

l-vector representation based on GMM and DNN

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Introduction

- JFA intuition
 - A supervector for a speaker should be decomposable into speaker independent, speaker dependent, channel dependent, and residual components
 - A given speaker GMM supervector s can be decomposed as follows:

$$s = m + Vy + Ux + Dz$$

The diagram illustrates the decomposition of a speaker GMM supervector s into four components. The equation $s = m + Vy + Ux + Dz$ is shown. Arrows point from labels below to each term in the equation: m is labeled "Ideal" speaker supervector; Vy is labeled Speaker-independent component; Ux is labeled Speaker-dependent component; and Dz is labeled Channel-dependent component. A separate arrow points from the label "Speaker-dependent residual component" to the entire equation.

- JFA的初衷是移除说话人均值超矢量在本征信道空间的影响，让 y （说话人空间）具有很好的抗信道失配能力
- 但，信道条件本身很难用数学公式来明确界定它，导致可能 x （信道空间）包含说话人信息
- 论文[2]中，也证明了信道因子包含了说话人信息。
- 且，JFA因子分析训练语料要求高，计算复杂

I-vector based GMM

- An i-vector system uses a set of low-dimensional total variability factors (w) to represent each conversation side. Each factor controls an eigen-dimension of the total variability matrix (T), and are known as the i-vectors.

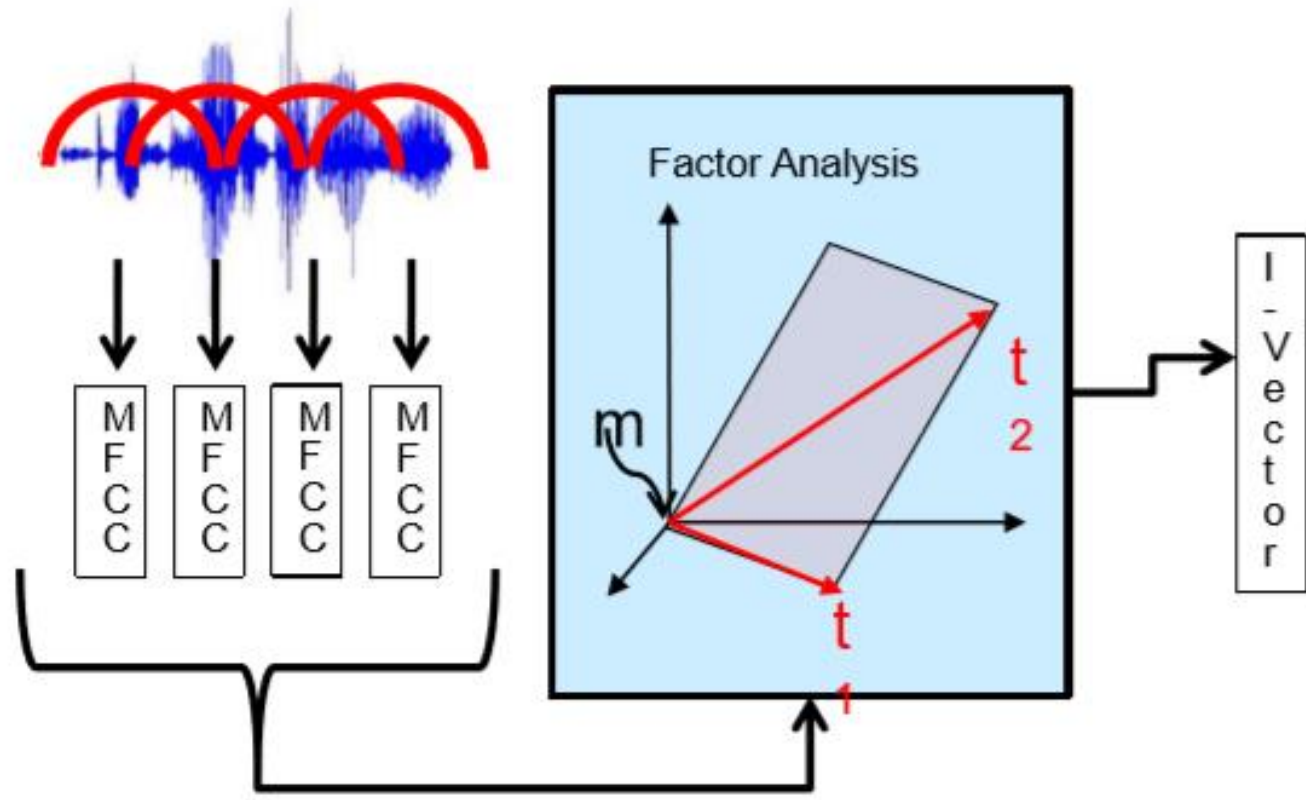
$$s = m + Tw$$

The diagram illustrates the equation $s = m + Tw$. Three arrows point from labels below to the variables in the equation: one from 'Conversation side supervector' to s , one from 'Total-variability matrix' to T , and one from 'i-vector' to w .

Conversation side supervector

Total-variability matrix

i-vector



- 计算流程

- 1. 计算Baum-Welch统计量:

$$N_c = \sum_{t=1}^L P(c|y_t, \Omega)$$

$$F_c = \sum_{t=1}^L P(c|y_t, \Omega) y_t,$$

- 在Baum-Welch统计量中，定义一阶统计量

$$\tilde{F}_c = \sum_{t=1}^L P(c|y_t, \Omega) (y_t - m_c),$$

- 2. EM算法: **T**

- E步:

- 计算隐变量 \mathbf{w} 的后验分布

- $p(\mathbf{w}|\mathcal{X}) = \mathcal{N}(\mathbf{w}|\mathbf{L}^{-1}\mathbf{T}^T\boldsymbol{\Sigma}^{-1}\mathbf{F}, \mathbf{L}^{-1})$ 其中, $\mathbf{L} = \mathbf{I} + \mathbf{T}^T\boldsymbol{\Sigma}^{-1}\mathbf{N}\mathbf{T}$

- M步:

- 更新全局差异空间矩阵 \mathbf{T}

- 3. i-vector 提取: **w**

$$w = (I + T^t \Sigma^{-1} N(u) T)^{-1} \cdot T^t \Sigma^{-1} \tilde{F}(u).$$

I-vector based DNN

- 基本思想
 - 利用基于深度神经网络的语音识别模型DNN-ASR替换通过非监督聚类的高斯混合模型UBM。
- 特点
 - DNN能从大量样本中学习到高度抽象的音素特征，并对噪声有很强的免疫力。

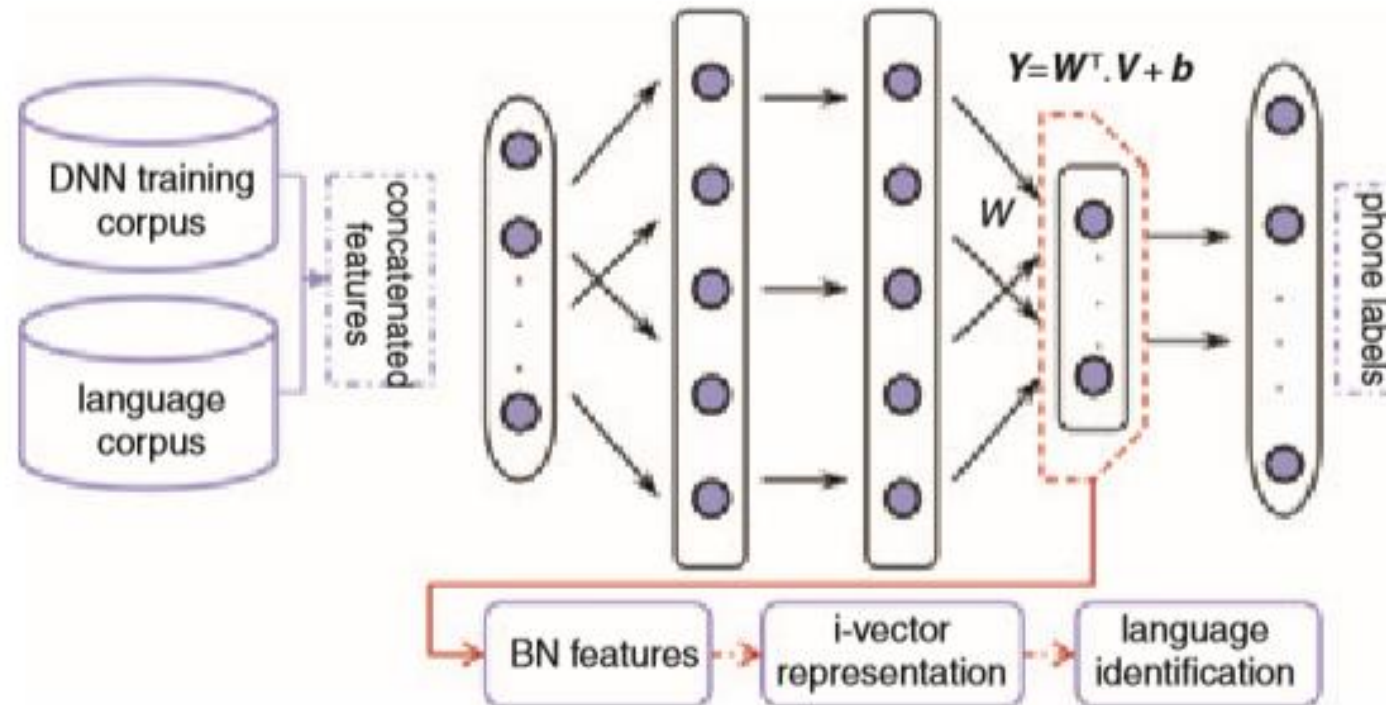


Fig 2 Proposed i-vector representation based on BN features for automatic LID [3]

Conclusion

- GMM i-vector & DNN i-vector不同
 - 用于计算充分统计量的后验概率不同
 - 训练方式不同
- I-vector 中T矩阵同时对说话人和信道两个空间建模， w 也带有信道信息，所以后续应做i-vector的信道补偿工作
 - 在[1]中提到的有3种（1）类内协方差归一化WCCN（2）线性判别分析LDA（3）扰动属性投影 NAP
 - 之后，PLDA

Reference

- [1] Front-End Factor Analysis for Speaker Verification
- [2] Discriminative and generative approaches for long and shortterm speaker characteristic modeling application to speaker verification
- [3] i-vector representation based on bottleneck features for language identification