Sept. 13, 2018 Université Paris Diderot

Phonological regularity and the role of phonotactics in speech error analysis: segmental and syllable markedness

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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, Nooteboom 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.”

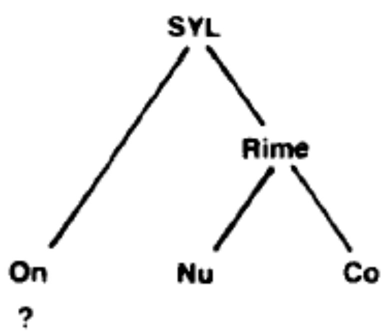
Regularity as a hard constraint

Early models: grammatical regularity not really explained, but the result of a built-in design features

Spreading-interactive model of Dell 1986

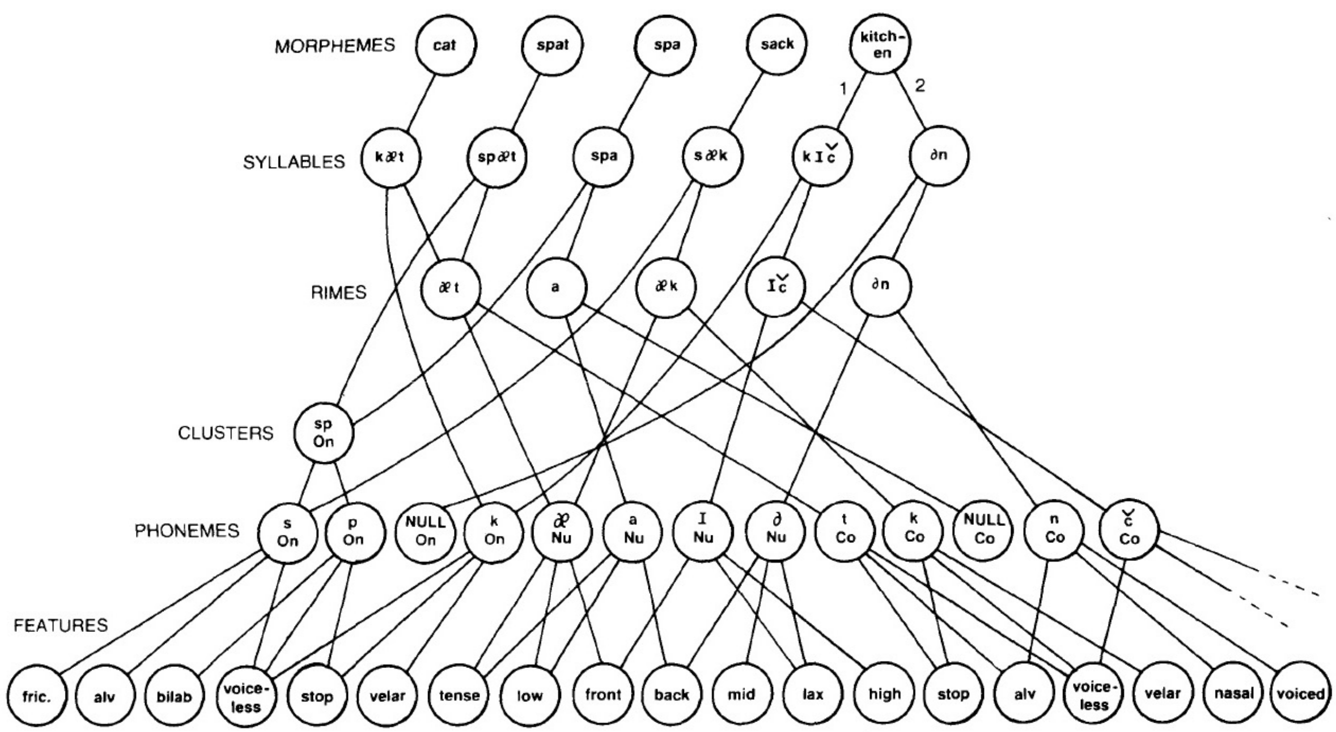
- Mental lexicon: activation dynamics for selecting valid linguistic units
- Tactic frames: productive capacity for language (simple sentence trees, word trees, and syllables. (a.k.a. 'structural matrix') ***This is a clear role for grammar!***

Tactic frame



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

Mental lexicon (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 need mechanisms sensitive to frequency could be at work.

Dell et al. 1993: regularity without tactic frames

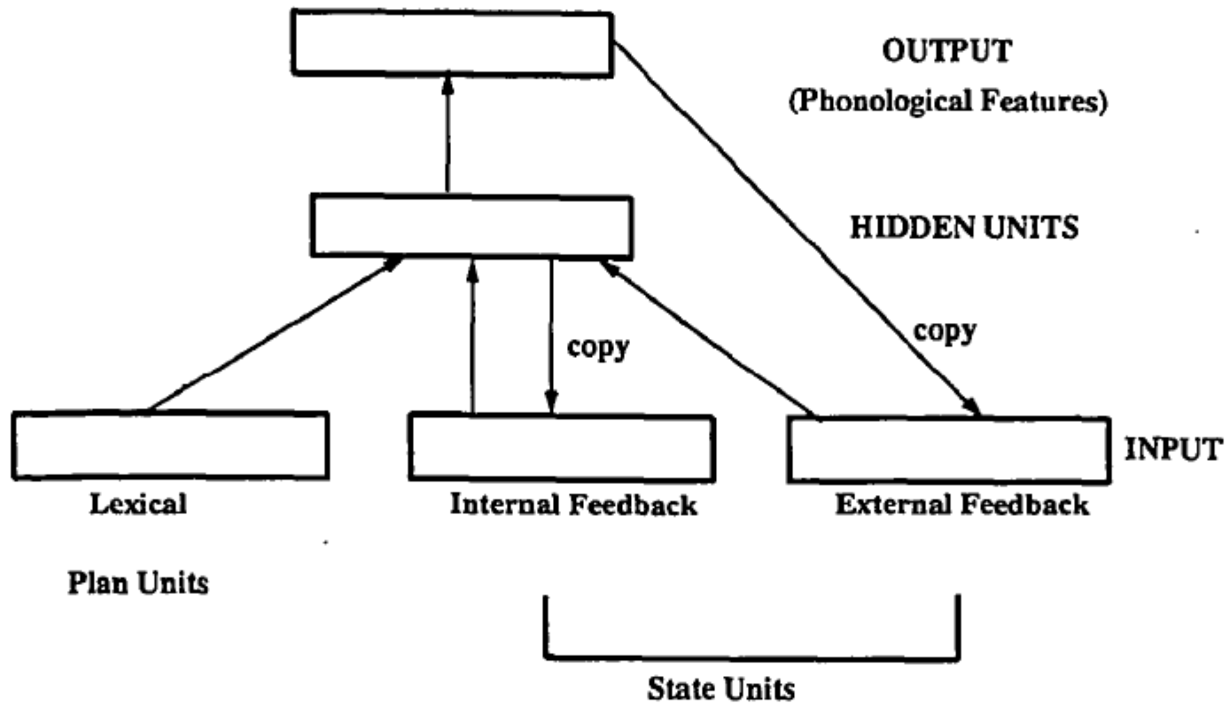
Dell et al. (1993): simple recurrent network proposed as a model of phonological encoding. Trained on a sample of English words and tested against a set of phonological benchmarks characteristic of speech error patterns (i.e., phonological regularity, CV substitutions, syllabic constituent effect, word-onset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

Problem: regularity seems to be in principle achievable without tactic frames, but far undershoots Stemberger's standard of 99%)

99% standard too high: 94.5% new standard

Alderete & Tupper 2018, WIREs Cognitive Science

Perceptual biases: 99% standard for phonological regularity is likely too high, because Stemberger corpus collected using ‘online’ collection methods, prone to perceptual biases.

New Standard: new dataset (SFUSED English) shows speech errors admit many more phonotactic violations, standard is closer to 94.5% phonologically regular.

Chance levels: in some contexts, degree of regularity above what would be expected to be phonologically regular by chance; in other contexts, this is not the case (word-initial errors)

Dell et al. 1993: surprisingly good fit with the SRN generated regularity and regularity found in SFUSED

Word-onset effect: Dell et al. 1993 also predicts more errors word-initially because frequency structure does not have prior probability to predict initial sounds.

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.

What about regularity beyond categorical classification of well-formedness?
Global systems of phonotactics predict if a word is grammatical or ungrammatical. But well-formedness is more gradient in nature, and predictable from combination of specific phonotactic patterns. How might grammar play a role in shaping speech errors at the granular level?

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?

Focus and approach

SFU Speech Error Database: principal dataset, largest speech error collection to date, methodologically robust

Segmental markedness: examine a set of consonant substitution errors in SFUSED English, test for role of cross-linguistic markedness

Syllable structure markedness: examine deletion and addition errors in SFUSED English, test for role of markedness for syllables

Model implications: how do findings fit with current models of phonological encoding?

SFU Speech Error Database (SFUSED)

Current languages

SFUSED English (10,104 errors)

SFUSED Cantonese (2,549 errors)

Goals

- Build a multi-purpose database that supports all types of language production research
- Linguistically sophisticated coding of errors
- Explicit processing assumptions and coding that support probing of psycho-linguistic biases
- Examine how the structure of non-Indo-European languages impacts language production processes

Methods

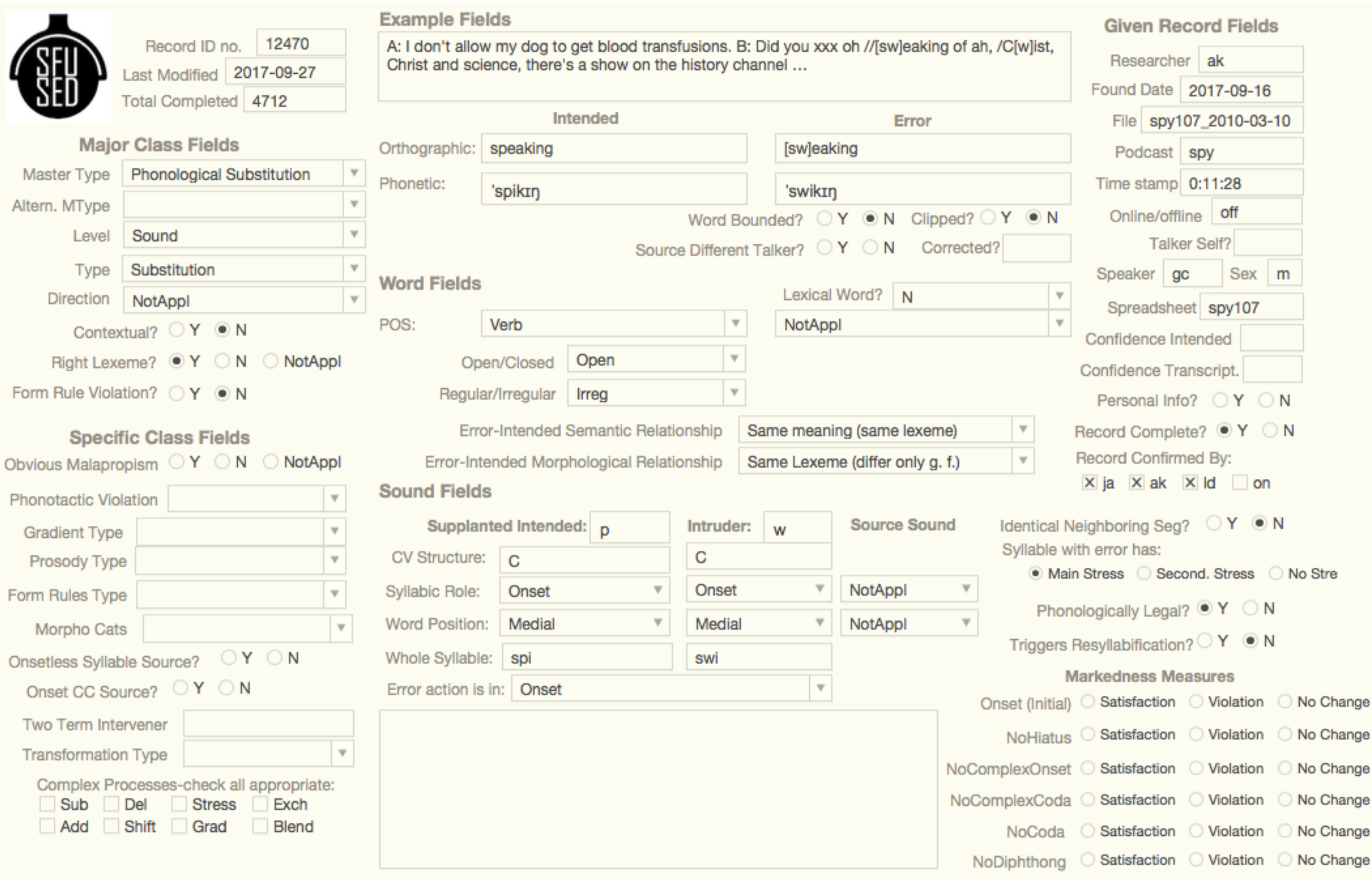
Offline collection from audio recordings (see Chen 1999 on Mandarin speech error database)
- -errors collected from podcasts on different topics
- -podcasts selected for having natural unscripted speech, usually Western Canada and U.S. (Midlands dialect 'Standard American')
- -multiple podcasts (8 currently) 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

SFUSED English interface



Record ID no. 12470
Last Modified 2017-09-27
Total Completed 4712

Major Class Fields
Master Type: Phonological Substitution
Altern. MType:
Level: Sound
Type: Substitution
Direction: NotAppl
Contextual? Y N (N)
Right Lexeme? Y N NotAppl (Y)
Form Rule Violation? Y N (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:	speaking	[sw]eaking
Phonetic:	'spikɪŋ	'swikɪŋ

Word Bounded? Y N (N) Clipped? Y N (N)
Source Different Talker? Y N Corrected?

Word Fields
Lexical Word? N
POS: Verb / NotAppl
Open/Closed: Open
Regular/Irregular: Irreg
Error-Intended Semantic Relationship: Same meaning (same lexeme)
Error-Intended Morphological Relationship: Same Lexeme (differ only g. f.)

Sound Fields

	Supplanted Intended: p	Intruder: w	Source Sound
CV Structure:	C	C	
Syllabic Role:	Onset	Onset	NotAppl
Word Position:	Medial	Medial	NotAppl
Whole Syllable:	spi	swi	

Error action is in: Onset

Given Record Fields
Researcher: ak
Found Date: 2017-09-16
File: spy107_2010-03-10
Podcast: spy
Time stamp: 0:11:28
Online/offline: off
Talker Self?
Speaker: gc Sex: m
Spreadsheet: spy107
Confidence Intended
Confidence Transcript.
Personal Info? Y N
Record Complete? Y N (Y)
Record Confirmed By: [X] ja [X] ak [X] ld [ ] on

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

Advantages

Alderete & Davies 2018, Language and Speech

Reliability and data quality
-audio recording supports data collection separate from verification by another researcher
-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, with allows measures that are not possible with online collection, e.g., collection metrics
-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
-collect more errors that occur in fast speech

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], but 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

Focus: single consonant substitutions

Example: ... in each pixel /**r**un ^row at a time.
(Intended: *one*, *w* → *r*)

- Most common type of error in all speech error corpora in normal speakers, so able to get sufficient data
- Can study segmental markedness by considering differential effect of markedness on feature structure.
- Cross-linguistic markedness makes predictions about marked and unmarked values of features: e.g., voiced marked relative to unvoiced
- Prior (and current) research: consonant pairs that differ in a single feature.

Method: single feature consonant substitutions

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

Sound Intruder

Sound Suppl..	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
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	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				

Test: single feature consonant substitutions

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

Sound Intruder

Sound Suppl..	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
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

Sound Suppl..	p	b	t	d	k	g	f
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					1
n			3	12	1		
ŋ							
l		1			1	3	
r	1			1			
w	1	2	1	2			1
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

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

see Stemberger 2007

Baseline frequencies: estimating relative risk

	Event	General Population
Condition 1	a	b
Condition 2	c	d

mutually exclusive

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

Null hypothesis: RR = 1

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

RR(sz) = 7.07

Baseline frequencies: estimating relative risk

	Event	General Population
Condition 1	a	b
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mutually exclusive

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

Null hypothesis: RR = 1

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

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):

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

Agresti 1996

Example: log(*RR*)= 1.956, 95% confident log(*RR*) =/ 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

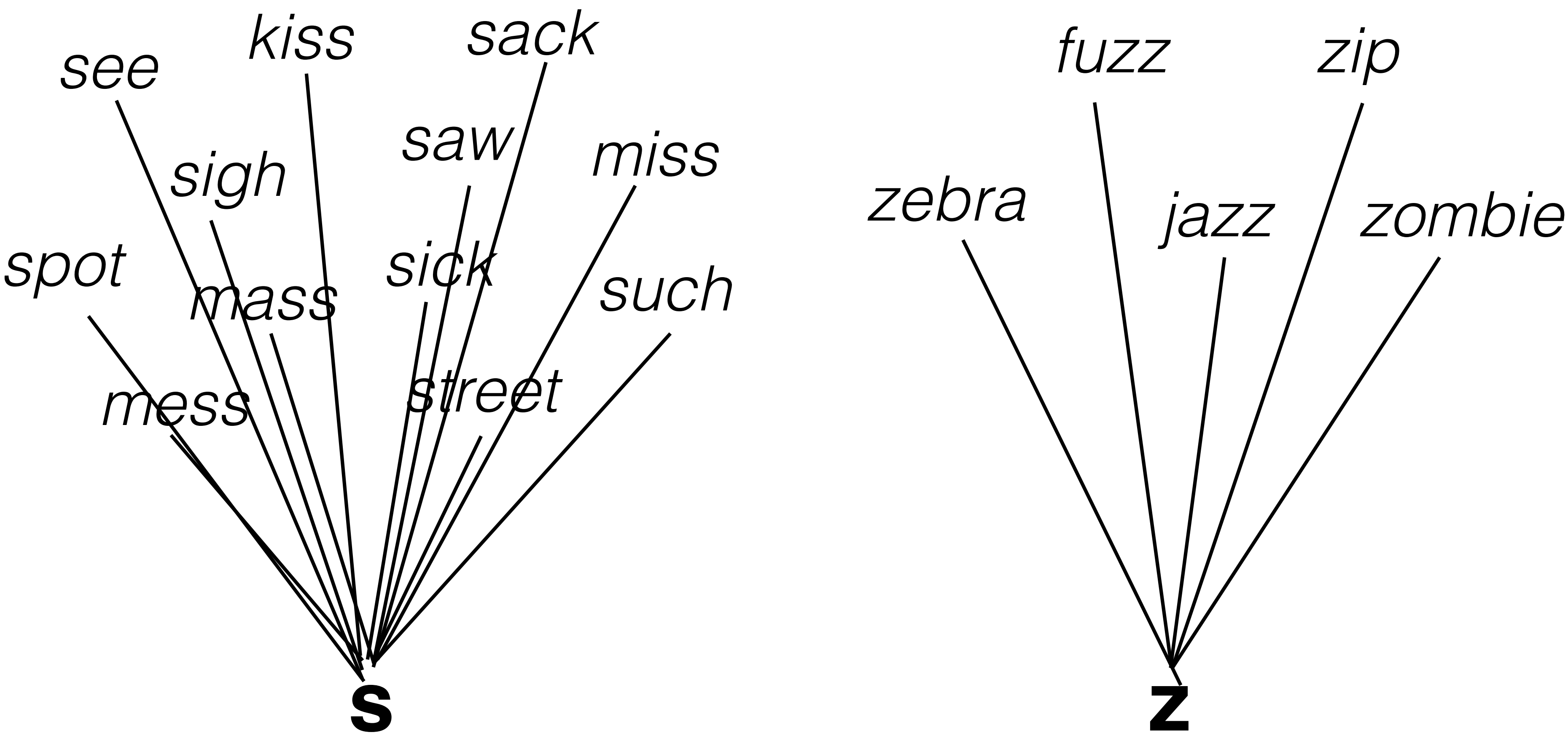
Finding: majority of place-changing substitutions significant, especially those involving coronals.

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.

Frequency bias via interactive spreading



Output bias for frequent segments (Dell 1986 et seq.): frequency effect commonly assumed to result from interactive spreading from words with frequent sounds; activation of neighbouring words feeds into high frequency segment, can tip the scales in favor of frequent segment.

Conclusion: 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.

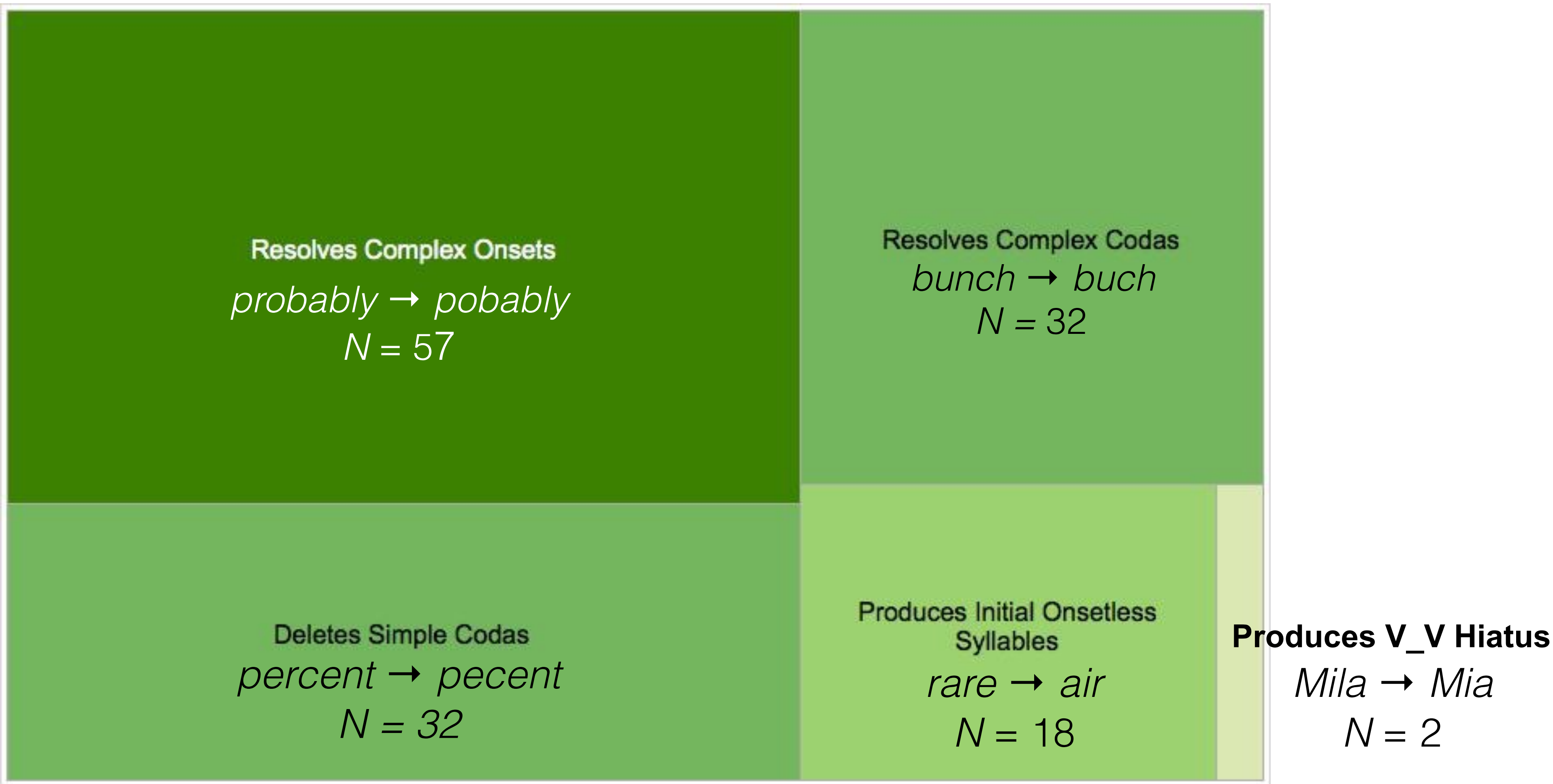
Deletions in SFUSED English

CV Structure	Count	Example
C	157	… everybody $immediately $/s_arts bidding … (*starts,* 344)
CC	6	You're not going to squish it into the /s_een (*screen*, 1662)
V/Onglide	8	Which, it goes back to the /bulling thing. (*bullying, 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

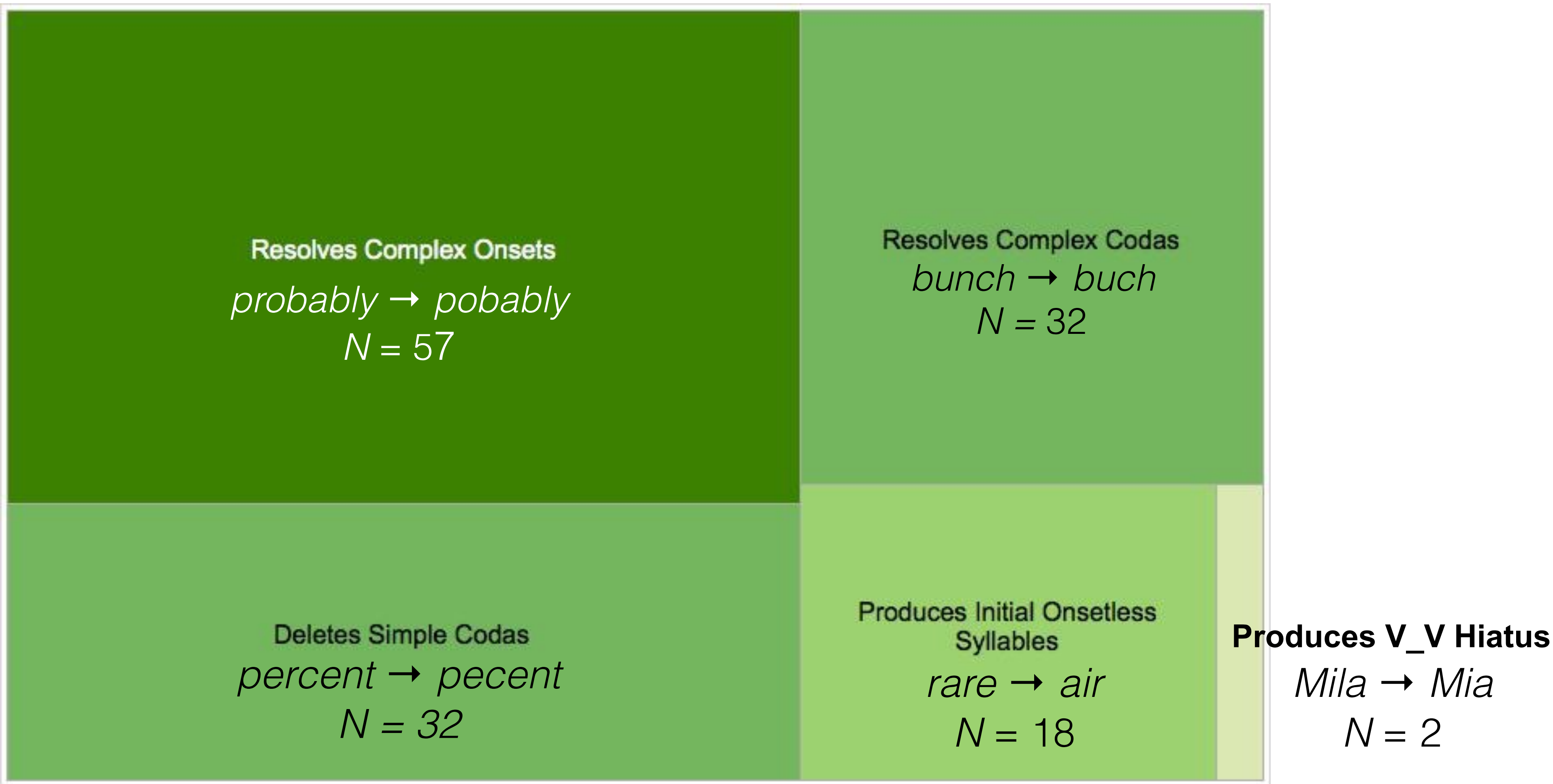
- Vast majority improve on markedness (resolve marked clusters or coda consonants), 121/141 = 86%



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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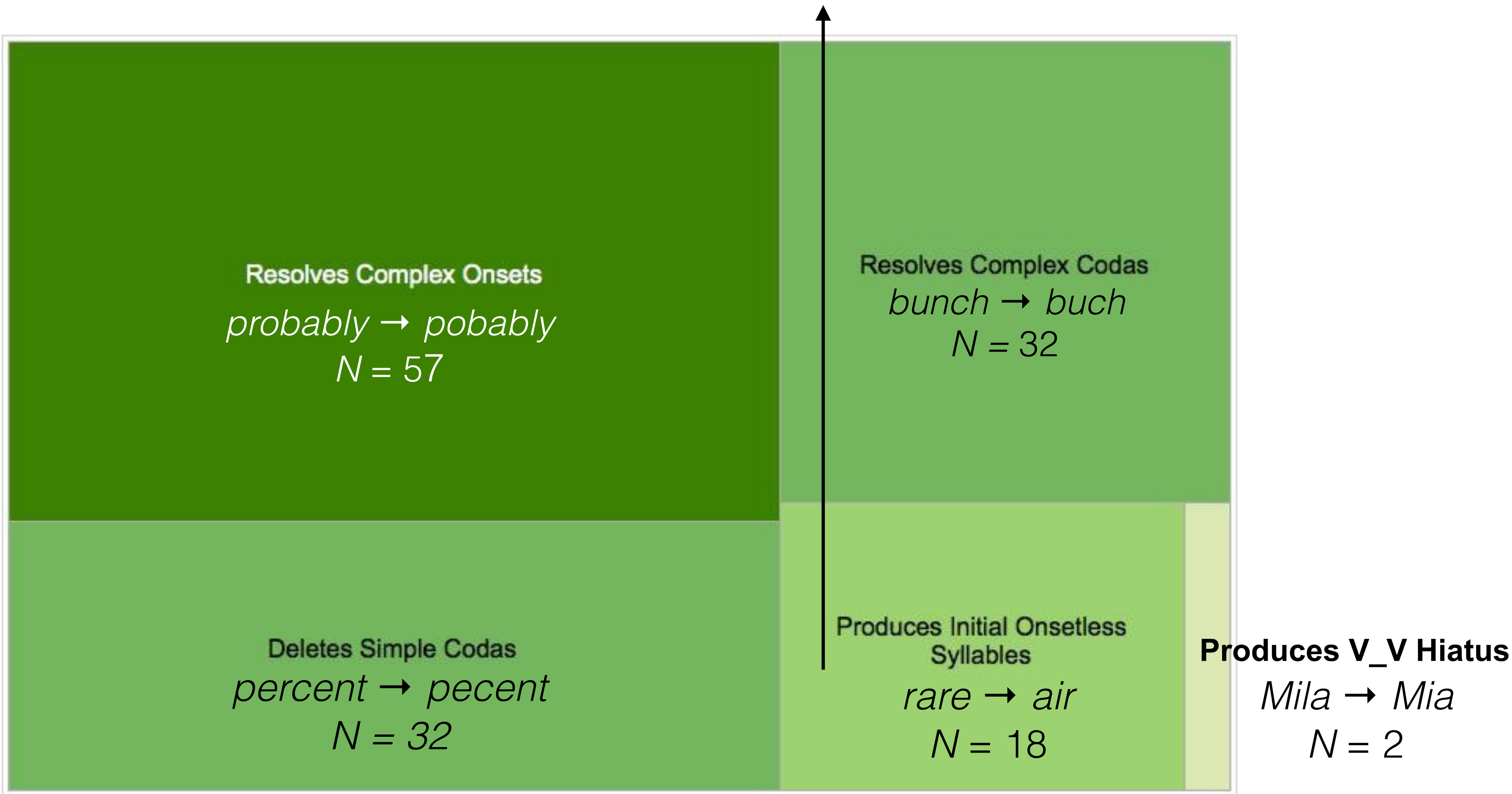
- 17/18 cases have “triggers” that have been shown to induce deletion

$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 that codas (more opportunities 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 are at the heart of phonotactic constraints.

Question

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

Additions in SFUSED English

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

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.

… but sometimes he had ^pretty /b**r**ad ^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)

X(4)2 = 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

X(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! Test for independents of only contextual errors likewise not significant.

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.
- Major caveat: need to relate deletion and addition facts to token frequencies that relativize patterns to error opportunity.

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

More potential markedness effects

Coda condition effects: no clear effect of markedness
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: baselines rather small, hard to tell

- 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%).

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 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 syllables (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)

Explanation of frequency effects

- Stems from interactivity in lexical network: type frequency effects a direct result from links to actual words.
- Frequency from learning: repeated exposure to words re-enforces associations between plan and sequence.

Implications: but we still do need syllables ...

Missing: explicit syllabification algorithm for organizing segments in a frame.

Roles for syllables in phonological encoding:

Syllable position constraint (Boomer and Laver 1968, Fromkin 1971)
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 represent and select syllables in phonological encoding (see O'Seaghda 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 plannng.

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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 from a particular pattern to test specific hypothesis.

Stemberger 1992: actually there is considerable overlap in the patterns of errors collected in naturalistic and experimental settings. So speech errors ‘in the wild’ present valid data patterns worthy of analysis.

Some patterns no suitable for experimental study: % 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 and extended, 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

Alderete & Davies 2018, Language and Speech

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	m̃	ṽ	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