Class 11: Audio Recognition and Alignment

Theme: Audio

Computational Analysis of Text, Audio, and Images, Fall 2023

Aarhus University

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Aarhus University

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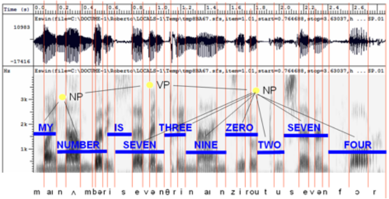

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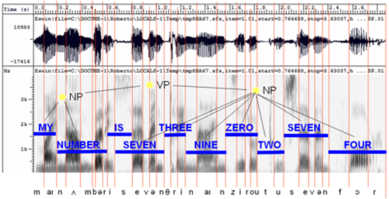

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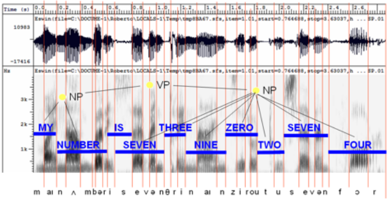

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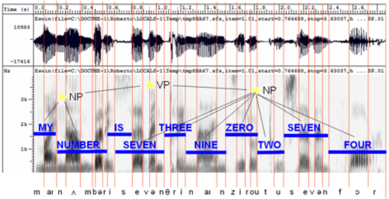

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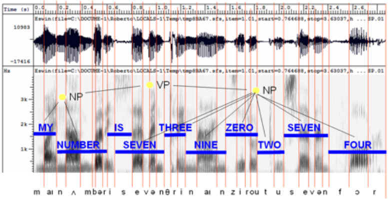

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- Indirect text analysis (e.g. hostile rhetoric removed in official transcripts)

Open-Source Tools

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	Whisper	**Wav2Vec 2.0**
Learning	weak-supervision	self-supervision
Input	log-mel spectrograms	raw waveforms
Languages	> 100	$> 1,400$
Architecture	encoder/decoder	encoder
Output	processed	raw
Timestamps	segment-level	character-level
Error	$5 - 30\%$	$20 - 50\%$
Time (hours)	5.8	222.0

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Other (paid) systems as well, but Whisper and Wav2Vec 2.0 are the best options:

- Google Cloud Platform
- Amazon
- Assembly AI

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⇝ WER is a generalization of Levenshtein's distance to the word-level rather than the character-level

Exercise

Consider the following two sentences:

- Target: “The cat is sleeping on the mat”
- ASR: “The a cat is sweeping on mat”

1. Compute the WER
2. Discuss weaknesses of the WER metric and potential alternative metrics

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$\rightsquigarrow$ decomposes audio to the speaker-level

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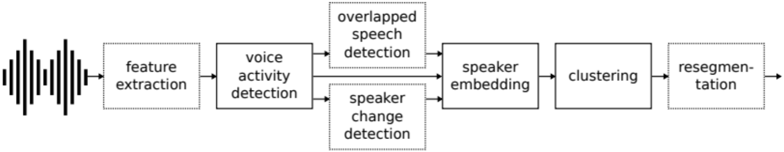

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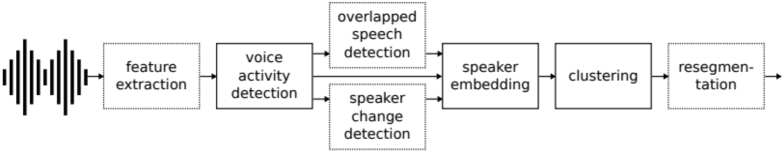

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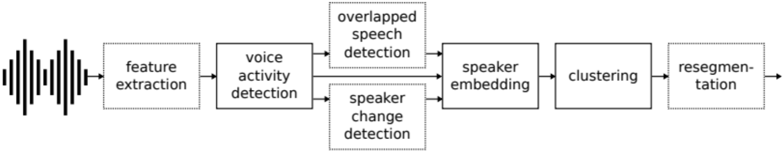

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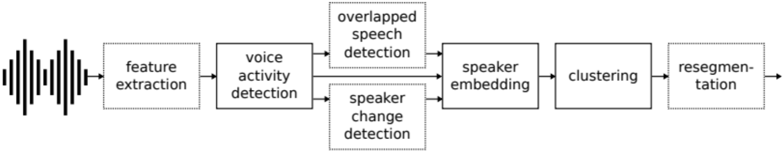

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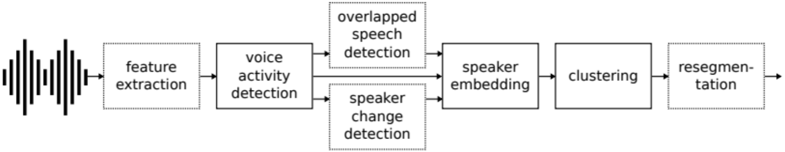

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- Encoded with neural networks – pretrained models work surprisingly well

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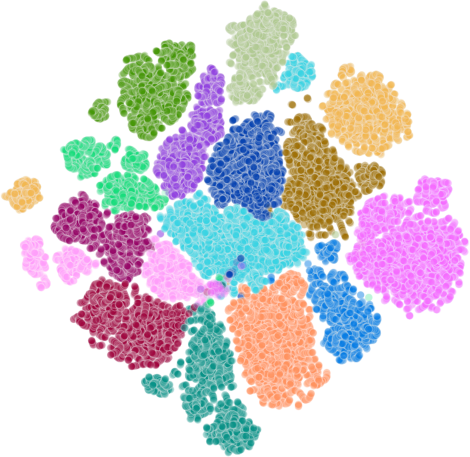

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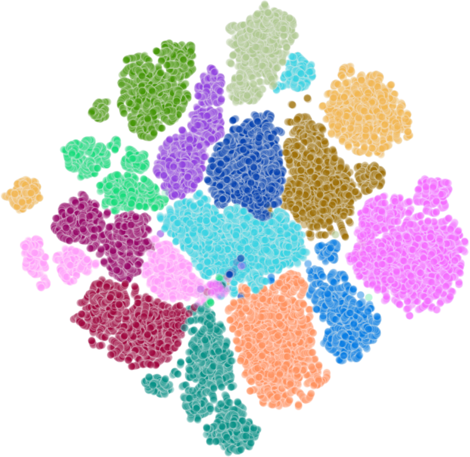

⇝ Embeddings are fixed-length *x*-vectors (Snyder *et al.*, 2018) computed on diarized speech segments and then reduced using t-SNE

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- Generally requires a supervised setup, but a weakly supervised setup is possible if we have auxiliary targets

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Speaker diarization functions as a preprocessing step that simplifies the subsequent tasks – when combined, you have a powerful annotation pipeline (Rask, 2023)

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6. Apply matching scheme to map candidates to targets to obtain speaker names for segments $i \in \{1, \ldots, K\}$

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6. Apply matching scheme to map candidates to targets to obtain speaker names for segments $i \in \{1, \ldots, K\}$
7. Generate speaker embeddings for each segment i and assign as reference audio for each identified speaker

Weakly-Supervised Speaker Recognition (Rask, 2023)

When speech-level transcripts are available for the recording we want to annotate, we can combine speaker diarization and ASR to perform weakly-supervised speaker identification using fuzzy string matching:

1. Diarize recording $\mathcal{R}$ with signal $y(n)$ into K segments s_i with $i \in \{1, \dots, K\}$
2. Apply ASR on each segment s_i to obtain K candidate texts
3. Obtain M auxiliary targets from transcript
4. Preprocess and vectorize texts candidates and targets into vectors $\mathbf{C}$ and $\mathbf{T}$
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$\rightsquigarrow$ Joint speaker diarization, ASR, and speaker recognition using unsupervised and weakly-supervised learning

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- Combining diarization and ASR is equivalent to aligning at the speech-level
- The level of alignment depends on where we think the *variation* is in each modality

Exercise

1. Discuss the difference between audio measurement when using the speech-level compared to the word-level.
2. Compare audio measures with text measures (e.g. using a dictionary) when we use speeches as the unit of analysis.

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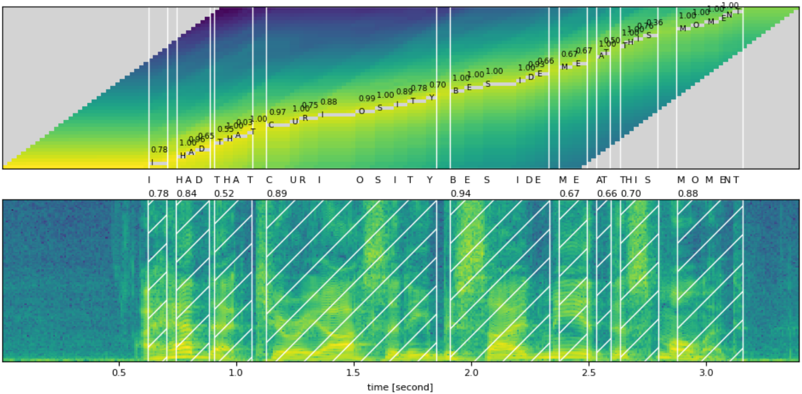

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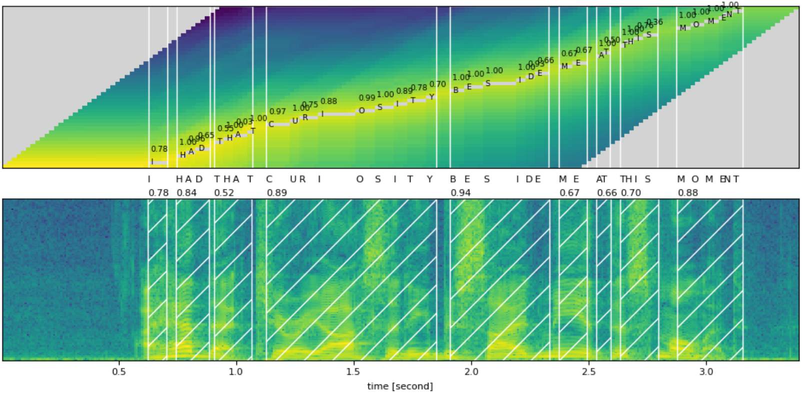
We can also align each audio and text at the level of each word:



⇝ Combines wav2vec2.0 with a phoneme model as overhead to perform character-level ASR

⇝ Alternative approach: Faster Whisper or WhisperX

⇝ Alignment is non-destructive – we can go back and forth between levels

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See you next week!

Theme: Audio

Computational Analysis of Text, Audio, and Images, Fall 2023

Aarhus University

References i

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