What echo reduplication reveals about phonological similarity

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Outline

- **Background: echo reduplication**
  - Properties of echo reduplication crosslinguistically
- **Experiment: identity and similarity**
  - Similarity avoidance in Bengali echo reduplication
- **Analysis: measurement of similarity**
  - Measurement of consonant similarity in Bengali
- **General discussion**
  - Summary and further questions

Background

Properties of echo reduplication crosslinguistically

Echo reduplication

- **Subtractive reduplication**

  Bengali

  [goli] 'alley'

  [oli goli] 'alleys, etc.'

- **Fixed-segment (S_F) reduplication**

Bengali	*English*
[kaʃi] 'cough'	[kɔf] 'cough'
[kaʃi t_Faʃi] 'cough, etc.'	[kɔf ʃm_Fɔf] 'cough$_{DISMISSIVE}$'

Echo reduplication

- **Subtractive reduplication**

  Bengali

  [goli] ‘alley’

  [oli goli] ‘alleys, etc.’

- **Fixed-segment (S_F) reduplication**

Bengali	*English*
[kaʃi] ‘cough’	[kɔf] ‘cough’
[kaʃi t_Faʃi] ‘cough, etc.’	[kɔf $ʃm_F$ɔf] ‘$cough_{DISMISSIVE}$’

Fixed-segment reduplication

- In FSR, **fixed material** (S_F) associated with a particular construction is found in the R **instead of a copy of B material**
- The fixed material can be:
  - A consonant (most common)
  - A vowel
  - A CV sequence
  - A stem

Fixed-segment reduplication

- **Consonantal S_F**

  Kashmiri (Koul): S_F = [ʋ$_F$][1]

  [nalkɨ] 'faucet'

  [nalkɨ ʋ$_F$alkɨ] 'faucet, etc.'

- **Vocalic S_F**

  A-Hmao (Mortensen 2005): S_F = [í$_F$]

  [andʑʱǎu] 'mouth'

  [ándʑʱí$_F$ ándʑʱǎu] 'cheeks, nose, etc.'

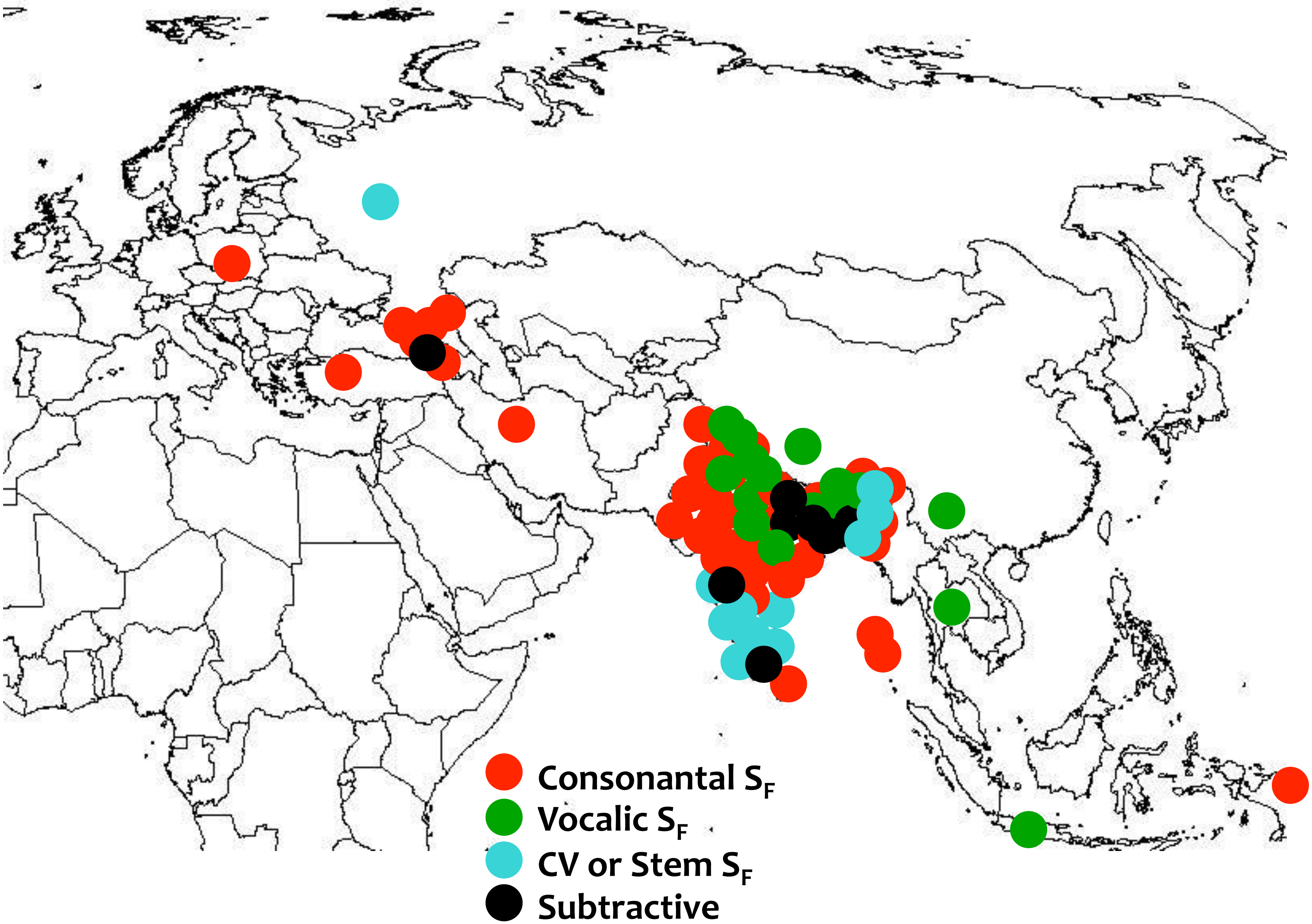
[1] IPA: Koul & Wali (2006)

Fixed-segment reduplication

- **[CV] S_F**
  - *Tamil (Keane 2001)*: S_F = [ki$_F$][1]
  - [ʋeɭːai] 'white'
  - [ʋeɭːai ki$_F$ɭːai] 'white, etc.'
- **Stem S_F**
  - *Russian (Podobryaev 2012)*: S_F = [xuj$_F$] < 'penis'
  - [málʲtɕik] 'boy'
  - [málʲtɕik xuj$_F$álʲtɕik] 'boy$_{\text{DISMISSIVE}}$'

[1] IPA: Keane (2004)

Languages reported to have echo reduplication



Echo reduplication

- Typically conveys **generalization**
  - 'X, etc.'
  - 'X and associated things'
  - 'X in general'
  - 'superset of which X is a member'
- In some lgs, it conveys a **dismissive** tone
  - Russian: [málʲtɕik xuj$_F$álʲtɕik] 'boy$_{\text{DISMISSIVE}}$'
  - English: [dɑktɚ ʃm$_F$ɑktɚ] 'doctor$_{\text{DISMISSIVE}}$'

Obligatory BR-nonidentity

- Most salient **phonological property** of echo reduplication is **obligatory BR-nonidentity**
  - ≥1 phonological difference between B and R
- **Presence of S_F** in R usually enough to **generate BR-nonidentity**

  Kashmiri (Koul)

  [nalkɨ] ⇨ [nalkɨ $ʋ_F$alkɨ] 'faucet, etc.'
- **But what if it isn't?**

  Kashmiri (Koul)

  [ʋaːzɨ] ⇨ ??[ʋaːzɨ $ʋ_F$aːzɨ]?? 'cook, etc.'

Obligatory BR-nonidentity

- Lgs avoid such cases of potential BR-identity by either:
  - Using a designated **backup S_F**
  - Choosing from among the **other S_F options**
  - **Modifying the B** instead of in R
  - Deeming the phrase **ineffable**

Obligatory BR-nonidentity

- Many lgs have a **backup S_F**, kept on reserve for cases of BR-identity

Abkhaz (Vaux 1996): S_F = [m_F] (⇨ [$tʃ_F$])

/gáʤakʼ/ ⇨ [gáʤakʼ m_Fáʤakʼ] 'fool, etc.'

/tʃəkʼ/ ⇨ [tʃəkʼ m_Fəkʼ] 'horse, etc.'

/maát/ ⇨ *[maát $m_F$aát-] ⇨ [maát $tʃ_F$aát-] 'money, etc.'

Obligatory BR-nonidentity

- Other lgs have **multiple S_F options**, always choosing one that avoids BR-identity

Farsi (Ghaniabadi et al. 2006): S_F = [m_F] ~ [p_F]

/tærɒzu/ ⇨ [tærɒzu $m_F$ærɒzu] ~ [tærɒzu $p_F$ærɒzu] 'scale, etc.'

/zæɾif/ ⇨ [zæɾif m_Fæɾif] ~ [zæɾif p_Fæɾif] 'slender, etc.'

/mive/ ⇨ *[mive $m_F$ive] ~ [mive $p_F$ive] 'fruit, etc.'

/piɾ/ ⇨ [piɾ m_Fiɾ] ~ *[piɾ p_Fiɾ] 'old, etc.'

Obligatory BR-nonidentity

- Some lgs even go so far as to **modify B** when R with S_F would be identical to it

Classical Tibetan (Beyer 1992): S_F = [a_F] (⇨ B [o_F])

/ndźog/ ⇨ [ndźa_Fg ndźog] 'jumbled up'

/glen/ ⇨ [gla_Fn glen] 'very stupid'

/ŋan/ ⇨ *[ŋa_Fn ŋan] ⇨ [ŋan ŋo_Fn] 'miserable'

Obligatory BR-nonidentity

- Lastly, some lgs simply deem cases of echo BR-identity to be **ineffable**

  Turkish (Swift 1963): S_F = [m_F]

  /haʊłu/[1] ⇨ [haʊłu m_Faʊłu] 'towel, etc.'

  /citap/ ⇨ [citap $m_F$itap] 'book, etc.'

  /masa/ ⇨ *[masa $m_F$asa] 'table, etc.' ⇨ NO OUTPUT

[1] IPA: Zimmer & Orgun (1999)

Obligatory BR-nonidentity

- Crosslinguistically, **BR-identity in echo reduplication is ungrammatical**
- Trivedi's (1990) survey of FSR in ~100 Indian lgs found **obligatory BR-nonidentity in every lg**
- Seems clear... but I still have one question: **How sensitive is BR-nonidentity?**

Survey

- For example, let's consider English

  English: S_F = [ʃm_F]

  /dɑktɚ/ 'doctor' ⇨ [dɑktɚ ʃm_Fɑktɚ]
  'doctor$_{DISMISSIVE}$'

  /skul/ 'school' ⇨ ?

  /smuð/ 'smooth' ⇨ ?

  /ʃmuz/ 'schmooze' ⇨ ?

  /ʃmalts/ 'schmaltz' ⇨ ?

  /ʃnɑz/ 'schnozz' ⇨ ?

Curiosity from literature

- In Nevins & Vaux (2003), 95% of speakers avoided [ʃm_F] in R of [ʃmuz] 'schmooze'
  - *[ʃmuz ʃ$m_F$uz] due to BR-nonidentity
  - Fits with cross-linguistic pattern
- Interestingly, 30% of speakers also avoided [ʃm_F] in R of [ʃnɑz] 'schnozz'
  - *[ʃnɑz ʃm_Fɑz]…but why?
  - BR-nonidentity generalized to **BR-dissimilarity**

Curiosity from literature

- What does this mean?
  - Explanation 1:
    - **30%** of speakers have a **BR-dissimilarity constraint**
    - **65%** have a **BR-nonidentity constraint**
  - Explanation 2:
    - **95%** have a **BR-dissimilarity constraint**, of which:
    - **30%** felt [ʃn] and [ʃm_F] are **too similar**
    - **65%** felt [ʃn] and [ʃm_F] are **sufficiently dissimilar**

Is this English-specific?

- Or maybe we're assuming too much from this one data point…
- Is English echo reduplication a weird case?
  - **Not as common** as in other languages
  - [ʃm]-reduplication is somewhat **humorous**
  - [ʃm] and [ʃn] are **highly marked** in English
- Maybe this is just a weird fact of English…

Motivation for an experiment

- To find out if echo reduplication involves BR-nonidentity or BR-dissimilarity…
- We need to study a lg in which:
  - Echo reduplication is a **fully productive, linguistic feature**
  - **S_F isn't such a marked sound**

Experiment

What echo reduplication reveals about phonological similarity

Experiment: question

- Question: **how sensitive is BR-assessment**?
  - **Only sensitive** to exact **BR-identity**
    - Any BR-difference should suffice
  - **Also sensitive** to relative **BR-similarity**
    - Some BR-differences aren't dissimilar enough

Experiment: language

- Test case: **Bengali** echo reduplication
  - Default S_F: $[t_F]$
  - Backup S_F: $[m_F]$ $[f_F]$ $[p_F]$ $[u_F]$…
- Why Bengali?
  - Echo reduplication is a very **common feature**
  - Default $[t_F]$ is a relatively **unmarked sound**
  - Many **contrastive but phonetically similar** phonemes: [tʰ] [d] [ʈ] [ʈʰ] [tɕ]…

Experiment: basic idea

- So we know that a word like [bʱidʑːa] 'having gotten wet' ⇨ [bʱidʑːa $t_F$idʑːa]…
- …and that a word like [tika] 'vaccine' ⇨ *[tika $t_F$ika] ⇨ [tika $m_F$ika]…
- …but what about a word like [tʰajʃːa] 'having stuffed'?
  - Will it act like [bʱidʑːa]? [tʰajʃːa $t_F$ajʃːa]
  - Or like [tika]? *[tʰajʃːa $t_F$ajʃːa] ⇨ [tʰajʃːa $m_F$ajʃːa]

Experiment: subjects and procedure

- **Production experiment** with native speaker adults (n=30)
- Heard audio recording of a word
  - Order was randomized for each speaker
- Asked to **produce echo reduplicated form**
  - Did speaker use default [t_F]?
  - Or did he/she use a backup S_F?

Experiment: stimuli

- 60 test words fell under **three conditions**:
  - **Identity**: **[t]-initial** words
  - **Similarity**: words with **[t]-like initials**
    - Coronal obstruents: [t^h] [d] [t̪] [t̪^{h}] [tɕ] [s]~[tɕ^h] [ʃ]
  - **Control**: words with **non-[t]-like initials**
    - Coronal sonorants: [n] [l] [ɹ]
    - Non-coronals: [k] [h] [p] [f] [b$^{\text{ɦ}}$] [m]

Experiment: stimuli

Bengali consonant inventory (Khan 2010)

Identity **Similarity** **Control**

	Labial	Dental	Alveolar	Post-Alv	Velar/Glot
Stop	p b bʱ	t̪ t̪ʰ d̪ d̪ʱ	t tʰ d dʱ		k kʰ g gʱ
Affricate			tɕ tɕʰ dʑ dʑʱ		
Fricative	f	s		ʃ	h
Liquid		l ɹ			
Nasal	m	n			(ŋ)

Experiment: stimuli

Bengali consonant inventory (Khan 2010)

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Fricative	f	s		ʃ	h
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Nasal	m	n			(ŋ)

Experiment: hypothesis 1

- Hypothesis 1: BR-assessment is **only identity-sensitive**
  - **Identity** words will **never** use [t_F]
  - **Similarity** words will behave like **Control** words
  - **Control** words will **always** use [t_F]
- **Identity** ≠ **Similarity** = **Control**

  *[$t \ldots t_F$] ≠ [$t^h \ldots t_F$] = [$b^ɦ \ldots t_F$]

Experiment: hypothesis 2

- Hypothesis 2: BR-assessment is **sensitive to phonetic similarity** across phonemes
  - **Identity** words will **never** use [t_F]
  - **Similarity** words will behave like **Identity** words
  - **Control** words will **always** use [t_F]
- **Identity** = **Similarity** ≠ **Control**

  *[$t…t_F$] ≠ *[$t^h…t_F$] = [$b^ɦ…t_F$]

Experiment: hypothesis 3

- Hypothesis 3: BR-assessment is **strongest in cases of identity**, but also **sensitive to phonetic similarity** across phonemes
  - **Identity** words will **never** use $[t_F]$
  - **Similarity** words will **sometimes** use $[t_F]$
  - **Control** words will **always** use $[t_F]$
- **Identity** ≠ **Similarity** ≠ **Control**

  $*[t...t_F]$ ≠ $?[t^h...t_F]$ = $[b^ɦ...t_F]$

Results

- The results were surprising:
- While Hypothesis 3 came closest, none of the hypotheses was borne out!
  - **Identity** ≠ **Similarity** = **Control**
  - **Identity** = **Similarity** ≠ **Control**
  - **Identity** ≠ **Similarity** ≠ **Control**
- Lots of variation across speakers and words
- But one thing was clear:

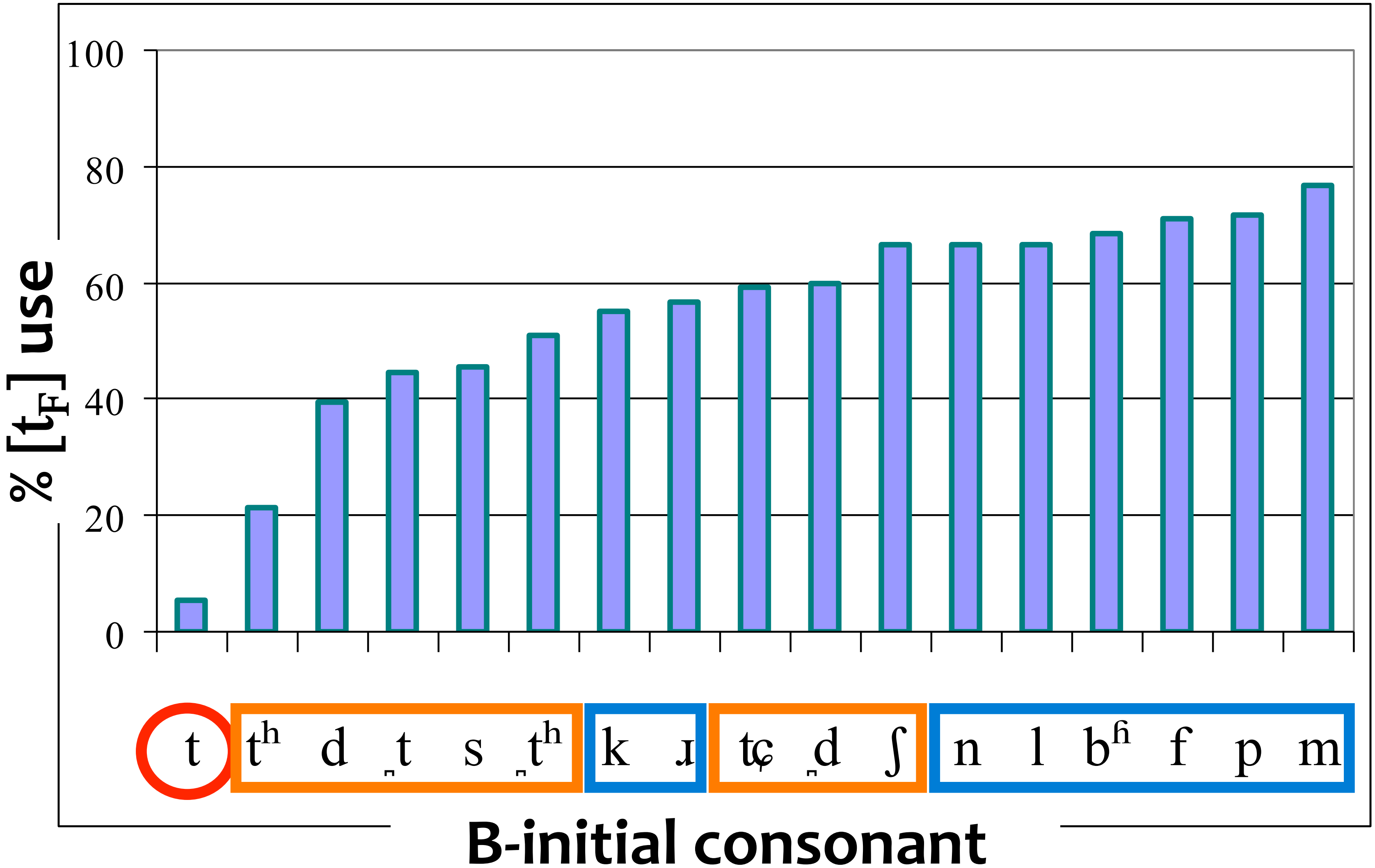
Results: general pattern

- BR-assessment is **sensitive to similarity**
- But, this sensitivity is **gradient**
- The **more similar** a consonant is to [t], the **less likely** it is to be replaced by $[t_F]$

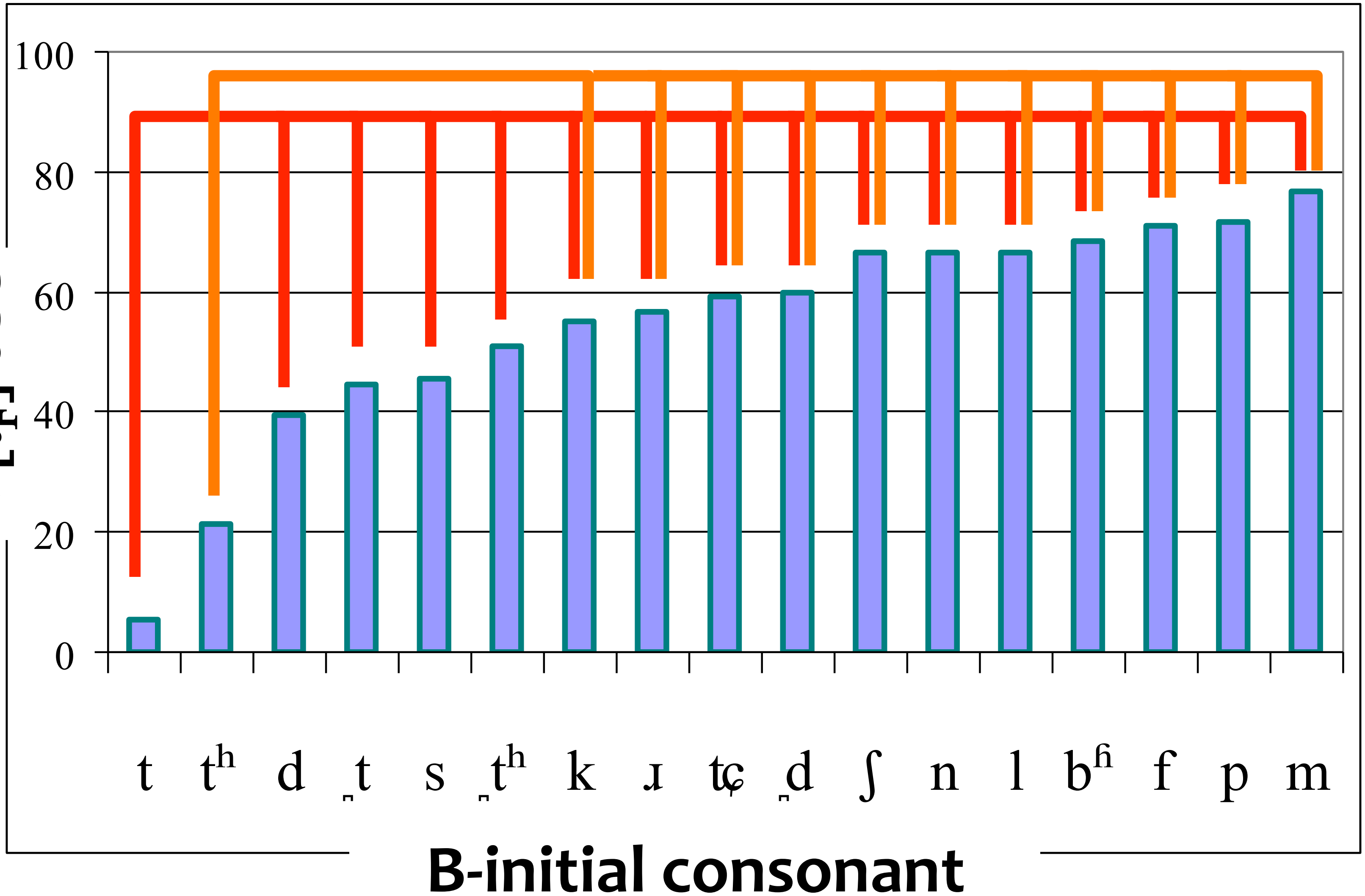
[t] $[t^h]$ [d] [t̪] … $[b^{ɦ}]$ [f] [p] [m]

Least likely to use $[t_F]$ ⟷ **Most likely to use $[t_F]$**

Results: grouped by initial consonant



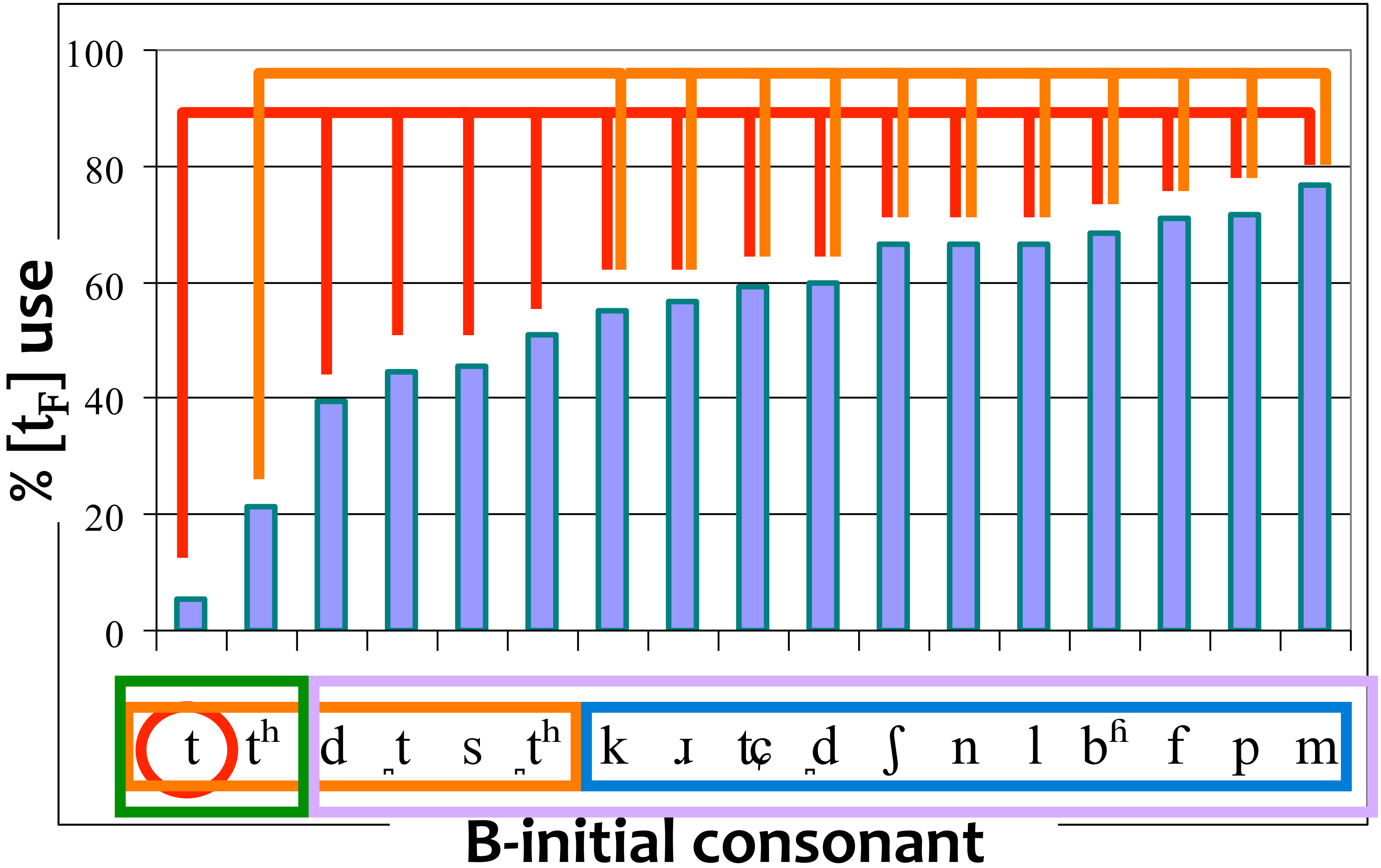
Results: significant differences



Results: design issues?

- Was there a problem with the setup?
- Should the similarity condition and control condition be redefined?

Results: clustering



Results: gradient similarity

- No, there is **no clustering of consonants** into two or three categories
- Furthermore, **heavy overlap** across the clusters that are found
- Clearly, **similarity is gradient**

New question

- It' s clear some **measurement of similarity** is needed in Bengali echo reduplication
- So then how do speakers **calculate the similarity** of a pair of sounds?

Analysis

Measurement of consonant similarity in Bengali

Models of similarity

- Phonological similarity has been **measured in different ways** in the literature
- Most metrics incorporate:
  - **Shared natural classes**
  - Correlation with **lexical cooccurrence**
- Can either of these model Bengali speakers' notions of similarity?

Shared natural classes: introduction

- One method[1] of calculating similarity is by comparing the **number of natural classes** of which two sounds are members
  - [t] and [n] share [+cor] but not [voi] or [son]
  - [t] and [p] share [-son] and [-voi] but not [cor]
  - [t] and [v] share [-son] but not [voi] or [cor]
- The **more similar** two consonants are, the **more natural classes** they will share

[1] Frisch, Pierrehumbert, & Broe (2004)

Shared natural classes: introduction

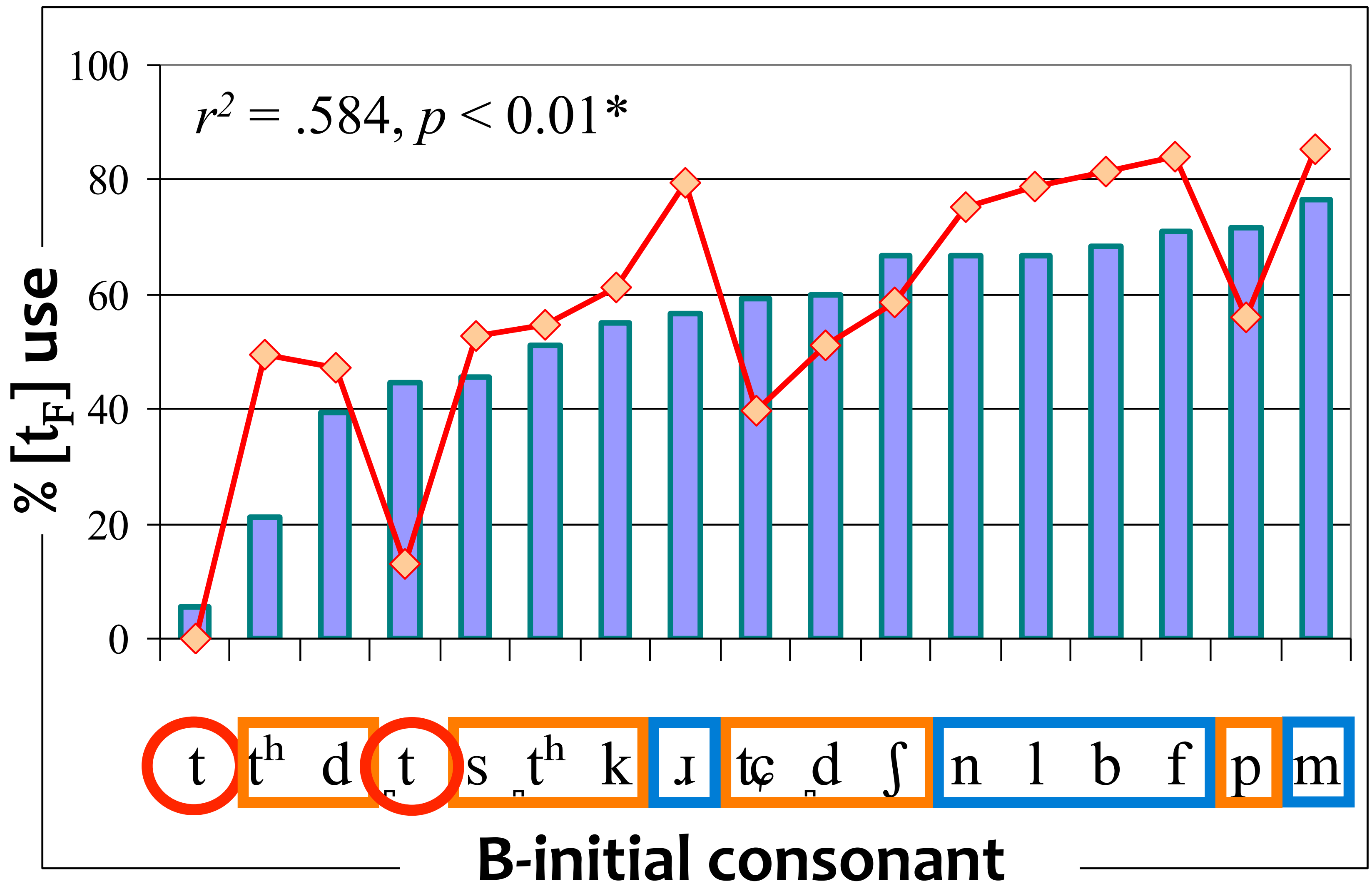
- This measure takes **lg-specific details** into account, due to different inventories
  - Aspiration is contrastive in Bengali, not English
  - [b] and [d] share [-asp] in Bengali, not English
- Can we apply the SNC metric to the echo reduplication results in Bengali?

Shared natural classes metric

- In a model of similarity based on **shared natural classes**…
- …the similarity of a consonant C_1 to [t] can be calculated as follows

$$sim(C_1, t) = \frac{\text{\# shared natural classes}}{\text{\# shared natural classes} + \text{\# non-shared natural classes}}$$

SNC predictions (line) vs. observed (bars)



SNC metric: discussion

- SNC metric does fairly well ($r^2 = .584$)
- However, where it doesn't do well is the most crucial area: **coronal obstruents**
  - How can we adjust this model to reflect that [t] is more similar to [tʰ] than to [t̪]?
  - Is there a way to designate **certain features as being more important** than others?

Feature weighting

- What if we incorporated **different weights for different features**, reflecting their importance in similarity measurement?
  - Weighting [distributed] over [aspiration] will make ([t], [t̪]) more different than ([t], [tʰ])
- What would such a metric look like?

Similarity equation

- In a model of similarity based on **shared weighted features**…
- …the similarity of a consonant C_1 to [t] can be calculated as follows

$$sim(C_1, t) = \exp\left(-\sum_{i=1}^{\#features} w_i(1-\delta_i(C_1, t))\right)$$

w_i = weight of the feature f_i

$\delta_i(C_1, t)$ = 1 (feature value shared) or 0 (not shared)

Where do these weights come from?

- So how do we determine w_i?
- Maybe **lexical statistics**?

Lexical cooccurrence: introduction

- Many studies[1] claim that the **lexicon of a lg reflects notions of similarity**
- The **more similar** two consonants are, the **less often they will cooccur** within roots
  - Words like [fʌʤ] and [pɛg] are common
  - Words like *[ʃʌʤ] and *[pɛb] are underattested
- Can we apply this to the Bengali data?

[1] McCarthy (1994) and many others

Lexical cooccurrence: metric

- We can turn this around:
- Sound pairs that are **underattested** within roots must be perceived as **more similar**
- Thus, **lexical statistics** can be converted into a **similarity score**

Lexical cooccurrence: metric

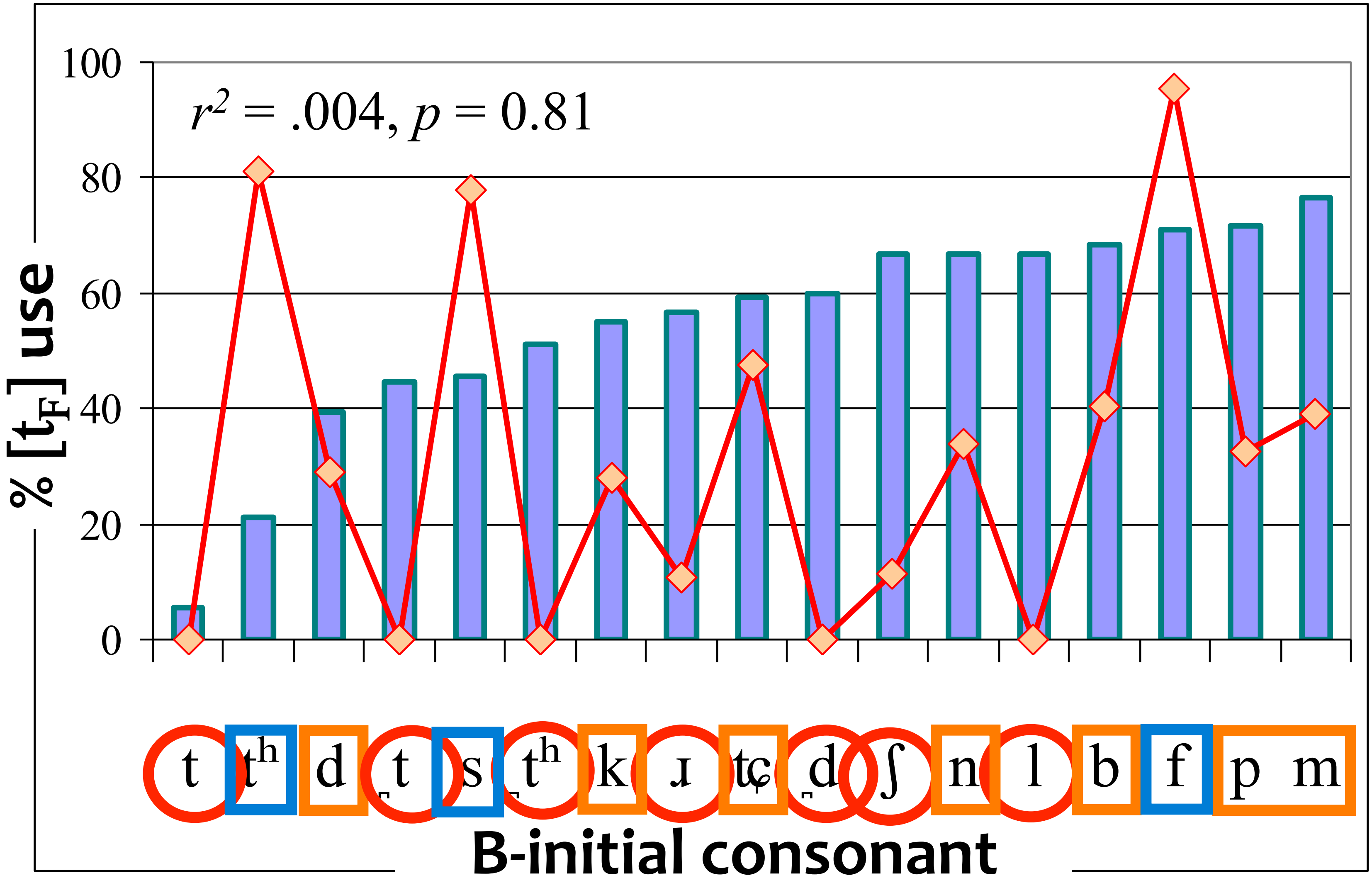
- In a model of similarity based on **lexical cooccurrence statistics**…
- …the **similarity of a consonant C_1 to [t]** can be calculated as follows

$$sim(C_1, t) = \frac{\dfrac{obs[C_1VCV]}{\text{all roots}} \times \dfrac{obs[CVtV]}{\text{all roots}}}{\dfrac{obs[C_1VtV]}{\text{all roots}}}$$

Lexical cooccurrence: data

- Used a **Bengali corpus** (Mallik et al. 1998) to examine roots where **[t] cooccurs with a consonant (C)**
- Plugged in the numbers to get a **similarity score** for each C paired with [t]
- Compared those similarity scores to the $[t_F]$-use patterns from my experiment

Lexical cooccurrence: results



Lexical cooccurrence: discussion

- The lexical cooccurrence model of similarity **fails to predict** the observed $[t_F]$-avoidance patterns ($r^2 = .004$)
- It appears that the **Bengali lexicon does not reflect the notions of similarity** at work in the productive grammar
- Thus, we cannot use lexical statistics to adjust our natural classes model

Can weights be used at all?

- So how else can we determine what the weights should be?
- Can weights help us at all?
- Let's see if we can use the **variation in the data itself** to determine the weights…
- …and then worry about **where the weights are coming from** at some other time

Probability equation

- Probability of $[t_F]$-use in the echo R of a C_1-initial B can be calculated as follows

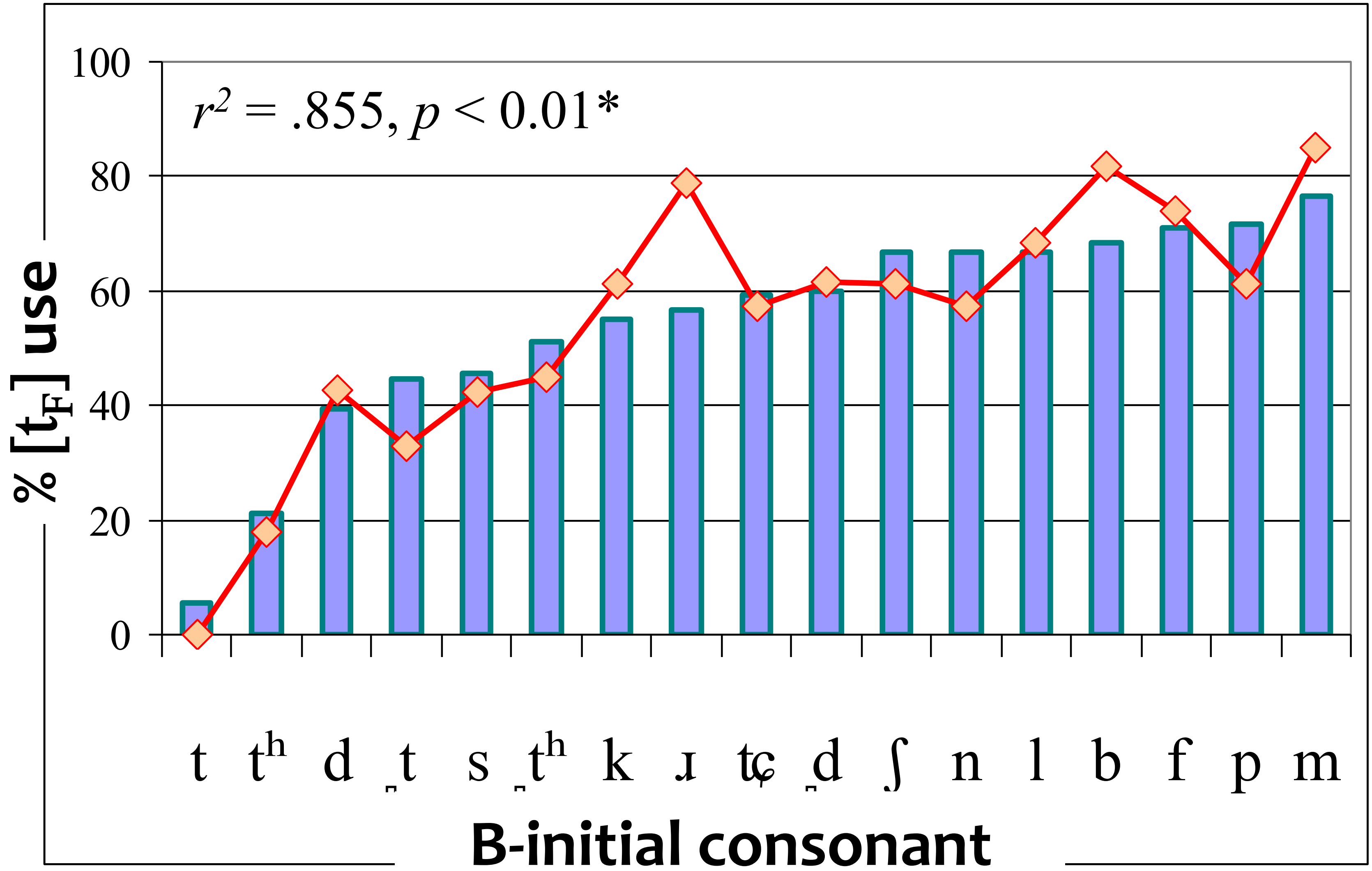
$$P = ((m!) \div (n!(m-n)!)\ (1-sim(C_1, t))^n\ (sim(C_1, t))^{m-n}$$

Probability that C_1-initial base will be reduplicated with $[t_F]$ *n* times out of a total of *m* trials

m = number of reduplications for C_1-initial word

n = number of reduplications with $[t_F]$ for C_1-initial word

Feature weighting (line) vs. observed (bars)



Feature weighting: discussion

- A model of similarity that takes **feature weights** into account can closely model the data ($r^2 = .855$)
- Of course, in our case, we used the data to determine the weights

I'll talk about some ideas of where this could independently come from in a minute…

General discussion

Summary and further questions

Summary

- Crosslinguistically, B and R in echo reduplication must be sufficiently different
- In most lgs/studies, this is taken to be a **categorical nonidentity constraint**
  - "B and R must be **non-identical**"
  - Assumes that sound pairs can be categorized as either "identical" or "non-identical"
  - Even one BR feature mismatch should suffice

Summary

- Data from English show that the constraint is actually **sensitive to phonetic similarity**, not just identity
  - "B and R must be **dissimilar**"
  - Still assumes categorical grouping of sound pairs: "identical", "similar", and "dissimilar"

Summary

- Experimental data from Bengali confirm that **BR-assessment is sensitive to phonetic similarity**, not just identity
- The data also show that in fact, **similarity is gradient**
  - **Cannot group sound pairs categorically** as "identical", "similar", and "dissimilar"

Summary

- Speakers compute the **similarity score of two sounds** using a metric that takes different **feature weights** into account
- We can derive the feature weights from the pattern itself…
- …but where do speakers actually get these weights from independently?

Summary

- Weights do not come from the lexicon
  - Similarity in echo reduplication is ***not* correlated with lexical patterns**

Further questions

- Alternatively, feature weights could come **directly from the phoneme inventory**
  - The features that are weighted heavily are:
    - [voice]: 0.554
    - [distributed] (=dental vs. alveolar): 0.400
    - [strident]: 0.249
    - [spread glottis] (=aspiration): 0.198
  - All others are weighted 0.1

Further questions

- These are also the features that help make the Bengali phoneme inventory so **coronal-heavy**
- In fact, of all features, these make the **most phonemic contrasts on their own** in the lg
- Thus, there might be **independent evidence of their "weight"**
- Need to do more work to confirm this

Further questions

- How much of this is **language-specific**?
  - Coronal-heavy inventory?
- How much is **universal**?
  - Feature inventory?
- Future studies on **similarity-sensitive phenomena in other lgs** will take on these questions to build this model of similarity

Thank you!

Special thanks to Kie Ross Zuraw, Colin Wilson, Bruce Hayes, Farida Amin Khan, the 30 participants in my experiment, and everyone in attendance here.