



The Use of Phone Categories and Cross-Language Modeling for Phone Alignment of Panãra



Emily P. Ahn^a, Eleanor Chodroff^a, Myriam Lapierre^a & Gina-Anne Levow^a

^aUniversity of Washington, USA

^aUniversity of Zurich, CH

1. Motivation

- > Automatic forced alignment aids field linguists, phoneticians, etc.
- > Goal: phone-align Panãra data in a limited data scenario via 2 strategies:
 - Cross-language modeling
 - > E.g. English/French to align Bribri¹
 - Broaden phone categories
 - > Worked for sentence alignment⁴

2. Data

Panãra (ISO: kre)

- Jê language spoken in Brazil
- ~700 speakers



Phoneme Inventory⁶

Consonants

	Bilabial	Alveolar	Palatal	Velar
Singleton obstruent	p	t	s	k
Geminate obstruent	pp	tt	ss	kk
Singleton nasal	m	n	ɲ	ŋ
Geminate nasal	mm	nn		
Approximant	w	r	j	

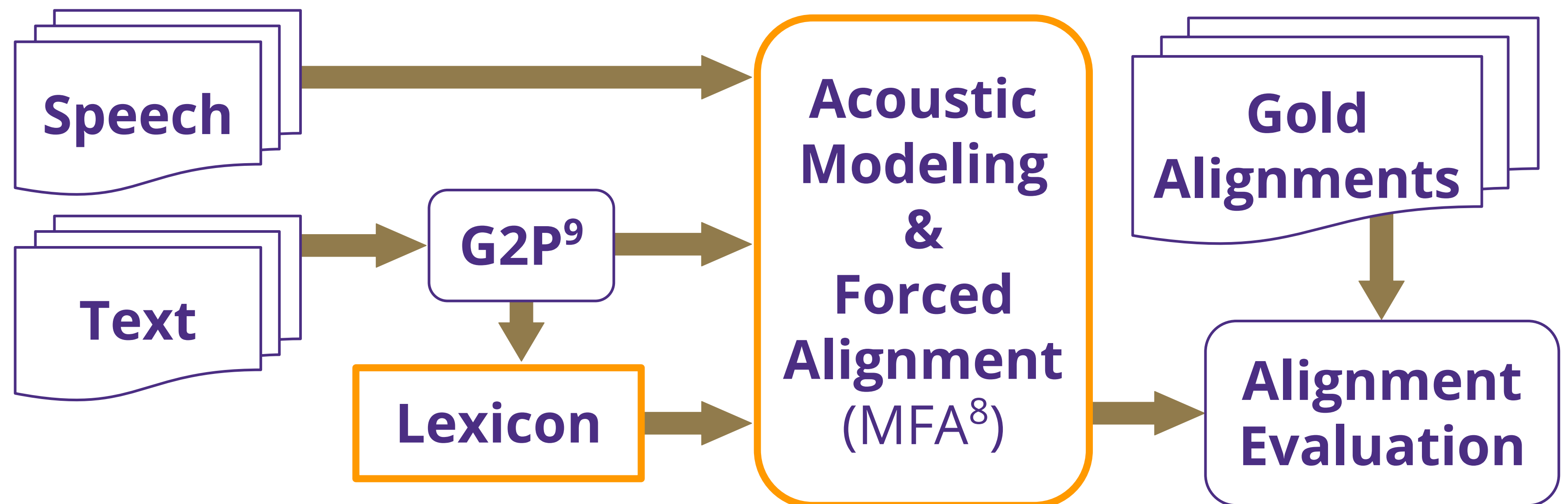
Vowels

Short oral			Short nasal		
i	u	u	ĩ	ũ	ũ
e	ɣ	o	ẽ	ɣ̃	õ
ɛ	a	ɔ			
Long oral			Long nasal		
i:	u:	u:	ĩ:	ũ:	ũ:
e:	ɣ:	o:	ẽ:	ɣ̃:	õ:
ɛ:	a:	ɔ:			

Dataset

- 35 min speech, narrative style
- 4 speakers (2 male, 2 female)
- Orthographically transcribed by Myriam Lapierre, corrected with native speakers

3. Pipeline & Methods



Lexicon Manipulation

Broaden phone categories via 2 strategies:

1. No Diacritics

Ex:

ɔ	297
ɔ:	37
õ	5
	339

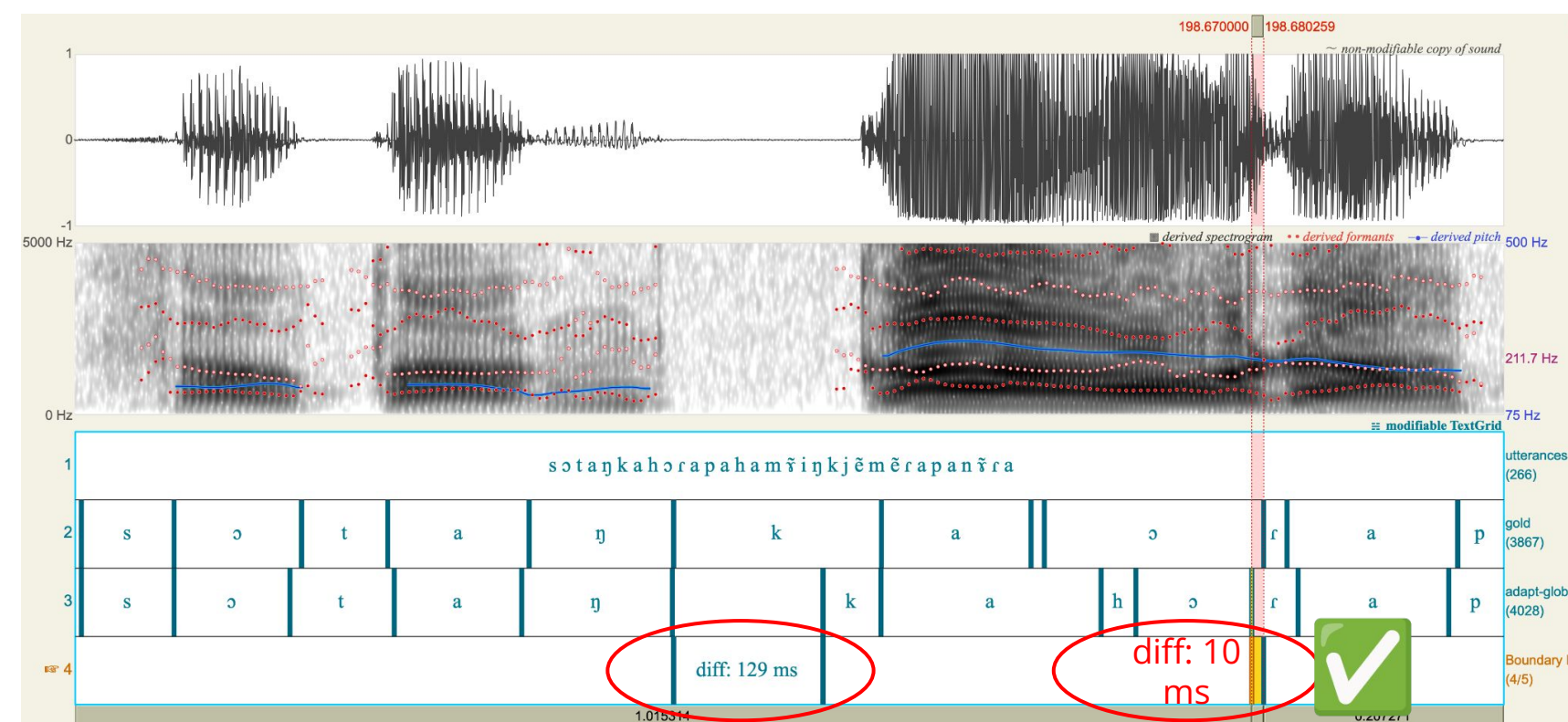
2. Natural classes from SCA⁷

(Sound-Class-Based Phonetic Alignment)

No.	CL	Description	Examples	No.	CL	Description	Examples
1	A	unrounded back vowels	a, ɔ	15	P	labial plosives	p, b
2	B	labial fricatives	f, β	16	R	trills, taps, flaps	r
3	C	dental / alveolar affricates	ts, dx, tʃ, ɟʃ	17	S	sibilant fricatives	s, z, f, ʒ
4	D	dental fricatives	θ, ð	18	T	dental / alveolar plosives	t, d
5	E	unrounded mid vowels	e, ɛ	19	U	rounded mid vowels	ɔ, o
6	G	velar and uvular fricatives	ɣ, x	20	W	labial approx. / fricative	v, w
7	H	laryngeals	h, ʔ	21	Y	rounded front vowels	u, y
8	I	unrounded close vowels	i, ɪ	22	O	low even tones	11, 22
9	J	palatal approximant	j	23	1	rising tones	13, 35
10	K	velar and uvular plosives	k, g	24	2	falling tones	51, 53
11	L	lateral approximants	l	25	3	mid even tones	33
12	M	labial nasal	m	26	4	high even tones	44, 55
13	N	nasals	n, ŋ	27	5	short tones	1, 2
14	O	rounded back vowels	ɔ, ɒ	28	6	complex tones	214

Evaluation

Phone Onset Boundary Accuracy⁸: % of system onsets within 20 ms of manually annotated gold onsets



Original Text	Panãra Orthography	Haa māmă jynkjân rasu hapôô
After Lexicon Manipulation	Panãra Explicit	h a : m ɣ̃ m ɣ̃ j u ŋ k j ɣ n r a s u h a p o :
	Panãra No Diacritics	h a m ɣ̃ m ɣ̃ j u ŋ k j ɣ n r a s u h a p o
	TIMIT English Explicit	h a m ə m ə j ɪ ŋ k j ɛ n r a s u h a p oʊ
	Broad (SCA) ⁷	H A M E M E J I N K J E N R A S Y H A P U
	MFA Global English Explicit	h a : m ɔ m o j u ŋ k j o n r a s u h a p o :

Experiments

1. Language-specific + broaden phones

Panãra-only trained models

- Explicit: all Panãra phones
- No Diacritics: ⚡ length/nasal markers
- Broad natural class⁷

2. Cross-language + broaden phones

English model trained on TIMIT² (4 hours, 519 speakers from US)

–“Full”: 224 min, 495 speakers

–“Small”: 26 min, 51 speakers

- Explicit: all Panãra phones mapped to TIMIT English phones
- Broad natural class⁷

3. Large, pretrained English model

English MFA⁸ acoustic model 2.2.1 pretrained on 3770 hours speech from US, UK, Nigeria, India

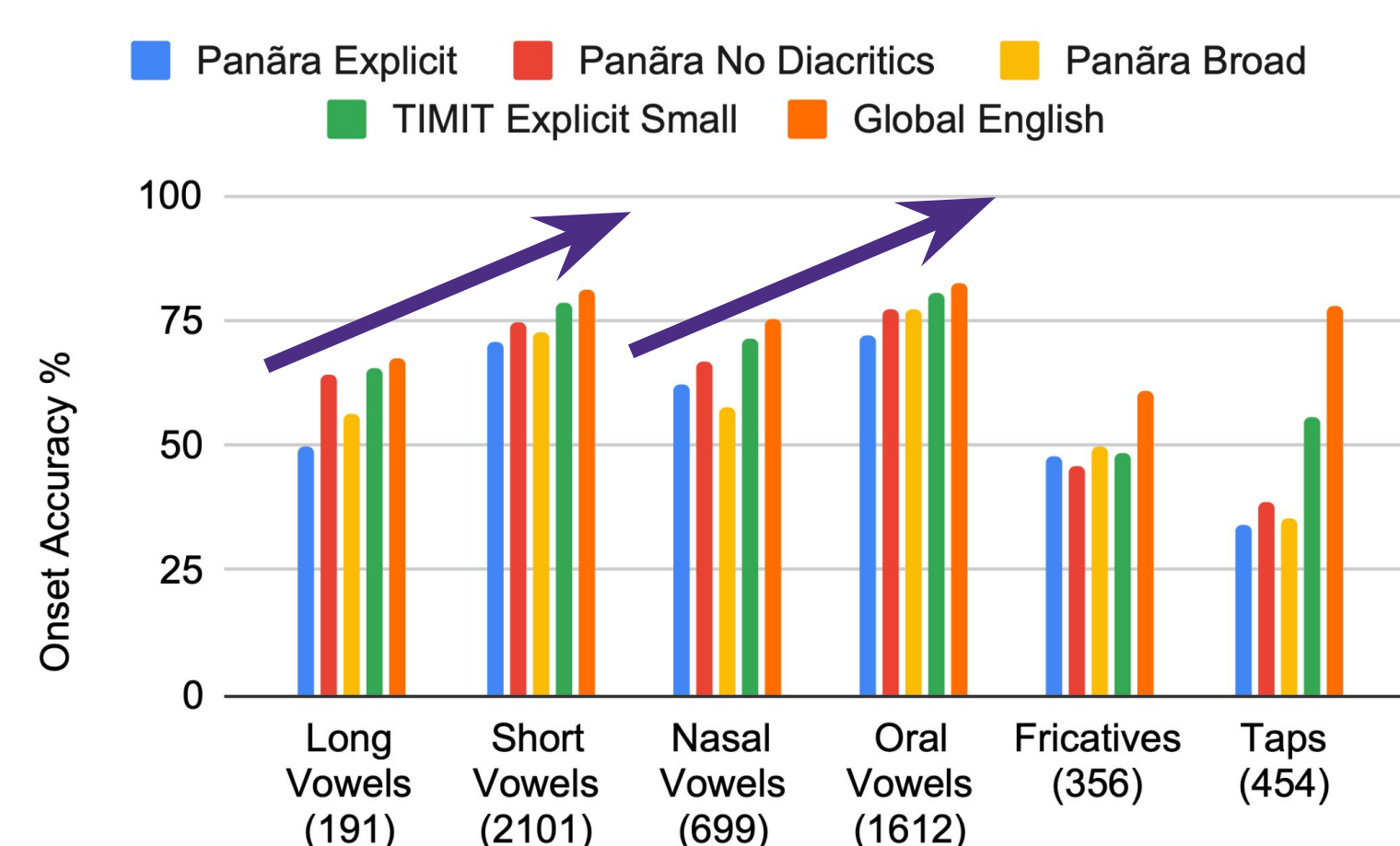
- Explicit: all Panãra phones mapped to Global English phones

4. Results

- Broadening phone categories **improved** alignment accuracy in **language-specific (Panãra only)** training
- Broadening phone categories **did not improve** alignment accuracy in **cross-language (English-Panãra)** training
- A large, pretrained English model **outperformed previous strategies**.

Trained Dataset	Trained Settings (# phone categories)	Onset Accuracy within 20ms (%)
Panãra	Explicit (63)	60.20
	No Diacritics (29)	62.35
	Broad (17)	61.92
English (TIMIT)	Explicit Full (46)	62.65
	Explicit Small (46)	66.09
	Broad Full (19)	56.07
	Broad Small (19)	61.14
English (Global MFA)	Explicit (100)	69.82

5. Analysis



Phone natural class affected onset accuracy

- Long & Nasal vowel boundaries more difficult than Short & Oral
 - Long & Nasal vowels typologically less common³
- Poor [h] alignment in Fricatives
 - variable [h] insertion in onsetless syllables⁵
- Poor [r] alignment in Taps
 - vowel insertion within a complex onset⁵, e.g. /krɾ/ → [kVɾɾ] ‘thigh’

6. Conclusion

Summary

- We tested phonetic granularity effects in acoustic modeling and alignment of Panãra
- For best alignment performance: use a large acoustic model for cross-language alignment

Future Work

- > Apply techniques to other language varieties
- > Automatic phone category/granularity discovery
- > Multilingual, language-agnostic alignment

References

- Coto-Solano, R., & Solórzano, S. F. (2017). Comparison of Two Forced Alignment Systems for Aligning Bribri Speech. In *CLEI ELECTRONIC JOURNAL*.
- Garofolo, J. S. (1993). TIMIT Acoustic Phonetic Continuous Speech Corpus. *Linguistic Data Consortium*, 1993.
- Gordon, M. K. (2016). *Phonological Typology*. Oxford University Press.
- Hoffmann, S., & Pfister, B. (2013). Text-to-speech Alignment of Long Recordings Using Universal Phone Models. In *Interspeech*.
- Lapierre, M. (2023a). The Phonology of Panãra: A Prosodic Analysis. In *International Journal of American Linguistics*.
- Lapierre, M. (2023b). The Phonology of Panãra: A Segmental Analysis. In *International Journal of American Linguistics*.
- List, J. M. (2012). SCA: Phonetic Alignment Based on Sound Classes. In: Lassiter, D., Slavovik, M. (eds) *New Directions in Logic, Language and Computation*.
- McAuliffe et al. (2017). Montreal Forced Aligner: Trainable Text-speech Alignment Using Kaldi. In *Interspeech*.
- Mortensen et al. (2018). Epitran: Precision G2P for Many Languages. In *LREC*.

Acknowledgments

We thank Hossep Dolatian for idea inspiration, and Bridget Tyree for help with annotations.

