Supervised Approaches for Language and Speaker Recognition

PhD Thesis Defense Presentation
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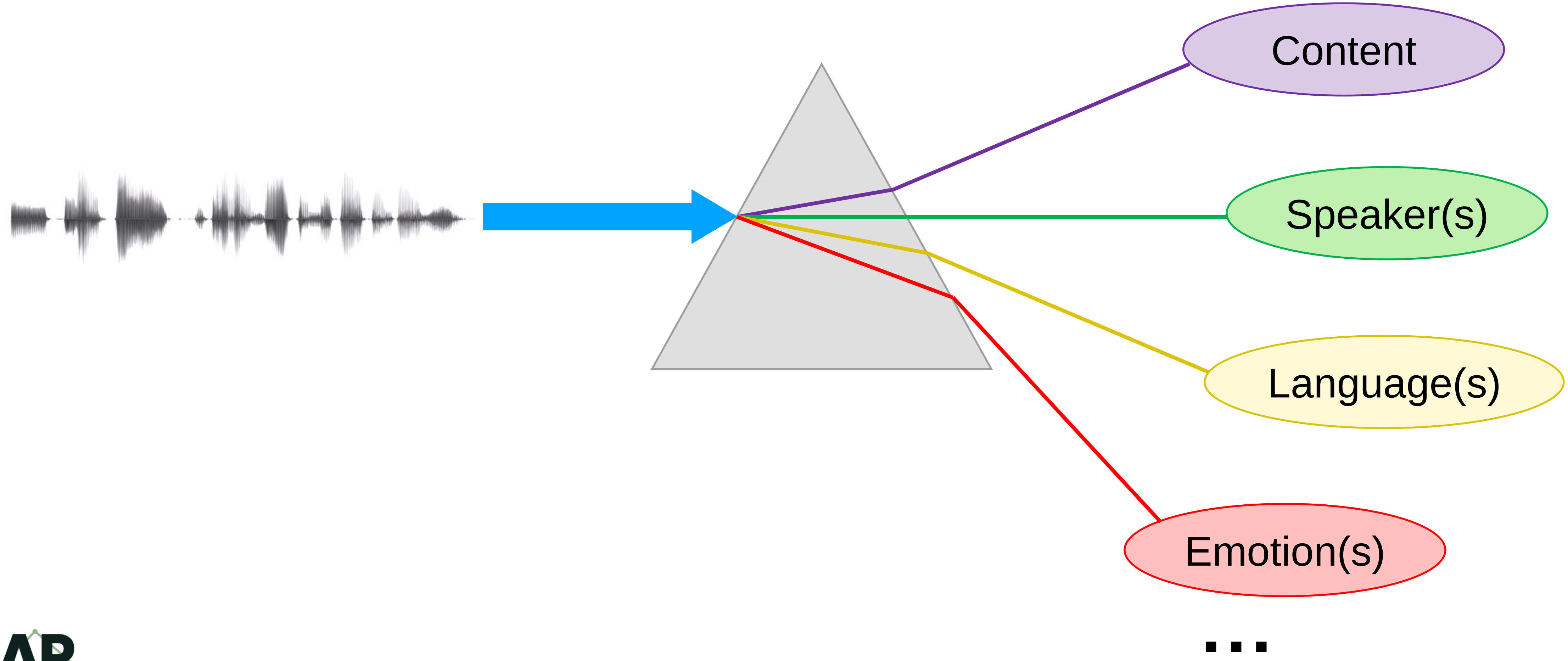
Roadmap

- Importance of Language and Speaker Recognition
- Brief Background Literature
- Supervised i-vector modeling for language recognition
- Supervised Neural Network Models for speaker verification
- Summary
- Recent advances and future perspectives

Introduction

Speech – A multitude of information



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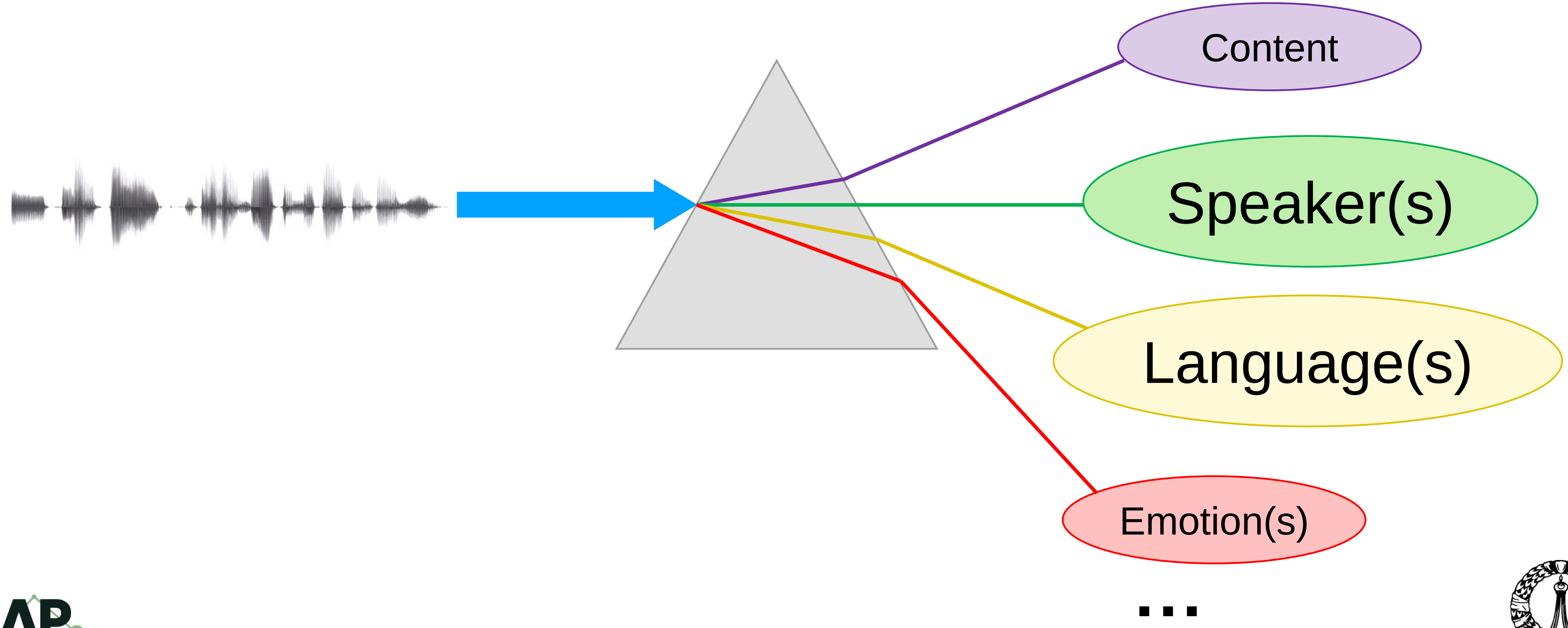
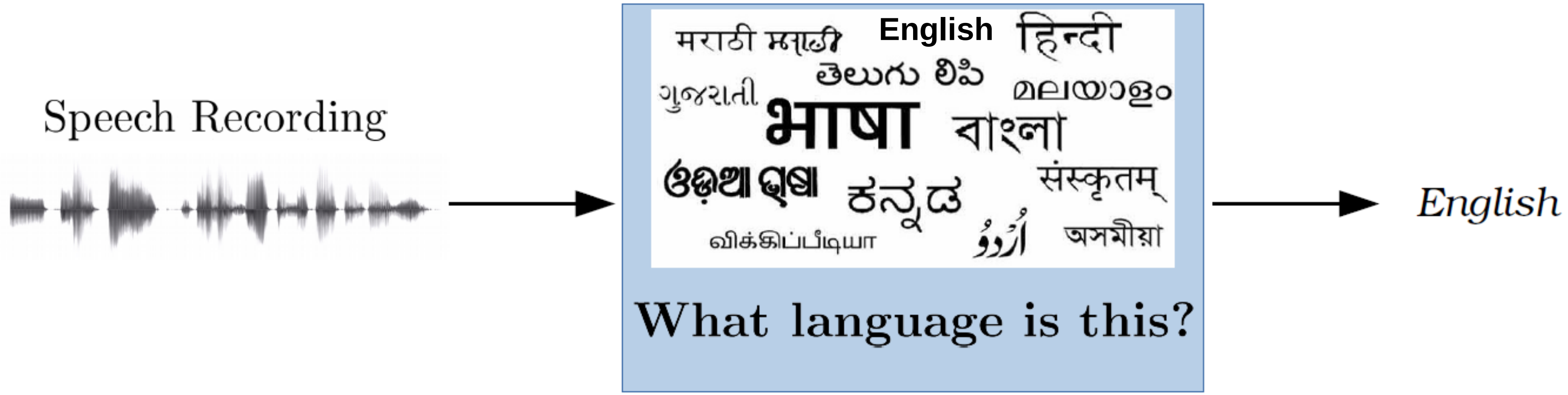


Problem statements

- Language/Accent Classification



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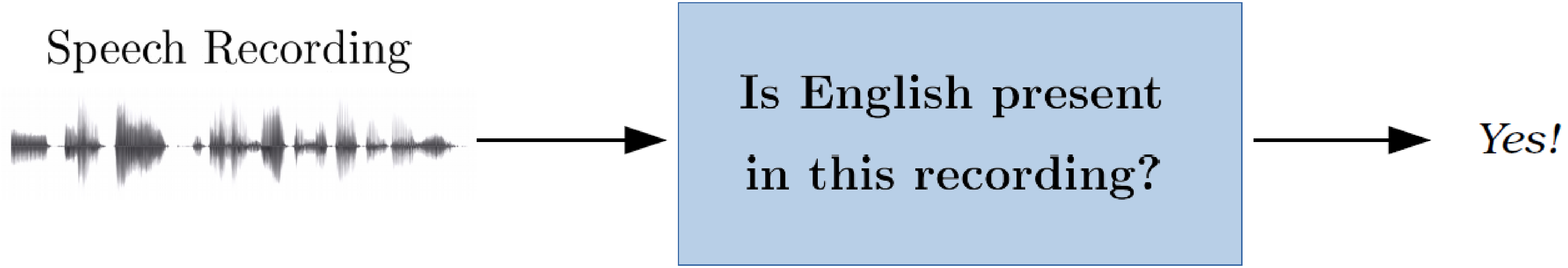
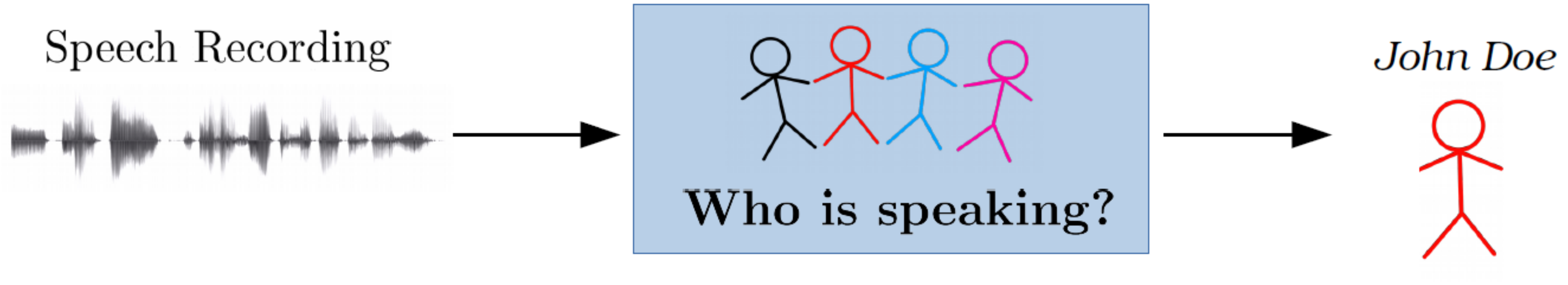
- Language/Accent Detection

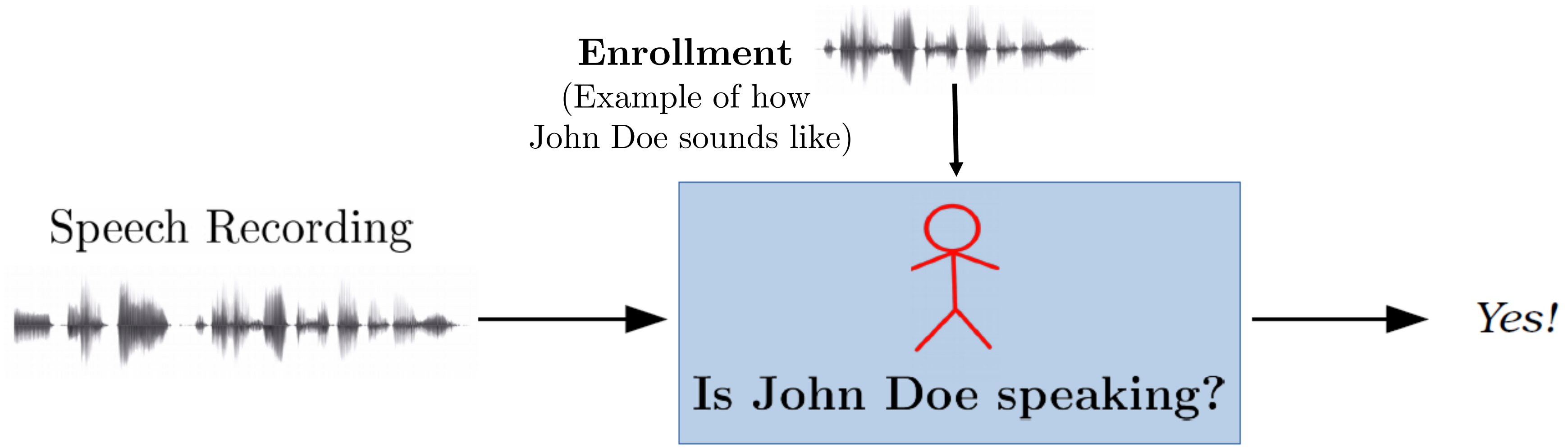


Problem statements

- Speaker Classification



- Speaker Verification / Detection



Applications

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- Voice based authentication systems – In personal devices and call centers

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- Personalized smart home systems that responds to only authorized users

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- Basis for Speaker & Language Diarization & Multi-speaker /Multilingual speech technologies.

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- Variations in emotion and prosody
- Mimicry and spoofing

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- Speaker and language are both segment level properties.
    - Segments of duration ranging from as low as 1 second to a few minutes can be associated with a single speaker/language label.
    - A certain duration of speech must be processed to determine the speaker/language.
    - Longer the duration, lesser is the uncertainty of speaker and language.

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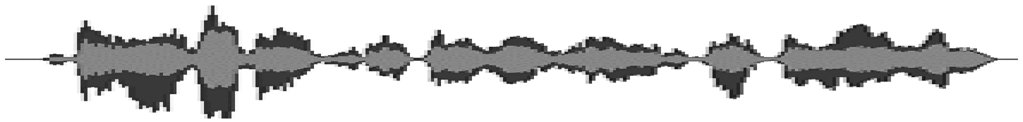
- A common practice in Speaker/Language Recognition research is to use the approaches used in speaker recognition for language recognition, and vice-versa.
- Similar approaches are found to achieve the state-of-the-art in both speaker and language recognition.

A Brief Background…

Gaussian Mixture Models

Douglas Reynolds, "*A Gaussian mixture modeling approach to text-independent speaker identification*", 1992.

Gaussian Mixture Models



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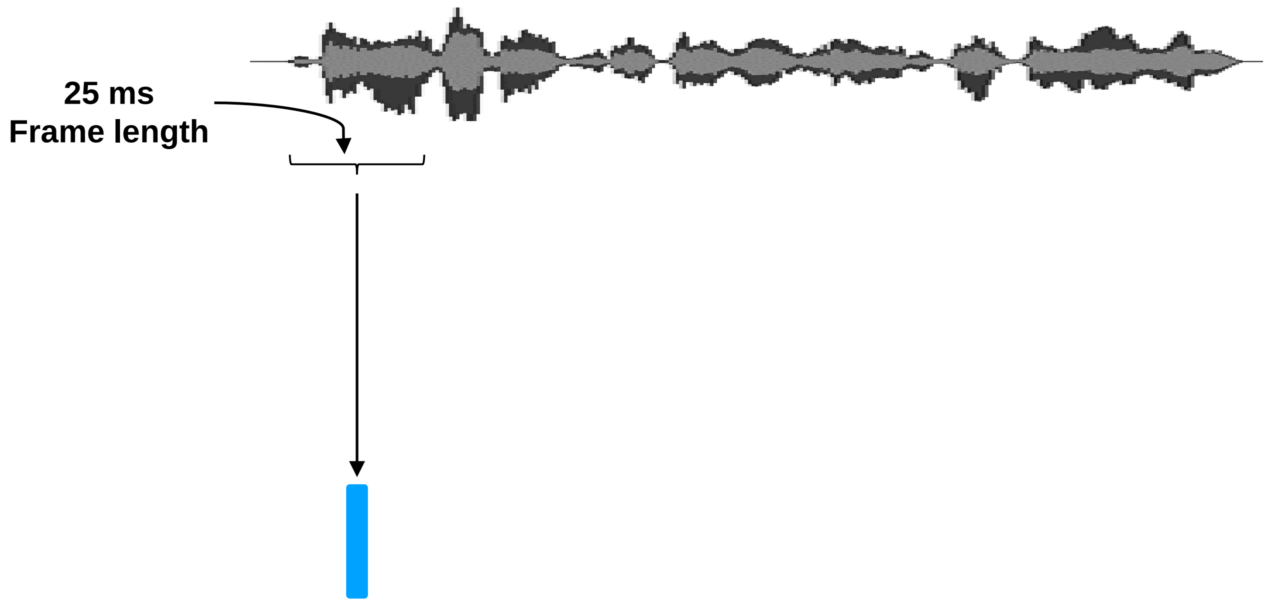

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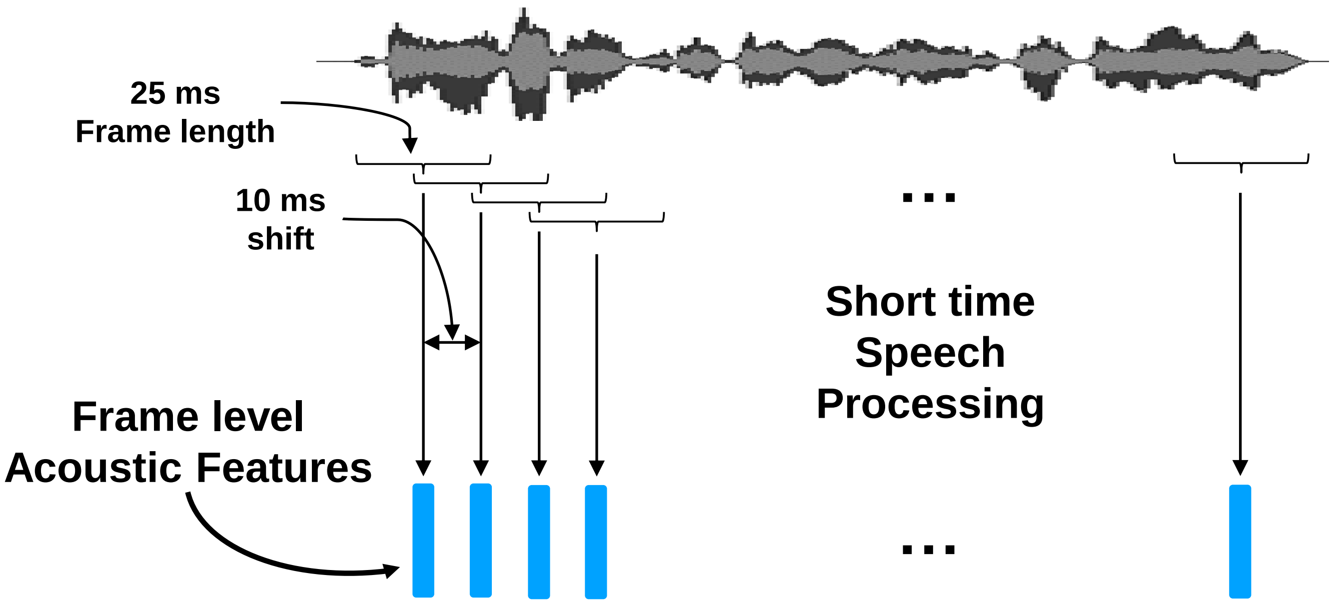

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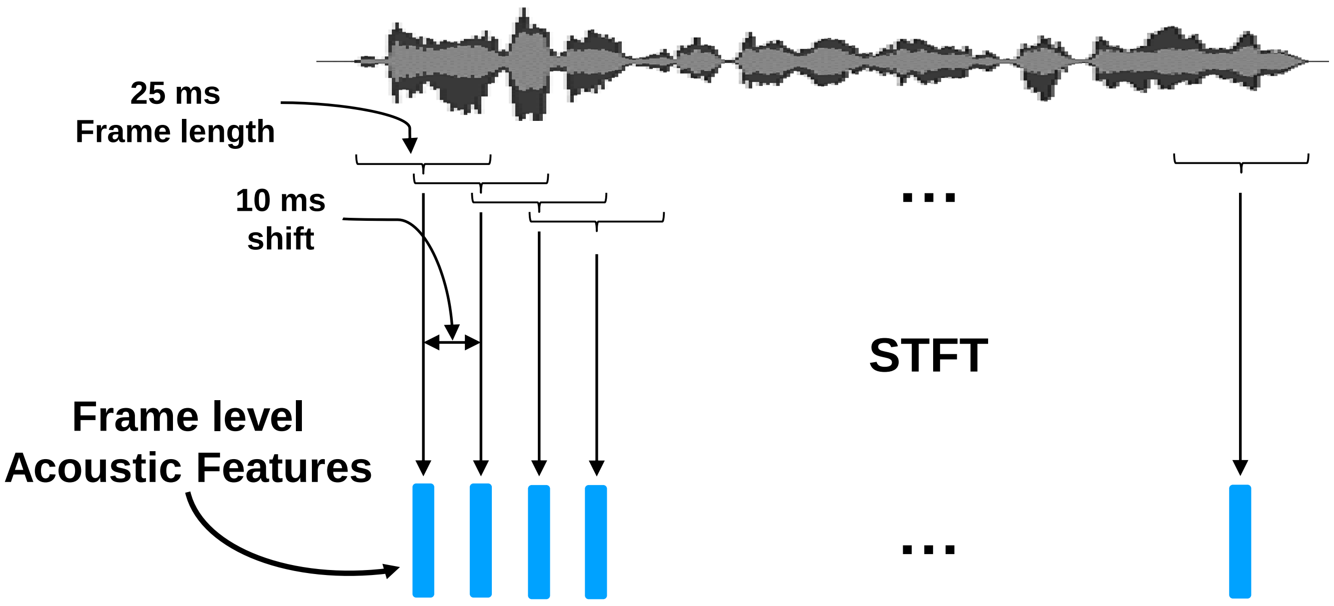

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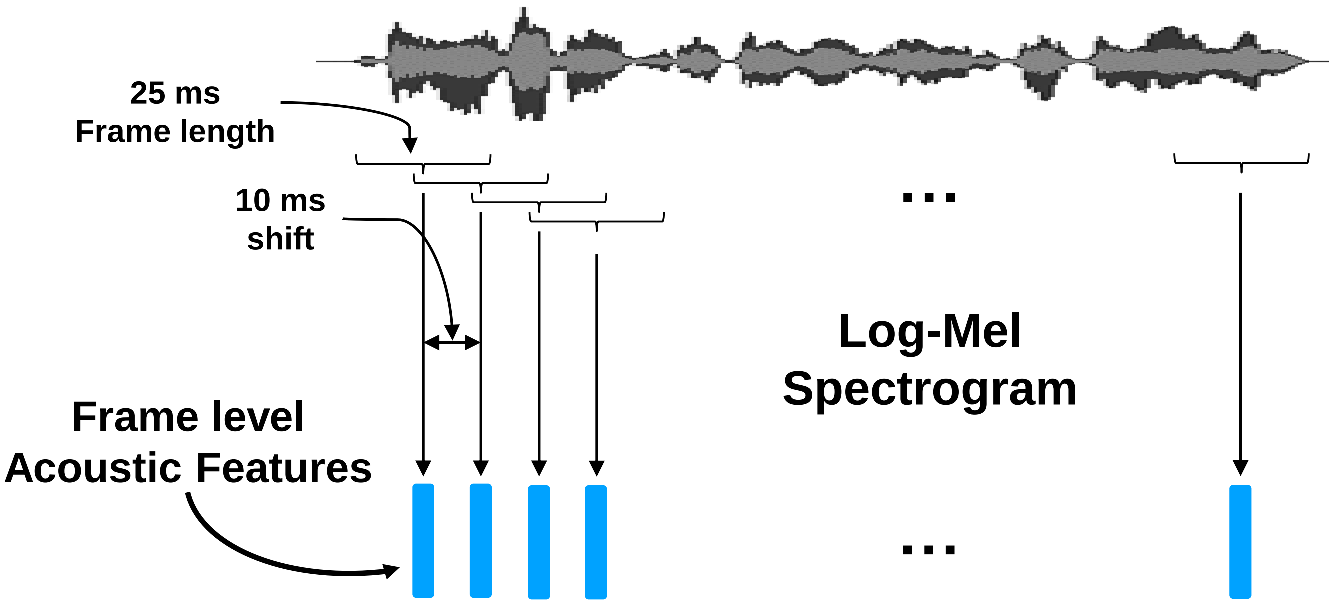

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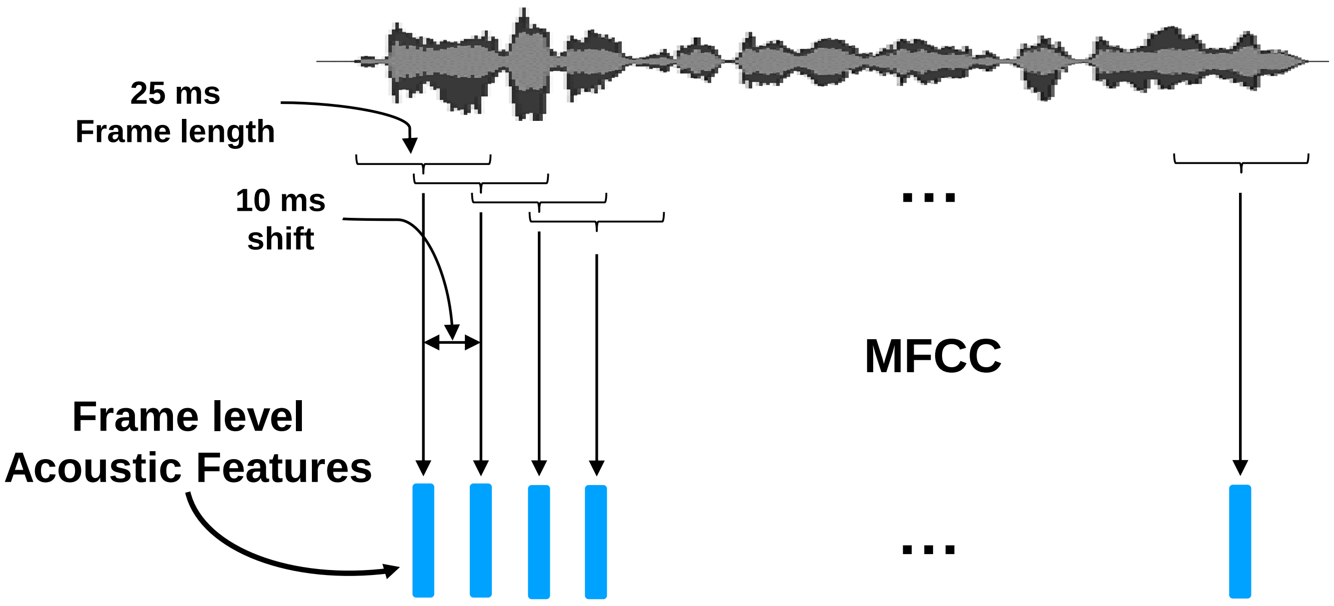

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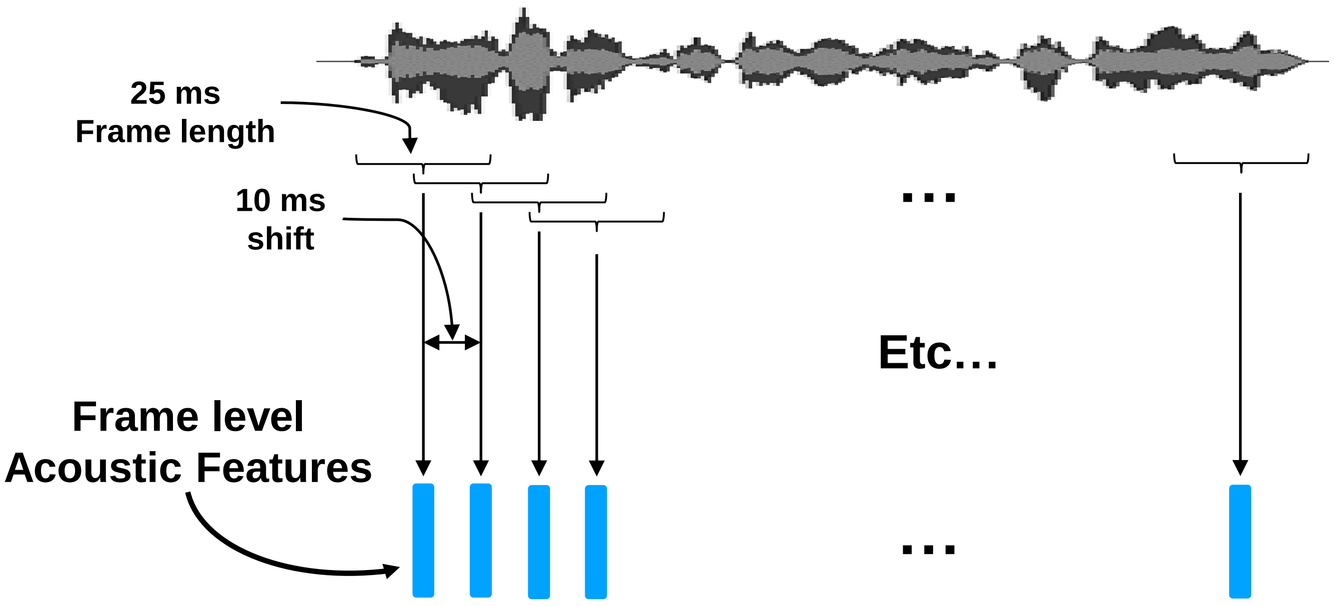

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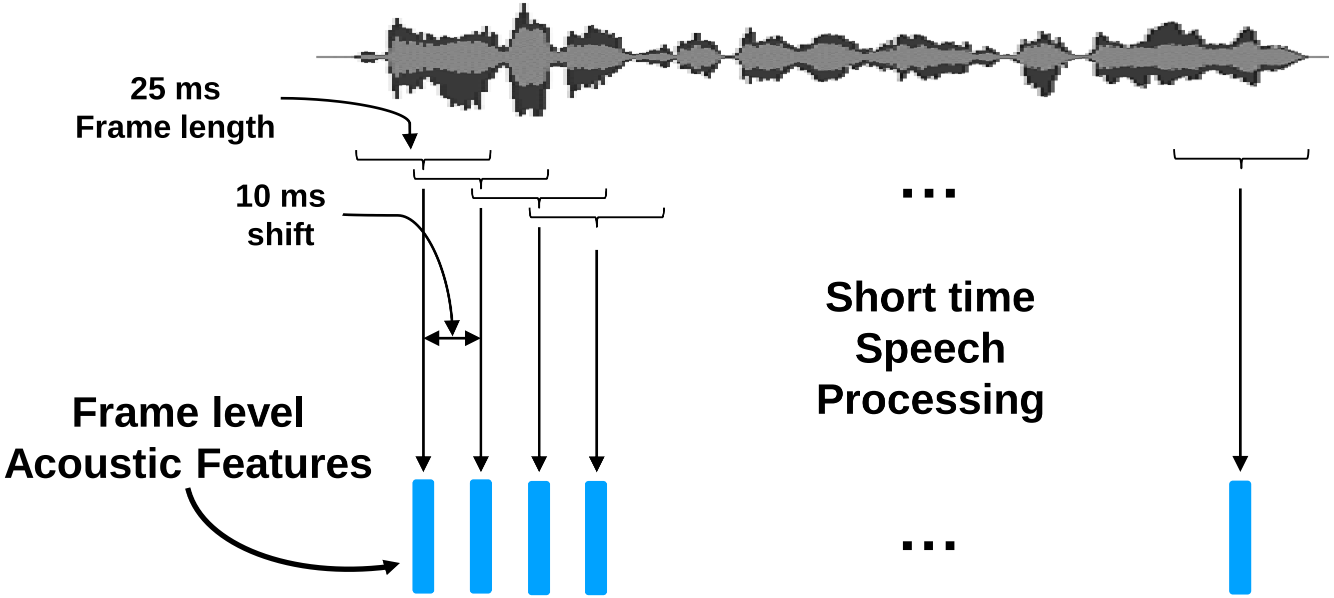

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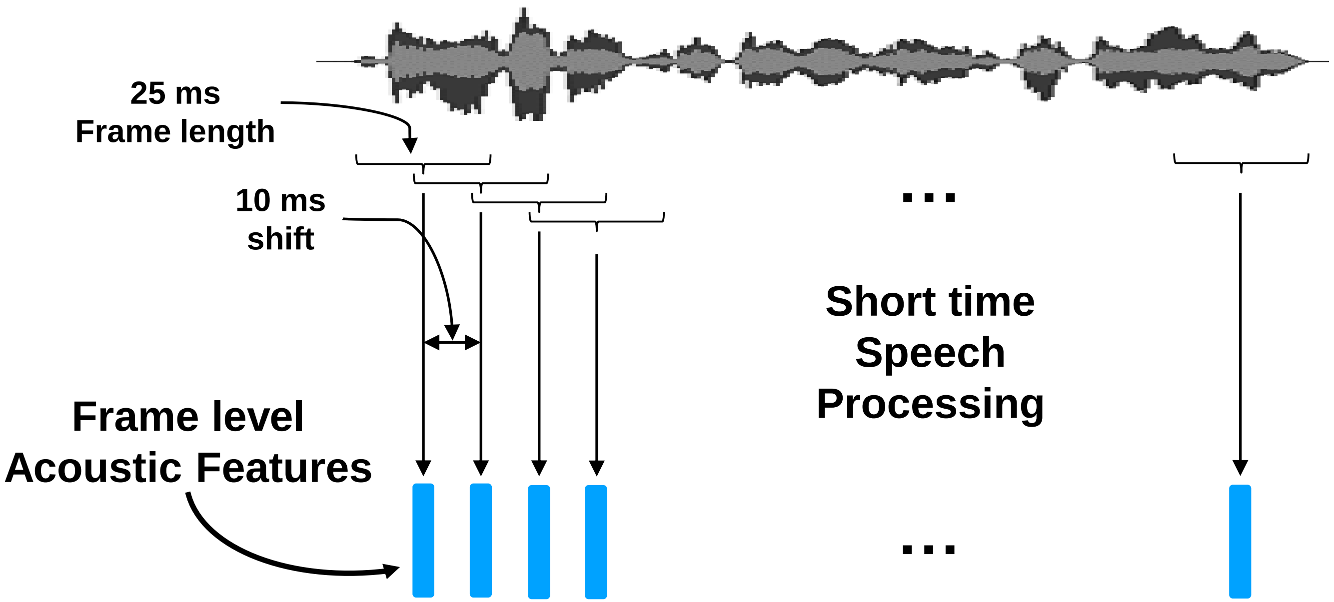

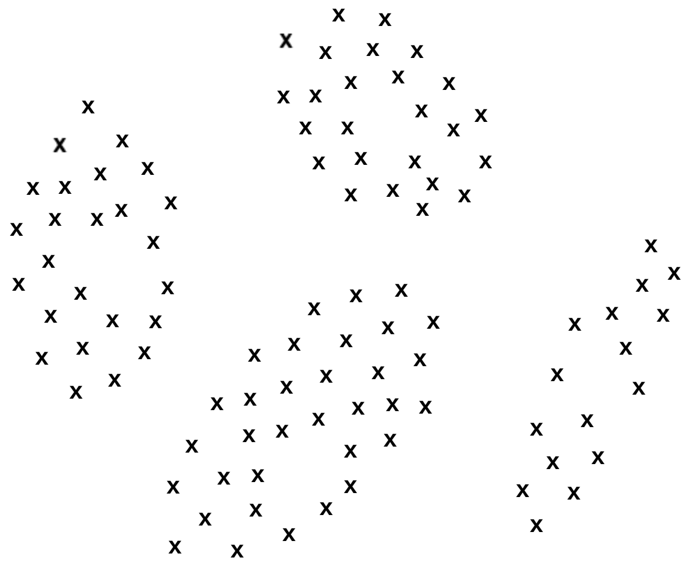

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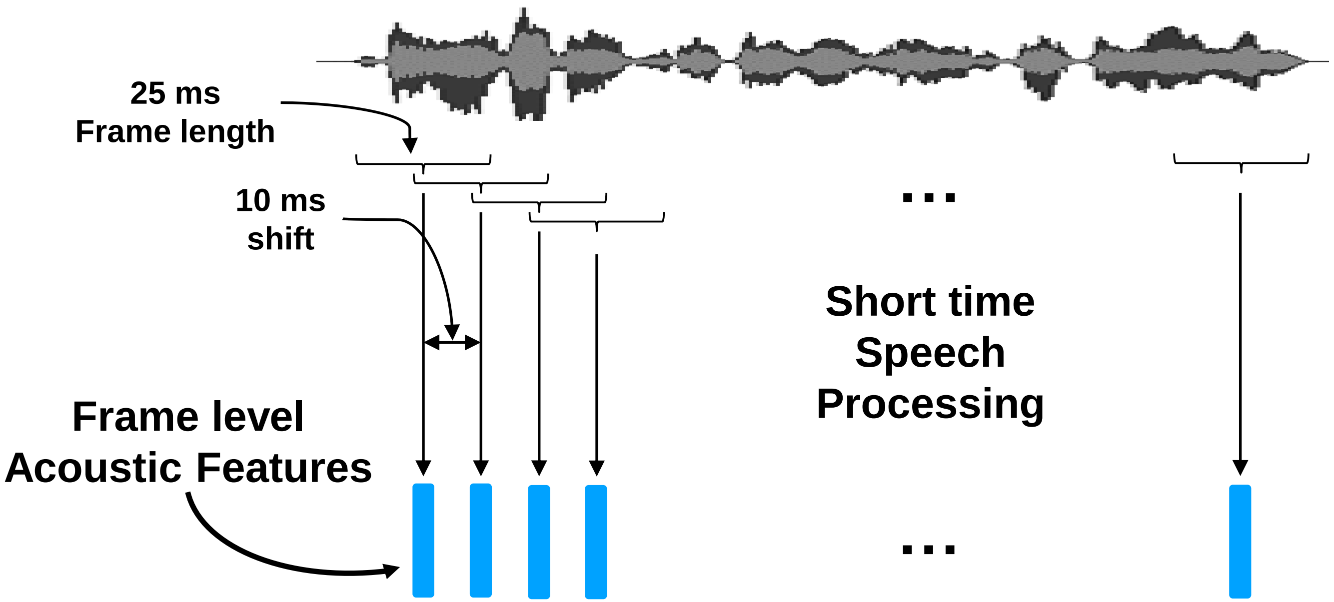

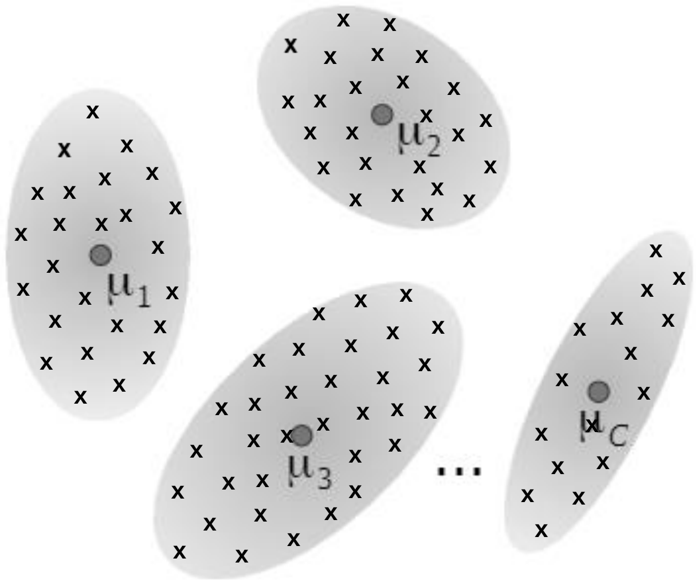

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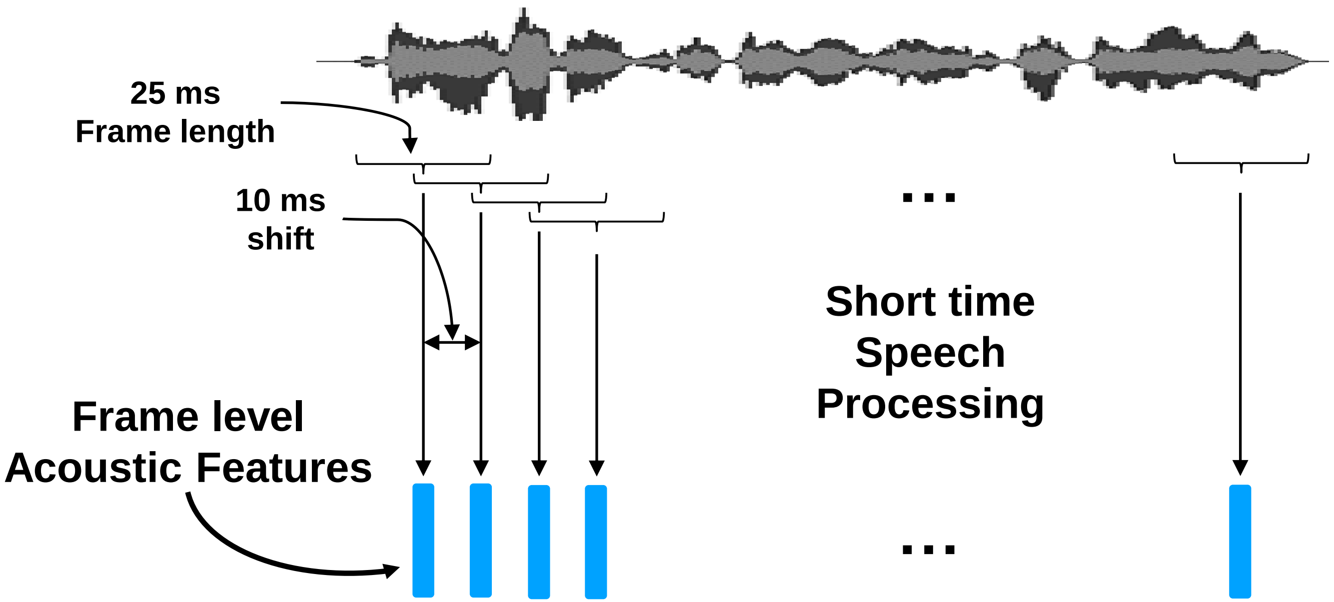

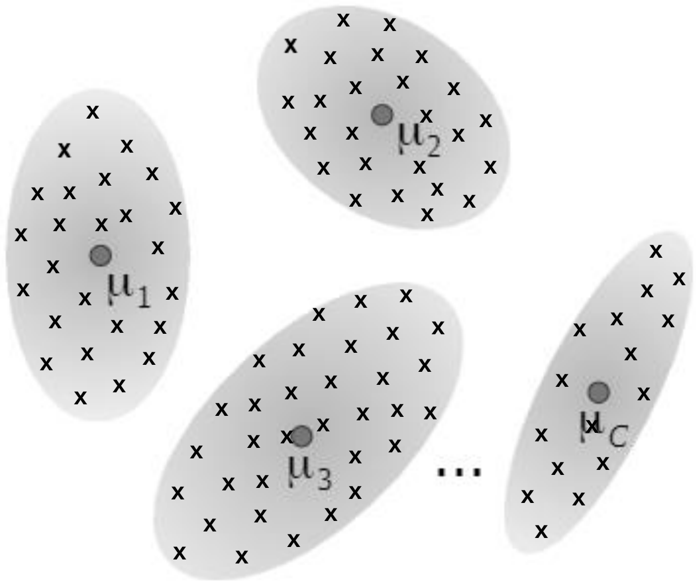

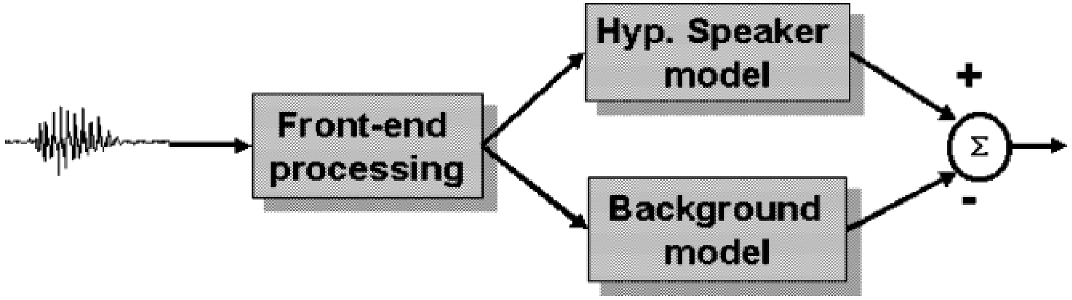

$$\frac{p(Y \mid H_0)}{p(Y \mid H_1)} \begin{cases} \geq \theta & \text{accept } H_0 \\ < \theta & \text{reject } H_0, \end{cases}$$

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Adaptation of GMM

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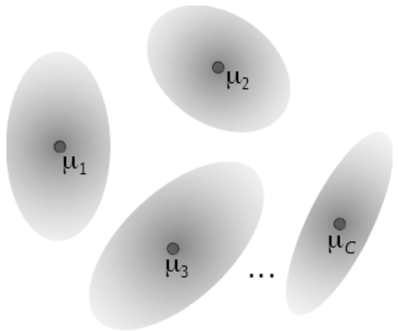
- A large dataset of speech, with many speakers is used to estimate a GMM Background Model.



GMM-UBM

$$\lambda = \{\pi_c, \boldsymbol{\mu}_c, \Sigma_c\}_{c=1}^{C}$$

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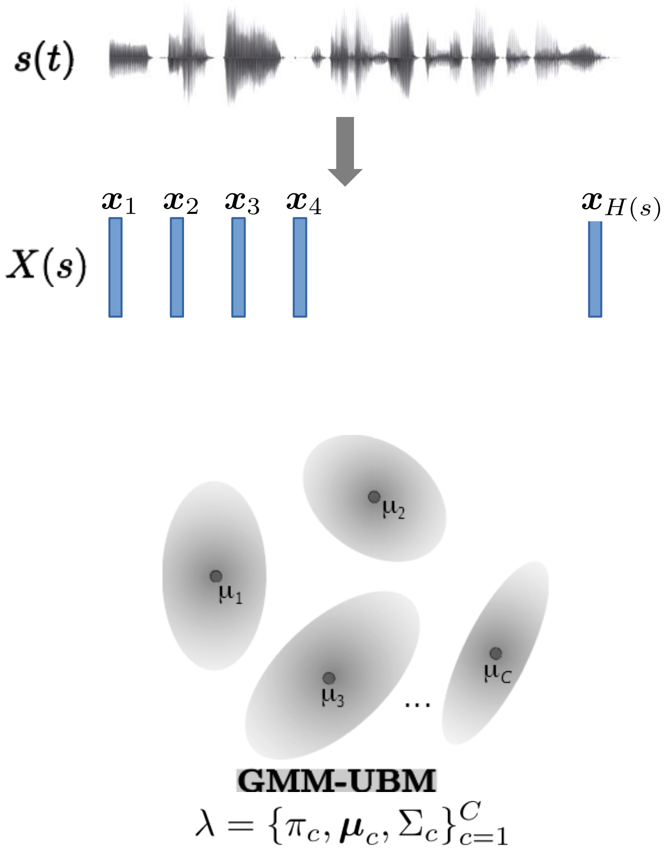

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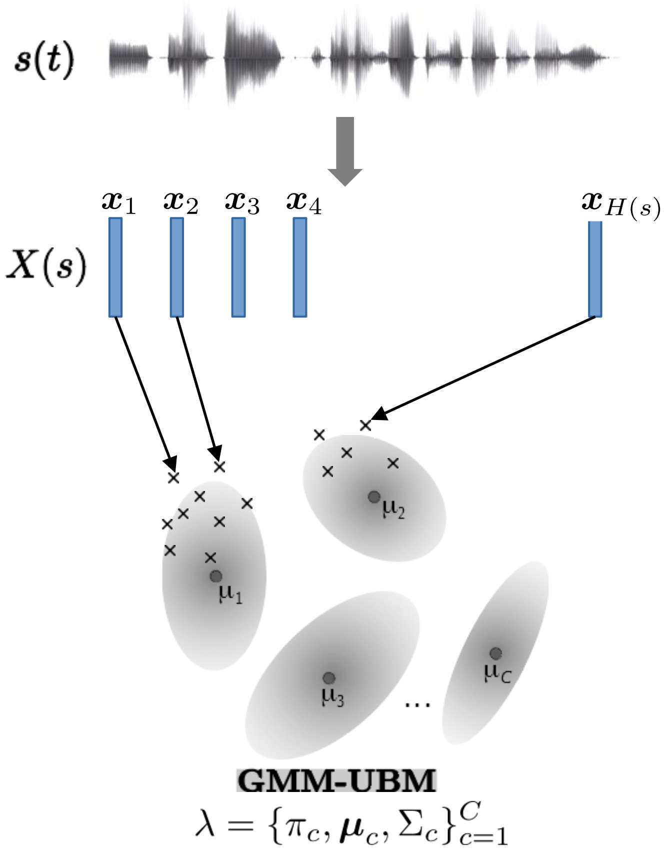

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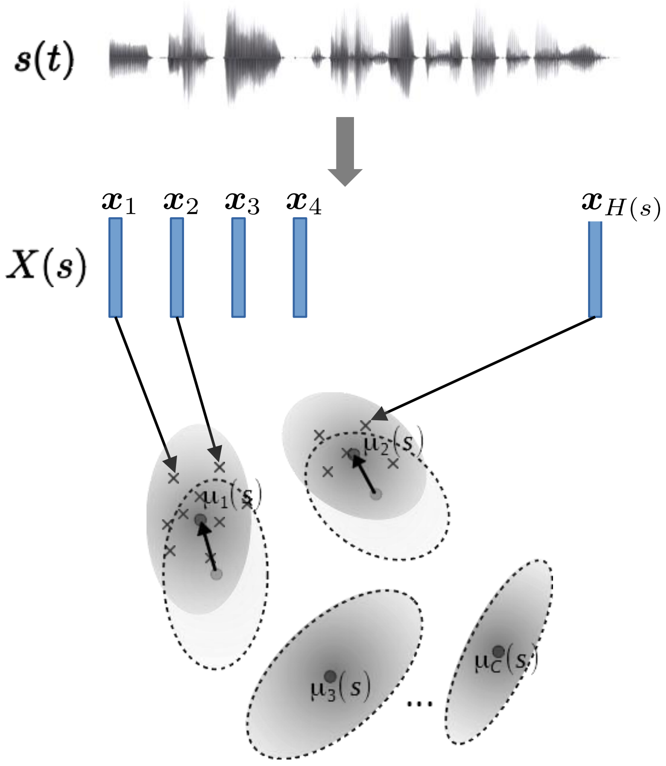

$$\lambda(s) = \{\pi_c, \boldsymbol{\mu}_c(s), \Sigma_c\}_{c=1}^{C}$$

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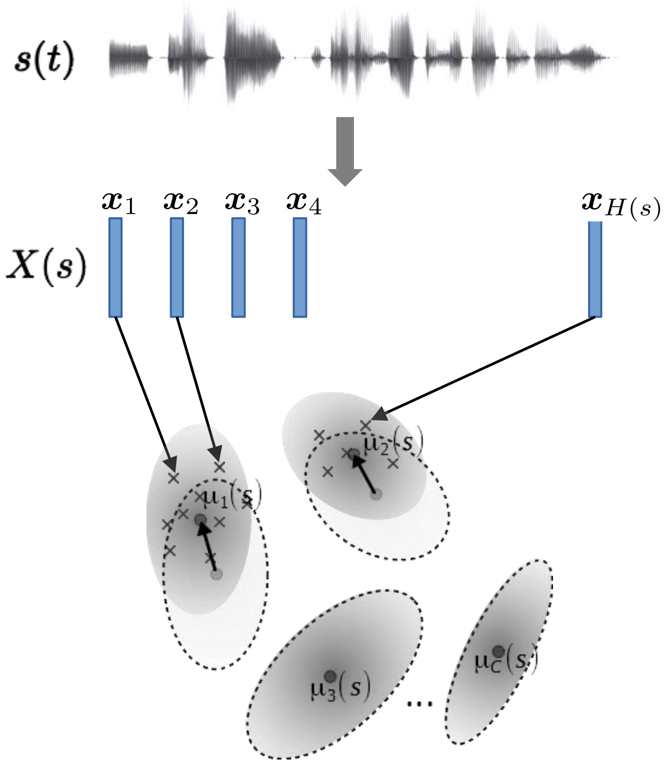
- The GMM log likelihoods of a test utterance is computed using the Background model (null hypothesis) and target speaker model (target hypothesis)… and then we compute a log likelihood ratio.
- Decision is made by thresholding the LLR based on the required criterion (Min Bayes Risk, Neyman-Pearson)



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LEAP

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supervector — $M(s)$

UBM Mean component — $\mathbf{M}$

Speaker dependent component — $\mathbf{Vy}$

Channel Dependent component — $\mathbf{Ux}$

Residual component — $\mathbf{Dz}$

Where: $\mathbf{x}, \mathbf{y}, \mathbf{z} \sim \mathbf{N}(\mathbf{0}, \mathbf{I})$

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- The Adapted GMM mean components concatenated as a single vector is called a “supervector”.

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$$\mathbf{LLR} = \mathbf{log}\left(\frac{\mathbf{p}(\boldsymbol{X_e}, \boldsymbol{X_t}|\boldsymbol{H_t})}{\mathbf{p}(\boldsymbol{X_e}, \boldsymbol{X_t}|\boldsymbol{H_{nt}})}\right) = \mathbf{log}\left(\frac{\mathbf{p}(\boldsymbol{X_e}, \boldsymbol{X_t})}{\mathbf{p}(\boldsymbol{X_e})\mathbf{p}(\boldsymbol{X_t})}\right)$$

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Front-end Factor Analysis

- The speaker dependent and independent terms of the JFA model were combined as one total variability term as follows:

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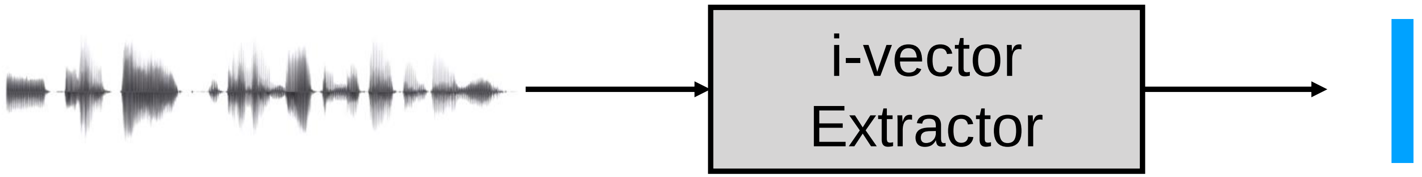
Supervector

Mean component

Total Variability component

- The MAP estimate of y for a speech segment is called an i-vector, which is a fixed dimensional representation (embedding) of the "total variability" of the segment.



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Back-End Models

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$$\boldsymbol{y} = \underbrace{\boldsymbol{y_s}}_{\text{Speaker Factor}} + \underbrace{\boldsymbol{y_c}}_{\text{Channel Factor}} + \underbrace{\boldsymbol{\epsilon}}_{\text{residual}}$$

Back-End Models

- Probabilistic Linear Discriminant Analysis (PLDA)

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residual

Speaker Factor

Channel Factor

- Gaussian Back-end (GB)

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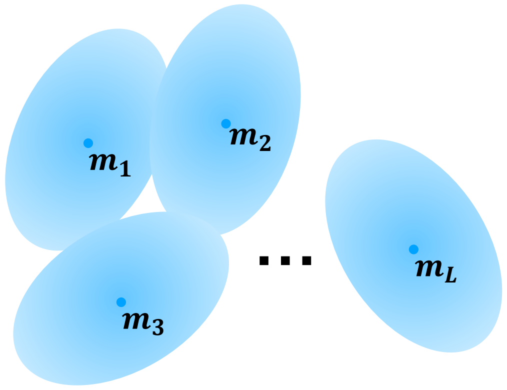

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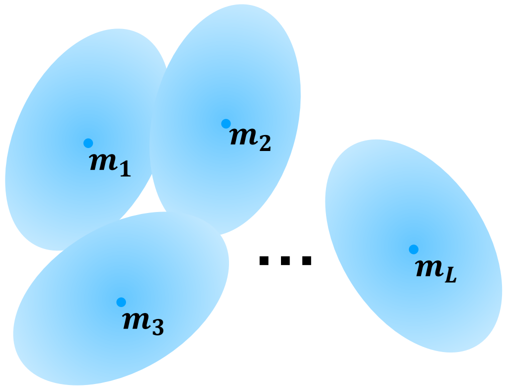

- Support Vector Machines

Back-End Models

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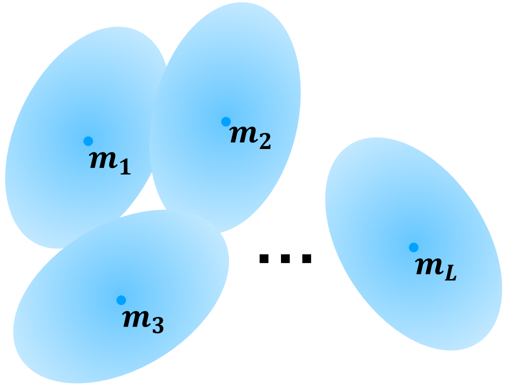
residual

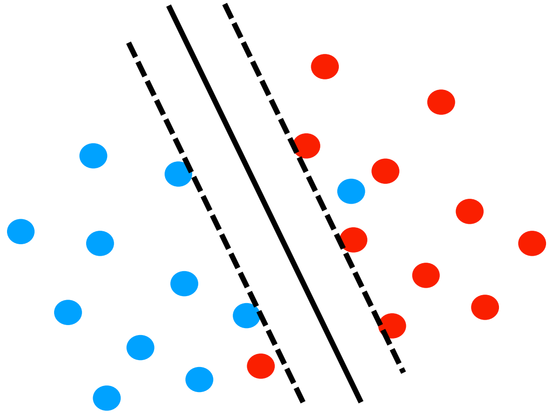
Speaker Factor

Channel Factor

- Gaussian Back-end (GB)



- Support Vector Machines



Back-End Models

- Probabilistic Linear Discriminant Analysis (PLDA)

$$\boldsymbol{y} = \boldsymbol{y_s} + \boldsymbol{y_c} + \boldsymbol{\epsilon}$$

residual

Speaker Factor

Channel Factor

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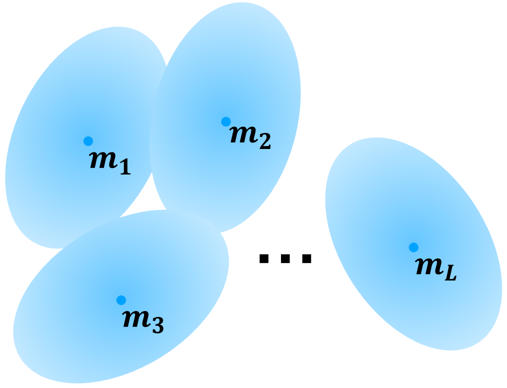

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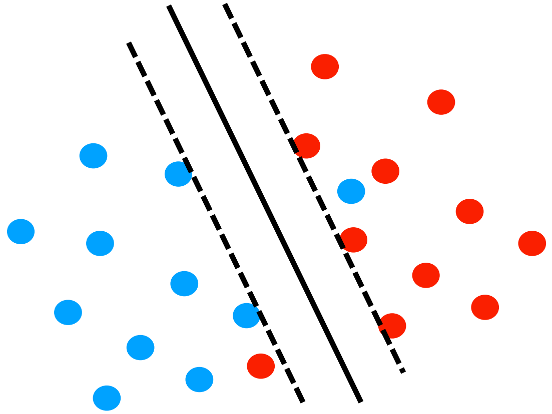

- Neural Networks

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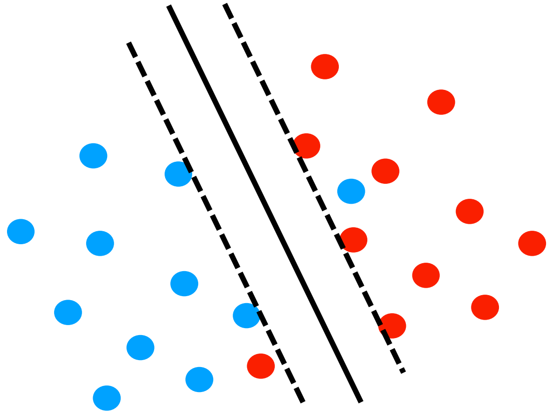

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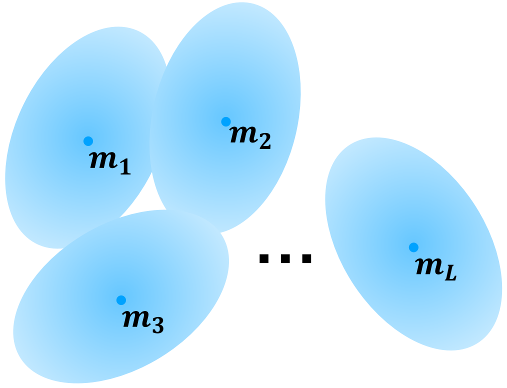

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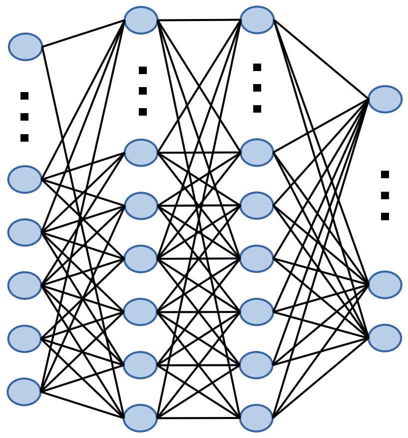
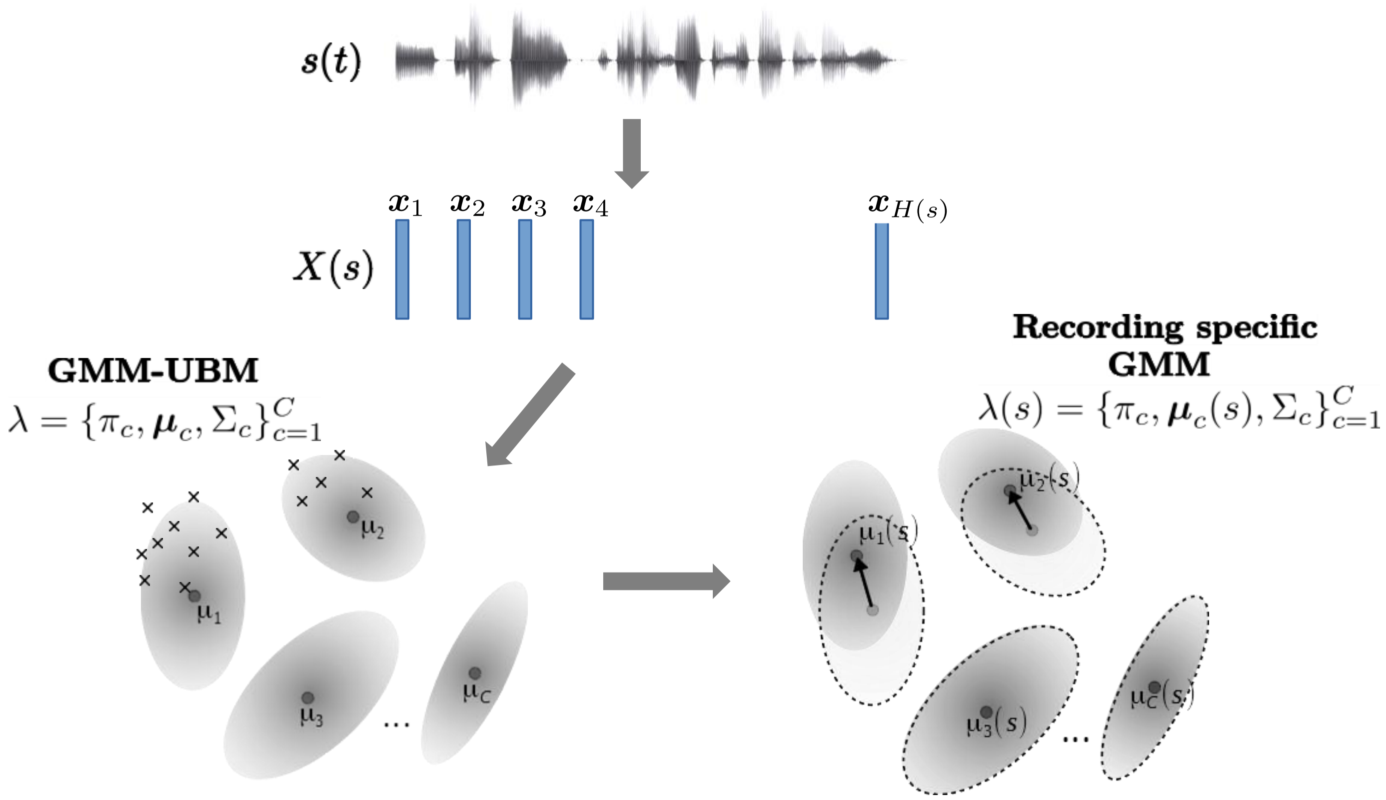
Embeddings



Logits

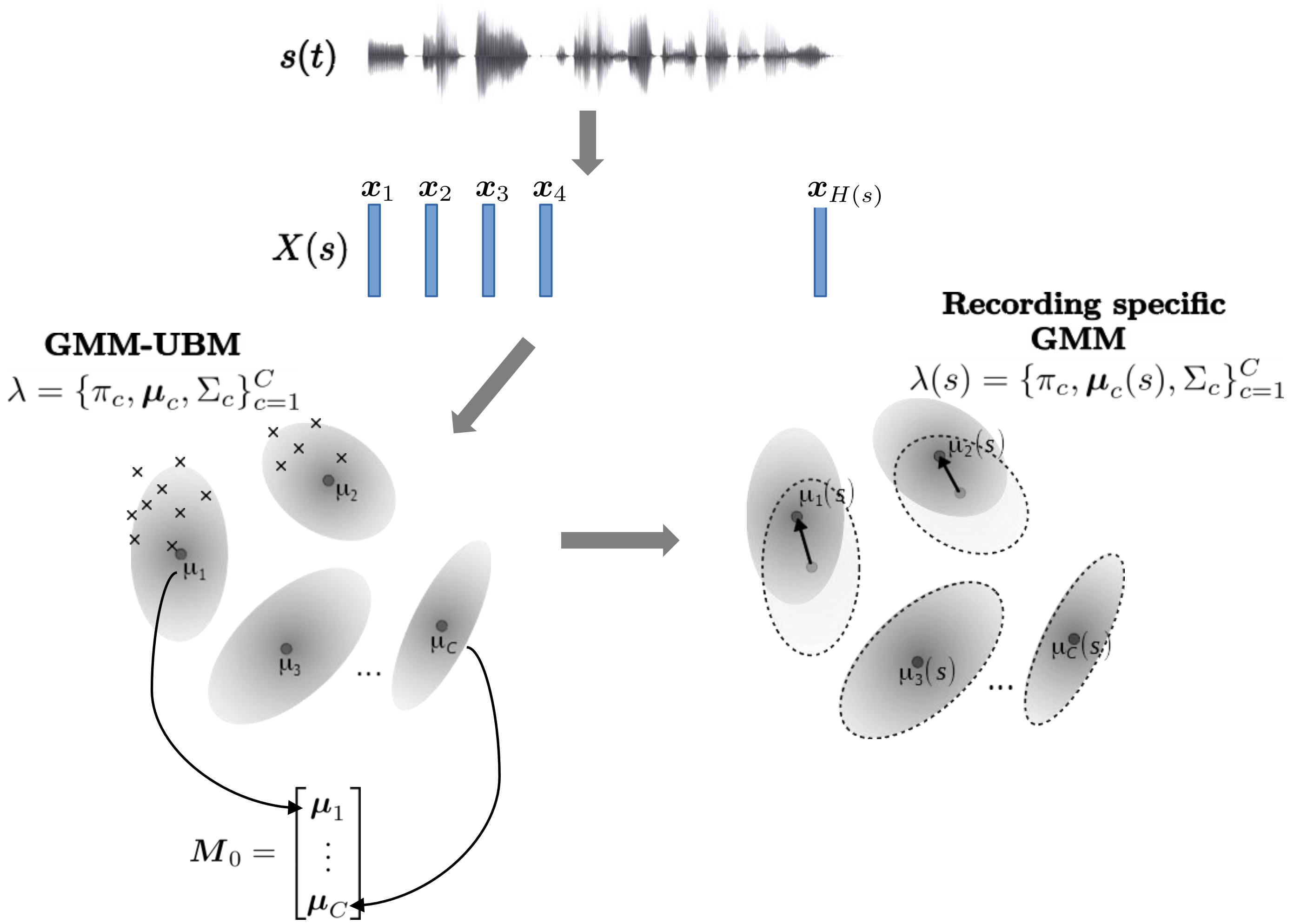
Supervised I-vector Model

Motivation



$s(t)$
x_1 x_2 x_3 x_4 $x_{H(s)}$
$X(s)$
GMM-UBM
$\lambda = \{\pi_c, \boldsymbol{\mu}_c, \Sigma_c\}_{c=1}^{C}$
Recording specific GMM
$\lambda(s) = \{\pi_c, \boldsymbol{\mu}_c(s), \Sigma_c\}_{c=1}^{C}$
μ_1 μ_2 μ_3 μ_C
$\mu_1(s)$ $\mu_2(s)$ $\mu_3(s)$ $\mu_C(s)$

Motivation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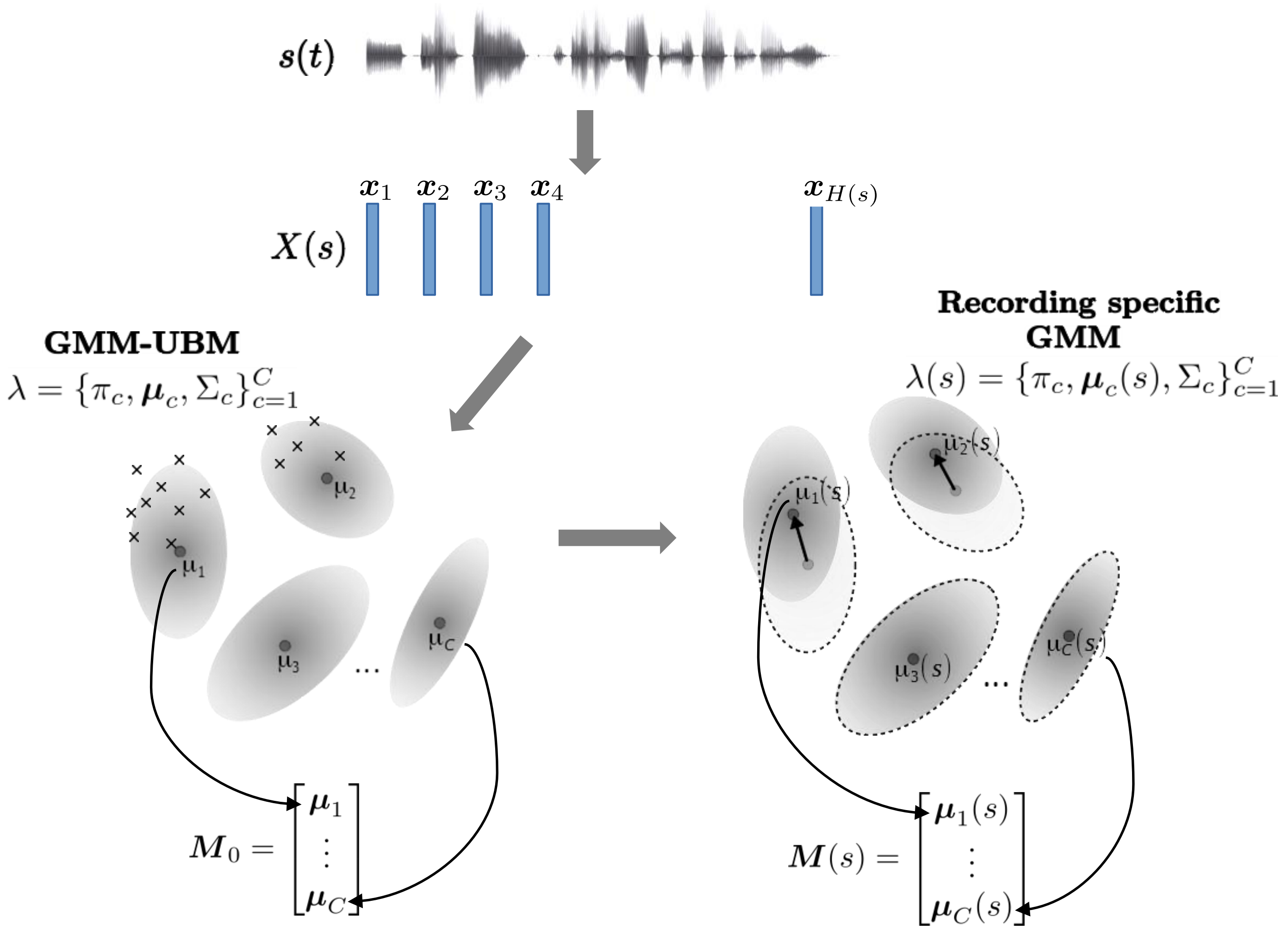
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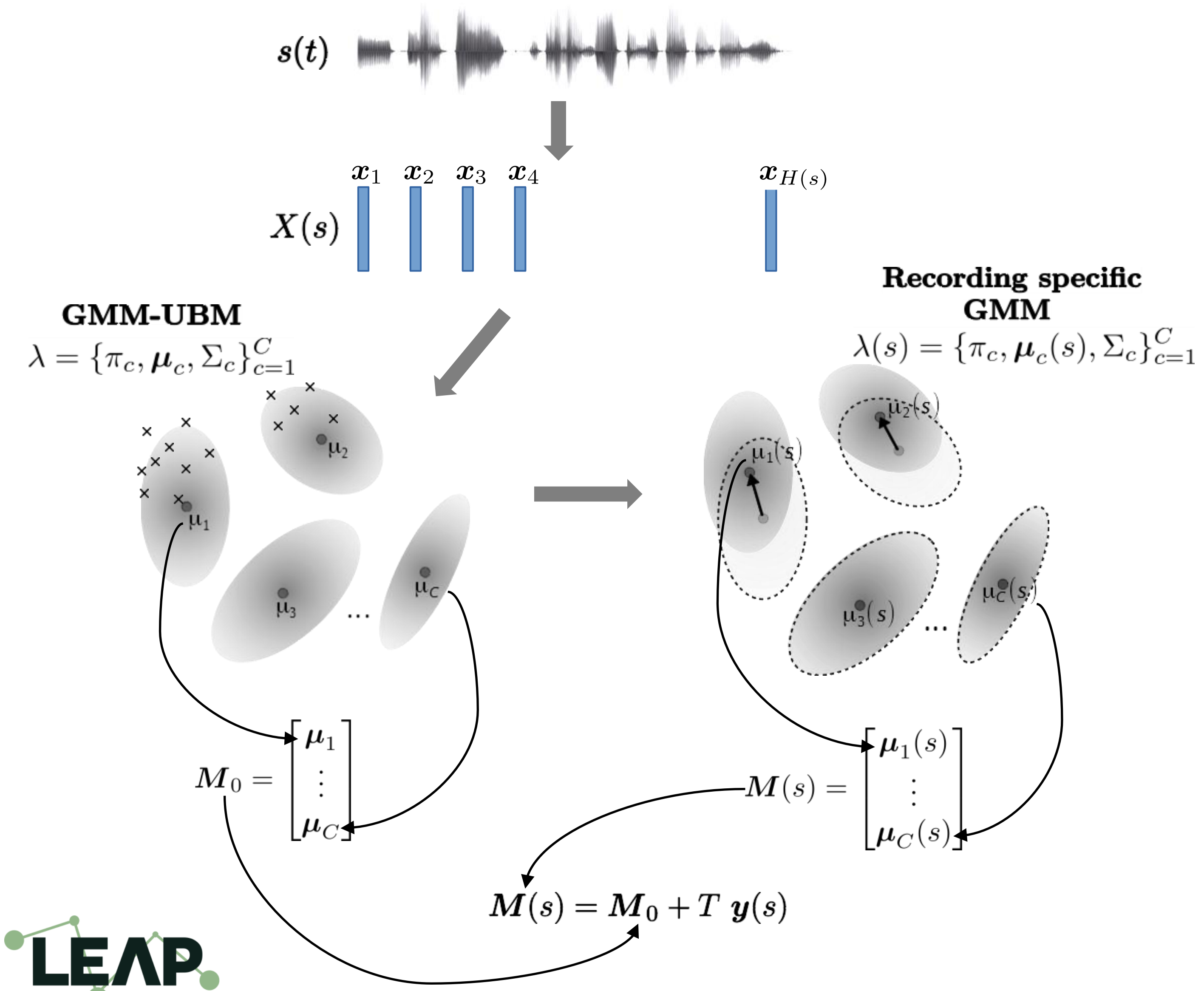

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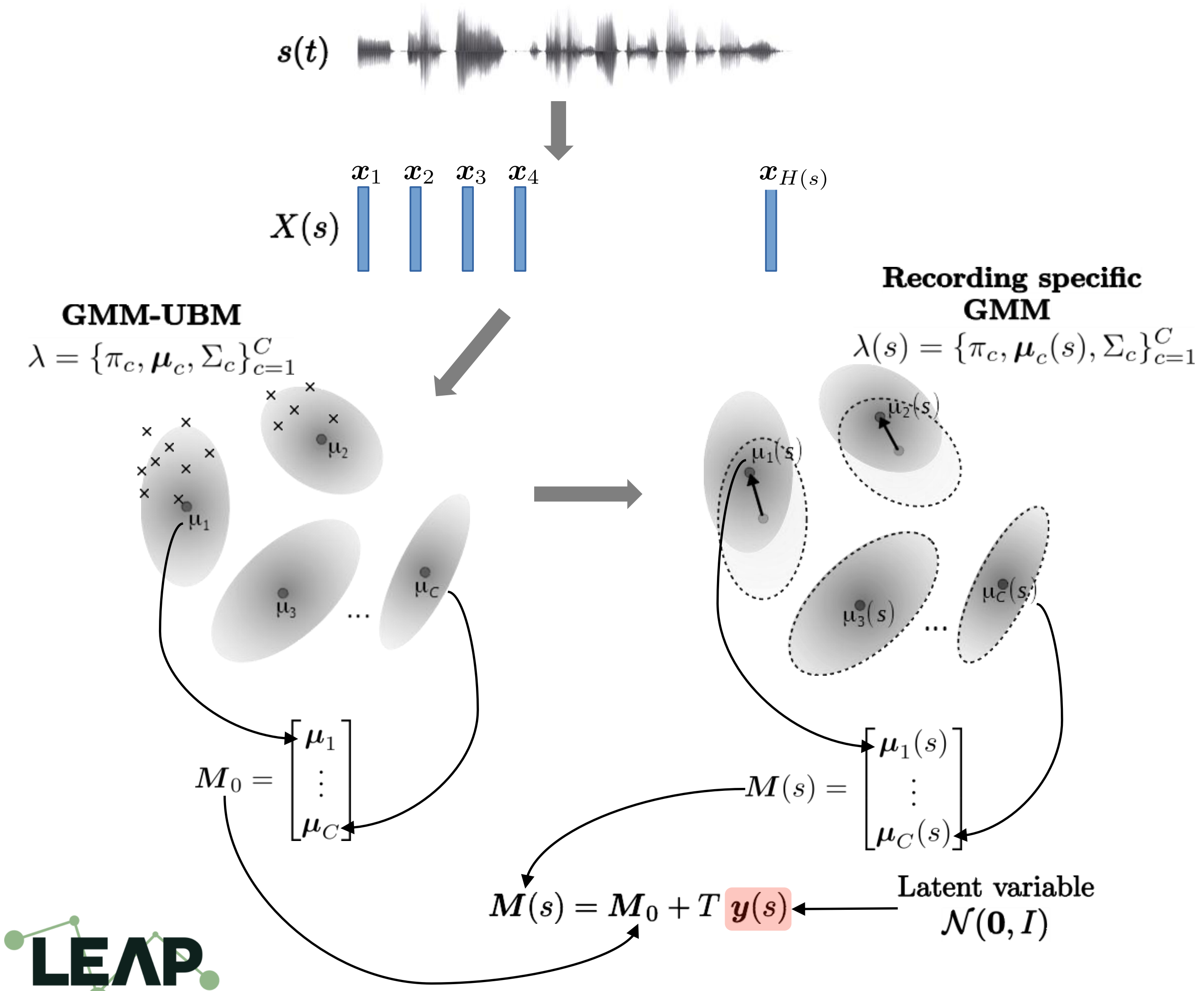

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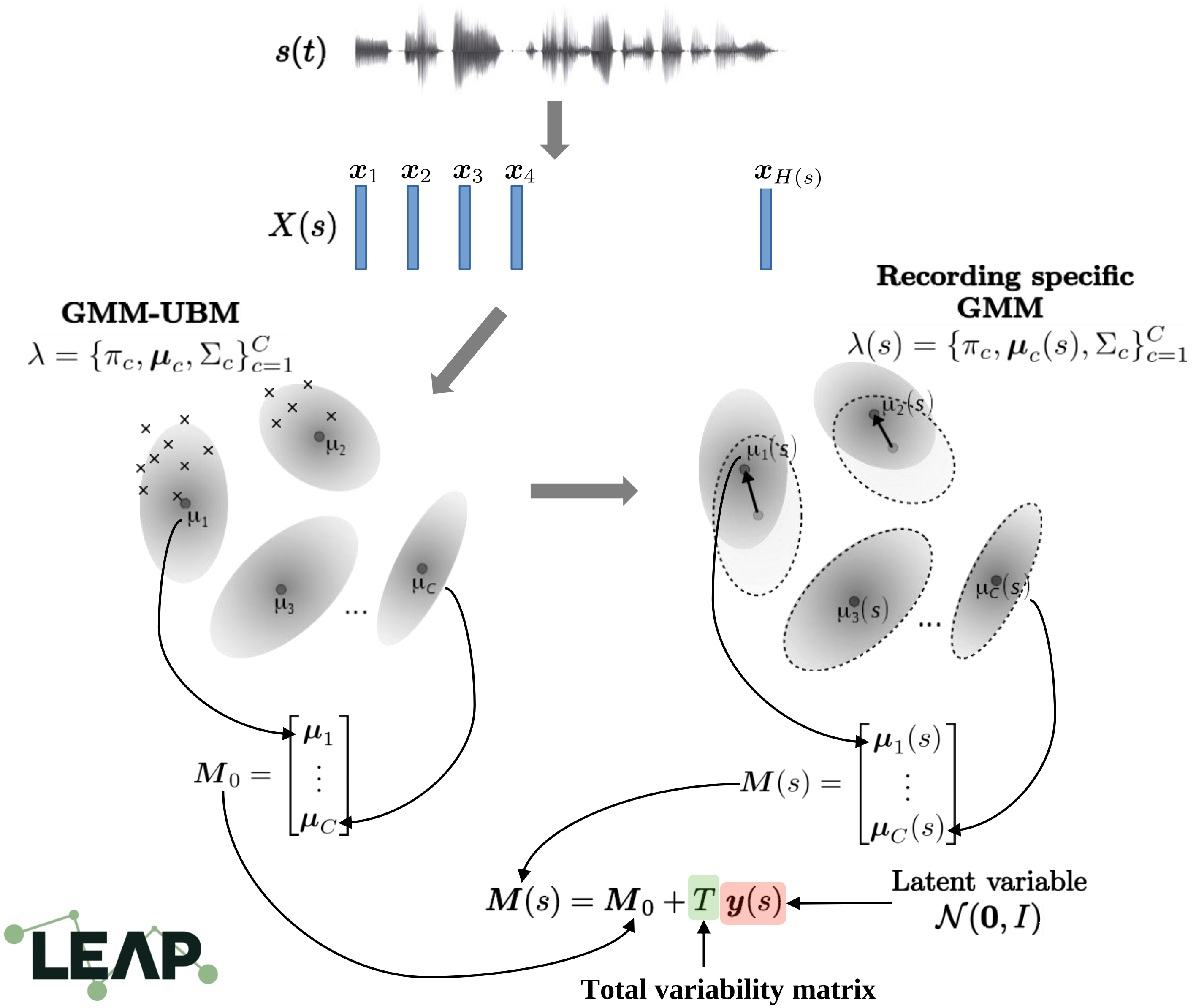
Motivation



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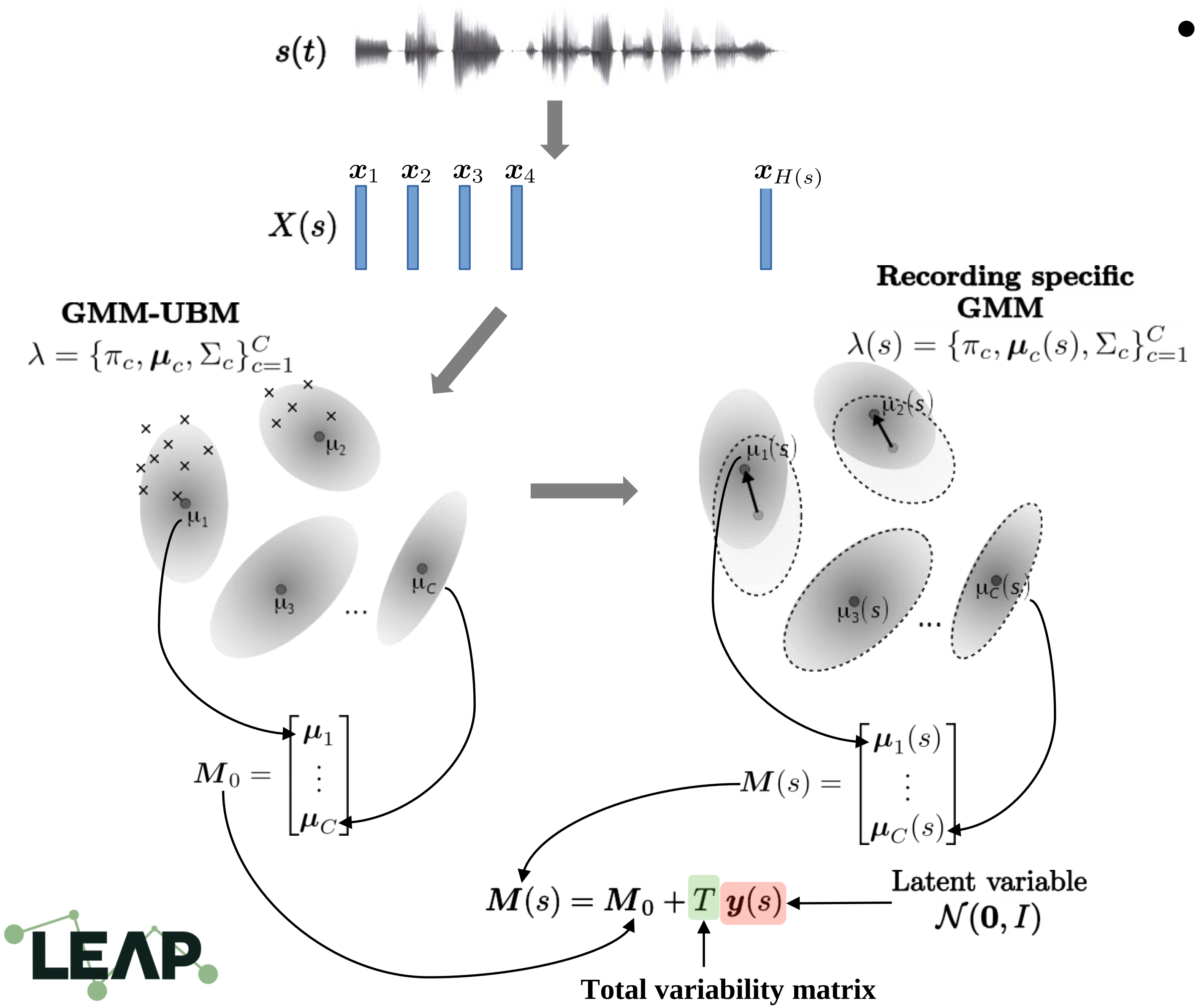
Total variability matrix

Motivation



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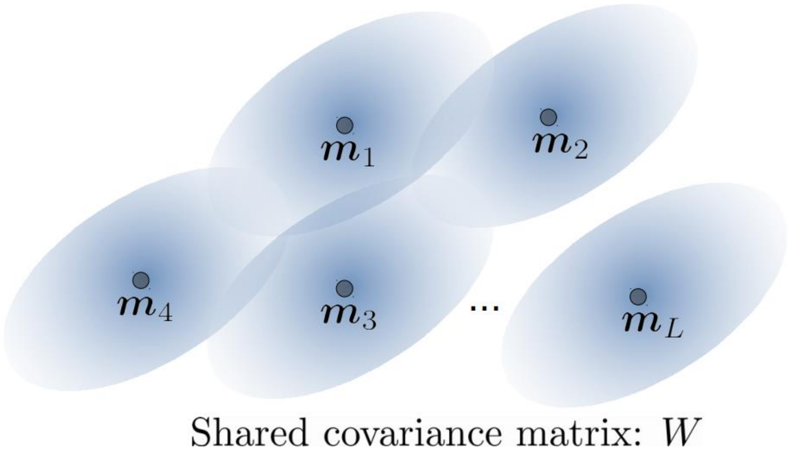

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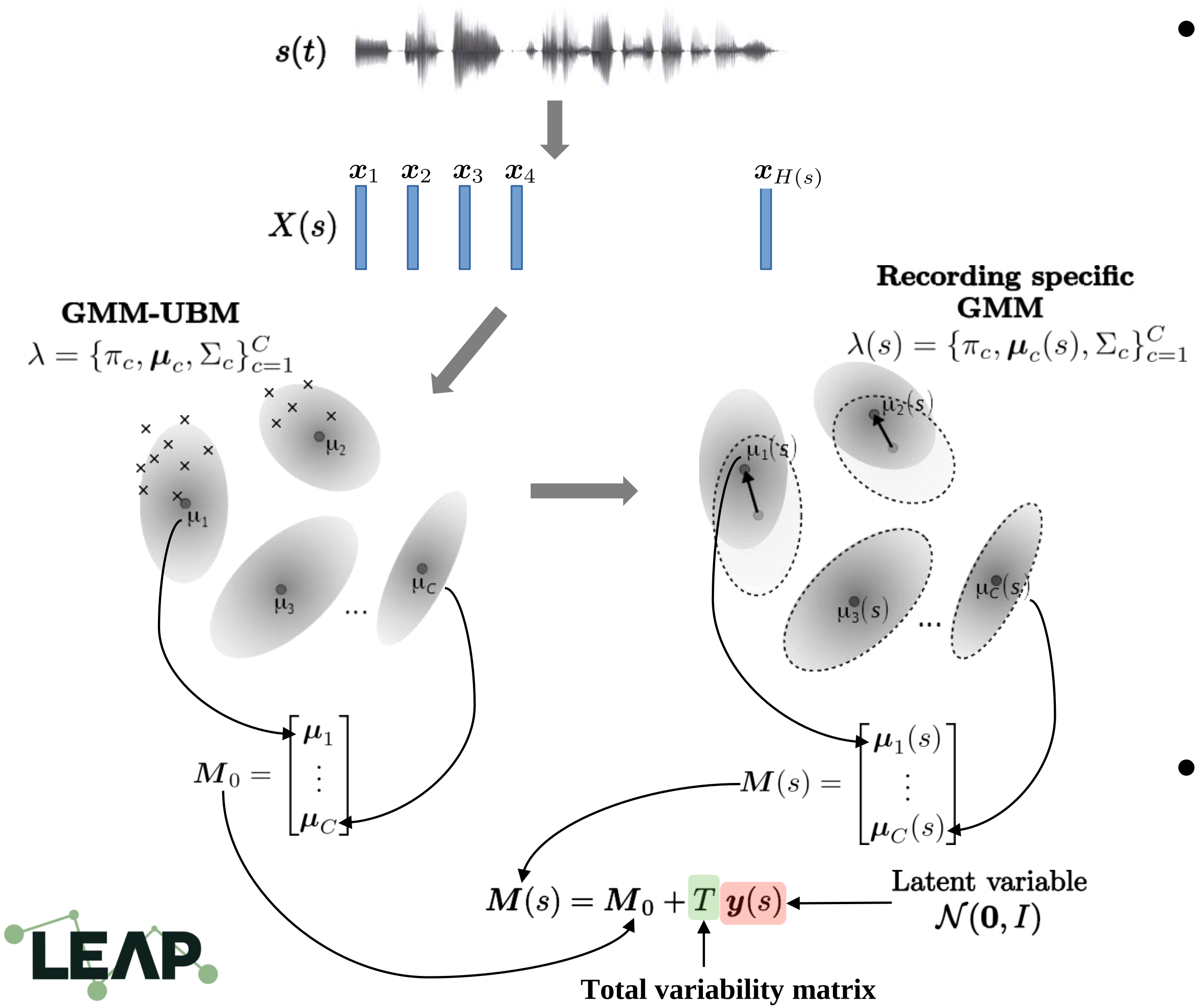

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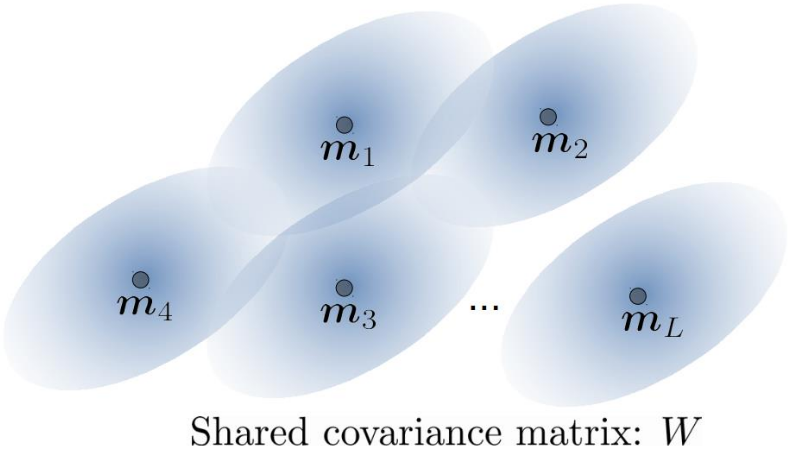

- The label log-likelihoods are computed as

$$\log \mathrm{p}(\boldsymbol{y} \mid l) = \boldsymbol{y}^{\intercal} W^{-1} \boldsymbol{m}_l - \frac{1}{2} \boldsymbol{m}_l^{\intercal} W^{-1} \boldsymbol{m}_l$$

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- i-vectors have a standard normal assumption in the front-end, but a GMM assumption in the back-end.
- Can we train the front-end i-vector model with a mixture Gaussian prior, making the assumptions consistent with the back-end?

The s-vector model

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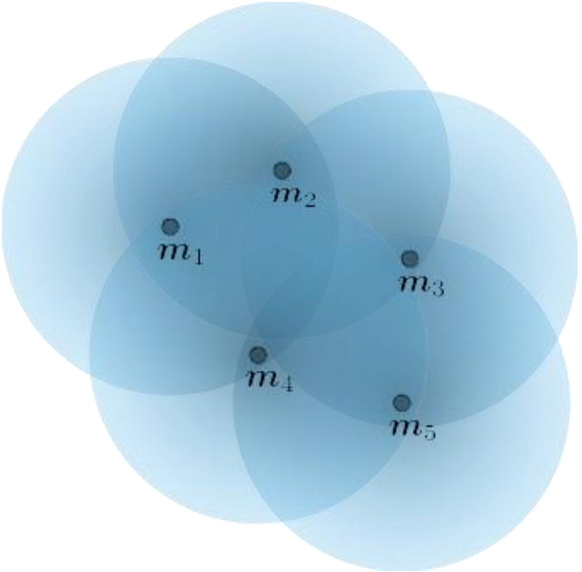
$$p(\boldsymbol{y}(s) | l(s) = l) = \mathcal{N}(\boldsymbol{y}(s); \boldsymbol{m}_l, I)$$

$$p\big(\boldsymbol{y}(s)\big) = \sum_{l=1}^{L} p(l)\mathcal{N}(\boldsymbol{y}(s); \boldsymbol{m}_l, I)$$



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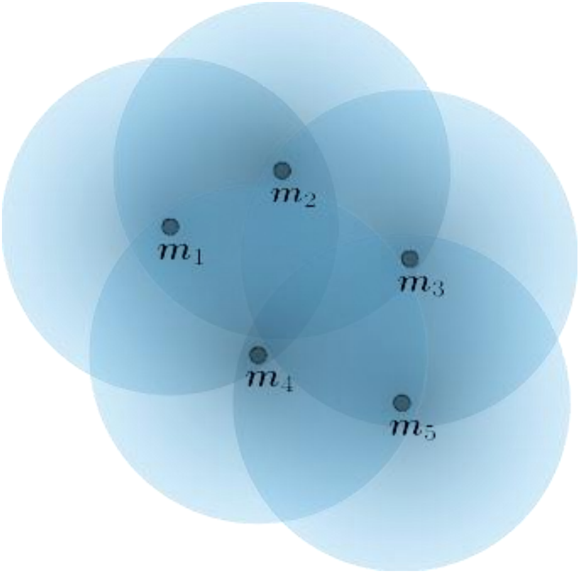

- The parameters of the s-vector model are denoted as:

$$\Theta = \{T, \boldsymbol{m}_1, \dots, \boldsymbol{m}_L\}$$

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Joint likelihood of features & Labels

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$\hat{\boldsymbol{y}}(s) \leftarrow$ **i-vector** **(MAP estimate)**

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$\hat{\boldsymbol{y}}(s) \longleftarrow$ **i-vector** **(MAP estimate)**

- In the s-vector model, the **posterior distribution** of $\boldsymbol{y}$ is given by

$$p(\boldsymbol{y}(s)|X(s)) = \sum_{l} p(l|X(s))\mathcal{N}(\mathcal{L}(s)^{-1}(m_l + T^T\Sigma^{-1}\mathbf{F}(s))\,,\ \mathcal{L}(s)^{-1})$$

LEAP

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Extracting i-vectors / s-vectors

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$\hat{\boldsymbol{y}}_l(s) \leftarrow$ **Class conditioned s-vector**

Extracting i-vectors / s-vectors

- Approach 1: PCA for dimensionality reduction (PCA s-vectors)

$$\begin{pmatrix} \hat{y}_1(s) \\ \hat{y}_2(s) \\ \vdots \\ \hat{y}_L(s) \end{pmatrix} \longrightarrow \boxed{\begin{array}{c}\text{PCA}\\ \text{Transformation}\end{array}} \longrightarrow \hat{\boldsymbol{y}}_{\boldsymbol{PCA}}(s)$$

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$$\hat{\boldsymbol{y}}_{\boldsymbol{avg}}(s) = \frac{1}{L}\sum_{l} \hat{\boldsymbol{y}}_l(s)$$

Extracting i-vectors / s-vectors

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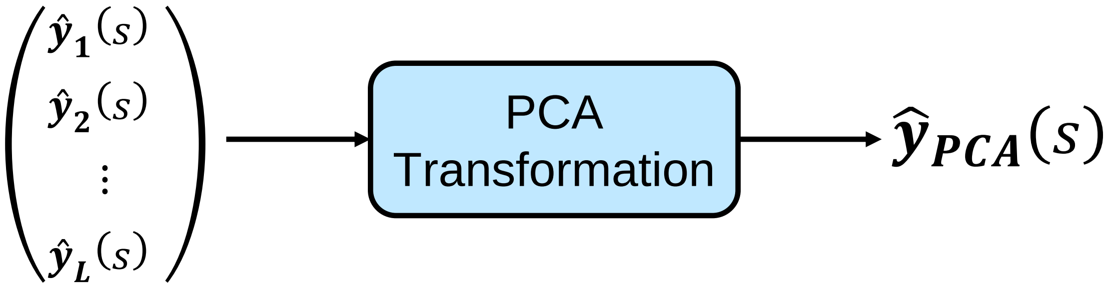

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$$\hat{\boldsymbol{y}}_{\boldsymbol{avg}}(s) = \frac{1}{L}\sum_{l} \hat{\boldsymbol{y}}_l(s)$$

- Approach 3: Minimum mean squared error s-vectors (MMSE s-vectors)

$$\hat{\boldsymbol{y}}_{\boldsymbol{MMSE}}(s) = \sum_{l} p(l|X(s))\hat{\boldsymbol{y}}_l(s)$$

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$$\hat{\boldsymbol{y}}_{\boldsymbol{MMSE}}(s) = \sum_{l} p(l|X(s))\hat{\boldsymbol{y}}_l(s)$$

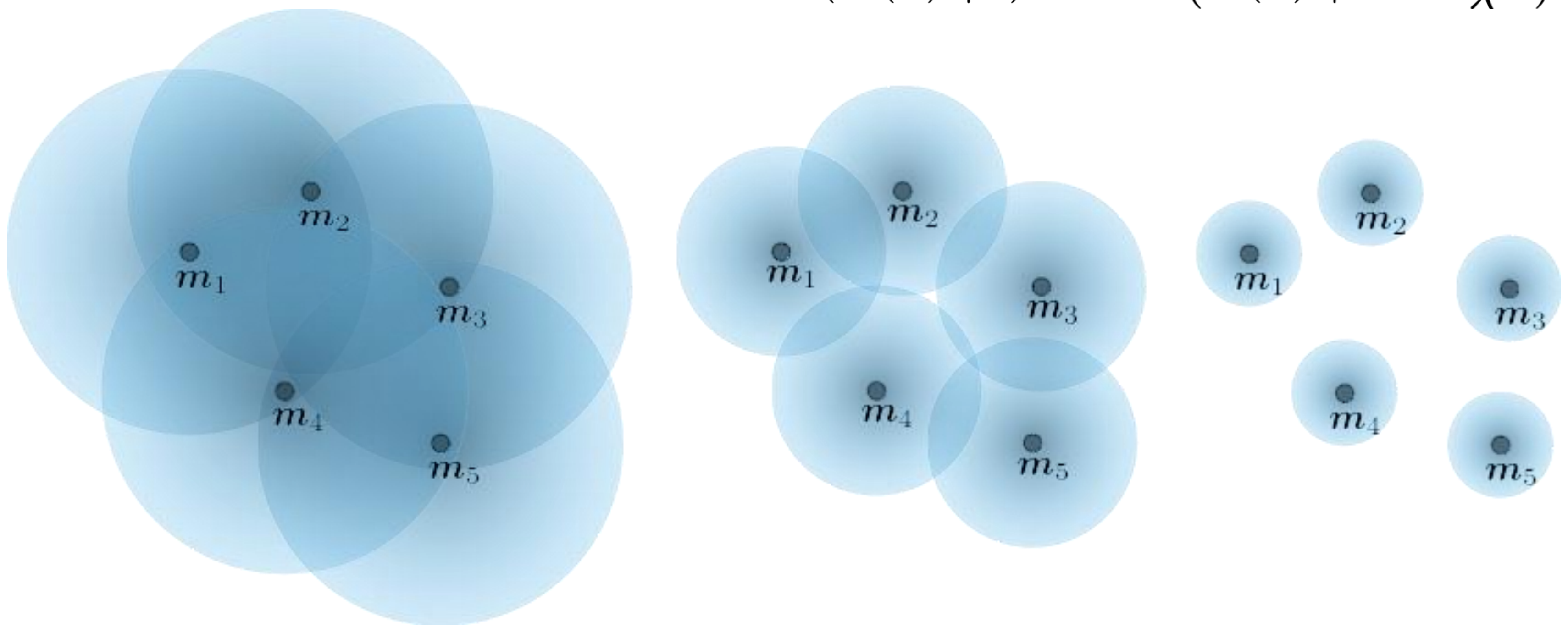
- Oracle s-vectors (cheat) : To understand the limits of this model.

$$\hat{\boldsymbol{y}}_{\boldsymbol{oracle}}(s) = \hat{\boldsymbol{y}}_{l(s)}(s)$$

Re-weighting the priors

- By re-weighting the prior covariance, the model can be made more discriminative

$$\mathrm{p}(\boldsymbol{y}(s) \mid l) = \mathcal{N}\left(\boldsymbol{y}(s) \mid \boldsymbol{m}_l, \tfrac{1}{\lambda} I\right)$$

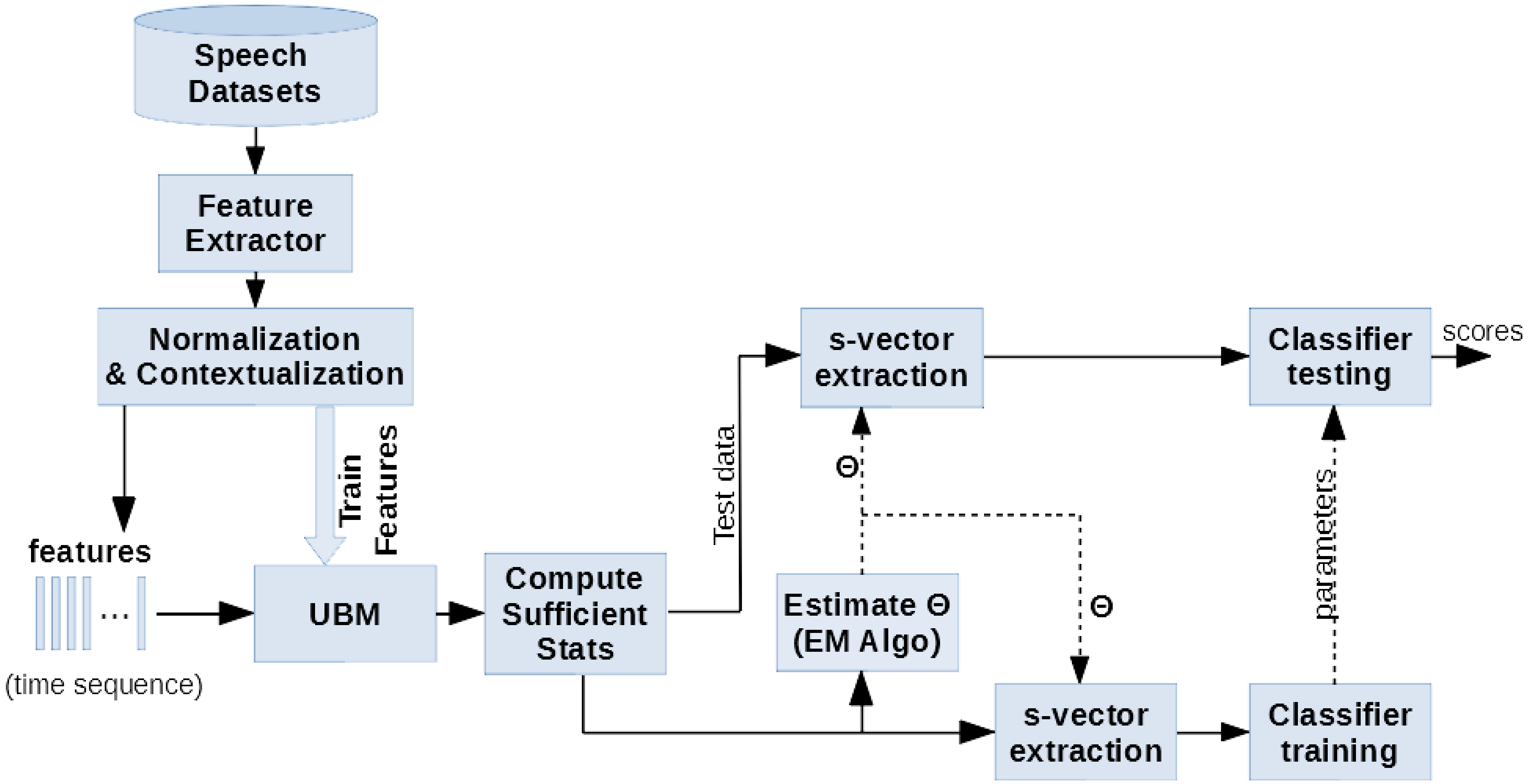


$\lambda = 1$ $\lambda = 3$ $\lambda = 5$

Experiments – NIST LRE 2017

Cluster	Target Languages	#files	Total Duration (hours)
Arabic	Egyptian Arabic (ara-arz)	440	190.9
	Iraqi Arabic (ara-acm)	1406	130.8
	Levantine Arabic (ara-apc)	3509	440.7
	Maghrebi Arabic (ara-ary)	919	81.8
Chinese	Mandarin (zho-cmn)	3331	379.4
	Min Nan (zho-nan)	95	13.3
English	British English (eng-gbr)	98	4.8
	General American English (eng-usg)	2448	327.7
Slavic	Polish (qsl-pol)	587	59.3
	Russian (qsl-rus)	1221	69.5
Iberian	Caribbean Spanish (spa-car)	688	166.3
	European Spanish (spa-eur)	121	24.7
	Latin American Spanish (spa-lac)	898	175.9
	Brazilian Portuguese (por-brz)	444	4.1

Experiments – NIST LRE 2017



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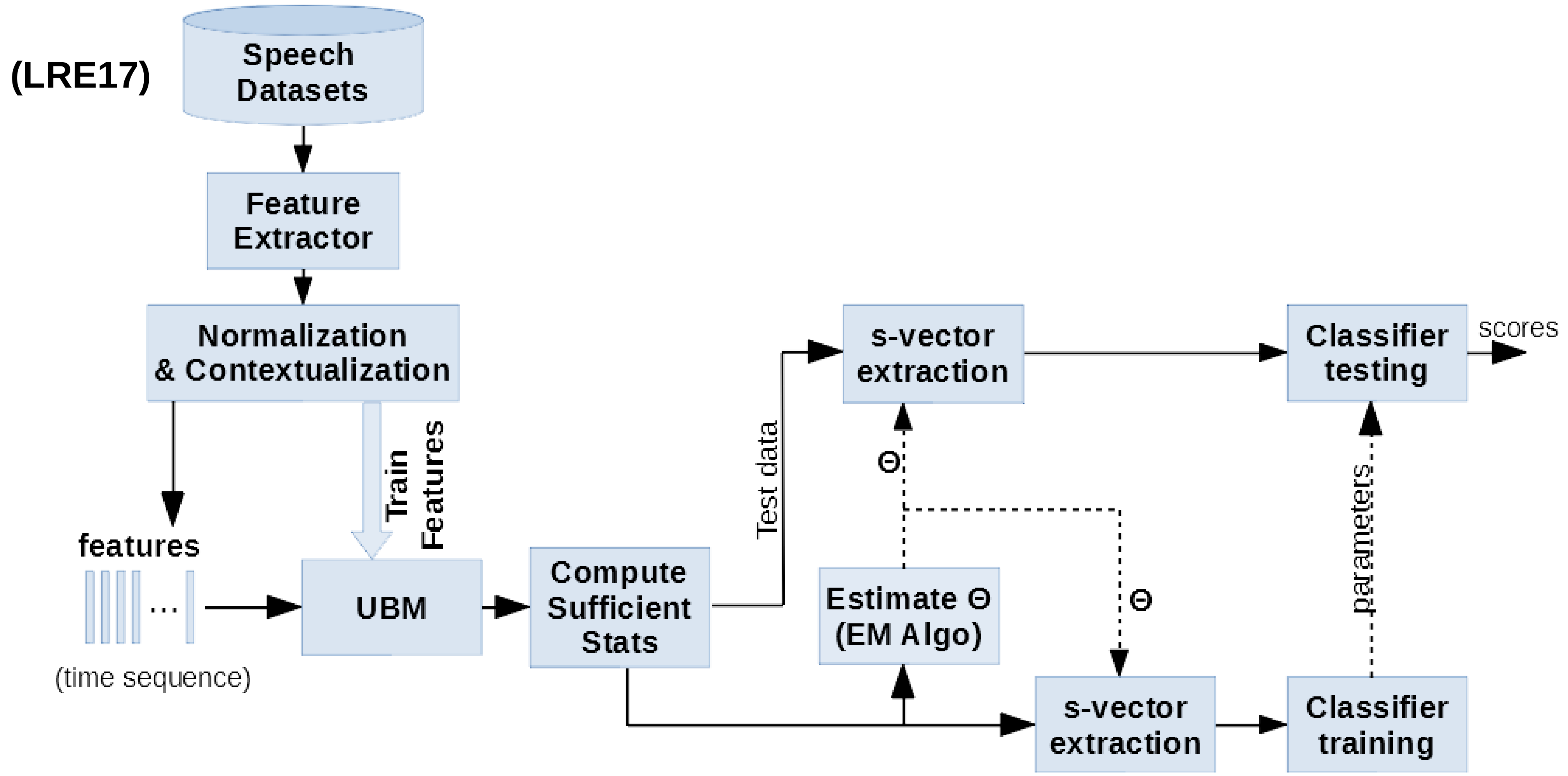

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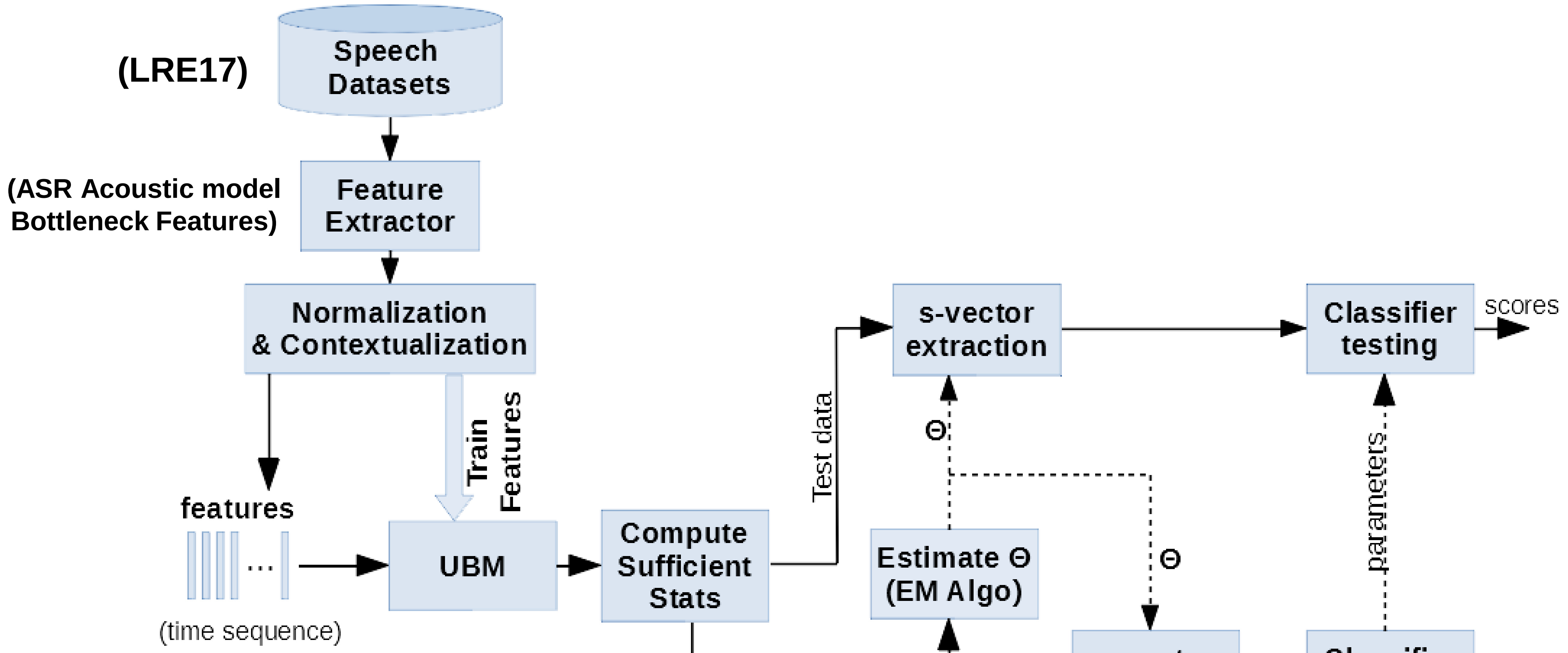

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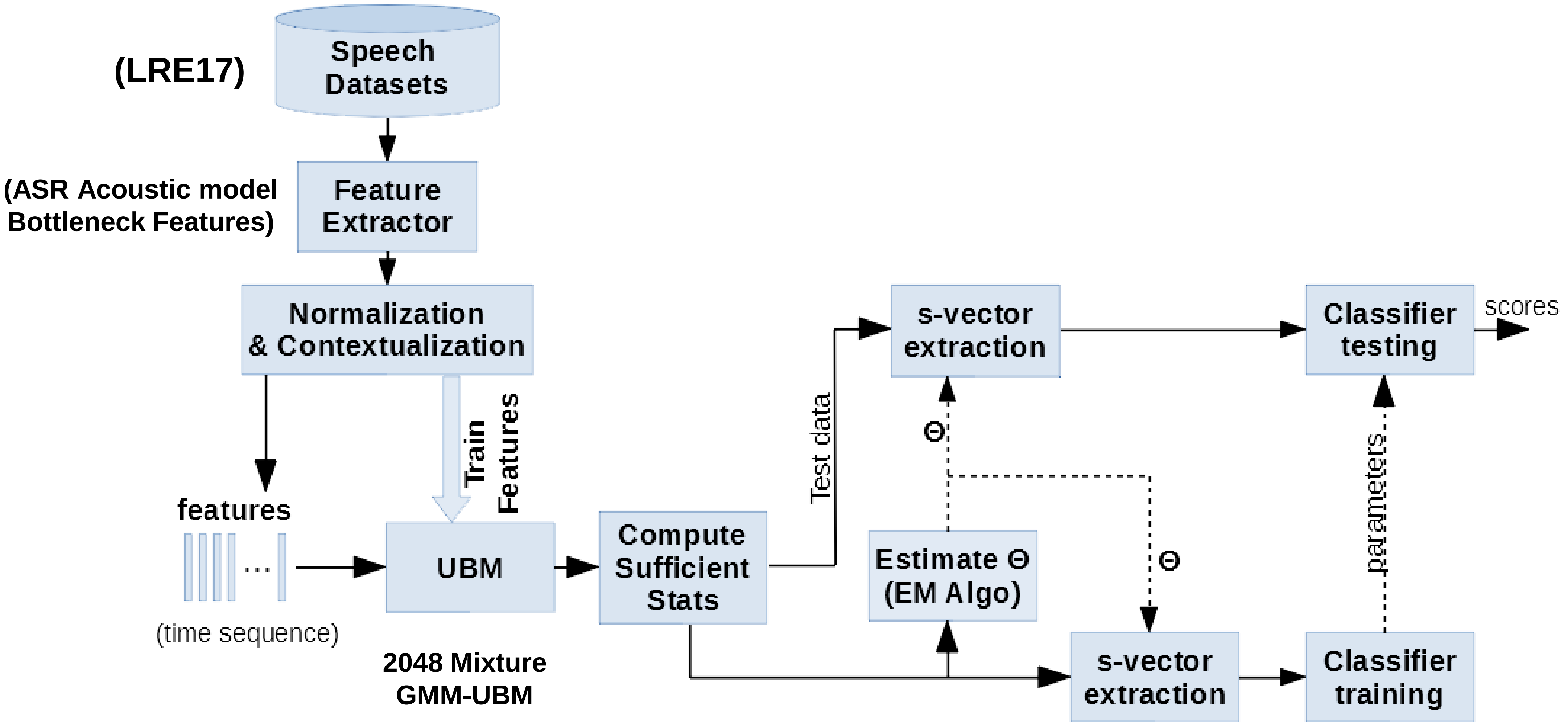

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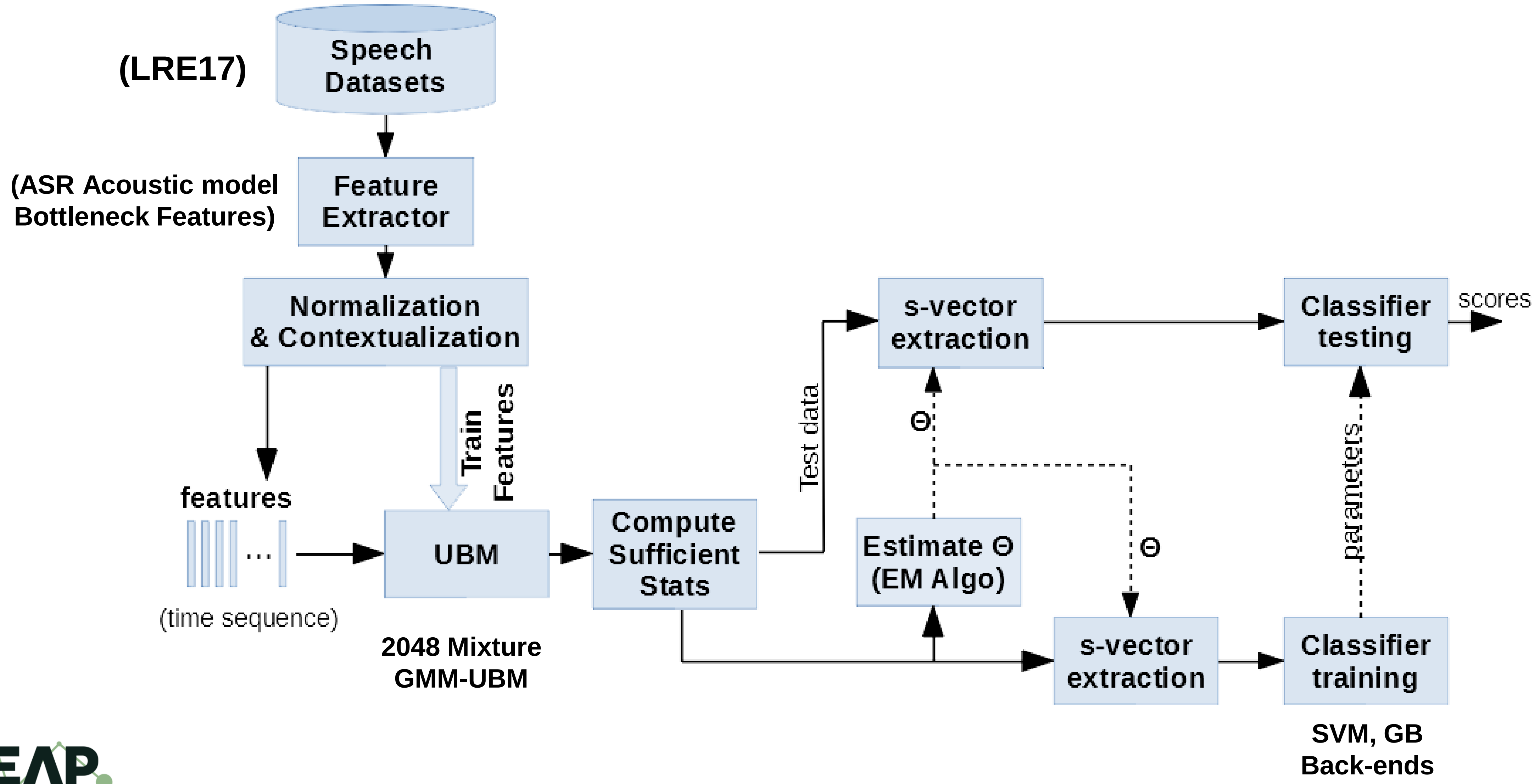

Results

- Results on LRE17 Development Dataset (3661 test examples) with SVM Back-end.

	Dev Performances : $100C_{primary}$ [EER (%)] {Accuracy(%)}		
Model config.	3 sec	10 sec	30 sec
Unsupervised i-vector [1]	52.7 [16.6] {51.8}	27.1 [7.5] {74.0}	13.1 [3.6] {87.8}
Sup. i-vector [2]	47.2 [15.1] {61.1}	20.2 [5.7] {80.9}	14.8 [4.1] {85.1}
Simplified Sup. i-vector [2]	58.2 [19.6] {47.8}	27.3 [7.8] {73.6}	13.4 [3.7] {87.7}
LSTM [3]	53.7 [15.39] {52.7}	33.8 [9.7] {69.2}	32.0 [8.81] {70.9}
HGRU [4]	53.1 [15.09] {57.5}	27.6 [6.6] {76.9}	25.5 [6.1] {78.6}
Average s-vector	47.8 [14.3] {56.3}	22.4 [6.2] {78.3}	12.2 [**3.3**] {88.0}
PCA s-vector	57.6 [18.2] {50.4}	27.0 [7.4] {74.6}	12.1 [3.4] {88.2}
Approx. MMSE s-vector	51.1 [15.3] {54.1}	23.9 [6.1] {77.4}	12.1 [3.3] {88.3}
MMSE s-vector	**44.4** [**14.7**] {**63.5**}	**19.5** [**5.9**] {**83.7**}	**11.7** [3.4] {**89.4**}
Oracle s-vector (cheat)	13.0 [3.9] {88.3}	5.6 [1.7] {94.4}	5.0 [1.1] {94.9}

[1] Dehak et. al., "*Language Recognition via i-vectors and dimensionality reduction*", Interspeech 2011
[2] M. Li et. al., "Simplified supervised i-vector modeling …" CSL 2014
[3] R. Zazo et. al., "Evaluation of an LSTM RNN system …" Odyssey 2016
[4] B. Padi et. al., "End-to-end language recognition using attention based HGRUs" ICASSP 2019

Results

- Results on LRE17 Evaluation Dataset (25k test examples) with SVM Back-end.

	Eval Performances : $100C_{primary}$ [EER (%)] {Accuracy(%)}		
Model config.	3 sec	10 sec	30 sec
Unsupervised i-vector [1]	53.6 [16.1] {53.8}	29.9 [8.6] {72.4}	16.7 [3.9] {83.0}
Sup. i-vector [2]	46.1 [14.7] {59.6}	25.6 [7.3] {76.4}	19.9 [5.1] {80.9}
Simplified Sup. i-vector [2]	57.2 [19.1] {49.8}	29.8 [8.4] {71.4}	16.7 [4.1] {82.8}
LSTM [3]	55.2 [15.4] {54.7}	35.4 [8.7] {72.1}	28.1 [7.3] {76.1}
HGRU [4]	55.4 [15.3] {55.1}	32.3 [7.5] {74.1}	23.3 [4.9] {83.0}
Average s-vector	49.7 [13.9] {58.5}	27.0 [7.0] {75.3}	15.7 [**3.7**] {84.0}
PCA s-vector	58.2 [17.7] {54.1}	30.5 [8.2] {73.7}	15.8 [3.8] {83.9}
Approx. MMSE s-vector	52.2 [14.6] {56.8}	27.8 [7.1] {74.7}	15.8 [3.6] {84.0}
MMSE s-vector	**43.7** [**13.5**] {**61.2**}	**23.7** [**6.5**] {**77.4**}	**15.4** [3.8] {**84.5**}
Oracle s-vector (cheat)	12.6 [3.6] {86.9}	6.5 [1.6] {92.9}	5.7 [1.4] {93.6}

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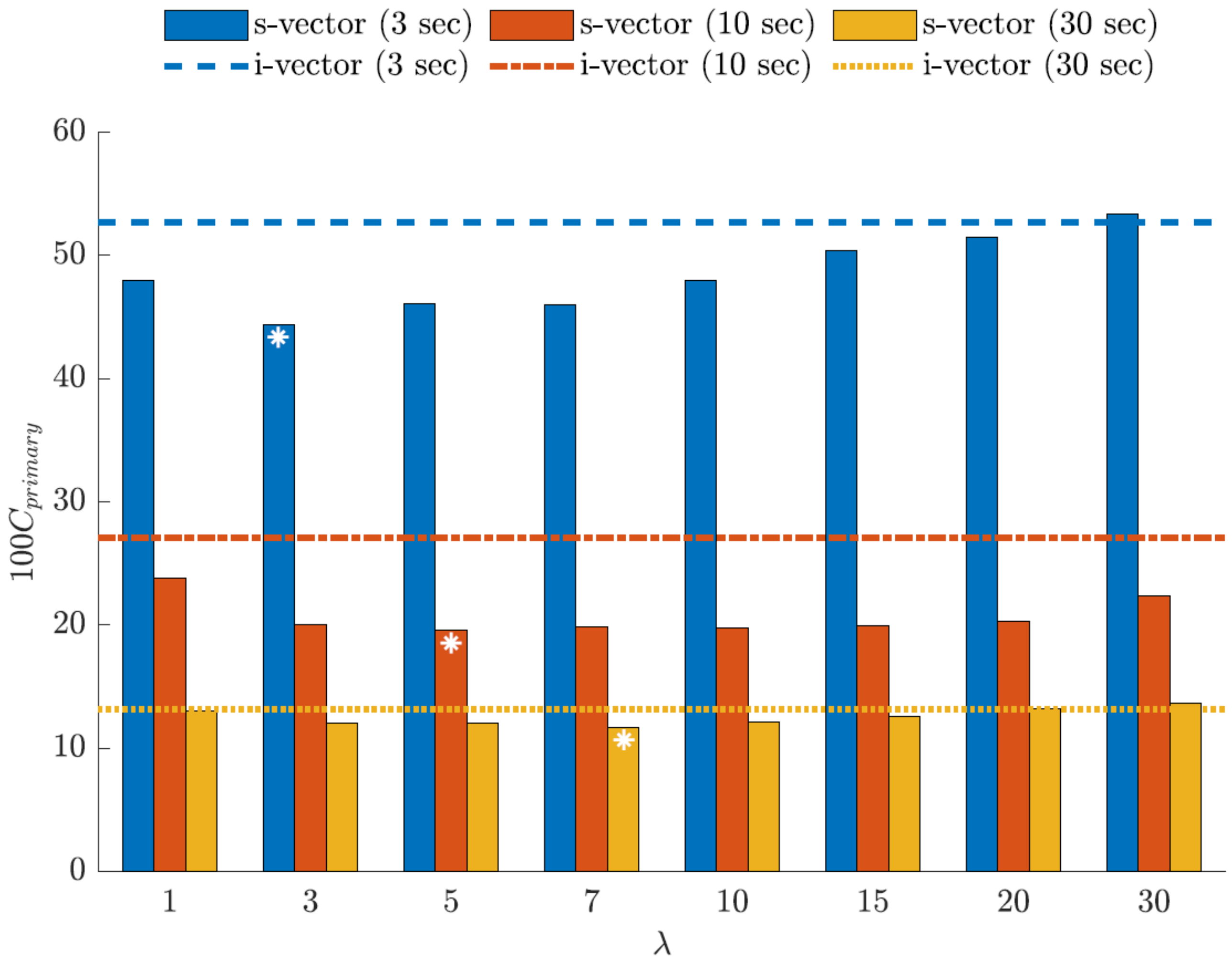
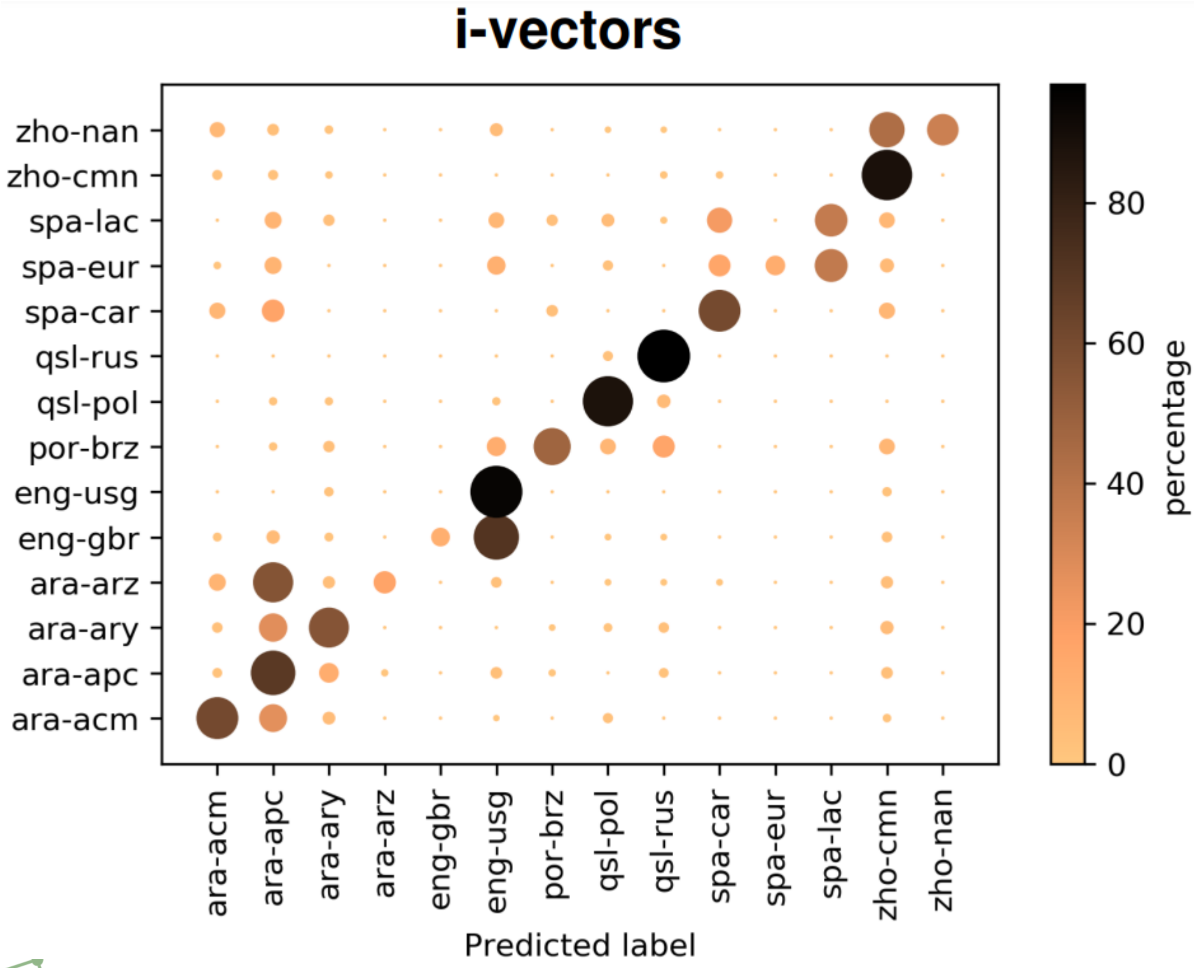
Results

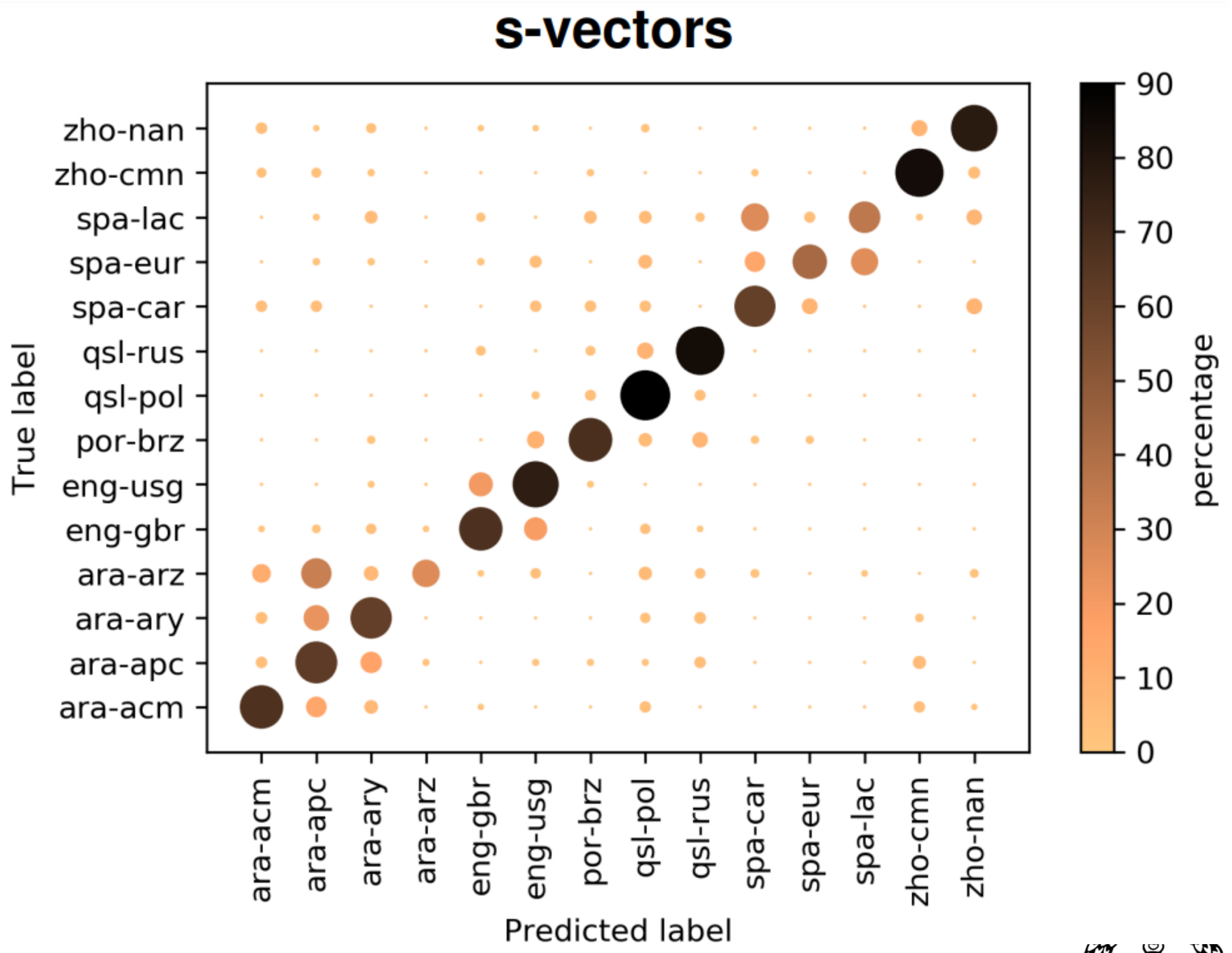
- Variation of $C_{Primary}$ with λ for various durations for MMSE s-vectors.



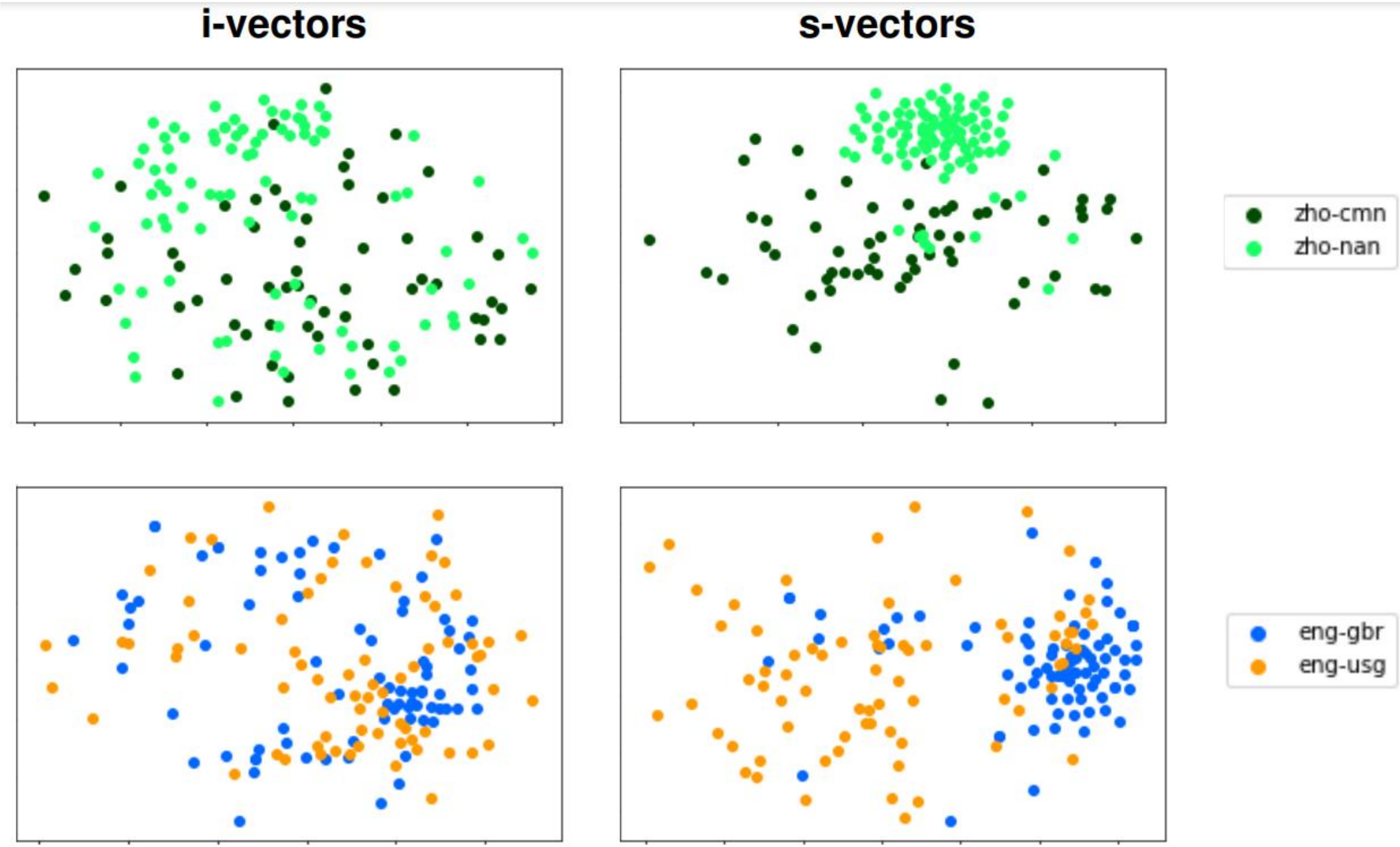
Results

- Comparison of confusion matrices for 3 sec condition with LRE2017 dev set.





t-SNE Visualization



Summary of s-vector modeling

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- Downside: Memory/time requirement increases linearly with number of class labels used.

Supervised Neural Network Models for Speaker Verification

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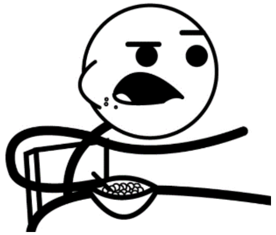

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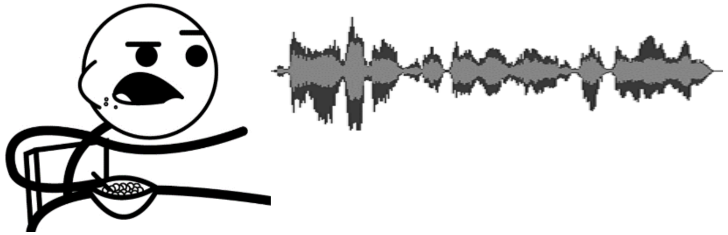
Enrollment Recording x_e



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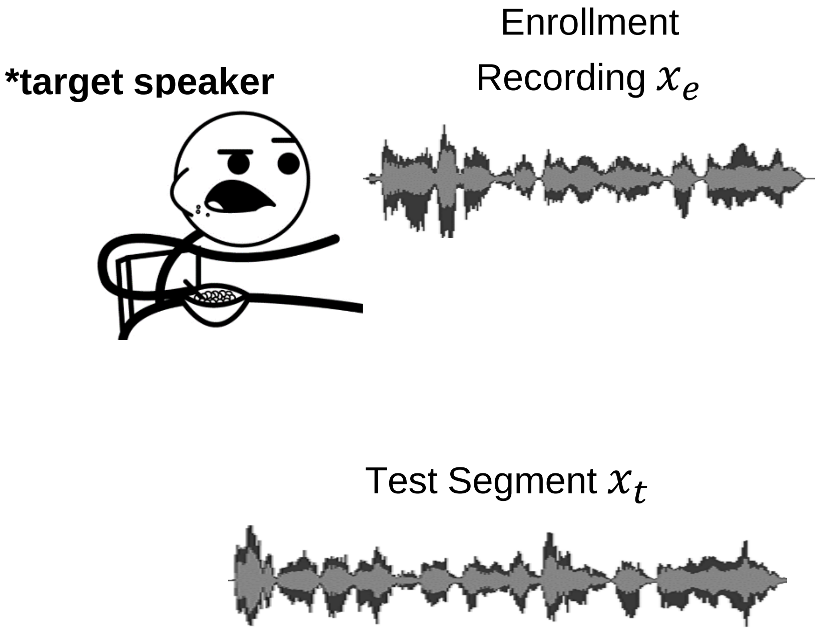

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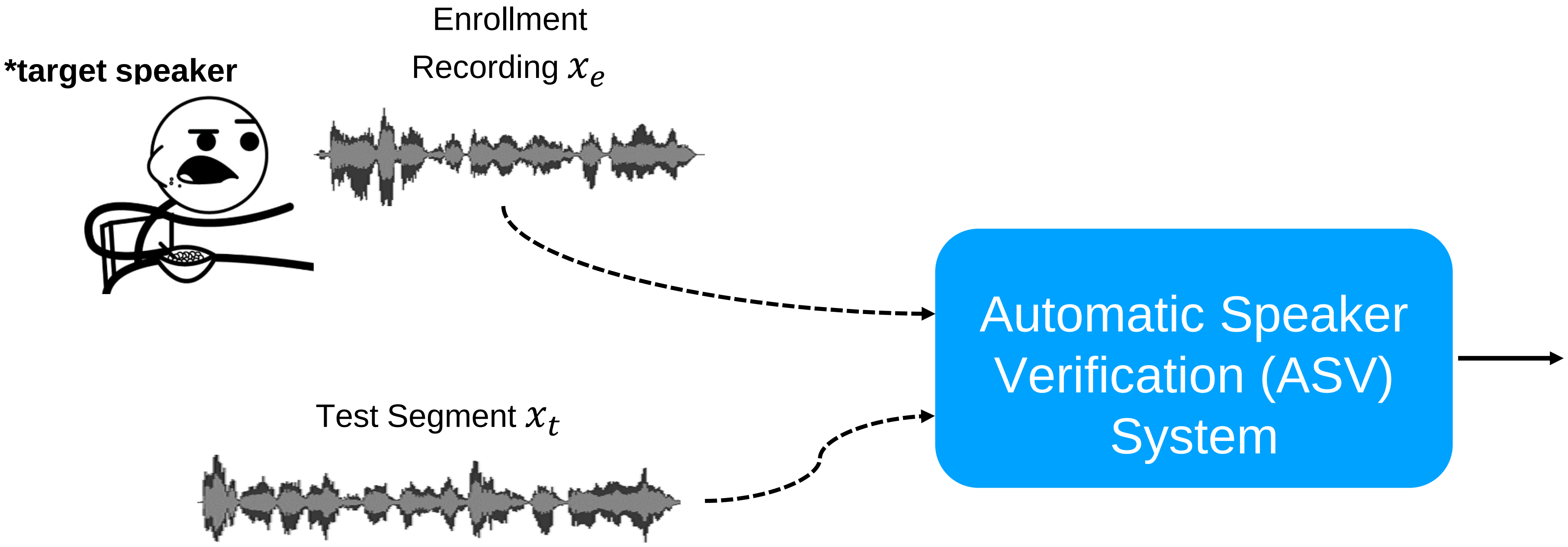

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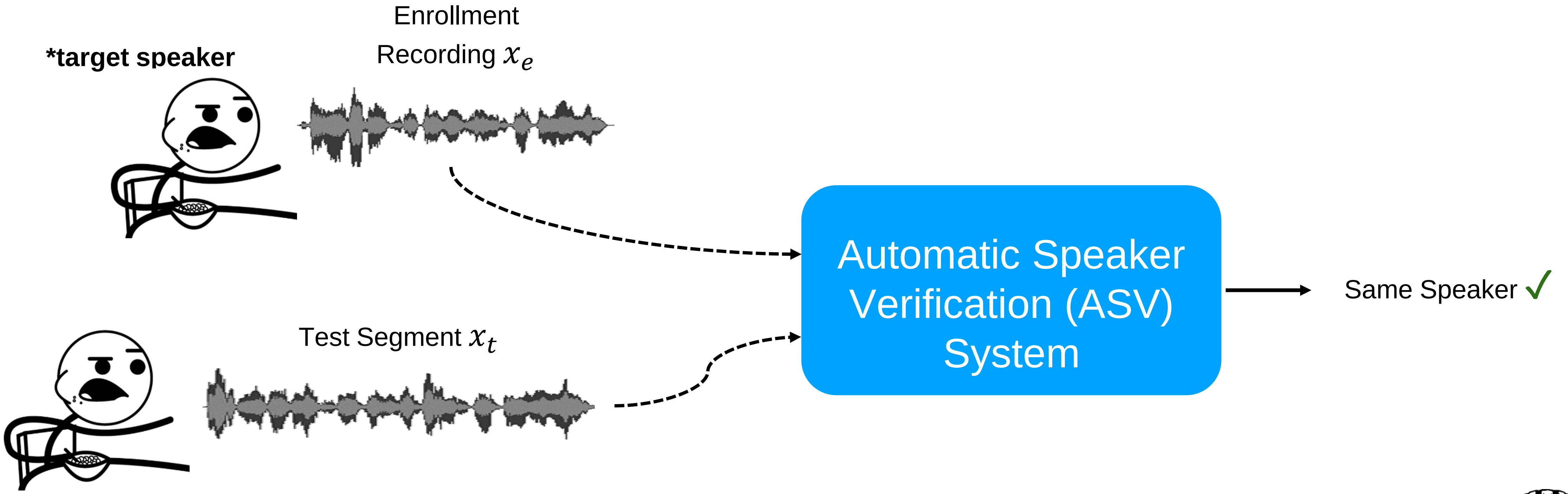

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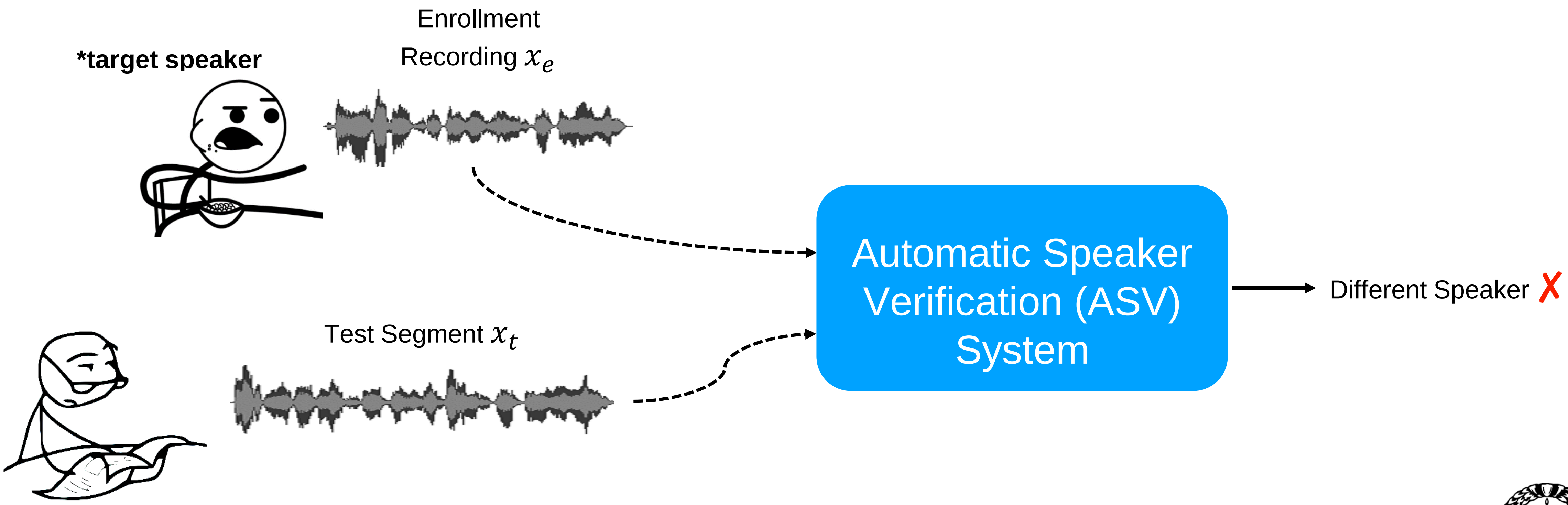

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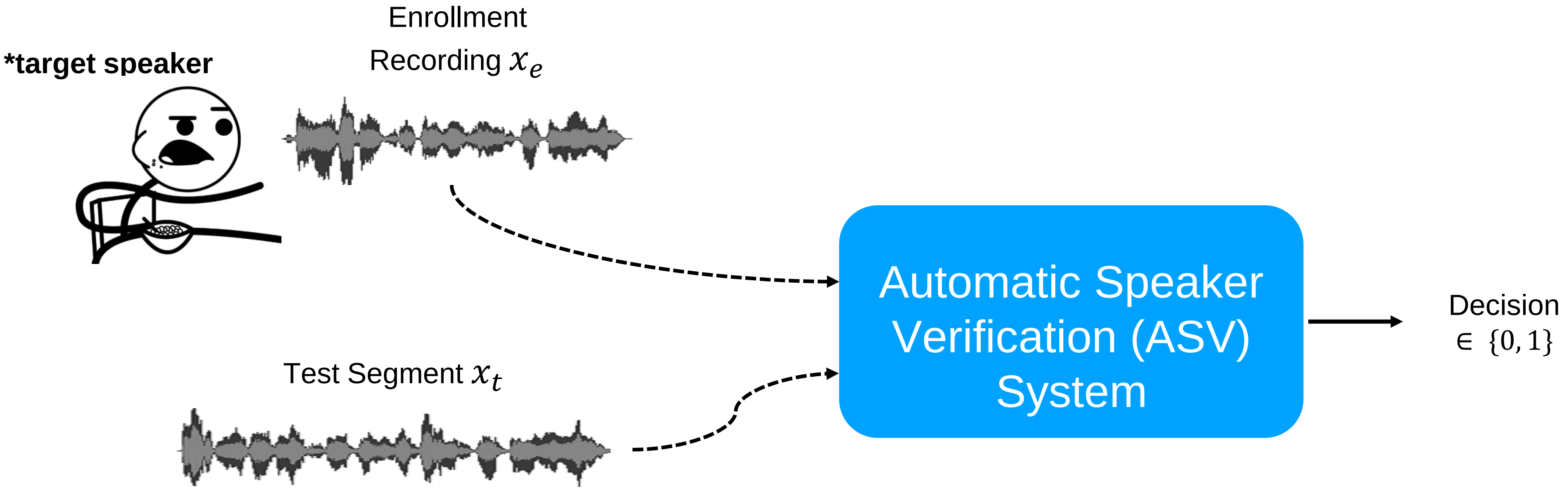

General Pipeline of NN based ASV

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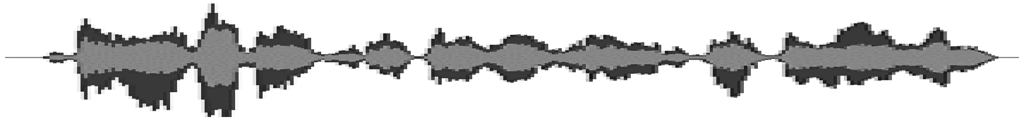

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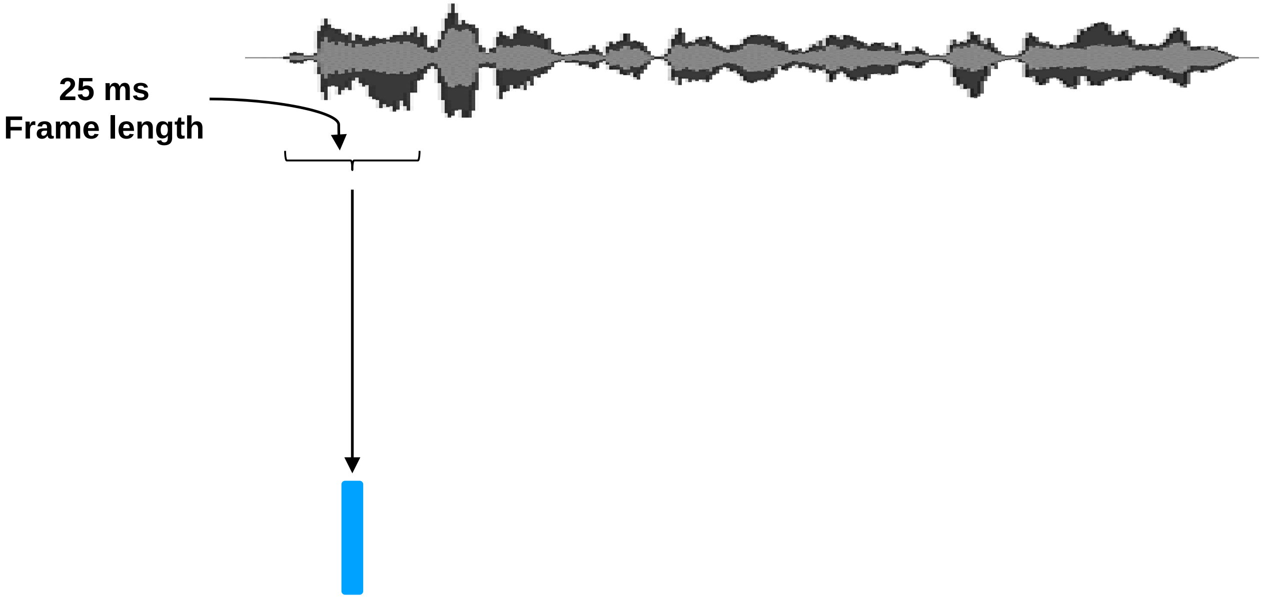

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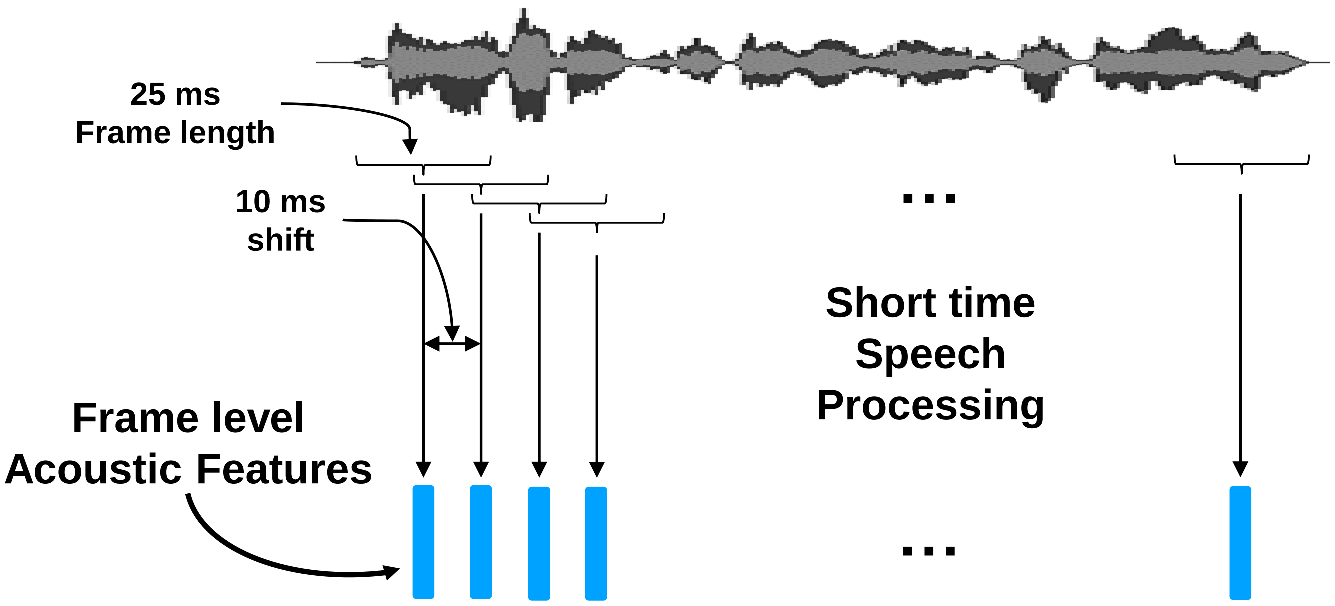

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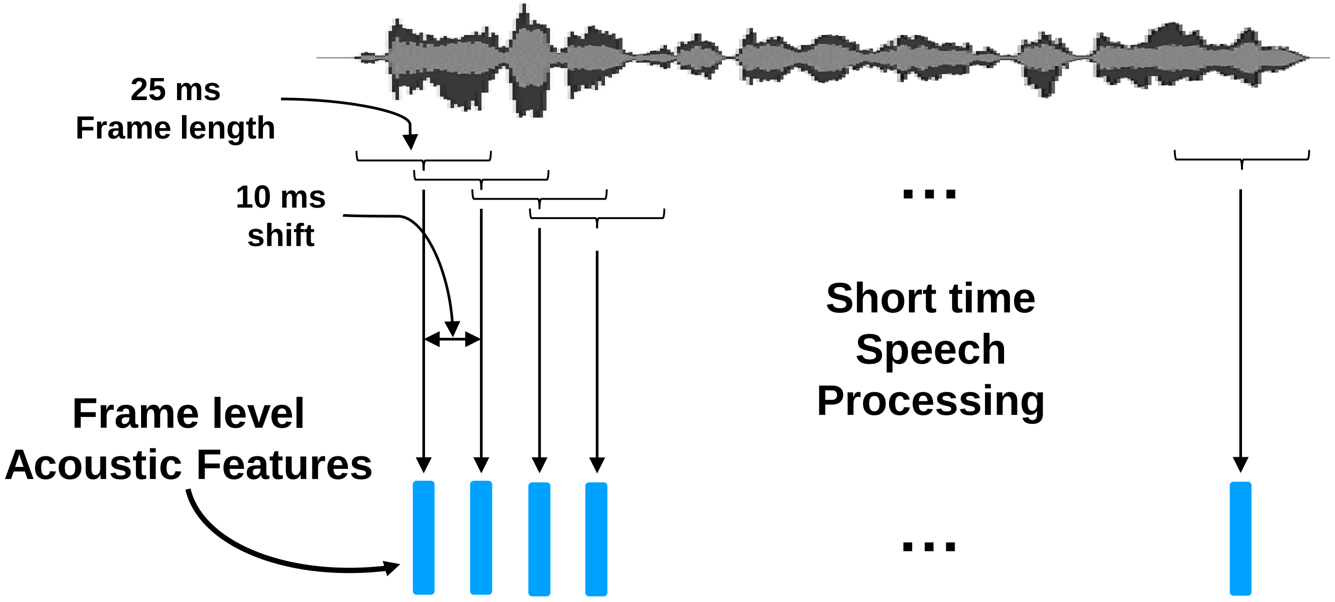

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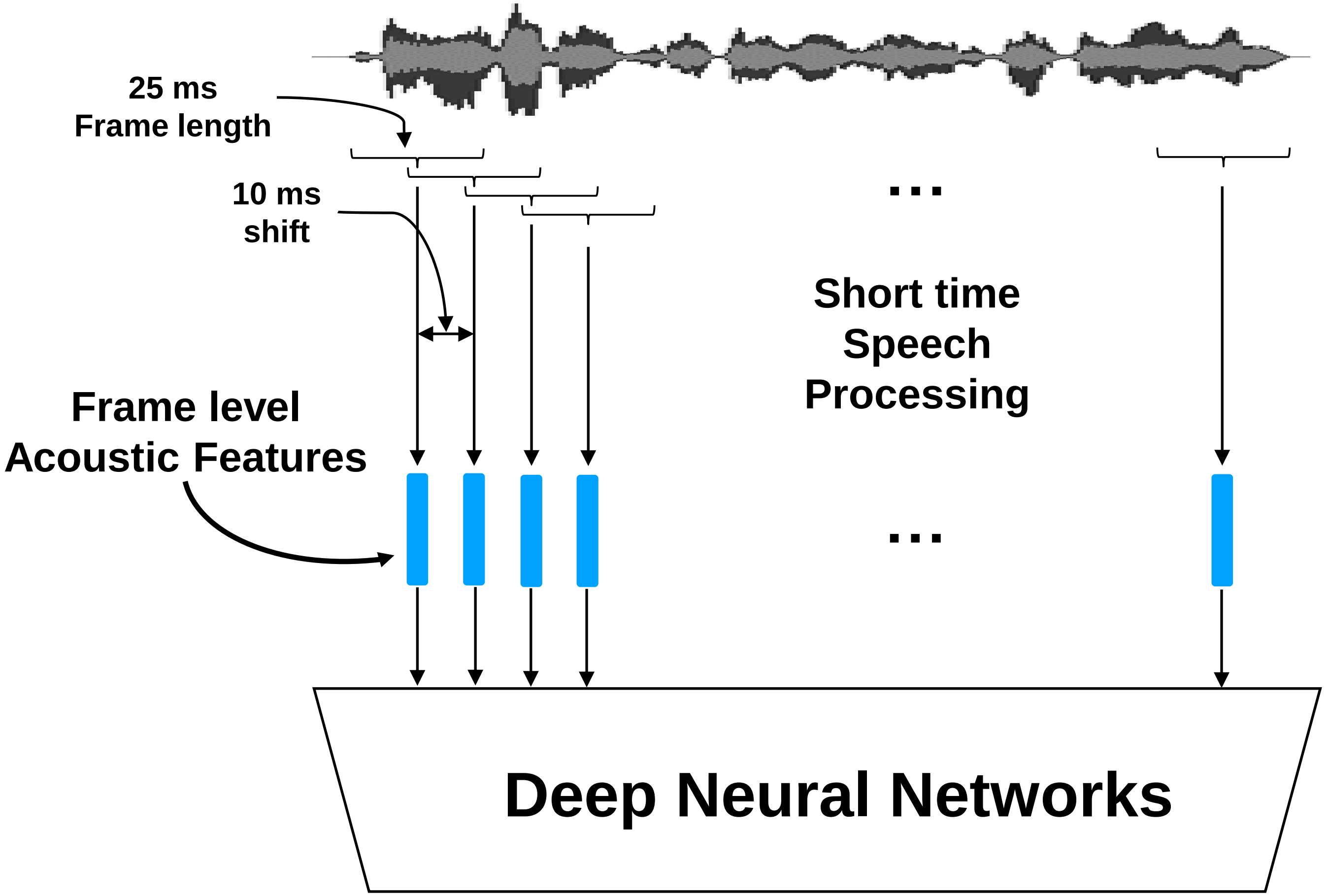

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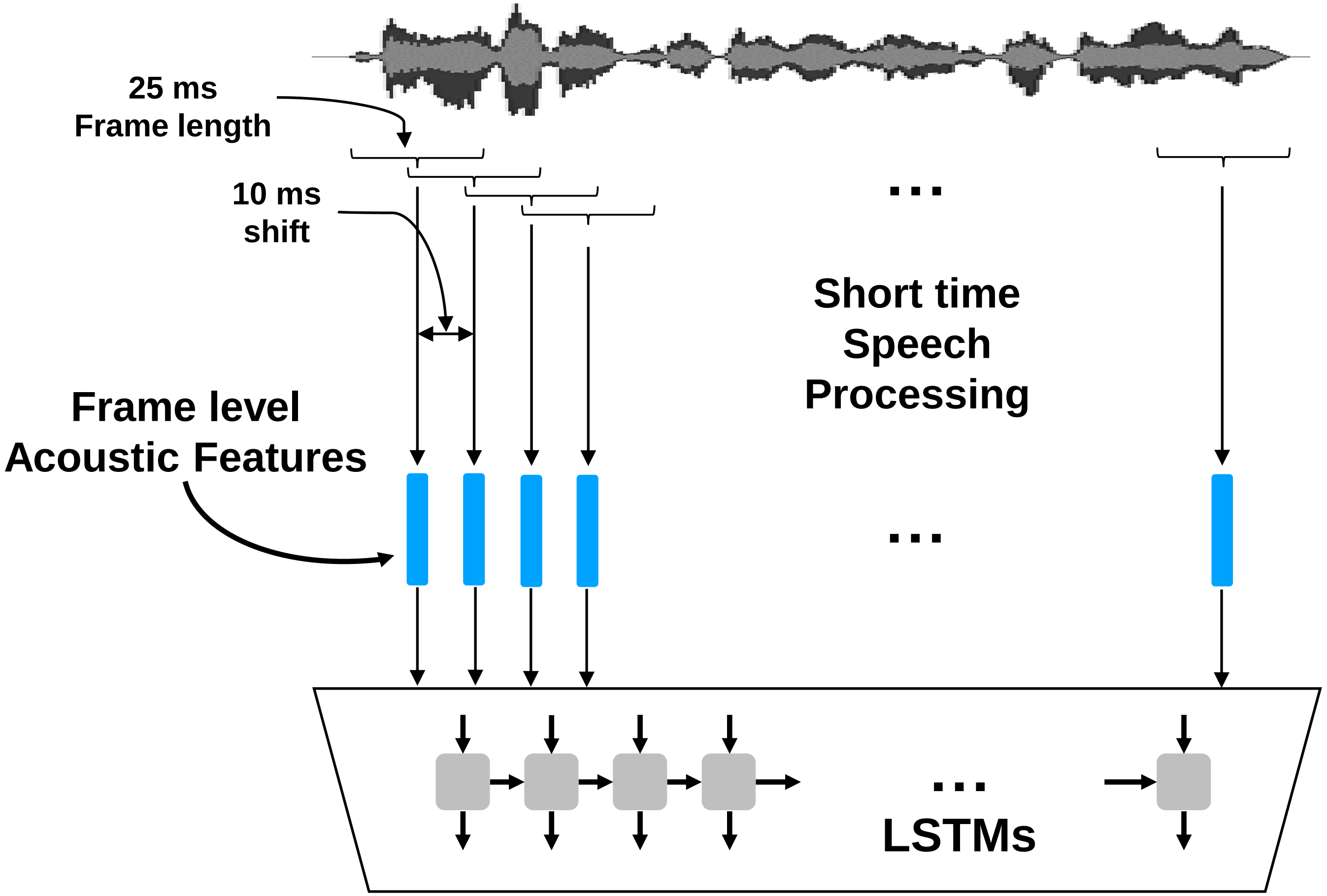

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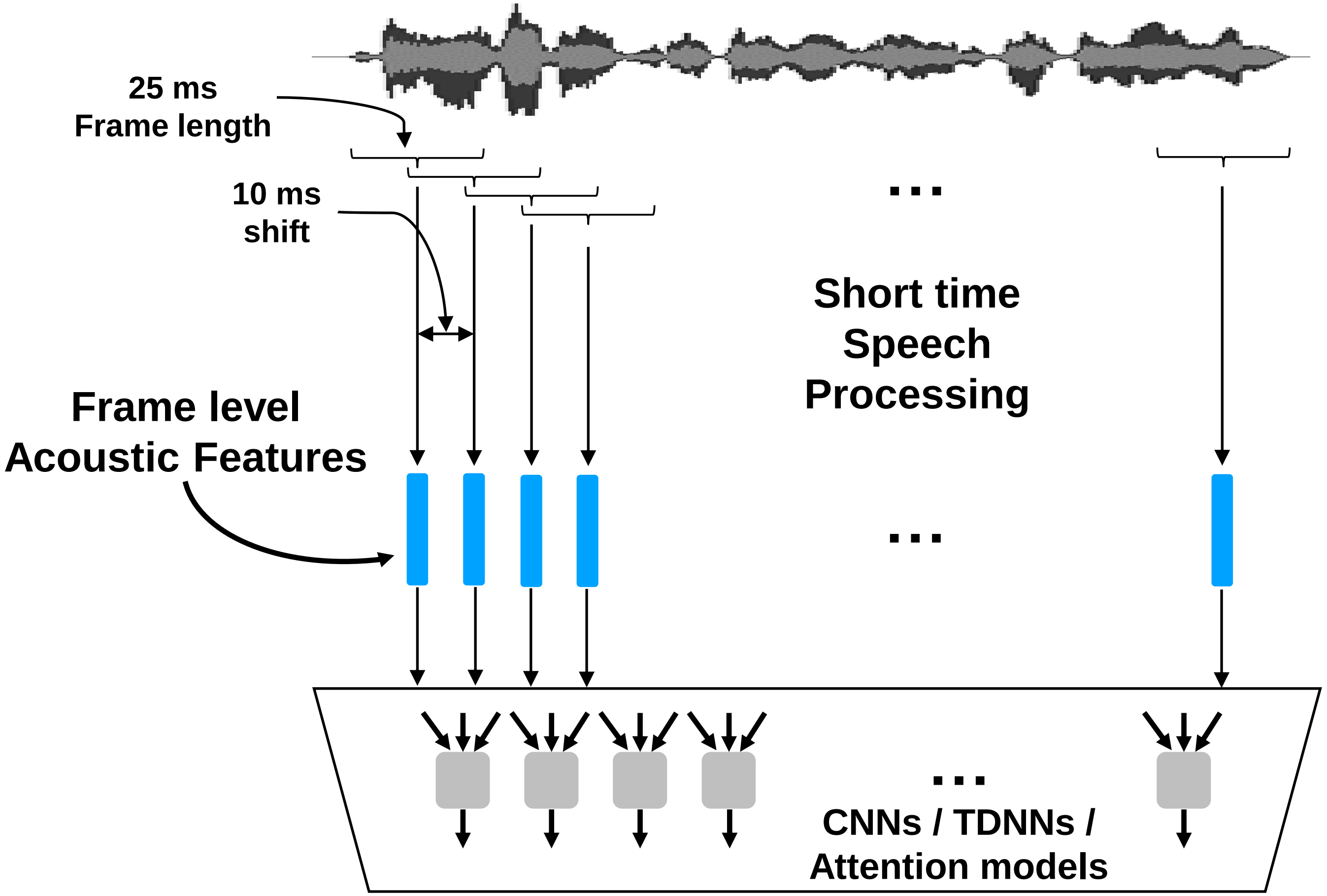

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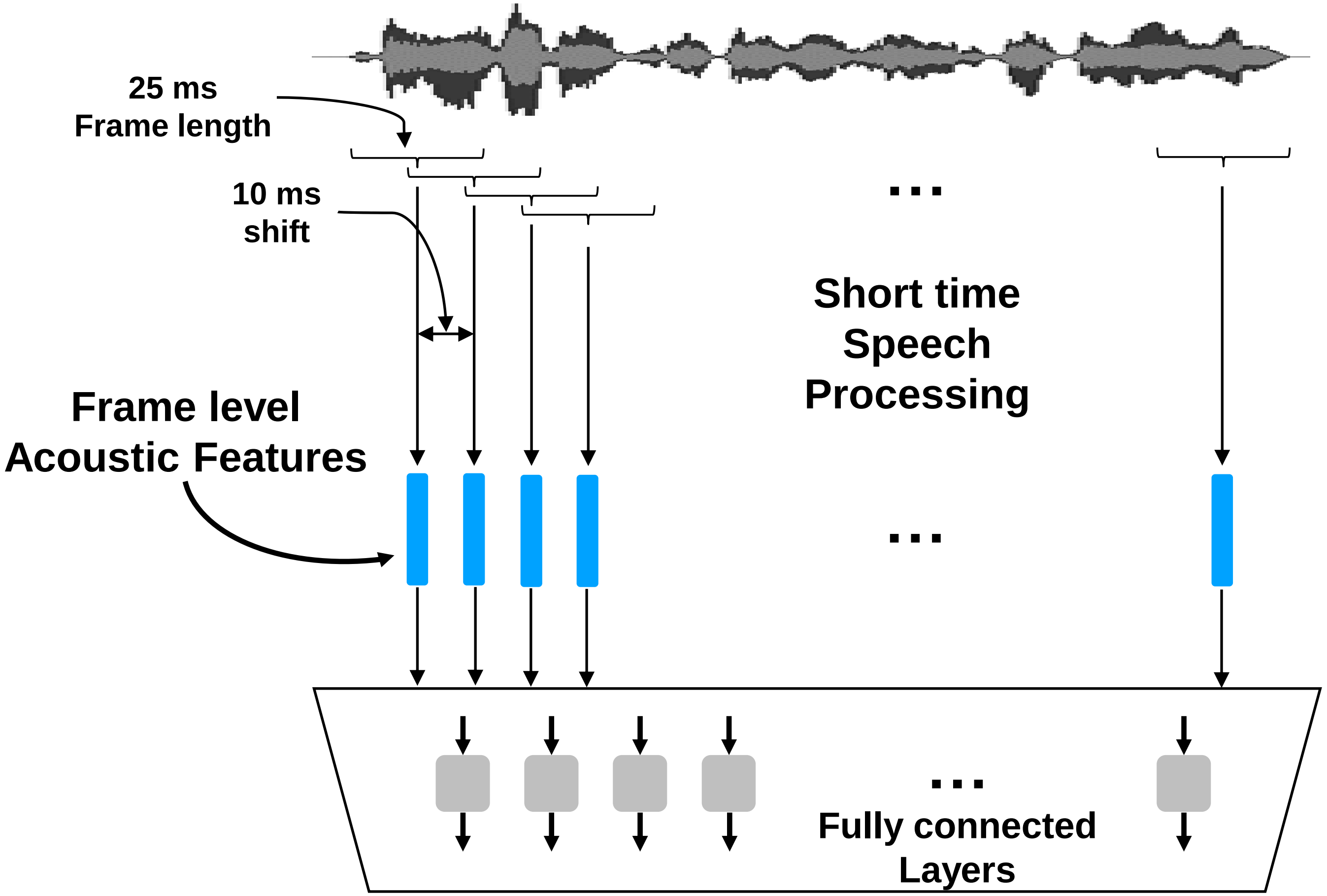

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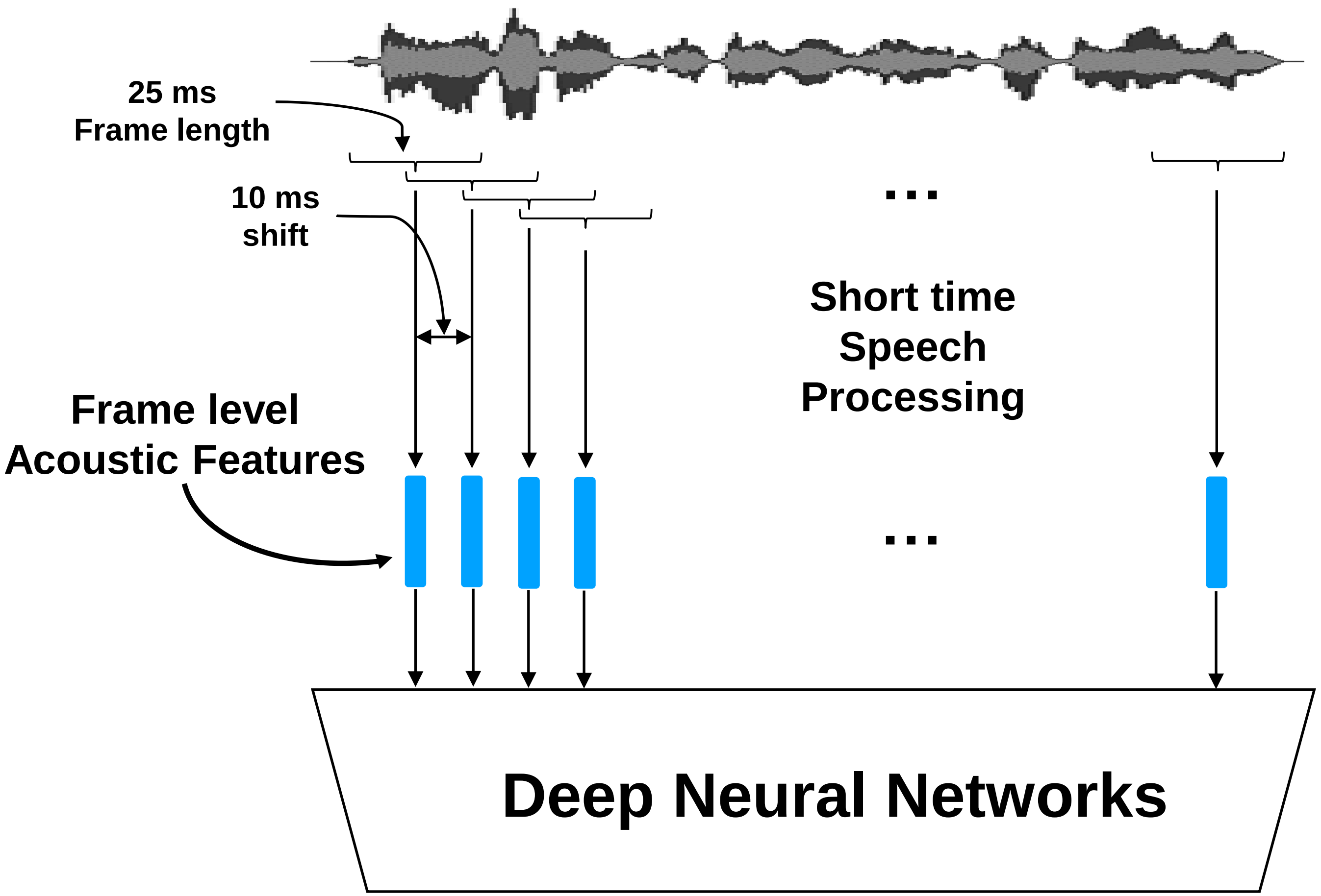

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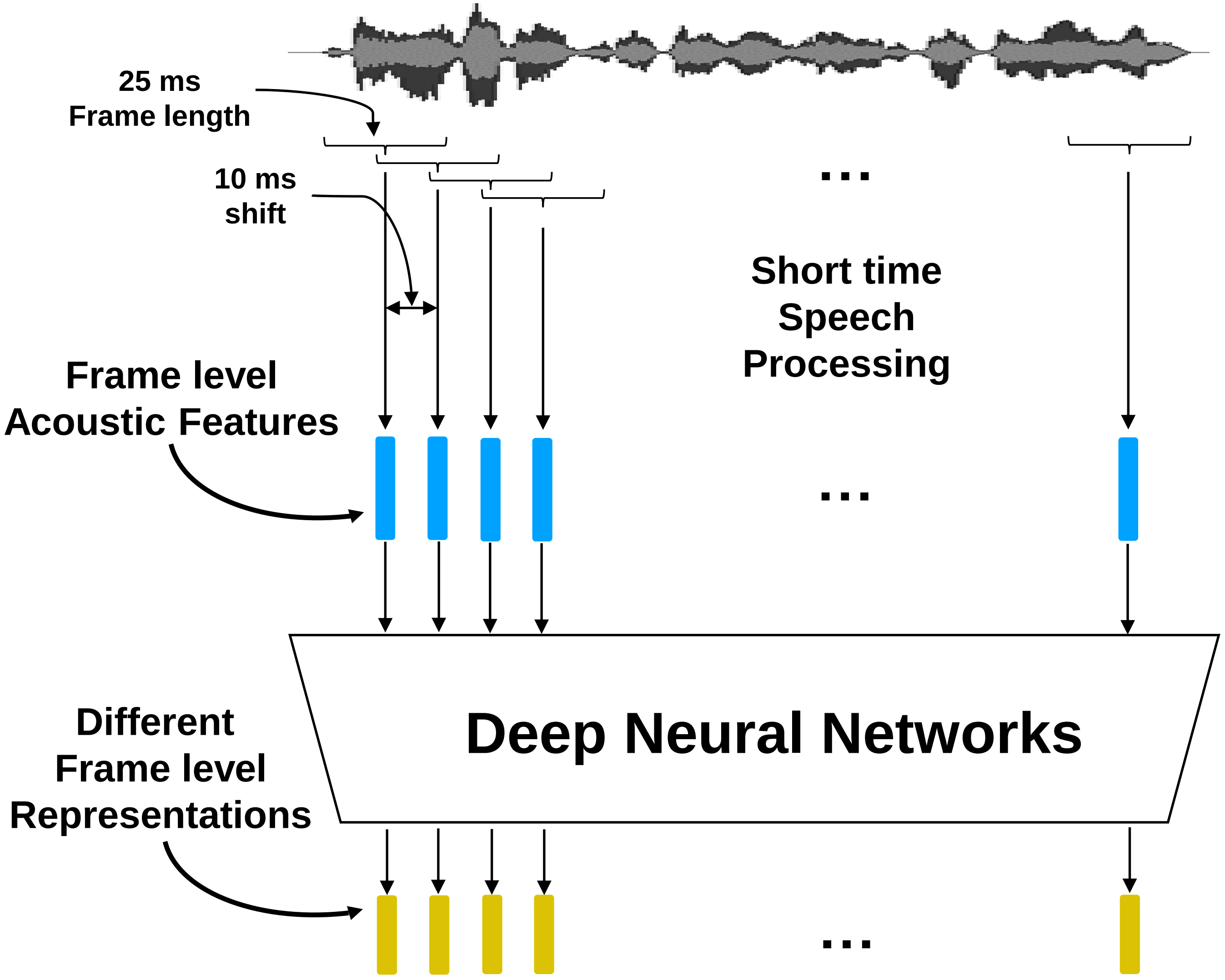

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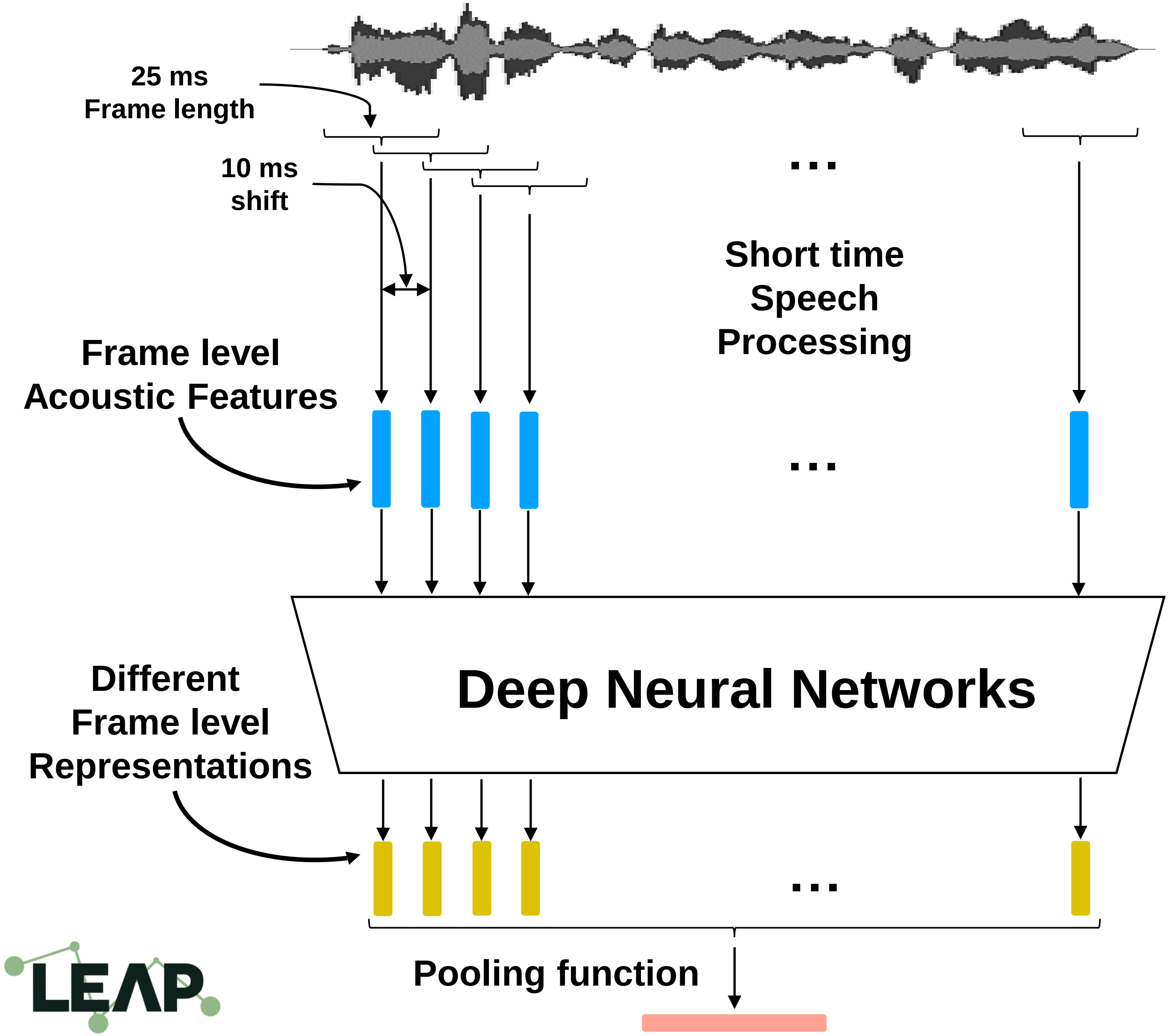

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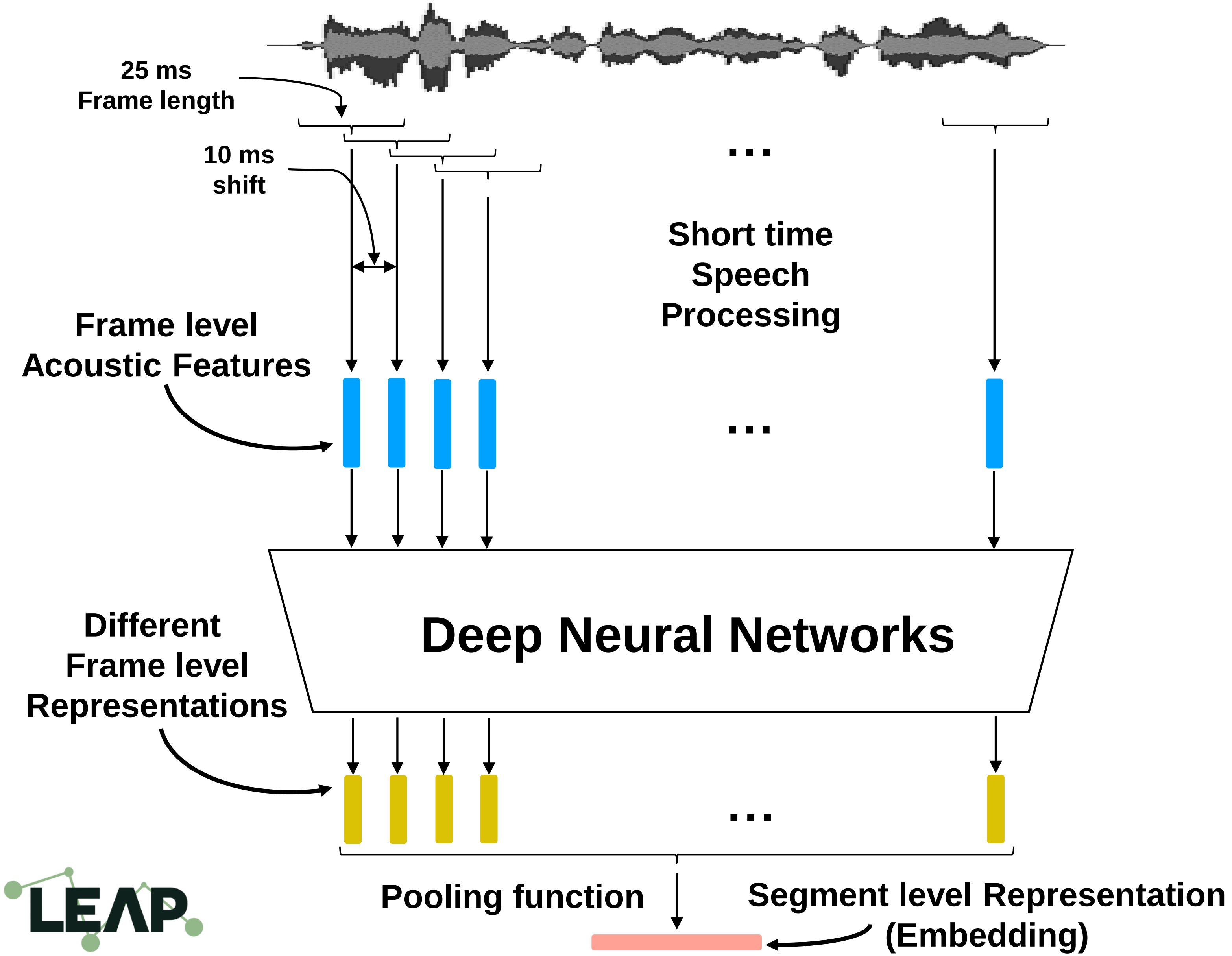

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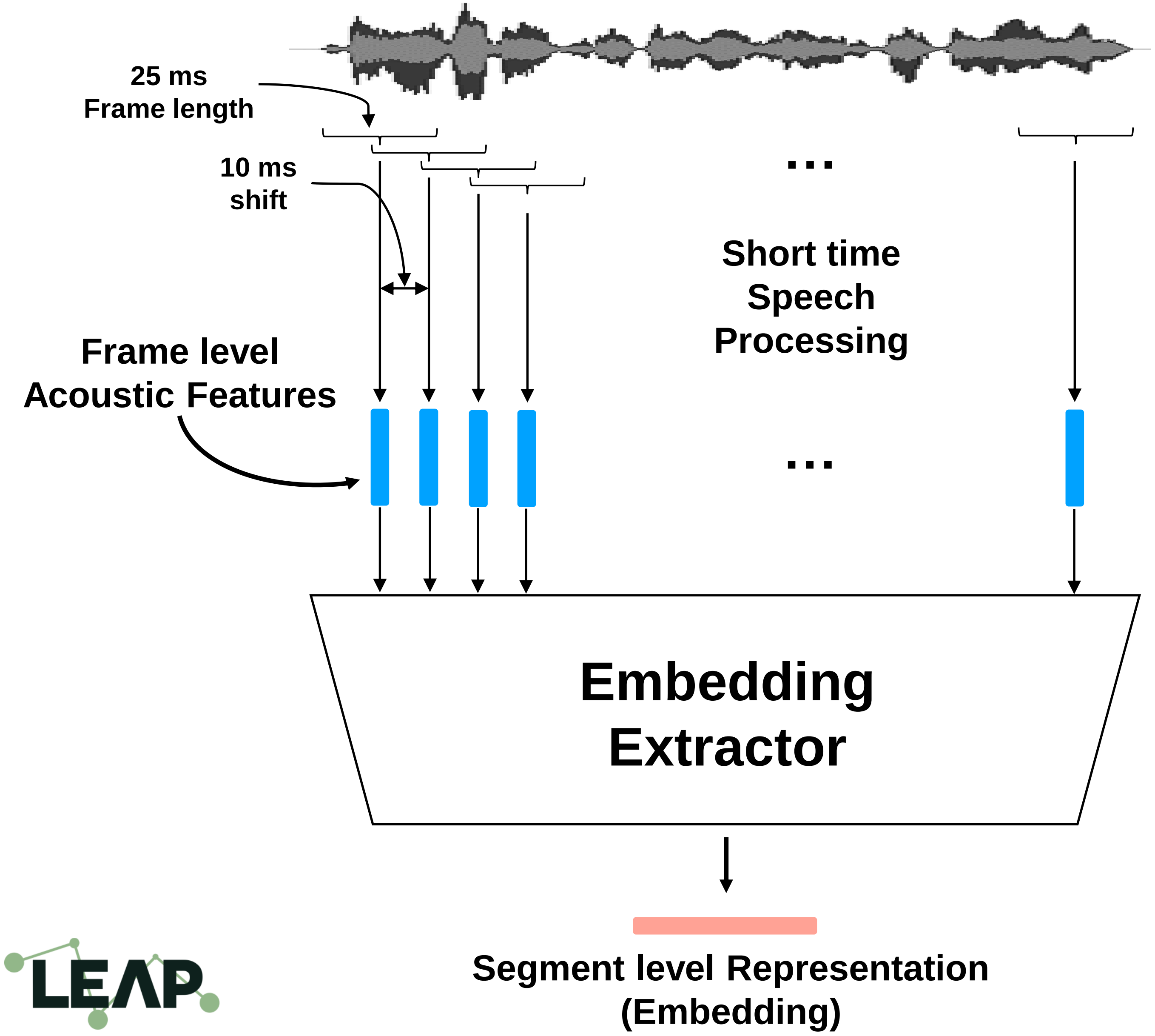

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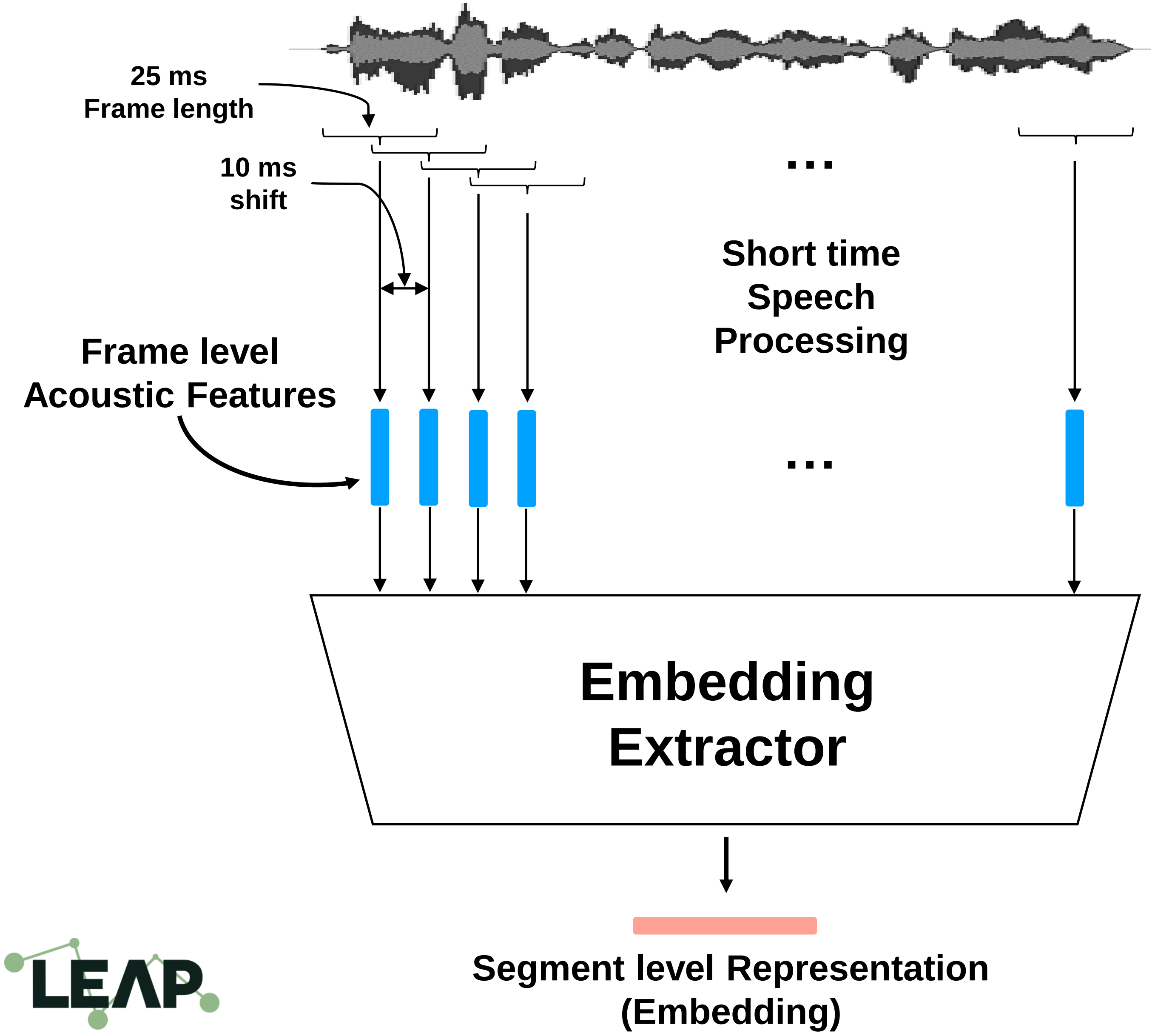

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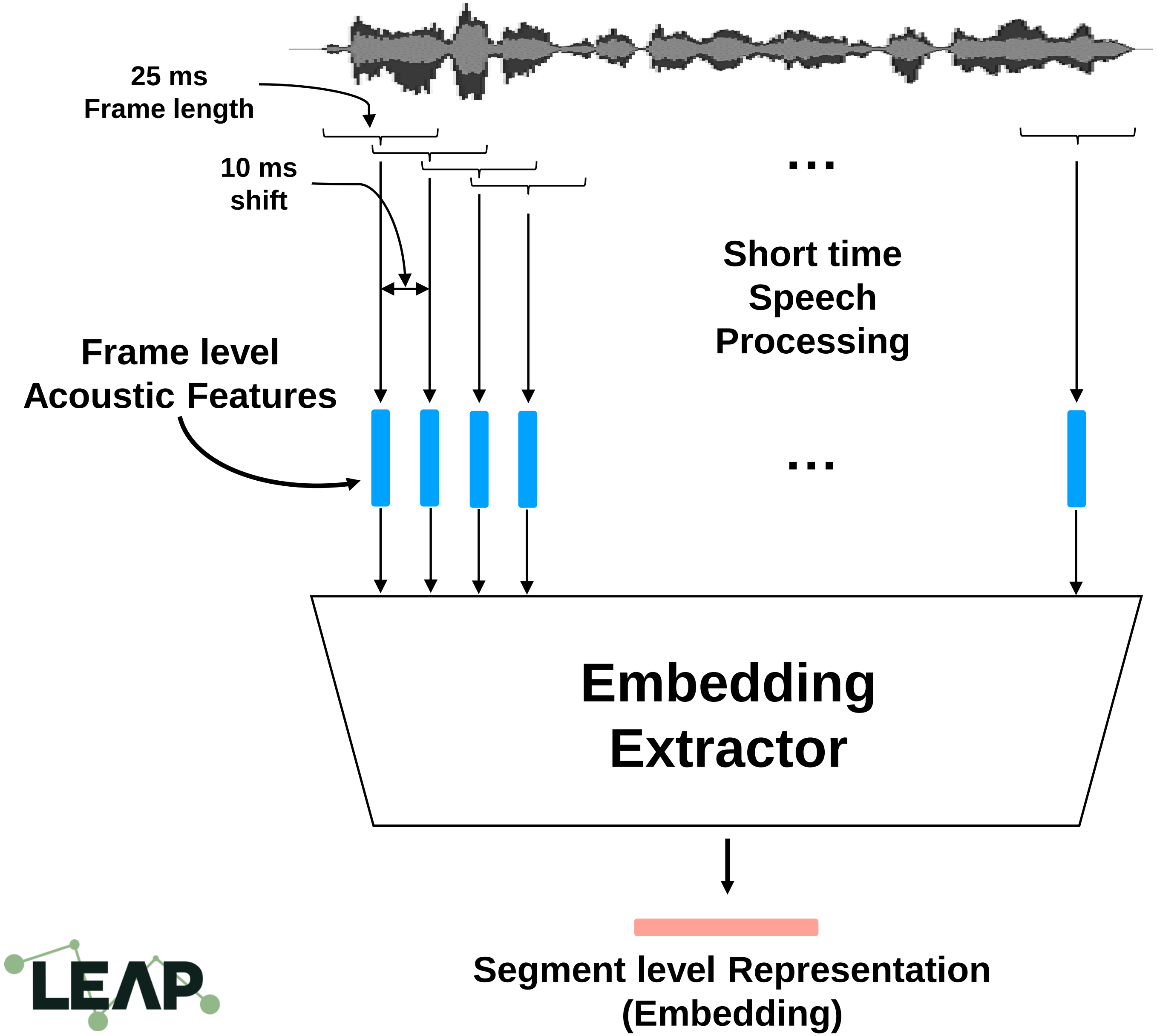

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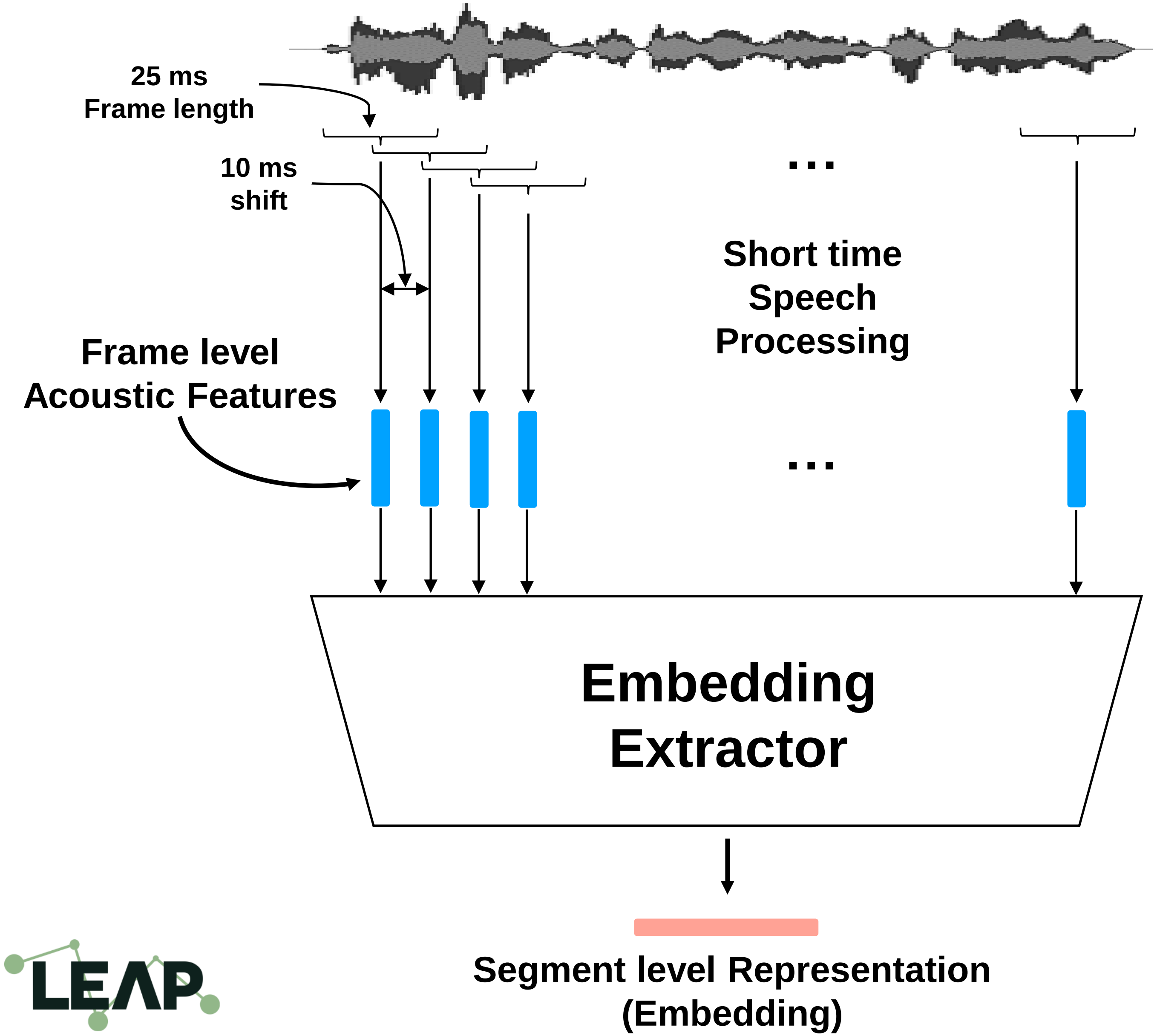

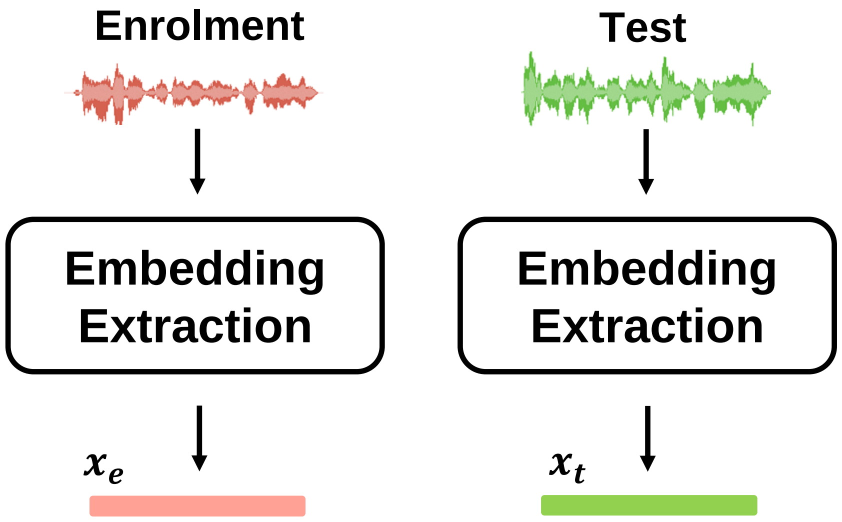

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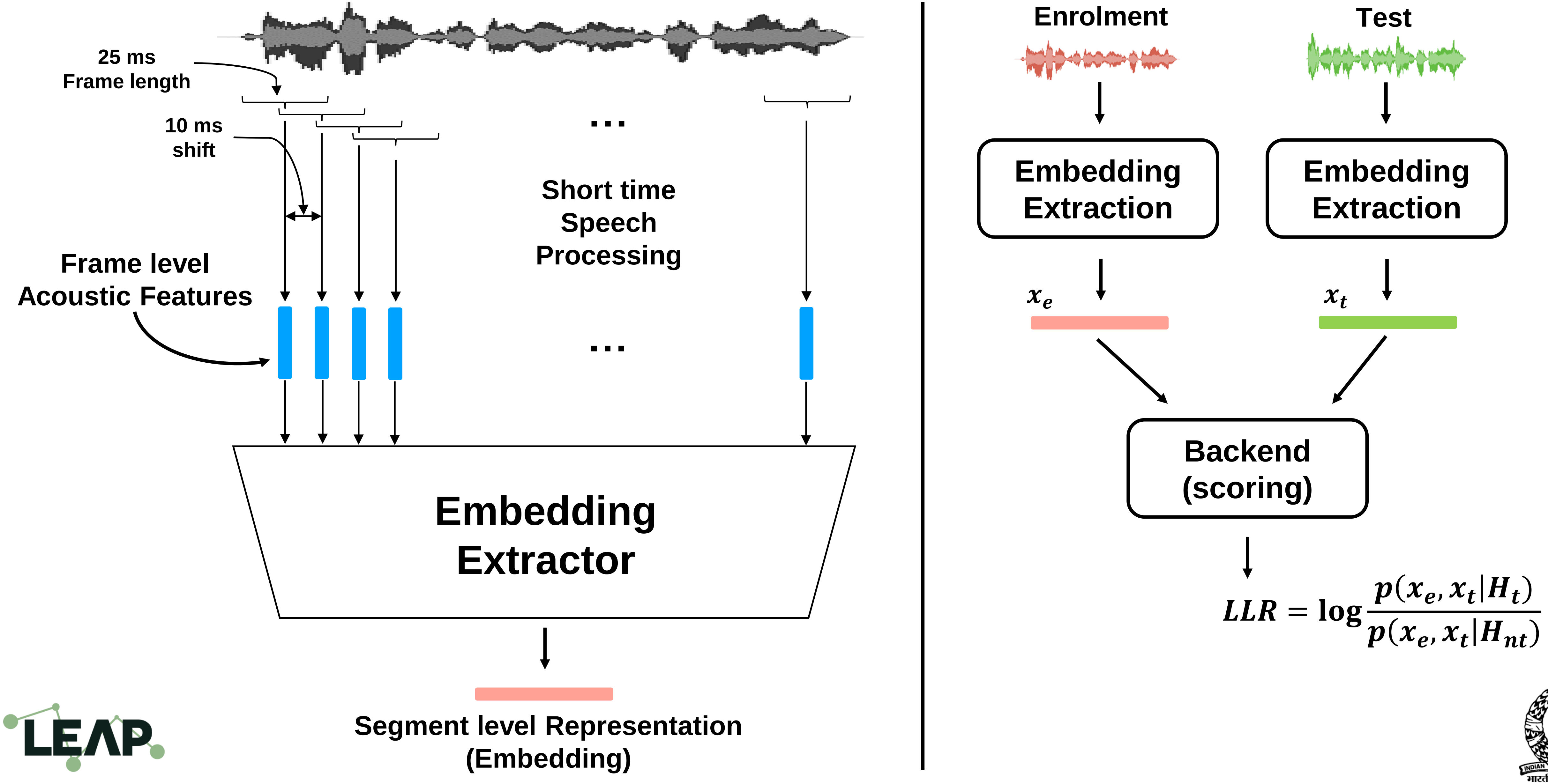

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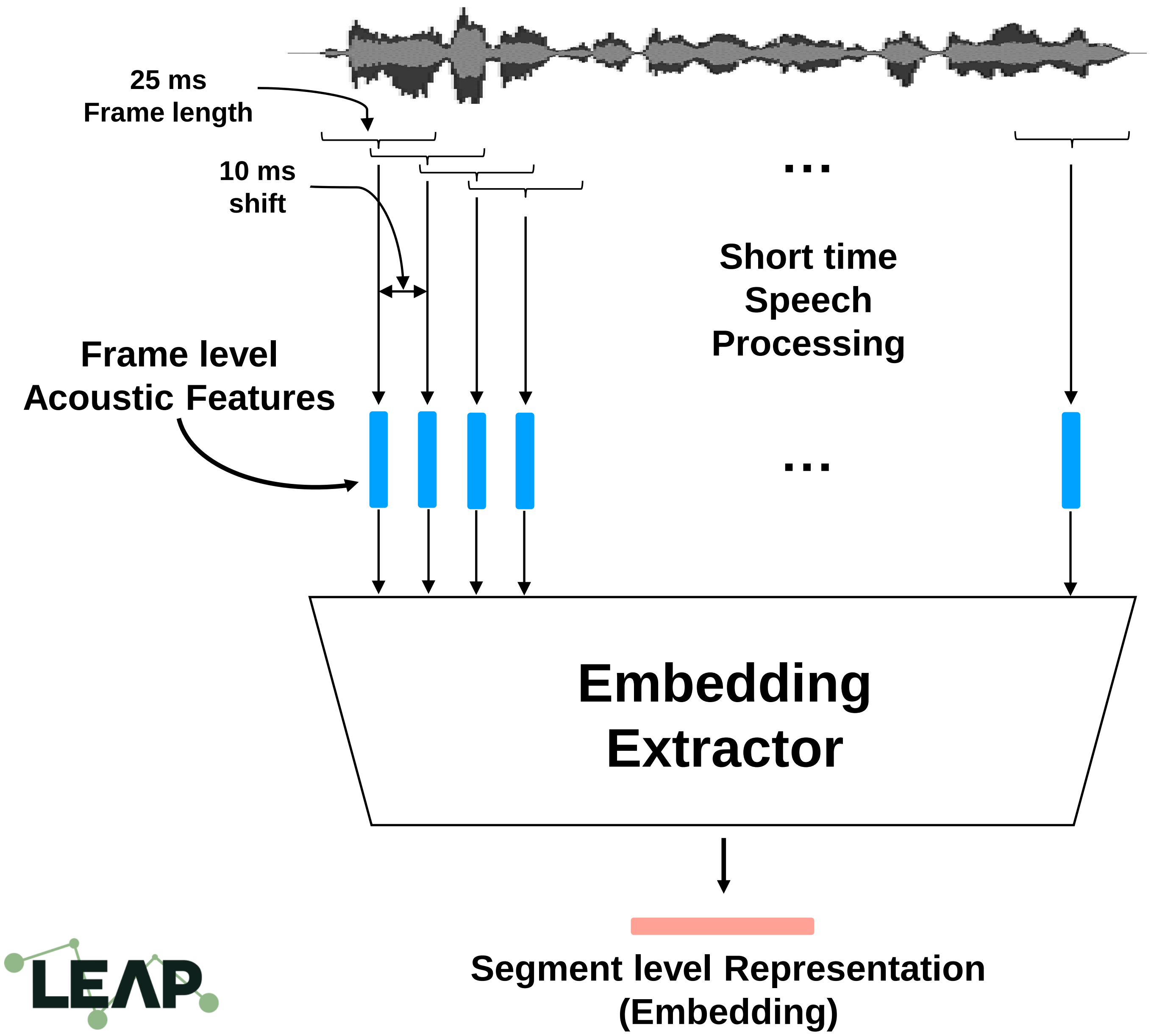
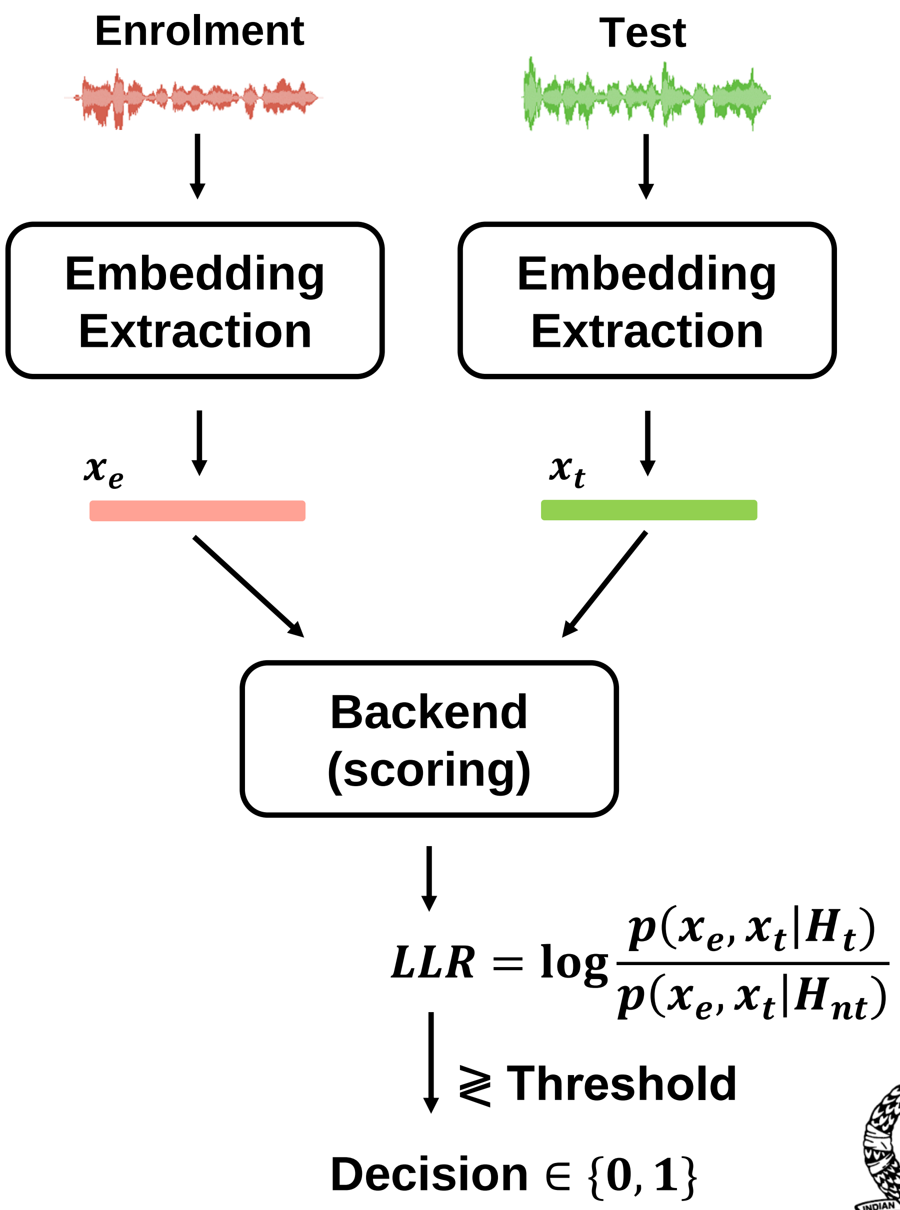
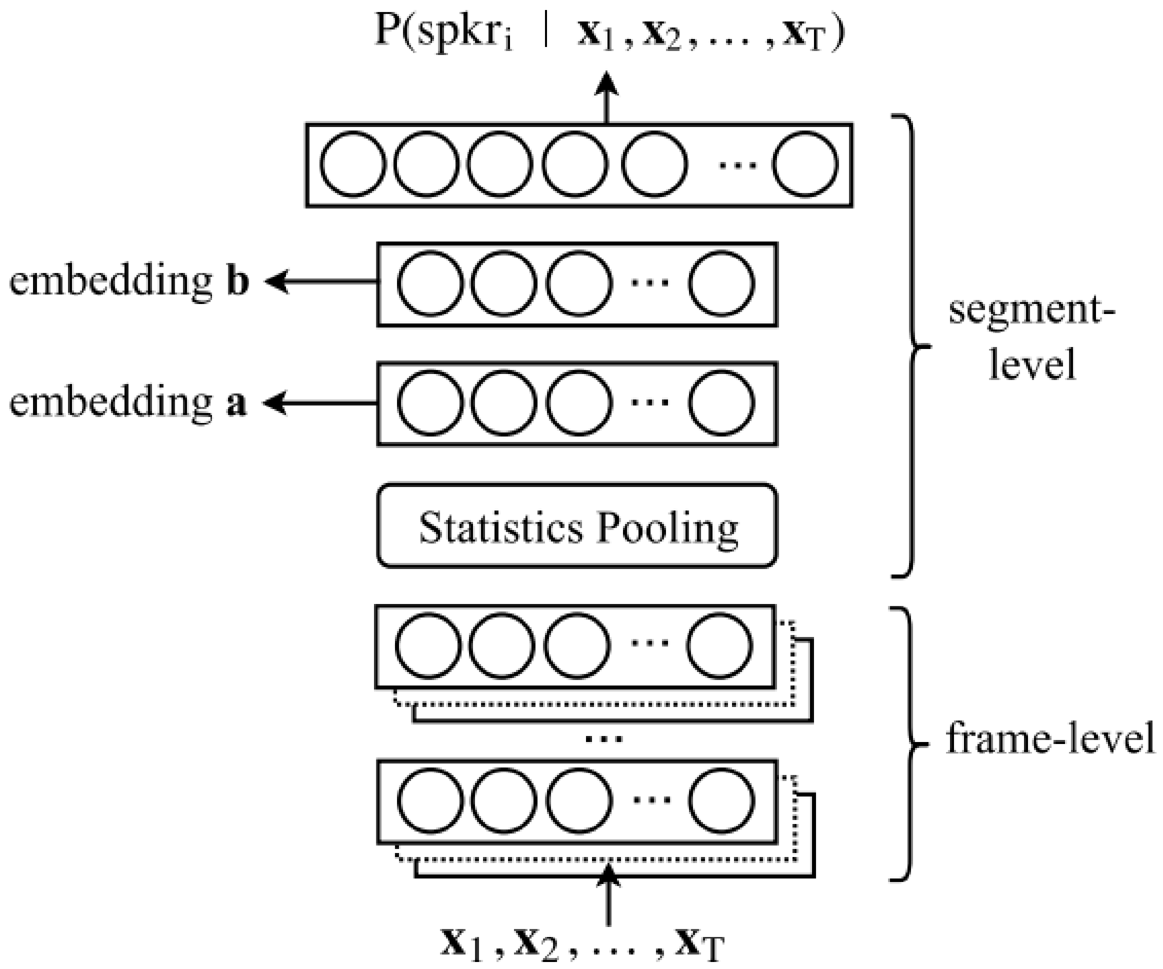
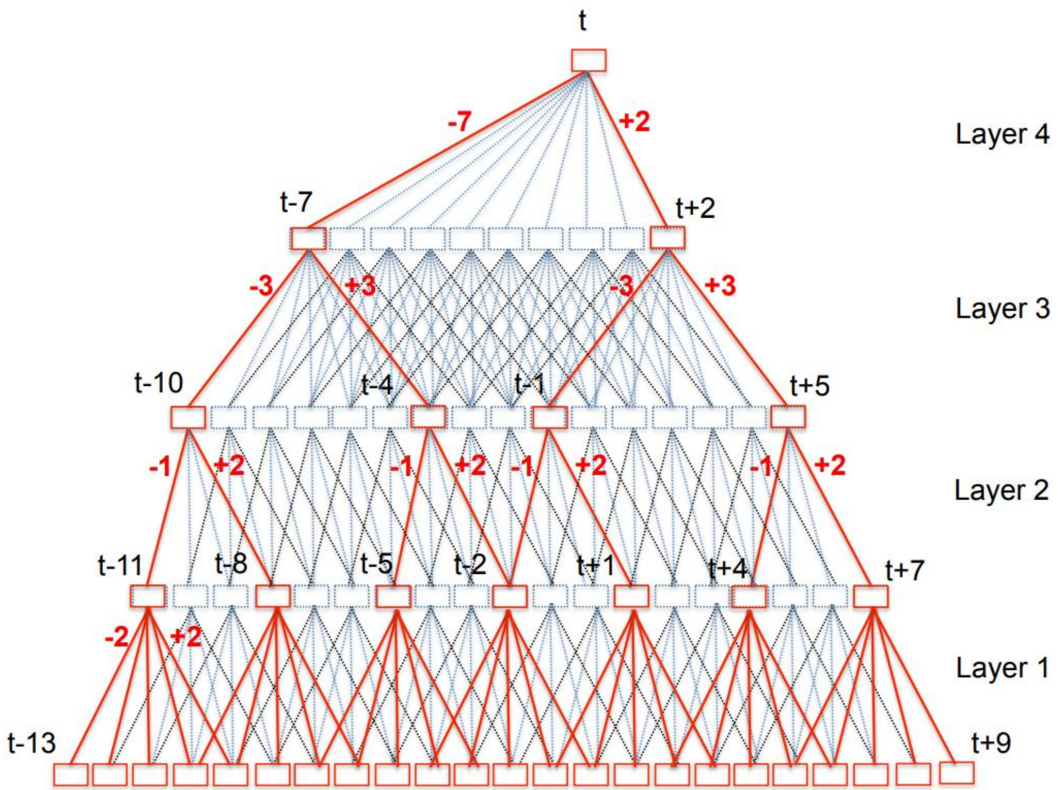




The X-vector Model





Snyder et.al., “X-vectors: Robust DNN Embeddings for Speaker Recognition”, 2018

Gaussian Probabilistic LDA

S. Ioffe, “*Probabilistic Linear Discriminant Analysis*”, 2006

Gaussian Probabilistic LDA

$\boldsymbol{x_r}$

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x_r

↓

Centering,
Dim. Reduction (LDA),
Unit Length Norm

↓

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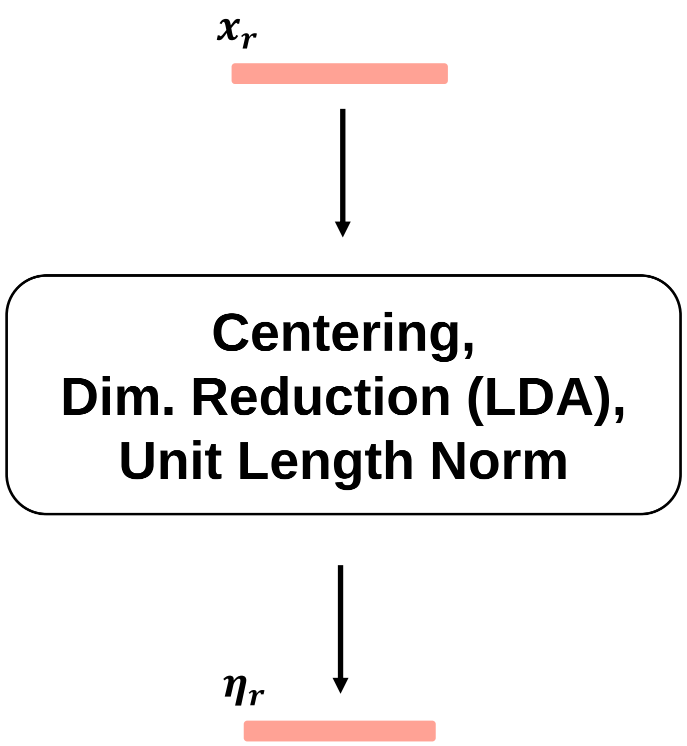

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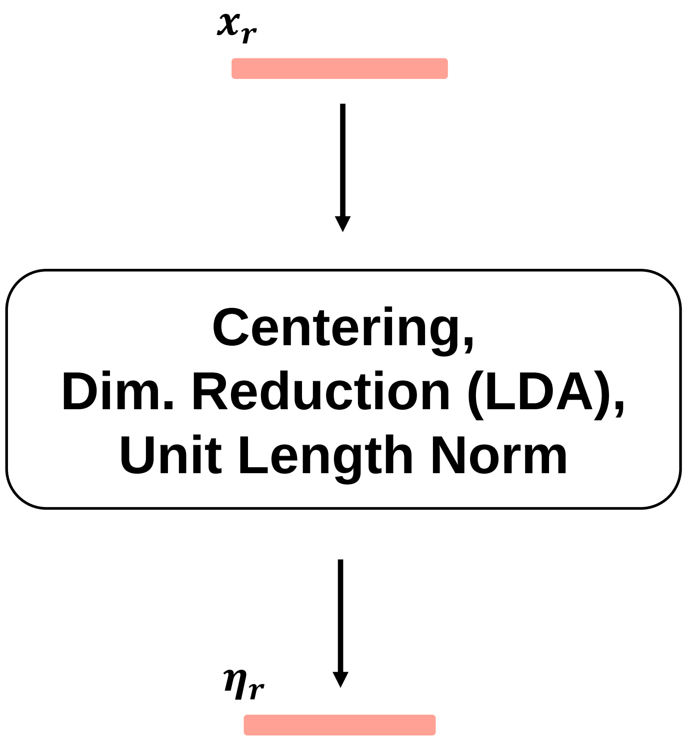

$$\eta_r = \Phi\omega + \epsilon_r$$

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Embedding

Latent
Speaker
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Embedding ($\boldsymbol{\eta_r}$)

Speaker Subspace matrix ($\boldsymbol{\Phi}$)

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LLR:

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Some quadratic function of η_e and η_t

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Neural PLDA (NPLDA)

Ramoji et al., “*NPLDA: A Deep Neural PLDA model for speaker verification.*”, Odyssey 2020

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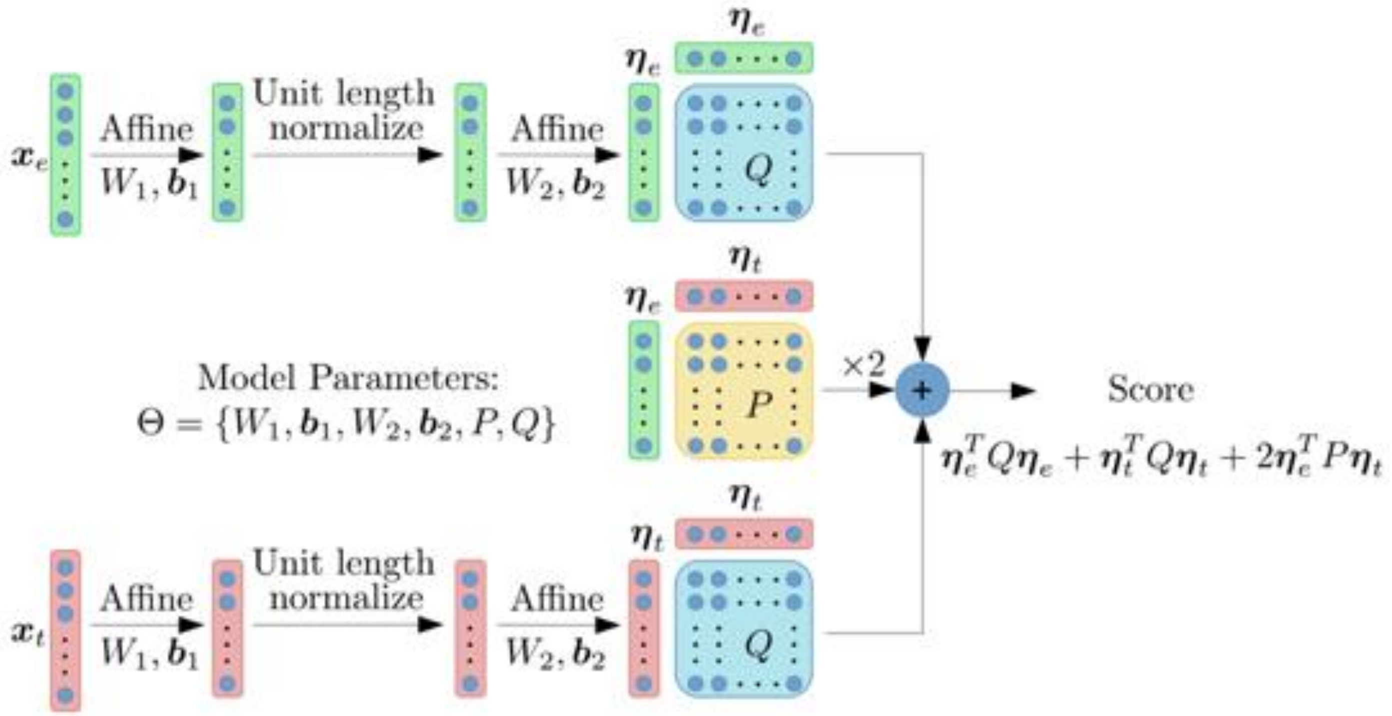

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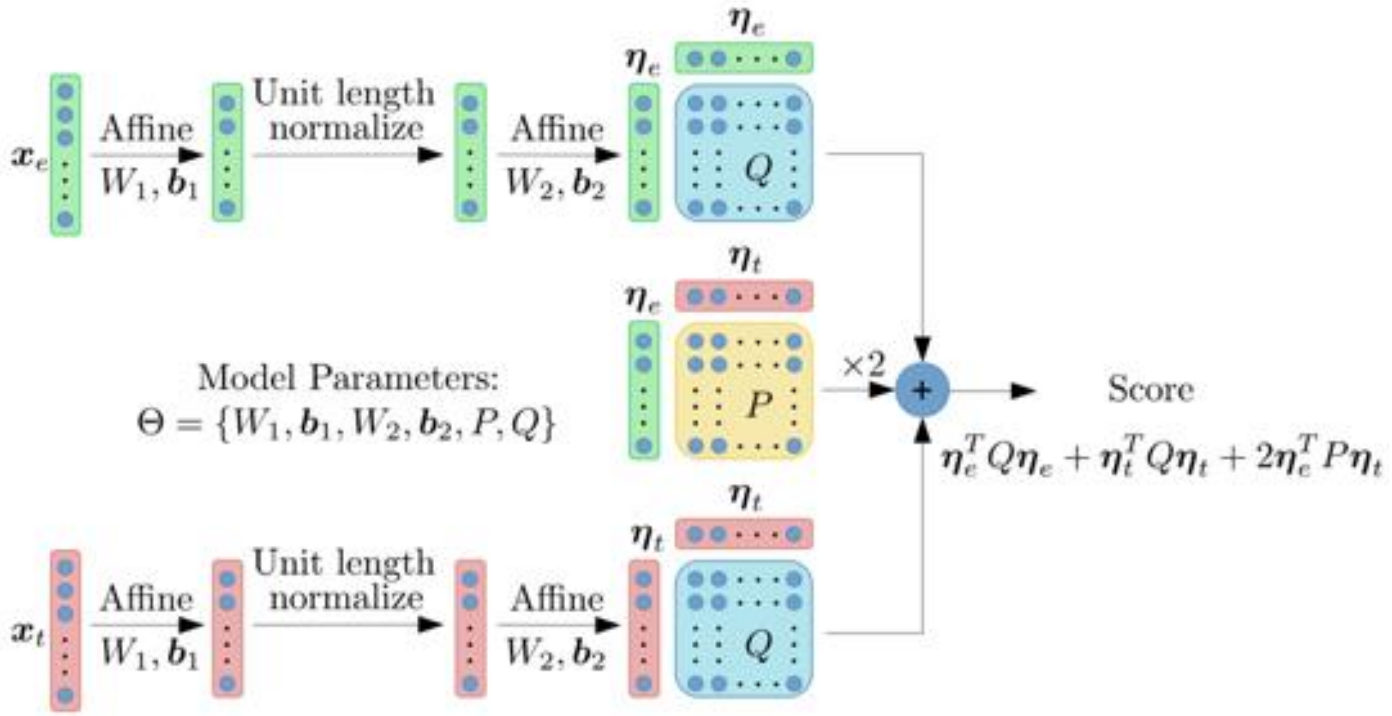

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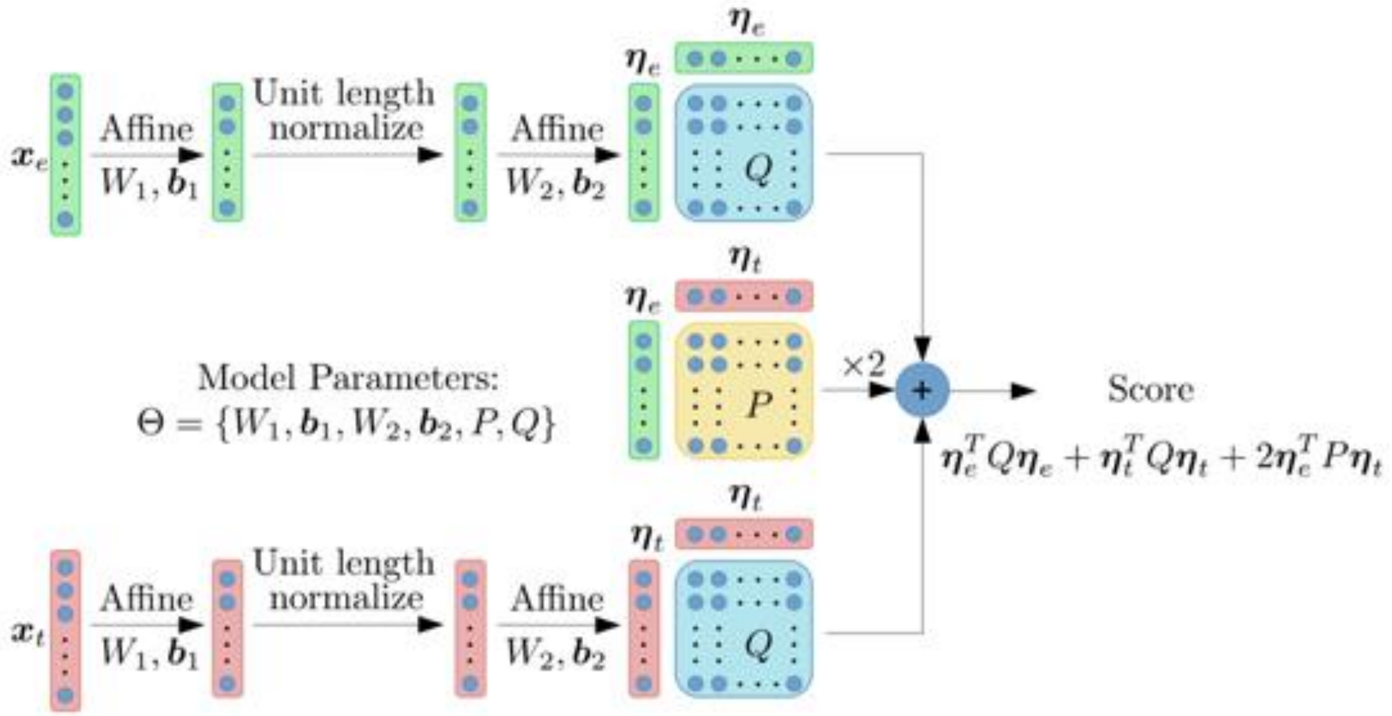

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Evaluation Metrics

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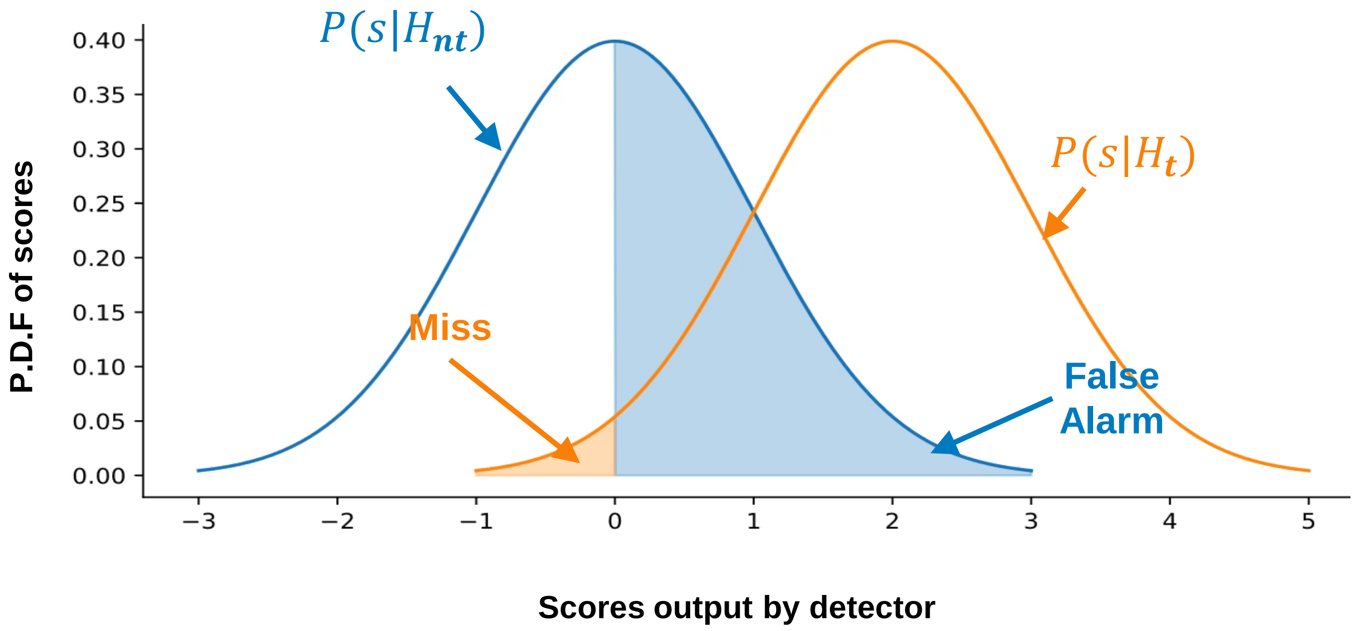

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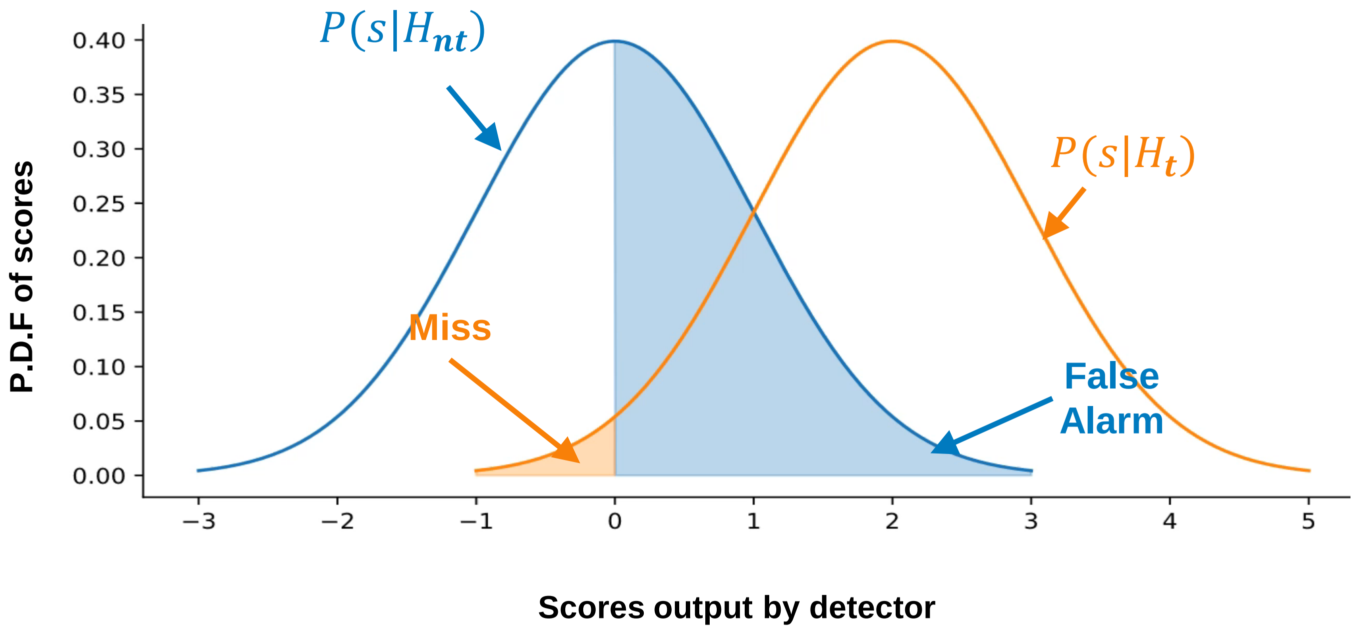

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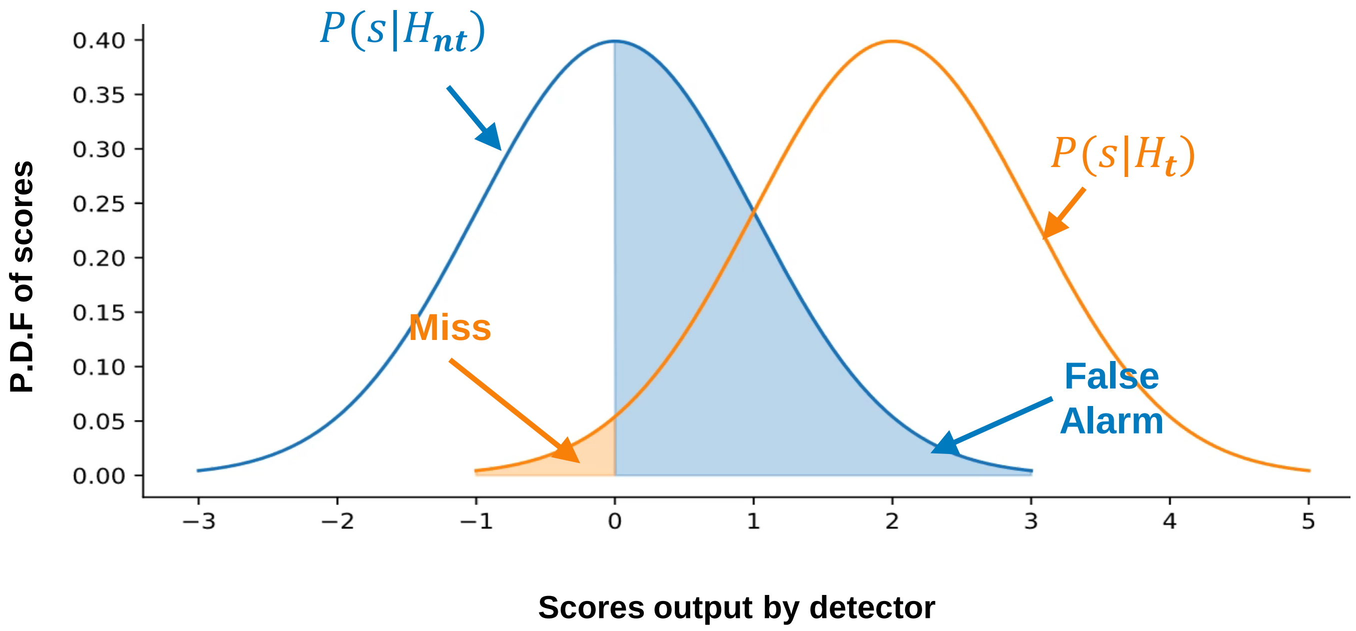

$$\text{DCF (Bayes risk)} = C_{Miss} \times P_{Target} \times P_{Miss}(\theta) + C_{FA} \times (1 - P_{Target}) \times P_{FA}(\theta)$$

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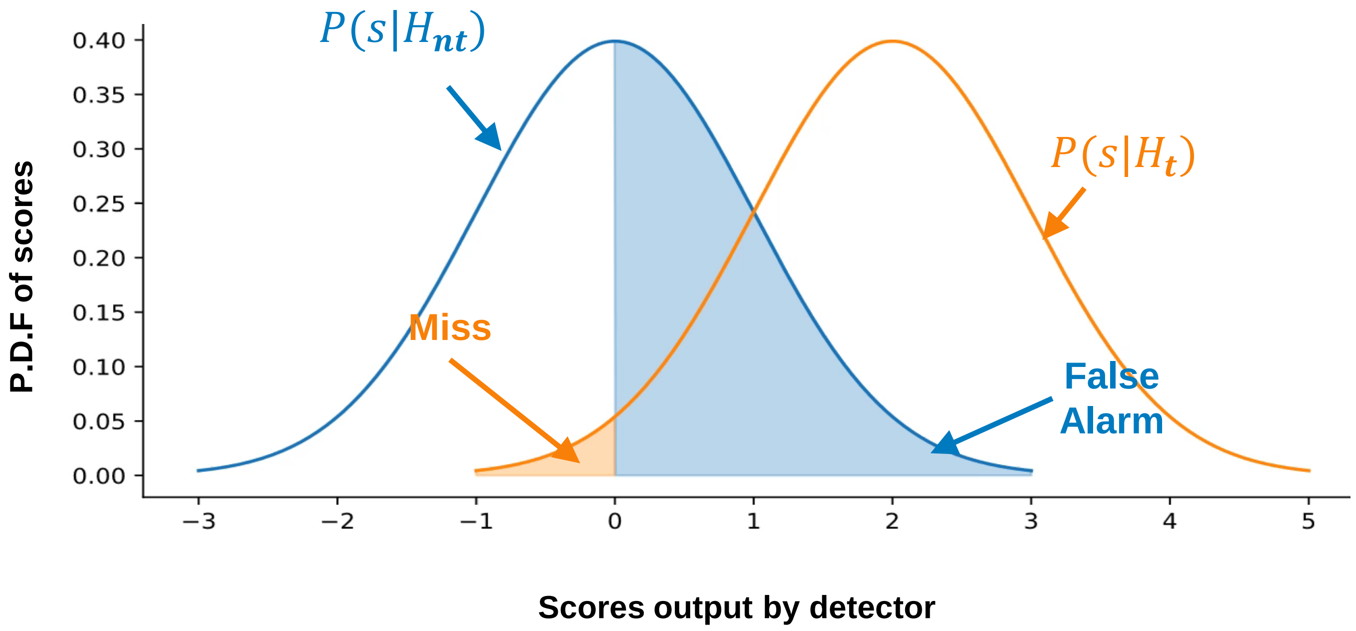

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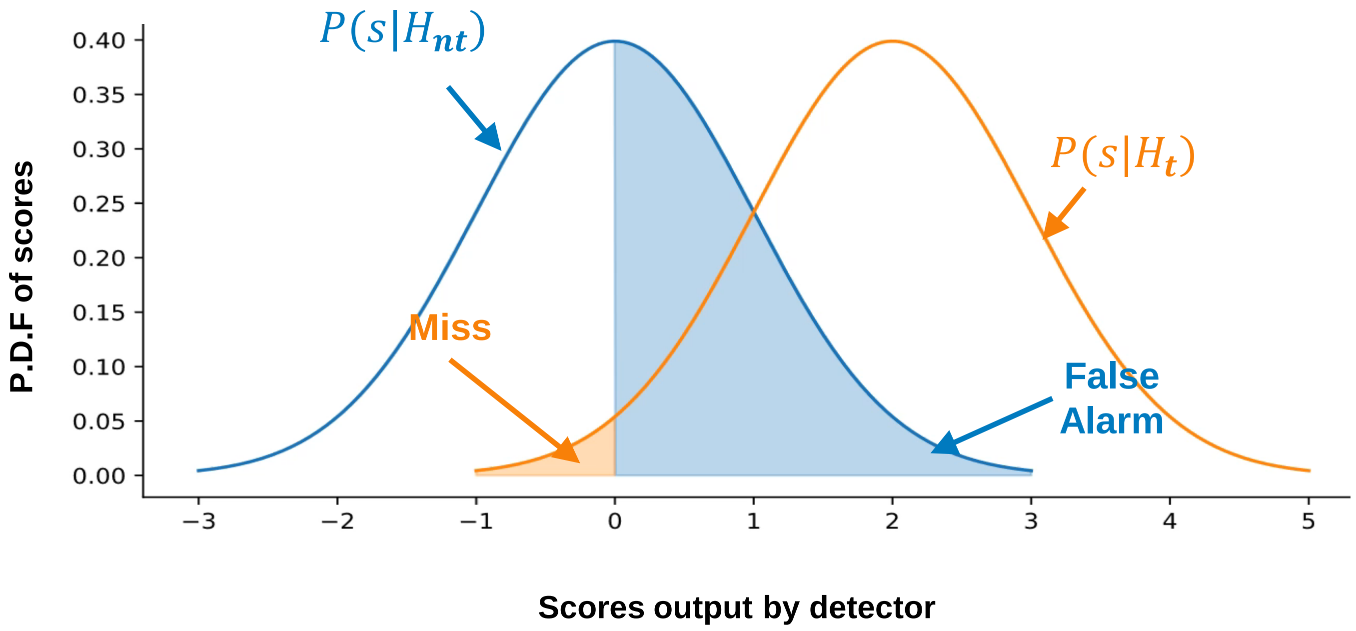

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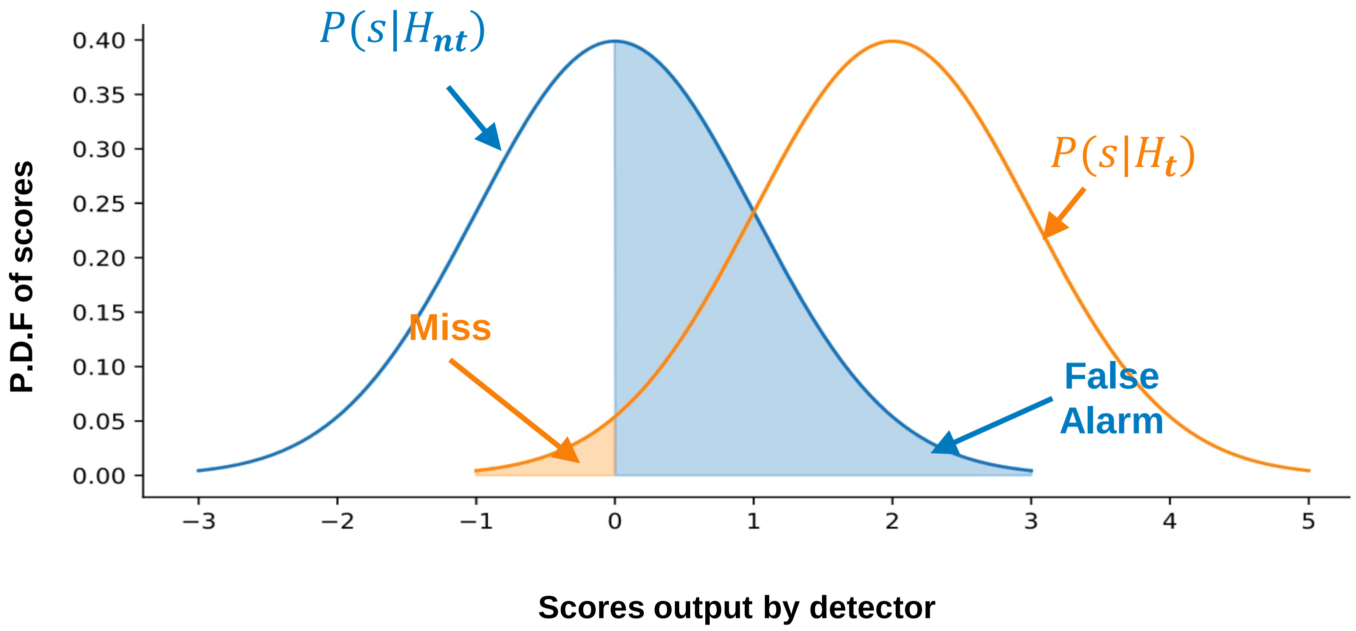

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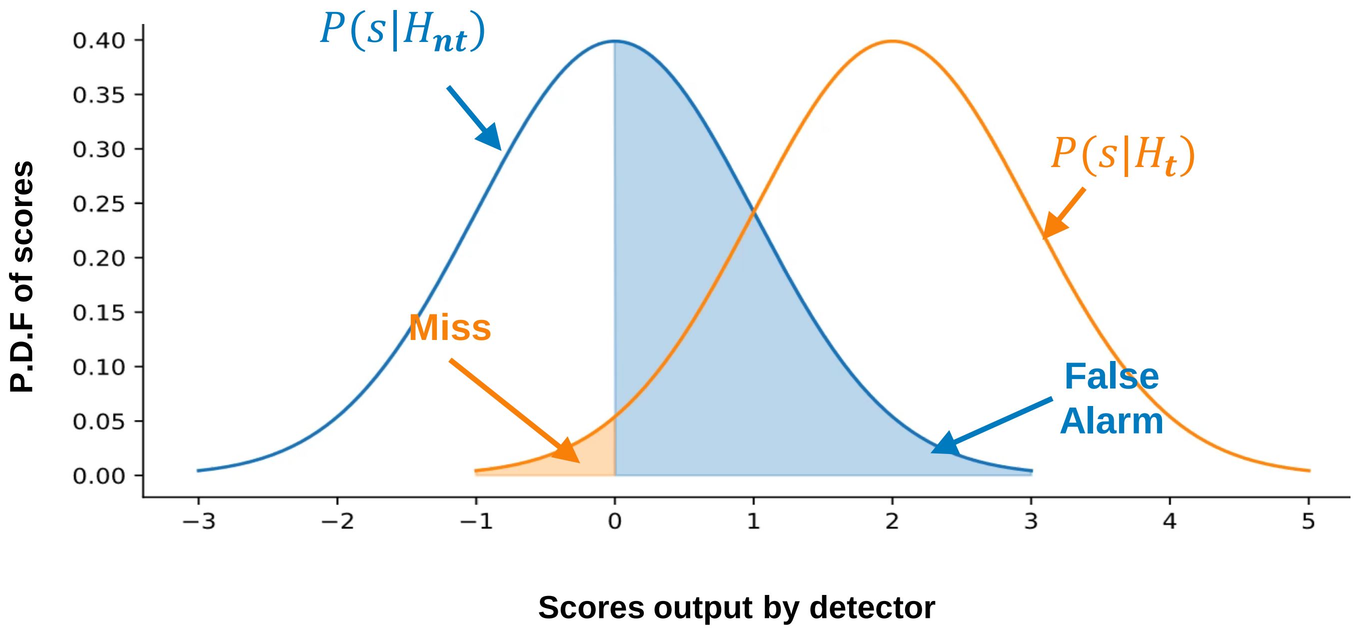

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- Equal Error Rate (EER)

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[1] N Brümmer et. al., “Application Independent Evaluation of speaker detection
[2] L. Ferrer et. al., “*A discriminative condition-aware backend for speaker verification*” ICASSP 2020

Experiments

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  - A 5-fold augmentation strategy is used that adds four corrupted copies of the original recordings to the training – Clean, Noise, Babble, Music, Reverberation

Experiments on NPLDA

- **Test Datasets Description:**
  - ***SITW (Speakers in the Wild) Dataset:***
    - Consists of ***300 speakers*** across clean interviews, red carpet interviews, stadium conditions, indoor and outdoor conditions.
    - The evaluation set consists of ***721,788 trials***
  - ***VOiCES Challenge 2019 Dataset:***
    - Re-recorded read speech in acoustically challenging, noisy and reverberent environments.
    - The Development set contains 16k segments 196 speakers, and 4 Million trials
    - The Test set contains 11k segments from 100 speakers, 3.6 Million trials

Results on NPLDA

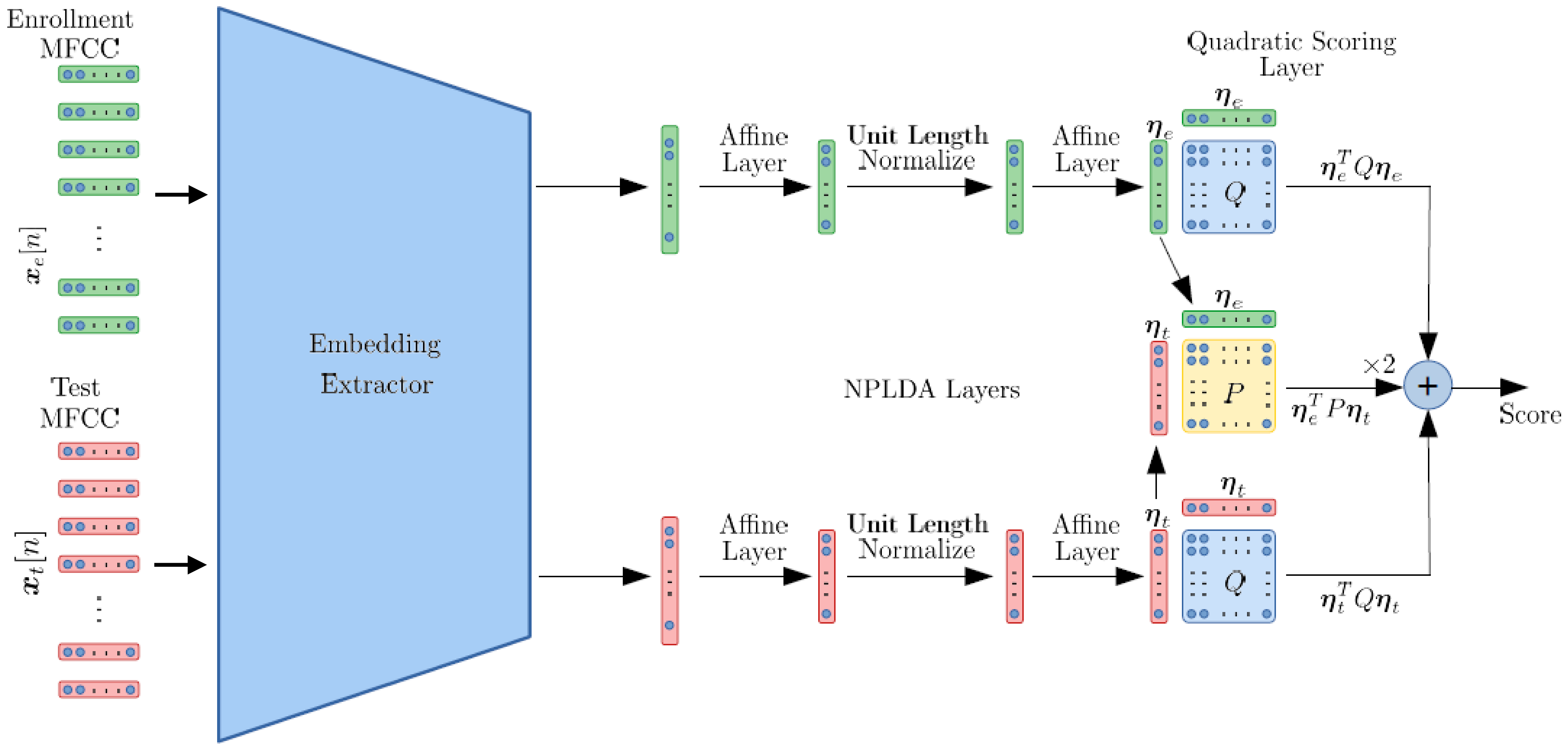
Model	PLDA Train Dataset	SITW Core-Core		VOiCES Dev		VOiCES Eval	
		EER (%)	minDCF	EER (%)	minDCF	EER (%)	minDCF
GPLDA	VoxCeleb	2.79	0.29	2.79	0.31	7.35	0.57
GPLDA	VoxCeleb Augmented	2.79	0.29	2.79	0.30	6.38	0.53
Gaussian Backend	VoxCeleb	3.19	0.31	3.14	0.33	7.58	0.60
Gaussian Backend	VoxCeleb Augmented	3.06	0.31	2.89	0.30	6.63	0.53
DPLDA	VoxCeleb Augmented	2.98	0.32	3.05	0.36	6.65	0.56
NPLDA	VoxCeleb	2.14	0.23	2.20	0.26	6.72	0.51
NPLDA	VoxCeleb Augmented	**2.05**	**0.20**	**1.91**	**0.23**	**6.01**	**0.49**
NPLDA (BCE Loss)	VoxCeleb Augmented	2.10	0.22	2.32	0.26	6.34	0.53

Table 1: Performance of systems on SITW Eval Core-Core, VOiCES Dev and VOiCES Eval using the GPLDA baseline model, Gaussian backend, Discriminative PLDA (DPLDA) and the proposed NPLDA model. We also report the use of binary cross-entropy (BCE) Loss in the NPLDA model place of the soft detection cost. The best scores are highlighted.

- Relative improvements in the range of 9% to 23% in terms of EER, and 11% to 31%in terms of minDCF.

Ramoji et al., “*NPLDA: A Deep Neural PLDA model for speaker verification.*”, Odyssey 2020

End-to-End Siamese NPLDA Model



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- The GPU requirements for the E2E-NPLDA increases linearly with total audio duration per batch

    - Was estimated to be >200GB for 2048 trials of 20 sec segments.

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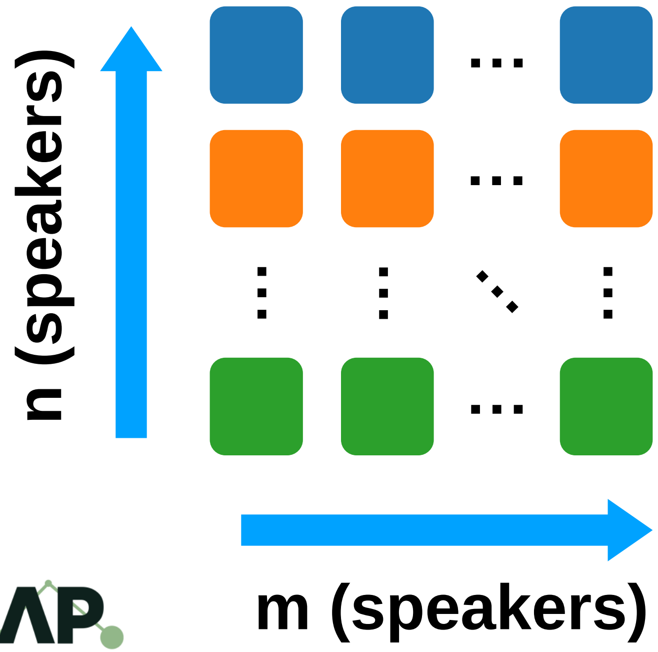

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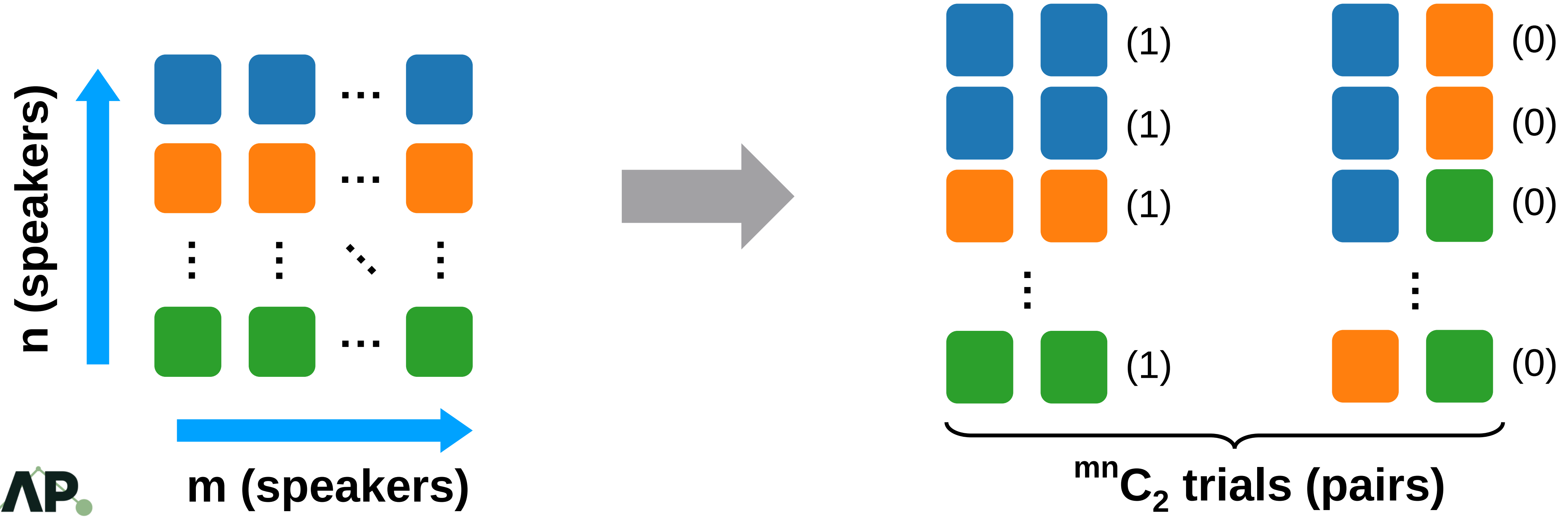
- As we had a GPU limit of 16 Gb, the neural network architecture we used could process a total audio duration of 130 secs per batch (~64 utterances of 20 secs each)

- To confine the E2E-NPLDA to meet the GPU memory constraints, but also have >2k trials per batch, we used a low-memory trial sampling algorithm:



Results of NPLDA and E2E models

- Results with a factorized TDNN [1] x-vector architecture trained on VoxCeleb 1 & 2 datasets show robust improvements of the model across various test domains.

Model	Init.	SITW-E		VOiCES-D		VOiCES-E		SRE18 D-V		SRE18 E-V	
		EER	C_{Min}	EER	C_{Min}	EER	C_{Min}	EER	C_{Min}	EER	C_{Min}
GPLDA	-	2.68	0.276	2.15	0.268	6.01	0.490	7.41	0.449	15.82	0.610
GB	-	3.47	0.346	2.94	0.315	7.28	0.548	12.76	0.486	17.46	0.647
DPLDA	-	2.90	0.280	2.21	0.273	6.00	0.480	7.82	0.444	13.02	0.553
NPLDA	GPLDA	1.78	0.178	1.49	0.176	5.18	0.432	**6.17**	0.337	12.38	0.467
E2E-NPLDA	GPLDA	1.96	0.177	1.48	0.181	5.45	**0.396**	**6.17**	**0.226**	**12.19**	0.497
E2E-NPLDA	NPLDA	**1.67**	**0.165**	**1.36**	**0.166**	**4.99**	0.407	7.00	0.263	12.68	**0.455**
Relative improvements for E2E-NPLDA over GPLDA in %		38	40	37	38	17	19	17	50	23	25
Relative improvements for E2E-NPLDA over NPLDA in %		6	7	9	6	4	6	-13	19	-2	3

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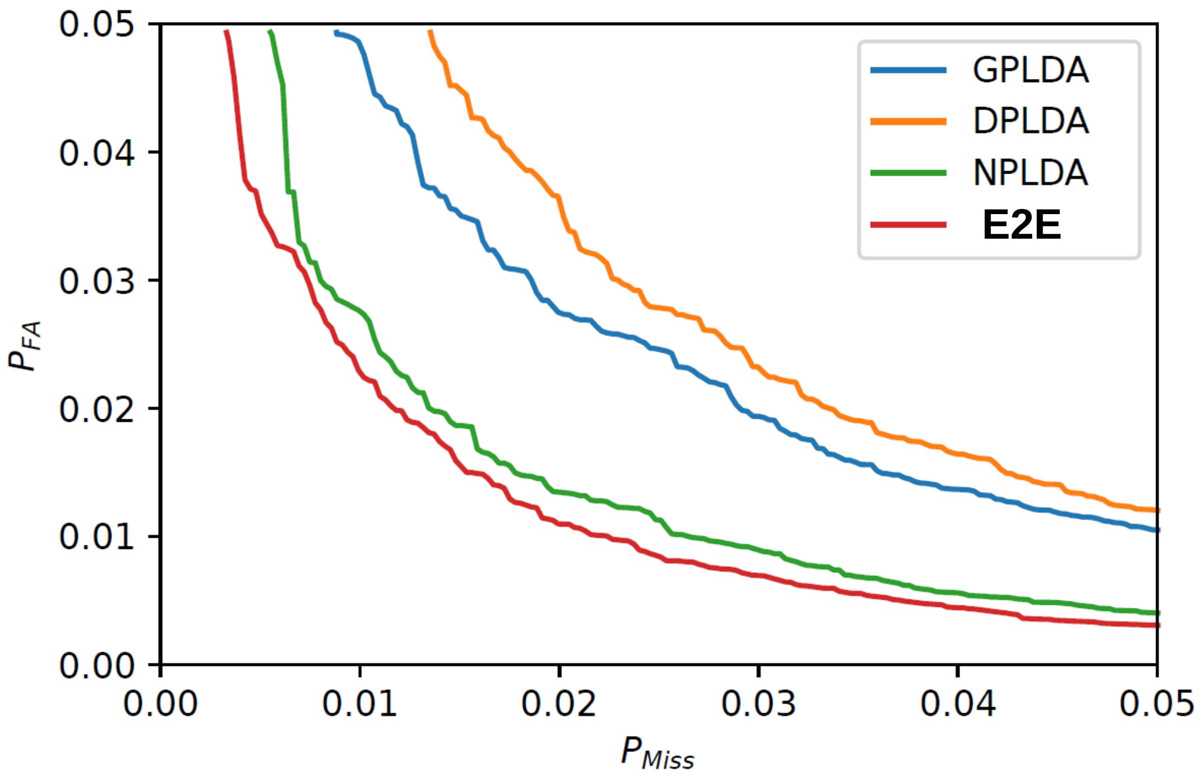
A look at the Detection Error Tradeoffs



- Detection Error Tradeoff curves are shown for two baseline models (Generative Gaussian PLDA and Discriminative PLDA), Neural PLDA backend, and E2E-NPLDA models.

- Consistent improvements seen across a wide range of thresholds, using many evaluation datasets.

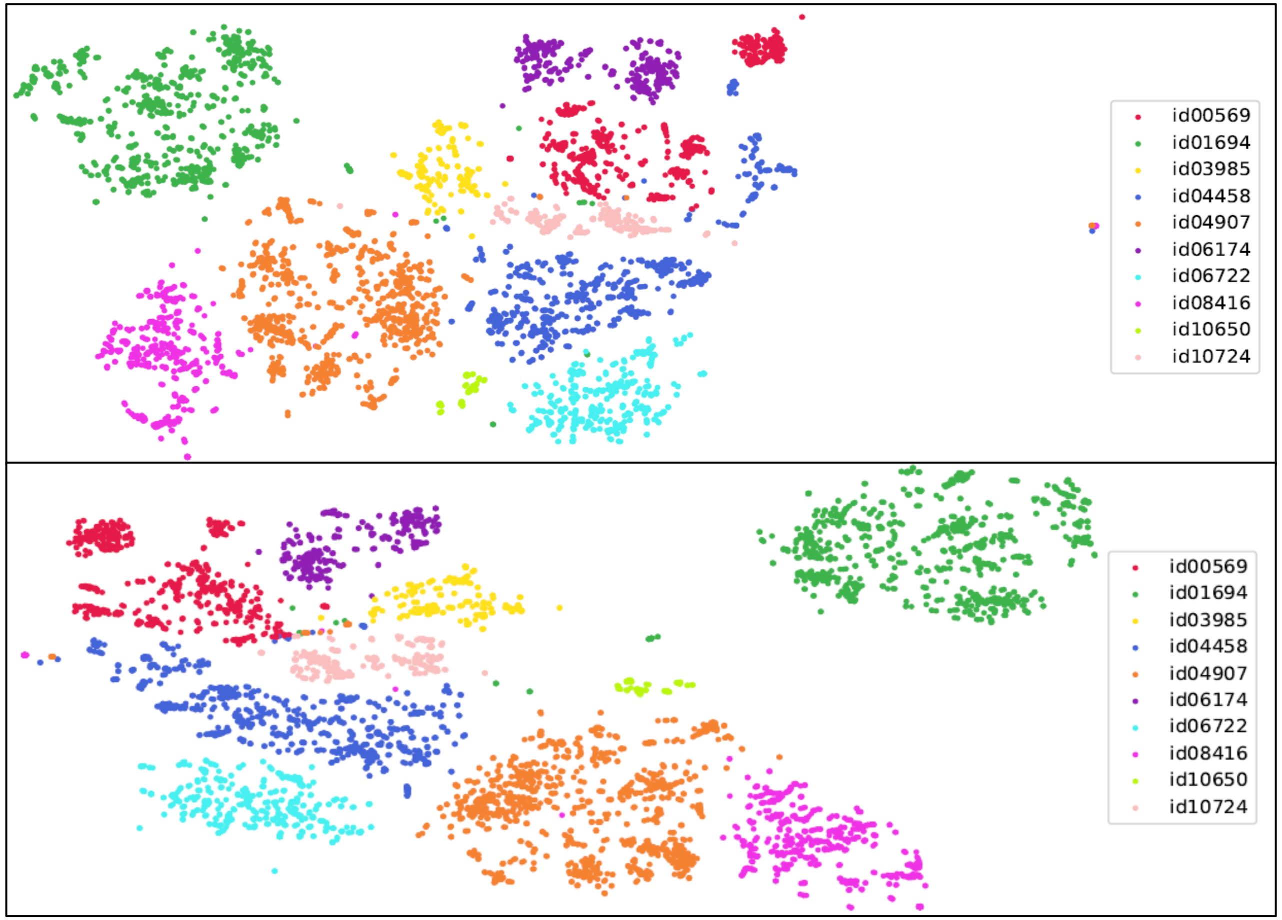
Visualization of Embeddings

Visualization of Embeddings

- t-SNE plots show that the embeddings extracted from the SiamNN models are better suited for the verification task than the original embedding extractor (x-vector model).

Original (x-vector) Embeddings

E2E-NPLDA Embeddings



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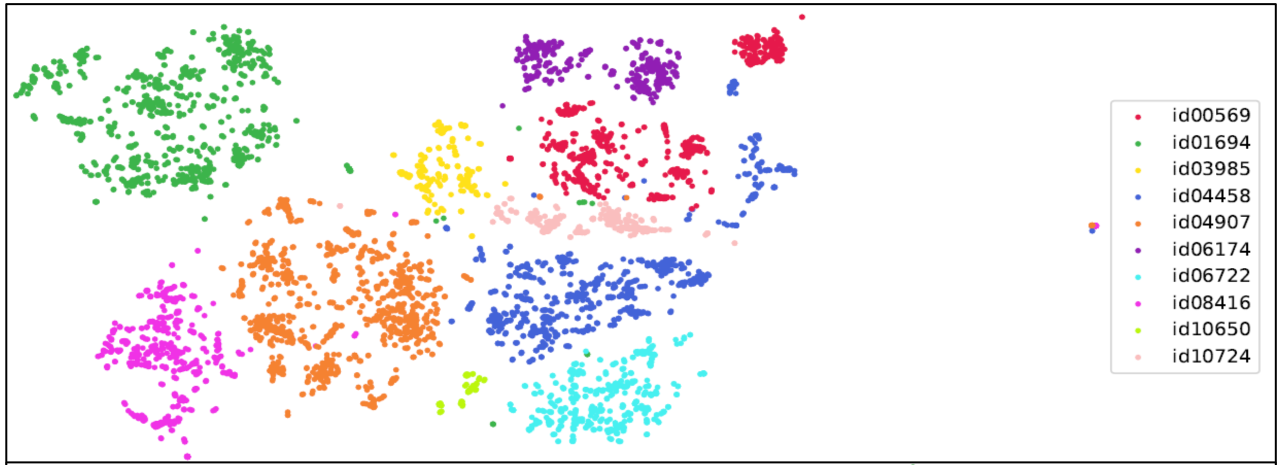
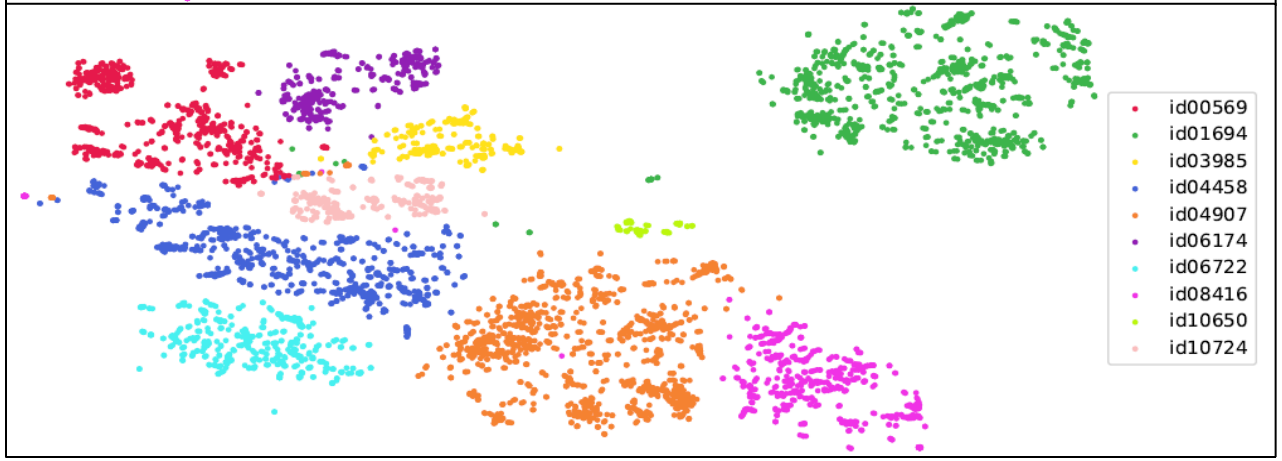


F-Ratio = 8.7

E2E-NPLDA Embeddings



F-Ratio = 15.4

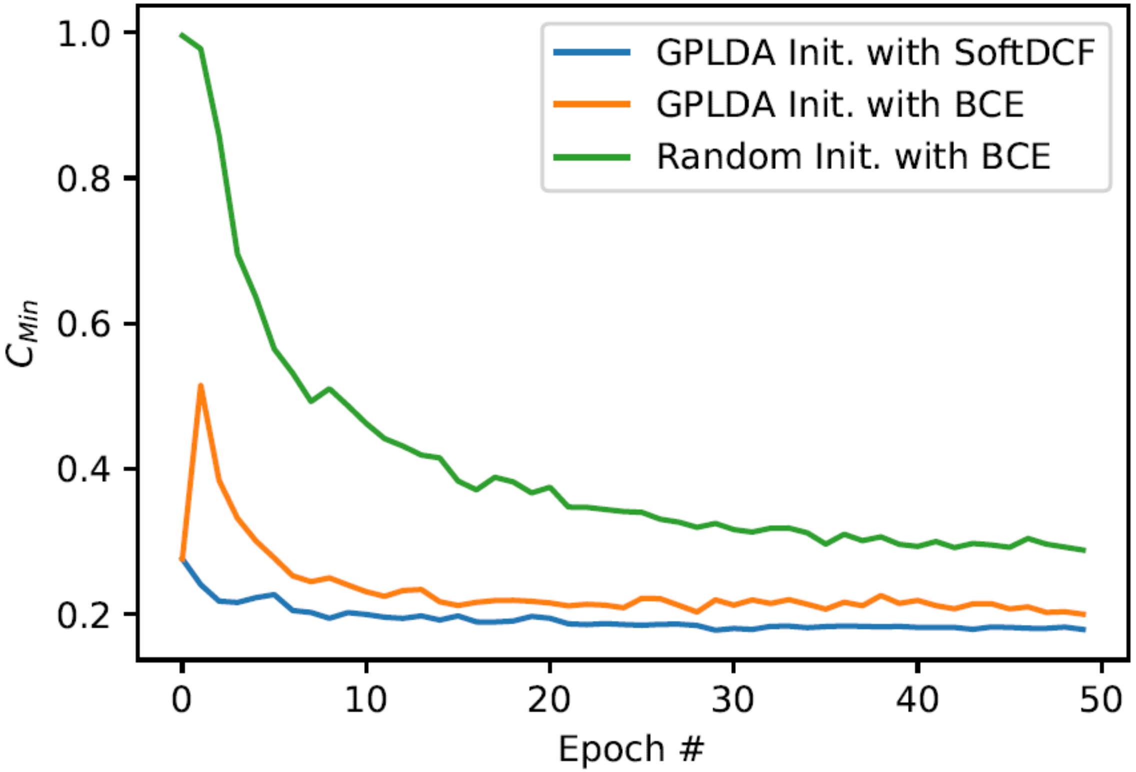
Comparison of Loss functions (NPLDA)

- Comparison of SoftDCF loss with Binary Cross-Entropy and its weighted versions

Embedding Extractor	Init.	Loss Fn.	SITW-E		VOiCES-D		VOiCES-E		SRE18 D-V		SRE18 E-V	
			EER	C_{Min}	EER	C_{Min}	EER	C_{Min}	EER	C_{Min}	EER	C_{Min}
ETDNN	GPLDA	BCE	2.11	0.237	2.52	0.298	6.93	0.585	7.41	0.379	13.02	0.542
		Cllr	2.08	0.241	2.56	0.318	7.30	0.64	8.64	0.449	13.85	0.616
		WCllr	2.19	0.223	2.21	0.26	6.67	0.498	7.41	0.416	**12.38**	0.513
		SoftDCF	2.10	0.209	1.79	0.223	5.69	0.450	7.41	0.377	12.55	0.533
FTDNN	GPLDA	BCE	1.89	0.199	2.10	0.229	6.40	0.538	10.70	**0.337**	**12.38**	0.545
		Cllr	1.95	0.214	2.06	0.246	6.71	0.605	11.11	0.370	13.02	0.561
		WCllr	1.94	0.195	1.95	0.214	5.80	0.474	9.88	0.374	**12.38**	0.500
		SoftDCF	**1.78**	**0.178**	**1.49**	**0.176**	**5.18**	**0.432**	**6.17**	**0.337**	**12.38**	**0.467**

Comparison of Initialization methods

- SoftDCF loss function converges to the best loss values when initialized with GPLDA params.



- With random init, the SoftDCF loss converges to a saddle point where val. $C_{min} = 1$, and all the gradients are 0.

Recent Advances related to our work

- Lots of improvements in the network architecture for speaker verification
  - ResNets, ECAPA-TDNN, Transformer based architectures.
- Exhaustive application of various novel loss functions and their combinations:
  - Classification objectives:
    - Angular Margin (AM) and Additive Angular Margin (AAM) Softmax loss
  - Metric Learning objectives:
    - Angular Prototypical loss

J. S. Chung et. al., "*In defence of metric learning for speaker recognition*" Interspeech 2020

Recent Advances related to our work

Table 4.7: Comparison of the results using the FTDNN models trained on VoxCeleb-2 dataset. The models are tested with VoxCeleb-1 original test set and other evaluation sets. The table also provides comparison with other published works.

Model	Training loss	Back End	Vox1 Test		SITW E		Voices E	
			EER	C_{min}	EER	C_{min}	EER	C_{min}
FTDNN Xvector	Softmax	GPLDA	2.67	0.18	3.2	0.21	6.68	0.38
E2E-NPLDA	Softmax	NPLDA	**2.27**	**0.14**	**2.65**	**0.16**	6.61	**0.35**
VGG-M [1]	Softmax+contrastive	-	5.94	-	-	-	-	-
Resnet34 [1]	Softmax+contrastive	-	4.83	-	-	-	-	-
Resnet50 [1]	Softmax+contrastive	-	3.95	-	-	-	-	-
ResNet34L [2]	Angular	Cosine	2.39	0.17	3.55	0.25	11.1	0.71
ResNet34L [2]	Angular	GPLDA	3.58	0.22	4.16	0.27	10.22	0.54
ResNet34L [2]	Angular	NPLDA	2.46	0.17	3.06	0.21	8.58	0.47

[1] A. Nagrani et. al., "*VoxCeleb: Large scale speaker verification in the wild* ", CSL 2020
[2] J. S. Chung et. al., "*In defence of metric learning for speaker recognition*" Interspeech 2020

Advantages and Disadvantages

- The NPLDA and the corresponding E2E architectures are capable of significantly improving a PLDA based speaker verification model.
- The improvements are consistent over several test sets, over the PLDA model, indicating that it is a robust approach.
- While the softDCF loss helps us achieve the best improvements compared to other loss functions such as the binary cross-entropy and its weighted versions, it is highly sensitive to factors such as batch size, learning rate, and the warping factor α.
- The softDCF loss requires the parameters to be initialized with the Generative PLDA parameters, and not suitable for a fully end-to-end training of the network.

Concluding remarks…

Summary and Contributions

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- Speaker and Language – Two very important, independent attributes of speech.

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    - Algorithms & Derivations, Embedding Extraction methods.
  - PLDA inspired Siamese neural networks for Speaker Verification.
    - NPLDA backend architecture, E2E training, loss functions and their detailed comparison.

Future Perspectives

- Neural network based generative models for speaker and language embedding extraction for recognition.

- Neural Network approaches for language recognition, particularly for lang diarization.

- Self-supervised Learning for speaker and language recognition.

- Architectures for *speaker detection* in conversational settings.

    - *Cross Attention* between enrollment and test segments that can better model the speaker in language/accent/emotion mismatched cases, and overlapped speech.

Publications based on this thesis

- Journal articles

  - S. Ramoji, S. Ganapathy, “Supervised I-vector modeling for language and accent recognition,” Computer Speech \& Language 60, (2020): p.101030.

  - S. Ramoji, P. Krishnan, S. Ganapathy, “PLDA inspired Siamese networks for speaker verification,” Computer Speech \& Language 76, (2022): p.101383.

Publications based on this thesis

- Conference Publications
  - S. Ramoji, S. Ganapathy, “Supervised I-vector Modeling-Theory and Applications,” in Proc. Interspeech (2018): p.1091-1095.
  - S. Ramoji et. al., “The LEAP speaker recognition system for NIST SRE 2018 challenge,” in Proc. ICASSP (2019): p.5771-5775.
  - S. Ramoji, P. Krishnan, S. Ganapathy, “NPLDA: A Deep Neural PLDA Model for Speaker Verification,” in Proc. Odyssey (2020): p.202-209.
  - S. Ramoji, P. Krishnan, S. Ganapathy, “LEAP System for SRE 2019 CTS Challenge - Improvements and Error Analysis,” in Proc. Odyssey (2020): p.281-288.
  - S. Ramoji, P. Krishnan, S. Ganapathy, “Neural PLDA Modeling for End-to-End Speaker Verification,” Proc. Interspeech (2020): p.4333-4337

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- Finally, and most importantly, I extend my sincere thanks to my parents, whose love and support can simply not be measured. I dedicate my PhD thesis to them.

Thank you for your attention !