

Distance-based decay in long-distance phonological processes

Jesse Zymet

University of California, Los Angeles

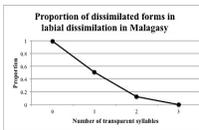
1. Introduction

- Long-distance phonological processes display *distance-based decay*: rate of application decreases as transparent distance between the trigger and target increases.
- This is challenging for approaches to assimilation and dissimilation in which distance does not play a role.
- My account uses the maximum entropy framework (Smolensky and Legendre 2006, et seq.) and a decay function to account for the effect in three processes across four languages.
- The account is implementable in ABC (Hansson 2001, et seq.) with weighted constraints and probabilistic output.

2. Empirical background

Distance-based decay can be observed in a variety of different long-distance phonological processes:

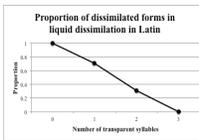
Transparent syllables (σ)	Faithful forms	Dissimilated forms	% of dissim'd forms
n = 0	4	989	99.6%
n = 1	196	201	50.6%
n = 2	28	4	12.5%
n = 3	4	0	0%



(Local 1) /ba.bu+u/ → [ba.bu-i]
(Local 2) /tu.r+u/ → [tu.r-i]

(Nonlocal 1) /ru.va+u/ → [ru.va-u]
(Nonlocal 2) /un.dan+u/ → [un.dan-i]

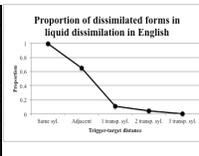
Transparent syllables (σ)	Faithful forms	Dissimilated forms	% of dissim'd forms
n = 0	0	131	100%
n = 1	20	49	71.0%
n = 2	29	13	31.0%
n = 3	4	0	0.0%



(Local 1) /so.l+a:lis/ → [so.l-a:ris]
(Local 2) /mu.l+a:lis/ → [mu.l-a:ris]

(Nonlocal 1) /pa.le.+a:lis/ → [pa.le.-a:ris]
(Nonlocal 2) /a.le.+a:lis/ → [a.le.-a:ris]

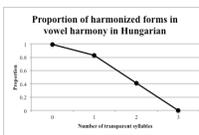
Trigger-target distance	Faithful forms	Dissimilated forms	% of dissim'd forms
Same syllable	1	303	99.7%
Adjacent syls	60	39	65%
1 transp. syl.	85	10	10.5%
2 transp. syls	24	1	4.0%
3 transp. syls	4	0	0.0%



(Local 1) /soo.l+əl/ → [soo.l-ə]
(Local 2) /kan.da.l+əl/ → [kan.da.l-ə]

(Nonlocal 1) /sə.laj.v+əl/ → [sə.laj.v-əl]
(Nonlocal 2) /kə.ləm.n+əl/ → [kə.ləm.n-ə]

Transparent syllables (σ)	Faithful forms	Harmonized forms	% of harm'd forms
n = 0	4.32	6284.68	99.9%
n = 1	128.04	633.96	83.2%
n = 2	60.79	42.35	41.1%
n = 3	8	0	0%



(Local 1) /ob.lək+nek/ → [ob.lək-nək]
(Local 2) /bi.ro.+nek/ → [bi.ro.-nək]

(Nonlocal 1) /kə.li.be.r.+nek/ → [kə.li.be.r.-nek]
(Nonlocal 2) /bo.ri.+nek/ → [bo.ri.-nek]

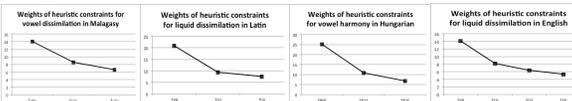
3. Statistical analysis

Likelihood ratio tests over generalized linear models of the data reveal the following:

- The **number of transparent syllables comes out significant** in producing the decay effect for all of the covered languages ($p < 0.001$ for all languages except Latin, for which $p = 0.03$).
- When number of transparent segments was pit against number of transparent syllables, the **number of transparent segments did not come out significant**.
- In Latin, triggers in onset-noninitial position are associated with lower application rates ($p < 0.001$), while labial consonants and velar consonants were not significant (contra Cser 2010).
- In English, triggers in onset-noninitial position or in coda position are associated with lower application rate ($p < 0.001$); velar consonants were associated with lower application rates ($p = 0.02$), while labial consonants were not.
- In Hungarian, height of transparent vowels is significantly related to likelihood of application ($p < 0.001$) as noted by Hayes and Londe 2008.

4. Account rationale

- Positing distance-based markedness constraints is too powerful: learners never acquire small weights for local constraints and large weights for nonlocal ones.
- My account is an extension of Kimper 2011, who proposes a better option: posit one nonlocal markedness constraint whose weight is then scaled with distance.



- Distance-based constraints show that the weight of markedness of cooccurrences decreases with distance in an inverse-exponential fashion (also predicted by Kimper 2011).

- I posit $d(x) = 1/x^k$, where x is syllabic distance (0 if the trigger and target are in the same syllable, 1 if they are adjacent, etc.), and k is a real-valued parameter.

- E.g., in Latin, $d(x)$ scales the weight of markedness as follows:

/...lσ ⁺ +alis/ (e.g., /lapid+a:lis/)	*1, 1 w = 10.97 ≈ 0.33 violations	IDENT([lat]) w = 4.53	Score	Harmony	Predicted probability	Observed probability
[...lσ ⁻ -a:lis]			10.97 + 0.33	$e^{-10.97+0.33}$	$e^{-10.97+0.33}$	0.69
[...lσ ⁻ -a:ris]		1	4.53 + 1	$e^{-4.53+1}$	$(e^{-10.97+0.33} + e^{-4.53+1})$ ≈ 0.70	0.31
					$(e^{-10.97+0.33} + e^{-4.53+1})$ ≈ 0.30	

5. Fitting the model parameters

- Three parameter values must be found: the weight of markedness, the weight of faithfulness, and the decay parameter k .
- I found parameter values that minimize the summed difference between the observed and predicted probabilities.
- As it turns out, **we do not need language-specific values of k** .
- Setting $k = 0.98$ constant across languages and letting the learner determine weights leads to a model with minimal error:
- My current findings suggest that swapping the inverse exponential model for a linear model results in compromised fit.

Vowel dissimilation in Malagasy		Liquid dissimilation in Latin	
w: w	11.60	w: w	10.31
w: y	5.86	w: y	4.34
k	0.98	k	0.98
Error	0.01	Error	0.01
Vowel harmony in Hungarian		Liquid dissimilation in English	
w: w	26.78	w: w	10.86
w: y	15.79	w: y	5.94
k	0.98	k	0.98
Error	0.78	Error	0.02

6. Implementation in ABC

- We can scale the weight of correspondence using $d(x)$.
- Imagine we want to account for a consonant harmony process. Suppose that the value of $d(x)$ at two transparent syllables is 0.5.

/C'σ'C/	AGREE[F] w = 24	CORR-CCT[F] w = 8	IDENT([F]) w = 4	Score	Harmony	Predicted probability
[C'σ'C]	1			24 + 1 = 24	e^{-24}	$\frac{e^{-24}}{(e^{-24} + 2e^{-4})}$ ≈ 0.00
[C'σ'σ']		0.5		8 + 0.5 = 4	e^{-4}	$\frac{e^{-4}}{(e^{-24} + 2e^{-4})}$ ≈ 0.50
[Cσ'C]			1	4 + 1 = 4	e^{-4}	$\frac{e^{-4}}{(e^{-24} + 2e^{-4})}$ ≈ 0.50

7. Sources of data

- Malagasy: Beaujardière 1994; www.malagasyword.org
 Latin: The Perseus Digital Library
 English: The Oxford English Dictionary
 Hungarian: Hayes, Zuraw, Siptar, and Londe 2006

8. Selected references

- Hansson, G. 2001. Theoretical and typological issues in consonant harmony. Doctoral dissertation, UC Berkeley.
- Kimper, W. 2011. Competing triggers: Transparency and opacity in vowel harmony. Doctoral Dissertation, University of Massachusetts Amherst.
- Smolensky, P. & Legendre, G. 2006. The harmonic mind: from neural computation to Optimality-theoretic grammar. Cambridge, Massachusetts: MIT Press.