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UCSC Phlunch Lecture

**Phonological regularity,
perceptual biases, and the role of
grammar in speech error analysis**

John Alderete, Simon Fraser University

in collaboration with:

Monica Davies (UBC) and Paul Tupper (SFU)

Speech errors tend to respect grammar

“First law” of tongue slips (due to Wells 1951)

Speech errors respect phonotactic constraints, only produce legal phonological combinations (Boomer & Laver 1968, Nootboom 1967, Garrett 1980)

Phonological constraints active in repairs (Fromkin 1971: 41)

play the victor → *flay the pictor* (exchange of *p* and *v*, *vl* → *fl*)

Syntactic regularity in speech errors (Garrett 1980, Bock 2011)

- Category constraint (word substitutions respect part of speech labels), producing licit but unintended sentences.
- Sentence blends, role mis-assignments, and spurious agreement relations tend to respect grammar too.

Bock 2011: 332

“The most striking thing about attested syntactic errors is that, like other kinds of speech errors, they occur within a structural matrix that resists modification.”

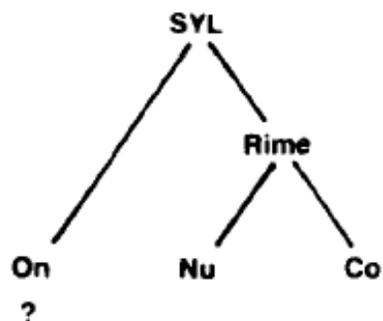
Regularity as a hard constraint

Early models: grammatical regularity not really explained, but the result of a built-in “structural matrix”

Spreading-interactive model of Dell 1986

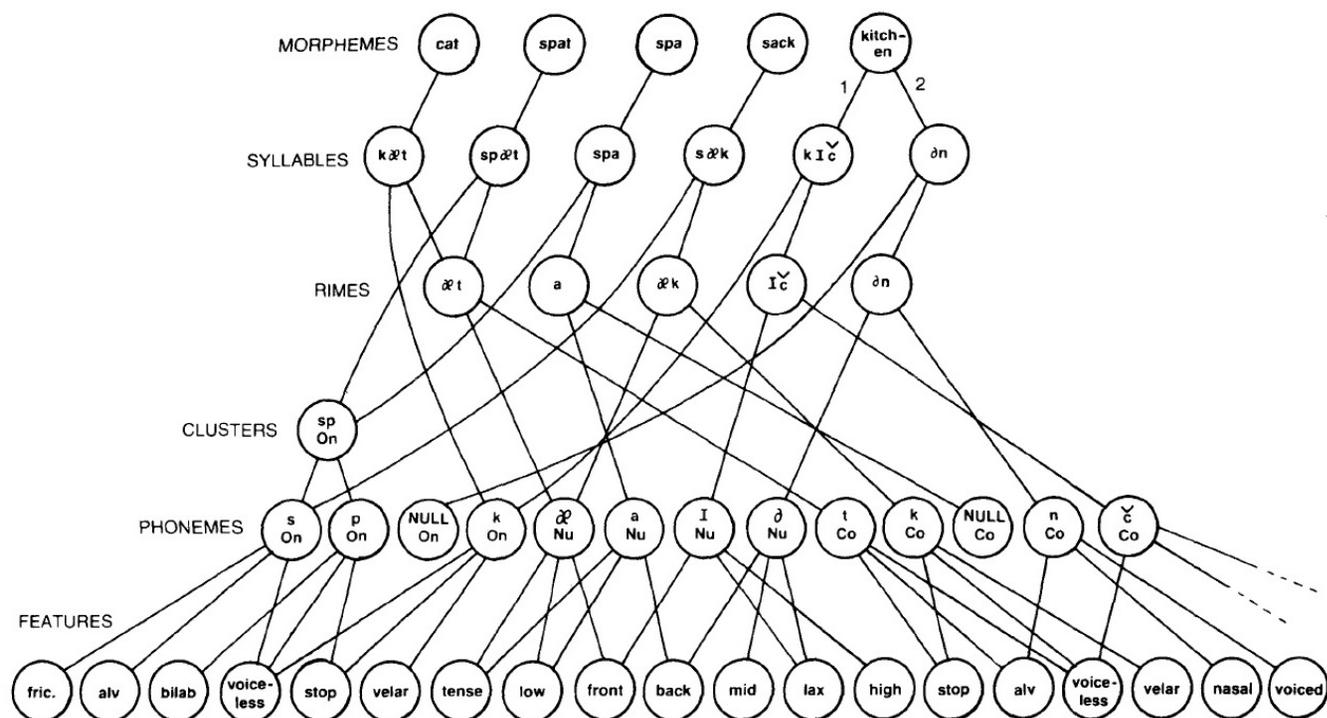
- Mental lexicon: activation dynamics for selecting valid linguistic units
- Tactic frames: productive capacity for language (builds sentence trees, word trees, and syllables. (a.k.a. ‘structural matrix’) **This is a clear role for grammar!**

Tactic frame



Result: *v/* is not a valid onset for intended word *play* because [*v/*, Onset] is not a node in the mental lexicon.

Mental lexical (fragment)



But regularity is not a hard constraint

Stemberger 1983: phonological regularity is very high, but speech errors do violate English phonotactics, approx. 1% of the time (37 violations/6,300 examples); standard of 99% phonological regularity

... in the first floor /**dl**orm — dorm room

I /**sth**ough— thought I said ‘moff’

... knowledge of the cooperative /**rp**in— principle

Problem: need a model that can produce phonotactic violations (rarely); not possible if regularity is a hard constraint.

Issue (Stemberger): the dominance of phonological regularity in speech errors does not entail that speech errors are controlled directly by phonotactic constraints—other independently needed mechanisms sensitive to frequency could be at work.

Dell et al. 1993: regularity without tactic frames

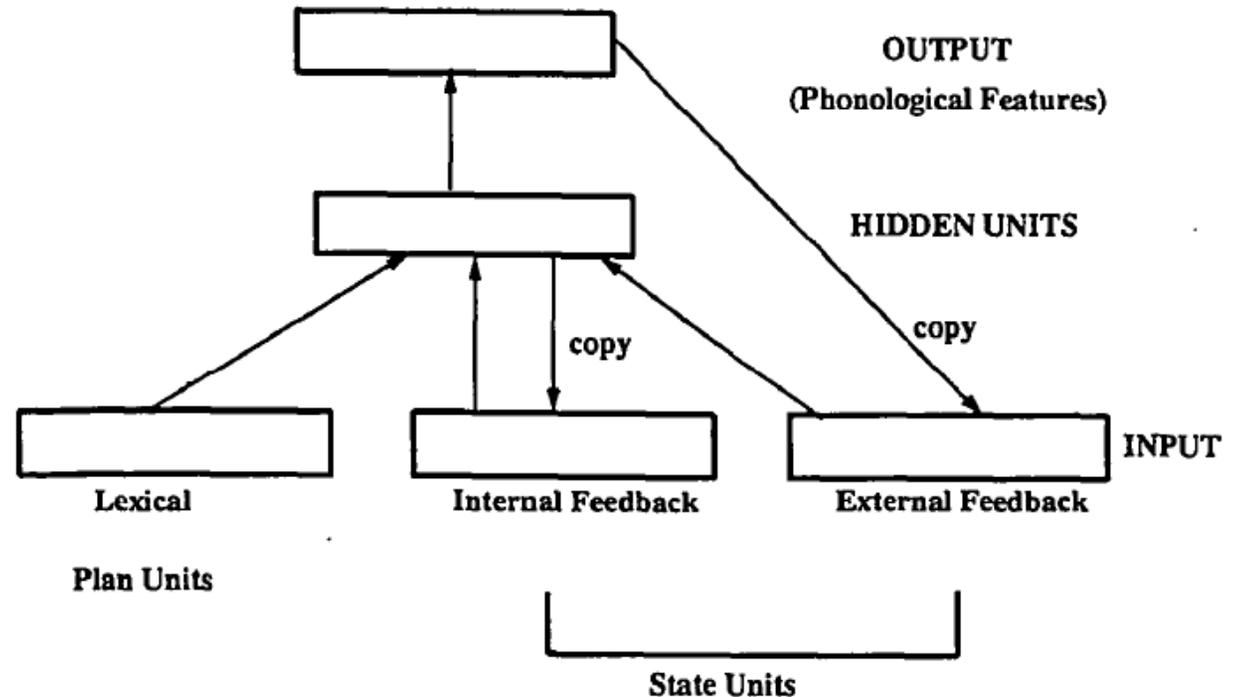
Dell et al. (1993): simple recurrent network proposed as a model of phonological encoding. Trained on a sample of English words and tested against a set of phonological benchmarks characteristic of speech error patterns (i.e., phonological regularity, CV substitutions, syllabic constituent effect, word-onset asymmetry)

Network features:

Sequential: outputs a single segment, then another, in sequence

Recurrent: current segment processed in tandem with knowledge of past segments

Distributed representations: segments are represented as a vector of feature values (cf. distinctive features)



Result: given certain parameters (trained on frequent vocabulary, internal and external input), the model produces errors that are **phonotactically regular about 96.3% of the time**

Upshot: regularity seems to be achievable without tactic frames (But a little below Stemberger's standard of 99%)

Questions

Just how much phonological grammar is there in phonological encoding?

The success of Dell et al's SRN suggests that some phonological structures (e.g., syllable templates) may not need to be formal mechanisms in model of language production processes.

Is cross-linguistic markedness a factor in the structure of speech errors, and if so, how is it incorporate into phonological encoding?

- Markedness is an important ingredient to contemporary phonological grammar (Constraints and Repairs, Optimality Theory, HG, MaxEnt)
- Markedness has also be argued to be a factor in the structure of speech errors (Blumstein 1973, Goldrick 2002, Goldbrick and Rapp 2007, Romani and Calabrese 1998), or not (e.g., Shattuck-Hufnagel and Klatt 1979)
- If markedness is a factor in the structure of speech errors, how is it included in model implementations?

How does methodology affect description of phonological regularity?

- Perceptual biases may reduce the rate of phonologically illicit errors (Dell et al. 1993) and other phonological effects (Alderete & Davies 2016)
- If speech errors are collected in such a way that these biases are reduced, does that effect phonological regularity and other phonological factors?

Focus and approach

SFU Speech Error Database: principal dataset

Describe a methodology for collecting speech errors and demonstrate that it is more reliable and robust to perceptual bias than prior work. SFUSED methods for data collection/analysis.

Re-assess phonological regularity in English speech errors Just how phonologically regular are speech errors? (How common are phonotactic violations?)

Examine a host of dimensions of cross-linguistic markedness to see if it has a major impact on the structure of speech errors.

SFU Speech Error Database (SFUSED)



Current languages

English 'sfusedE' (10,104 errors)

Cantonese 'sfusedC' (2,549 errors)

Goals

- Build a multi-purpose database that documents the rich structure in spontaneous speech errors.
- Examine how the structure of non-Indo-European languages impacts language production processes
- Projected date of release to general public: 2019

sfusedE interface

Record ID no.
Last Modified
Total Completed

Major Class Fields

Master Type
Altern. MType
Level
Type
Direction

Contextual? Y N
Right Lexeme? Y N NotAppl
Form Rule Violation? Y N

Specific Class Fields

Obvious Malapropism Y N NotAppl
Phonotactic Violation
Gradient Type
Prosody Type
Form Rules Type
Morpho Cats
Onsetless Syllable Source? Y N
Onset CC Source? Y N
Two Term Intervener
Transformation Type

Complex Processes-check all appropriate:
 Sub Del Stress Exch
 Add Shift Grad Blend

Example Fields

A: I don't allow my dog to get blood transfusions. B: Did you xxx oh //[sw]eaking of ah, /C[w]ist, Christ and science, there's a show on the history channel ...

Intended	Error
Orthographic: <input type="text" value="speaking"/>	<input type="text" value="[sw]eaking"/>
Phonetic: <input type="text" value="'spikɪŋ"/>	<input type="text" value="'swikɪŋ"/>
Word Bounded? <input type="radio"/> Y <input checked="" type="radio"/> N Clipped? <input type="radio"/> Y <input checked="" type="radio"/> N	
Source Different Talker? <input type="radio"/> Y <input type="radio"/> N Corrected? <input type="text"/>	

Word Fields

POS:
Lexical Word?
Open/Closed
Regular/Irregular
Error-Intended Semantic Relationship
Error-Intended Morphological Relationship

Sound Fields

Supplanted Intended:	Intruder:	Source Sound
CV Structure: <input type="text" value="C"/>	<input type="text" value="C"/>	
Syllabic Role: <input type="text" value="Onset"/>	<input type="text" value="Onset"/>	<input type="text" value="NotAppl"/>
Word Position: <input type="text" value="Medial"/>	<input type="text" value="Medial"/>	<input type="text" value="NotAppl"/>
Whole Syllable: <input type="text" value="spi"/>	<input type="text" value="swi"/>	
Error action is in: <input type="text" value="Onset"/>		

Given Record Fields

Researcher
Found Date
File
Podcast
Time stamp
Online/offline
Talker Self?
Speaker Sex
Spreadsheet
Confidence Intended
Confidence Transcript.
Personal Info? Y N
Record Complete? Y N
Record Confirmed By:
 ja ak ld on

Identical Neighboring Seg? Y N
Syllable with error has:
 Main Stress Second. Stress No Stre
Phonologically Legal? Y N
Triggers Resyllabification? Y N

Markedness Measures

Onset (Initial) Satisfaction Violation No Change
NoHiatus Satisfaction Violation No Change
NoComplexOnset Satisfaction Violation No Change
NoComplexCoda Satisfaction Violation No Change
NoCoda Satisfaction Violation No Change
NoDiphthong Satisfaction Violation No Change

Key methodological decisions

Offline collection from audio recordings (see Chen 1999 on Mandarin speech error database)

- errors collected from podcasts on different topics
- podcasts selected for having natural unscripted speech, usually Western Canada and U.S. (Midlands dialect 'Standard American')
- multiple podcasts (8 currently) with different talkers, approx. 50 hours of each podcast
- record dialectal and idiolectal features associated with speakers (because habitual, so not an error); listeners develop expectations about individuals

Multiple data collectors

- reduces collector bias, allows it to be studied (collector ID associated with all records)
- total of 13 data collectors

Training regime

- undergraduate students with introduction to formal linguistics, phonetics and phonology
- given phonetic training in transcription and tested for transcription accuracy
- introduction to speech errors, definition and illustration of all types
- training through listening tests: assigned pre-screened recordings, asked to find errors; learn by reviewing correct list of errors. Trainees that reach a certain level of accuracy and coverage can continue.

Classification separate from data collection

- data collectors use established protocol for finding errors in audio recordings, submit errors in spreadsheet format
- data analysts (must be different than collector) verify the error, classify it using the SFUSED fields

Advantages of methodology

Summary of findings from Alderete & Davies 2016

Reliability and data quality

- audio recording supports data collection separate from verification by another researcher; typical 25% of proposed errors don't meet standards
- with different collectors, can minimize collector bias and measure it if it exists
- audio recordings help in spotting idiolectal features and phonetic structures

Metrics

- audio recordings have a duration, which allows measures that are not possible with online collection, e.g., collection metrics ("minutes per error")
- supports much better estimates of speech error frequency; using capture-recapture methods, we find that speech errors are much more frequent than reported in prior work (an error at least every 48.5 seconds, probably more)

Data discovery

- audio recordings allow acoustic analysis, probe fine-grained phonetic detail
- can address frequent cry for "more context" (can be recovered)
- with a time metric, can investigate time-based effects like speech rate

Better sample of true population of speech errors

- sample has much higher coverage, likely three to four times better
- less 'easy to hear' and more 'hard to hear' speech errors, reduce impact of perceptual biases
- collect more errors that occur in fast speech

Offline: less 'easy to hear' errors

Online data collection (most prior research): requires on-the-spot observation, only collect errors with high degree of confidence.

Offline (SFUSED): collection from audio recordings, can replay and listen to slow speech

Result: speech error patterns in SFUSED more diffuse, less concentrated in highly salient errors like blends or exchanges.

Exchanges in SFUSED Ex. *We can just wrap mine in a /torn /korkilla* (corn tortilla, 1495)
Early data collection had 1,100 errors collected online. Sample balanced for experience.

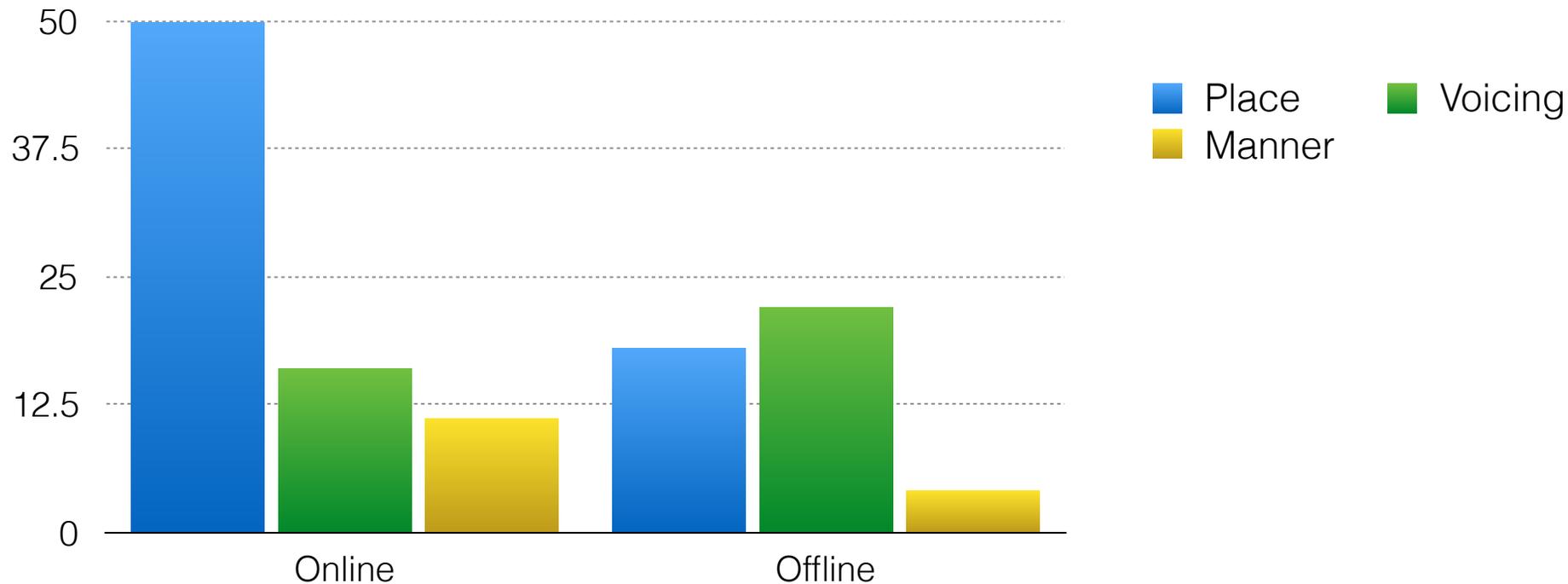
	Offline	Online
Morphemes		6
Phrases		1
Sounds	1	25
Words	1	15
Totals	2 (0.38% of 533)	47 (5.6% of 839)

Offline: more 'hard to hear' errors

Finding: errors in mis-pronunciation are easier to detect in place than voicing (Cole et al. 1978).

Online: counts reflect this perceptual bias

Offline: counts don't reflect this bias; more voicing errors detected than place.



Summary: online vs. offline (Alderete & Davies 2016)

Sound errors

- Online errors have more corrected errors than offline errors.
- Online has a stronger repeated phoneme effect than offline errors.*
- Online errors have a stronger lexical bias than offline errors. (*)
- Online errors have a weaker word-onset effect than offline errors.*
- Online errors are more likely to be contextual than offline errors.*
- Online errors have more perseverations and exchanges than offline errors.*
- Online sound substitutions are more symmetric and more concentrated in a small number of substitutions than offline errors, which are more diffuse and asymmetrical.*

Word errors

- Online errors have less additions and deletions and more blends than offline errors.*
- Online word substitutions are much more likely to be in nouns than offline errors, which are more diffuse across lexical and function categories.*
- Online errors tend to respect the category constraint more than offline errors.

* = significant association from chi square test

How does methodology affect data composition?

How phonologically regular are speech errors in sfusedE?

English phonotactics

Guiding assumption: a word is phonotactically licit if it can be syllabified within a well-formed syllable of English (Kahn 1976, Giegerich 1993, Jensen 1993)

Onset	Peak	Coda
(s)(C1)(C2)	X4 (X5)	(C6)(C7)(C8)(C9)

Conditions:

All C positions are optional.

Banned C1: *ŋ ʒ*, Banned Codas: *h, j, w*.

Onset clusters: obstruent + sonorant

Appendix + C, C always a voiceless stop, *sf* rare/loans

Banned onset clusters: vd fric/affricate + sonorant, labial + *w*, coronal nonstrident + *l*,
θw fjV fw fl sr sh gw stw skl

Onglide *j*: part of peak because of limited distribution, but cannot occur in *CCju* cluster.

Coda clusters X5+C6: falling sonority (*r > l > nasals > obstruents*) and *s + p t k*; *lg* is banned.

C7-9 are appendices limited to coronal obstruents

Nasal + obstruent clusters agree in place and the obstruent is voiceless.

Tense vowels and diphthongs are bimoraic (fill X4 and X5), lax vowels are short fill X4.

Stressed and final syllables are bimoraic (lax vowels occur in closed syllables) and all syllables maximally trimoraic (syllables tense vowels only have simple codas)

Examples of phonotactic violations

Substitutions

Illicit onsets/appendices

1500 ... by the maps at the ^selection /**[ʃkrin]** (screen)

5739 ... they shoot, /**[ʒu]** shoot The Thick of It ... (you)

Illicit codas/rimes

1245 ... Their HOV /**[laɪŋ]** xxx lane is like one driver (lane)

5898 Vin Diesel got kicked off of /Rei**[ŋ]**deer Games ... (reindeer)

Nonnative sounds

5964 ... first of all, Katrina /**[kly]**= clearly defined (clearly)

Additions

Illicit onsets, appendix + onset

49 ... get the Ferrari down a /**[flju]** xxx few ^floors? (few)

1278 I don't like the ^/**vr**iral ^marketing. (viral)

5599 ... talking a ^dream, what that ^dream /**[mr]**eans ... (means)

Illicit codas/rimes

1526 The ^person /**[keɪmp]** ^up to the desk.

(SFUSED record ID # on left)

More examples

Deletions

3954 ... Lisa, /**S**reech and Lisa. (Screech)

8943 ... I think you're a /**h**u[**ŋ**ə]= hunk-a-rama.

Exchanges

4581 ... the children in the trailer for /**M**oon[ra**ŋ**] /**K**eez= Moonrise Kingdom.

Sequential Blends

4453 ... A diary is a /**[sb]**ook xxx a very special book.

5278 ... you can't quite /**[pjɪrt]** xxx put your finger on.

7211 ... because we /**[spɪlkf]** xxx we, we speak film

Word Blends

870 /**[sastæ]** makes me frisky. (pasta, sauce)

7120 Top ten /**th**ways to make me cry (things, ways)

7270 ... /so[**m-bw**ʌn-di] xxx uh in the ... (someone, somebody)

Results by error type

Observations: % of phonotactic violation differs by type, but overall % of irregularity much higher than 1% found in Stemberger's corpus.

Error type	Example	<i>N</i>	Violations	% of <i>N</i>
Substitutions	pleep for <i>sleep</i>	1,376	44	3.20
Additions	bluy for <i>buy</i>	358	33	9.22
Deletions	pay for <i>play</i>	169	3	1.78
Exchanges	heft lemisphere for <i>left hemisphere</i>	37	2	5.41
Shifts	<i>splare backforests</i> for <i>spare blackforests</i>	7	0	0.0
Sequential Blends	Tennedy for <i>Ted Kennedy</i>	57	4	7.02
Word Blends	tab for <i>taxi/cab</i>	72	4	5.56
<i>Totals</i>		2,076	90	4.34

Perceptual bias: missed phonotactic violations

Conjecture: Dell et al. 1993 point out that there is probably a perceptual bias against phonotactic violations. Listeners may regularize them or simply fail to hear them.

Probe: Alderete and Davis 2016 used balanced sample of online vs. offline errors and found a significant association between methodology and regularity ($\chi(1)^2=7.902$, $P=0.0049$).

	Offline	Online
Phonotactic Violations	17 (3.19%)	8 (0.95%)
No Violations	516 (96.81%)	831 (99.05%)

Perceptual bias: all sound errors

Conjecture: Dell et al. 1993 point out that there is probably a perceptual bias against phonotactic violations. Listeners may regularize them or simply fail to hear them.

Probe: counting all sound errors and blends, % of phonotactic violations higher ($X^2 = 16.9618$, $p < .05$); note effect does not depend on what counts as a violation.

		Offline	Online
Phonotactic Violations	Phonotactic Violations	76 (5.5%)	11 (1.6%)
No Violations	No Violations	1,326 (94.5%)	660 (98.4%)

Discussion: comparison with SRN

New standard: 93-95% phonologically regular, cf. 99% of Stemberger 1983, (94.5% regularity reported in offline data still probably affected by perceptual bias)

Goodness of fit: Dell et al. 1993 simple recurrent network tested a variety of parameters that compare well with these findings.

- Models trained on frequent vocabulary and with both internal and external representations: **96.5% regularity**
- Range for other assumptions about input: **89-95% regularity**
- Many of the errors with phonotactic violations resemble the phonotactically illicit errors we have found, with illegal clusters and initials.

Limitations

- Model trained only on three segment words, so no polysyllabic words
- Didn't really allow for additions, which account for a lot irregularity (perhaps 1/3)
- Phonotactics likely slightly different than one used here (likely less stringent).
- Didn't account for prosody (stress in errors) and other structures.

Take home: with the new standard, tactic frames (cf. syllable templates) are not obviously necessary to the analysis of phonotactic regularity in speech errors.

Discussion: other potential roles of grammar?

Markedness

- Markedness is “the stuff” of most grammars in contemporary phonology. If we could find a role for markedness, this would be a clear role.
- Focus is on cross-linguistic markedness, not language particular markedness relations, because latter is hard to separate from frequency.

Frequency

- Frequency structure is increasingly a part of formal grammar, e.g., weights in Harmonic Grammar and MaxEnt grammar.
- Often overlaps markedness (marked is less frequent), but not always.
- Language production: frequency is a standardly assumed output bias in language production (Dell 1986); may be difficult to separate from its use in grammar

Feature specification (‘anti-frequency’)

- Feature specification is a core assumption in linguistic grammar, and has also been argued to account for speech error facts (Stemberger 1991)
- Specified sounds (because contrastive) override unspecified (because predictable): e.g., palatal bias in consonant substitutions.

***How does segmental markedness
shape speech errors?***

Background: segmental markedness

Bias for marked → unmarked mappings in speech errors at segmental level

Experimentally induced speech errors

- Kupin 1982: disyllabic tongue twisters, unmarked forms preferred
- Goldrick 2002: implicit learning paradigm, examined substitutions where markedness and frequency make different predictions.

Example: [t] is unmarked relative to [s], also less frequent

[s] → [t] > [t] → [s] supports markedness account

Aphasic speech

- Blumenstein 1973: single feature consonant substitutions favour marked → unmarked mappings (just Broca's and Wernicke's aphasics, not conduction aphasics)
- Romani et al. 2002: markedness superior to frequency in aphasic consonant substitutions
- Goldrick and Rapp 2007: brain-damaged subject with deficit in post-lexical phonological processes, more accurate with coronals /t d/ (93%) than dorsals /k g/ (86%)

Against markedness as a factor

Some studies have found no effect of markedness, and segment substitutions reflect baseline frequencies ('availability'): Shattuck-Hufnagel & Klatt 1979, Stemberger 1991

Test: single feature consonant substitutions

Procedure: take a consonant confusion matrix ($N= 1,506$)

Sound Suppl..	Sound Intruder																								
	p	b	t	d	k	g	f	v	θ	ð	s	z	ʃ	ʒ	tʃ	dʒ	m	n	ŋ	l	r	w	j	h	
p		27	10		10		10	1							2		2	1							
b	14		1	1	9	1	1	1	8			1					7			3			2		
t	7	2		15	13	1	2	1	2	2	2	3	3		10			7		6	1			1	1
d	1	8	3		1	6			2	2	3	3				6		5		2	3				
k	10	2	17	2		16					2	1	2		3	1			1	1	1				2
g		3		2	15		1	1			1		1					1							
f	8	3	2			1		6	3		9	1								1	1			1	1
v		9	1		1	1	11			2		2				2	1	1		1	3	3			
θ	2		3	2	2		1			2	13	1	1		1					1					
ð		1	3	3		1		2	2		1	1			1	1	1			4					1
s		1	8	1	4	1	4	1	12	1		7	55		5			2		1					1
z		1		2		1		2	3	1	8		4	1		2	1			1	2				
ʃ				1		1	1		1		14	1		1	6								1		
ʒ											1														
tʃ			4		4						5		5	3		1						1			1
dʒ			1	7	1	3					1			1	5										1
m		2	8				1	1		1		1							24		3		6		
n			3	12	1						1	1					16			4	8	5		1	1
ŋ																			1						
l			1		1	3				2			1				4	3	2		21	6	2		
r		1			1					1					1	1	3				41		12	2	
w		1	2	1	2		1	1								4					8	15			
j			1			2								1		1					2	3			
h			1	4	1	4	3	1		1		3			1						2				

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p		27	10		10		10	1							2		2	1							
b	14		1	1	9	1	1	1	8			1					7			3		2			
t	7	2		15	13	1	2	1	2	2	2	3	3		10			7		6	1		1	1	
d	1	8	3		1	6			2	2	3	3				6		5		2	3				
k	10	2	17	2		16					2	1	2		3	1			1	1	1				2
g		3		2	15		1	1			1		1					1							
f	8	3	2			1			6	3		9	1							1	1				1
v		9	1		1	1	11				2	2				2	1	1		1	3	3			
θ	2		3	2	2		1				2	13	1	1							1				
ð		1	3	3		1			2	2		1	1			1	1	1							1
s		1	8	1	4	1	4																		
z		1		2		1																			
ʃ					1		1	1																	
ʒ																									
tʃ			4			4																			
dʒ			1	7	1	3																			
m		2	8																						
n				3	12	1																			
ŋ																									
l			1			1	3																		
r		1			1																				
w		1	2	1	2																				
j			1										2												
h			1	4	1	4	3	1																	

Test: examine consonant pairs that differ in a single feature, adjust for baseline frequencies

Mapping	Count	Baseline
---------	-------	----------

p → b 27 *p* produce 50 times in 1000

b → p 14 *b* produced 29 times in 1000

Baseline frequencies: estimating relative risk

	Event	General Population
Condition 1	a	b
Condition 2	c	d

mutually exclusive

$$RR = \frac{a/b}{c/d}$$

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	Event	General Population
Condition 1	a	b
Condition 2	c	d

mutually exclusive

$$RR = \frac{a/b}{c/d}$$

Stemberger 2007
data from sfusedE

	Voicing [s z]	Token Frequency
z → s	8	16
s → z	7	99

$$RR(sz) = 7.07$$

Baseline frequencies: estimating relative risk

Stemberger 2007
data from sfusedE

	Event	General Population
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	Voicing [s z]	Token Frequency
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$$RR = \frac{a/b}{c/d}$$

$$RR(sz) = 7.07$$

Test results: are the observed differences significant (not due to chance)?
And if so, what direction (favour marked or unmarked structure?)

Baseline frequencies: estimating relative risk

Stemberger 2007
data from sfusedE

	Event	General Population
Condition 1	a	b
Condition 2	c	d

	Voicing [s z]	Token Frequency
z → s	8	16
s → z	7	99

mutually exclusive

$$RR = \frac{a/b}{c/d}$$

$$RR(sz) = 7.07$$

Test results: are the observed differences in probability of two events significant (not due to chance)? And if so, what direction (favour marked or unmarked structure?)

95% confidence interval (testing null hypothesis that $\log(RR) = 0$):

$$\log RR \in \left(\log \frac{a/b}{c/d} - 1.96 \sqrt{\frac{1}{a} + \frac{1}{c}}, \log \frac{a/b}{c/d} + 1.96 \sqrt{\frac{1}{a} + \frac{1}{c}} \right) \quad \text{Agresti 1996}$$

Example: $\log(RR) = 1.956$, 95% confident $\log(RR) \neq$ zero, can reject null hypothesis. Direction (sign): favours unmarked segment [s].

Results: [voice], [anterior], [continuant], [nasal]

Voicing

Unmarked	Marked	Direction	Significant?
p	b	marked	N
t	d	marked	N
k	g	unmarked	N
f	v	unmarked	N
s	z	unmarked	Y

Continuancy

Unmarked	Marked	Direction	Significant?
p	f	unmarked	N
b	v	unmarked	N
t	s	unmarked	Y
d	s	unmarked	N

Anteriority

Unmarked	Marked	Direction	Significant?
s	ʃ	unmarked	N
t	tʃ	unmarked	Y
d	dʒ	unmarked	Y

Nasality

Unmarked	Marked	Direction	Significant?
b	m	marked	N
d	n	unmarked	N

Finding: 4 of 14 consonant pairs reached 95% significance, all in the direction predicted by markedness (some pairs not reported due to insufficient data)

Results: place features

Coronal - Labial

Unmarked	Marked	Direction	Significant?
t	p	unmarked	Y
d	b	unmarked	Y
n	m	unmarked	Y
s	f	unmarked	Y

Labial - Dorsal

Unmarked	Marked	Direction	Significant?
p	k	marked	N
b	g	unmarked	N

Coronal - Dorsal

Unmarked	Marked	Direction	Significant?
d	g	marked	N
t	k	unmarked	Y

Finding: majority of place-changing substitutions significant, especially those involving coronals.

Markedness distinct from frequency bias?

Feature	Unmarked	Marked	Direction	Significant?	Frequency bias?
[voice]	s	z	unmarked	Y	Y
[anterior]	t	tʃ	unmarked	Y	Y
[anterior']	d	dʒ	unmarked	Y	Y
[continuant]	t	s	unmarked	Y	N
Place	t	p	unmarked	Y	Y
Place	d	b	unmarked	Y	Y
Place	n	m	unmarked	Y	Y
Place	s	f	unmarked	Y	Y
Place	t	k	unmarked	Y	Y

Confound: while there are many significant results supporting a role for markedness, 8 of the 9 cases could be explained with an output bias for frequent segments (type frequency, interactivity in the lexicon). [t] → [s] is the same mapping Goldrick (2002) found to support the markedness account using experimental methods.

Take home: weak support for a role for markedness in consonant substitutions.

***How does syllable structure markedness
shape speech errors?***

Background: syllable structure constraints in deletions and additions

Cluster resolution

Frequent observation in aphasic speech that errors resolve clusters (Blumstein 1973, Romani and Calabrese 1999)

Onsets vs. Codas

- Goldrick and Rapp 2007: brain-damaged subject with deficit in post-lexical phonological processes found to be more accurate with onsets (96%) than codas (91%)
- Béland and Paradis (1997): set of 700 sound errors in aphasic found to systematically avoid marked syllables: #_V, V_V, CCV, CVC, CVCC; parallels drawn between speech errors and loanword adaptations

Sonority dispersion

Romani and Calabrese 1999, Romani et al. 2002: syllable structure in aphasic speech reduces syllable complexity, including increasing the sonority dispersion from onset to peak (e.g., *ka* > *la*)

Coda Condition effects

Béland, Paradis, and Bois (1993): in group study of aphasics, found preference for coda substitutions that removed independent Place specification in coda.

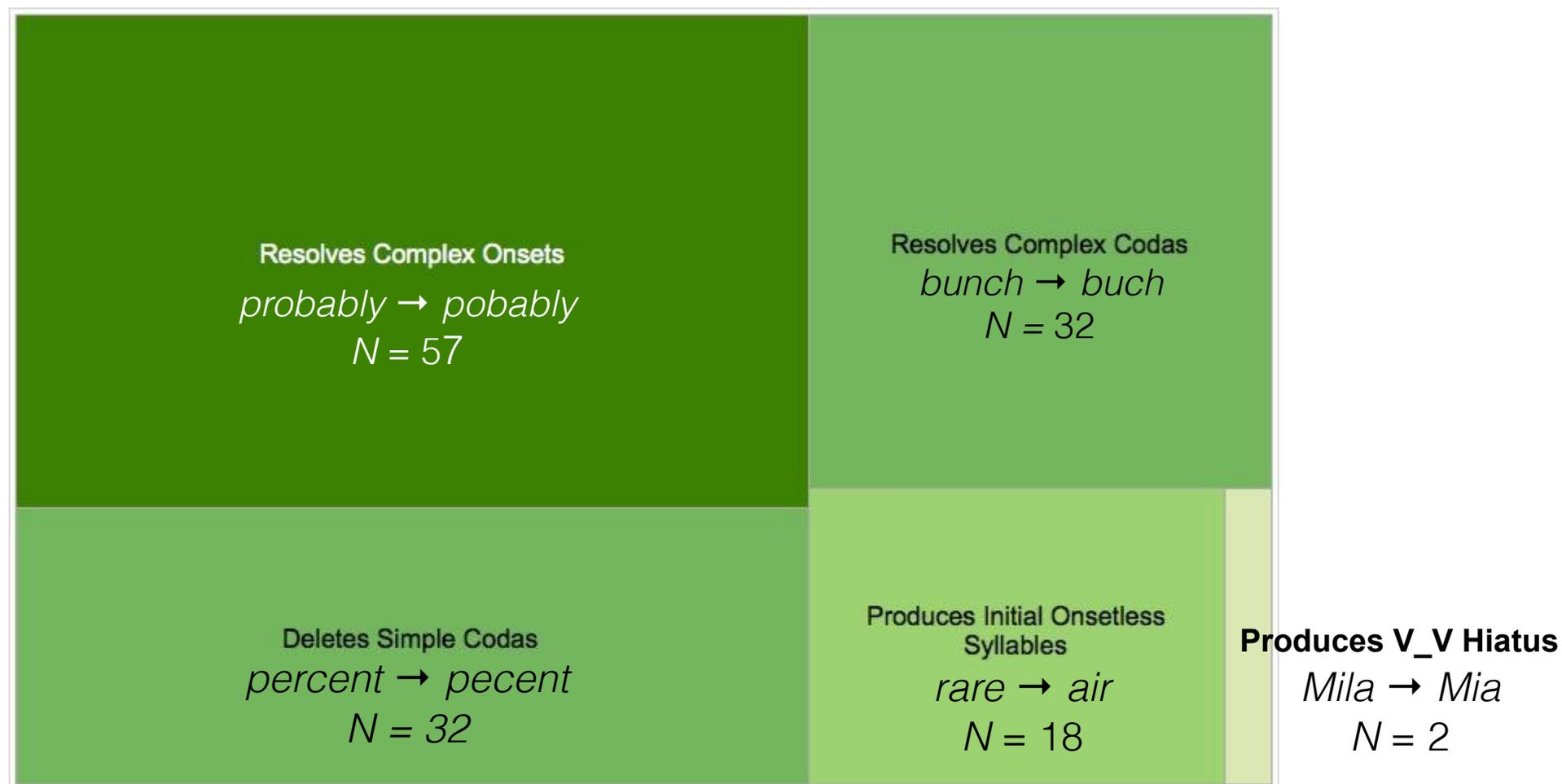
Deletions in sfusedE

CV Structure	Count	Example
C	157	... everybody \$immediately \$/s_arts bidding ... (<i>starts</i> , 344)
CC	6	You're not going to squish it into the /s_eeen (<i>screen</i> , 1662)
V/Onglide	8	Which, it goes back to the /bulling thing. (<i>bullying</i> , 3930)
CV, CVC, VC	13	how are you going to \$/rember xxx remember stuff ... (4174)

- Single consonant deletions dominate the data: real focus
- Hard to see patterns in minority deletions, but syllable deletions tend to be neutral on markedness, and vowel deletions tend to improve.

Single consonant deletions

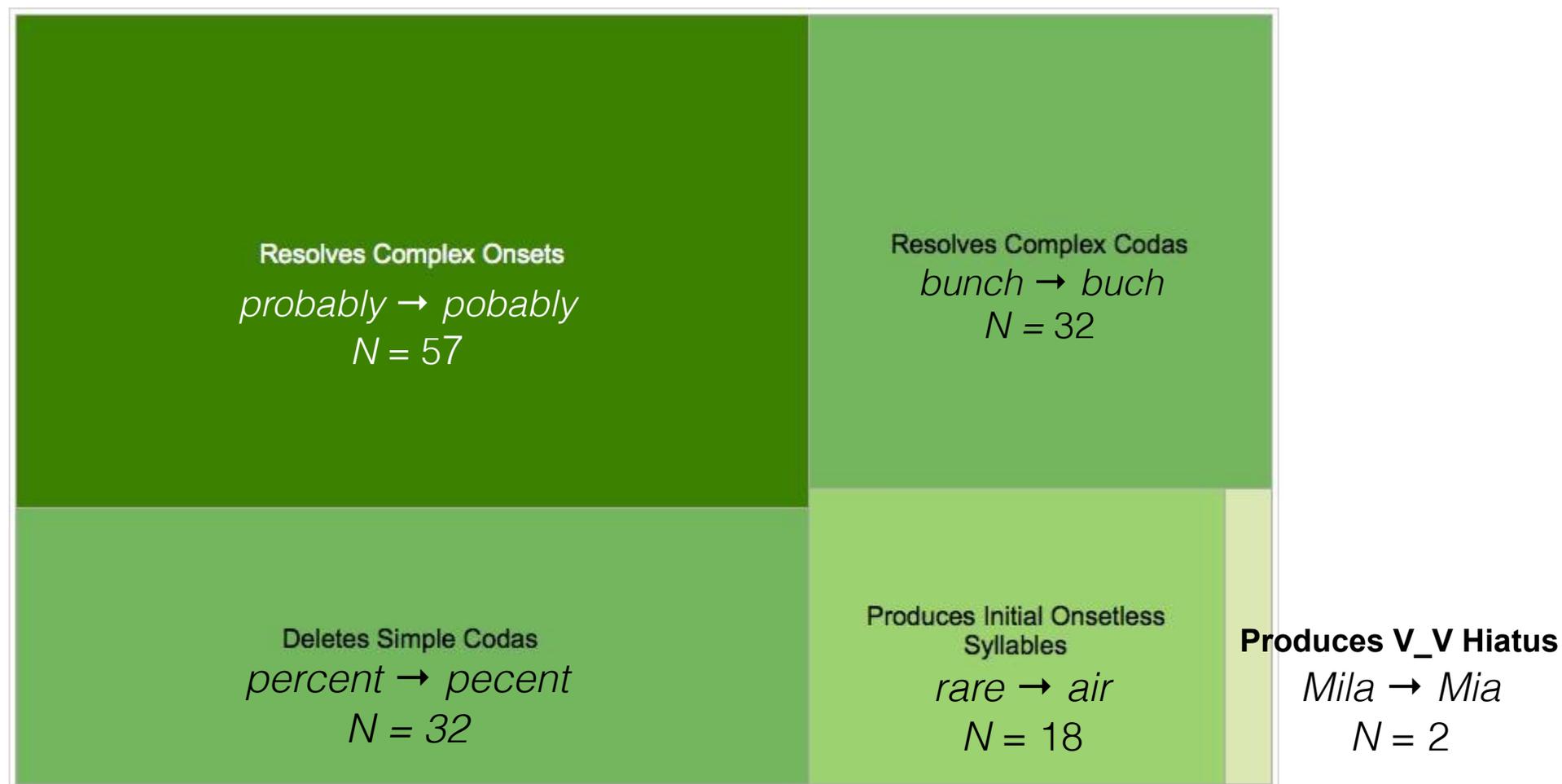
- Vast majority improve on markedness (resolve marked clusters or coda consonants), $121/141 = 86\%$



Single consonant deletions

Rare cases of marked onsetless syllables are **strongly supported by context**:

- 14/18 cases have onsetless syllable in neighbouring four words,
- 17/18 cases have “triggers” that have been shown to induce deletion

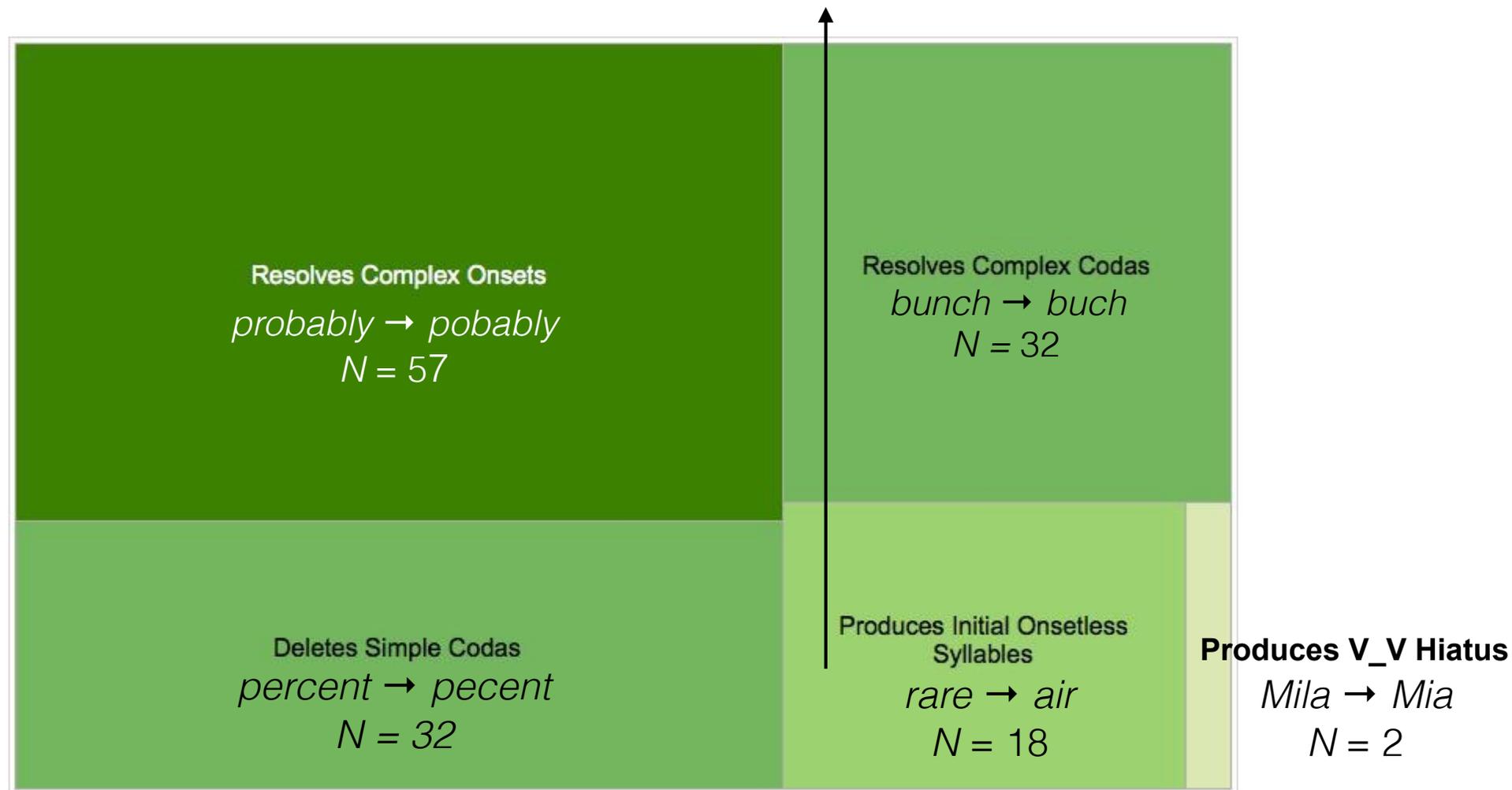


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\$Stress \$^errors \$^are \$really \$/air. (*rare*, 4701)



Single consonant deletions

What is the impact of baseline frequency here?

- Seems all the more significant that very common CV syllables rarely lose an onset.
- Why is it that onset deletions (n=77) are comparable to coda deletions (n=64) when onsets are preferred by markedness? Perhaps also a baseline effect, because onsets are more common than codas (more chances for onset errors)

Reality check

Most phonotactic constraints ban consonants in onsets and rimes.

Markedness constraints encode these constraints. Perhaps the reason deletions have a markedness explanation is because deletions almost always delete consonants, and consonants are at the heart of phonotactic constraints.

Question

How do deletions compare with additions, which 'throw a wrench' into phonotactics.

Additions in sfusedE

CV Structure	Count	Example
C	333	They're /pl ^l as= passing over the ^plains of the ... (<i>passing</i> , 10)
CC	3	My /tumbly's xxx getting ^rumbly. (<i>tummy</i> , 1537)
V/Onglide	22	It was a ^really ^squishy /bally. (<i>ball</i> , 1811)
CV	21	It's not like you'll be /contributiting much. (<i>contributing</i> , 1615)
Misc	15	What was that ^conversation we were /hav[ən]ing? (<i>having</i> , 4057)

Similar patterns with deletions:

- vowel additions tend to remove marked structure
- syllable-sized units tend to be neutral
- single consonant additions dominate the data

Single consonant additions

- Consonant additions by their nature lead to markedness violations; syllable structure constraints ban all Cs, except CV.
- Majority of additions (77%) involve unmarked → marked mappings.



Single consonant additions

- Like single consonant deletions, a large percentage of unmarked → marked mappings have strong support from context.
- Additions that produce marked CC onsets: 87.1% of them are contextual (cf. 72.9% for substitutions), and a majority of them (61.5%) involve source sounds from a CCVC syllable.



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... but sometimes he had ^pretty /brad ^breath. (*bad*, 1675)



Comparing deletions and additions

Contexts	Deletions	Additions
Resolves/creates marked Onset CCs	57 (40.43)	137 (44.05)
Resolves/creates marked Coda CCs	32 (22.70)	48 (15.43)
Resolves/creates Coda Cs	32 (22.70)	54 (17.36)
Creates/fills marked #_V	18 (12.77)	68 (21.86)
Creates/fills V_V hiatus	2 (1.42)	4 (1.29)

$\chi^2(4) = 8.871$,
 $p = 0.0645$
not significant

Is context associated with error type?

- Higher percentage of additions to fill onsetless syllables than deletions that create them.
- Also comparatively larger percentage of deletions of coda consonants than additions.
- Trend is in the direction predicted by markedness, but **not significant**.

Deletions vs. additions: noncontextual errors

Conjecture: perhaps markedness effect is stronger in non-contextual errors, less influenced by competition from neighbouring sounds (source sounds).

Contexts	Deletions	Additions
Resolves/creates marked Onset CCs	16 (47.06)	24 (58.54)
Resolves/creates marked Coda CCs	7 (20.59)	4 (9.76)
Resolves/creates Coda Cs	10 (29.41)	8 (19.51)
Creates/fills marked #_V	1 (2.94)	5 (12.20)
Creates/fills V_V hiatus	0	0

$\chi(3) = 4.695$,
 $p = 0.1955$
not significant

Finding: no significant association between context and error type. Exclusion of contextual errors seems to erase the quite large distinction between deletions and additions!

Deletions vs. additions: Wrap-up

- Deletions are consistent with a strong effect of syllable structure markedness.
- Additions, far more in number, exhibit an opposite effect, relatively equal in magnitude.
- Unmarkedness to markedness mappings in deletions could therefore simply be due to the nature of deletion and fact that most phonotactics ban consonants.
- Single consonant errors dominate both deletions and additions.

Conclusion: again, lack of strong evidence for markedness constraints in shaping speech errors.

More negative results in sfusedE

Coda condition effects

Step sample of consonant substitutions found no preference for replacing non-coronals with coronals in coda position (both medial and final codas).

- Non-coronal → non-coronal > non-coronal → coronal
- No distinction between coronal → coronal and coronal → non-coronal
- Same patterns found in non-contextual substitutions only.

Ban on tense vowels in CVCC syllables

- Expectation: if speech errors are sensitive to this constraint, expect additions that create a CVCC syllable to prefer nuclei with lax vowels
- Finding: small sample (total 14 observations), but roughly half additions have lax vowels and half have tense vowels

Summary: cross-linguistic markedness

Segmental markedness

- 9 of 29 consonant pairs that differ in one feature show an effect of markedness
- But only 1 (t>s) of these 9 is best explained as a preference for unmarked segments.

Syllable structure effects

Marked syllable structures: #_V, V_V, CVC, CCV, CVCC

- Deletions seem to favour marked → unmarked
- But additions favour the opposite order, unmarked → marked to the same degree
- Consonant substitutions don't seem to favour independent Place specification in codas (Coda Condition effects)
- Consonant additions don't seem sensitive to tense/lax distinction in CVCC syllables

Take homes

New standard for regularity: errors of phonological encoding are phonotactically regular about 94-95% of the time (cf. prior standard of 99%).

Methodology: this new standard is documented using methods less prone to bias; so lower standard is likely the result of perceptual bias.

Grammar in phonological regularity? Syllable structure templates do not seem to be necessary to overall phonological regularity. Models of phonological encoding without them seem consistent with the fact.

Cross-linguistic markedness? A detailed examination of both segmental and syllable structure markedness did not reveal a strong role for markedness independent of frequency.

Implications for speech production models?

Ingredients of a sufficient model

- Output bias for frequent sounds (consonant confusions)
- Output bias for frequent sequences (general phonotactics)

Models that meet these criteria

- SRN of Dell et al. 1993
- Original Dell-net of Dell 1986 (with some overkill)
- Harmonic Grammar with weights for important constraints (Goldrick and Daland 2009)
- Two step interactive model (Dell et al. 1997)

Missing

Explicit syllabification algorithm for organizing segments in a frame.

Implications: but we still do need syllables ...

Roles for syllables in phonological encoding:

Syllable position constraint (Boomer and Laver 1968, Fromkin 1971, Garrett 1975)

Onsets slip with onsets, codas with codas, etc.

Syllable errors in languages like Mandarin (Chen 2000)

Whole syllables slip at rates greater than expected by chance (probably only in languages with very small syllabaries)

Masked Priming (Ferrand, Segui and Grainger 1996, cf. Schiller 1998)

Shorted masked syllables speed up picture naming if exact syllable in test word.

Implicit priming (Chen, Chen, Dell 2002, cf. Meyer 1991)

Syllables implied in production planning because facilitate picture named in cued recall experiments (may be a language particular effect).

Syllables are stored

Common assumption: Syllables can be stored in the mental lexicon without being actively generated in tactic frames. Assumed in most models built off the Dell (1986) spreading-activation model, and some have argued that languages like Mandarin actually select syllables in phonological encoding (see O'Seaghdha et al. 2010)

Syllable position constraint: filler-role bindings from Legendre and Smolensky 2006, syllable position a kind of similarity effect.

Syllable errors and implicit priming in Mandarin: syllables are stored and selected in phonological encoding (see 'proximate unit' hypothesis of O'Seaghdha et al. 2010)

Masked priming: if syllables are stored, then should prime later words that have identical syllables.

Conclusion: while a syllable template does not appear to be intrinsic to phonological encoding, syllables seem to be necessary representations in the mental lexical and production planning.

Contributors to SFUSED

Director/analyst/data collector:

John Alderete

Research associates

Paul Tupper (SFU)

Alexei Kochetov (Toronto)

Stefan A. Frisch (USF)

Monica Davies (UBC)

Analysts/data collectors

Holly Wilbee (English)

Monica Davies (English)

Olivia Nickel (English)

Queenie Chan (Cantonese)

Macarius Chan (Cantonese)

Data collectors

Jennifer Williams (English)

Julie Park (English)

Rebecca Cho (English)

Bianca Andreone (English)

Dave Warkentin (English)

Crystal Ng (Cantonese)

Gloria Fan E (Cantonese)

Amanda Klassen (English)

Laura Dand (English)

Future projects

SFUSED is designed as a multi-purpose database and we actively seek out new project proposals.

New projects can improve the data quality through data cleaning, and also extend the database by introducing new fields.

The database can be imported to Tableau and then explored much faster and more deeply.

Projects can combine questions from linguistic theory (e.g., ‘psychological reality of X’) or experimental paradigms.

Contact: alderete@sfu.ca

Why are we still collecting speech errors?

Problem: speech errors 'in the wild' are very time-consuming, prone to mistakes in observation and interpretation; often can't get enough data on a particular pattern.

Stemberger 1992: actually there is considerable overlap in the patterns of errors collected in naturalistic and experimental settings.

However, some patterns differ in two datasets, limitations: % of exchanges, lexical bias, non-native segments, phoneme frequency effects, etc.

This research shows that a new approach to data collection (offline, many listeners), has potential for new observations, e.g., phonological regularity

Large databases can be re-purposed, not really true of experiments.

Offline methodology is actually very efficient (see Alderete & Davies 2016 for research costs estimates); can produce a database of 3,000 errors in about the same amount of time it takes to run two experiments.

Idiolectal features are very important in understanding errors (habitual, so not an error), but can only really analyze them after a few hours of listening to a single talker.

Estimating error frequency

Prior assumption: speech errors are rare in general (**error every 5-6 minutes**), motivates focus on normal language production

Problem: prior estimates of error frequency based on online collection, and many failed to address the fact of missed errors (though all studies concede they miss them).

Capture-recapture: common tool in ecology for estimating a population when exhaustive is impossible or impractical

Take home: speech errors occur much more commonly than enumerated in prior research, at least as often as **48.5 seconds** (upper bound because of non-homogeneity)

Second	A	B	C	AB	AC	BC	ABC	n	\bar{m}	\bar{v}	SPE
2,100	2	18	3	2	0	3	5	33	16.3	49.3	42.60
1,690	6	5	4	5	0	2	9	31	13.48	44.48	38.00
1,993	2	9	5	1	0	1	5	23	20.08	43.08	46.26
2,385	6	6	5	8	2	1	5	33	11.7	44.70	53.36
4,143	24	9	1	5	1	1	3	44	21.84	65.84	62.93
3,000	9	2	7	3	5	1	2	29	10.63	39.63	75.70
1,800	9	9	3	2	0	1	1	25	29.87	54.87	32.81
2,377	15	2	4	3	2	1	3	30	13.39	43.39	54.78
2,400	18	4	6	1	2	0	7	38	41.93	79.93	30.03

*From Alderete
and Davis 2016*