Speech Enhancement and Diarization

Introduction to Human Language Technology

Matthew Maciejewski

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or, towards:

The Cocktail Party Problem[1]

[1]E.C. Cherry, *Some Experiments on the Recognition of Speech, with One and with Two Ears.* The Journal of the Acoustical Society, 1953
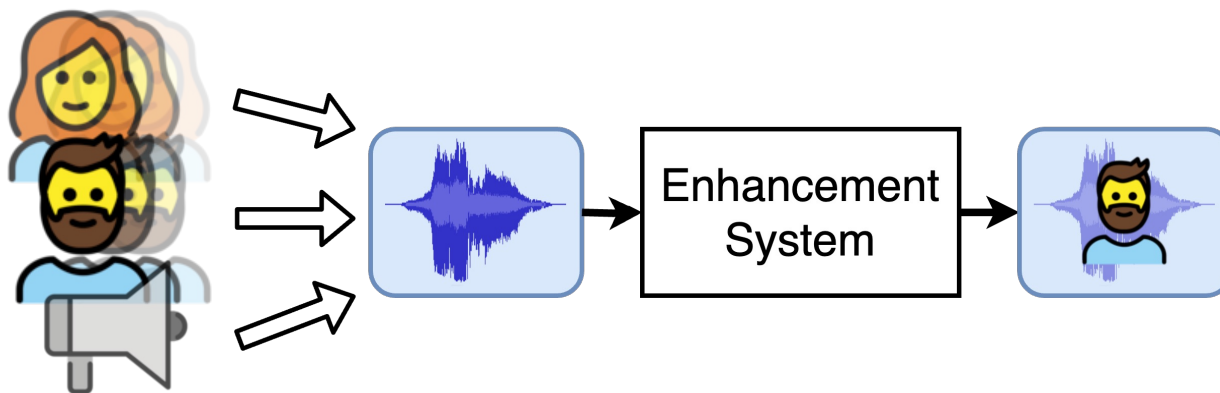
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Speech Enhancement (and Separation)

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What is speech enhancement?

- Recordings of speech often have a lot of degradation and interfering sounds

- Speech enhancement is the task of removing interferences or reconstructing the clean speech

Enhancement System

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Why do we care?

- Human listening can always be the end goal

- Degraded audio often leads to degraded performance of downstream systems

- Robust speech technology often integrates techniques developed in enhancement

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Mathematical Formulation

Input: $$x(t) = s(t) + n(t)$$

Output: $$y(t) = \hat{s}(t)$$

We can also treat $n(t)$ more precisely:

Reverberation: $$x(t) = s(t) * h_{RIR}(t)$$

Separation: $$x(t) = s_1(t) + s_2(t)$$

All together: $$x(t) = \sum_{c=1}^{C} [s_c(t) * h_c(t)] + \sum_{k=1}^{K} n_k(t)$$

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Performance Evaluation

- Full Reference
  - **SI-SDR**, SNR, (SDR, SIR, SAR), …
  - **PESQ**, STOI, POLQA, …
- No Reference
  - Human listening tests! (**MOS**)
  - ITU P.563, SRMRnorm, …
  - DNSMOS, SQAPP, …
- Downstream Evaluation
  - Impact on downstream speech tasks

$$\text{SI-SDR} = 10 \log_{10} \frac{|s|^2}{|s - \beta \hat{s}|^2}$$
$$\text{for } \beta \text{ s.t. } s \perp s - \beta \hat{s}$$

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Significance of Ground Truth

Issues of ground truth are a significant aspect of waveform-level tasks

- Non-full-reference metrics have large downsides and typically require synthetic mixtures

- Neural network training targets typically require targets and also require synthetic mixtures
  - Domain mismatch can be a significant problem

- Practical approaches often avoid trying to directly optimize the output waveform

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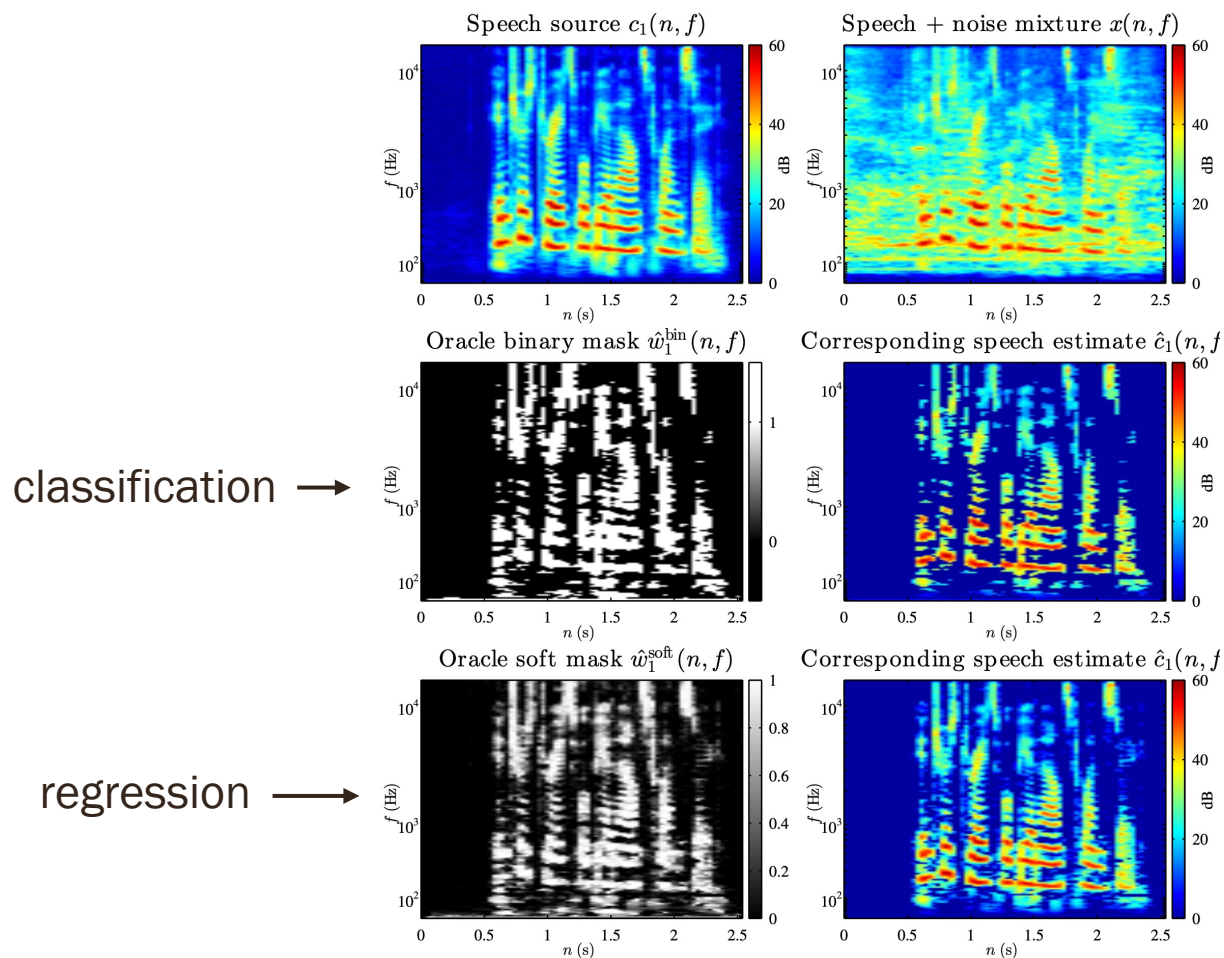UNIVERSITY

General Approach

- Speech enhancement methods generally fall under the umbrella of "filtering", with some further broad categorizations:

  temporal filtering vs. **spectral filtering**

  estimation vs. **decomposition**

- These distinctions are in some sense arbitrary and can often be considered equivalent

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Mask-Based Enhancement

classification →

regression →

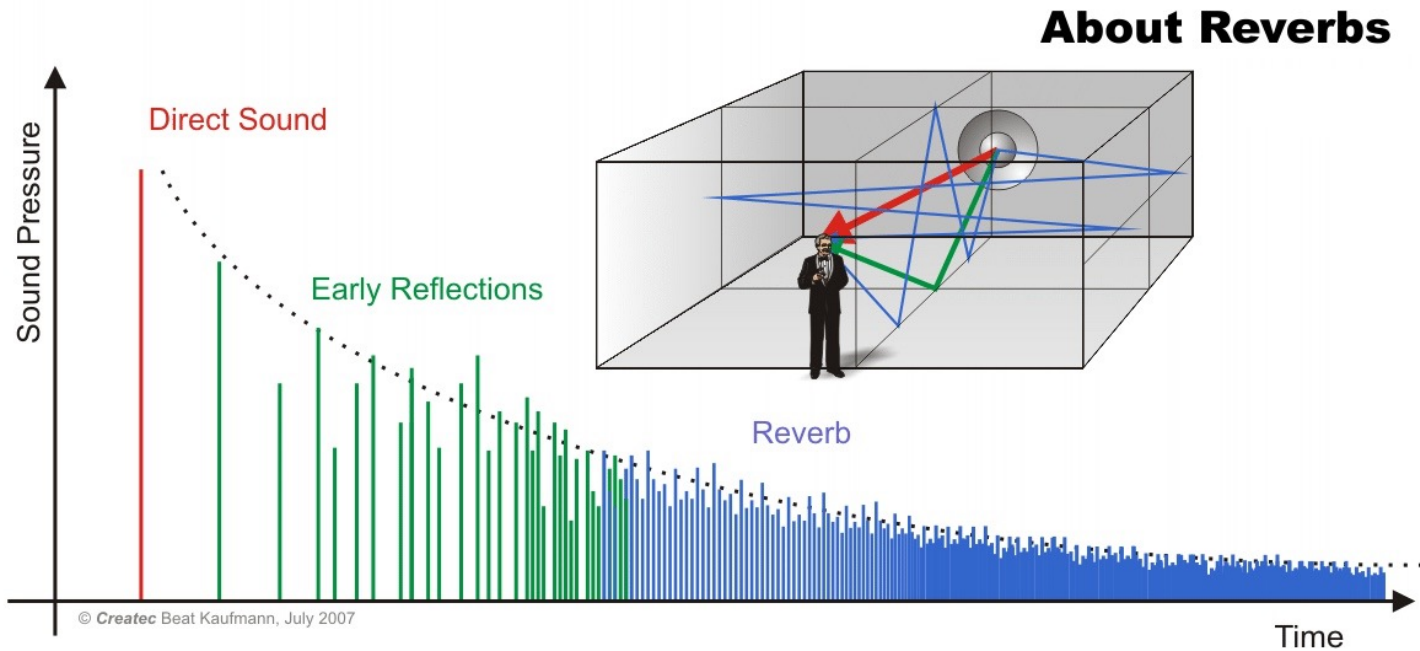Image credit: Vincent, et al. *Audio Source Separation and Speech Enhancement*

How do we estimate the filters?

- Can be learning-free, unsupervised, supervised

- Estimation of speech presence probability, noise distribution, SNR, power spectra, etc.

- Nonnegative Matrix Factorization (NMF)
  - Decompose magnitude/power spectrum into set of distinct basis spectra

- Independent Component Analysis (ICA)
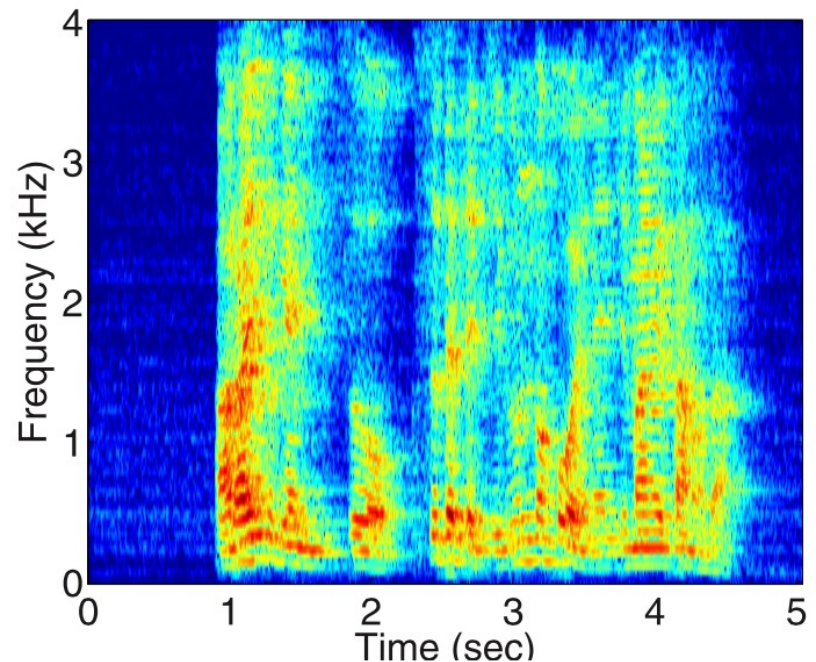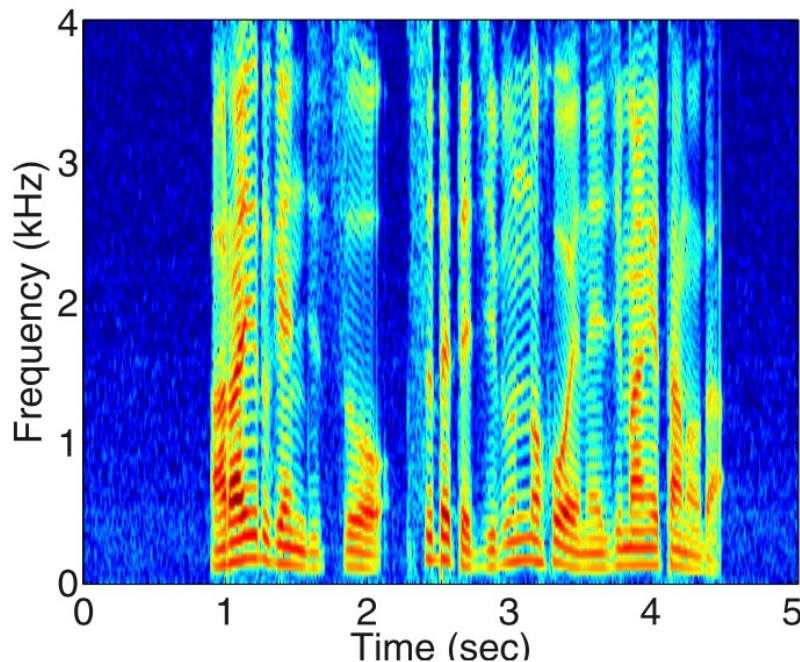 - Assumes mixture of mutually-independent stochastic source signals

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Reverberation

- Room Impulse Response (RIR) captures room reflections and mixes via convolution

© *Createc* Beat Kaufmann, July 2007

Image credit: *Createc* Beat Kaufmann

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Spectral Effect of Reverberation

- Reverb results in spectral smearing

Image credit: Cohen, et al. *Speech Processing in Modern Communication*

De-Reverberation

- Most successful practical approach is Weighted Prediction Error (WPE)[1,2] dereverberation
- The late tail reverberation is estimated and cancelled via delayed linear prediction
  - Iterative procedure to continually update inverse filter
- Avoiding early reflections minimizes corruption of direct path and issue of relative non-stationarity
- "Deep" extension via neural speech Power Spectral Density (PSD) estimation[3]

 [1]T. Nakatani (2010) [2]T. Yoshioka (2012) [3]K. Kinoshita (2017)
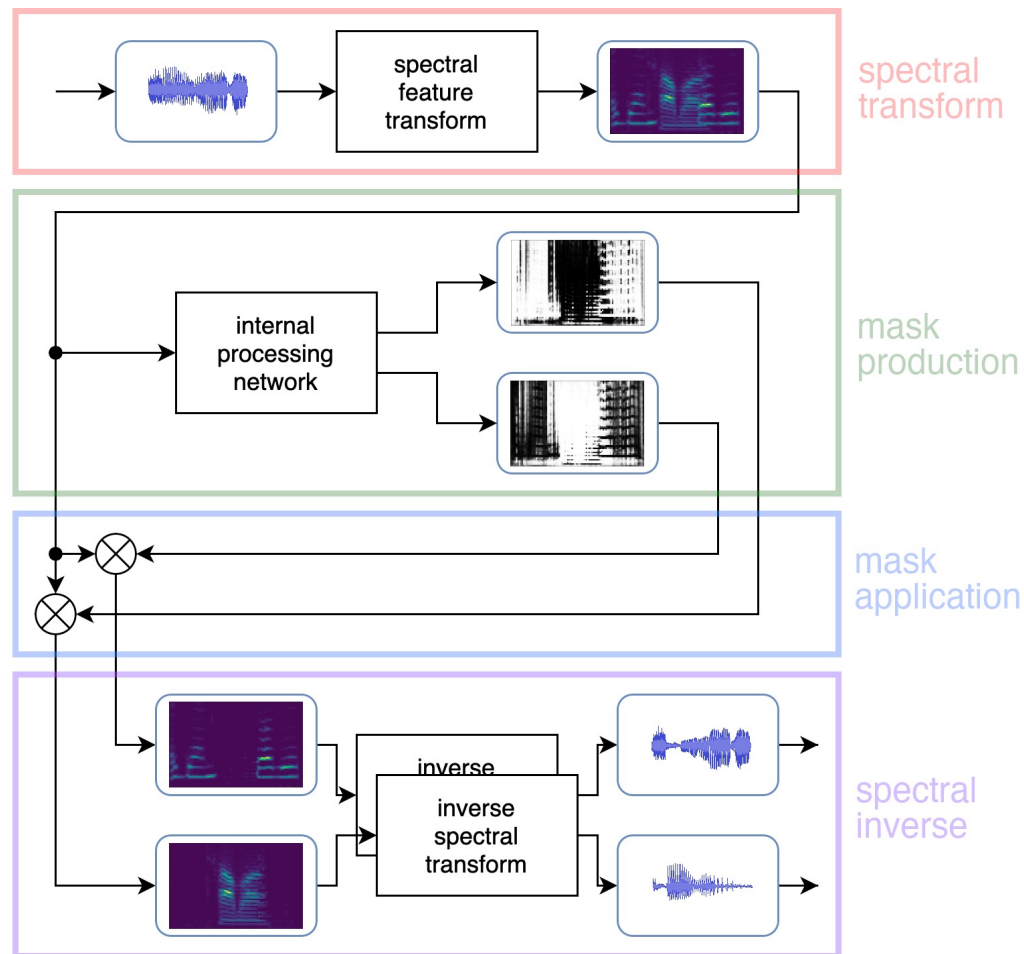
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Speech Separation

- Speech separation aims to estimate single-speaker waveforms from overlapping speech

- Relies on the spectral sparsity of speech

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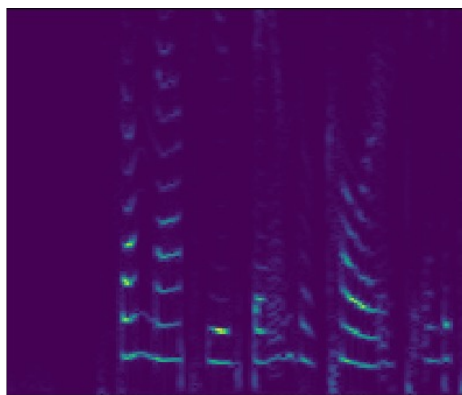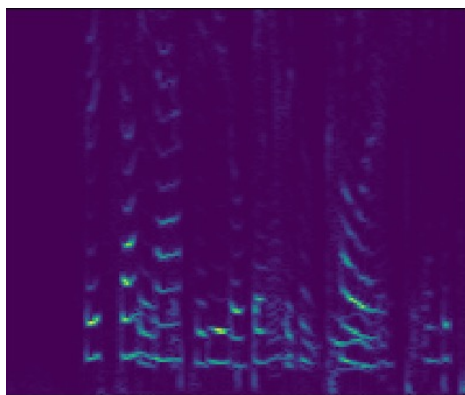
Separation Pipeline

Challenges in Training

Foundational approaches on mask-based loss:

- Deep Clustering (DPCL)
  - Extract embedding for each STFT bin
  - Ensure self-similarity of dominant bins from a speaker

- Permutation-Invariant Training (PIT)
  - Compute minimum loss across all output permutations, backpropagate from best permutation

- State-of-Art systems dominated by learned spectral transforms with SI-SDR PIT loss

[1]J.R. Hershey (2016) [2]D. Yu (2016)

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Target Speaker Extraction

- Given a recording and an enrollment utterance or speaker representation, produce the clean speech of the enrolled speaker

- Has elements of both speech separation and speech enhancements

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Multichannel Enhancement

- Collecting audio simultaneously with multiple microphones gives more information for the underlying signals

- Particularly: multiple sensors allows for localization, and multiple sources generally have different locations

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Formulation

$$x(t) = \sum_{j=1}^{J} c_j(t)$$

diffuse source → just $c_j(t)$

point source → (time-invariant) spatialization

$$c_j(t) = a_j(t) * s_j(t)$$

$$a_j(t) = \left[a_{1j}(t), \ldots, a_{Ij}(t)\right]^{\mathrm{T}}$$

can be RIR, delay/attenuation

$x \in \mathbb{R}^{I \times T}$
I microphones

$c \in \mathbb{R}^{I \times T}$
spatialized sources

Can approximate in STFT domain:

$$a_j(n, f) \sim a_j(f)$$
$$c_j(n, f) = a_j(f)s_j(n, f)$$
$$x(n, f) = A(f)s(n, f)$$

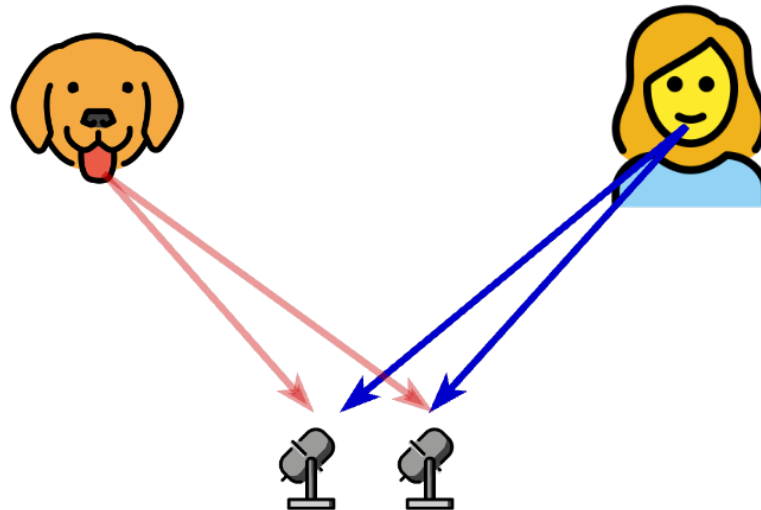"steering vector":
$$a_j(f) \rightarrow d_j(f)$$

$$d_j(f) = \begin{bmatrix} \frac{1}{\sqrt{4\pi r_{1j}}} e^{-2j\pi r_{1j} v_f / c} \\ \vdots \\ \frac{1}{\sqrt{4\pi r_{Ij}}} e^{-2j\pi r_{Ij} v_f / c} \end{bmatrix} \approx \begin{bmatrix} e^{-2j\pi r_{1j} v_f / c} \\ \vdots \\ e^{-2j\pi r_{Ij} v_f / c} \end{bmatrix}$$

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Beamforming

- "Delay and sum" beamforming aligns target signal temporally and misaligns other signals for constructive/destructive interference

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TDOA Estimation

- Beamforming requires the "time difference of arrival" (TDOA)

- Generalized Cross-Correlation with Phase Transform (GCC-PHAT)[1]

- Minimum Variance Distortionless Response (MVDR) beamformer is computed in STFT domain by minimizing the power of the interfering signal
  - Weights can be computed from speech TF mask
  - Amenable to neural estimation

[1]C.H. Knapp (1976)

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...questions?

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(Speaker) Diarization

What is speaker diarization?
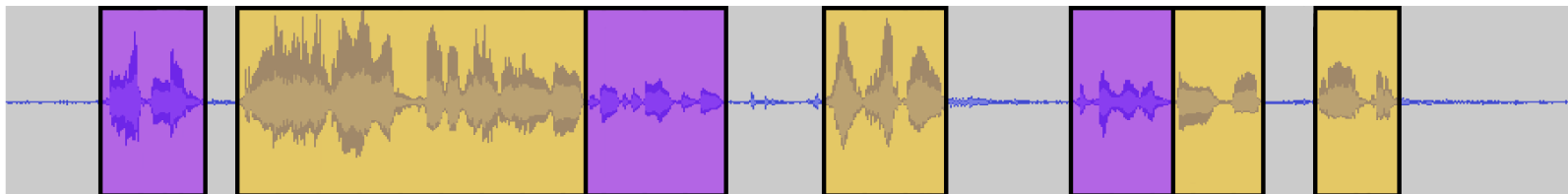
Who spoke when?

*other types of diarization exist, most notably language diarization

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Why do we care?

- Many speech systems "malfunction" in multi-talker scenarios
  - Closed captioning or meeting transcription
  - Target speaker recognition

- Conversational analysis
  - Biomarkers for emotional state
  - Study of child language acquisition
  - Social role (e.g. interruptions)
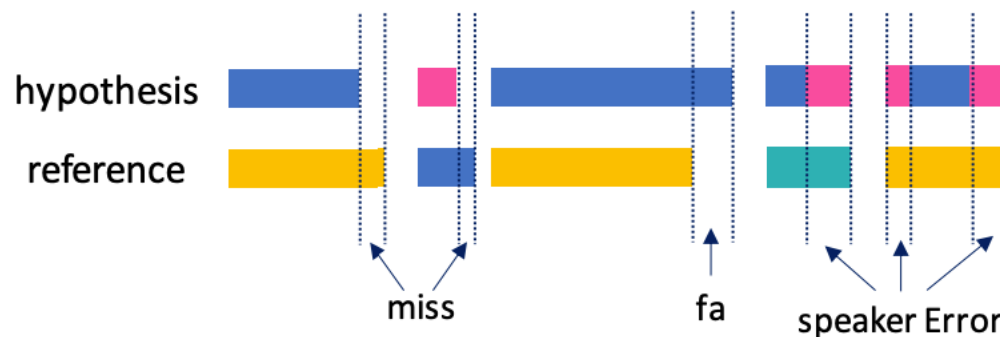
Mathematical Formulation

- "label-free" time series multi-label classification

$$x[t] \longrightarrow \boxed{\text{System}} \longrightarrow \boldsymbol{y}[t]$$
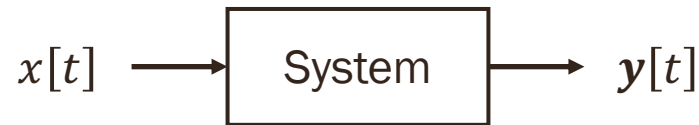
$$\boldsymbol{y} \in \{0, 1\}^{T \times S}$$

Order of speakers $s_i \in S$ does not matter

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Metrics

- Diarization Error Rate (DER%)

$$\text{DER} = \frac{false\_alarm + missed\_speech + speaker\_error}{total\_speech}$$

- Jaccard Error Rate (JER%)

$$\text{JER} = \frac{1}{S}\sum_{i=1}^{S}\frac{false\_alarm_i + missed\_speech_i}{speech_i}$$

Image credit: Paola Garcia

Approaches to Diarization

- **Traditional "Clustering" Approaches**
    - Multi-stage pipelines with independent components
    - Individually tuned
    - Less conducive to overlap detection

- **Neural (End-to-End) Approaches**
    - Trained to produce outputs directly
    - Can be jointly optimized
    - Data hungry

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Traditional Approach
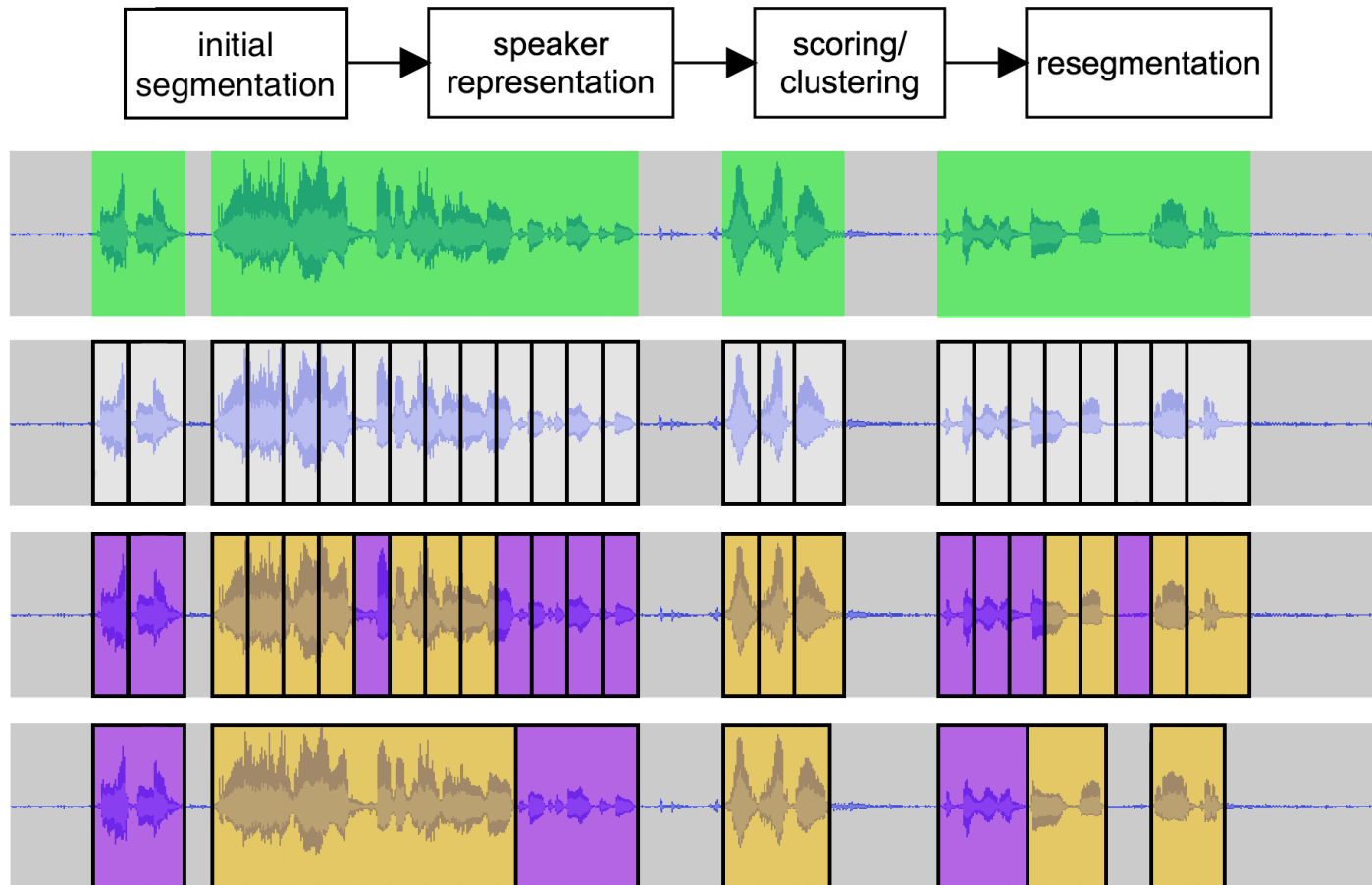
Initial Segmentation

- Speech Activity Detection (SAD)
  - Basic speech presence classifier
  - Generally neural, statistical has been used

- Less commonly can be more sophisticated
  - Speaker change detection
  - Overlap detection

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Speaker Representation

- Out-of-the-box Speaker ID systems
  - i-vectors, x-vectors, d-vectors

- Typically extracted under a sliding window

- Scoring can be tuned to test conditions or smaller speaker variability

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Clustering

- Many clustering approaches
    - Agglomerative clustering
    - Spectral clustering

- Major challenge is speaker counting
    - Oracle (not necessarily optimal!)
    - Speaker counting
    - Thresholding/Calibration

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Resegmentation

- Variational Bayes HMM of x-vectors (VBx)
  - Probabilistic model treating x-vectors as observation of latent states corresponding to speakers
  - Models the temporal aspect of conversations

- Target Speaker Voice Activity Detection (TS-VAD)
  - Speaker-specific speech activity classifier based on input speaker representation
  - Handles overlap!

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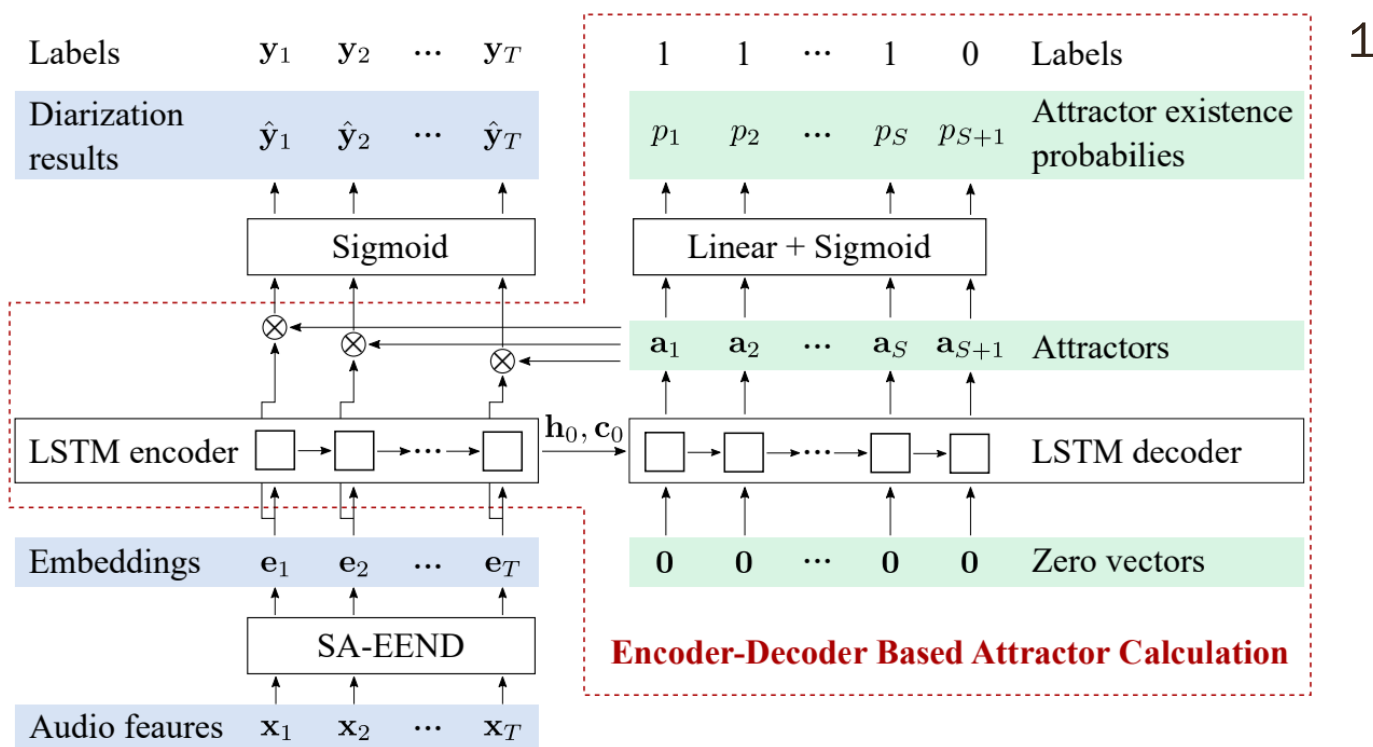UNIVERSITY

Neural Diarization

- Most methods derived from End-to-End Neural Diarization (EEND)[1] approach

[1]Y. Fujita (2019)
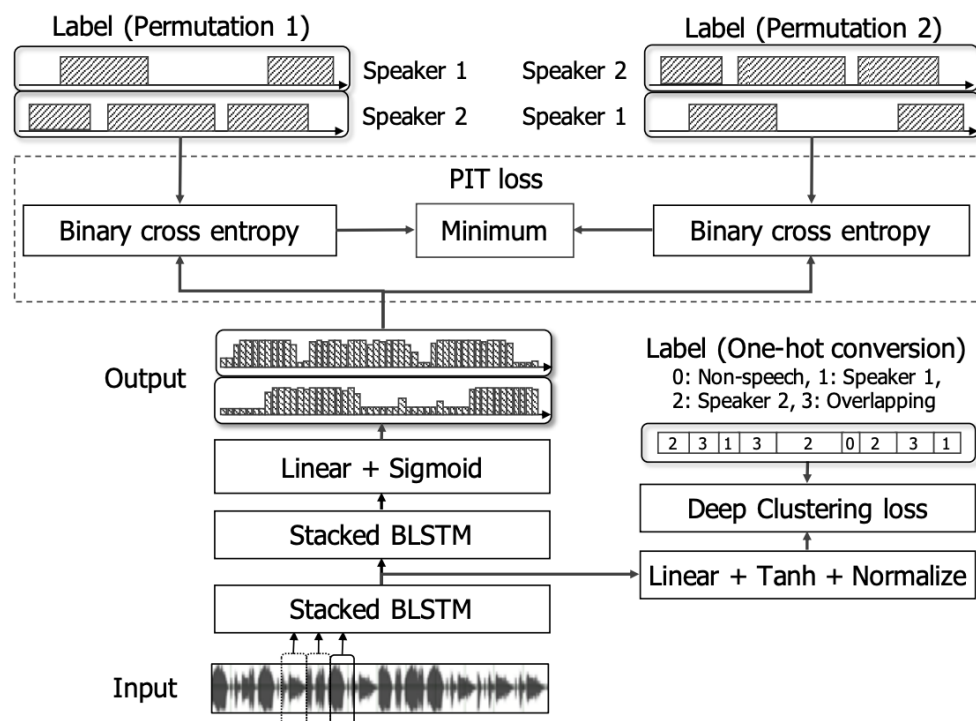
Extension to Arbitrary Speakers

- Encoder-Decoder Attractors (EEND-EDA)[1] are used to model a variable number of speakers


 [1]S. Horiguchi (2020)

Practical Considerations

- Large amounts of data are required

- Memory requirements in training
  - Someone may talk long periods apart

- Processing long recordings
  - Must track speakers across block processing

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System Ensembling

- Different systems may have different strengths and weaknesses (e.g. traditional vs. neural)
- DOVER[1] and overlap-aware extension DOVER-Lap[2]

[1]A. Stolcke (2019)   [2]D. Raj (2021)
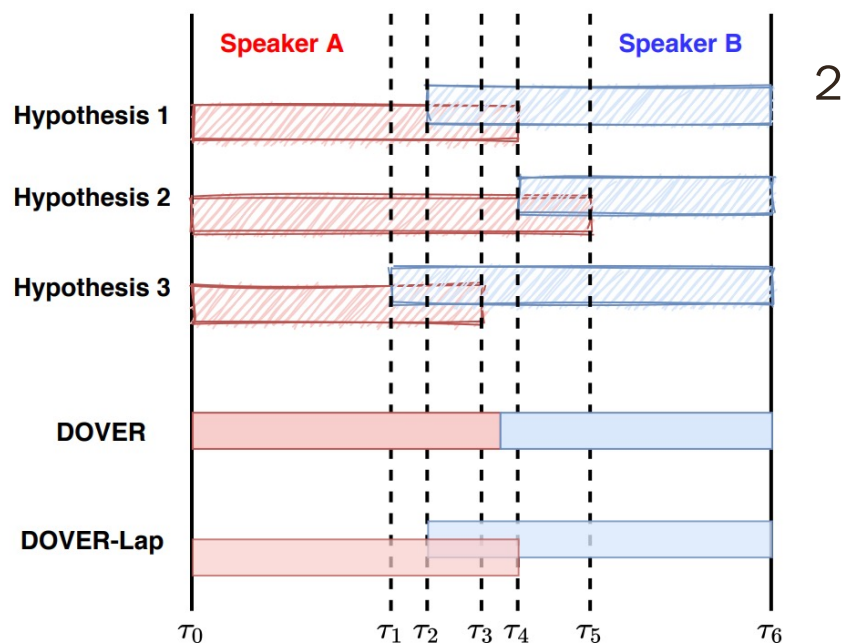
Multichannel Diarization

- Multiple microphones improve localization, and different talkers will be in different locations
  - They may, however, move around

- Directional information from beamforming may be integrated into the system

- Multiple audio signals may be used directly in the system, integrating beamforming implictly

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Multimodal Diarization

- Video may contain useful information for diarization and we would like to use it

- Audio-visual diarization has been successfully done using lip region of interest features[1]
  - Occlusions and out-of-frame issues pose a challenge

 [1]He, et al. *End-to-End Audio-Visual Neural Speaker Diarization*

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