Embedding Grammar in a Quantitative Framework:
Case Studies from Phonology and Metrics

Class 2: Frequency Matching in Hungarian/More on Models

1. Last time

- Gradience in general
- Law of Frequency Matching—with the challenge of explaining it, *and* the deviations.
- Basics of maxent — how to derive gradient outputs given constraint weights and violations

2. Today

- A bigger case study of the Law of Frequency Matching — with one particular kind of deviation from it — conjectured to be UG.
- Learning challenges for computational linguists
- Other models of gradience

3. Suggested reading

- Hayes and Londe (2006), on course website

HUNGARIAN VOWEL HARMONY

4. Sources

- Hayes and Londe (2006)
  - Basic work establishing applicability of Law of Frequency Matching
- Hayes/Zuraw/Siptár/Londe (submitted)
  - Further study emphasizing the UG problem (below)
- Both on course website.

5. Background: the UG problem

- UG = Universal Grammar
- One long-standing research interest of generative linguistics is locate aspects of language that are grounded in human nature — at some level, genetically coded.
- These aspects can be:
  - Characteristics specific to the language faculty (UG **narrowly** construed)

- Other innate properties of humans (cognitive, phonetic, etc.) that determine properties of language (UG **broadly** construed)
- The distinction is not crucial in this context.

6. Finding UG using just analysis is hard

- The usual method is to pursue **typology**: one formulates grammars for many languages, all pointing toward the same underlying theory (e.g. Hayes 1995).
- **However**: language typology may reflect factors other than UG; notably factors of language change
  - Refs: Myers 2002, Baroni 2002, Blevins 2004, Wilson 2006, Koo and Cole 2006, Moreton (to appear a), etc.

7. UG: the experimental program

- There has recently been a great upwelling of interest in **experiments addressing UG**.
  - Non-exhaustive references: Schane, Tranel, & Lane (1974), Pertz and Bever (1975), Saffran & Thiessen (2003), Albright and Hayes (2003), Pater and Tessier (2003), Pycha et al. (2003), Wilson (2003, 2006), Buckley and Seidl (2005), Kawahara (2006), Koo and Cole (2006), Zhang and Lai (2006), Albright (2007), Becker, Ketrez and Nevins (2007), Graff (2007), Zuraw (2007), Berent et al. (2007, 2008), Berent et al. (2008), Thatte (2007)

8. Ernestus and Baayen (2003—course website): "Predicting the unpredictable"

- Not a UG experiment, but relevant here.
- Dutch has classical Final Devoicing, as in
  - [–sonorant] → [–voice] / ___ $]_{word}$

Final		Before vowel	
[v?r??**it**]	'widen'	[v?r??**id**-?n]	'to widen'
[v?r??**it**]	'reproach'	[v?r??**it**-?n]	'to reproach'

9. Ernestus and Baayen (2003): the Dutch data

- The alternation patterns are unevenly distributed in the Dutch lexicon:
  - many cases of [**p**#] ~ [**p**V], few of [**p**#] ~ [**b**V]
  - few cases of [**f**#] ~ [**f**V], many of [**f**#] ~ [**v**V]

10. Ernestus and Baayen (2003): the idea behind the study

- Could Dutch speakers use a knowledge of the statistical regularities in the lexicon to "undo Final Devoicing", guessing the suffixed form from the isolation form for novel stems?
  - This would be "predicting the unpredictable".

11. Ernestus and Baayen (2003): Wug test

- Give subjects imaginary base forms, ask them to identify the suffixed form.
  - Hear [?k d?u**p**] “I daup”, reply with *dau**b**en* or *dau**p**en*
  - Hear [?k t?**f**] “I taf”, reply with *ta**f**en* or *ta**v**en*

12. Ernestus and Baayen (2003): results respected Law of Frequency Matching

- Many cases of [**p**#] ~ [**p**V], few of [**p**#] ~ [**b**V], **so** most (but not all) subjects prefer *daup ~ daupen*
- Few cases of [**f**#] ~ [**f**V], many of [**f**#] ~ [**v**V], **so** most (but not all) subjects prefer *taf ~ taven*

13. Becker, Nevins, and Ketrez (ms.—course website)

- A study similar to Ernestus and Baayen’s, but for Turkish, which also has “undoable” Final Devoicing.
  - many cases of [**p**#] ~ [**b**V], few of [**p**#] ~ [**p**V] (Dutch has the opposite disparity.)
  - few cases of [**t**#] ~ [**d**V], many of [**t**#] ~ [**t**V]
- New element: they checked the lexicon for **VC environments**. Examples:
  - Voicing alternation is more common after **high vowels**
  - [t?] ~ [d?] alternation is more common **after back vowels**

14. Becker et al.’s results

- C-internal environments, such as place of articulation: Turkish speakers acted just like Dutch speakers, obeying the Law of Frequency Matching.
- Environments based on preceding vowel: **null result**
  - no frequency matching
  - in fact, no evidence that speakers are aware of the lexical pattern at all

15. Becker et al.’s interpretation

- They claim a **new kind of argument for UG**.
- The information needed to pass the Wug test with VC environments was made available to Turkish speakers in childhood.
- But they cannot pass this test for these environments—why not?
- Reason: UG *isn’t good enough* to detect the crucial generalizations here.
- Specifically: roughly, they claim that in UG, the only permitted vowel-consonant interactions are those involving a **shared feature**, like nasality or backness.

16. The general prediction made under Becker et al.’s approach

- The Law of Frequency Matching will hold true only for those phonological patterns that can be expressed in UG.

- For others, language learners are **at a loss**—there is no learning without UG help.

17. I'm skeptical of this view

- Earlier research gives strong evidence for productive phonological patterns that are totally arbitrary.
- Examples:
  - Yidi? productively epenthesizes [u] after nasals, extending the pattern to new stems (Hayes 1999)
  - English uses the regular past ending after every verb ending in a voiceless fricative; and wug-testing shows this is productive (Albright and Hayes 2003)

18. What is really going on: a conjecture

- People *do* have a strong (but not unlimited) inductive learning capacity for unnatural phonology.
- But there is a **bias** (Wilson 2006, *Cognitive Science*) for grammars that obey principles of UG.
  - Wilson has formalized bias with maxent. More on this below.
- Becker et al.'s experiment was sensitive enough to pick up the UG-based patterns (like for place of articulation), but not the arbitrary VC ones.
- My colleagues and I haven't worked on Turkish, but can offer evidence from another language.

19. Some Hungarian wug-testing

- Two papers:
  - Hayes and Londe (2006)—establish frequency matching; other issues in phonology.
  - Hayes, Zuraw, Siptár, and Londe (submitted): extend this result, take on the UG issue

20. The basics of Hungarian vowel harmony

- Hungarian vowel inventory:
  - **Back** [u, uː, o, oː, ?, aː] "**B**"
  - **Front rounded** [y, yː, ø, øː] "**F**"
  - **"Neutral"** [i, iː, eː, ?] "**N**"
- Most suffixes alternate, agreeing in backness with the nearby vowels of the stem.
- We'll deal just with the dative suffix: [-n?k] ~ [-n?k].

21. The vowel harmony generalizations

- For a nice overview consult Siptár and Törkenczy (2000).
- If the closest stem vowel is back, then back suffixes:

- [?bl**?**k-n**?**k] ‘window-dat.’
- [bi**?o?**-n**?**k] ‘judge-dat.’
- [glyk**o?**z-n**?**k] ‘glucose-dat.’

- If the closest stem vowel is front rounded, then front suffixes:
  - [**y**?t-n**?**k] ‘cauldron-*dat*.’
  - [?of**ø?**r-n**?**k] ‘chauffeur-*dat*.’

22. The vowel harmony generalizations (cont.)

- If all neutral (front unrounded), then generally front
  - [k**?**rt-n**?**k] ‘garden-dat.’
  - [ts**i?**m-n**?**k] ‘address-dat.’
  - [r**?**p**?**s-n**?**k] ‘splinter-dat.’

23. Hungarian vowel harmony: the zones of variation

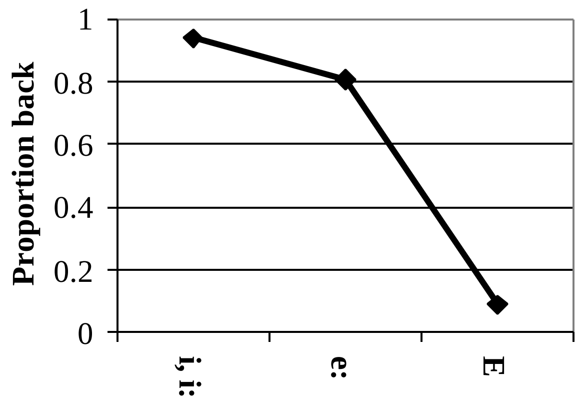
- If a back vowel is followed by one or more front unrounded vowels (…BN, …BNN), *the lexicon takes over!*
- Harmony is unpredictable, and the behavior of every stem must be memorized.
- But there are quantitative lexical generalizations, just like in Dutch and Turkish.

24. Hungarian vowel harmony in the zones of variation: quantitative generalizations

- Source of the counts
  - Hayes and Londe’s (2006) study, based on Googling thousands of stems to obtain user frequencies.

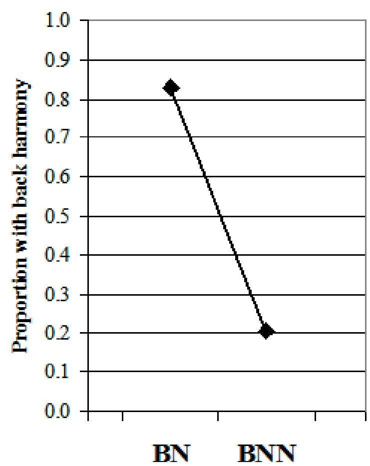
25. Height effect

- … Back + [i, i?] stems mostly take back suffixes;
- … Back + [e?] stems take front more often;
- … Back + [?] stems (? is low) usually take front suffixes.

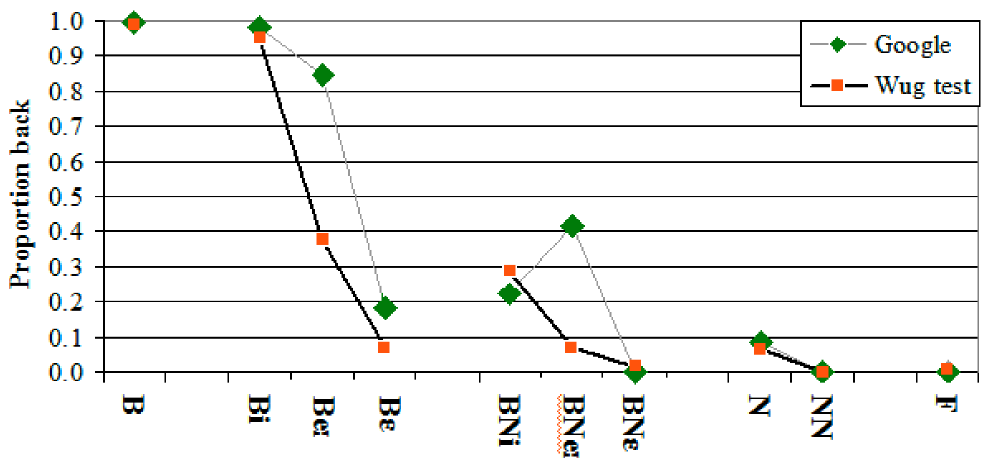


26. Count effect

- Stems with **two** neutral vowels after a back take front suffixes more often than stems with just one.



27. Hayes/Londe Wug test: speakers match lexical frequencies



28. Hungarian so far

- The vowel harmony system obeys a number of generalization, including statistical generalizations (Height effect, Count effect) governing the zones of variation.
- In wug testing, speakers respond to the statistical generalizations, in accord with the Law of Frequency Matching.

29. Hayes and Londe's analysis I: UG principles assumed

- UG favors **assimilation of single features** (cf. Becker et al.)
- UG favors **local** triggers over distal (cf. [ɡlyk**o?**z-n**?**k])
- **"Spread bad vowel"** (Kaun 1995) Perceptually weak frontness → strong frontness harmony trigger (they need more help, hence trigger harmony more)
  - [y, y?, ø, ø?], with backness perceptually obscured by rounding, are stronger triggers.
  - Lower front vowels, which aren't as front as higher ones, are stronger triggers.

30. Hayes and Londe's analysis II: constraints

AGREE(back) with local back
AGREE(back) with back
AGREE(back) with local low front
AGREE(back) with local nonhigh front
AGREE(back) with local front
AGREE(back) with local front + front
AGREE(back) with front rounded
AGREE(back) with local front rounded

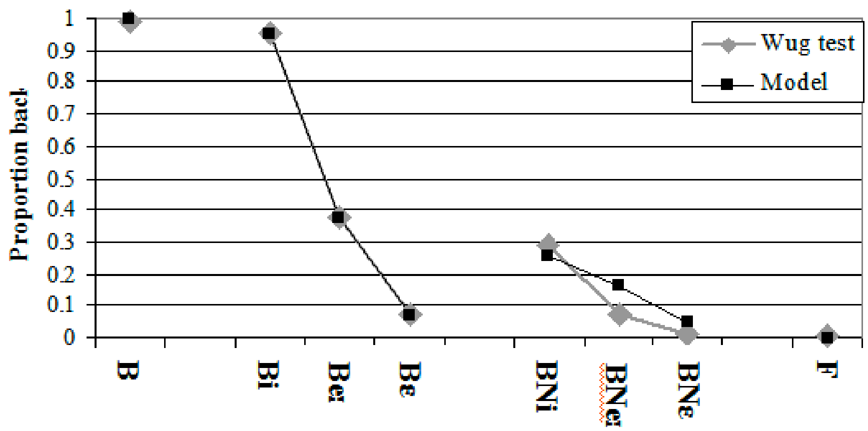
31. The constraints reflect the UG theory

- Every constraint is an AGREE() constraint for backness.
- Those which are restricted to particular classes single out "bad vowels", in Kaun's sense.
- 6/8 constraints are restricted to local environment; i.e. penalize only disagreement with the local stem vowel.

32. Finding the right weights

- Hayes/Londe did a maxent analysis (as well as others) and got a good match to the observed data.
- Training data: use the Google data corpus frequencies for the training lexicon

33. Matchup to the wug test results, using this grammar



34. Local summary

- Hayes and Londe offer a first-pass analysis of the Hungarian system, which
  - uses only UG-based constraints
  - is tuned by training on a data corpus
  - correctly predicts the behavior of Hungarian speakers when wug-tested—they obey the Law of Frequency Matching

35. Hungarian beyond UG: are there unnatural constraints?

- Hayes and Zuraw did an intensive search of the Hungarian lexical data (Excel + search programs), looking for **consonant** environments that favor front or back suffixes, within the zones of variation.
- These turned out to exist! We picked the best four.

36. Four unnatural vowel harmony constraints

- Prefer front suffixes when the stem ends in a **bilabial noncontinuant** ([p, b, m])
- Prefer front suffixes when the stem ends in a **sibilant** ([s, z, ?, ?, ts, t?, d?])
- Prefer front suffixes when the stem ends in a **coronal sonorant** ([n, ?, l, r])
- Prefer front suffixes when the stem ends in **two consonants**
  - All have statistically significant effects in the lexicon
  - None has a particularly plausible UG basis.

37. One more unnatural vowel harmony constraint

- All-N words are (weakly) a zone of variation, too, since a few of them take idiosyncratic back suffixes. Examples:
  - [hi?d-n?k] 'bridge-dat.'
  - [?i?p-n?k] 'whistle-dat.'

- [d?re?k-n?k] 'waist-dat.'

- In this zone:
  - Prefer back suffixes when the stem is monosyllabic and has the vowel [i?] (like [hi?d] and [??p])

38. Question: do Hungarian speakers internalize the unnatural constraints?

- Becker et al. would presumably predict, "no".
  - This is a vowel-consonant interaction not based on shared features.
- We can find out by doing a new wug test.

39. Design of the new wug test

- All our wug stems were from the zones of variation: BN, BNN, N.
- To increase sensitivity, we tested 1703 wug stems — each subject got a separate batch, thus reducing the chance of unwanted factors about particular stems playing a role.
- Also to increase sensitivity, we used many (131) consultants

40. Choice of wug words

- They were designed to test the unnatural constraints, and otherwise statistically resemble Hungarian words in every possible respect.
- Each consultant got 13 words, as for example in the following batch.

Number	*bilabial*	*coronal sonorant*	*sibilant*	*CC*	*example*
2	no	no	no	no	[ko?de]
2	no	no	no	**yes**	[pr?tt]
2	no	no	**yes**	no	[t??nd?nd??]
1	no	no	**yes**	**yes**	[s?lha?re???]
2	no	**yes**	no	no	[n?n]
1	no	**yes**	no	**yes**	[vur?ld?m]
2	yes	no	no	no	[ha??k?m]
1	**yes**	no	no	**yes**	[ke?bb]

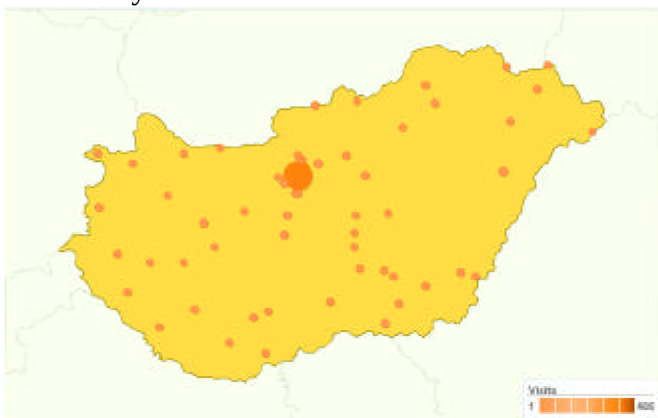
41. Subject recruitment

- To obtain authentic data, we ran our test on the Web, using Google Ad Words to recruit subjects living in Hungary.

- This yielded 131 subjects, after discarding non-Hungarians, under-18's, non-finishers.

42. Where our subjects came from

Source: www.google.com/analytics/



43. Sample test page

(original version entirely in Hungarian)

Hálupem

Hálupem was a goddess worshipped by the early pagan Hungarians. It is believed that Hálupem was the goddess of weaving. Not just the Hungarians but also neighboring peoples celebrated ___-dat.'s divine powers.Please check one:

☐ *Hálupemnak*

☐ *Hálupemnek*

Please rate each one:

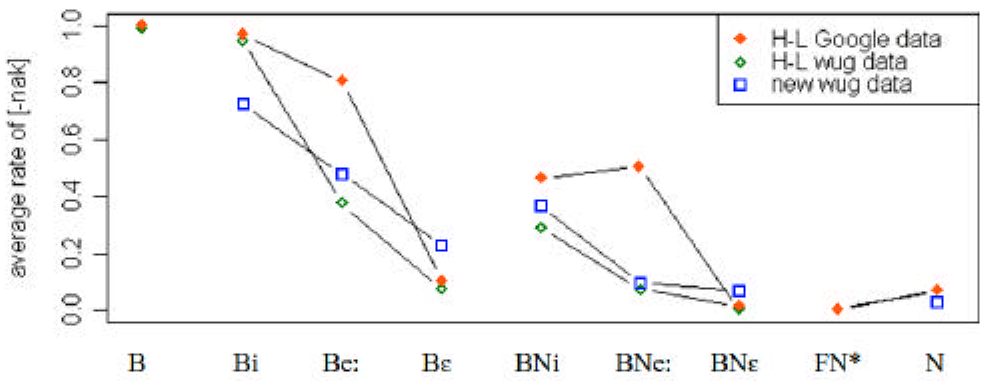
Hálupemnak:

worst						best
1	2	3	4	5	6	7
○	○	○	○	○	○	○

Hálupemnek:

worst						best
1	2	3	4	5	6	7
○	○	○	○	○	○	○

44. Results I: Hayes/Londe experiment is replicated



- Note “depolarization” effect—probably due to modeling bad forms to the subjects (ca. Albright and Hayes 2003).

45. Results II: 4/5 of the unnatural constraints had a significant effect

- Test: logistic regression; probability that the environment has no effect on outcome

```
Monosyllable with [i:]      0.241
Final bilabial              0.000
Final coronal sonorant      0.016
Final sibilant              0.046
Final CC                    0.000
```

- We suspect that the [i?] environment is also significant, but our test was not designed to check it and lacked enough forms.

46. Other statistical results

- The same test showed massive significance for all of the natural constraints.
- The effect size is smaller for the unnatural constraints, as expected.

47. Discussion

- Unlike Becker et al., we found a noticeable effect for unnatural constraints.
- Suggested conclusion: people *do* learn unnatural phonology, but
  - ➢ it’s harder for them to learn
  - ➢ it’s harder for us to detect — perhaps only experiments with many subjects and items will suffice

48. Maxent modeling: Goal

- Eludicate how Hungarian speakers, exposed to lexical data, learn the unnatural constraints and use them in forming their linguistic intuitions.

49. The basis for learning

- 13 constraints, as given above
  - 8 natural, from Hayes/Londe
  - 5 unnatural, based on our discovered unnatural environments

50. Grammar L: train the weights against the lexicon

- We used the same Google frequency data that Hayes and Londe used.
- To assign weights, we used an early version of the Maxent Grammar Tool (course website).
- Weights obtained:

AGREE(back) with local back	4.00
AGREE(back) with back	5.35
AGREE(back) with local low front	2.99
AGREE(back) with local nonhigh front	1.48
AGREE(back) with local front	1.64
AGREE(back) with local front + front	4.05
AGREE(back) with front rounded	1.72
AGREE(back) with local front rounded	3.74
Front suffix if final bilabial consonant	2.46
Front suffix if final coronal sonorant	1.08
Front suffix if final sibilant	0.91
Front suffix if final CC	1.75
Back suffixes if monosyllable with [iː]	2.37

51. Basic performance of Grammar L (correlations)

- Basic check: its predictions correlate well with the frequencies of the data from which it was trained: $r = .992$
- To check against the Wug test, we used a **preference score**; i.e. subject's [-n?k] preference minus [-n?k] preference.
  - Correlation is not as good, but still substantial: $r = .546$ — confirming the Law of Frequency Matching
- The unnatural constraints help: without them, we get a correlation of only $r = .521$

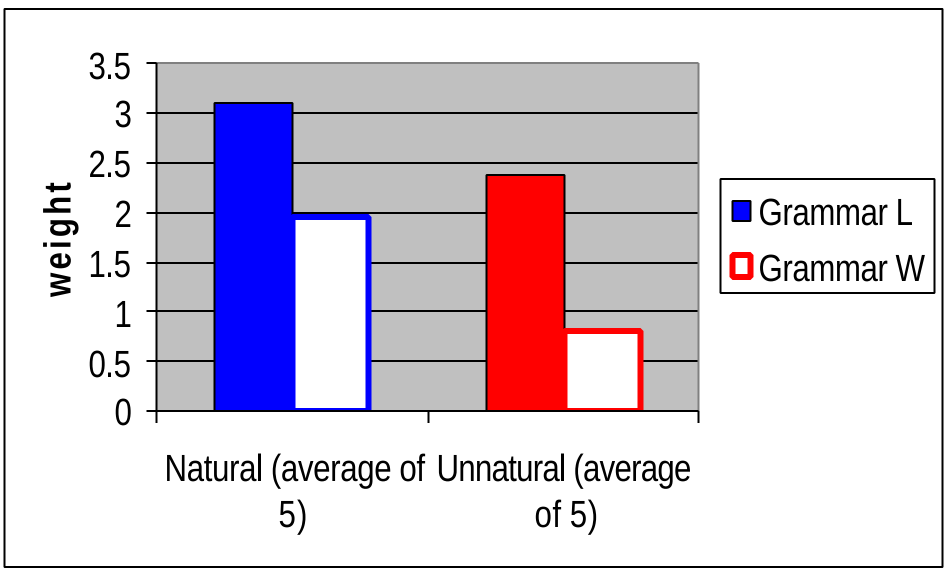
52. What are native intuitions in the same terms? Grammar W

- Grammar W is obtained by using the wug test data as the basis for constraint weighting.
- This is *not* a learning simulation (children are not told their parents' intuitions).
- Rather, it is an assessment of the importance of the constraints in forming adult native speaker intuitions.

53. Weight comparison: Grammar L vs. Grammar W

Natural constraints:	W	L
AGREE(back, local)	NA	4.00
AGREE(back, nonlocal)	3.58	5.35
AGREE(low front, local)	1.05	2.99
AGREE(non-high front, local)	.95	1.48
AGREE(front, local)	2.22	1.64
AGREE(double front, local)	1.94	4.05
AGREE(front rounded, nonlocal)	NA	1.72
AGREE(front rounded, local)	NA	3.74
Unnatural constraints:		
USE FRONT / bilabial ___	1.04	2.46
USE FRONT / [+cor,+son] ___	.43	1.08
USE FRONT / sibilant ___	.37	.91
USE FRONT / CC ___	.69	1.75
USE BACK / [C_0i?C_0] ___	.80	2.37

54. Analyzing the weight comparison



- Observe: a bigger "hit" (.34 vs. .63) for the unnaturals.

55. What's going on?

- Depolarization: weights lower overall.
- Natural vs. unnatural: language learners can pick up unnatural environments, but give them less credence.
- Further details (constraint by constraint) can be accounted for, perhaps, with a simplicity bias.

56. More modeling results

- The best fitting model we can find uses two parameters: overall weakening, and unnaturalness bias. These are used to multiply all the constraints, and just the unnatural constraints (values: .56, .70)
- This achieves a correlation of r = .569 to the wug test data.

57. In progress

- We think we can show that the alleged "weakness" of the unnatural constraints can be demonstrated statistically—we're doing a Monte Carlo simulation to show this.

58. Summary

- Both the earlier Hayes/Londe experiment and our subsequent web experiment found confirmation for the Law of Frequency Matching.
- We got opposite results from Becker et al., concerning whether unnatural environments can have effects in phonology, and don't know why (though we have guesses).
- But the unnatural constraint seem to be "weaker", tantalizing evidence that there may be UG effects in learning.

TWO LEARNABILITY PUZZLES ARISING FROM THIS WORK

59. Learnability puzzles I: handling the listed items

- The maxent grammars given were "tailor made"—learn from lexicon, and test on wug data.
- But real life is more complicated—more tasks for the grammar to do.
- Forms in the zones of variation get the outcome specified in the lexicon.
- I think the simplest and best supported theory for this is Zuraw's: they're listed.
- But suppose they are listed. We must make sure that the listed form gets used, and not the one created by the phonological grammar.
- So: the weight of USE LISTED (Zuraw 2000) is very high.
- I've been able to get results vaguely in the right direction, but not what is really needed: reliable rendering of listed forms, reliable frequency-matching in novel forms.

60. Learnability puzzles II: how to hobble?

- We don't know how to "hobble" a constraint for its unnaturalness.

61. One potential way to hobble: the Gaussian prior

- Our favorite paper on "Biases" is Wilson (2006).
- He biases his constraints using a Gaussian prior, with lower sigma for a priori less likely constraints.

- Gaussian prior: maximize probability of learning data, but adding a penalty for positive weights:

$$\log \mathrm{PL}_{\bar{w}}(\bar{y}|\bar{x}) - \sum_{i=1}^{m} \frac{(w_i - \mu_i)^2}{2\sigma_i^2}$$

  - ➢ If mu is zero, then a constraint gets punished for having a large weight, especially when sigma is small.

62. But hobbling with a constraint-specific prior is very tricky

- If you hobble, other constraints will get different values too.
- E.g., two constraints, one hobbled, 50/50 learning data: the other constraint weakens itself so as still to derive 50/50 outputs.
- We suspect that Wilson succeeded because of particular, unusual properties of his grammar; we cannot get the same results in ours.

OTHER CONSTRAINT-BASED THEORIES OF GRADIENCE

63. OT with free-variation strata

- Anttila (1997a, 1997b)
- Group the constraints into strata; rank the strata, but rank at random within strata.
- This predicts a specific distribution of outputs.
- Very tightly constrained model; our Hungarian is an example it seems unable to deal with.

64. Stochastic OT

- Invented by Paul Boersma (1997); applied to phonology by Boersma and Hayes (2001).
- Give every constraint a "ranking value".
- When you run the grammar, jiggle the weights by adding to each ranking value a small random quantity. Then sort them and apply good-old OT to the result.

65. The learnability situation for stochastic OT

- Boersma invented an algorithm ("Gradual Learning Algorithm") for stochastic OT.
- It works pretty well for many simulations—though without maxent's uncanny accuracy.
- Behaves very strangely for others (my experience)
- and (ouch!) was found to fail to find the solution in a well-defined class of cases—Pater (2008), course web site

   - Pater, Joe. 2008. Gradual learning and convergence. *Linguistic Inquiry* 39. 334-345.
- Magri (ms.), course web site, has a beautiful demonstration of *why* GLA fails: sometimes the right answer isn't even in its search space! (= grammars obtainable by legal ranking values adjustments.
- Magri has a better GLA, which he proves to converge, but only for non-stochastic grammar.

66. Noisy Harmonic Grammar

- Paper by Boersma and Pater (course web site).
   - Boersma, Paul, and Joe Pater. 2008. Convergence properties of a gradual learning algorithm for Harmonic Grammar. Amsterdam and Amherst, MA: University of Amsterdam and University of Massachusetts ms. Rutgers Optimality Archive.
- This is like the simple Harmonic Grammar described last time (lowest penalty score wins), but as with Stochastic OT you add a bit of noise to each constraint weight when you "apply" the grammar.

67. The learnability situation for stochastic OT

- Same as for stochastic OT: there is a learnability proof, but only for the non-stochastic applications

68. Where maxent differs sharply from these models

- **Harmonically bounded** candidates can semi-win (i.e. have more than zero probability)
- A candidate is harmonically bounded if some other candidate has a strict subset of its violations.
- Scholars differ in whether harmonically bounded candidates should ever win. Keller and Asudeh (*Linguistic Inquiry 2002*) thinks they should; I've found slightly better performance in textsetting.[1] I'd say not letting them win is the majority current view.

69. Model-shopping: my own feelings

- Once burned, twice shy, re. using algorithms that don't have a convergence proof.
- Some empirical worries re.
   - Constraint ganging (all versions of Harmonic Grammar)
   - Harmonically bounded semi-winners (maxent)

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1 http://www.linguistics.ucla.edu/people/hayes/papers/HayesSlidesForStanfordGradienceWorkshop.pdf

A QUICK OVERVIEW OF HOW LEARNING IN MAXENT WORKS

70. Source

- This discussion follows the attempted layman's explanation in Hayes and Wilson (2008) (course website).

71. Core idea: "Objective function"

- Defines the "goal" of learning.
- This is separated from the (varying) computational algorithms can be used to achieve it.
- *Maximize the predicted probability of the observed forms*
- hence, minimizes the predicted probability of the unobserved forms
- Predicted probability of observed forms is quite calculable: calculate each one as given last time, then multiply them all together.

72. Metaphor: the objective function is a mountain

- If we have just two constraints, let North-South be the axis for Constraint1's weight, and East-West be the axis for Constraint2's weight, and height be the predicted probability of the observed data under any weight assignment.
- Climb the mountain, and you will be standing at the point of optimum weights.

73. Two beautiful theorems

- The mountain has but one peak (=is convex; has no local maxima)
- The slope along any axis (if height expressed as a log) is *Observed Violations – Expected Violations*, a calculable quantity.
- So you can always reach the top, simply by persistently climbing uphill.
- This may sound trivial but remember that the mountain actually exists in *n*-dimensional space, where *n* is the number of constraints.

74. The rest is implementation

- Ascending gradients efficiently is a popular challenge for computer scientists; both Goldwater and Johnson (2003) and the Maxent Grammar Tool adopt the "Conjugate Gradient" algorithm.

75. Next time

Phonological well-formedness (*blick* - *?bloick* - **bnick*) and how to predict it with maxent.