13.0 Speaker Variabilities: Adaption and Recognition

References:

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4. Jolliffe, " Principal Component Analysis ", Springer-Verlag, 1986
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7. " A Compact Model for Speaker-adaptive Training", International Conference on Spoken Language Processing, 1996
8. " A Tutorial on Text-independent Speaker Verification", EURASIP Journal on Applied Signal Processing 2004
9. "An Overview of Text-independent Speaker Recognition: from Features to Supervectors", Speech Communication, Jan 2010
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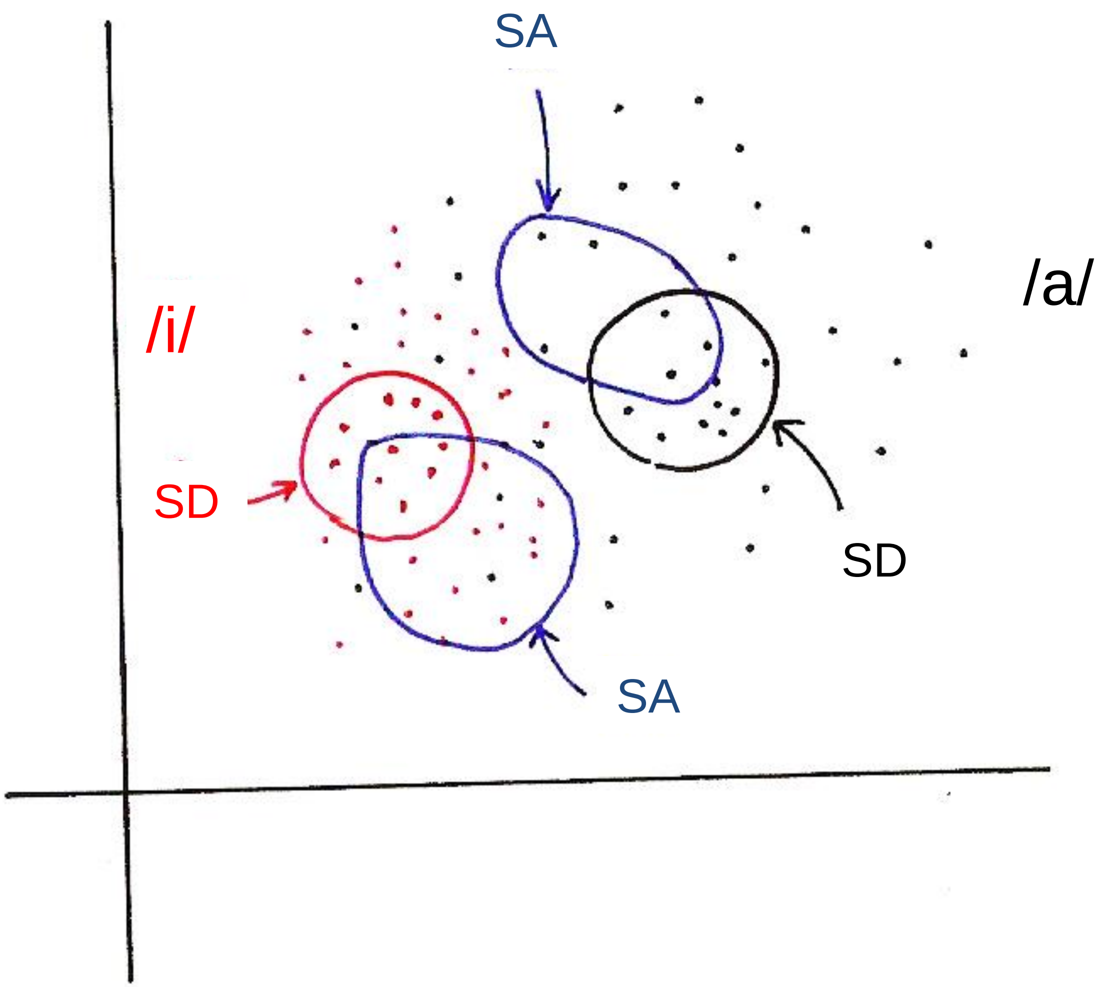
Speaker Dependent/Independent/Adaptation

- **Speaker Dependent (SD)**
  - trained with and used for 1 speaker only, requiring huge quantity of training data, best accuracy
  - practically infeasible
- **Multi-speaker**
  - trained for a (small) group of speakers
- **Speaker Independent (SI)**
  - trained from large number of speakers, each speaker with limited quantity of data
  - good for all speakers, but with relatively lower accuracy
- **Speaker Adaptation (SA)**
  - started with speaker independent models, adapted to a specific user with limited quantity of data (adaptation data)
  - technically achievable and practically feasible
- **Supervised/Unsupervised Adaptation**
  - supervised: text (transcription) of the adaptation data is known
  - unsupervised: text (transcription) of the adaptation data is unknown, based on recognition results with speaker-independent models, may be performed iteratively
- **Batch/Incremental/On-line Adaptation**
  - batch: based on a whole set of adaptation data
  - incremental/on-line: adapted step-by-step with iterative re-estimation of models

    e.g. first adapted based on first 3 utterances, then adapted based on next 3 utterances or first 6 utterances,...

Speaker Dependent/Independent/Adaptation



MAP (Maximum A Posteriori) Adaptation

- **Given Speaker-independent Model set $\Lambda=\{\lambda_i=(A_i, B_i, \pi_i), i=1, 2,...M\}$ and A set of Adaptation Data $\overline{O} = (o_1, o_2,...o_t,...o_T)$ for A Specific Speaker**

$$\Lambda^* = \arg\max_{\Lambda} \text{Prob}[\Lambda|\overline{O}] = \arg\max_{\Lambda} \frac{\text{Prob}[\overline{O}|\Lambda]\text{Prob}[\Lambda]}{\text{Prob}[\overline{O}]} = \arg\max_{\Lambda} \text{Prob}[\overline{O}|\Lambda]\text{Prob}[\Lambda]$$

- **With Some Assumptions on the Prior Knowledge Prob [Λ] and some Derivation (EM Theory)**
  - example adaptation formula

$$\mu_{jk}^* = \frac{\tau_{jk}\mu_{jk} + \Sigma_{t=1}^{T}[\gamma_t(j,k)o_t]}{\tau_{jk} + \Sigma_{t=1}^{T}\gamma_t(j,k)}$$

μ_{jk} : mean of the k-th Gaussian in the j-th state for a certain λ_i

μ_{jk}^* : adapted value of μ_{jk}

$$\gamma_t(j,k) = [\frac{\alpha_t(j)\beta_t(j)}{\Sigma_{j=1}^{N}\alpha_t(j)\beta_t(j)}][\frac{c_{jk}N(o_t;\mu_{jk},U_{jk})}{\Sigma_{m=1}^{L}c_{jm}N(o_t;\mu_{jm},U_{jm})}]$$

↑

$$\gamma_t(j) = P(q_t = j|\overline{O},\lambda_i)$$

τ_{jk}: a parameter having to do with the prior knowledge about μ_{jk}

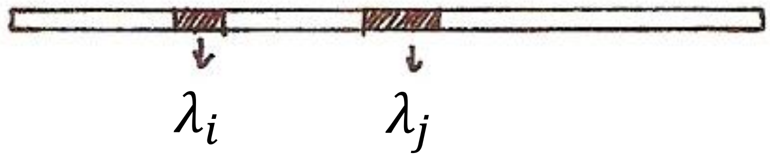
may have to do with number of samples used to train μ_{jk}

  - a weighted sum shifting μ_{jk} towards those directions of o_t (in j-th state and k-th Gaussian)

    larger τ_{jk} implies less shift

- **Only Those Models with Adaptation Data will be Modified, Unseen Models remain Unchanged — MAP Principle**
  - good with larger quantity of adaptation data
  - poor performance with limited quantity of adaptation data

MAP Adaptation



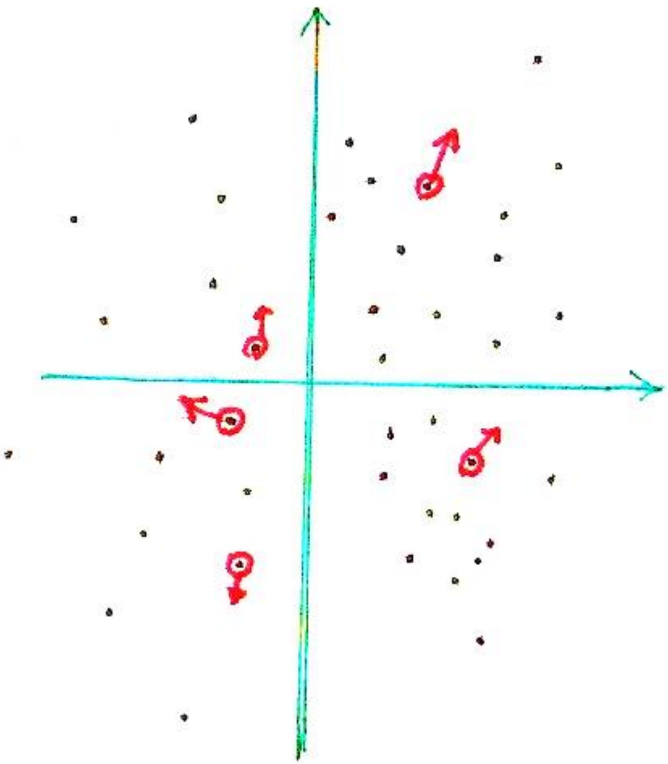
$$\frac{a\vec{v} + b\vec{o}}{a + b} = \lambda\vec{v} + (1 - \lambda)\vec{o}$$

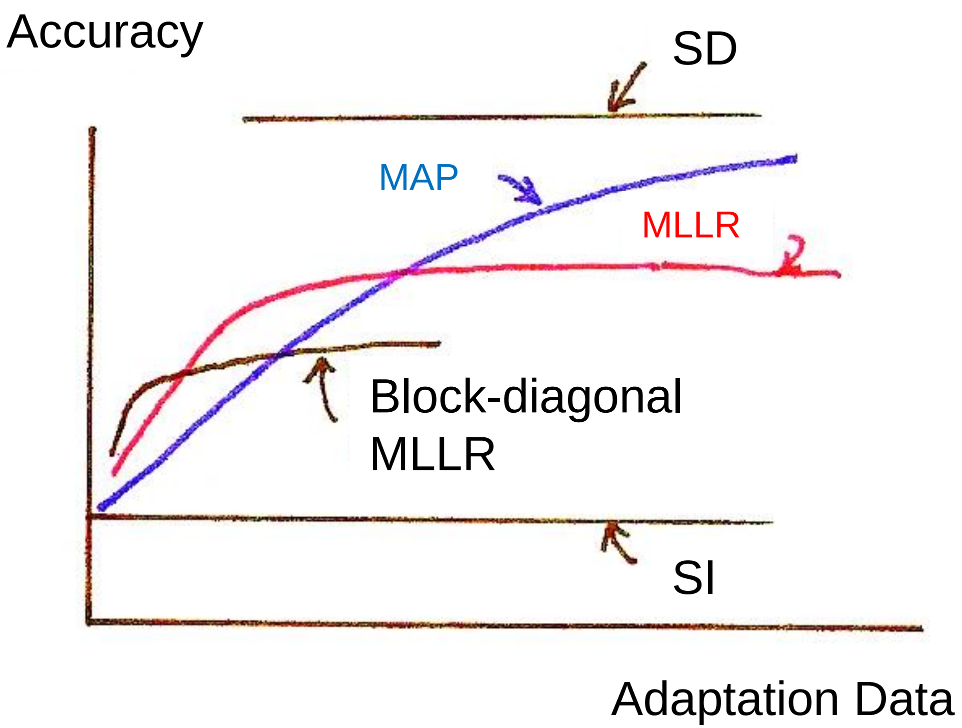
$$\Rightarrow \frac{a\vec{v} + (\sum_i b_i)\vec{o}}{a + (\sum_i b_i)}$$

$$\Downarrow$$

$$\frac{a\vec{v} + (\sum_t b_t \vec{o}_t)}{a + (\sum_t b_t)}$$

MAP Adaptation





Maximum Likelihood Linear Regression (MLLR)

- **Divide the Gaussians (or Models) into Classes C_1, C_2,...C_L, and Define Transformation-based Adaptation for each Class**

$$\mu^*_{jk} = A\,\mu_{jk} + b \qquad , \ \mu_{jk} : \text{mean of the k-th Gaussian in the j-th state}$$

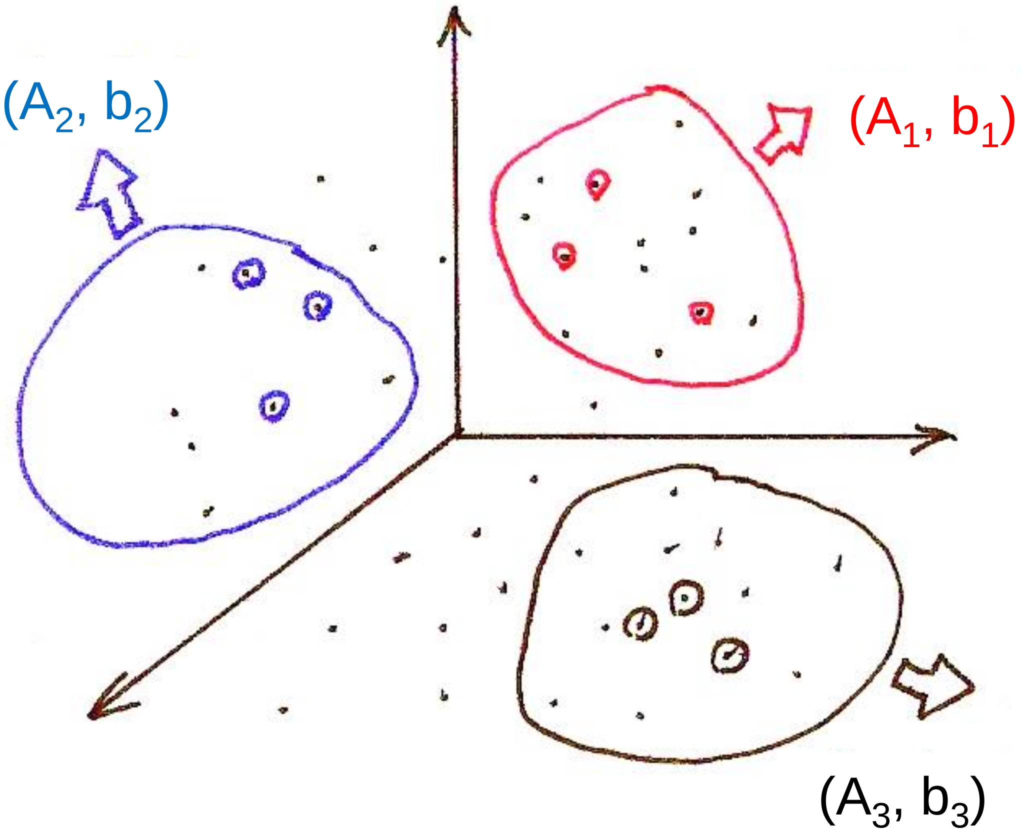
  - linear regression with parameters A, b estimated by maximum likelihood criterion

$$[A_i, b_i] = \underset{A,b}{\arg\max}\ \text{Prob}[\overline{O} \mid \Lambda, A_i, b_i] \ \text{ for a class } C_i$$

$$A_i, b_i \ \text{ estimated by EM algorithm}$$

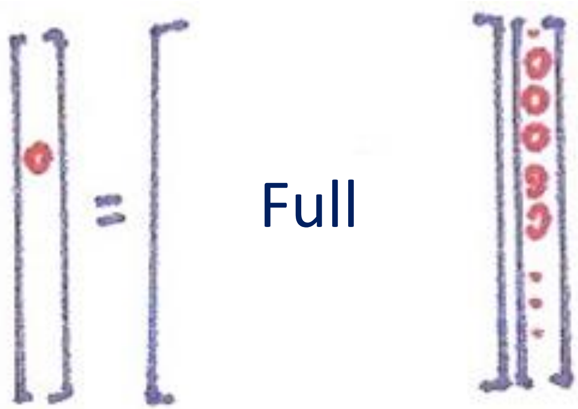
  - All Gaussians in the same class updated with the same A_i, b_i: parameter sharing, adaptation data sharing
  - unseen Gaussians (or models) can be adapted as well
  - A_i can be full matrices, or reduced to diagonal or block-diagonal to have less parameters to be estimated
  - faster adaptation with much less adaptation data needed, but saturated at lower accuracy with more adaptation data due to the less precise modeling
- **Clustering the Gaussians (or Models) into L Classes**
  - too many classes requires more adaptation data, too less classes becomes less accurate
  - basic principle: Gaussian (or models) with similar properties and “ just enough” data form a class
  - data-driven (e.g. by Gaussian distances) primarily, knowledge driven helpful
- **Tree-structured Classes**
  - the node including minimum number of Gaussians (or models) but with adequate adaptation data is a class
  - dynamically adjusting the classes as more adaptation data are observed
- **Feature-based MLLR (fMLLR)**

MLLR

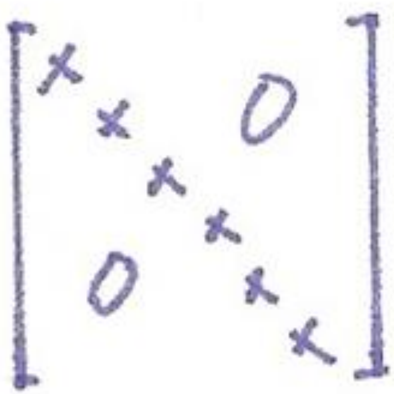


MLLR

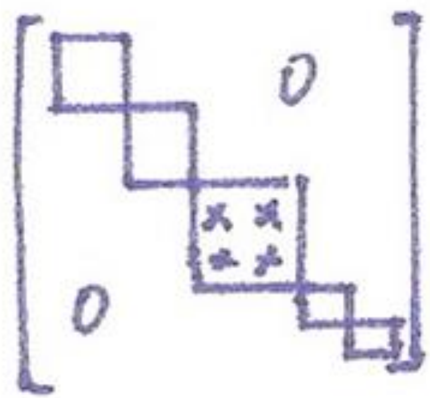
$$\vec{y} = A\vec{x}$$



Full

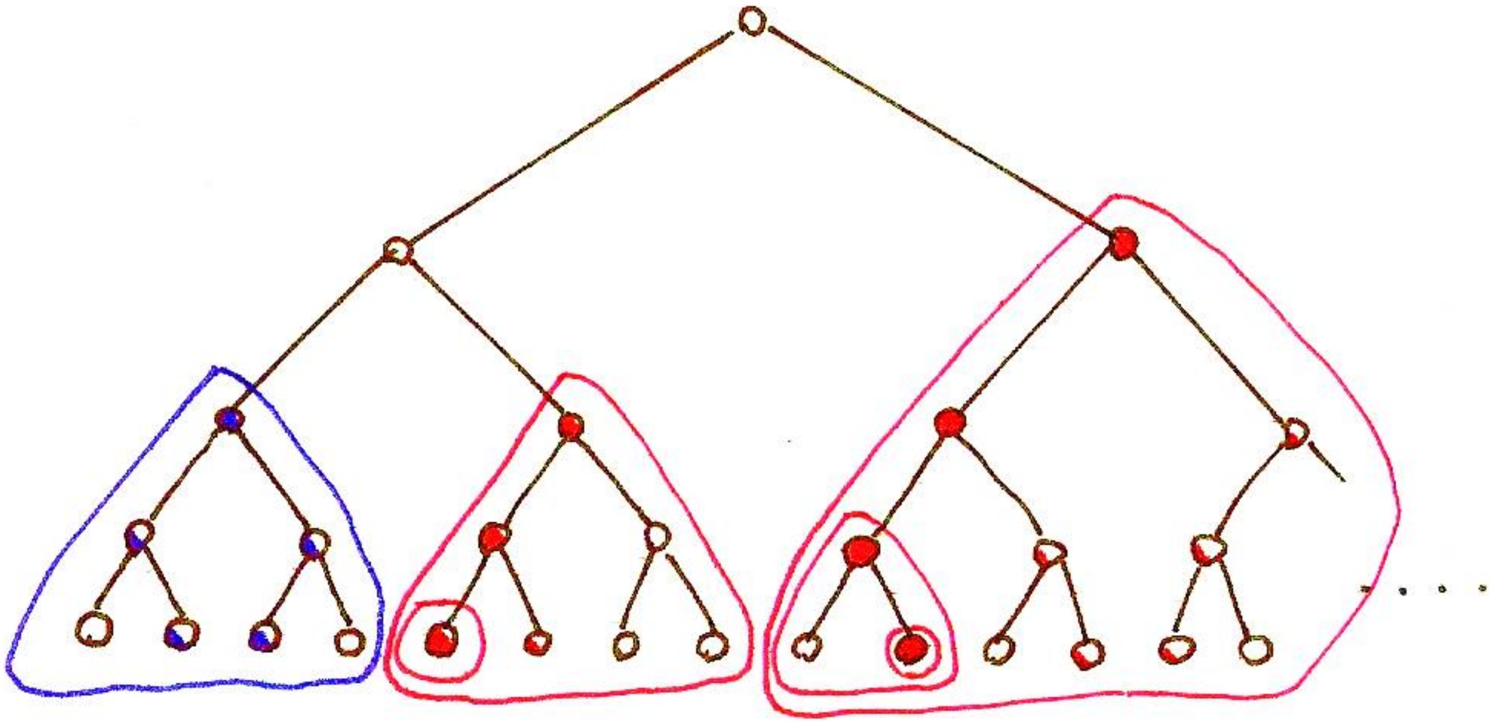


Diagonal



Block-diagonal

MLLR



Principal Component Analysis (PCA)

- **Problem Definition:**
  - for a zero mean random vector $\boldsymbol{x}$ with dimensionality $\boldsymbol{N}$, $x \in R^N$, $E(x)=0$, iteratively find a set of k ($k \leq N$) orthonormal basis vectors $\{\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots, \boldsymbol{e}_k\}$ so that
    (1) $var(\boldsymbol{e}_1^T \boldsymbol{x})=max$ *(x has maximum variance when projected on* e_1 *)*
    (2) $var(\boldsymbol{e}_i^T \boldsymbol{x})=max$, subject to $\boldsymbol{e}_i \perp \boldsymbol{e}_{i-1} \perp \ldots\ldots \perp \boldsymbol{e}_1$, $2 \leq i \leq k$
    (x has next maximum variance when projected on e_2 *, etc.)*
- **Solution: $\{\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots, \boldsymbol{e}_k\}$ are the eigenvectors of the covariance matrix Σ for x corresponding to the largest k eigenvalues**
  - new random vector $\boldsymbol{y} \in \boldsymbol{R}^k$: the projection of x onto the subspace spanned by $\boldsymbol{A}=[\boldsymbol{e}_1\ \boldsymbol{e}_2 \ldots\ldots \boldsymbol{e}_k]$, $\boldsymbol{y}=\boldsymbol{A}^T\boldsymbol{x}$
  - a subspace with dimensionality $k \leq N$ such that when projected onto this subspace, y is "closest" to x in terms of its "randomness" for a given k
  - $var(e_i^T x)$ is the eigenvalue associated with e_i
- **Proof**
  - $var(e_1^T x) = e_1^T E(x x^T) e_1 = e_1^T \Sigma e_1 = max$, subject to $|e_1|^2=1$
  - using Lagrange multiplier

$$J(e_1)= e_1^T E(x x^T)e_1 - \lambda(|e_1|^2-1) \ , \quad \frac{\partial J(e_1)}{\partial e_1} = 0$$

$$\Rightarrow E(xx^T)\, e_1 = \lambda_1 e_1 \, , \ var(e_1^T x) = \lambda_1 = max$$

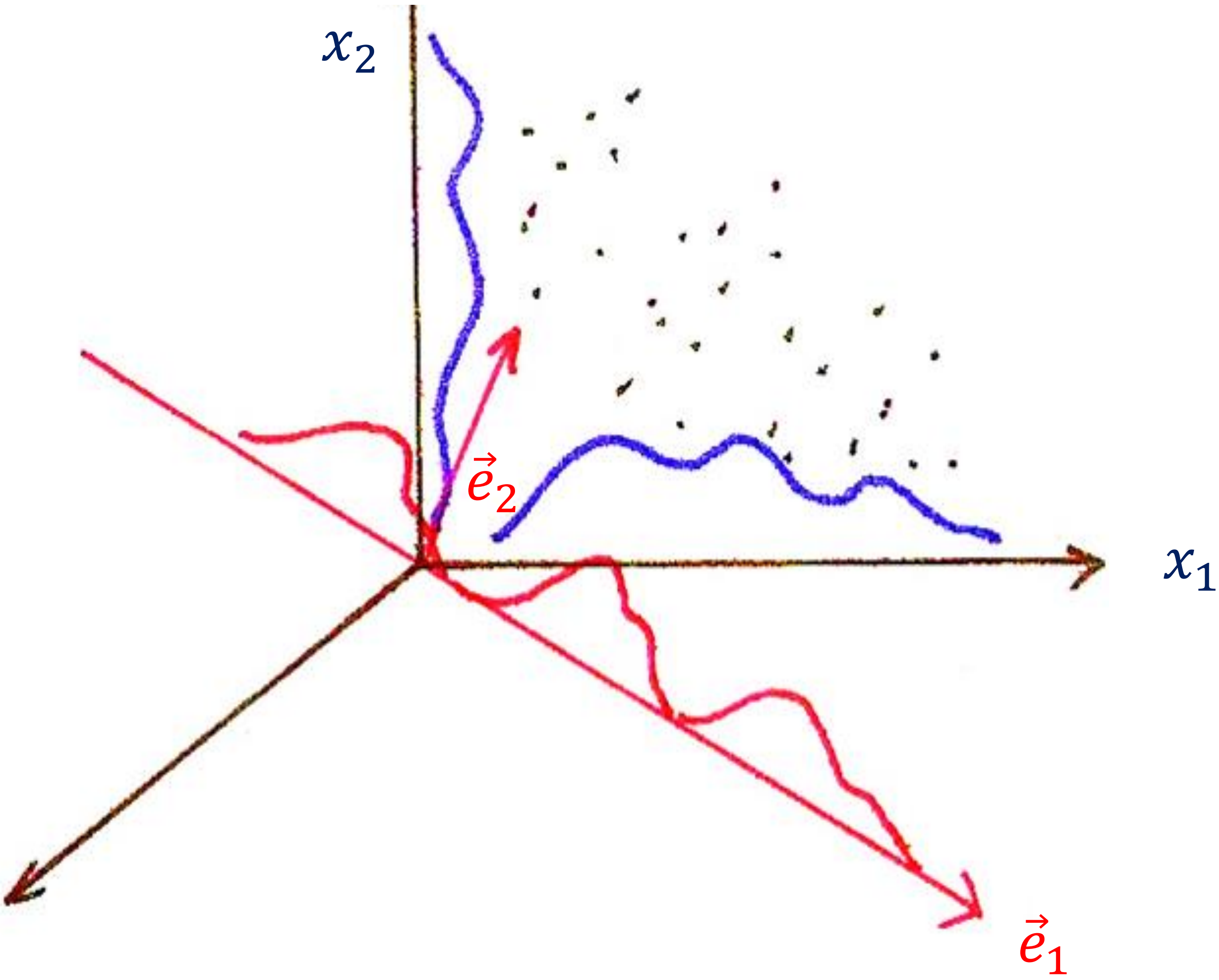
  - similar for e_2 with an extra constraint $e_2^T e_1 = 0$, etc.

$$A\upsilon = u$$

$$A\upsilon = \lambda\upsilon$$

eigenvector eigenvalue

PCA



PCA

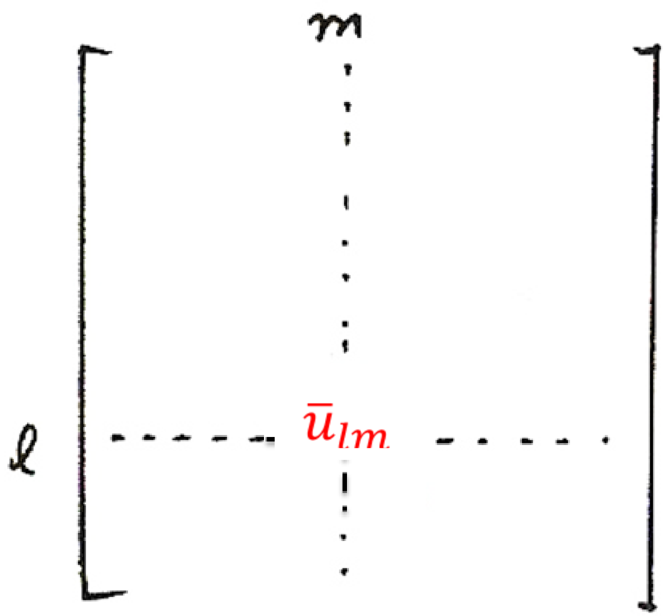
$$\begin{bmatrix}\cdots & e_{1k}^T & \cdots\end{bmatrix}\begin{bmatrix}\vdots \\ x_k \\ \vdots\end{bmatrix} = \vec{e}_1 \cdot \vec{x}$$

$$= \underbrace{|\vec{e}_1|}_{\substack{\parallel \\ 1}}|\vec{x}| \cos\theta$$

$$\vec{y} = A^T\vec{x} = \begin{bmatrix}\overrightarrow{e}_1^T \\ \overrightarrow{e}_2^T \\ \vdots \\ \overrightarrow{e}_k^T\end{bmatrix}\vec{x}$$

Basic Problem 3 (P.35 of 4.0)

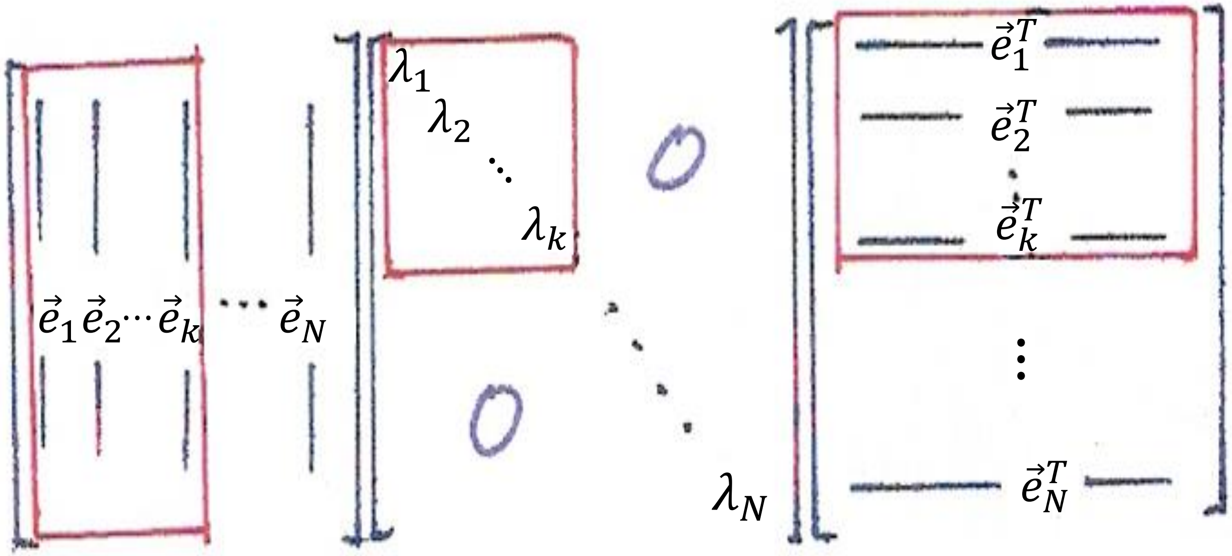
$\bar{U} =$



$$= E\left(\begin{bmatrix} x_1 - \bar{x}_1 \\ x_2 - \bar{x}_2 \\ \vdots \\ \vdots \end{bmatrix} [x_1 - \bar{x}_1, x_2 - \bar{x}_2, \cdots]\right)$$

$$\bar{u}_{lm} = E[(x_l - \bar{x}_l)(x_m - \bar{x}_m)]$$

PCA



$$\approx \Sigma$$

$$= \Sigma$$

$$= E[x\, x^T]$$

$$= E[(x-\overline{x})(x-\overline{x})^T]$$

$$\sum \vec{e}_i = \lambda_i \, \vec{e}_i$$

eigenvector — eigenvalue

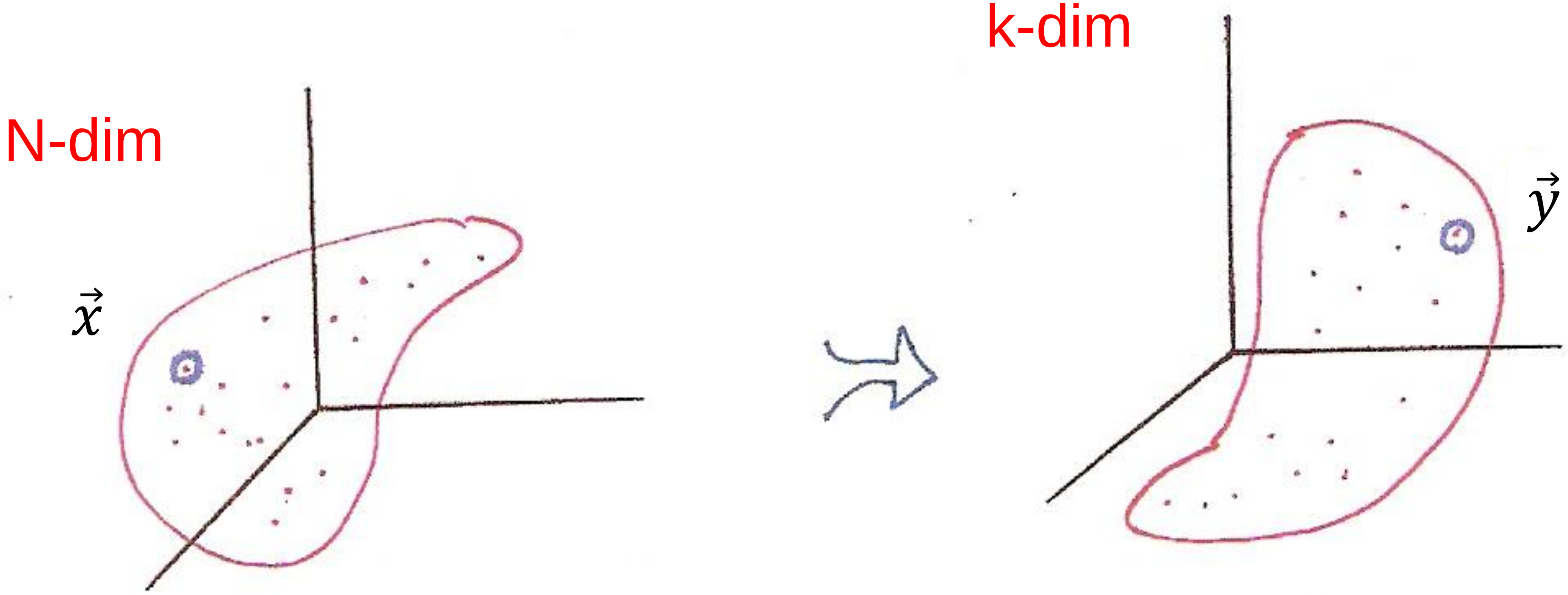
$$Av = u$$

$$Av = \lambda v$$

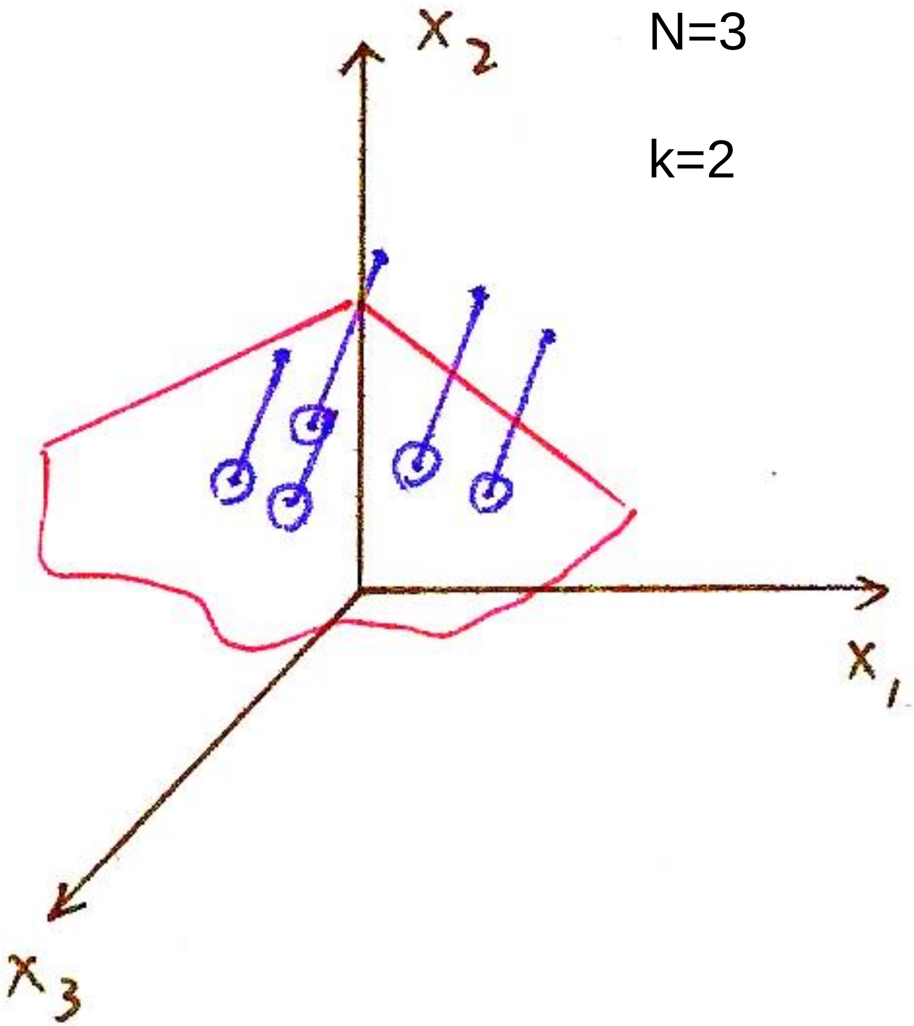
eigenvector eigenvalue

PCA

$$\vec{y} = A^T \vec{x}$$



PCA



N=3

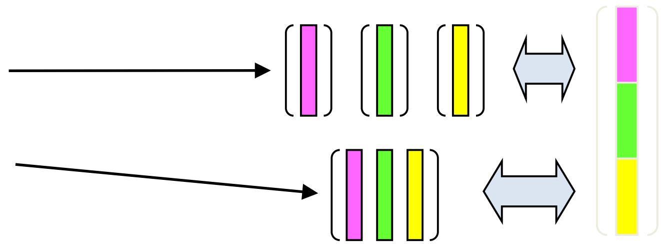
k=2

Eigenvoice

- **A Supervector x constructed by concatenating all relevant parameters for the speaker specific model of a training speaker**
  - concatenating the mean vectors of Gaussians in the speaker-dependent phone models
  - concatenating the columns of A, b in MLLR approach
  - x has dimensionality N (N = 5,000 × 3 × 8 × 40 = 4,800,000 for example)

  ·SD model mean parameters (*m*)

  ·transformation parameters (A, b)



- **A total of L (L = 1,000 for example) training speakers gives L supervectors $\mathbf{x}_1,\mathbf{x}_2,\ldots\mathbf{x}_L$**
  - $x_1, x_2, x_3 \ldots\ldots x_L$ are samples of the random vector x
  - each training speaker is a point (or vector) in the space of dimensionality N
- **Principal Component Analysis (PCA)**
  - $x' = x - E(x)$, $\Sigma = E(x' x'^T)$,

    $\Sigma \approx [e_1, e_2 \ldots. e_K][\lambda_i][e_1, e_2 \ldots. e_k]^T$,$[\lambda_i]$: diagonal with λ_i as elements

    $\{\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots\ldots \boldsymbol{e}_k\}$: eigenvectors with maximum eigenvalues $\lambda_1 > \lambda_2 \ldots > \lambda_k$

    k is chosen such that λ_j, j>k is small enough (k=250 or 50 for example)

Eigenvoice

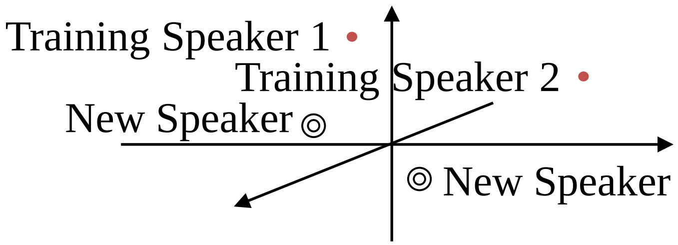
- **Principal Component Analysis (PCA)**
  - $x' = x - E(x)$, $\Sigma = E(x' x'^T)$,

    $\Sigma \approx [e_1, e_2 .... e_K][\lambda_i][e_1, e_2 .... e_k]^T$, $[\lambda_i]$: diagonal with λ_i as elements

    $\{\boldsymbol{e}_1, \boldsymbol{e}_2, ... \boldsymbol{e}_k\}$: eigenvectors with maximum eigenvalues $\lambda_1 > \lambda_2 ... > \lambda_k$

    k is chosen such that λ_j, j>k is small enough (k=50 for example)
- **Eigenvoice Space: spanned by $\{\boldsymbol{e}_1, \boldsymbol{e}_2, ... \boldsymbol{e}_k\}$**
  - each point (or vector) in this space represents a whole set of tri-phone model parameters
  - $\{\boldsymbol{e}_1, \boldsymbol{e}_2, ... \boldsymbol{e}_k\}$ represents the most important characteristics of speakers extracted from huge quantity of training data by large number of training speakers
  - each new speaker as a point (or vector) in this space, $y = \sum_{i=1}^{k} a_i e_i$
  - a_i estimated by maximum likelihood principle (EM algorithm)

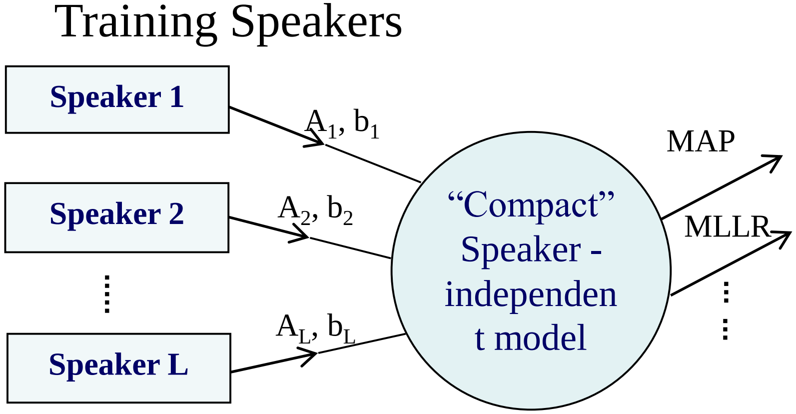
    $\bar{a}^* = \arg\max_{\bar{a}} \text{Prob}[\bar{O} \mid \sum_{i=1}^{k} a_i e_i]$



- **Features and Limitations**
  - only a small number of parameters $a_1 ... a_k$ is needed to specify the characteristics of a new speaker
  - rapid adaptation requiring only very limited quantity of training data
  - performance saturated at lower accuracy (because too few free parameters)
  - high computation/memory/training data requirements

Speaker Adaptive Training (SAT) and Cluster Adaptive Training (CAT)

- **Speaker Adaptive Training (SAT)**
  - trying to decompose the phonetic variation and speaker variation
  - removing the speaker variation among training speakers as much as possible
  - obtaining a "compact" speaker-independent model for further adaptation
  - y=Ax+b in MLLR can be used in removing the speaker variation
- **Clustering Adaptive Training (CAT)**
  - dividing training speakers into R clusters by speaker clustering techniques
  - obtaining mean models for all clusters(may include a mean-bias for the "compact" model in SAT)
  - models for a new speaker is interpolated from the mean vectors
- **Speaker Adaptive Training (SAT)**

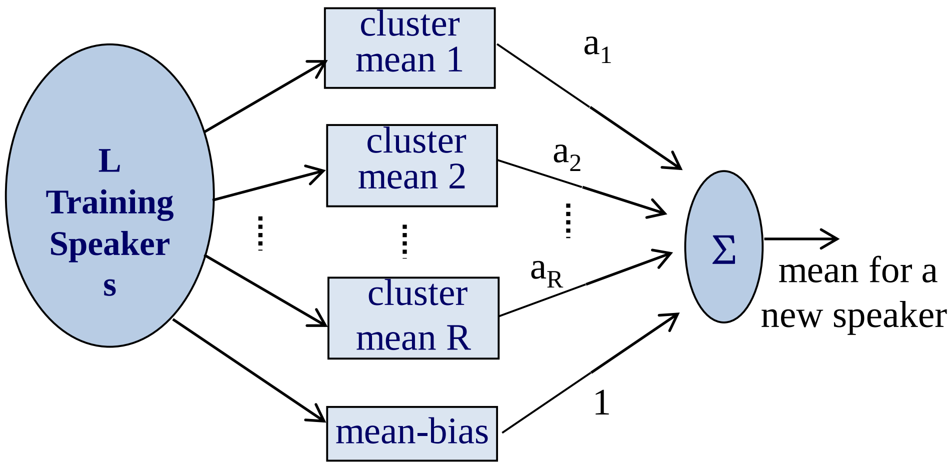


Original SI : $\Lambda^* = \arg\max_{\Lambda} \text{Prob}(\bar{o}_{1,2\ldots L} | \Lambda)$

SAT : $[\Lambda_c^*, (A,b)_{1,\ldots L}^*] = \arg\max_{\Lambda_c, (A,b)_{1,\ldots L}} \text{Prob}(\bar{o}_{1,2\ldots L} | \Lambda_c, (A,b)_{1,\ldots L})$

EM algorithm used

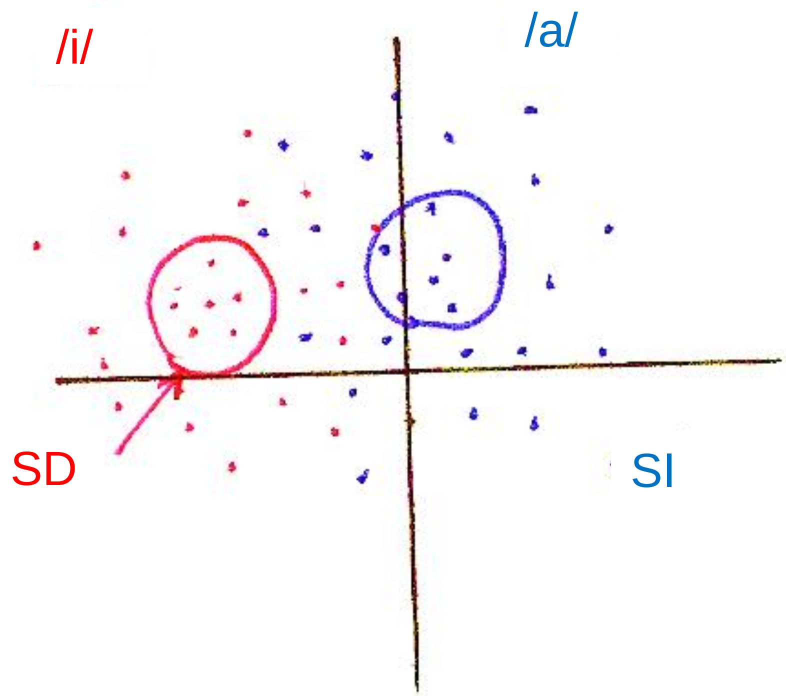
- **Cluster Adaptive Training (CAT)**



$m^* = \sum_{i=1}^{R} a_i m_i + m_b$, m_i: cluster mean i, m_b: mean-bias

a_i estimated with maximum likelihood criterion

SAT



$$\vec{y} = A\vec{x} + \vec{b}$$

$$\vec{x} = A^{-1}\,\vec{y} - A^{-1}\vec{b}$$

Speaker Recognition/Verification

- **To recognize the speakers rather than the content of the speech**
  - phonetic variation/speaker variation
  - speaker identification: to identify the speaker from a group of speakers
  - speaker verification: to verify if the speaker is as claimed
- **Gaussian Mixture Model (GMM)**

  $\lambda_i=\{(w_j, \mu_j, \Sigma_j,), j=1,2,...M\}$ for speaker i

  for $\overline{\mathrm{O}} = o_1 o_2 \ldots o_t \ldots o_T$, $\quad b_i(o_t) = \sum_{j=1}^{M} w_j N(o_t; \mu_j, \Sigma_j)$
  - maximum likelihood principle

  $$i^* = \arg\max_{\mathrm{i}} \mathrm{Prob}(\overline{\mathrm{O}} | \lambda_{\mathrm{i}})$$
- **Feature Parameters**
  - those carrying speaker characteristics preferred
  - MFCC
  - MLLR coefficients A_i, b_i, eigenvoice coefficients a_i, CAT coefficients a_i
- **Speaker Verification**
  - text dependent: higher accuracy but easily broken
  - text independent
  - likelihood ratio test

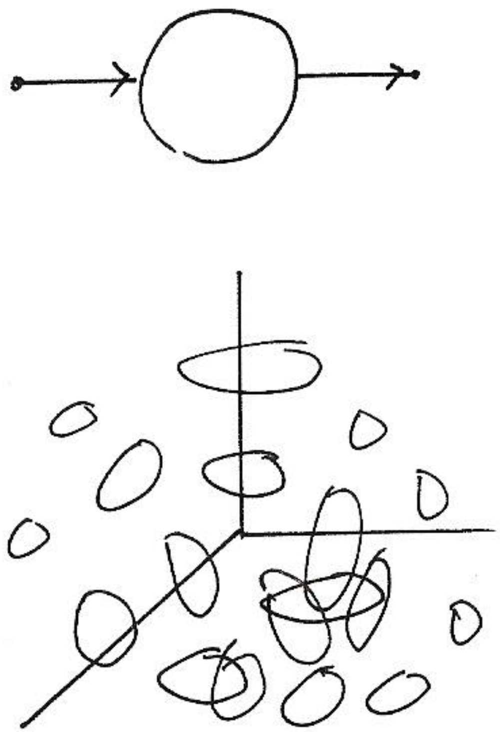
  $$\rho(\overline{\mathrm{O}}; \lambda_{\mathrm{i}}) = \frac{p(\overline{\mathrm{O}} | \lambda_{\mathrm{i}})}{p(\overline{\mathrm{O}} | \overline{\lambda}_{\mathrm{i}})} > th$$

  $\overline{\lambda}_{\mathrm{i}}$: background model or anti-model for speaker i, trained by other speakers, competing speakers, or speaker-independent model

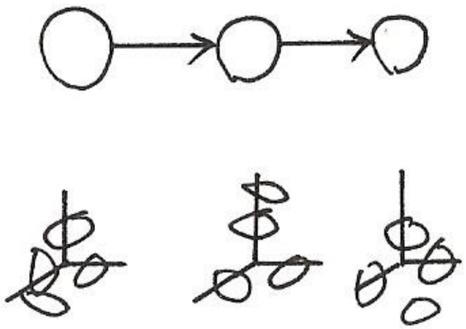
  th : threshold adjusted by balancing missing/false alarm rates and ROC curre
  - speech recognition based verification

Speaker Recognition

Gaussian Mixture Model (GMM)



HMM



Likelihood Ratio Test

- **Detection Theory— Hypothesis Testing/Likelihood Ratio Test**
  - 2 Hypotheses: H_0, H_1 with prior probabilities: $P(H_0)$,$P(H_1)$
    observation: X with probabilistic law: $P(X|H_0)$, $P(X|H_1)$
  - MAP principle

    choose H_0 if $P(H_0|X) > P(H_1|X)$
    choose H_1 if $P(H_1|X) > P(H_0|X)$

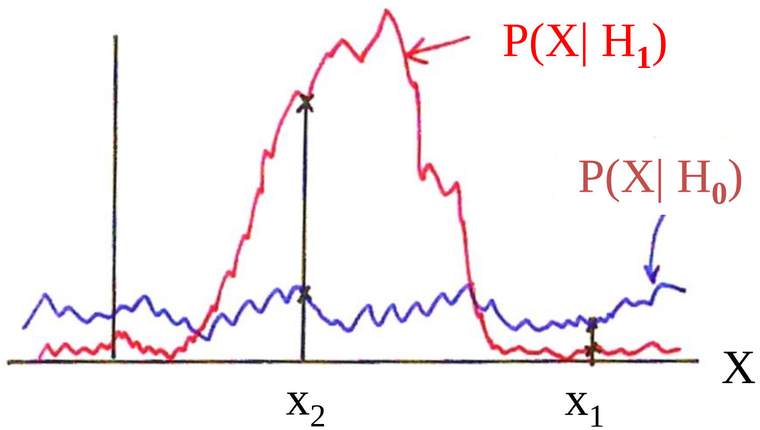
    $$\Rightarrow \frac{P(H_0|X)}{P(H_1|X)} \underset{H_1}{\overset{H_0}{\gtrless}} 1$$

  - Likelihood Ratio Test

    $P(H_i|X) = P(X|H_i)P(H_i)/P(X)$, i=0,1

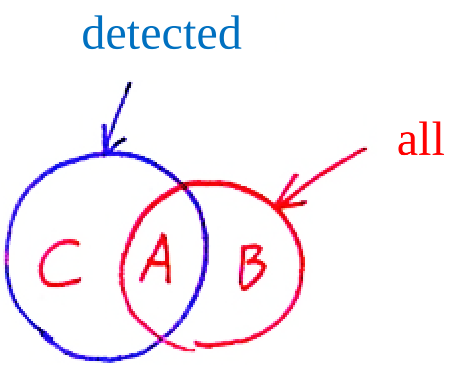
    $$\Rightarrow \frac{P(X|H_0)}{P(X|H_1)} \underset{H_1}{\overset{H_0}{\gtrless}} \frac{P(H_1)}{P(H_0)} = Th$$

    likelihood ratio-Likelihood Ratio Test



  - Type I error: missing (false rejection)
    Type II error: false alarm (false detection)
    false alarm rate, false rejection rate, detection rate, recall rate, precision rate
    Th: a threshold value adjusted by balancing among different performance rates

Receiver Operating Characteristics (ROC) Curve



$$\text{Missing rate} = \frac{B}{A+B} = 1 - \frac{A}{A+B}$$

recall

$$\text{False Alarm rate} = \frac{C}{A+C} = 1 - \frac{A}{A+C}$$

precision