
[course site]

#DLUPC

Day 3 Lecture 2

# Speaker Recognition

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# Acknowledgments

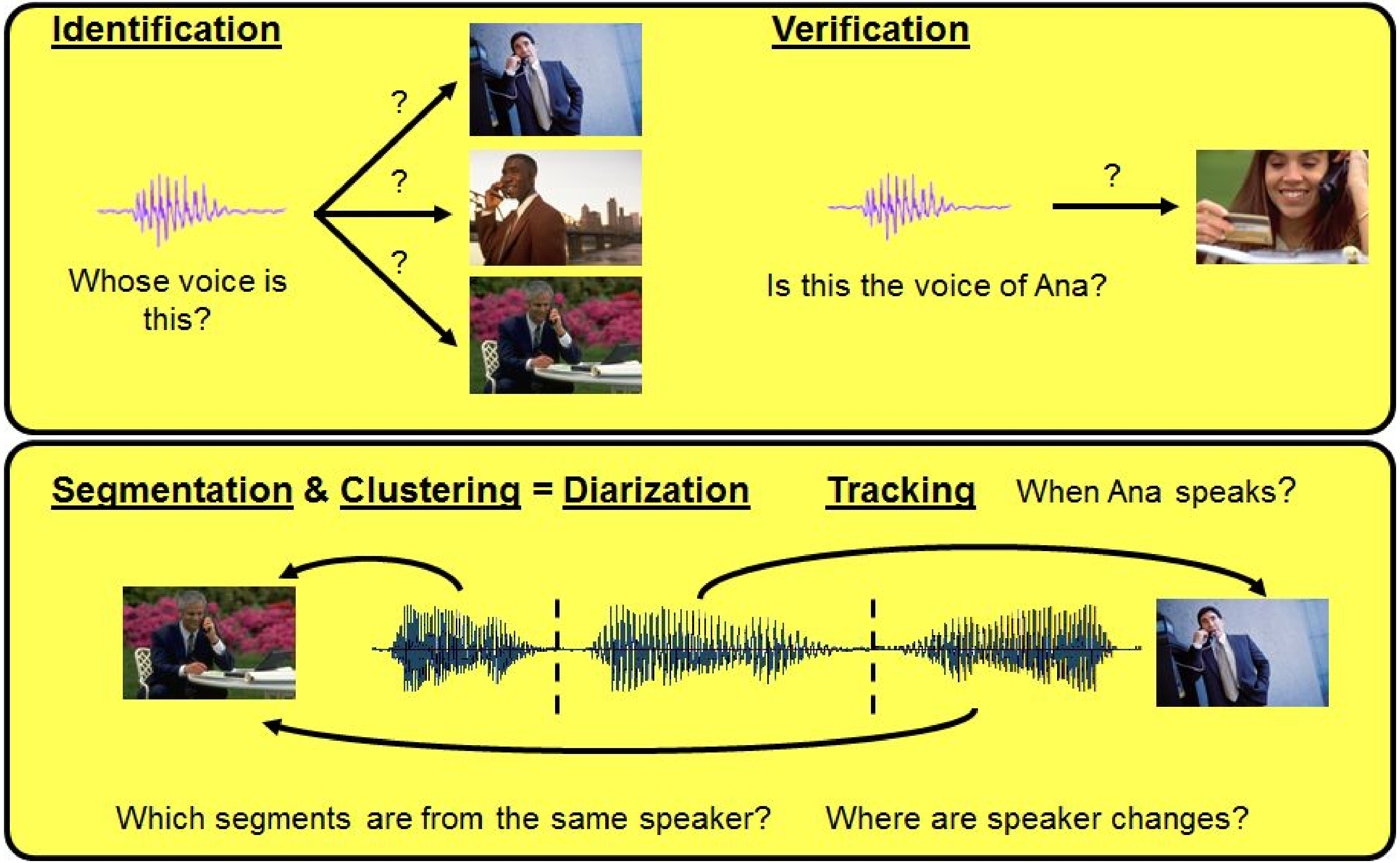
Miquel India, Omid Ghahabi, Pooyan Safari
Ph.D. candidates

TALP Research Center

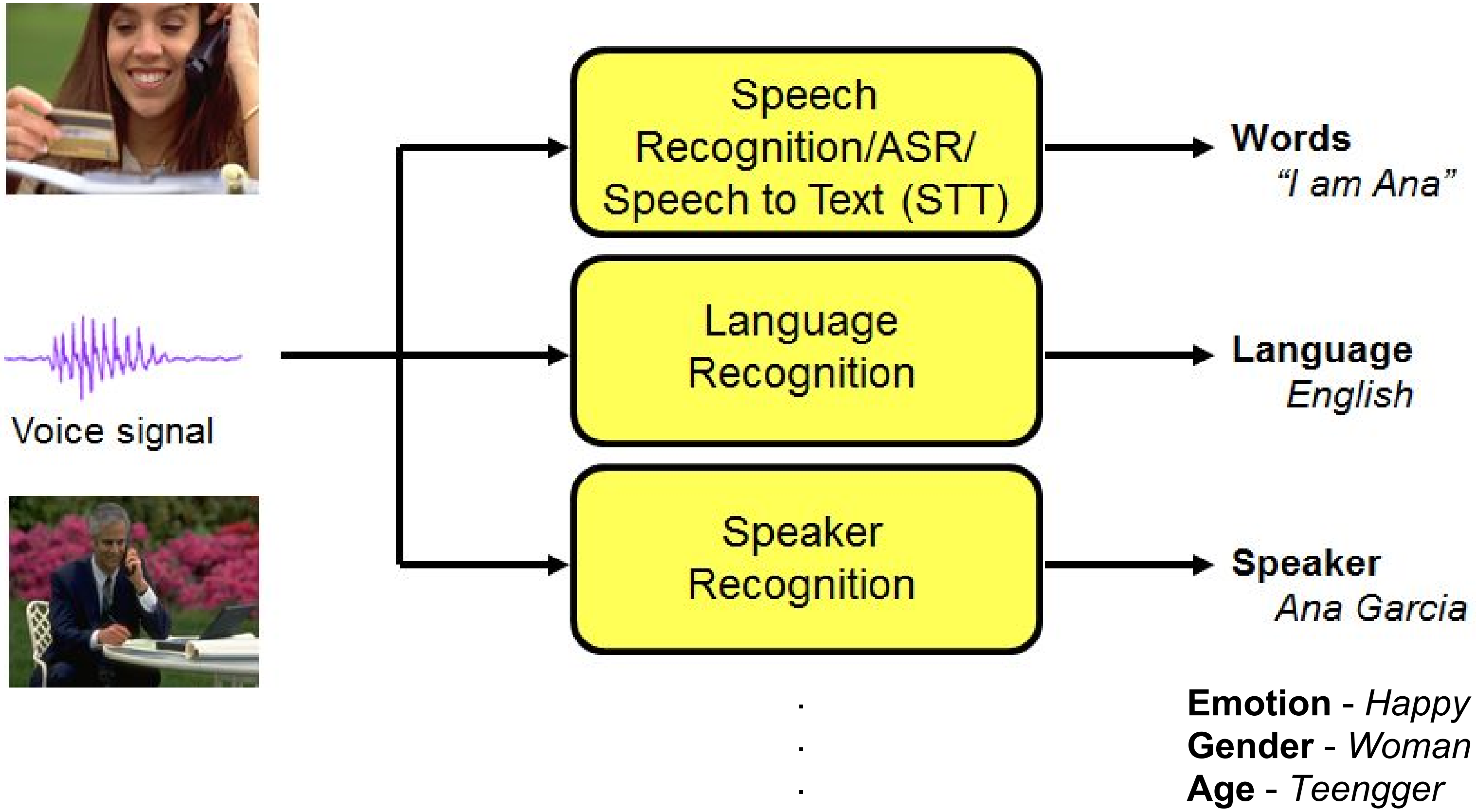
# Outline

- State-of-the-art Speaker Recognition
- DL in Speaker Recognition
    - End-to-End
    - Front-End
        - Features
        - i-vector Extraction
        - Features to Embeddings
        - Vectors to Embeddings
    - Back-End

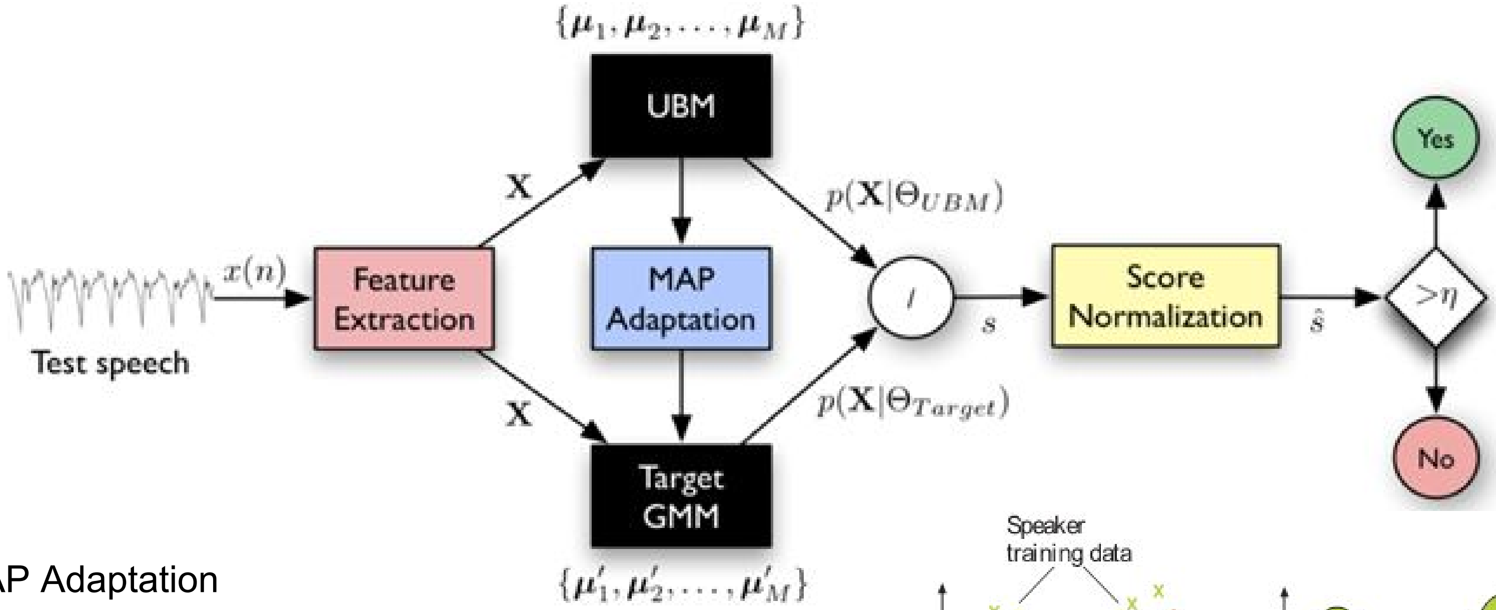
# Speaker Recognition Tasks



# Speech Recognition Tasks

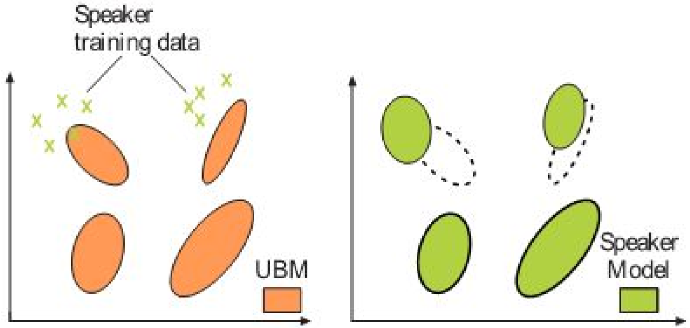


# GMM-UBM Universal Background Model



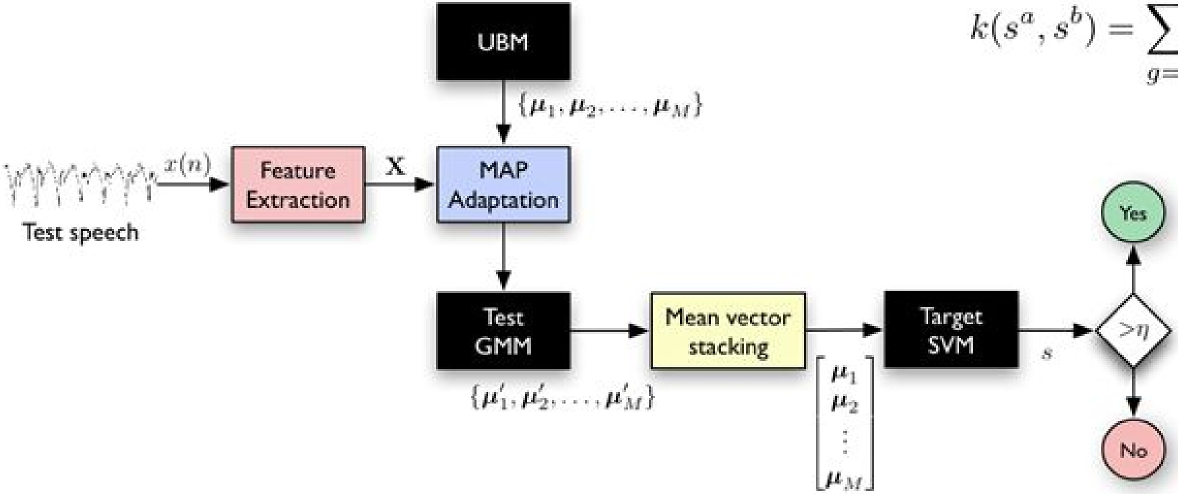

MAP Adaptation

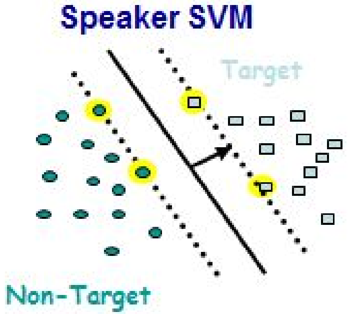
$$\mu_{client\_map} = (1-\alpha)\mu_{world} + \alpha.\mu_{client\_ML}$$



# Supervectors

$$k(s^a, s^b) = \sum_{g=1}^{G} \left( \sqrt{\lambda_g} \boldsymbol{\Sigma}_g^{-\frac{1}{2}} \boldsymbol{\mu}_g^a \right)^{\mathbf{T}} \left( \sqrt{\lambda_g} \boldsymbol{\Sigma}_g^{-\frac{1}{2}} \boldsymbol{\mu}_g^b \right)$$



# i-vectors

$$s = m + Tw$$

Speaker Supervector

Speaker-independent Component

Total-variability Matrix

i-vector

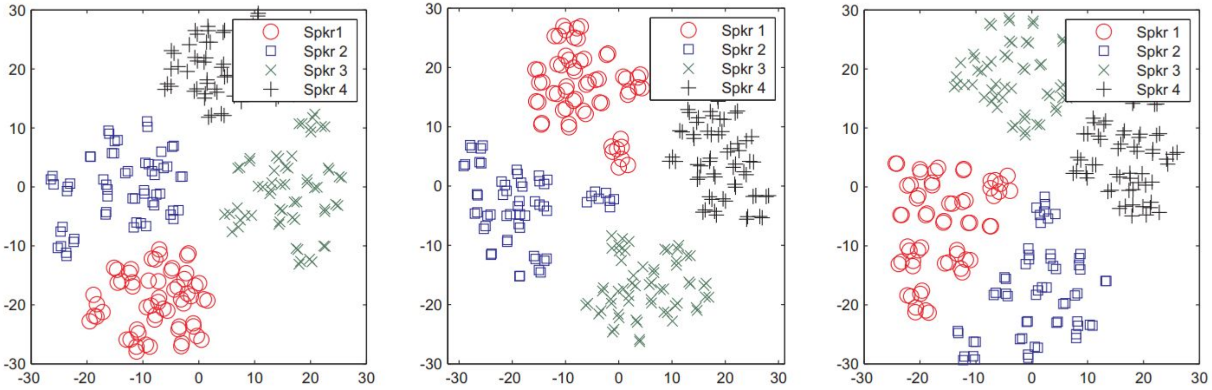
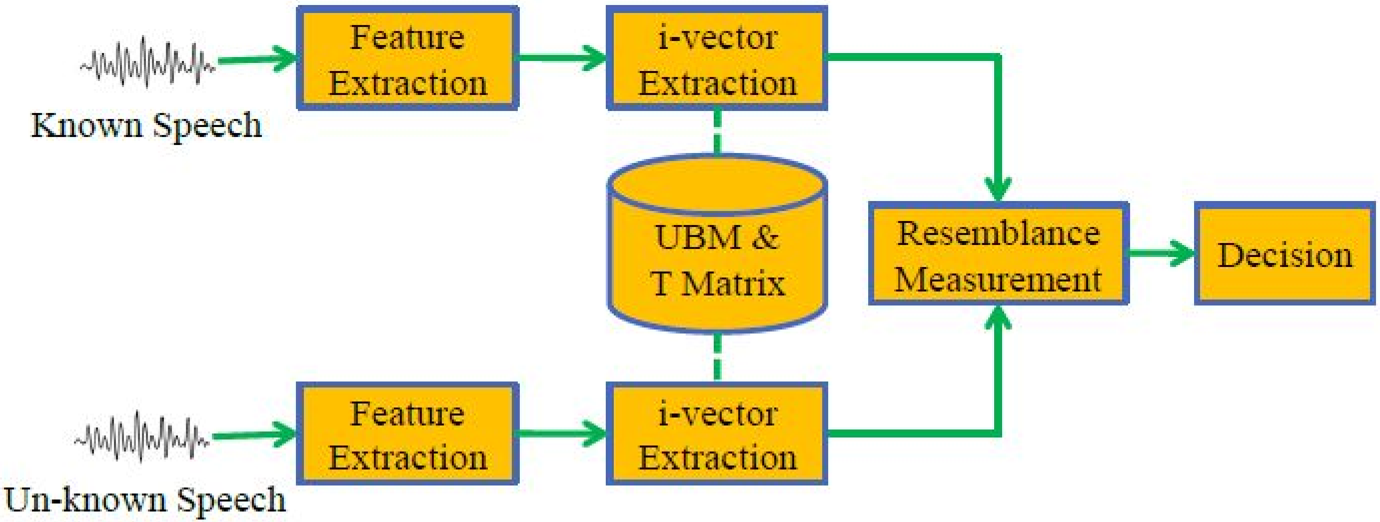



Fig. 6. t-SNE visualization of i-vectors obtained from speaker verification system using (a) IFCC, (b) FDLP and (c) MFCC features.

K. Vijayan et al./Speech Communication 81 (2016) 54–71

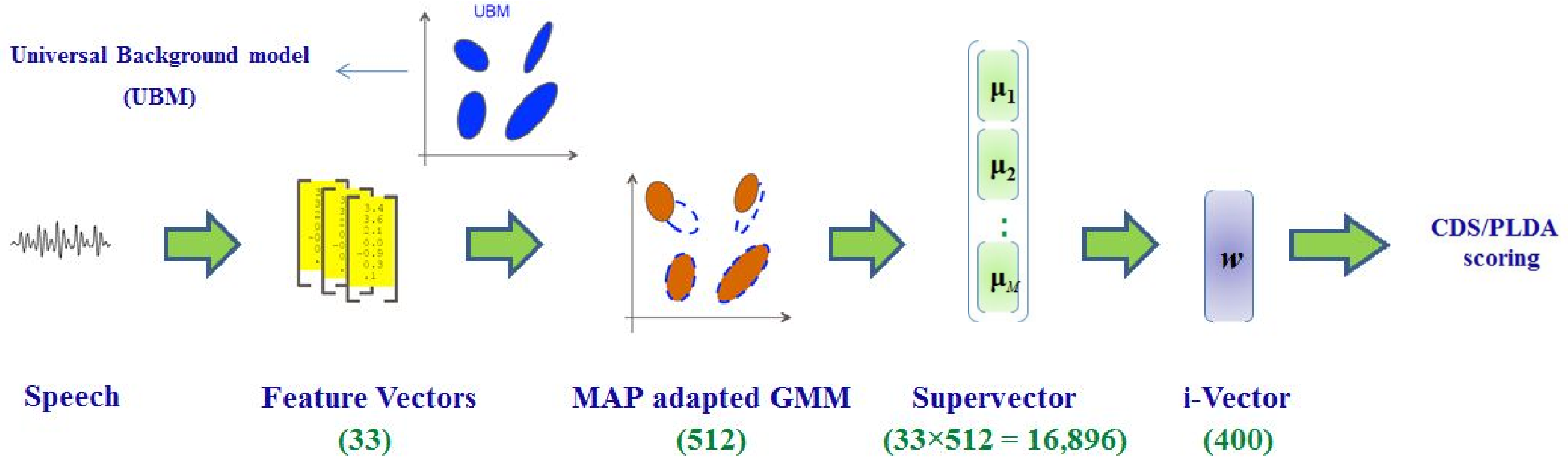
# i-vector Scoring



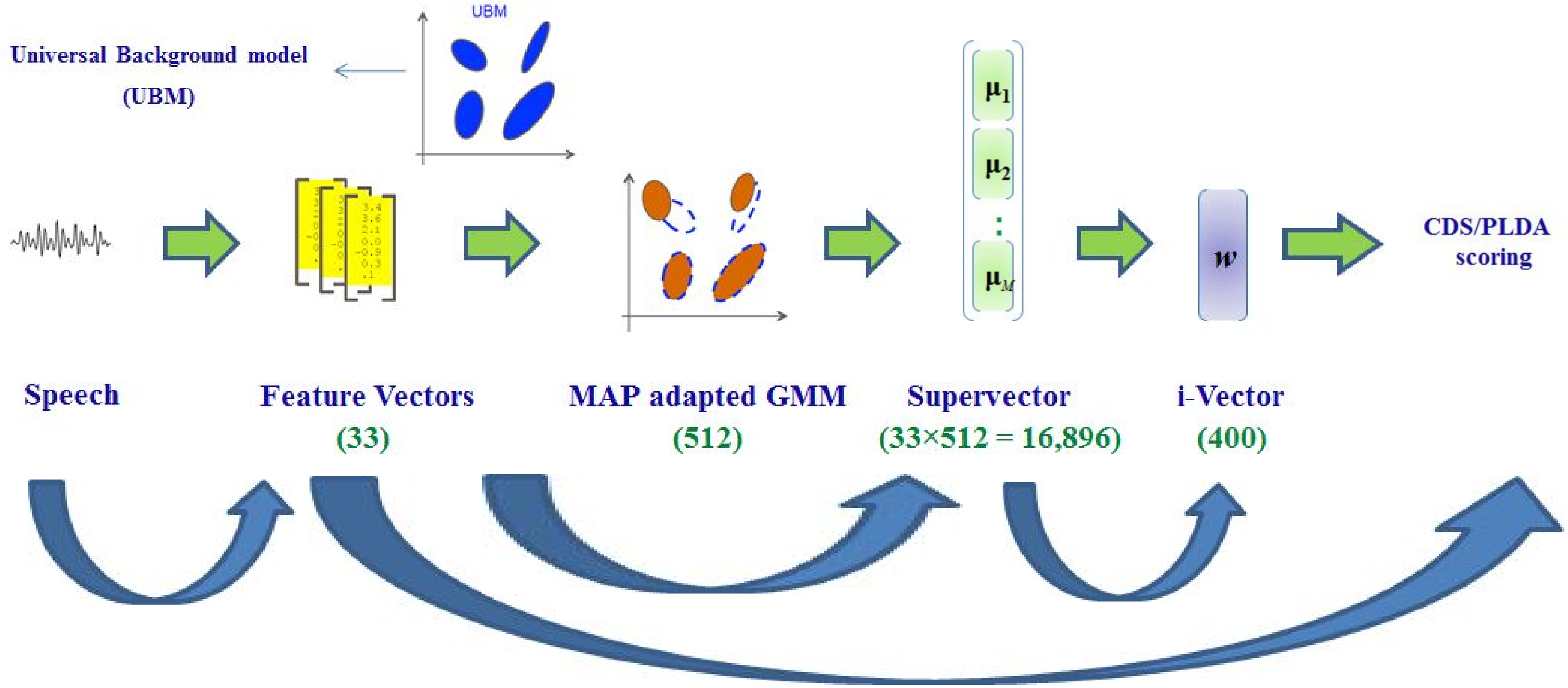

## Resemblance Measurement

- Cosine Distance Scoring $$score(\mathbf{w}_1, \mathbf{w}_2) = \frac{\mathbf{w}_1^T . \mathbf{w}_2}{\|\mathbf{w}_1\| . \|\mathbf{w}_2\|} = cos(\theta_{\mathbf{w}_1, \mathbf{w}_2})$$
- Probabilistic Linear Discriminant Analysis (PLDA)

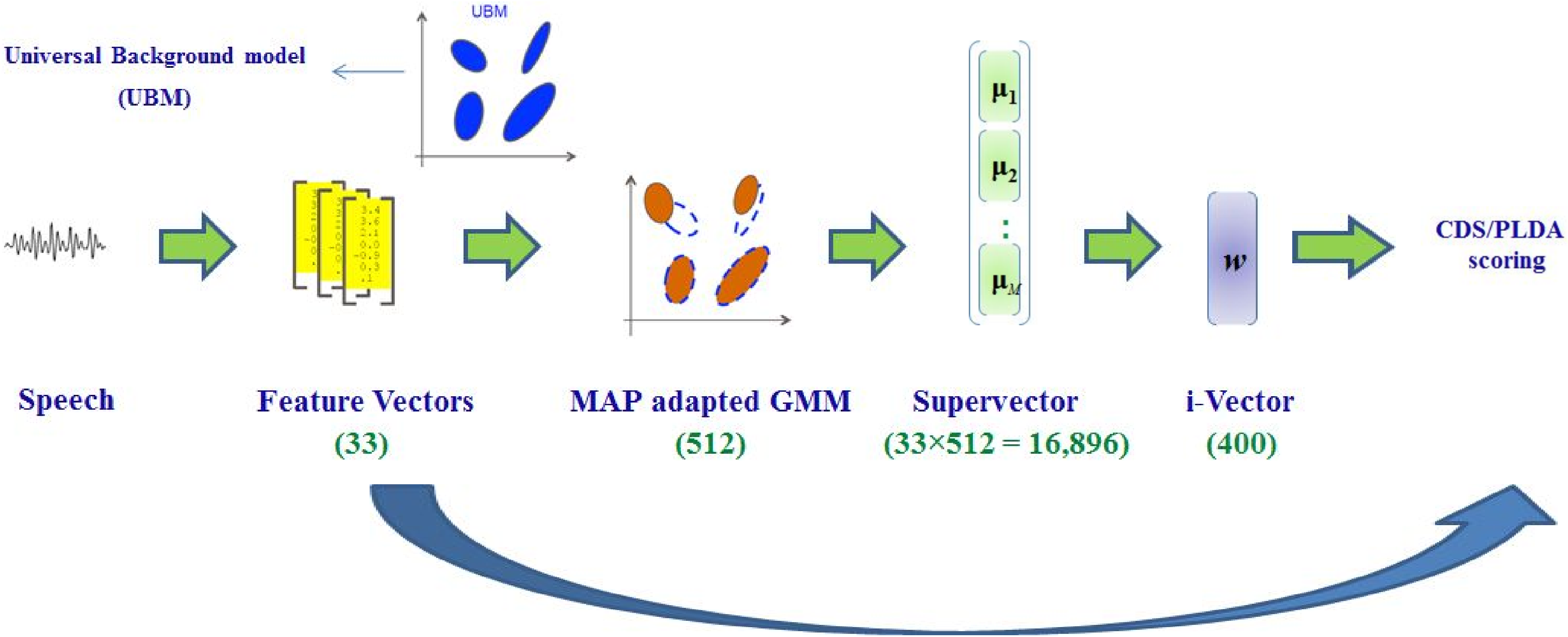
# SoA Speaker Recognition



# DL in Speaker Recognition

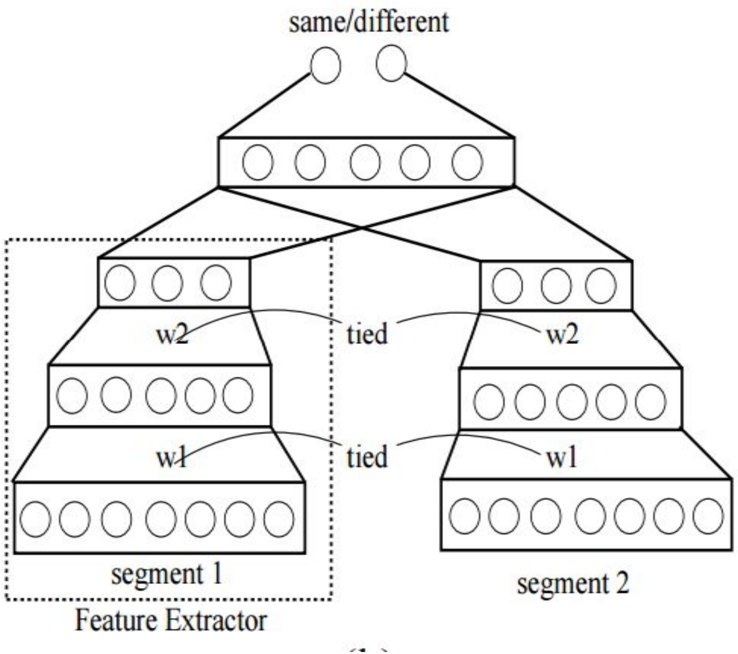


# End-to-End

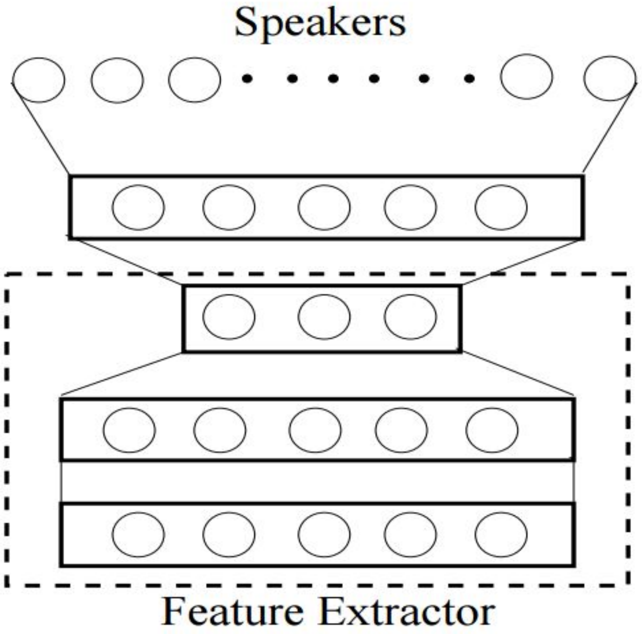


Universal Background model (UBM)
UBM
CDS/PLDA scoring
Speech
Feature Vectors (33)
MAP adapted GMM (512)
Supervector (33×512 = 16,896)
i-Vector (400)

# End-to-End



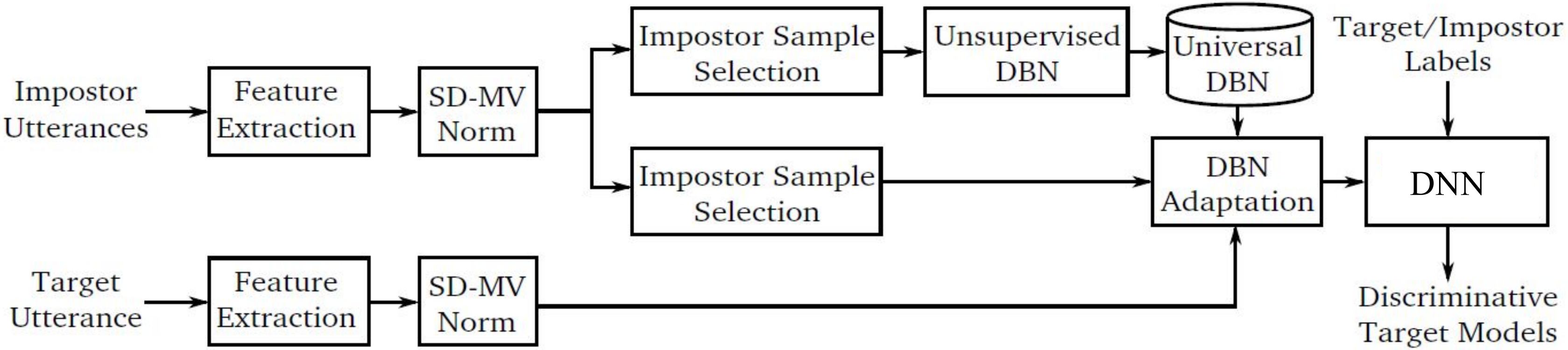

Speaker Verification




Speaker Identification

Yella, S.H., Stolcke, A., "A comparison of neural network feature transforms for speaker diarization." Proc. *INTERSPEECH* 2015.

# ADBN Feature Classification




P. Safari, O. Ghahabi, J. Hernando, “Feature classification by means of Deep Belief Networks for speaker recognition”, Proc. EUSIPCO 2015

# ADBN Feature Classification

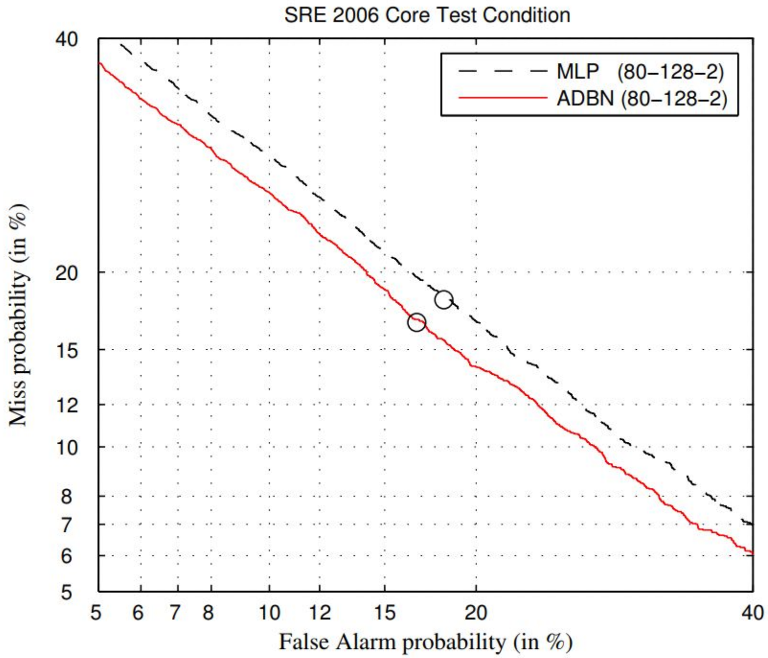
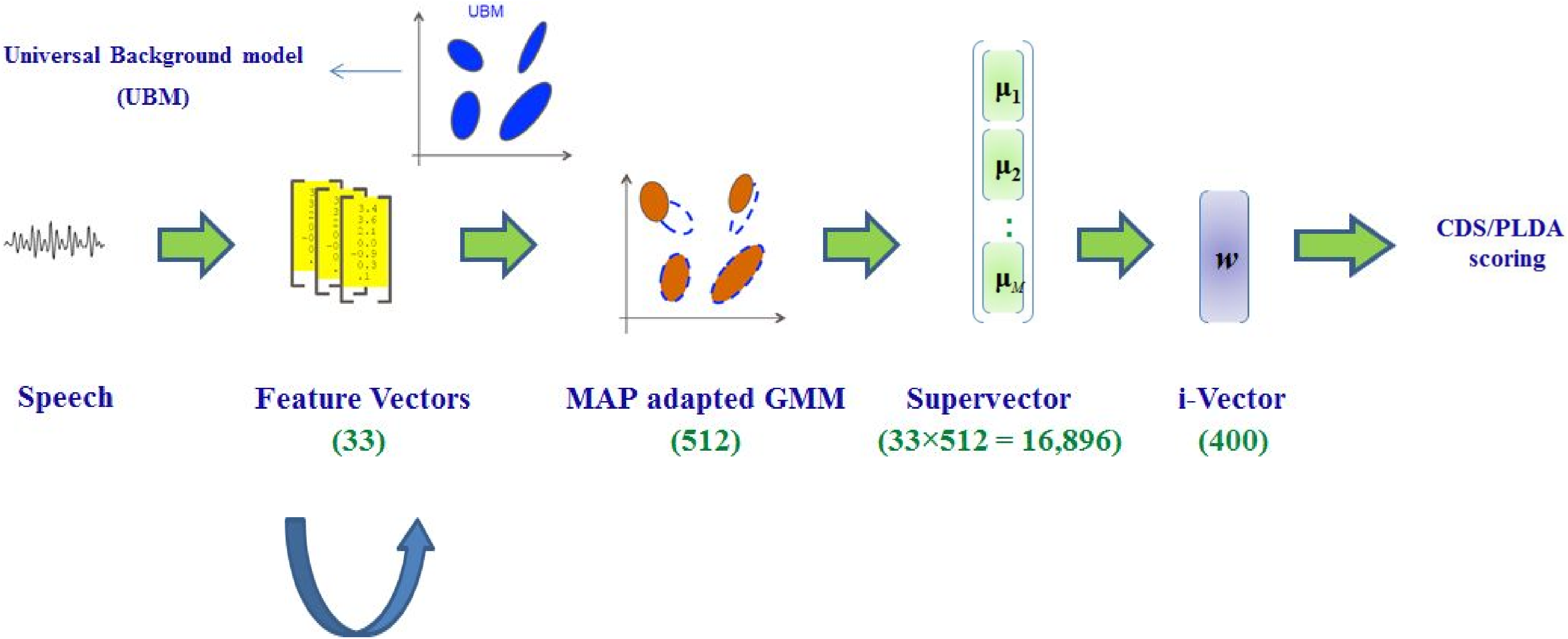
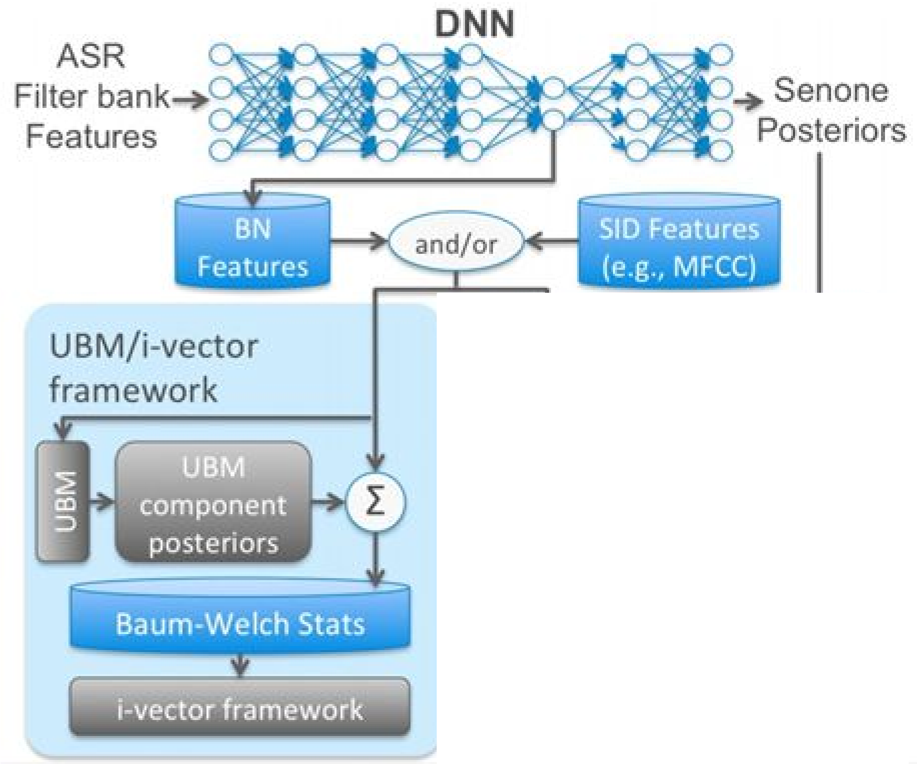



**Fig. 5.** Comparison of DET curves for MLP and the proposed ADBN.

# Front-End: Features



# ASR BN Features



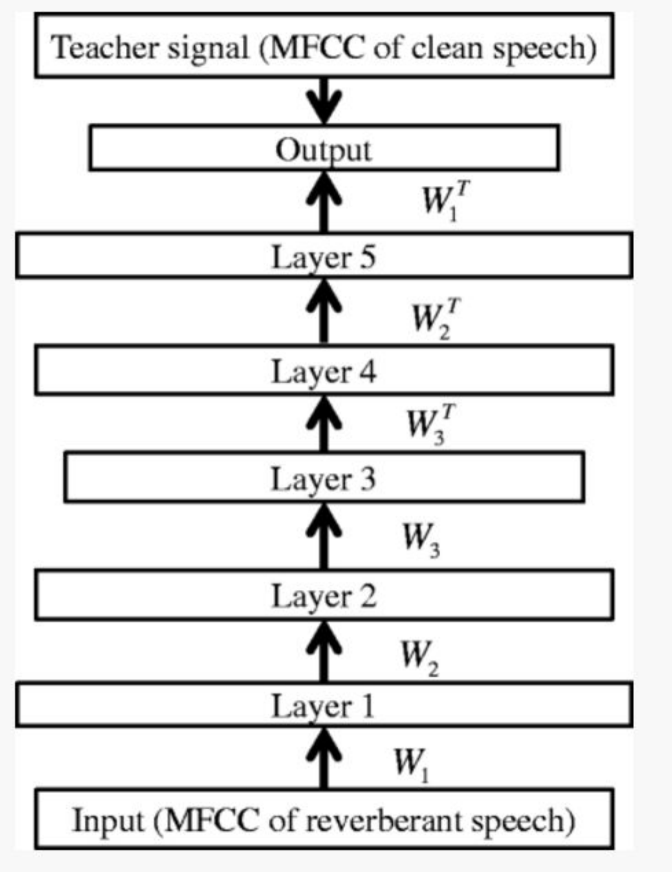

After M. Mclaren e al.,“Advances in deep neural network approaches to speaker recognition” ICASSP  2015.

# Denoising Autoencoder BN Features

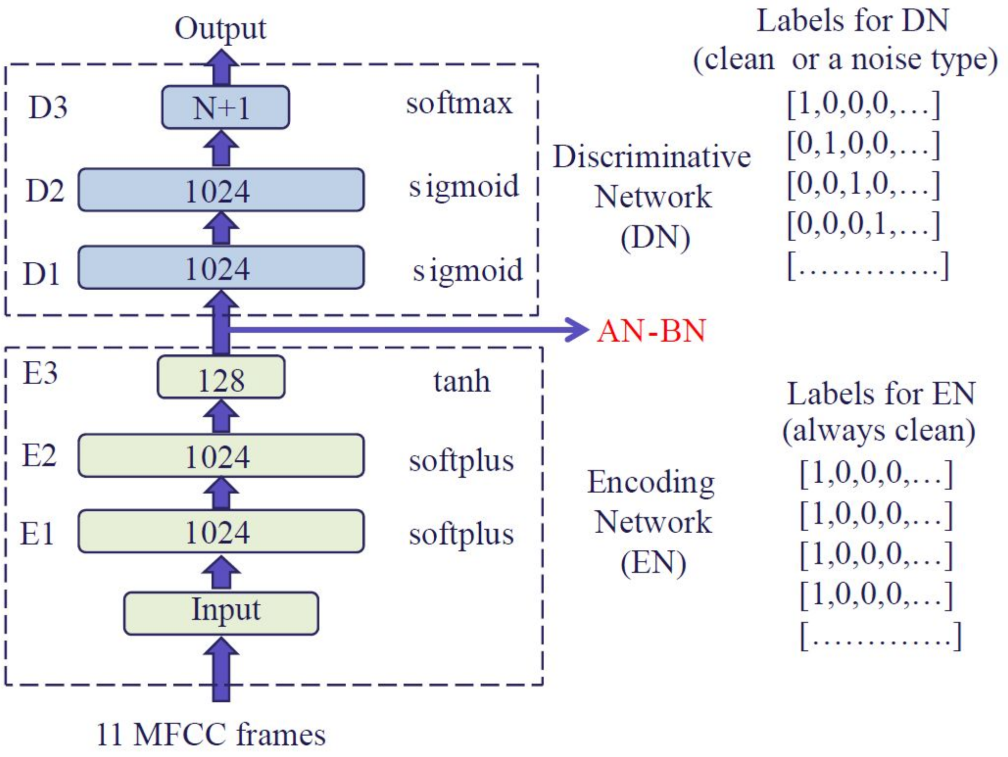
**Denoising autoencoder for cepstral domain dereverberation.**

- Transfrom noisy features of reverberant speech to clean speech features.
- Pre-Trainning with Deep Belief Networks (DBN)

*Zhang et al., Deep neural network-based bottleneck feature and denoising autoencoder-based fro distant-talking speaker identification, EURASSIP Journal on Audio, Speech, and Music Processing (2015) 2015:12*

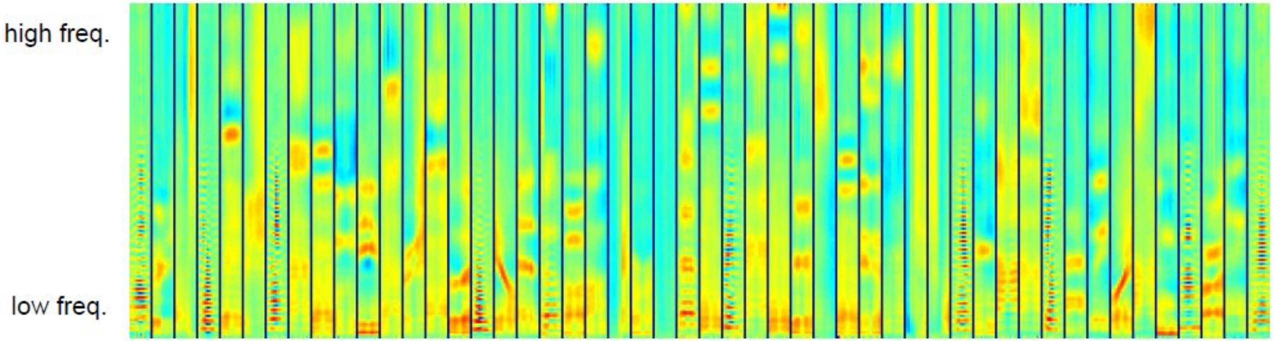


# Adversarial Networks BN Features




H. Yu, Z-H. Tan, Z. Ma, J. Guo, Adversarial Network Bottleneck Features for Noise Robust Speaker Verification, Proc. INTERSPEECH 2017

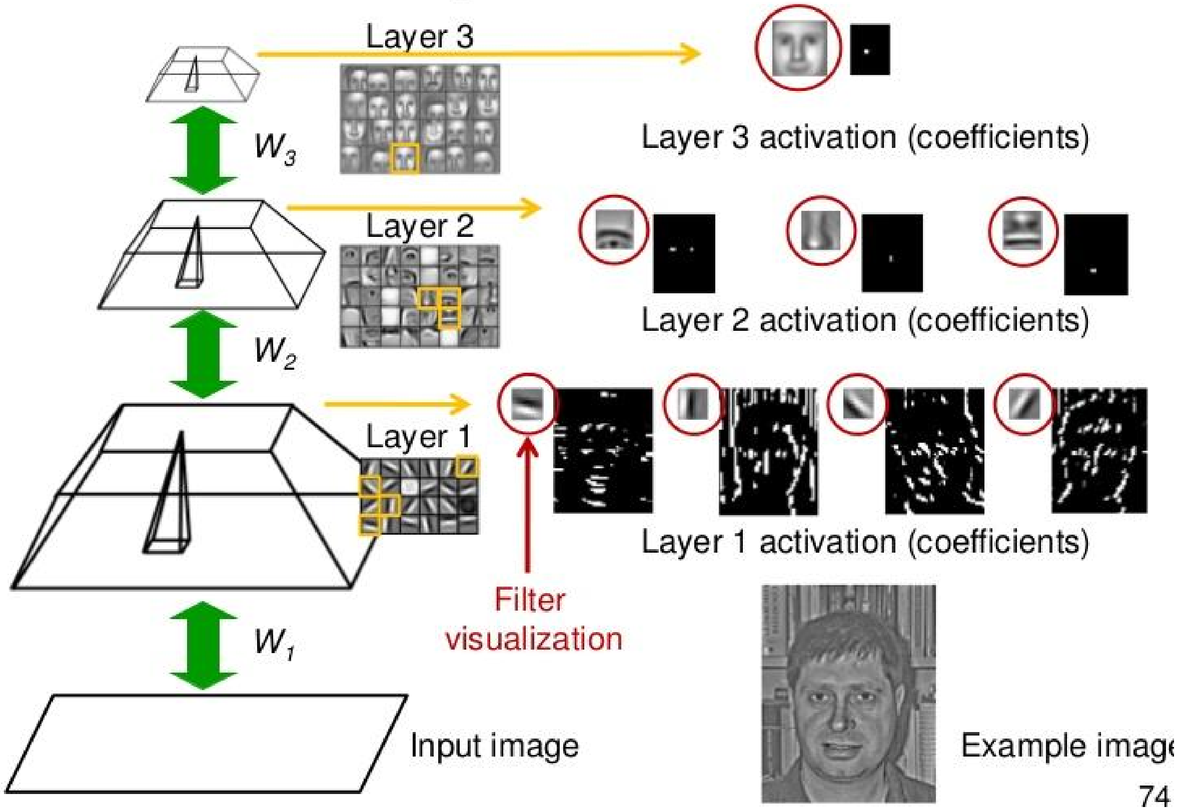
# CDBN Features



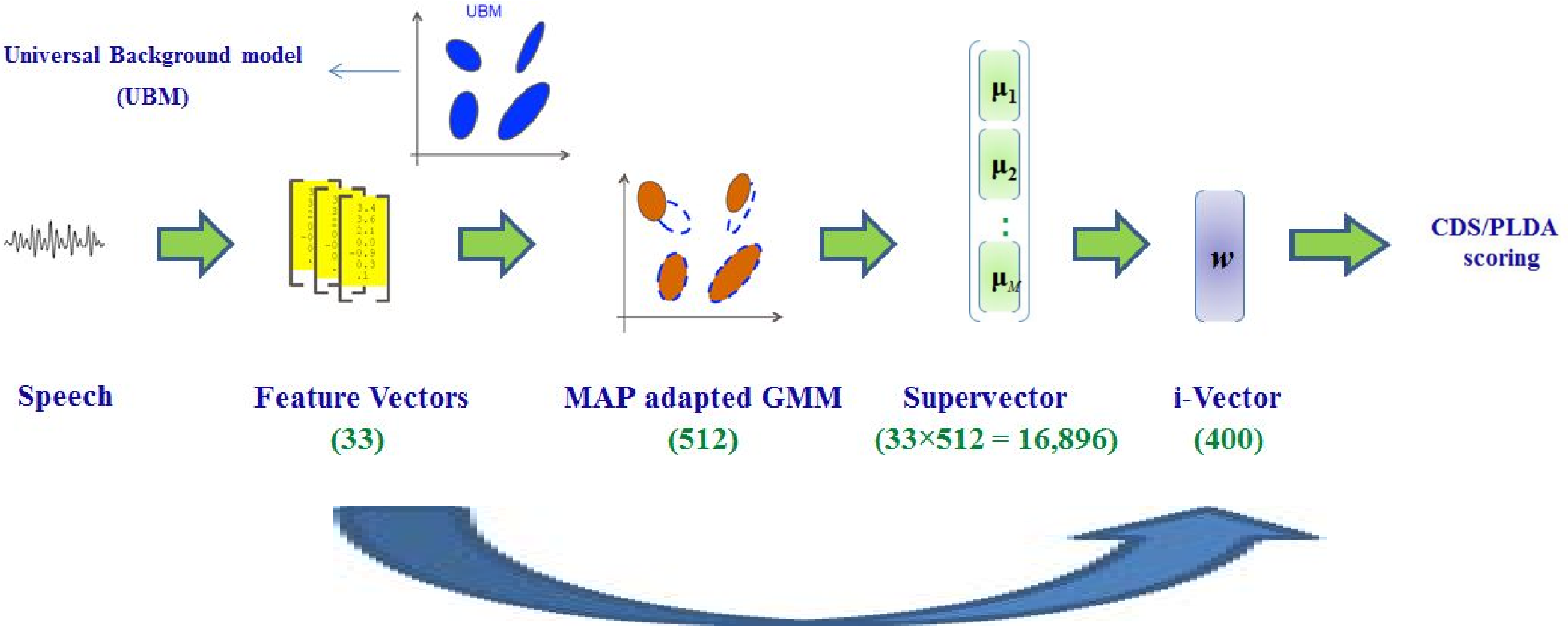

randomly selected first-layer CDBN bases

Unsupervised feature learning for audio classification using convolutional deep belifef networks, H. Lee et al., Advances in Neural Information Processing Systems, 22:1096–1104, 2009

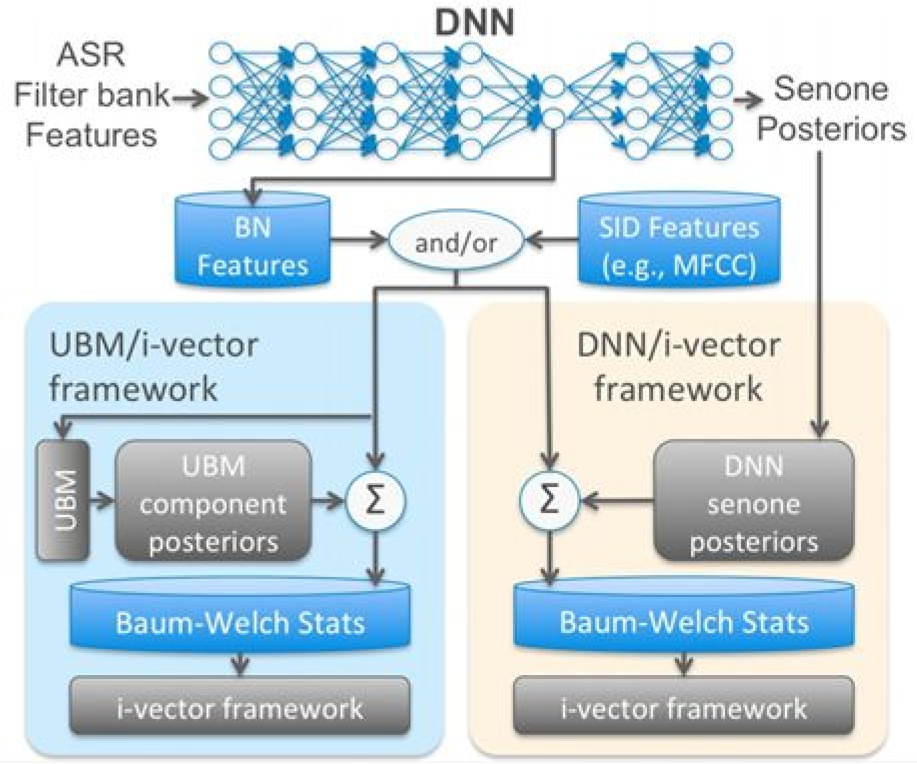
# CDBN Features



# Front-End: i-vector Extraction

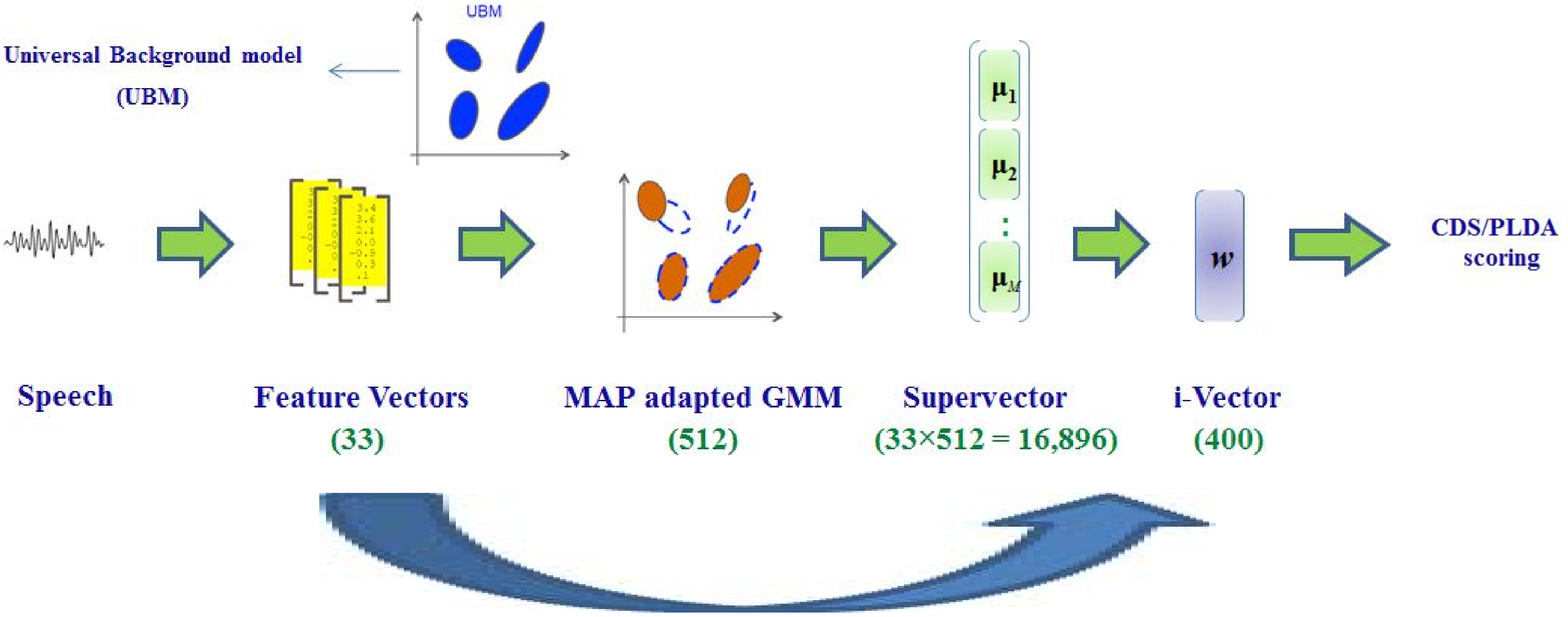


# DL Front-End: i-vectors

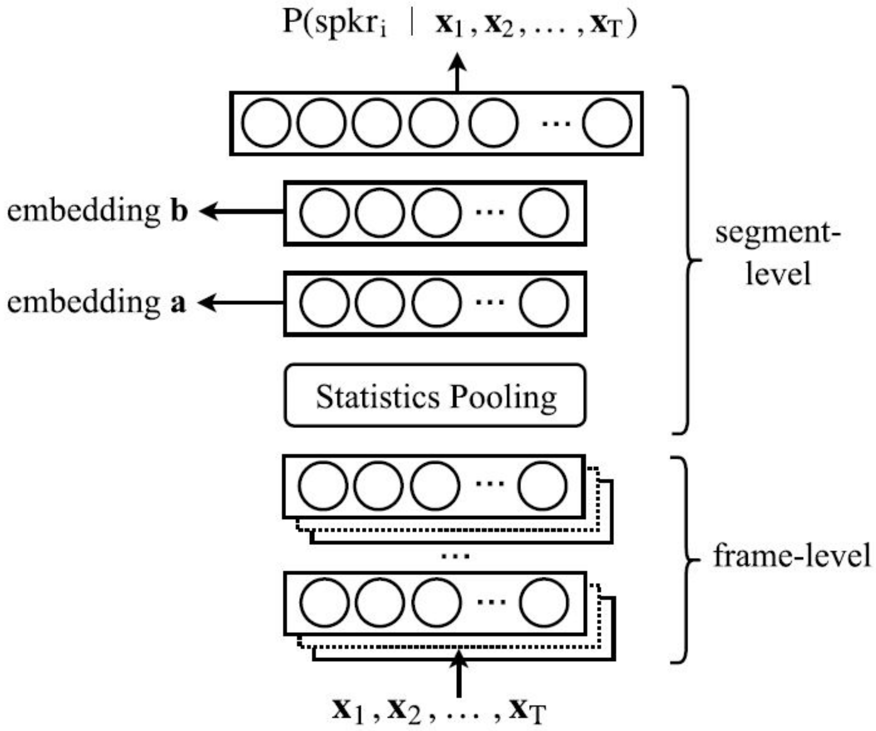



After M. Mclaren e al.,“Advances in deep neural network approaches to speaker recognition” ICASSP 2015.

# Front-End: Features to Embeddings

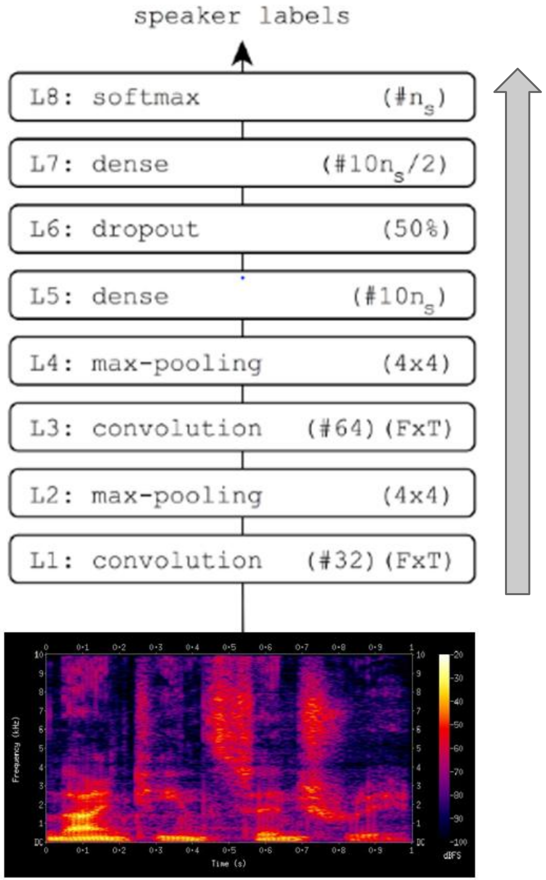


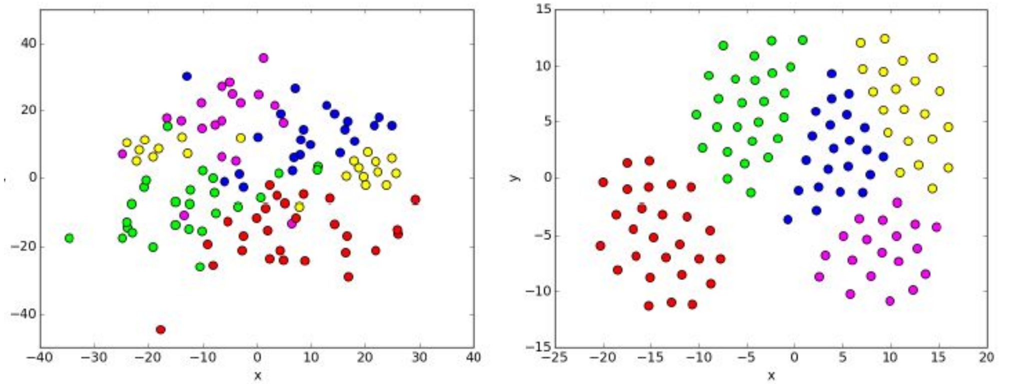
# DNN Embeddings




D. Snyder, D. Garcia-Romero, D. Povey, S. Khudanpur, Deep Neural Network Embeddings for Text-Independent Speaker Verification, Proc. INTERSPEECH 2017

# CNN Embeddings

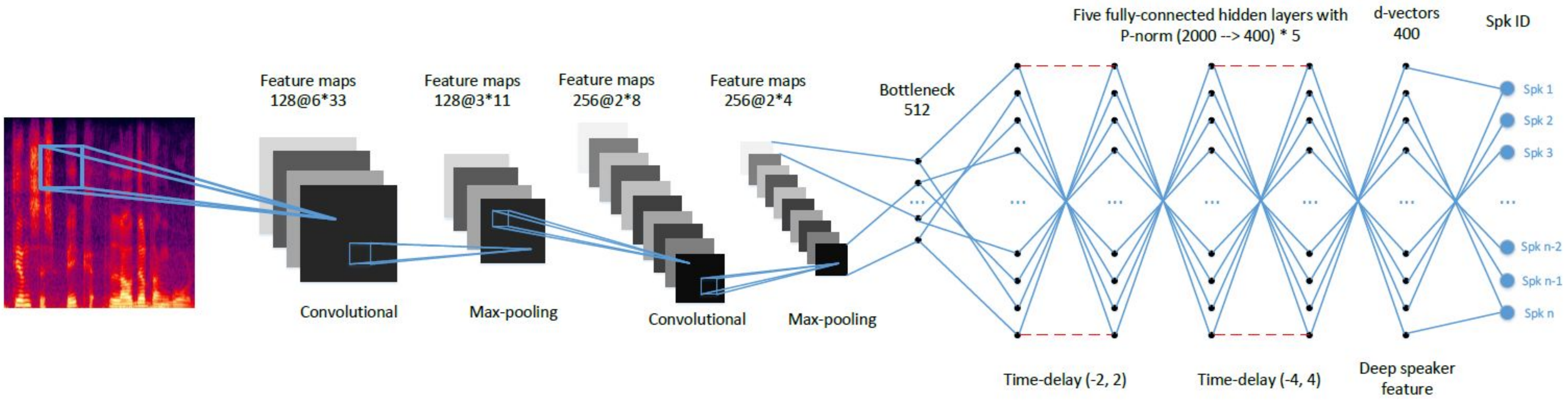


*Five Speaker representations in 2 dimensions.*
*Left figure show the output vector of the softmax layer L8.*
*Right figure correspond to the same output vector of L5 dense layer.*
*Differents colors are assigned to different speakers.*

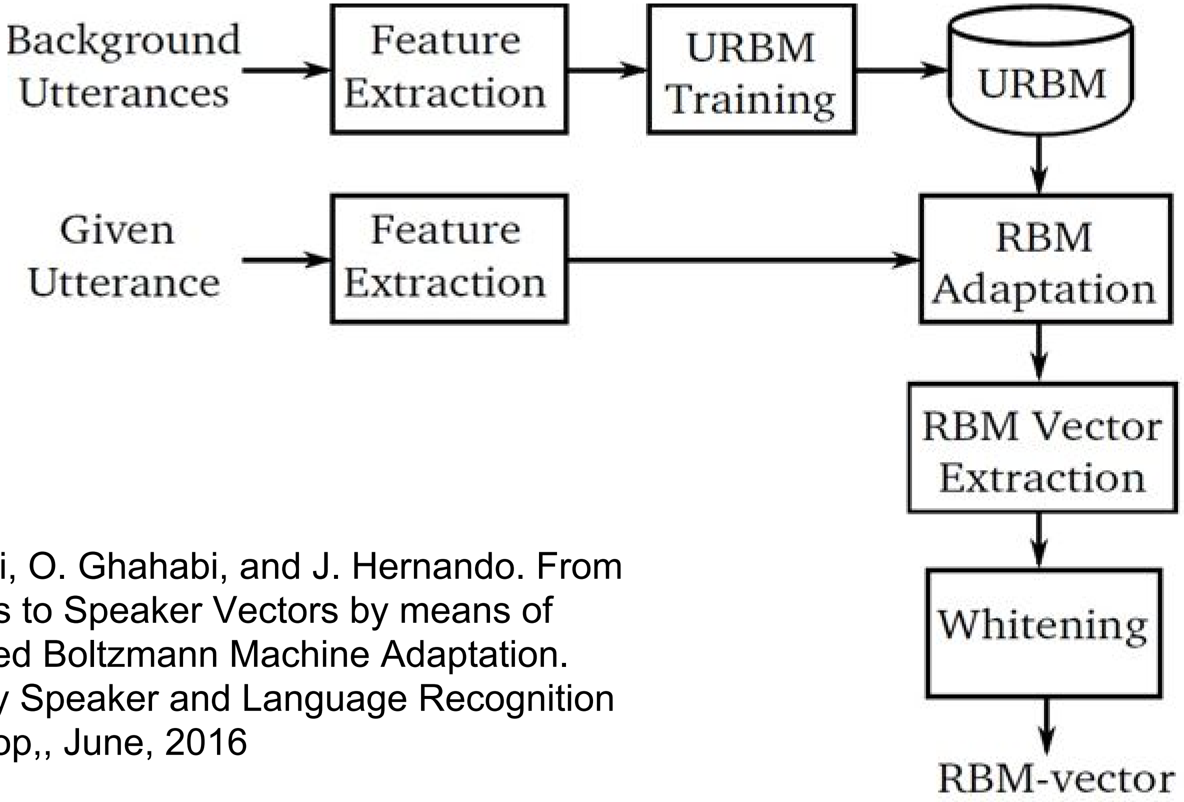
*Yanik Lukic et al. "Speaker Identification and Clustering using Convolutional Neural Networks". In 2016 IEEE International workshop on machine learning for signal processing. (2016)*

# Convolutional Time-Delay DNN Embeddings




L Li, Y Chen, Y Shi, Z Tang, D Wang, Deep Speaker Feature Learning for Text-independent Speaker Verification, Proc. INTERSPEECH 2017

# RBM Embeddings




P. Safari, O. Ghahabi, and J. Hernando. From Features to Speaker Vectors by means of Restricted Boltzmann Machine Adaptation. Odyssey Speaker and Language Recognition Workshop,, June, 2016

# RBM Embeddings

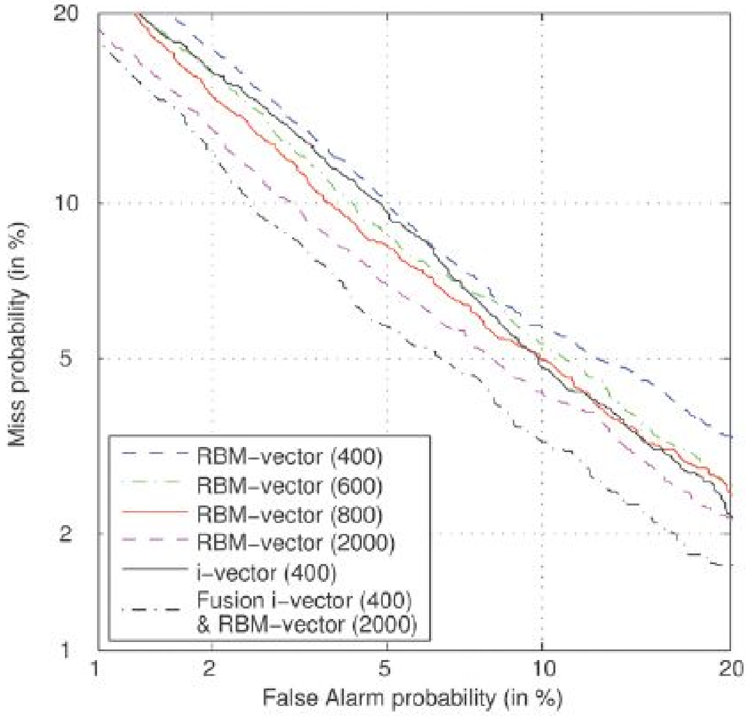
- RBM supervectors

$$
\begin{pmatrix}
\omega_{11} & \omega_{12} & \cdots & \omega_{1h} \\
\omega_{21} & \omega_{22} & \cdots & \omega_{2h} \\
\vdots & \vdots & \ddots & \vdots \\
\omega_{v1} & \omega_{v2} & \cdots & \omega_{vh}
\end{pmatrix}
\qquad
\begin{pmatrix}
\begin{pmatrix} \omega_{11} \\ \omega_{12} \\ \vdots \\ \omega_{1h} \end{pmatrix} \\
\begin{pmatrix} \omega_{21} \\ \omega_{22} \\ \vdots \\ \omega_{2h} \end{pmatrix} \\
\vdots \\
\begin{pmatrix} \omega_{v1} \\ \omega_{v2} \\ \vdots \\ \omega_{vh} \end{pmatrix}
\end{pmatrix}
$$

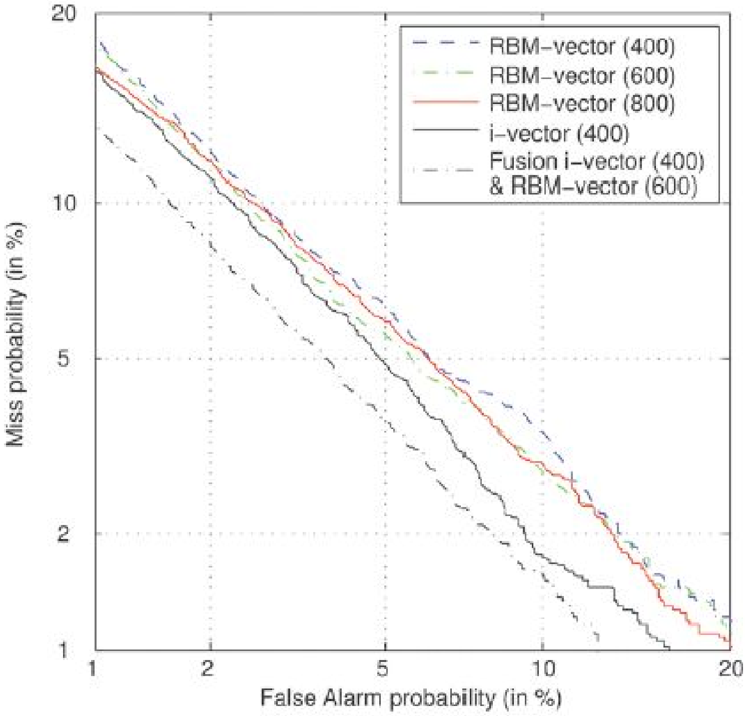
- Mean-normalization
- PCA whitening with dimension reduction
- PCA trained based on all background RBM supervectors
- The output of the whitening stage is called RBM-vector

# RBM Embeddings

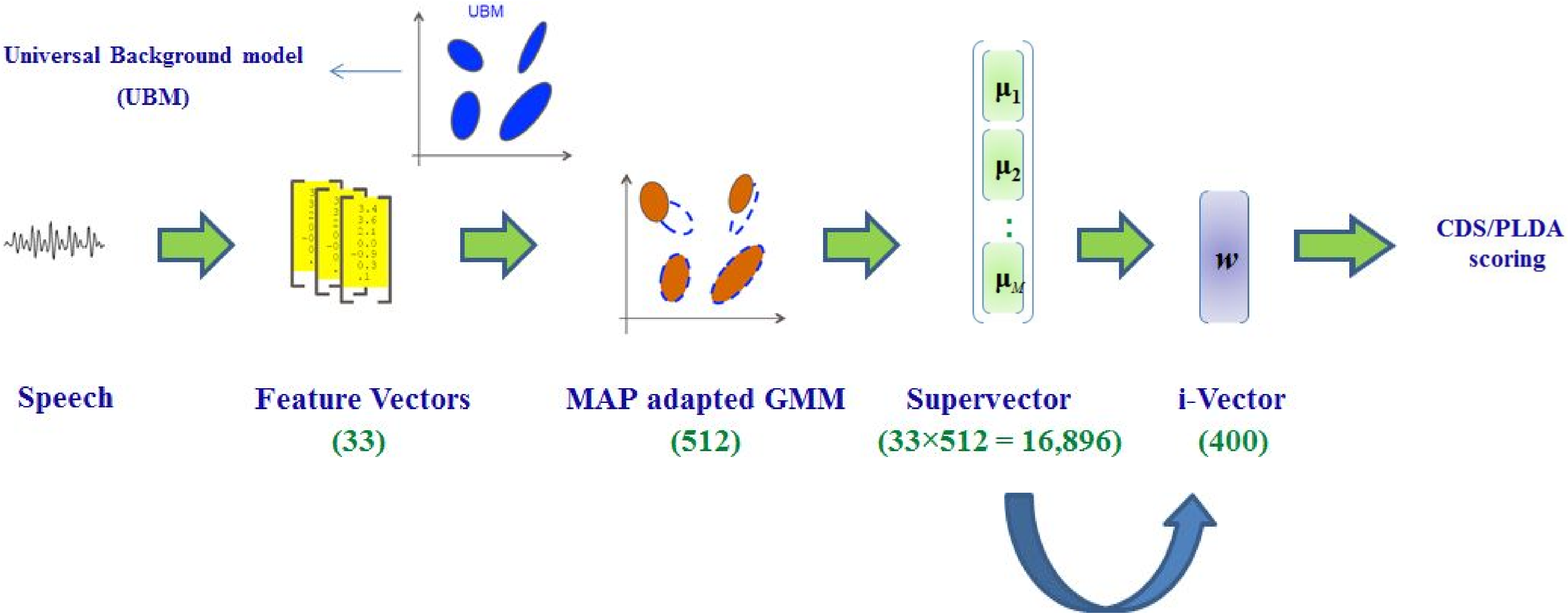
Cosine scoring



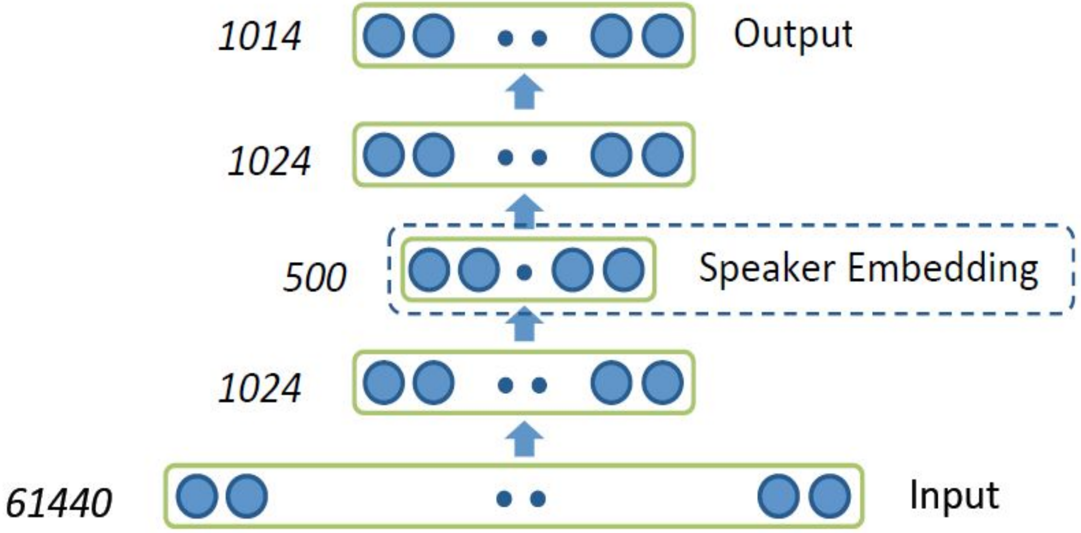

PLDA scoring



# Front-End: Vectors to Embeddings



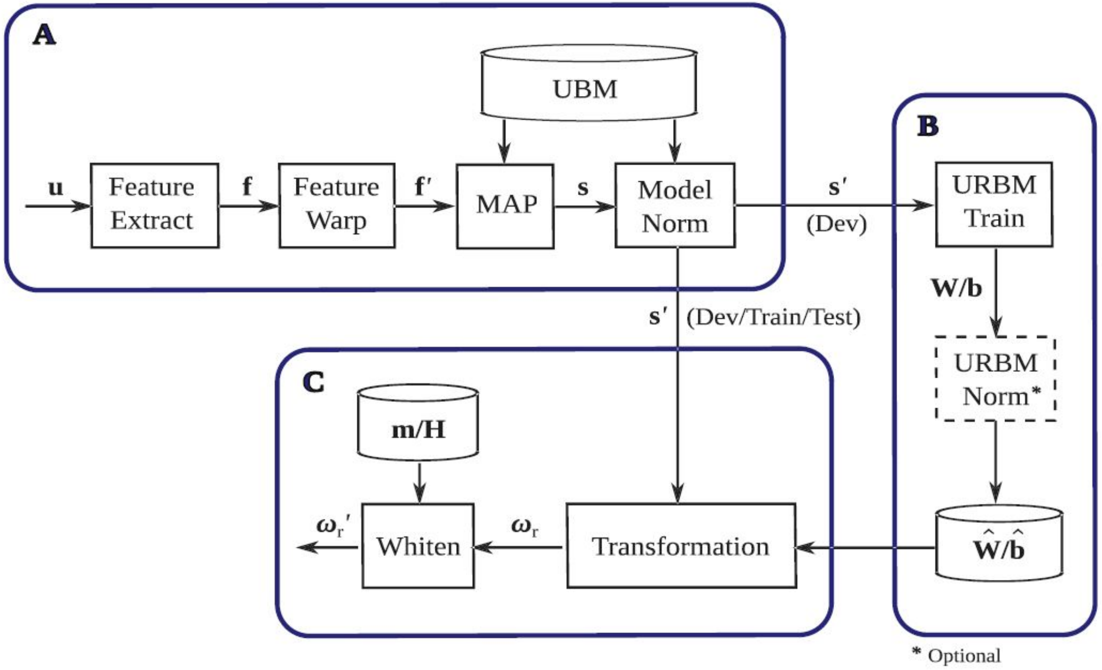
# From Supervectors to Embeddings




$$s_g = \frac{1}{\sum_t \gamma_g(t)} \sum_t \gamma_g(t)(x_t - \mu_g)$$

Mickael Rouvier et al. “Speaker Diarization trough Speaker Embeddings”. 23rd European Signal Processing Conference. (2015)

# GMM-RBM vectors



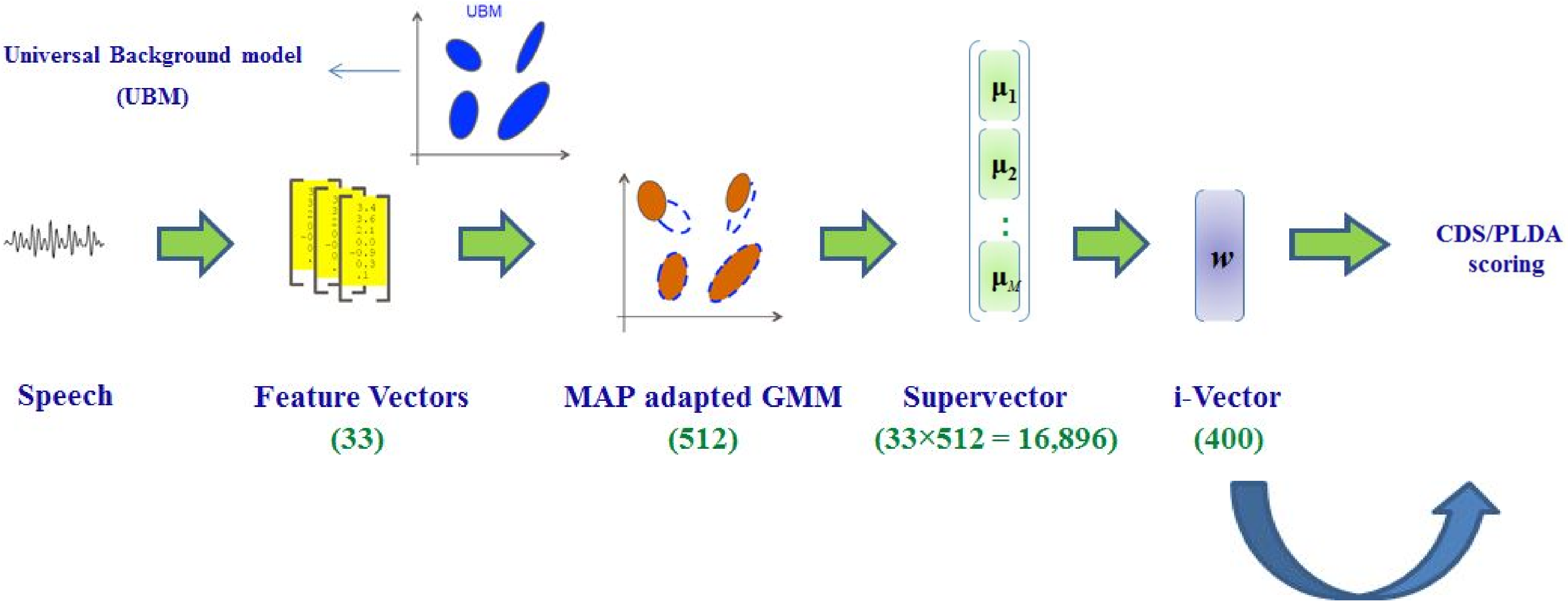

O. Ghahabi, J. Hernando, Restricted Boltzmann machines for vector representation of speech in speaker recognition, Computer Speech & Language, 47 (2018) 16-29

# GMM-RBM vectors

Performance comparison of proposed GMM−RBM vectors and conventional i-vectors on the **evaluation** set core test condition-common 5 of NIST 2010 SRE. GMM−RBM vectors and i-vectors are of a same size of 400.

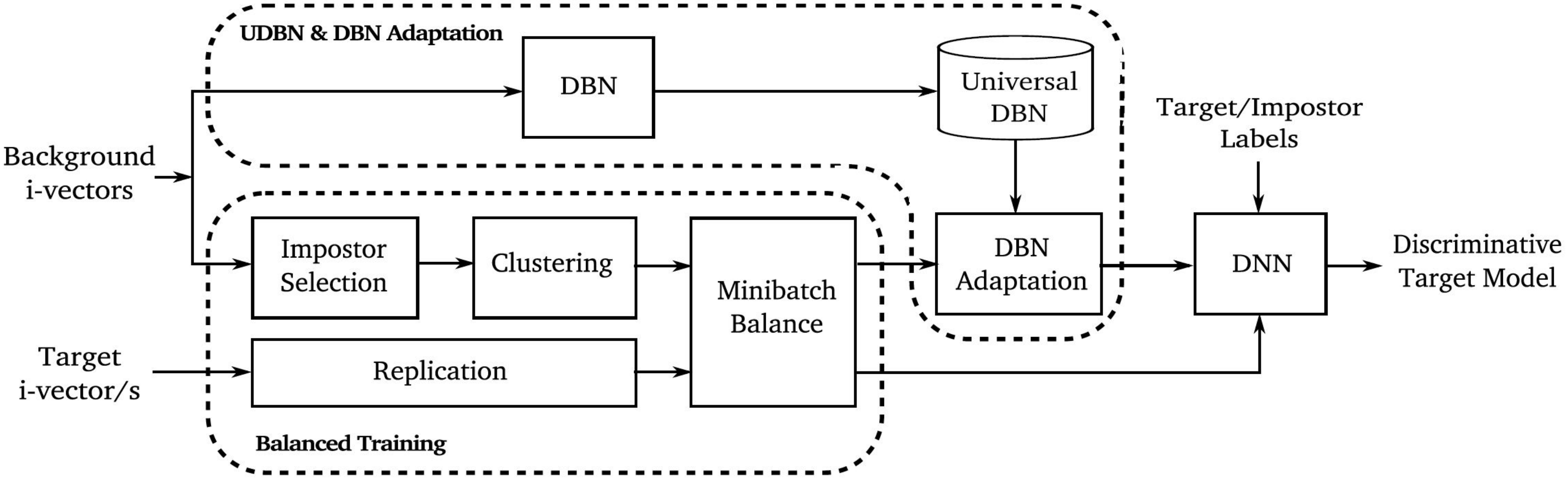
| | | Cosine | | PLDA | |
|---|---|---|---|---|---|
| | | EER (%) | minDCF | EER (%) | minDCF |
| [1] | i-Vector | 6.270 | 0.05450 | 4.096 | 0.04993 |
| [2] | GMM−RBM vector (trained with ReLU) | 6.638 | 0.06228 | 4.517 | 0.05085 |
| [3] | GMM−RBM vector (trained with VReLU) | 6.497 | 0.06099 | 3.907 | 0.05184 |
| Fusion [1] and [3] | | **5.791** | **0.05238** | **3.814** | **0.04673** |

# Back-End



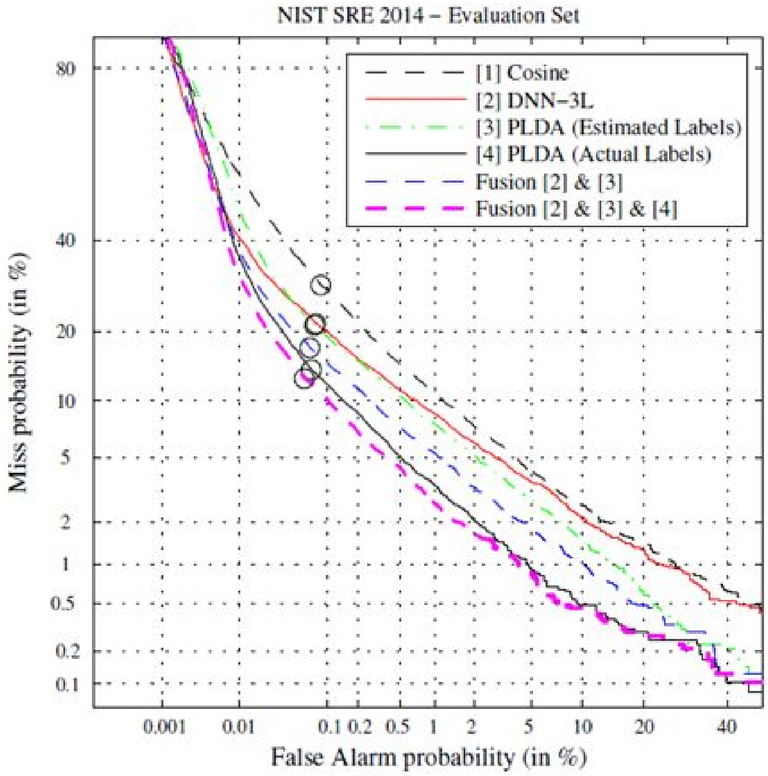
UBM
Universal Background model
(UBM)
$\mu_1$
$\mu_2$
$\mu_M$
$w$
CDS/PLDA
scoring
Speech
Feature Vectors
(33)
MAP adapted GMM
(512)
Supervector
(33×512 = 16,896)
i-Vector
(400)

# DNN i-Vector Back-End




O. Ghahabi, J. Hernando, Deep Learning Backend for Single and Multi-Session i-Vector Speaker Recognition, to be appear in IEEE Trans. Audio, Speech and Language Processing

# DNN i-Vector Back-End




| | Labeled Background Data | Prog Set EER | Prog Set minDCF | Eval Set EER | Eval Set minDCF |
|---|---|---|---|---|---|
| [1] Cosine | No | 4.78 | 386 | 4.46 | 378 |
| [2] PLDA (Estimated Labels) | No | 3.85 | 300 | 3.46 | 284 |
| [3] DNN-3L | No | 4.36 | 297 | 3.93 | 291 |
| Fusion [2] & [3] | No | **2.95** | **259** | **2.64** | **238** |
| [4] PLDA (Actual Labels) | Yes | 2.23 | 226 | 2.01 | 207 |
| Fusion [2] & [4] | Yes | 2.04 | 220 | 1.85 | 204 |
| Fusion [3] & [4] | Yes | 2.10 | 219 | 1.98 | 194 |
| Fusion [2] & [3] & [4] | Yes | **1.90** | **203** | **1.72** | **184** |

23% 37%

6% 11%

**NIST SRE 2014 i-Vector Challenge**

(more than 100 participants)

- Top 20 in the 1st Phase (unlabeled background data)
- 2nd rank in the 2nd Phase (labeled background data)