Speaker Adaptation

Steve Renals

Automatic Speech Recognition— ASR Lecture 11
2 March 2008

Overview

Speaker Adaptation

- Introduction: speaker-specific variation, modes of adaptation
- Speaker normalization: VTLN
- Model-based adaptation: MAP
- Model-based adaptation: MLLR
- Model-based adaptation: Speaker space models

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- Speaker dependent (SD) systems can result in word error rates 2–3 times lower than SI systems (given the same amount of training data)
- Speaker adaptive (SA) systems... we would like
  - Error rates similar to SD systems
  - Building on an SI systems
  - Requiring only a small fraction of the speaker-specific training data used by an SD system

Speaker-specific variation

- Acoustic model
  - Speaking styles
  - Accents
  - Speech production anatomy (eg length of the vocal tract)

  Also non-speaker variation, such as channel conditions (telephone, reverberant room, close talking mic) and application domain

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  Speaker adaptation of acoustic models aims to reduce the mismatch between test data and the models
- Pronunciation model: speaker-specific, consistent change in pronunciation
- Language model: user-specific documents (exploited in personal dictation systems)

Modes of adaptation

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    - Supervised: the word level transcription of the adaptation data is known (and HMMs may be constructed)
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  - Unsupervised: the transcription must be estimated (eg using recognition output)
- Static or dynamic
  - Static: All adaptation data is presented to the system in a block before the final system is estimated (eg as used in enrollment in a dictation system)
  - Dynamic: Adaptation data is incrementally available, and models must be adapted before all adaptation data is available (eg as used in a spoken dialogue system)

Approaches to adaptation

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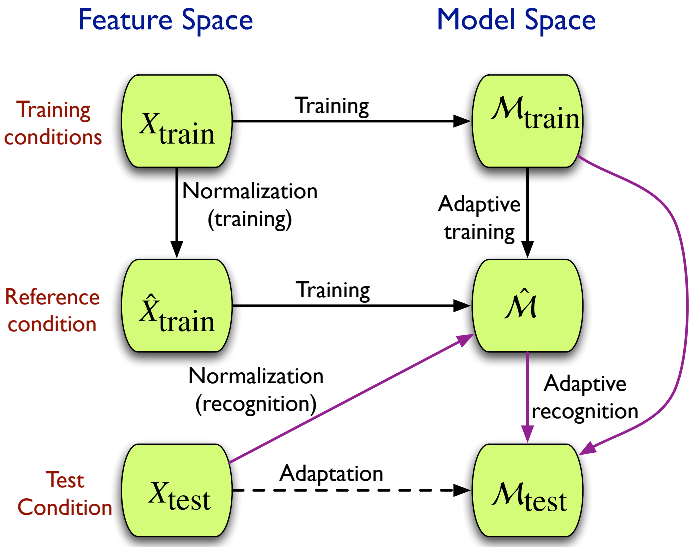
  - Maximum a posteriori (MAP) adaptation of HMM/GMM parameters
  - Maximum likelihood linear regression (MLLR) of Gaussian parameters
- Speaker space: Estimate multiple sets of acoustic models, characterizing new speakers in terms of these model sets
  - Cluster-adpative training
  - Eigenvoices

Adaptation and normalization of acoustic models



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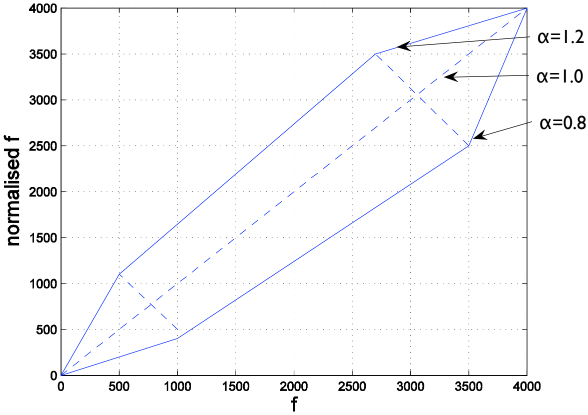
- VTLN: compensate for differences between speakers via a warping of the frequency axis

Approaches to VTLN

$$f \rightarrow \hat{f} = g_\alpha(f)$$

- Classify by frequency warping function
    - Piecewise linear

Warping functions: Piecewise linear



$$\hat{f} = \alpha f$$

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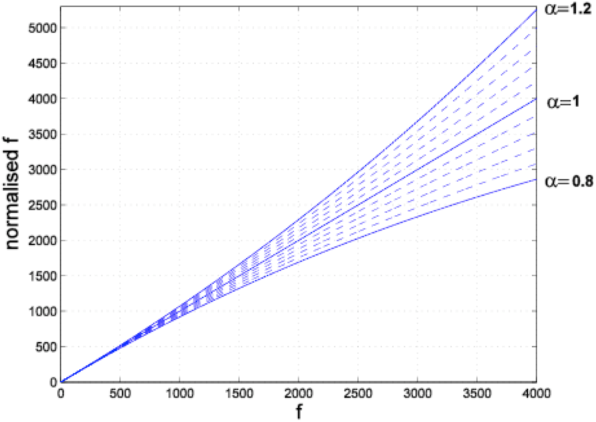

$$\hat{f} = \alpha^{3f/8000} f$$

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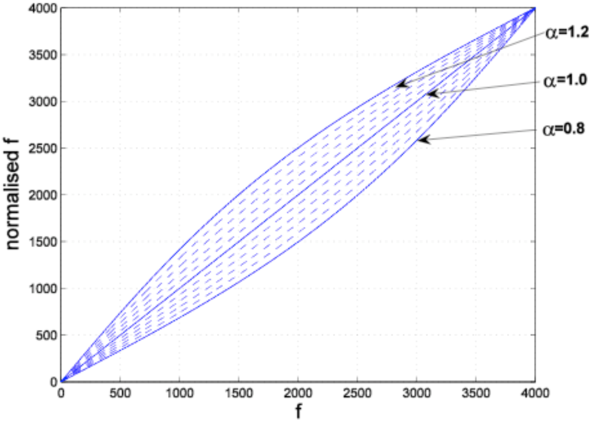

$$\hat{f} = f + \arctan \frac{(1-\alpha)\sin f}{1-(1-\alpha)\cos f}$$

Approaches to VTLN

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- Classify by frequency warping function
  - Piecewise linear
  - Power function
  - Bilinear transform
- Classify by estimation of warping factor α
  - Signal-based: estimated directly from the acoustic signal, through explicit estimation of formant positions
  - Model-based: maximize the likelihood of the observed data given acoustic models and a transcription. α is another parameter set so as to maximize the likelihood

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- These approaches require an accurate estimation of voiced parts of the speech signal

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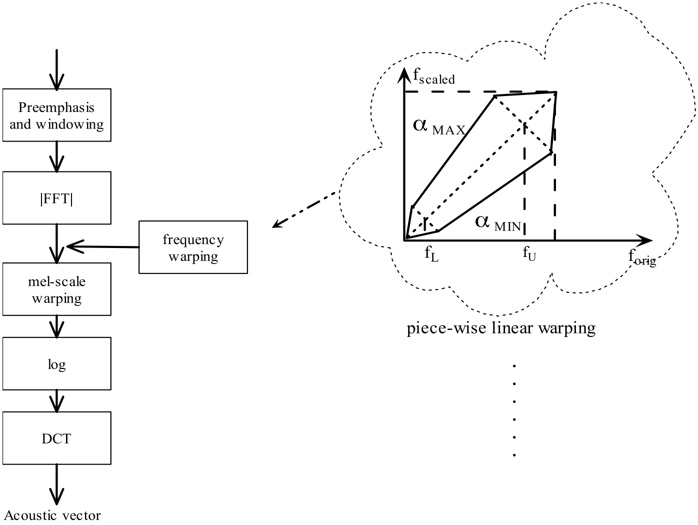
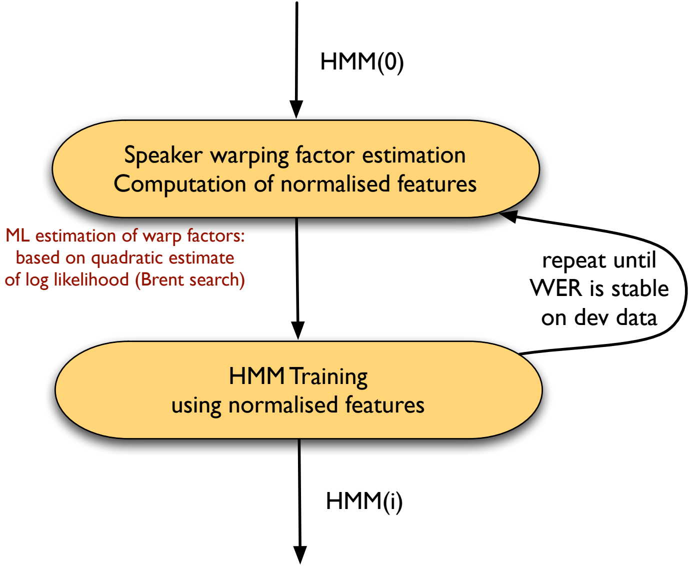
- Model-based VTLN does not directly estimate vocal tract size, rather it estimates an optimal frequency warping, which may be affected by other factors (eg $F0$)
- Exhaustive search for the optimal warping factor would be expensive
  - Approximate the log likelihood wrt α as a quadratic, and find the maximum using a line search (Brent's method)

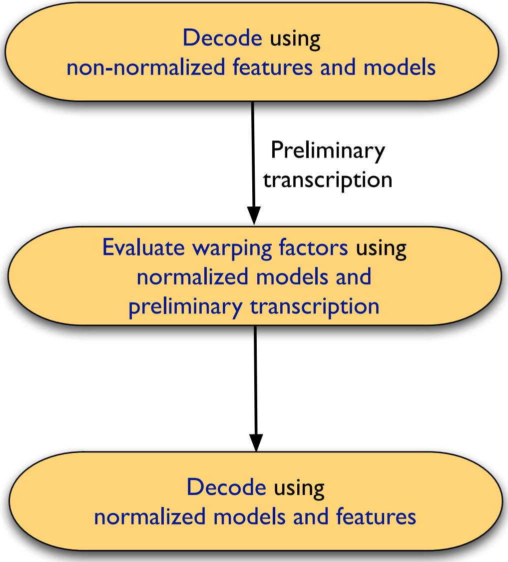
Model-based VTLN



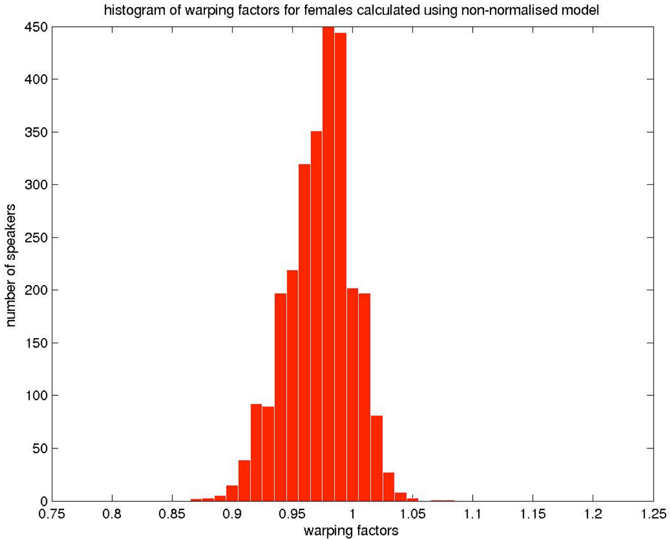
VTLN: Training



VTLN: Recognition



VTLN: Warp factor estimation, females, non-normalized



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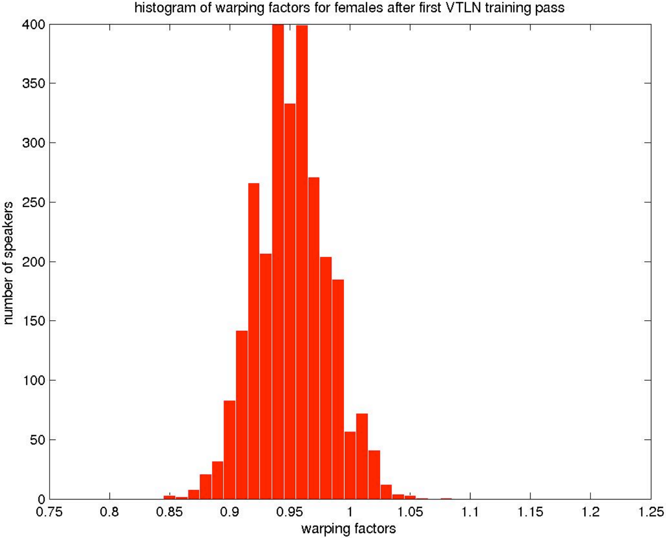
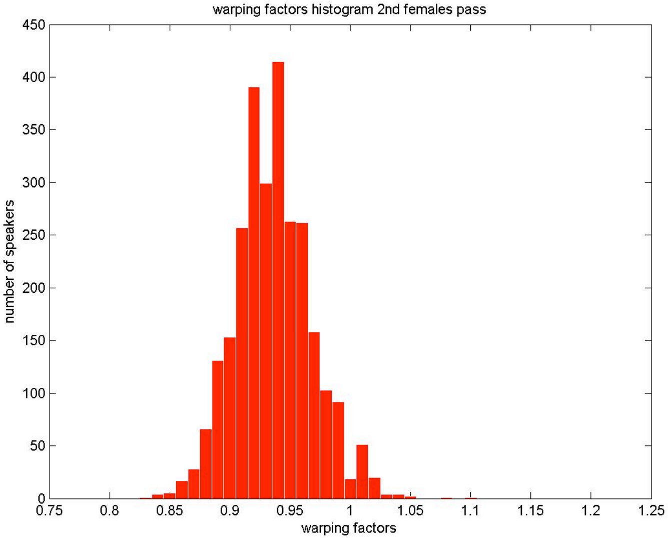
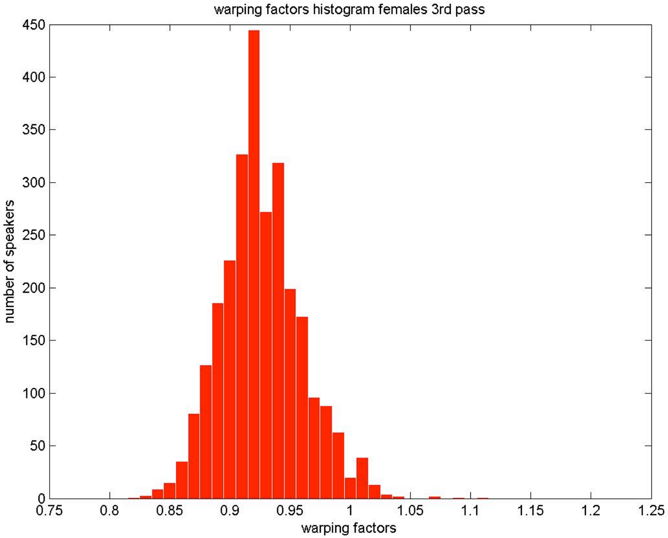


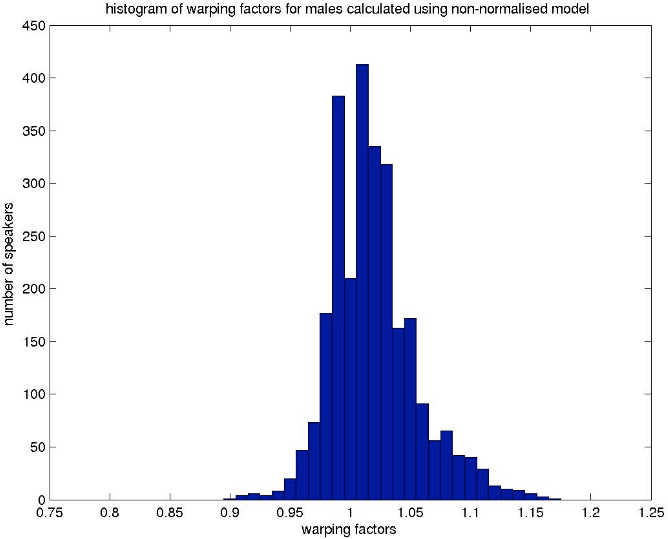
VTLN: Warp factor estimation, females, pass 2



VTLN: Warp factor estimation, females, pass 3



VTLN: Warp factor estimation, males, non-normalized



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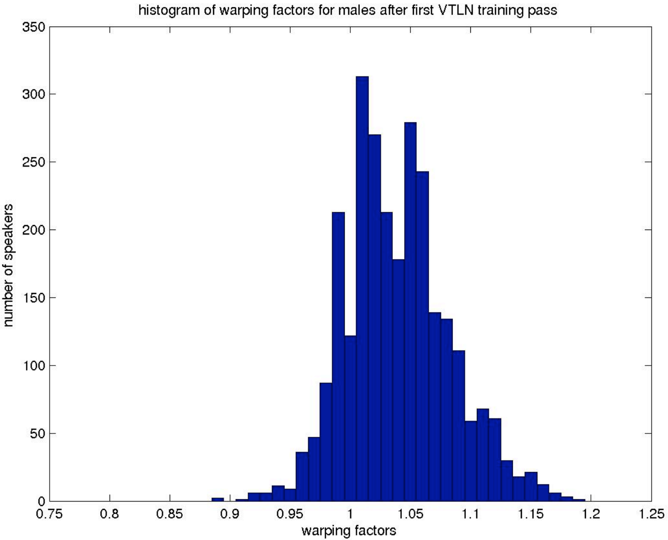

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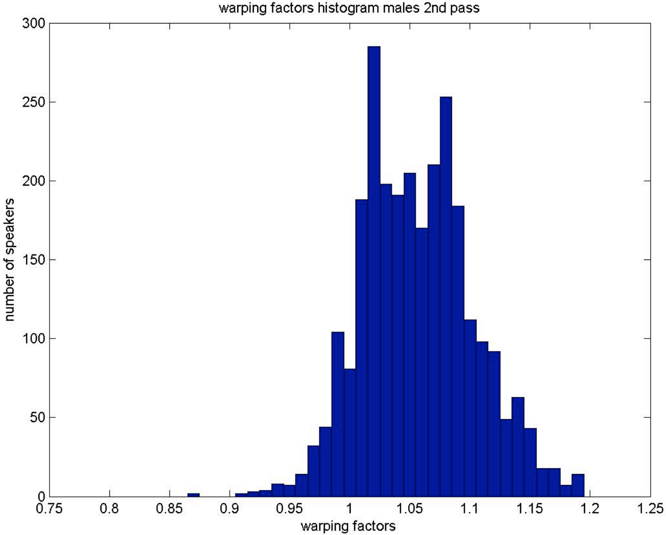

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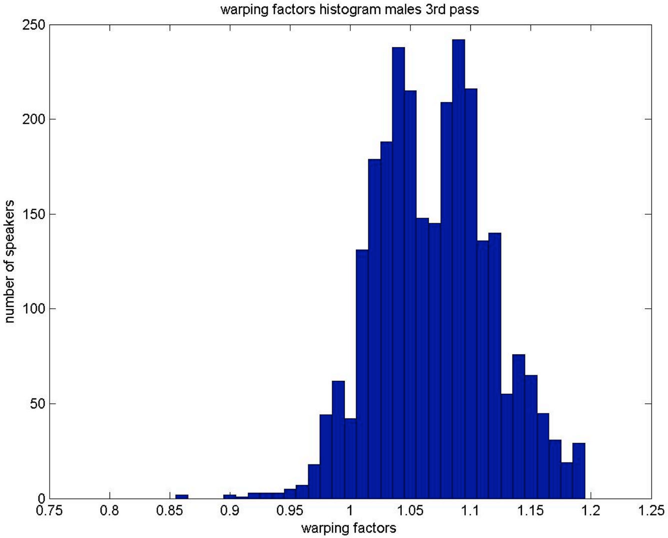

VTLN: WER (%) on conversational telephone speech

	Tot	Sub	Del	Ins	F	M
No adapt	37.2	24.2	8.8	4.2	36.7	37.6
Test only	36.4	23.6	8.5	4.3	36.1	36.7
1 pass	35.7	22.9	8.9	3.8	35.0	36.4
2 pass	35.0	22.5	8.8	3.7	34.2	35.8
3 pass	34.5	22.0	8.7	3.7	33.6	35.3
4 pass	34.2	22.0	8.6	3.6	33.3	35.1

- 7–10% relative decrease in WER is typical for VTLN
- VTLN removes the need for *gender-dependent* acoustic models

Interim Summary

- Speaker-specific variation
- Adaptation: supervised/unsupervised, static/dynamic
- Vocal tract length normalization (VTLN)
  - Warping functions
  - Signal based / model based
  - Online VTLN
- Next lecture: model-based adaptation

Speaker Adaptation 2

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Automatic Speech Recognition— ASR Lecture 12
9 March 2008

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- The use of a prior distribution, based on the SI models, means that less data is required to estimate the speaker-specific models: we are not starting from complete ignorance

Refresher: ML estimation of GMM/HMM

- The mean of the mth Gaussian component of the jth state is estimated using a weighted average

$$\boldsymbol{\mu}_{mj} = \frac{\sum_n \gamma_{jm}(n)\mathbf{x}_n}{\sum_n \gamma_{jm}(n)}$$

- Where $\sum_n \gamma_{jm}(n)$ is the component occupation probability
- The covariance of the Gaussian component is given by:

$$\boldsymbol{\Sigma}_{mj} = \frac{\sum_n \gamma_{jm}(n)(\mathbf{x}_n - \boldsymbol{\mu}_{jm})(\mathbf{x}_n - \boldsymbol{\mu}_{jm})^T}{\sum_n \gamma_{jm}(n)}$$

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  - $\mathbf{x}_n$ is the adaptation vector at time n
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- As the amount of training data increases, so the MAP estimate converges to the ML estimate

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  - Example: MAP adapting a conversational telephone speech system (100s of hours of data) to multiparty meetings (10s of hours of data) works well with MAP

SMAP: Structural MAP

- Basic idea share Gaussians by organizing them in a tree, whose root contains all the Gaussians
- At each node in the tree compute mean offset and diagonal variance scaling term
- For each node, its parent is used as a prior distribution
- This has been shown to speed adaptation compared with standard MAP, while converging to the same solution as standard MAP in the large data limit

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- There are relatively few adaptation parameters, so estimation is robust

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- If we define $\mathbf{W} = [\mathbf{bA}]$ and $\boldsymbol{\eta} = [1\boldsymbol{\mu}^T]^T$, then we can write:

$$\hat{\boldsymbol{\mu}} = \mathbf{W}\boldsymbol{\eta}$$

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If the observation vectors are d-dimension, then $\mathbf{A}$ is a $d \times d$ matrix and $\mathbf{b}$ is d-dimension vector

- If we define $\mathbf{W} = [\mathbf{bA}]$ and $\boldsymbol{\eta} = [1\boldsymbol{\mu}^T]^T$, then we can write:

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- In MLLR, $\mathbf{W}$ is estimated so as to maximize the likelihood of the adaptation data

MLLR: Maximum Likelihood Linear Regression

- MLLR is the best known linear transform approach to speaker adaptation
- Affine transform of mean parameters

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- A single transform $\mathbf{W}$ can be shared across a set of Gaussian components (even all of them!)

Regression classes

- The number of transforms may obtained automatically
- A set of Gaussian components that share a transform is called a regression class
- Obtain the regression classes by constructing a *regression class tree*
- Each node in the tree represents a regression class sharing a transform
- For an adaptation set, work down the tree until arriving at the most specific set of nodes for which there is sufficient data
- Regression class tree constructed in a similar way to state clustering tree
- In practice the number of regression may be very small: one per context-independent phone class, one per broad class, or even just two (speech/non-speech)

Estimating the transforms

- The linear transformation matrix W is obtained by finding its setting which optimizes the log likelihood
- Log likelihood

$$L = \sum_r \sum_n \gamma_r(n) \log \left(K_r \exp \left(-\frac{1}{2} (\mathbf{x}_n - \mathbf{W}\boldsymbol{\eta}_r)^T \boldsymbol{\Sigma}_r^{-1} (\mathbf{x}_n - \mathbf{W}\boldsymbol{\eta}_r) \right) \right)$$

  where r ranges over the components belonging to the regression class
- Differentiating L and setting to 0 results in an equation for $\mathbf{W}$: there is no closed form solution if $\boldsymbol{\Sigma}$ is full covariance; can be solved if $\boldsymbol{\Sigma}$ is diagonal (but requires a matrix inversion)
- Variance adaptation is also possible
- See Gales and Woodland (1996), Gales (1998) for details

MLLR in practice

- Mean-only MLLR results in 10–15% relative reduction in WER
- Provides improvement in addition to VTLN (another 5–10% relative reduction in WER, after VTLN)
- Few regression classes and well-estimated transforms work best in practice
- Robust adaptation available with about 1 minute of speech; performance similar to SD models available with 30 minutes of adaptation data
- Such linear transforms can account for any systematic (linear) variation from the speaker independent models, for example those caused by channel effects.

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- Basic idea use the same linear transform for both mean and covariance

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Equivalent to applying the linear transform to the data!

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- Similar improvement in accuracy to standard MLLR

Speaker-adaptive training (SAT)

- Basic idea Rather than SI seed (canonical) models, construct models designed for adaptation
- Estimate parameters of canonical models by training MLLR mean transforms for each training speaker
- Train using the MLLR transform for each speaker; interleave Gaussian parameter estimation and MLLR transform estimation
- SAT results in much higher training likelihoods, and improved recognition results
- But: increased training complexity and storage requirements
- SAT using cMLLR, corresponds to a type of speaker normalization at training time

Speaker Space Methods

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Cluster-adaptive training

- Basic idea Represent a speaker as a weighted sum of speaker cluster models
- Different cluster models have shared variances and mixture weights, but separate means
- For a new speaker, mean is defined as

$$\boldsymbol{\mu} = \sum_c \lambda_c \boldsymbol{\mu}_c$$

- Given the canonical models, only the λ_c mixing parameters need estimated for each speaker
- Given sets of weights for individual speakers, means of the clusters may be uopdated
- CAT can reduce WER in large vocabulary tasks by about 4–8% relative
- See Gales (2000) for more

Eigenvoices

- Basic idea Construct a speaker space from a set of SD HMMs
- Could regard each canonical model as forming a dimension of speaker space
- Generalize by computing PCA of sets of "supervectors" (concatenated mean vectors), to form speaker space: each dimension is an "eigenvoice"
- Represent a new speaker as a combination of eigenvoices
- Close relation to CAT
- Computationally intensive, does not scale well to large vocabulary systems
- See Kuhn et al (2000) for more

Summary

Speaker Adaptation

- One of the most intensive areas of speech recognition research since the early 1990s
- Substantial progress, resulting in significant, additive, consistent reductions in word error rate
- Close mathematical links between different approaches
- Linear transforms at the heart of many approaches