One size does not fit all: Tailoring the Montreal Forced Aligner (MFA) to your data

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July 16, 2025

Welcome!

Goals and schedule

- Introduction: Your MFA Toolbox
  - Technical overview of MFA
  - The essentials of alignment - mfa align
  - Leveling up - mfa adapt
- The basics: Levers for improving alignment
- Advanced techniques
  - Part 1: Resourced language example - English
  - Part 2: Adapting models to novel varieties
  - Part 3: Languages without MFA support
- Lunch (12pm-2pm)
- Afternoon session (2pm-5pm)
  - Bring-your-own-data
- `https://github.com/mmcauliffe/mfa-adaptation`

Introduction

- Speech-to-text Alignment
  - Goal is to match the orthographic representation of speech to the time it was spoken in the audio file
  - Sequence-to-sequence problem: map the sequence of audio to the sequence of orthographic text
    - We assume the text represents exactly what is spoken (i.e., the ground truth)

MFA

Montreal Forced Aligner

- A command line utility for performing forced alignment
- Converts audio transcriptions to phone and word intervals
- Pretrained models and dictionaries for 20+ languages
- Still gaps in coverage

So what can you do? How can you get quality alignments for your data?

Key concepts

Training vs. Target data

- Training data: used to train model
  - Inherent variability of acoustic data vs.
  - Modeling the variability (e.g., dialect-specific lexicons, phone sets, etc.)
- Target data: the dataset for which you're predicting phone labels
- Training data variability is typically a super-set of target data variability

Key concepts

For MFA training:

- Training data is known, represents a wide variety of input sources
- Target data is unknown

For today:

- Target data is known
- Adapting data (i.e., additional training data) and target data may be the same

Key question for today:

- How well does your target data map to the training data?
- We will demonstrate a few ways to experiment with MFA

Technical overview of MFA

MFA training

- Progressively more complex models
  - Monophone (Context independent phones)
  - Triphone (Context dependent phones)
  - LDA triphone
    - Feature transform based on phones
  - Speaker-adapted triphone
    - Feature transform based on speakers
  - Pronunciation probabilities
    - How likely is a given pronunciation?
    - How likely is silence to precede/follow a given pronunciation?

MFA training

- Progressively larger subsets
  - 10k utterances
  - 20k utterances
  - 50k utterances
  - 150k utterances (optional)
  - All utterances
- Subset logic has evolved over versions
  - Split between dialect dictionaries
  - Avoid speakers with single utterances
  - New in 3.3: Manually aligned utterances always included
- New in 3.3: Subset from sub-corpora
  - Prioritize read speech corpora earlier
  - Incorporate noisy corpora like CommonVoice later

So you have a pretrained model, now what?

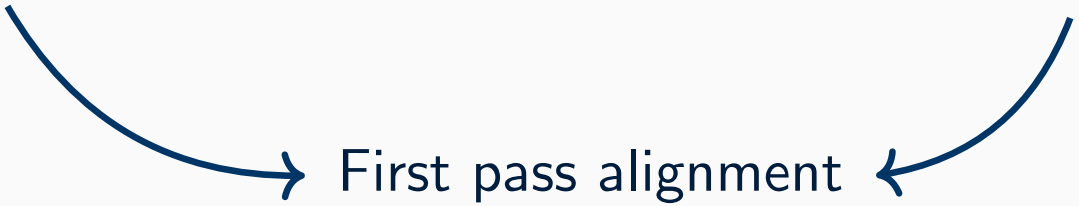
MFA alignment pipeline - First pass

Speaker-independent features

- Audio
- Acoustic model

Decoding graph

- Transcript
- Pronunciation dictionary



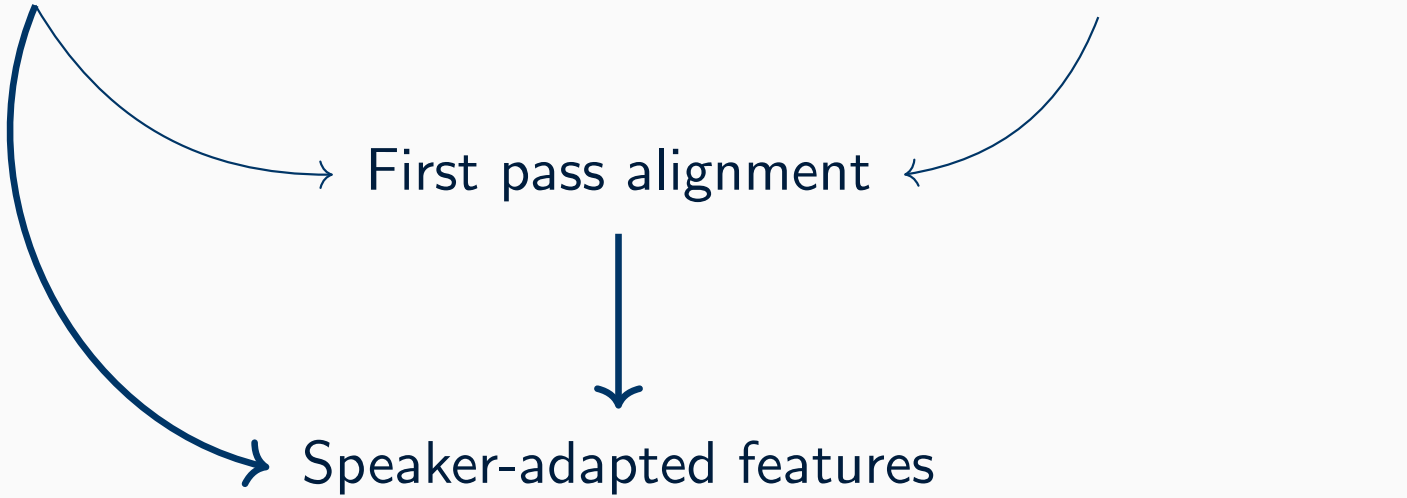
MFA alignment pipeline - Speaker adaptation

Speaker-independent features

- Audio
- Acoustic model

Decoding graph

- Transcript
- Pronunciation dictionary



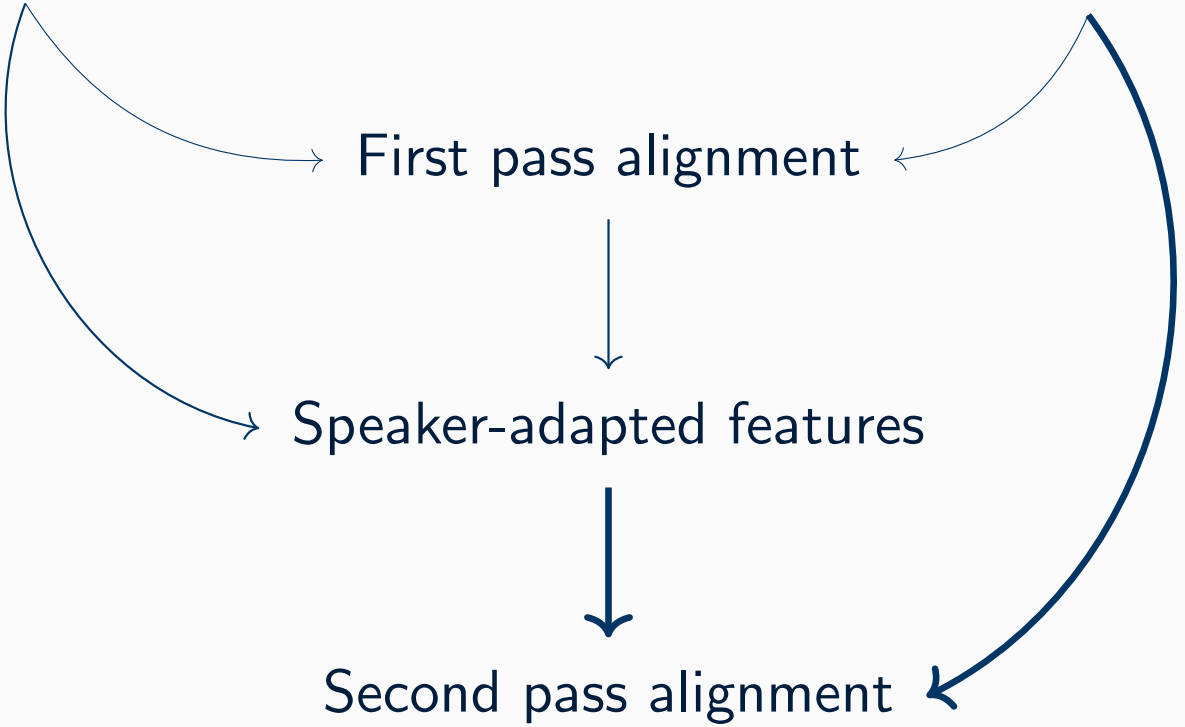
MFA alignment pipeline - Second pass

Speaker-independent features

- Audio
- Acoustic model

Decoding graph

- Transcript
- Pronunciation dictionary



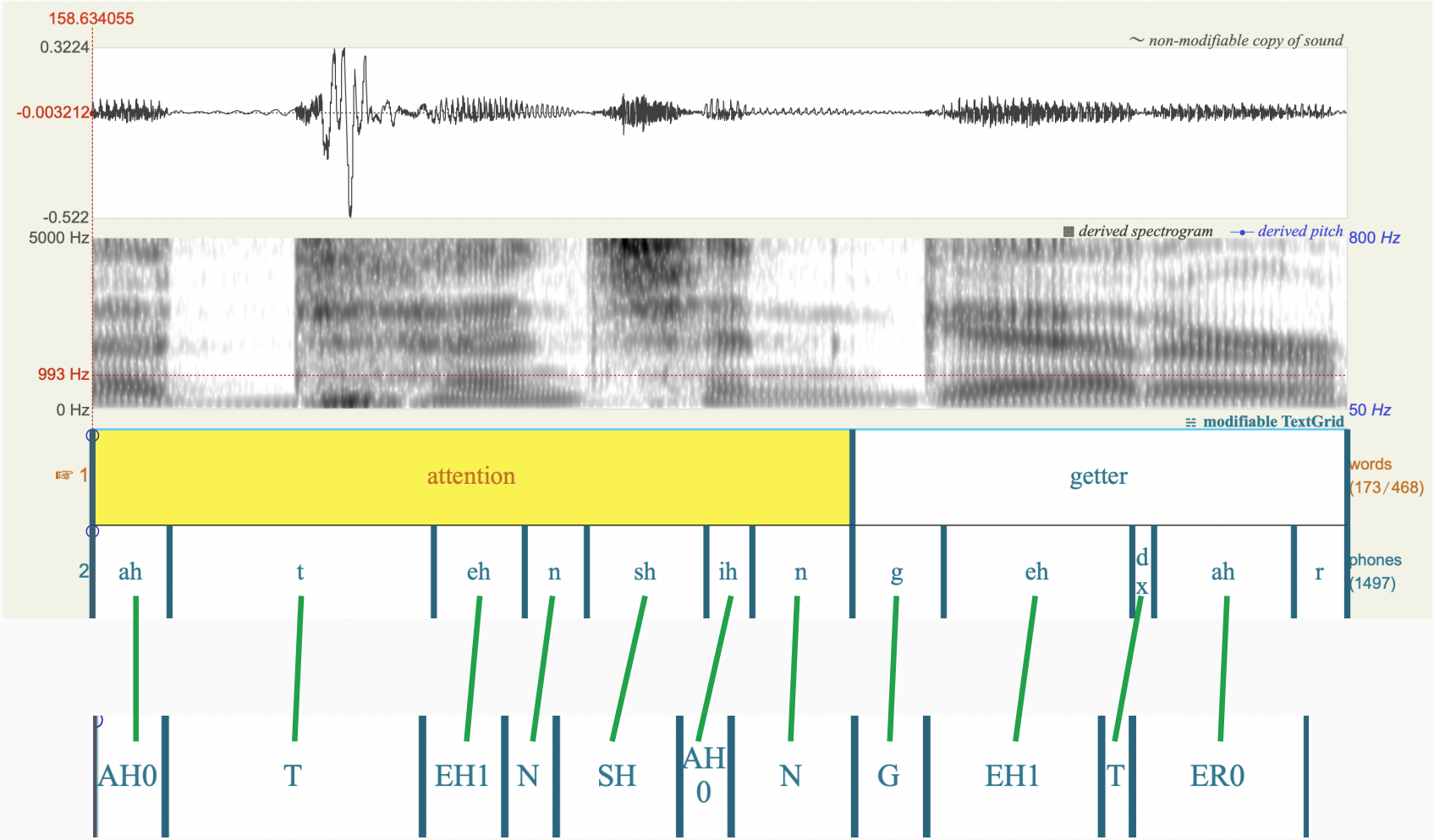
Evaluation

- Now you have alignments from the second pass
- But...how do we know the quality of alignments?
- Create an evaluation dataset with hand-corrected alignments
  - Evaluation metrics with reference alignments (mfa align –reference_directory)
- This can help us:
  - Select between different methods (align, adapt, etc.)
  - Select between different models (English vs. Mandarin)
  - Identify problematic utterances
- So, how do we do that?

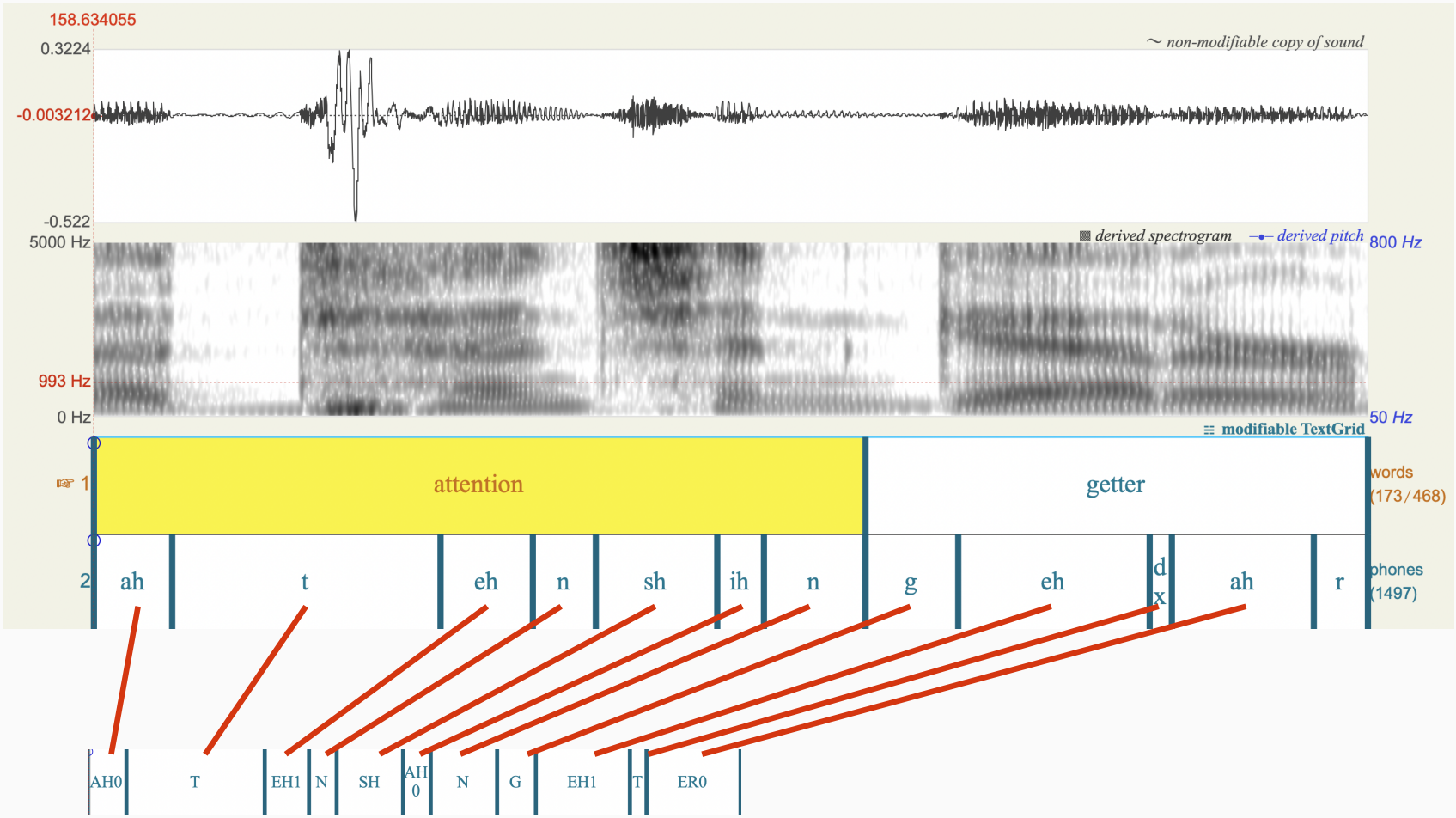
Evaluating alignments

- How can we quantify how "good" a model aligns a corpus?
- Typical metric: boundary recall within 20ms
  - For every boundary in reference alignments:
  - Is there a corresponding aligned boundary within 20ms window?
- Works ok when reference alignment is the same sequence of phones, but
  - What if there are pronunciation variants?
  - What if the evaluation data set is using a completely different phone set?
- MFA has two metrics based on an alignment of alignment intervals
  - Helps ensure that boundaries being compared are the same

Evaluating alignments - Pretty good alignment



Evaluating alignments - Pretty bad alignment



Evaluating alignments

- Levenshtein-esque alignment between reference intervals and aligned intervals

$$\textit{Overlap Cost} = -1 * \Big(|\textit{begin}_{\textit{aligned}} - \textit{begin}_{\textit{ref}}| + |\textit{end}_{\textit{aligned}} - \textit{end}_{\textit{ref}}| + \begin{cases} 0, & \textit{label}_1 = \textit{label}_2 \\ 2, & \textit{otherwise} \end{cases} \Big)$$

- Alignment score is the average overlap cost ignoring insertions/deletions

$$\textit{Phone Error Rate} = \frac{\textit{insertions} + \textit{deletions} + (2 * \textit{substitutions})}{\textit{length}_{\textit{ref}}}$$

The essentials of adaptation

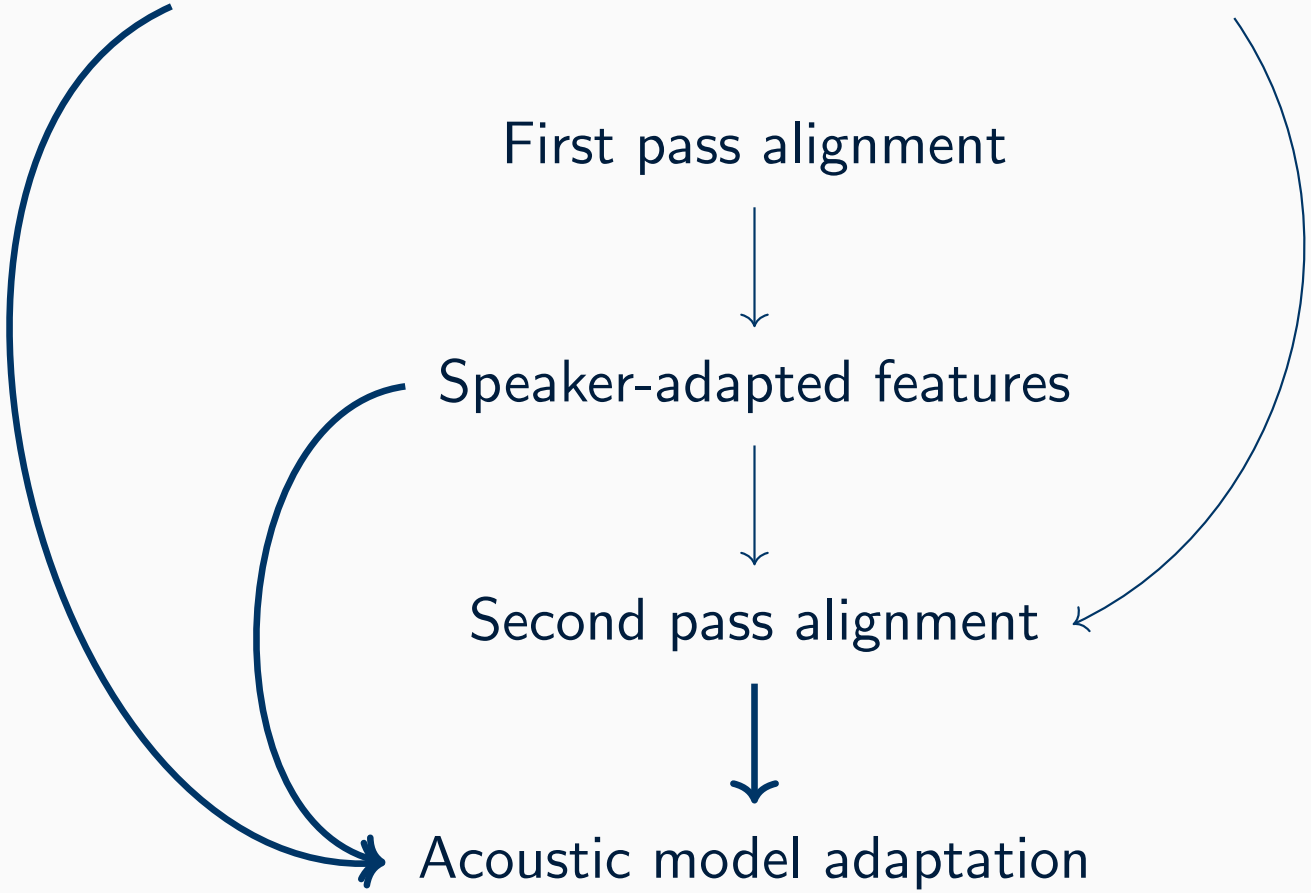
MFA adaptation pipeline

Speaker-independent features

- Audio
- Acoustic model

Decoding graph

- Transcript
- Pronunciation dictionary

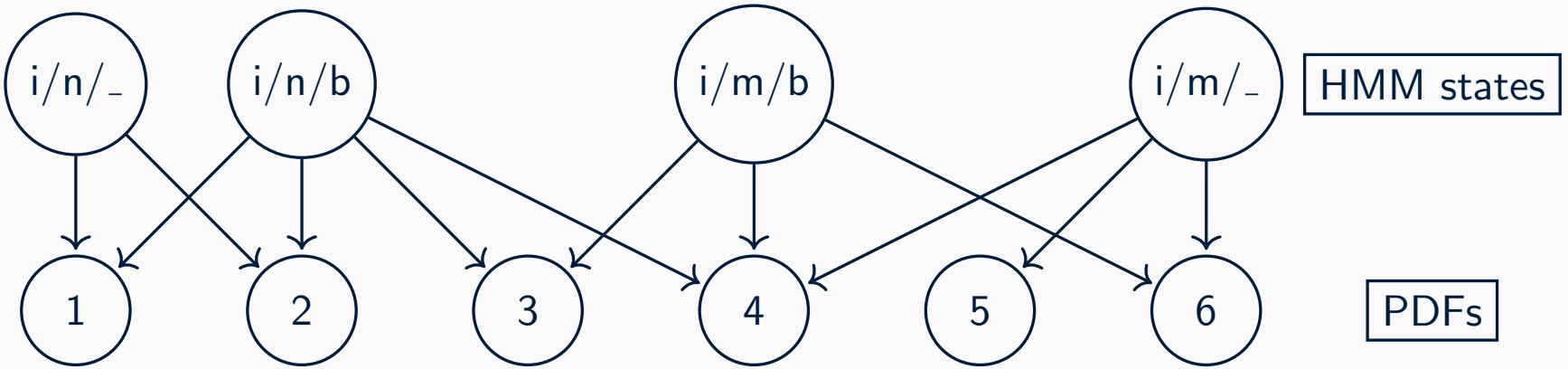


The essentials of alignment - mfa adapt

- Key point:
  - Adaptation uses automatic alignments
  - If alignments are poor quality, adaptation will be poor
- Reference alignments
  - New in 3.3!
  - Can use corrected alignments to guide all alignments
  - Implementation: penalize acoustic states that are not associated with the correct phone

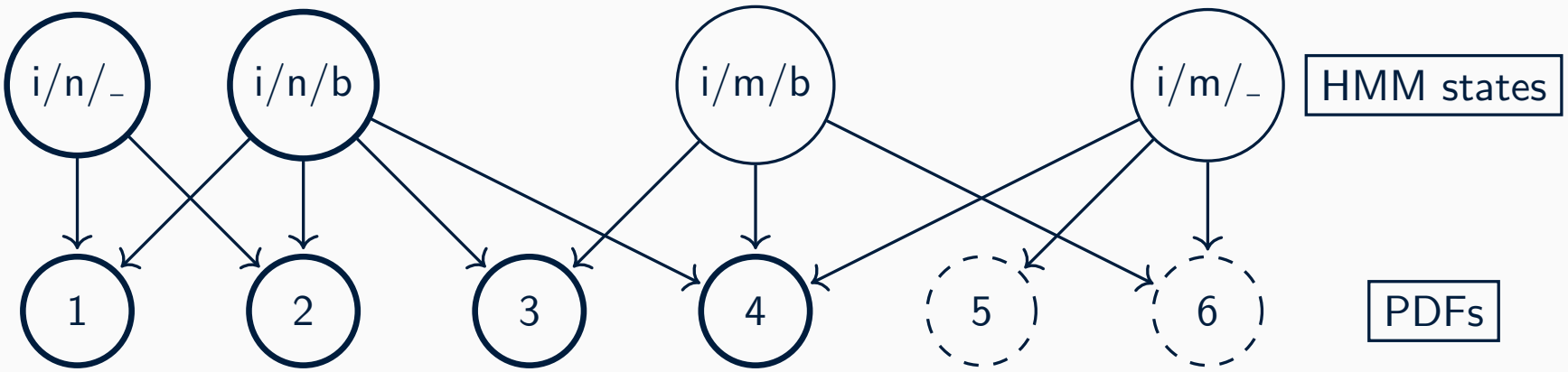
Schematic of phone clustering

- Three-phone sequence space is huge
- Cluster similar acoustic probability density functions (PDFs) across different phones
- Goal: capture allophonic/coarticulatory information
  - green beans
  - gr[i m b]eans?



How reference phones are used in align

- PDFs give log-likelihood based on acoustic features
- If there's a reference phone
  - If the PDF is mapped to that phone, return normal log-likelihood
  - If the PDF is not mapped to that phone, return extremely unlikly log-likelihood



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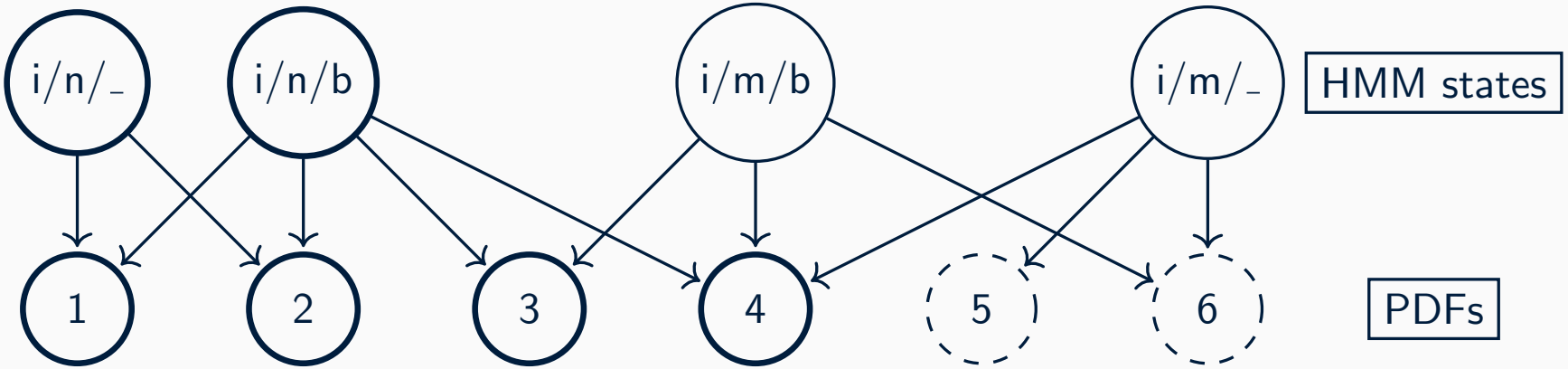
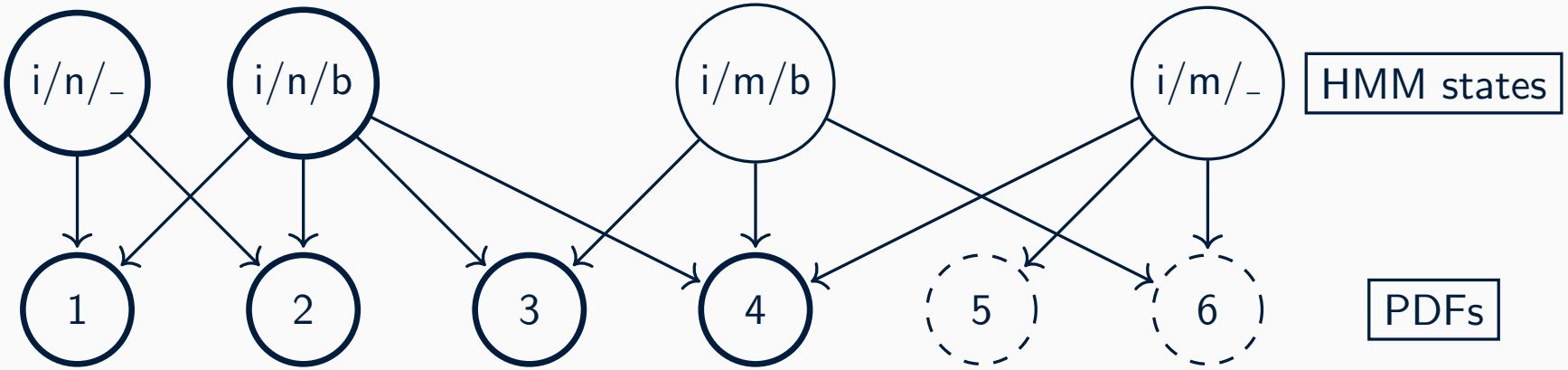


How reference phones are used in adapt

- Only PDFs that are used in alignments are adapted
- More data → better adaptation
- More variety → better adaptation



The basics: levers for improving alignment

Key factors

- Data Quality
  - Transcription accuracy (Description is analysis)
  - Out of Vocabulary items (OOVs)
- Data Quantity
  - More is better!
  - Variability (phones, styles, speakers)
- Target data similarity to Training data
- Experimentation - Try different things out!

Dictionary: OOVs

- Why do OOVs matter?
  - We want more instances a phone across different states
  - OOVs mean fewer examples of the phone(s)
  - Aligning OOV can cause errors downstream
- Add pronunciations
  - Target the ones with high Ns
  - Diminishing returns on single tokens

Transcripts: split long utterances

- Errors early on can be recovered from, can affect later alignments
- Split longer segments of transcripts ($>$ 1min)
- Use breath groups to segment
- When certain utterances have poor alignment (e.g., from OOVs) splitting the utterance into smaller segments

Variation and Speakers

- Data quantity and variation matters
- More data for a single speaker
  - Elicitation style - word lists and conversations
  - More data - phone environments, tokens, etc.
- More data across speakers
- Give separate speaker IDs for stylized speech (e.g., whispering, falsetto, story telling, etc.)

Ok that was a lot of information, let's take a 15 minute break before case studies!

Part 1 - MFA Supported Language

Overview

- Easiest use-case: Target data is similar to training data
- Inputs:
  - MFA supported language (English) acoustic model(s)
  - Speech corpus MFA format (audio, transcripts)
  - Dictionary
  - Manual reference alignments

Target data: Buckeye Corpus

- Buckeye Corpus (Pitt et al. 2007) with corrections, see data prep scripts[1]
- Conversational speech w/ ground truth for benchmarking alignment
- 40 speakers
    - all white, 20M/20F, distributed across age, Columbus OH

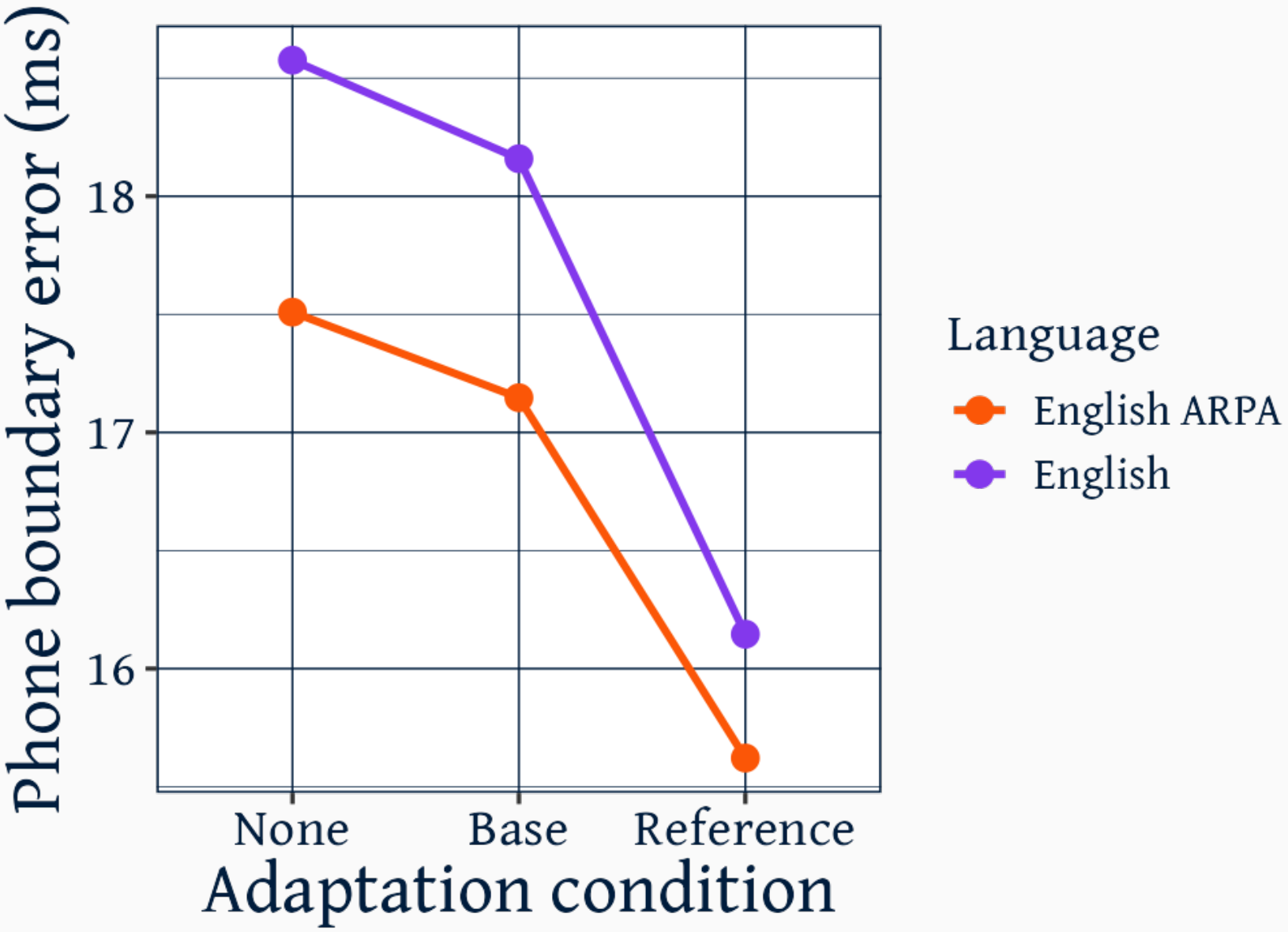
[1] https://github.com/MontrealCorpusTools/mfa-models/tree/main/scripts/alignment_benchmarks/data_prep

Training data

Model	Variety	Style	Hours	Speakers
English ARPA[a]	General US English	Read Speech	982	2,484
English MFA[b]	Multi-dialectal, Global English, L2 Speech	Conversational, Read Speech	3,771	78,975

[a] English (US) ARPA docs
[b] English MFA docs

Quality of alignments



Takeaways

- Adaptation
  - Alignments with English models already pretty good (18ms)
  - Running adapt still improves alignments *a little* (0.4ms)
  - Having oracle adaptation alignments improves them more (2ms)
- English ARPA outperforms English MFA
  - English ARPA source data is the same variety as target
  - English MFA source data is more, but global varieties

Part 2 - Novel Speech Variety

Overview

- Use case: Language is supported in MFA, but the variety of the target data is not represented in the model
- Inputs:
  - MFA supported language (English) acoustic model
  - Speech corpus MFA format (audio, transcripts)
  - Dictionary
  - Reference alignments (WhisperX)

Target data: VariCS Corpus

- Variation in Child Speech (VariCS)[2]
  - Recordings from 275 children speech
  - Age 5-12 years from Scotland, UK
  - Recorded in the primary schools, noisy environments etc.
  - Includes several tasks
    - For today, looking at the picture naming
    - because children, not entirely controlled but not fully spontaneous either
  - Transcribed by WhisperX - no adjustments made to transcript

[2] Christodoulidou et al., submitted

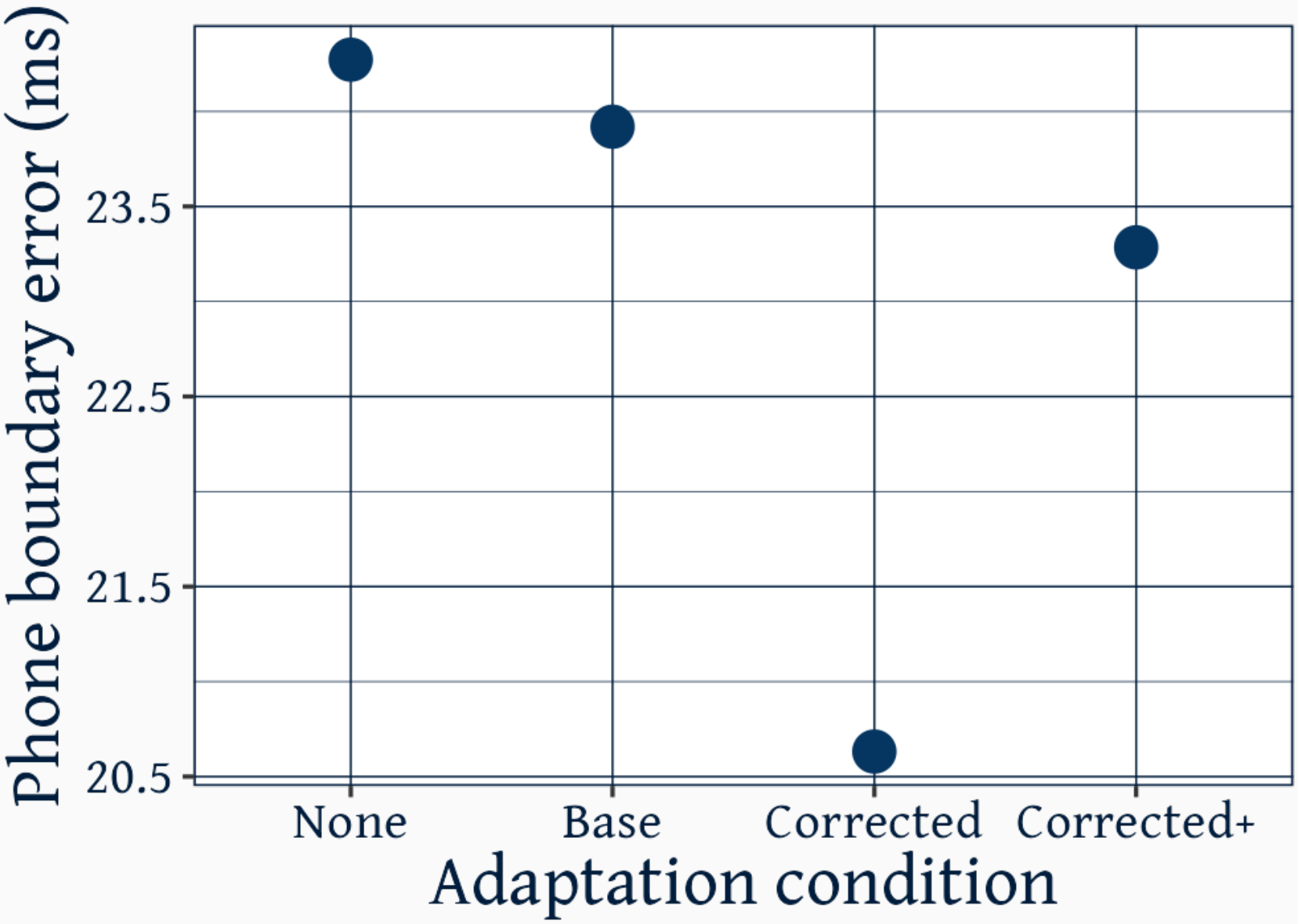
Target data: Evaluation subset

- Similar to Christodoulidou et al. (submitted)
- Eval set is 9 manually corrected files from 5 children
  - 9 manually corrected files from 5 children
  - 48 utterances per child
- Adaptation data sets
  - Base: 9 files from eval set without using manual alignments
  - Corrected: 50 manually corrected files
  - Corrected+: Corrected files plus all other uncorrected files

Training Data

- English US ARPA model
  - Different Target and Training Data
  - US $\rightarrow$ Scottish English
  - Adult Read Speech $\rightarrow$ Spontaneous-ish Children's Speech

Quality of alignments



Takeaways

- Generally larger error than for Buckeye (24ms vs 18ms)
- Adaptation
  - Base adaptation doesn't help that much (0.4ms)
  - Corrected helps the most (3.7ms)
  - Adding noisy adaptation data reduces gains (1ms)
  - More data isn't always better

Part 3 - Non-supported Language

Overview

- Use Case: There is no current language support for the target data
- Inputs
  - Speech corpus MFA format (audio, transcripts)
  - Dictionary (in Target language)
  - MFA Acoustic models of varying similarity to target data

Target data: Buckeye Corpus

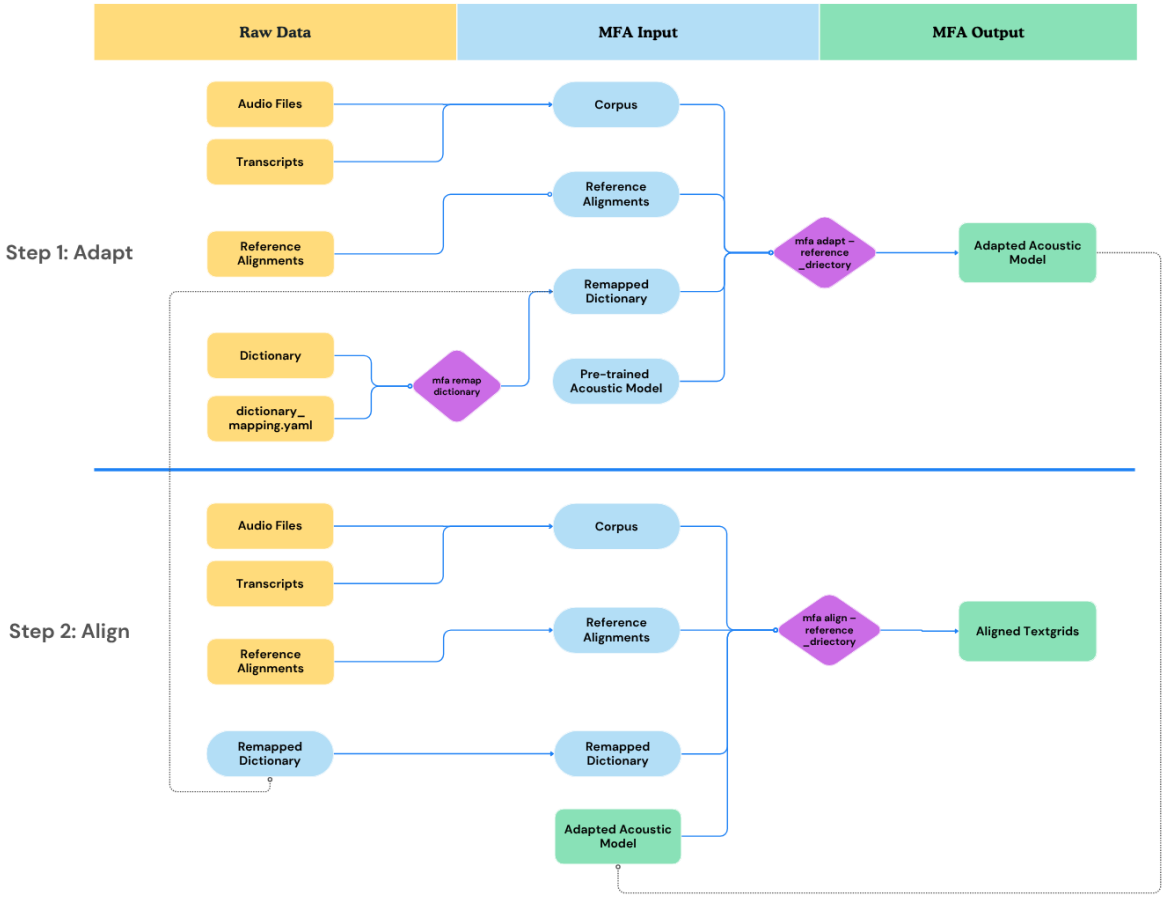
- Suspend disbelief, Buckeye represents the under-resourced variety
- Allows for comparisons across adapting with source languages that vary in degree of phone similarity
- English ARPA $\rightarrow$ English MFA $\rightarrow$ German $\rightarrow$ Czech $\rightarrow$ Mandarin

Training Data

Model	Variety	Style	Hours	Speakers*
English ARPA[a]	General US English	Read Speech	982	2,484
English MFA[b]	Multi-dialectal, Global English, L2 Speech	Conversational, Read Speech	3,771	78,975
German MFA[c]	German	Read Speech	1,315	18,012
Czech MFA[d]	Czech	Spontaneous, Read Speech	643	1,261
Mandarin[e]	Multi-dialectal	Read Speech	612	7,316

[a] English (US) ARPA docs
[b] English MFA docs
[c] German MFA docs
[d] Czech MFA docs
[e] Mandarin MFA docs

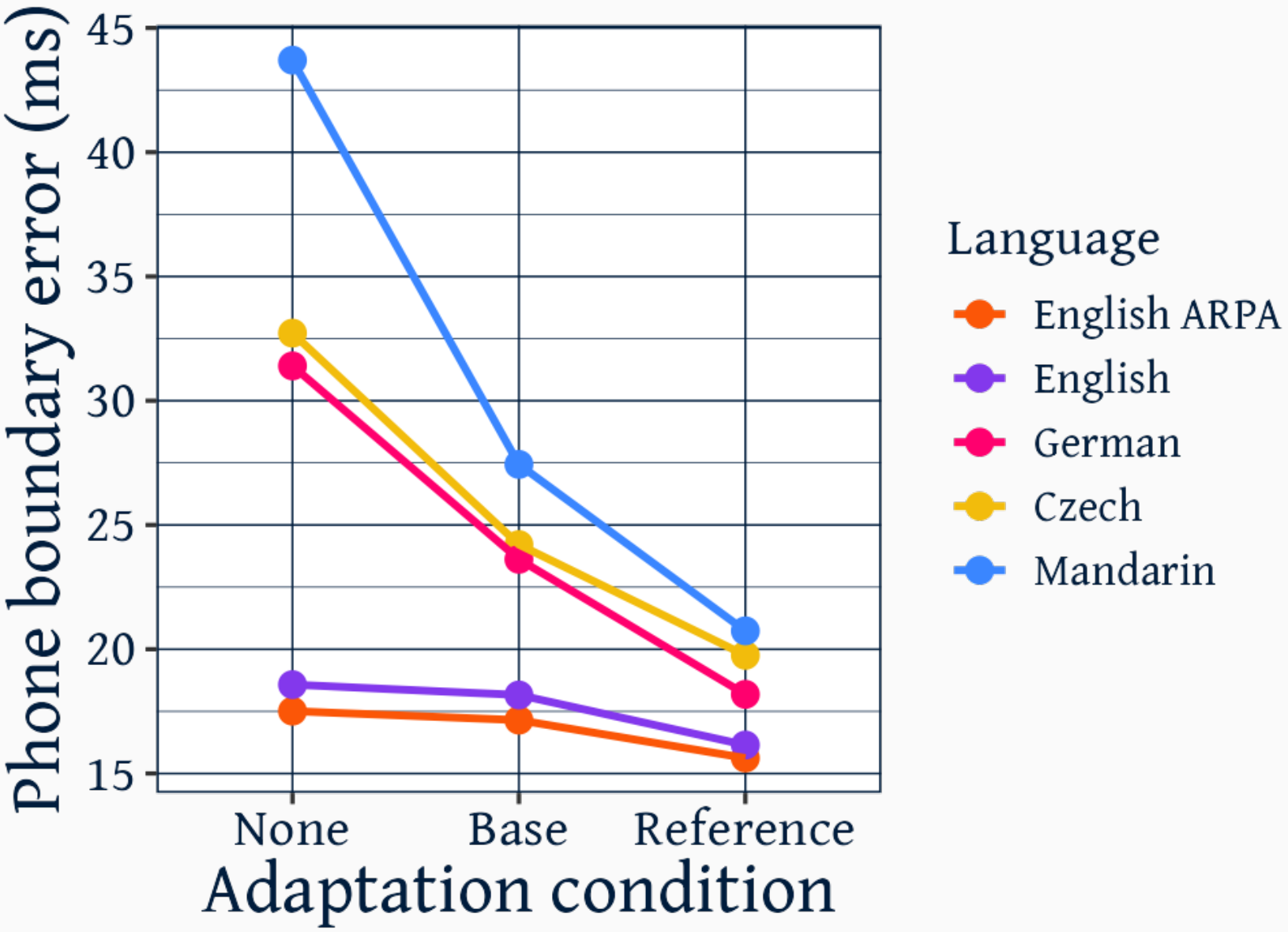
Methods


Raw Data
MFA Input
MFA Output
Step 1: Adapt
Audio Files
Transcripts
Reference Alignments
Dictionary
dictionary_ mapping.yaml
mfa remap dictionary
Corpus
Reference Alignments
Remapped Dictionary
Pre-trained Acoustic Model
mfa adapt – reference _driectory
Adapted Acoustic Model
Step 2: Align
Audio Files
Transcripts
Reference Alignments
Remapped Dictionary
Corpus
Reference Alignments
Remapped Dictionary
Adapted Acoustic Model
mfa align – reference _driectory
Aligned Textgrids

Target vs. Training Phones

Model	English → Training Phones
English ARPA	[p^h, p^j, p^w] → [P] [m̩] → [AH0 M]
German MFA	[ð] → [d, v] [θ] → [t, f] [ɔj] → [ɔʏ, ɔ j] [ɹ] → [ʁ, ɐ]
Czech MFA	[ej] → [ɛː, ɛ j] [aj] → [a j] [ð] → [d, v] [θ] → [t, f] [ɹ] → [r, ə]
Mandarin MFA	[ʤ] → [ʨ, ʈʂ, ʦ] [n̩] → [n̩ɳ] [ʃ] → [ɕ, ʂ, s] [ɹ] → [ɻ]

Quality of alignments



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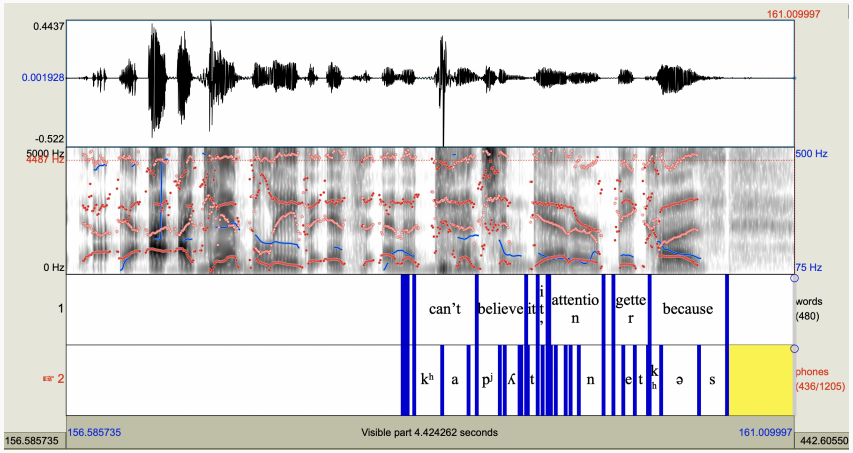

Figure 1: Mandarin - Align

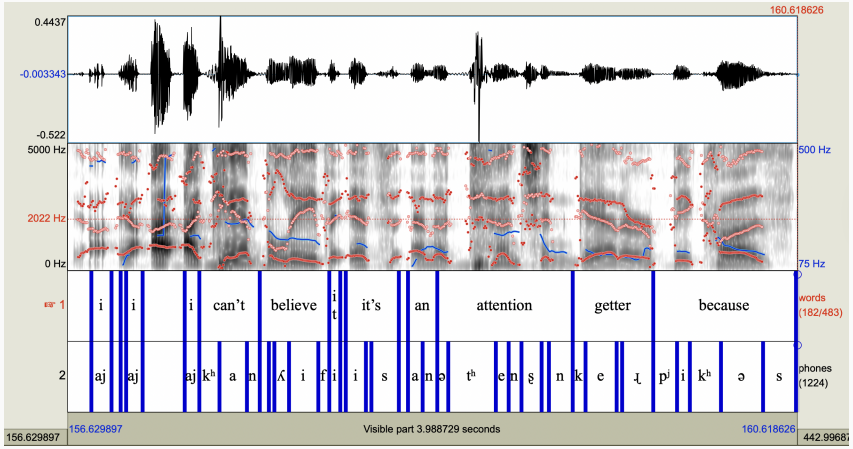

Figure 2: Mandarin - Adapt with reference

Quality of alignments

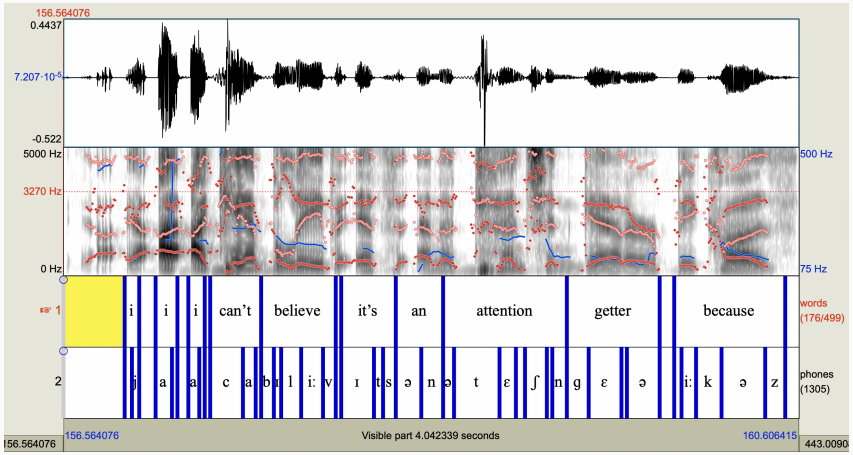

Figure 3: Czech - Align

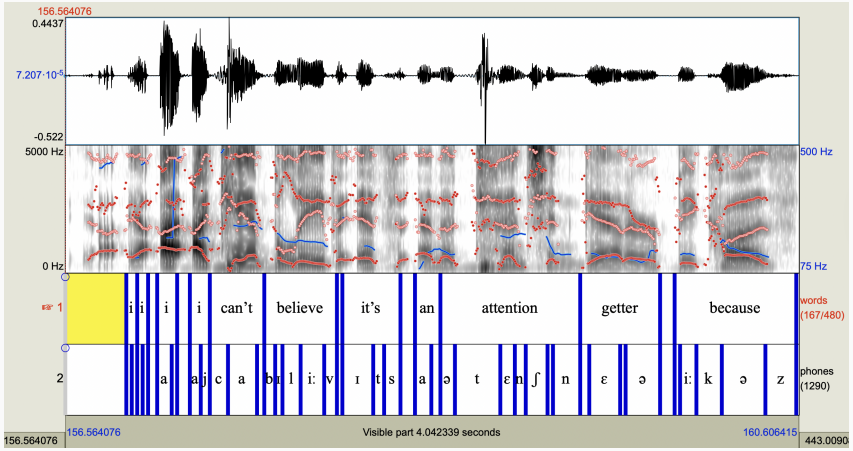

Figure 4: Czech - Adapt with reference

Quality of alignments

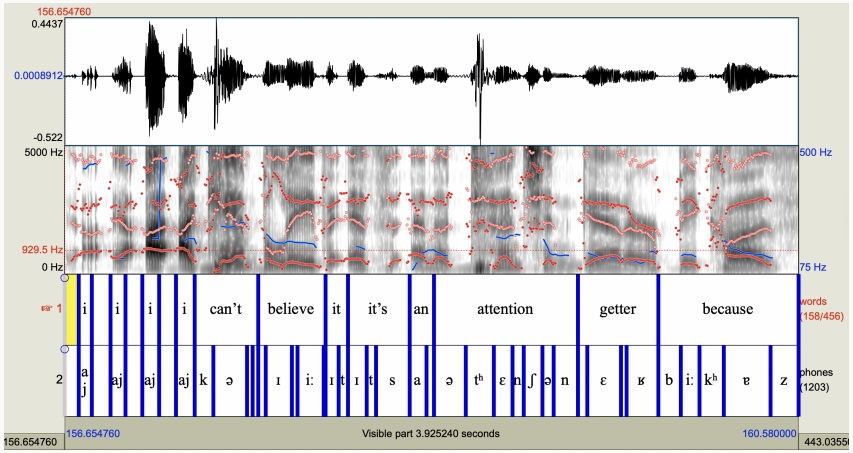

Figure 5: German - Align

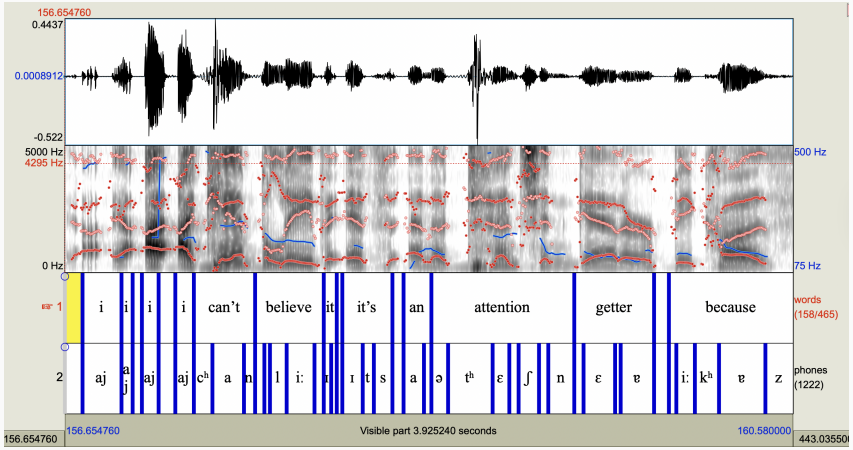

Figure 6: German - Adapt with reference

Takeaways

- Alignment performance follows similarity
  - English $<$ German $<=$ Czech $<$ Mandarin
- Adaptation
  - Adaptation helps Mandarin the most (16ms)
  - Adaptation still shows gains for German (7.8ms) and Czech (8.5ms)
  - Base adaptation gives a majority of the gains
    - Mandarin: 70%
    - Czech: 66%
    - German: 59%

Final Thoughts

Final Thoughts

- Adaptation generally helps
  - Generally shows decreased boundary errors
  - Beware that these are mean measures
  - Still investigations to be done on errors
  - I cannot confidently say that adaptation will help ALL cases
- Aim for high quality data
- Consider how similar your target and training data is

Final thoughts

- Don't be afraid to experiment!
- Invest in creating small eval set
  - Can just be spot-checked good alignments
  - mfa align ... —— include_original_text
  - Can spot-check Praat, Anchor
- Incorporate eval set into your final adaptation
  - No sense wasting high quality data
  - Lose evaluation on generalizing
  - Generalizability is not really a concern
  - You want the best alignments possible for a corpus, so it's fine to train on your eval data (eventually)

Align-a-thon at LabPhon 2026

- Ground truth alignments for English
  - Licensing issues
- Are some boundaries more important than others to phoneticians?
  - Silence to stop?
  - Stop to vowel?
  - Vowel to silence?

We'll be hosting an align-a-thon workshop at LabPhon 2026 in Montreal next summer!

Hope to see you there!

Thank You!

This workshop is supported by

Q&A