

# Creating and working with endangered language corpora

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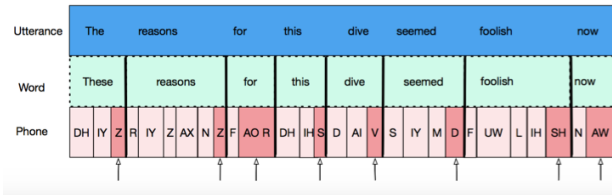
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# Meta-outline for the lectures

- 1 The analysis of complex tonal systems: motivations, methods, and analysis
- 2 Speech perception in the field
- 3 **Creating and working with endangered language corpora**
- 4 Higher-level prosody and tone

# The problem: fieldwork → spoken language corpus

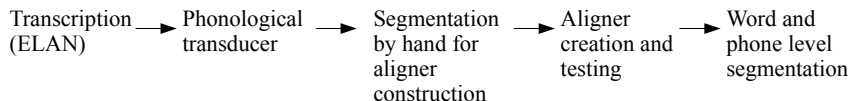


# The documentation framework

The typical framework for language documentation involves audio/video recording, linguistic description, and transcription.

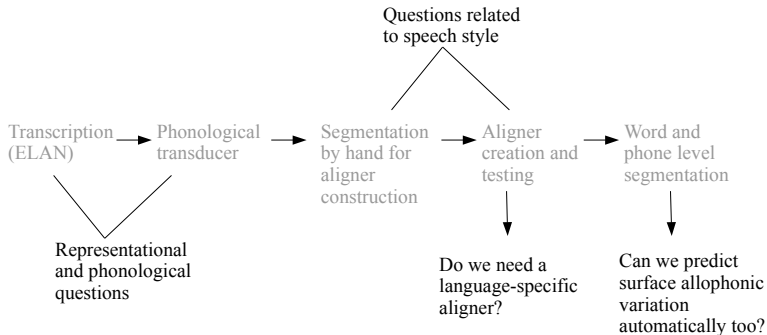
A documentation project where a team has transcribed and archived 30-40 hours of recordings is considered “complete.”

Yet in terms of speech corpus development, this reflects an early stage.



## Issues which arise along the way

Speech corpus development from endangered language documentation is complex and time-consuming, but research questions in speech production arise naturally in the process.



# Roadmap

Issues which arise in aligner development:

1. Can we use an existing forced aligner to align the corpus? Which one? (DiCanio et al., 2013)
2. What goes into creating a new aligner?

Issues which arise comparing transducer and aligner output to the speech signal:

3. Why is there so much variation in obstruent production?
4. Can we predict this in some way?

End goal: A multi-layered speech corpus that is prosodically-annotated.

# The Yoloxóchitl Mixtec corpus

- Otomanguan, spoken in Guerrero, Mexico (~2500 speakers).
- 120 hours of transcribed personal narratives, stories, and folklore; 30 speakers (Amith & Castillo García, 2009 – present).
- Phonological/phonetic fieldwork (Castillo García (2007), DiCano et al. (2014), DiCano et al. (2018a), DiCano et al. (2018b), Palancar et al. (2016)).



# Segmental phonology

DiCanio et al. (2018b)

	Bilabial	Dental	Alveolar	Post-alveolar	Palatal	Velar	Labialized Velar
Plosive	p	t <sub>n</sub>				k	k <sup>w</sup>
Nasal	m		n				
Post-stopped nasal	m <sup>b</sup>		n <sup>d</sup>			ŋ <sup>g</sup>	
Tap			r				
Affricate				tʃ			
Fricative	β	s <sub>n</sub>		ʃ			
Approximant			l		j		

	Front	Central	Back
Close	i, ĩ		u, ũ
Close-mid	e, ẽ		o, õ
Open		a, ã	



- All roots are minimally composed of bimoraic feet, consisting of either monosyllabic stems with long vowels (CVV) or disyllabic stems with shorter vowels (CVCV) (Castillo García, 2007). No codas.
- Glottalization occurs between vowels or before sonorants, e.g. /yaʔ<sup>4</sup>a<sup>1</sup>/ ‘grey’, /saʔ<sup>3</sup>ma<sup>4</sup>/ ‘cloth to wrap tortillas’
- Final syllables are prominent.
  - Nasal vowels only occur on stem-final syllables.
  - 9 tones on stem-final syllables, but only 5 on non-final syllables.
  - Restricted vowel contrasts on non-final syllables.
  - Final syllable lengthening

Morphology	‘to break’ (tr)	‘hang’ (tr)	‘to change’ (intr)	‘to peel’ (tr)	‘to get wet’
Stem	ta <sup>3</sup> ʔβi <sup>4</sup>	tʃi <sup>3</sup> kũ <sup>2</sup>	na <sup>1</sup> ma <sup>3</sup>	kwi <sup>1</sup> i <sup>4</sup>	tʃi <sup>3</sup> i <sup>3</sup>
NEG	ta <sup>14</sup> ʔβi <sup>4</sup>	tʃi <sup>14</sup> kũ <sup>2</sup>	na <sup>14</sup> ma <sup>3</sup>	kwi <sup>14</sup> i <sup>14</sup>	tʃi <sup>14</sup> i <sup>3</sup>
COMP	ta <sup>13</sup> ʔβi <sup>4</sup>	tʃi <sup>13</sup> kũ <sup>2</sup>	na <sup>13</sup> ma <sup>3</sup>	kwi <sup>1</sup> i <sup>4</sup>	tʃi <sup>13</sup> i <sup>3</sup>
INCOMP	ta <sup>4</sup> ʔβi <sup>4</sup>	tʃi <sup>4</sup> kũ <sup>2</sup>	na <sup>4</sup> ma <sup>13</sup>	kwi <sup>4</sup> i <sup>14</sup>	tʃi <sup>4</sup> i <sup>4</sup>
IS	ta <sup>3</sup> ʔβi <sup>42</sup>	tʃi <sup>3</sup> kũ <sup>2</sup> =ju <sup>1</sup>	na <sup>1</sup> ma <sup>32</sup>	kwi <sup>1</sup> i <sup>42</sup>	tʃi <sup>3</sup> i <sup>2</sup>

# Disyllabic words in YM

Twenty-six tonal melodies, including one minimal enneadecuplet (19 words).

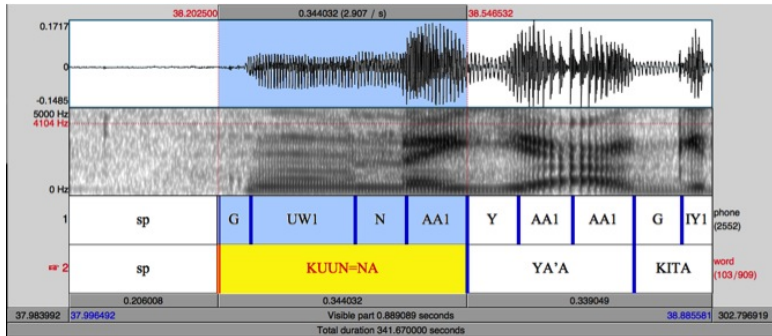
Melody	Word	Gloss	Melody	Word	Gloss
1.1	ta <sup>1</sup> ma <sup>1</sup>	<i>without appetite</i>	4.13	na <sup>4</sup> ma <sup>13</sup>	<i>is changing</i>
1.3	na <sup>1</sup> ma <sup>3</sup>	<i>to change (intr)</i>	4.14	nda <sup>4</sup> ta <sup>14</sup>	<i>is splitting up</i>
1.4	na <sup>1</sup> ma <sup>4</sup>	<i>soap</i>	4.24	ya <sup>4</sup> ma <sup>24</sup>	<i>Amuzgo person</i>
1.32	na <sup>1</sup> ma <sup>32</sup>	<i>I will change myself</i>	4.42	na <sup>4</sup> ma <sup>42</sup>	<i>I often pile rocks</i>
1.42	na <sup>1</sup> ma <sup>42</sup>	<i>my soap</i>	13.2	hi <sup>13</sup> ni <sup>2</sup>	<i>has seen</i>
3.2	na <sup>3</sup> ma <sup>2</sup>	<i>wall</i>	13.3	na <sup>13</sup> na <sup>3</sup>	<i>has photographed oneself</i>
3.3	na <sup>3</sup> ma <sup>3</sup>	<i>to change (tr)</i>	13.4	na <sup>13</sup> ma <sup>4</sup>	<i>has piled rocks</i>
3.4	na <sup>3</sup> ma <sup>4</sup>	<i>sprout</i>	14.2	na <sup>14</sup> ma <sup>2</sup>	<i>I will not change</i>
3.42	na <sup>3</sup> ma <sup>42</sup>	<i>I will pile rocks</i>	14.3	na <sup>14</sup> ma <sup>3</sup>	<i>to not change</i>
4.1	ka <sup>4</sup> nda <sup>1</sup>	<i>is moving (intr)</i>	14.4	na <sup>14</sup> ma <sup>4</sup>	<i>to not pile rocks</i>
4.2	na <sup>4</sup> ma <sup>2</sup>	<i>I am changing</i>	14.13	na <sup>14</sup> ma <sup>13</sup>	<i>to not change oneself</i>
4.3	na <sup>4</sup> ma <sup>3</sup>	<i>it is changing</i>	14.14	nda <sup>14</sup> ta <sup>14</sup>	<i>to not split up</i>
4.4	na <sup>4</sup> ma <sup>4</sup>	<i>is piling rocks</i>	14.42	na <sup>14</sup> ma <sup>42</sup>	<i>I will not pile rocks</i>

(Why a phonetician working on tone/prosody is interested in YM.)

# Forced alignment

A byproduct of an acoustic model in automatic speech recognition (ASR) system, where an acoustic model is a statistical pattern classifier.

(Adda-Decker and Snoeren, 2011; Gorman et al., 2011; Malfrère et al., 2003; Yuan and Liberman, 2009)



# Testing existing aligners on YM

(DiCano et al., 2013)

What if we tried to use a forced aligner, trained on English, on YM speech to do the job? Which aligners work better?

P2FA = “the Penn aligner” (Yuan and Liberman, 2008, 2009)

- Trained using the SCOTUS corpus.
- CMU phone set (phonemic)

hm-Align (Bunnell et al., 2005)

- Trained on data from the TIMIT corpus, which consists of read speech (Garofolo et al., 1993).
- ASEL Extended English phone set (allophonic)

# Phone sets and correspondences

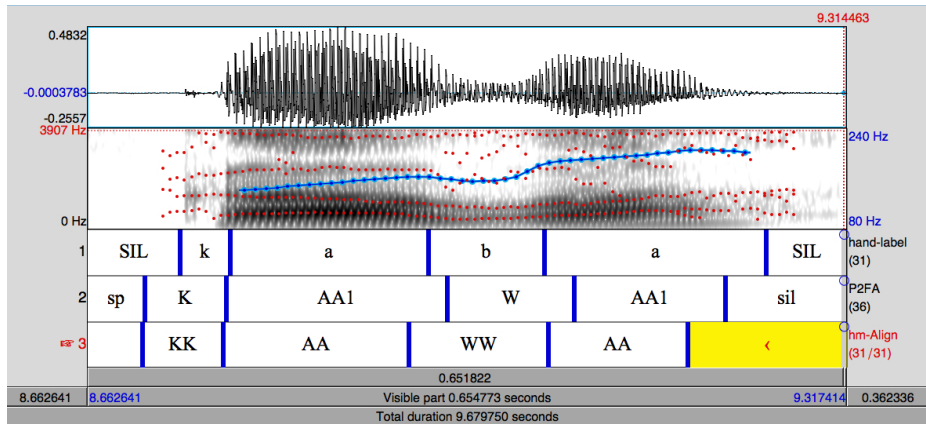
Coding for vowels/consonants, e.g. IY0 = [i] without stress, IY1 = [i] with stress; M = [m], N = [n], etc.

Mixtec	P2FA	hmAlign
/p/ [p]	P [p <sup>h</sup> , p]	PP [p]
/t/ [t]	T [t <sup>h</sup> , t, t̃, r]	TT [t]
/k/ [k]	K [k <sup>h</sup> , k]	KK [k]
/k <sup>w</sup> / [k <sup>w</sup> ]	K [k <sup>h</sup> , k]	KK [k]
/ʔ/ [ʔ]	T [t <sup>h</sup> , t, t̃, r]	TQ [t̃]

# Methods

- Corpus of 261 words spoken in isolation, repeated 6 times, by 10 native speakers = 15,660 words; hand-segmented.
- These consist of monosyllables and disyllables, e.g. /ko<sup>1</sup>o<sup>4</sup>/ 'snake', /n<sup>d</sup>a<sup>1</sup>βa<sup>1</sup>/ 'wooden staff'.
- Compared hand-labelled segmentation to that from forced aligners.
- Distance between boundaries compared using scripts written for Praat (Boersma and Weenink, 2016).

# Example



## Results: general

Agreement is better with hm-Align than with P2FA.

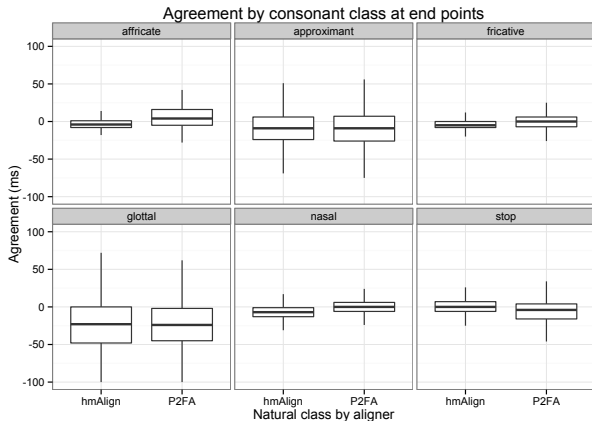
Threshold	P2FA	hm-Align
10 ms	32.3%	40.6%
20 ms	52.3%	61.4%
30 ms	65.7%	70.9%
40 ms	74.8%	81.2%
50 ms	79.6%	86.7%

Generally, agreement is between 70-90% accurate within 20 ms (Malfrère et al., 2003). So, this is slightly less than ideal.



# Results by consonant type

- Fricatives [s, ʃ, h] and nasals [m, n] are aligned well.
- Better alignment with hm-Align for stops [p, t, k] and affricates [tʃ].



# Discussion

- Better alignment with hm-Align than with P2FA.
- Differences in alignment resulted from training data and phone sets.
- The SCOTUS corpus (P2FA) is spontaneous speech and the TIMIT corpus (hm-Align) is read speech (more similar to elicited Mixtec speech). The speech style used in the recordings matters!
- hm-Align phone set had voiceless unaspirated stops and a glottal stop, allowing a better match to Mixtec phonetics than P2FA's.

# Segmentation in running speech

- Word-internal transitions are aligned better than word boundaries. Let's look at running speech.
- Examined a 17 minute narrative, *Adventures of the rabbit*, spoken by a 56 year old Mixtec male. Hand-segmentation took roughly 22 hours (1 minute running speech = 80 minutes of segmentation).
- Investigated only P2FA performance.

## Better alignment!

Approximately 18% more of the data falls within the 20 ms threshold in running speech.

	Elicited Speech		Running Speech
Threshold	hm-Align	P2FA	P2FA
10 ms.	40.6%	32.3%	41.3%
20 ms.	61.4%	52.3%	70.1%
30 ms.	70.9%	65.7%	83.6%
40 ms.	81.2%	74.8%	89.1%
50 ms.	86.7%	79.6%	91.5%

# Building a better pronunciation dictionary for spontaneous speech

- The transcription of the corpus most likely reflects the phonemic inventory found in “careful” speech. Most texts/narratives are not careful.
- The best transcription for forced alignment should match the phonetics.
- But, usually the “transcription” is a practical orthography which maintains morphological and lexical distinctiveness.

# Improving alignment via a phonological transducer

How do we tell an aligner that  $ki'^3in^3 = on^4 / k\tilde{i}\tilde{?}^3\tilde{i}^3 = \tilde{o}^4$  / 'you take' is pronounced  $[k^j\tilde{o}\tilde{?}^3\tilde{o}^4]$ ?

For words where there is regular pattern, we can create phonological rules that we apply to the transcription to give us something more phonetic.

1.  $ki'^3in^3 = on^4$     Input
2.  $ki'^3on^4$         Vowel replacement/harmony
3.  $ki'^3on^4$         Replace all preceding vowels if [-high]  
else [+high]  $\rightarrow$  glide
4.  $kyo'^3on^4$         Output

These rules are made more complex by combinations of vowel enclitics that create portmanteaux rules of harmony on the preceding word.

### YM Clitic pronouns (enclitics)

Person	Clitic	Person	Clitic
1S	= <sup>2</sup> /ju <sup>1</sup>	1P.INCL	=o <sup>4</sup> / e <sup>4</sup>
		1P.EXCL	=ndu <sup>3</sup> /ndu <sup>1</sup>
2S	=õ <sup>4</sup> /ũ <sup>4</sup>	2P	=ndo <sup>4</sup>
3SM	=ra <sup>3</sup> /ra <sup>1</sup>	3P	=na <sup>3</sup> /na <sup>1</sup>
3SF	=ã <sup>4</sup> /ẽ <sup>4</sup>		
3ANIM	=ri <sup>4</sup>		
3INAN	=a <sup>3</sup> /a <sup>2</sup> ; e <sup>3</sup> /e <sup>2</sup>		

ka<sup>13</sup>ʔβi<sup>3</sup>=ã<sup>4</sup>=e<sup>2</sup> → [ka<sup>13</sup>ʔβjẽ<sup>42</sup>]

PERF.count=3SF=3INAN

'She counted it.'

ELAN 5.0 - Yolox\_Elicit\_BAB551\_Frog-story\_2017-07-01-a\_ed-2018-04-14\_traducido\_Plus2Surface.eaf

Archivo Editar Comentario Línea Tipo Buscar Visualizar Opciones Ventana Ayuda

Parilla Texto Subtítulos Lexicón Comments Reconocedores Metadatos Controles

Nr	Anotación	Tiempo inicial	Tiempo final	Duración
4	i3nqa2 ya1 lu3u3 ka4ndu'3u4 ki4xin1 ka1a3 ndi4 tan42 ka4a i3na2 ba3 ka4a4=rí4 ka4ndu'3u4 nu14u3 t...	00:00:...	00:00:...	00:00:...
5	i4ndu'3u4 i3nda14 ndi3ku'3un3 tan3, i3nda14 xa'1a4=rí4 i4yo2 ke'3e2 tan3 i3nda14 xa'1a4=rí4 ndi4ka2 *...	00:00:...	00:00:...	00:00:...
6	ndi1xan4 ba42 yo3o3 ba42 i4nde4e4 ka1a3 nde4e4 tio1to1 nde4e4, ya1 *ventana** ndi4 tu4u4 yo1o4 b...	00:00:...	00:00:...	00:00:...
7	i3nqa(2)=e2 lu3u3 ka4ndu'3u4=a2 i4..., ka4ndu'3u4 nde3e3 ba42 lu3u3 ka1a3 tan3 ji4to(3)=a2 so'3o3 n...	00:00:...	00:00:...	00:00:...
8	tan3 ji4to(3)=a2, i4yo2 yo3o3 ba42 ji4to(3)=a2 nde'14e(4)=a2 ndi4 ndi1xan4 ba3 ji4to(3)=a2 mi4i4 kwi3in...	00:00:...	00:00:...	00:00:...
9	ya1 lu3u3 ka1a3 ndi4 ya1 ja4si4ki24 ba42 ka1a3 tan3 i4ndu'3u4, ji'4in4 i3na2 ja4si4ki24=a2 tu4u2=yu1...	00:00:...	00:01:...	00:00:...

00:00:57.280 Selección: 00:00:00.000 - 00:00:00.000 0

Yolox\_Elicit\_BAB551\_Frog-story\_2017-07-01-a.wav

00:00:50.000 00:00:51.000 00:00:52.000 00:00:53.000 00:00:54.000 00:00:55.000 00:00:56.000 00:00:57.000 01

Turns [1]

Benitu Adelaido Bruno [60]

Benitu Adelaido Bruno SURFACE1 [60]

Benitu Adelaido Bruno SURFACE2 [60]

Sections [1]

BAB Traducción [60]

14 tan3 ji4to(3)=a2, i4yo2 yo3o3 ba42 ji4to(3)=a2 nde'14e(4)=a2 ndi4 ndi1xan4 ba3 ji4to(3)=a2 mi4i4 kwi  
 di4 tã3 ji4twa2 i4yo2 yo3o3 ba42 ji4twa2 ndya'14a2 ndi4 ndi1xã4 ba3 ji4twa2 mi4i4 kwi3i3 ndi1xã4 xa'1a4  
 1 n tã3 ji4twa2, i4yo2 yo3o3 ba42 ji4twa2 ndya'14a2 ndi4 ndi1xã4 ba3 ji4twa2 mi4i4 kwi3i3 ndi1xã4 xa'1a4  
 iga y está mirando, no sabemos que está mirando, ve un par de huaraches que se va poner pues hay hua



# Multilingual content in endangered language corpora

<u>Transcription</u>	<u>X-SAMPA</u>
ka'13bỹẽ42	k a B J ~e
tu3kwe3	t u kw e
**playera*	p l a y e 4 a
**bote*	B o t e

## Troublesome (UR)

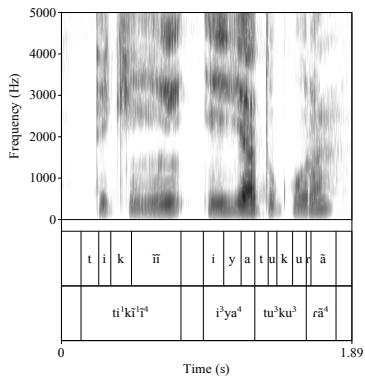
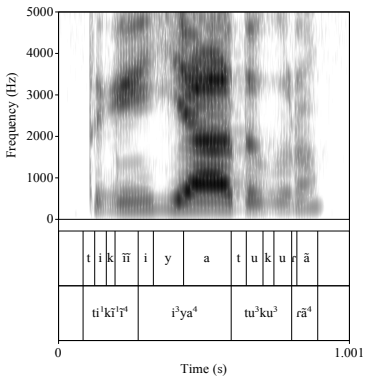
\*\*bote\*=an4 > βotjã4 harmony? tone?

# Consonant variability

But there are still mismatches between the input and output!

'...the sour tamale again, then.'

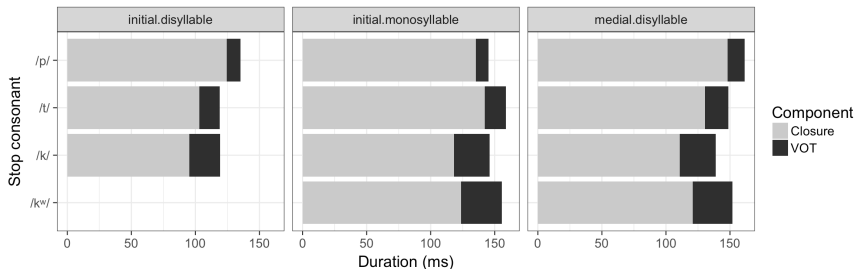
[ti<sup>1</sup>γĩ<sup>1</sup>ĩ<sup>4</sup> ja<sup>4</sup> du<sup>3</sup>γu<sup>3</sup> rã<sup>4</sup>] (left) vs. [ti<sup>1</sup>kĩ<sup>1</sup>ĩ<sup>4</sup> i<sup>3</sup>ja<sup>4</sup> tu<sup>3</sup>ku<sup>3</sup> rã<sup>4</sup>] (right)



# Variable obstruent lenition

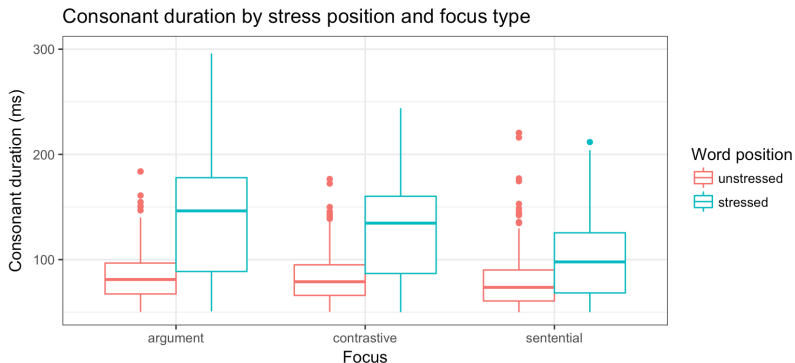
This lenition is not predictable by rule (the transducer won't help)!  
Castillo García (2007) does not discuss stop voicing/manner lenition.

Stops always have closure in elicited speech (8 speakers, 12 reps per stop context)  
(DiCano et al., 2018b)



# Prosodic structure

Might prosody contribute to variable obstruent lenition? Onsets in stressed syllables are longer than unstressed syllables (DiCano et al., 2018a).



## Obstruent lenition and word position in corpora

While infrequent (5-6% of all cases), certain stops (/k, d/) may be produced as voiced approximants in phrase-final position among AAVE speakers (StoryCorps corpus) (Davidson, 2011).

In Majorcan Spanish, full or partial voicing of voiceless stops /p, t, k/ was observed 35.6% of the time in a spontaneous speech corpus, but 3.7% of the time in a read speech corpus (Hualde et al., 2011). Voicing and lenition of phonologically voiceless stops was not sensitive to word position though.

Subsequent work on Spanish found higher rates of voicing in casual conversational speech (Lewis, 2001; Torreira and Ernestus, 2011).

Does the prosodic structure determine the patterns of lenition?

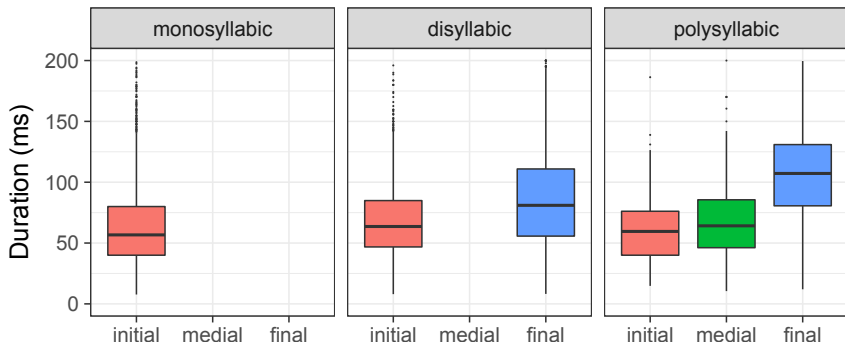
# Methods

- Corpus of 6 speakers (3 male, 3 female) producing spontaneous narratives in YM, totalling 107 minutes; force-aligned and corrected.
- Analysis of duration and percentage of voicing (our measure of lenition) during constriction/closure for /t, k, k<sup>w</sup>, s, ʃ, h, tʃ/. Recall that [h] is a free variant of /ʃ, s/.
- A total of 7892 segments were analyzed.
- Hand-labelling of corpus was done in a previous study (DiCanio et al., 2015), but words here were coded by stem position (initial, medial, final syllable), and word size (monosyllabic, disyllabic, polysyllabic).

- Duration was extracted with an existing Praat script.
- Voicing was extracted with a script written for Matlab (Chen, W-R). Percentage of voicing during constriction was calculated using a normalized low frequency energy ratio (Kasi and Zahorian, 2002).
- Two separate statistical analyses were run using lmerTest (Kuznetsova et al., 2017), one with duration as the dependent variable and another with percentage of voicing as the dependent variable.
- In each model, word size, word position, and consonant were treated as fixed effects while speaker and item were treated as random effects. No random slopes were included.

# Results: duration

## Consonant duration by word position

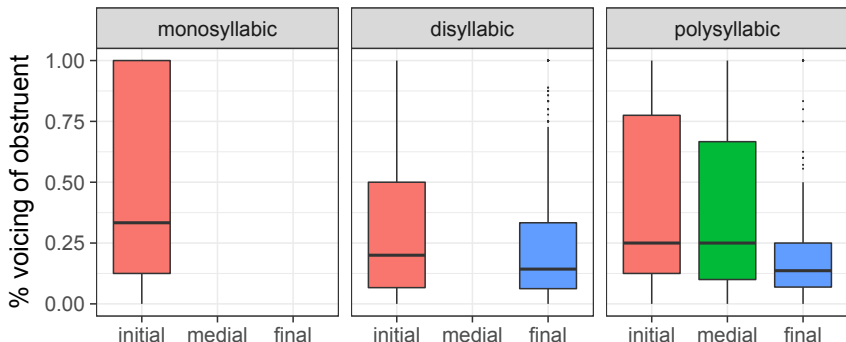


A strong effect of position on duration (initial vs. final) was found.



# Results: voicing

## Consonant voicing by position in words of different size



Obstruents in word-initial syllables had a larger percentage of voicing than those in word-final syllables.

## Discussion

Stem-initial obstruents were both shorter and more likely to be voiced or partially voiced than stem-final obstruents.

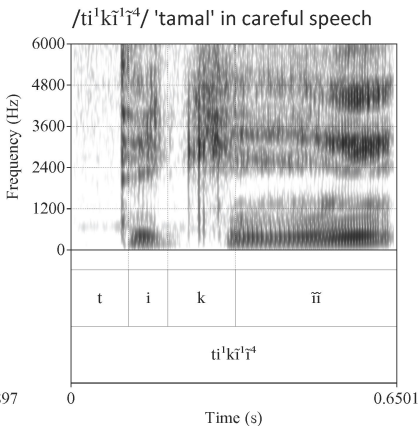
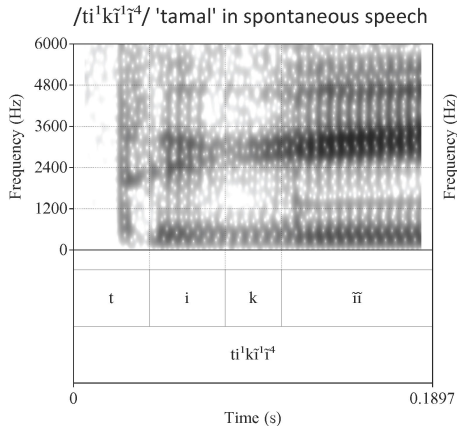
This pattern of lenition matches stress-related durational patterns observed in experimental data.

Unlike languages like English where word-initial position is the locus of domain-related strengthening (Fougeron and Keating, 1997), initial syllables in YM are weakened relative to medial or final syllables.

The prosodic structure of YM partially predicts the degree of voicing observed in the spontaneous speech data.

# How much phonetic variation occurs?

Obstruents in YM vary in terms of voicing *and* manner.



# Qualitative analysis of variation

Examined 89 minutes of corpus used for voicing/lenition study.

Praat script which scanned for the target phone and permitted user to select allophone.

4472 stop tokens (/t, k/) analyzed.

	Vcls stop	Partially vcd stop	Voiced stop	Voiced fric.	Voiced approx.	Nasal	Tap	Deleted
/t/	17.9%	33.0%	21.2%	15.8%	2.7%	6.6%	1.2%	1.6%
/k/	15.3%	20.0%	16.4%	33.5%	7.9%	1.5%	NA	4.8%

Realization	Stop	Voiced
/t/	72.1%	49.1%
/k/	51.7%	64.7%

Variation in manner/voicing for “voiceless unaspirated stops” is very common in running speech. Can a model be trained to detect it? Can we add this as a layer in our speech corpus?

Step	Layer	Method
1	Original transcription	ELAN
2	Surface phonological representation	Phonological transducer
3	Lexical and Phone-level segmentation	Forced alignment
4	<b>Surface phonetic variation</b>	???

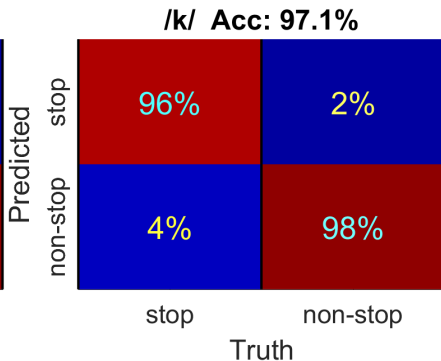
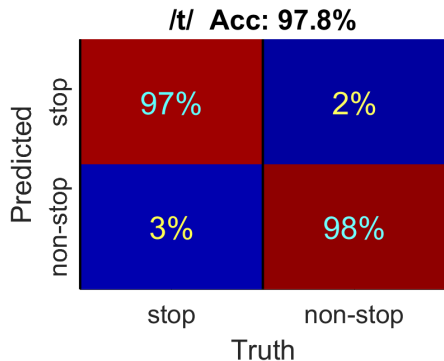
Predicting surface phonetic variation not only permits greater detail in the speech corpus, but allows one to examine low-level variation in speech production without needing to code the acoustic data by hand.

# Methods: DNN modelling

- We can use the allophonic labelling from the 4,472 stop tokens to train DNNs (Deep neural networks) to categorize surface phonetic allophones.
- Six models trained: 2-way, 3-way, 4-way models on /t/ and on /k/; (500 nrns) (Hinton et al., 2012).
- 20 MFCC coefficients extracted from each hanning-windowed (10 ms, 2ms step) acoustic signal (48 kHz > 16 kHz) for each stop token. MFCCs were standardized, normalized, and rescaled.
- Models trained on 80% of data, fine-tuned on 10% cross-validation set, and tested on remaining 10% (random split).

## 2-way categorization

High accuracy found – stop vs. non-stop



## 3-way categorization

Higher accuracy found – stop vs. fricative vs. sonorant (nasal or approximant). Sonorant realizations tend to be categorized as fricatives.

**/t/ Acc: 86.4%**

Predicted	stop	96%	5%	0%
	fric	5%	90%	41%
	nas	0%	5%	59%
		stop	fric	nas
		Truth		

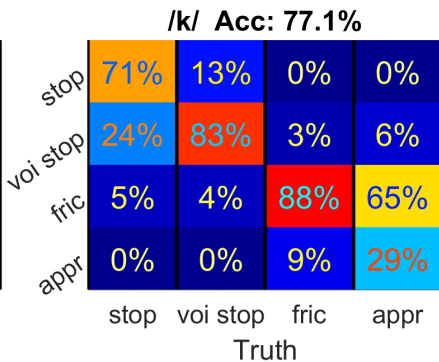
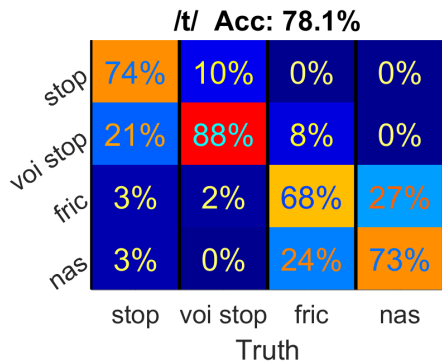
**/k/ Acc: 77.3%**

Predicted	stop	89%	6%	0%
	fric	11%	82%	91%
	appr	0%	12%	9%
		stop	fric	appr
		Truth		



## 4-way categorization

Good accuracy found – voiceless stop vs. voiced stop vs. fricative vs. sonorant (nasal or approximant).



- Limited training data, but the DNN models showed high accuracy.
- Excellent stop/continuant identification, though approximants were more poorly identified.
- The four-way model showed good performance in voiceless-voiced stop identification.
- DNN models can detect allophones from continuous speech, which is useful both for improving surface phonetic transcription.

Next steps: compare DNN against simpler models, test on other language data, apply model to corpus data

## General discussion

One can adapt an English-based forced aligner to get initial segmentation of a documentation corpus, but speech style matters in the choice of the aligner that is used (and in what one trains).

Even after creating a phonological transducer and language-specific aligner, one can observe variation within the surface phonetic representation of the corpus that is not captured.

For YM, prosodic structure explains this variation and it can be modelled based on some relatively simple human categorization data and included as an annotation layer in a speech corpus.

## Future directions

- Corpus has been completely transduced and alignment has been checked. (~ 1 million words)
- Improve DNN performance and expand to other consonant types; include an additional surface phonetic layer.
- Collaborative work at McGill integrating the existing corpus with Speech Corpus Tools.
- Corpus tone production.

# Acknowledgements



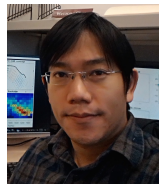
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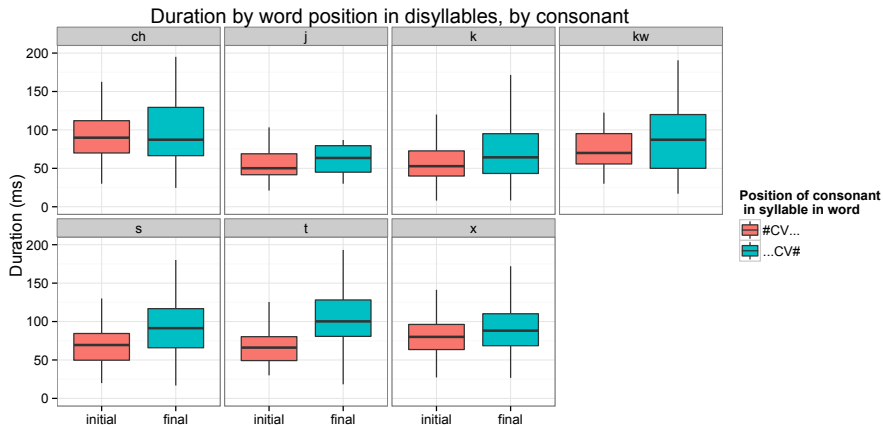


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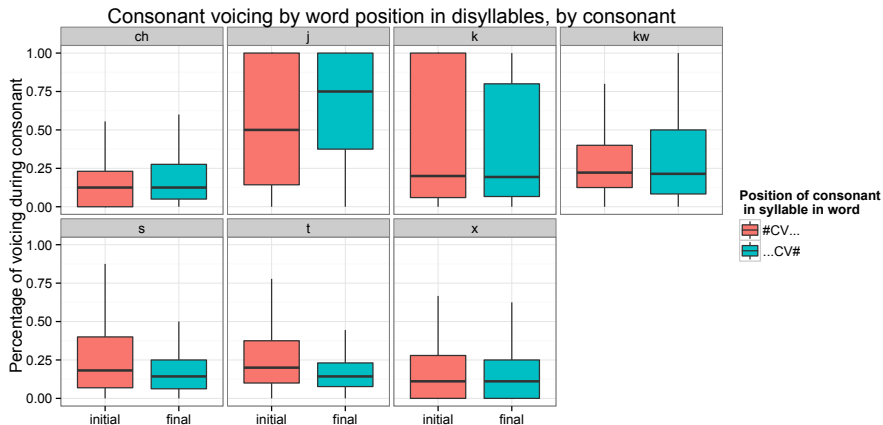
# Appendix

## Duration effects by consonant in disyllabic words



# Appendix

## Voicing effects by consonant in disyllabic words



- Adda-Decker, M. and Snoeren, N. D. (2011). Quantifying temporal speech reduction in French using forced speech alignment. *Journal of Phonetics*, 39:261–270.
- Baayen, R. H. (2008). *Analyzing Linguistic Data: A Practical Introduction to Statistics Using R*. Cambridge University Press, 353 pages.
- Boersma, P. and Weenink, D. (2016). Praat: doing phonetics by computer [computer program]. [www.praat.org](http://www.praat.org).
- Bunnell, H. T., Pennington, C., Yarrington, D., and Gray, J. (2005). Automatic personal synthetic voice construction. In *INTERSPEECH-2005*, pages 89–92.
- Castillo García, R. (2007). Descripción fonológica, segmental, y tonal del Mixteco de Yoloxóchitl, Guerrero. Master's thesis, Centro de Investigaciones y Estudios Superiores en Antropología Social (CIESAS), México, D.F.
- Davidson, L. (2011). Characteristics of stop releases in American English spontaneous speech. *Speech Communication*, 53:1042–1058.
- DiCanio, C., Amith, J. D., and Castillo García, R. (2014). The phonetics of moraic alignment in Yoloxóchitl Mixtec. In *Proceedings of the 4<sup>th</sup> Tonal Aspects of Language Symposium*. Nijmegen, the Netherlands.
- DiCanio, C., Benn, J., and Castillo García, R. (2018a). The phonetics of information structure in Yoloxóchitl Mixtec. *Journal of Phonetics*, 68:50–68.
- DiCanio, C., Nam, H., Amith, J. D., Castillo García, R., and Whalen, D. H. (2015). Vowel variability in elicited versus spontaneous speech: evidence from Mixtec. *Journal of Phonetics*, 48:45–59.
- DiCanio, C., Nam, H., Whalen, D. H., Bunnell, H. T., Amith, J. D., and Castillo García, R. (2013). Using automatic alignment to analyze endangered language data: Testing the viability of untrained alignment. *Journal of the Acoustical Society of America*, 134(3):2235–2246.



- DiCanio, C. and Whalen, D. H. (2015). The interaction of vowel length and speech style in an arapaho speech corpus. In *Proceedings of the 18<sup>th</sup> International Congress of the Phonetic Sciences*, Glasgow, Scotland.
- DiCanio, C., Zhang, C., Whalen, D. H., and Castillo García, R. (2018b). Phonetic structure in Yoloxóchitl Mixtec consonants. *Journal of the International Phonetic Association*.
- Fougeron, C. and Keating, P. A. (1997). Articulatory strengthening at edges of prosodic domains. *Journal of the Acoustical Society of America*, 101(6):3728–3740.
- Garofolo, J. S., Lamel, L. F., Fisher, W. M., Fiscus, J. G., Pallett, D. S., Dahlgren, N. L., and Zue, V. (1993). *TIMIT Acoustic-Phonetic Continuous Speech Corpus*. Linguistic Data Consortium, Philadelphia.
- Gorman, K., Howell, J., and Wagner, M. (2011). Prosodylab-aligner: A tool for forced alignment of laboratory speech. *Canadian Acoustics*, 39(3):192–193.
- Hinton, G., Deng, L., Yu, D., Dahl, G. E., Mohamed, A.-r., Jaitly, N., and Sainath, T. N. (2012). Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. *IEEE Signal Processing Magazine*, 29(6):82–97.
- Hualde, J. I., Simonet, M., and Nadeu, M. (2011). Consonant lenition and phonological recategorization. *Journal of Laboratory Phonology*, 2:301–329.
- Kasi, K. and Zahorian, S. A. (2002). Yet another algorithm for pitch tracking. In *Proceedings of ICASSP02*, pages 361–364. Orlando.
- Keating, P. A. and Huffman, M. K. (1984). Vowel variation in Japanese. *Phonetica*, 41:191–207.
- Koopmans van Beinum, F. (1980). *Vowel contrast reduction, an acoustic and perceptual study of Dutch vowels in various speech conditions*. PhD thesis, University of Amsterdam, The Netherlands., Academische Pers B. V., Amsterdam.

- Kuznetsova, A., Brockhoff, P. B., and Christensen, R. H. B. (2017). ImerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, 82(13):1–26.
- Ladefoged, P. (2003). *Phonetic Data Analysis*. Blackwell.
- Lewis, A. M. (2001). *Weakening of intervocalic /ptk/ in two Spanish dialects: Toward the quantification of lenition processes*. PhD thesis, University of Illinois at Urbana-Champaign.
- Lindblom, B. (1963). Spectrographic study of vowel reduction. *Journal of the Acoustical Society of America*, 35:1773–1781.
- Lindblom, B. (1983). The economy of speech gestures. In MacNeilage, P. F., editor, *The Production of Speech*, pages 217–243. Springer-Verlag.
- Lindblom, B. (1990). Explaining phonetic variation: a sketch of the H&H theory. In Hardcastle, W. J. and Marchal, A., editors, *Speech Production and Speech Modelling*, pages 403–439. Kluwer Academic Publishers.
- Malfrère, F., Deroo, O., Dutoit, T., and Ris, C. (2003). Phonetic alignment: speech synthesis-based vs. Viterbi-based. *Speech Communication*, 40:503–515.
- Meunier, C. and Espesser, R. (2011). Vowel reduction in conversational speech in French: The role of lexical factors. *Journal of Phonetics*, 39:271–278.
- Moon, S.-J. and Lindblom, B. (1994). Interaction between duration, context, and speaking style in English stressed vowels. *Journal of the Acoustical Society of America*, 96(1):40–55.
- Palancar, E. L., Amith, J. D., and Castillo García, R. (2016). Verbal inflection in Yoloxóchitl Mixtec. In Palancar, E. L. and Léonard, J.-L., editors, *Tone and Inflection: New Facts and New Perspectives*, chapter 12, pages 295–336. Mouton de Gruyter.
- R Development Core Team, Vienna, A. (2017). R: A language and environment for statistical computing [computer program], version 3.3.3. <http://www.R-project.org>, R Foundation for Statistical Computing.

- Torreira, F. and Ernestus, M. (2011). Realization of voiceless stops and vowels in conversational French and Spanish. *Journal of Laboratory Phonology*, 2:331–353.
- Yuan, J. and Liberman, M. (2008). Speaker identification on the SCOTUS corpus. In *Proceedings of Acoustics - 2008*.
- Yuan, J. and Liberman, M. (2009). Investigating /l/ variation in English through forced alignment. In *Interspeech - 2009*, pages 2215–2218.