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The Textsetting Problem: the Intersection of Phonology, Music Cognition, and Computation

I. STATING THE PROBLEM

1. First verse of folk song; first line

		Х				Х				Х				Х			
Х		Х		Х		Х		Х		Х		Х		Х		=	64
Х	Х	Х	Х	Х	Х	х	Х	х	Х	Х	Х	Х	Х	Х	Х		
It	was	late		in	the	nigh	t v	vhen	the	squi	ire	cam	e	hom	e		

("The Gypsy Laddie", recorded in the Appalachian Mountains ca. 1917 by Cecil Sharp)

2. Note on grids

- Height of column = strength of beat
- Rows = theoretically isochronous levels of periodicity

3. A later verse, first line

"Oh saddle to me my milk-white steed"

Х Х Х Х Х Х Х Х Х Х Х Х X X X X X X X X X Х X X X Х Х Х Oh, sad-dle to milk- white me my steed



4. An ill-formed setting

	Х				Х				Х				Х			
Х	Х		Х		Х		Х		Х		Х		Х		=	
X X	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х		64
																●
Oh, sad- o	dle				to	me	my	1	nilk	-	,	white	e	steed	l	

5. Shared intuitions

• Native speakers generally agree with one another on what settings should be preferred (Hayes and Kaun 1995—10 speakers, average of 2.2 settings per line).

6. Intuitions are sometimes gradient

• Example:



is perhaps not quite as good as the setting in (3), but surely not bad.

- Hayes-Kaun 1995 speakers show a modest preference for the type given in (3).
- This is typical, so we need to be able to predict such gradient intuitions as well.

7. The textsetting problem is a long established one

• Some references: Dell (1975, 2004), Stein and Gill (1980), Oehrle (1989), Halle and Lerdahl (1993), Halle (1999, 2004), Hayes and Kaun (1996), Hayes (in press), Keshet (2006 ms.)

8. Goals

- The analytical problem: find and state the principles that tacitly guide people when they set text in their language.
- We can and should do this explicitly—a machine implemented model that is trained from data and arrives at its own "intuitions" about textsetting.
 - \succ a sort of micro-Turing test.
- Why address this problem?
 - > We might learn more about musical and phonological structure.
 - > We can test computational theories proposed as models of mental operations.

9. Overview of talk

- Theory of musical rhythm
- Phonological theory: phrasing, stress patterns
- Probabilistic, constraint-based grammars, and computational systems for learning them.

MUSICAL RHYTHM

10. Metrical grids

- as above
- introducers: Lerdahl and Jackendoff (1983) A Generative theory of Tonal Music ; Liberman and Prince (1977) "On Stress and Linguistic Rhythm," Linguistic Inquiry

11. Purely-rhythmic principle (structural preferences)

- (These would hold true even in music without words.)
- From Lerdahl and Jackendoff (1983):
 - > If a position is to be empty, then the weaker it is (few x's in grid), the better.
 - Accented elements (e.g. stressed syllables) should be placed in strong positions.
 - Strong elements are long. E.g. we mentally parse the notes below as on the left, not on the right:



PHONOLOGY

12. Word stress

- English is a language with basically phonemic (unpredictable) stress (cf. *thórough/Thoreáux*), and in general, the stressed syllables of words must fall in strong positions.
 - See (4), where mismatching *sáddle* produces a bad setting.
- Special strictness of word stress:
 - In poetry (Kiparsky 1975) and song (Hayes and Kaun 1995), it has been found that stress + stressless or stressless + stress tend to match the rhythm more strictly when the two syllables involved are in the same word.

13. Stress in phrases

- English has rules determining the stress pattern when words are combined into phrases.
 - Example: verb + particle, like *went on*, has rising stress; hence

		х				Х				Х				Х	
х		Х		Х		Х		Х		Х		Х		Х	
Х	Х	Х	Х	Х	Х	Х	х	Х	Х	Х	Х	Х	Х	Х	Х
		He	Ţ	wen	t	on		till	he	cam	ne	to	his	den	

is slightly preferred to

		Х				Х				Х				Х	
Х		Х		Х		Х		Х		Х		Х		Х	
Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	х	Х	Х	х	Х	Х
He	1	wen	t	on		till		he	C	cam	e	to	his	den	

despite the defect of leaving the first two positions empty.

14. Phrasing

- Stressed syllables at the *ends* of phrases strongly prefer to be in strong rhythmic positions (Kiparsky 1977, Hayes and Kaun 1995)
- Line endings must coincides with phrase endings "run-ons" are disfavored (See Hayes and MacEachern (1996) "Are there lines in folk poetry?")

CONSTRAINT-BASED GRAMMARS

15. How to turn lists of constraints into explicit grammars?

- This is a major topic research in linguistics and related fields.
- One approach with a strong track record is Optimality Theory (Prince and Smolensky 1993 et seq.), the basis for much work in phonology.
- I here use a slightly different constraint-based approach, namely **maxent grammars** (Goldwater and Johnson 2003, Wilson 2006) Why?
 - We need to capture gradient intuitions (see (3) vs. (6) above).
 - Current Optimality-theoretic approaches don't converge (GLA: Pater 2008) or haven't been proven to converge.
 - > The math of maxent has been completely worked out and is fully trustable.

16. Overall approach

- We find every logically possible setting
 - ➢ With the grids used here, this is never more than about 14,000, so with a bit of fairly elementary computer use we can check them all.
 - > Checking all possibilities: essentially the "GEN" function of Optimality Theory.
- We set up a batch of constraints, and assess the number of constraint violations of each setting.
- Every constraint has a weight, a non-negative number that intuitively expresses its strength.
 The higher the weight, the worse a setting that violates it is likely to be sound.
- From this, a standard formula (below) predicts for each setting a **probability**—claimed to match up with its degree of well-formedness.

17. Some sample probabilities

• I haven't yet explained how these are obtained, but these illustrate the ability of the system to match intuition at a rough level.

He rode through woods and copses, too

• Top 6, plus two samples from the lunatic fringe. Probability is given in the right column.

		Х				Х				Х				Х		
Х		Х		Х		Х		Х		Х		Х		Х		
Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	
He		rode		through		woods		and		cop-		ses		too		0.817
	He	rode		through		woods		and		cop-		ses		too		0.090
He		rode		through		woods			and	cop-		ses		too		0.027
He		rode		thi	ougl	n woods		and		cop-		ses		too		0.027
He		rode		through		woods		and		cop-	ses			too		0.020
		he		rode th	roug	h woods		and		cop-	ses			too		5 x 10 ⁻⁷
	He	rode th	rou	ghwoods	and	cops-				ses				too	1	.2 10 ⁻¹²

18. How the math of maxent works

• For each candidate, Compute the **harmony**, ¹ which in notation is:

$$\mathbf{h}(x) = \sum_{i=1}^{N} w_i C_i(x)$$

where

 w_i is the weight of the *i*th constraint, $C_i(x)$ is the number of times that *x* violates the *i*th constraint, and $\sum_{i=1}^{N}$ denotes summation over all constraints ($C_1, C_2, ..., C_N$).

• Compute the "**Maxent value**":

Given a phonological representation x and its score h(x) under a grammar, the *maxent value* of x, denoted $P^*(x)$, is:

$$P^*(x) = \exp(-h(x))$$

¹ The concept of *harmony* is developed in Smolensky (1986) and subsequent work (Smolensky and Legendre 2006).

Hayes

• Compute the **probability**

Given a phonological representation x and its maxent value $P^*(x)$, the *probability* of x, denoted P(x), is:

$$P(x) = P^*(x) / Z$$
 where $Z = \sum_{y \in \Omega} P^*(y)$

That is, its share of maxent values among all candidates.

19. Where do the weights come from?

- This is a long standing problem.
- The approach taken here assumes that they are *learned*—you attend to data from the musical idiom around you, and this gives you the information you need.
- The relevant algorithm (e.g. Della Pietra et al. 1997) attempts to **maximize the predicted probability of the observed data**, a standard criterion in computer science.
- For an attempted clear layman's explanation of how the algorithm works, see Hayes and Wilson (2008).
- I would be happy to share with you the maxent software (work of Colin Wilson/Benjamin George) I used to do the simulations; bhayes@humnet.ucla.edu.

THE SPECIFICS OF THE PRESENT ANALYSIS AND SIMULATION

20. Data corpus

- Hayes and Kaun (1996): 10 consultants each chanted the text of 670 lines of traditional English folk song, in rhythm.
- Goal is to model the share of the vote that each setting got—this can serve as an approximation for gradient intuition.

21. Linguistic annotation of the lines

- Hayes and Kaun independently transcribed the data:
 - Stress values for each syllable (as in Chomsky and Halle 1968)
 - Phonological phrasing, using rules from Hayes (1989)'s synthesis of earlier literature (Selkirk 1980, Nespor and Vogel 1982)
- They achieved reasonably good intersubjective agreement.

Hayes

22. Grid — with labels of convenience for columns

		Х				Х				Х				Х	
Х		Х		Х		Х		Х		Х		Х		Х	
х	х	Х	х	Х	х	Х	х	Х	х	Х	х	Х	Х	Х	Х
М	W	S	W	М	W	S	W	Μ	W	S	W	Μ	W	S	W

where W = Weak, M = Medium, S = Strong

23. Constraints used

- No time to do these in detail, but a quick outline.
- I would like to try trimming, adding; i.e. this is preliminary.
- The numbers are the weights that were learned for each constraint in the simulation.
- The ups and downs of stress must match the rhythm:

5.00	REGULATE SW	"regulated" = stronger stress, or overt syllable vs. null
0.00	REGULATE MW	(turned out to be useless)
1.11	REGULATE SM	
0.32	*Phrase-Final Rise	special phonological context
1.19	*WORD-INTERNAL MISMATCH OF STRESS	special phonological context
0.89	*Stress In M	
2.53	*Stress In W	

• Use of null vs. overt syllable must reinforce the rhythm:

5.00	FILL STRONG	S positions can't be empty
2.40	FILL MEDIUM	M positions can't be empty
2.40	DON'T FILL W	W positions can't be filled

• Prefer to demarcate the lines with long pauses, by making their terminal positions empty:

2.59	DON'T FILL 1
4.60	DON'T FILL 16

• The durations of syllables as set in song must match their natural phonetic durations:

2.46 NON-WORD FINAL SYLLABLES ARE SHORT

• Inherent connections between metrical strength and duration:

1.37	STRONG IS LONG	Penalize gradiently when the S positions don't
		initiate a syllable linked to multiple positions.

• Avoid rhythmic obscurity: 4.75 AVOID LAPSE

*3 empties in a row

• Other:

1.40 WEAK RESOLUTION

stressless in S wants to be short — dunno why...

24. The simulation

- 425 Lines in the corpus (I removed lines found only in some stanza types)
- 8.4 Average # valid "votes" per line / 9 subjects
- 2.2 Average # of distinct settings among the votes
- Goal: find weights that predict the distribution of votes as accurately as possible
- I also did "cross-training" runs: train on one half, test on other; this yielded similar results.
- I used maxent software created by Colin Wilson.

25. Results I: sample output

This was shown above in (17).

26. Statistical report of results

- For the entire set of candidates, the correlation r of predicted probability vs. "vote share" is r = 0.883.
- This is only a rough measure, since most values for both voting and prediction are at or close to zero.

27. Results II: Data and predictions in bins

Predicted probability

	01	.12	.23	.34	.45	.56	.67	.78	.89	.9 - 1
01	48462	191	41	10	7	3	1			
.12	259	34	19	4	3	3	2	1	1	
.23	67	13	10	4	2	2	5		1	1
.34	26	12	11	1	4	2	4	3	3	
.45	12	13	6	3	6	3	2	4	4	
.56	6	6	8	4	8	3	7	3	7	
.67	3	1	5	5	3	6	17	6	14	1
.78	4	5	2	4	4	6	12	6	18	1
.89	2	4		4	3	12	20	13	33	5
.9 - 1		2	1	2	4	9	28	24	27	12

28. Improvements possible?

% volunteered by consultants

- The constraints could be improved, I think.
- Keshet (2006), working non-gradiently, has discovered some new and interesting rules, but I've not had time yet to implement them.

29. Differences between consultants

- Hypothesis: the set of constraints embodies the general theory, part of the competence of all participants.
- Individual idiosyncrasies must be due to consultant-specific weighting.
- We can detect this by training the weights on the data specific to each consultant.
- Example: RH vs. DS's weights for two constraints, which often conflict.

	NON-WORD FINAL	STRONG IS LONG
	Syllables are Short	
RH	1.472	3.418
DS	2.480	0.879

"The remarkable day that I was wed"

Consultant DS's setting satisfies NON-WORD FINAL SYLLABLES ARE SHORT:

		х				Х				х				Х	
х		Х		х		х		х		Х		Х		Х	
Х	Х	Х	Х	х	х	х	Х	Х	х	Х	х	Х	Х	Х	х
The	re-1	mar	-ka-	ble		day		that		İ		was		wed	

Consultant RH's setting satisfies STRONG IS LONG:

		Х				Х				Х				Х	
Х		Х		Х		Х		Х		Х		Х		Х	
Х	Х	X	X	Х	Х	Х	х	Х	Х	Х	Х	Х	Х	Х	Х
The	re-1	mar	-	ka-	ble	day		that		Ι		was		wed	

30. DS and RH's own grammars predict these settings as favorites

Probabilities:

	RH's choice	DS's choice
RH's grammar	0.689	0.065
DS's grammar	0.251	0.819

31. Upshot

• The maxent approach not only characterizes the data as a whole fairly well, but gives us a means of characterizing individual differences in style.

32. Caveat: do RH and DS really have different grammars?

• Maybe, but my guess is that they are construing the experimental situation differently:

- > Each commands a variety of idioms.
- > They accessed different ones in performing the experimental task.

33. Summary: Situating the approach

- The textsetting problem has traits seen elsewhere in cognitive science.
 - An identifiable structural basis, with a need for theoretical ideas taken from generative linguistics and formal music cognition.
 - Extensive gradience of native speaker intuitions and behavior, long a barrier to the use of structural approaches.
 - An "apples and oranges" problem, in which we have to weight the relative importance of constraints that have quite different teleologies.
- I think the right approach to such problems is a kind of "statistical generativism" (e.g., Boersma and Hayes (2001), Yang (2002)
 - > Traditional structural constraints are used, but
 - \succ ...embedded in a quantitative system that predicts gradience, and
 - \succ ... fine-tunes the grammar in response to learning data
- This kind of research implies we need corpora, experiments, easy-to-apply computational models. This is more work but I think the work can be fun and gets us more accurate and insightful results.

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