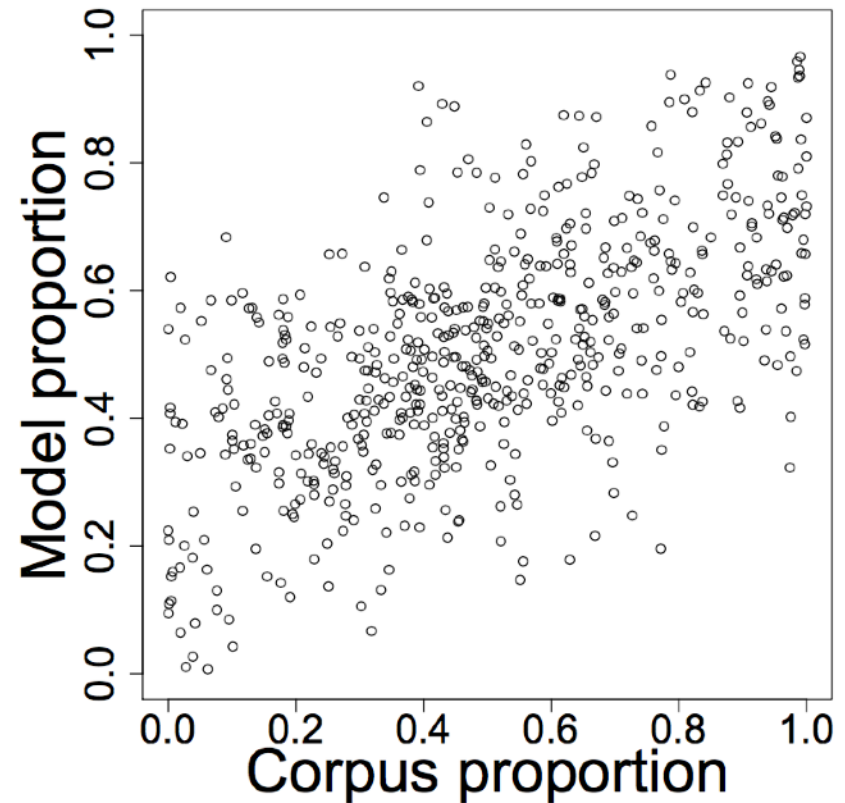
We call this *frequency-sensitive regularization*
of binomial ordering preference

Results: “best-guess” of preferences

Our OLD model



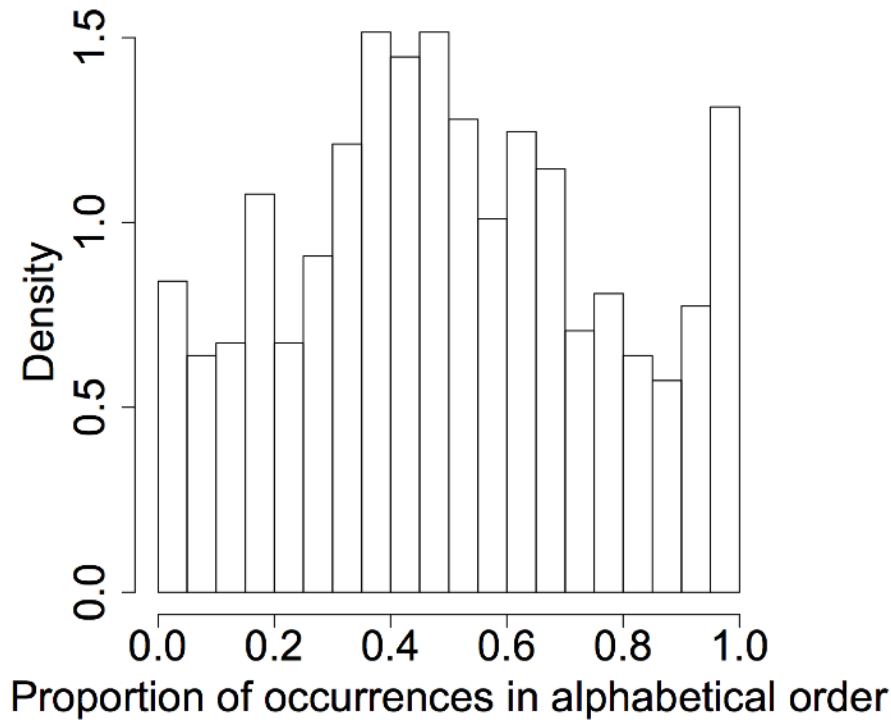
Our NEW model



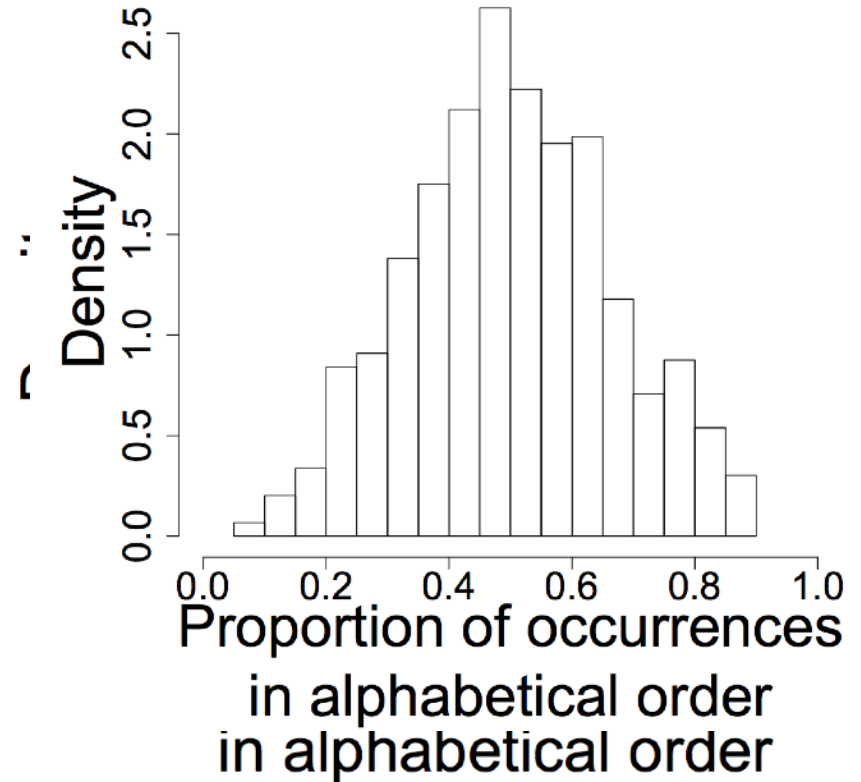
Results: distribution of binomial prefs.

Reality

Histogram of binomial types



Our ~~IDEV~~ model



Summary for today

- In language we must often model **multiple, overlapping, defeasible** constraints that drive preferences
 - One example: linear **ordering preferences**
 - e.g., linear ordering preferences in the **binomial construction**
- We can do this with **logistic regression**
- Viewed as a **Bayes Net**, logistic regression imposes a **parametric form** on $P(\text{outcome}|X_{1\dots m})$
- Logistic regression is extendable with a **hierarchical** component to handle item-specific idiosyncrasies
 - One version of this: **beta-binomial regression**

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