Speaker Adaptation

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Automatic Speech Recognition— ASR Lectures 13&14
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Overview

Speaker Adaptation

- Introduction: speaker-specific variation, modes of adaptation
- Model-based adaptation: MAP
- Model-based adaptation: MLLR
- Model-based adaptation: Speaker space models
- Speaker normalization: VTLN
- Adaptive training
- Adaptation for hybrid HMM / NN systems

Speaker independent / dependent / adaptive

- Speaker independent (SI) systems have long been the focus for research in transcription, dialogue systems, etc.
- Speaker dependent (SD) systems can result in word error rates 2–3 times lower than SI systems (given the same amount of training data)
- A Speaker adaptive (SA) system... we would like
  - Error rates similar to SD systems
  - Building on an SI system
  - 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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- Pronunciation model: speaker-specific, consistent change in pronunciation
- Language model: user-specific documents (exploited in personal dictation systems)

Modes of adaptation

- Supervised or unsupervised
  - Supervised: the word level transcription of the adaptation data is known (and HMMs may be constructed)
  - Unsupervised: the transcription must be estimated (eg using recognition output)

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- 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

- Model based: Adapt the parameters of the acoustic models to better match the observed data
  - Maximum a posteriori (MAP) adaptation of HMM/GMM parameters
  - Maximum likelihood linear regression (MLLR) of Gaussian parameters
  - Linear input network (LIN) for neural networks

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  - Vocal Tract Length Normalization (VTLN)
  - Constrained MLLR (cMLLR) — model-based normalisation!

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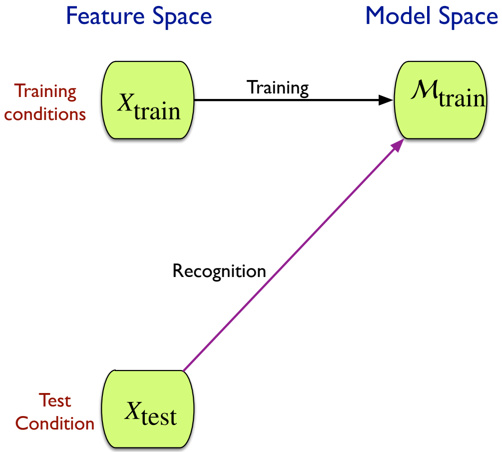
  - Vocal Tract Length Normalization (VTLN)
  - Constrained MLLR (cMLLR) — model-based normalisation!
- Speaker space: Estimate multiple sets of acoustic models, characterizing new speakers in terms of these model sets
  - Cluster-adapative training
  - Eigenvoices
  - Speaker codes

Adaptation and normalization of acoustic models



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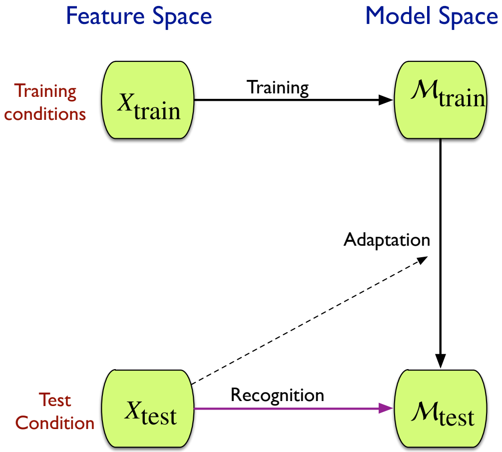

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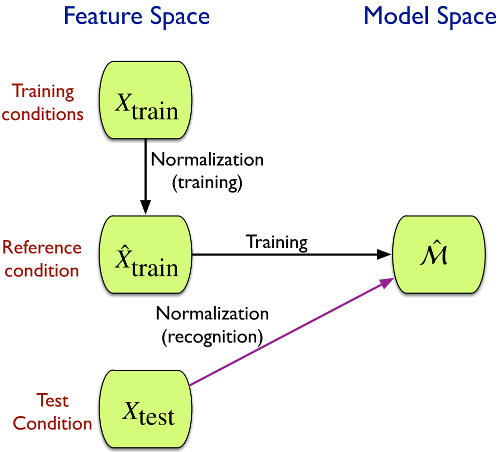

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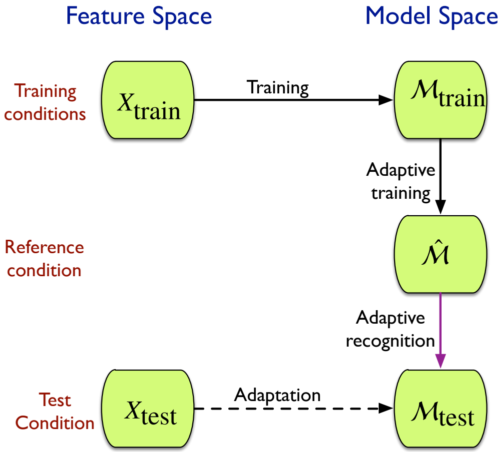

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- The use of a prior distribution, based on the SI models, means that less data is required to estimate the speaker-specific models: we are not starting from complete ignorance

Recall: 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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- As the amount of training data increases, so the MAP estimate converges to the ML estimate

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- MAP adaptation is very useful for domain adaptation:
  - Example: 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 organising 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

The Linear Transform family

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MLLR: Maximum Likelihood Linear Regression

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

$$\hat{\boldsymbol{\mu}} = \mathbf{A}\boldsymbol{\mu} + \mathbf{b}$$

  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:

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

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

Constrained MLLR (cMLLR)

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

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- Log likelihood for cMLLR

$$L = \mathcal{N}(\mathbf{A}\mathbf{x}_n + \mathbf{b}; \mu, \mathbf{\Sigma}) + \log(|\mathbf{A}|) \qquad \mathbf{A}' = \mathbf{A}^{-1}; \mathbf{b}' = \mathbf{A}\mathbf{b}$$

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  Equivalent to applying the linear transform to the data!
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- Iterative solution amenable to online/dynamic adaptation, by using just one iteration for each increment
- 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 updated
- CAT can reduce WER in large vocabulary tasks by about 4–8% relative
- For more, see Gales (2000), Cluster adaptive training of hidden Markov models, *IEEE Trans Speech and Audio Processing*, **8**:417–428.

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
- For more, see Kuhn et al (2000), Rapid speaker adaptation in eigenvoice space, *IEEE Trans Speech and Audio Processing*, **8**:695–707.

Feature normalization

- Basic idea: Transform the features to reduce mismatch between training and test
- *Cepstral Mean Normalization* (CMN): subtract the avergae feature value from each feature, so each feature has a mean value of 0. makes features robust to some linear filtering of the signal (channel variation)
- *Cepstral Variance Normalization* (CVN): Divide feature vector by standard deviation of feature vectors, so each feature vector element has a variance of 1
- Cepstral mean and variance normalisation, CMN/CVN:

$$\hat{\mathbf{x}}_i = \frac{\mathbf{x}_i - \boldsymbol{\mu}(\mathbf{x})}{\boldsymbol{\sigma}(\mathbf{x})}$$

- Compute mean and variance statistics over longest available segments with the same speaker/channel
- Real time normalisation: compute a moving average

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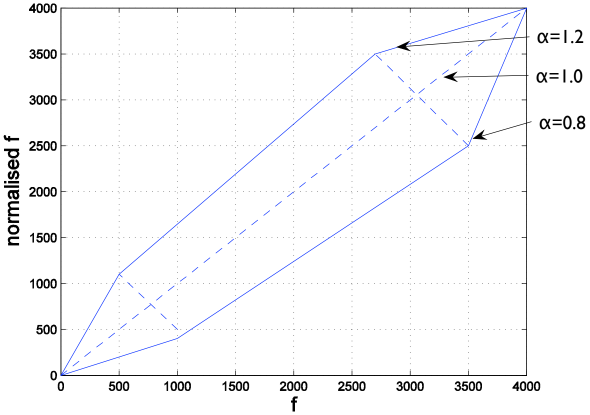
- VTLN: compensate for differences between speakers via a warping of the frequency axis

Approaches to VTLN

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

- Classify by frequency warping function
  - Piecewise linear
  - 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

Warping functions: Piecewise linear



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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 $F0$)

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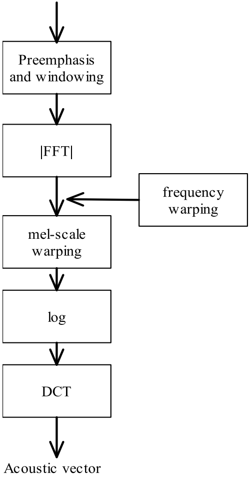
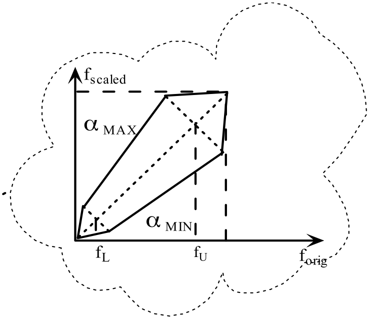
- After estimating the warp factors, normalize the acoustic data and re-estimate the models
- The process may be iterated
- Model-based VTLN does not directly estimate vocal tract size, rather it estimates an optimal frequency warping, which may be affected by other factors (eg $F0$)
- Exhaustive search 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)

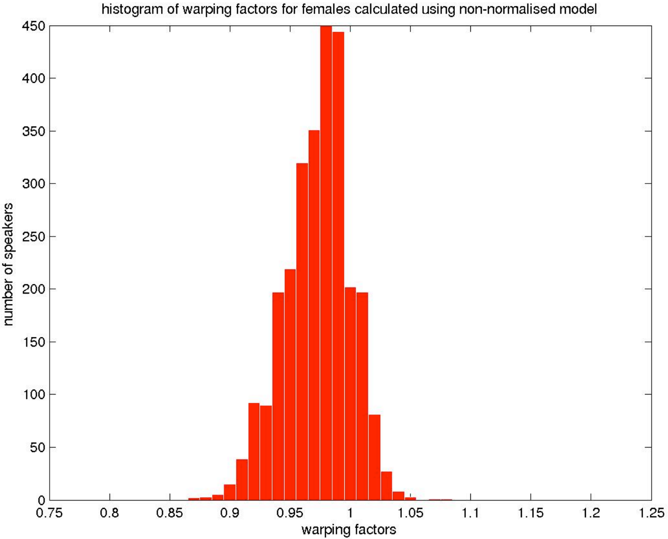
Model-based VTLN



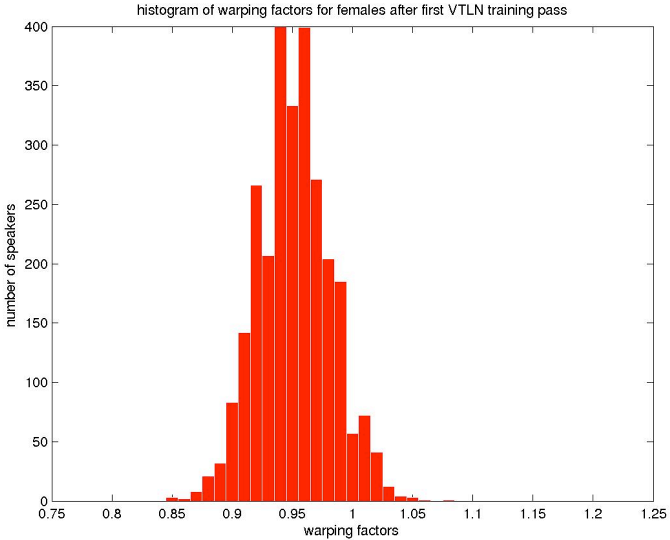


piece-wise linear warping

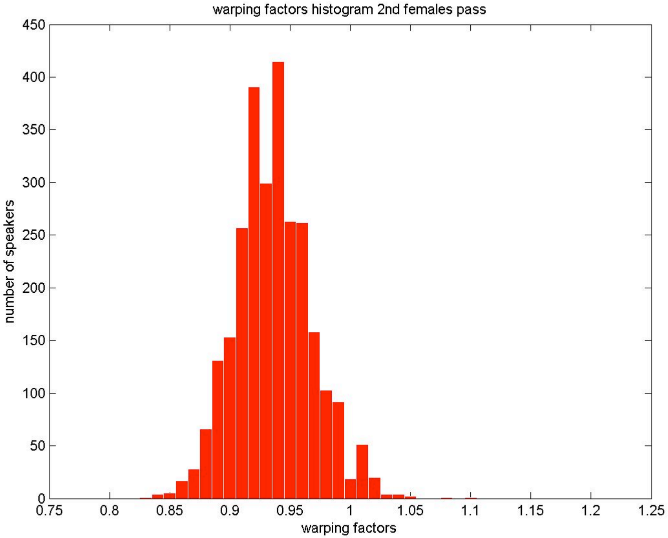
VTLN: Warp factor estimation, females, non-normalized



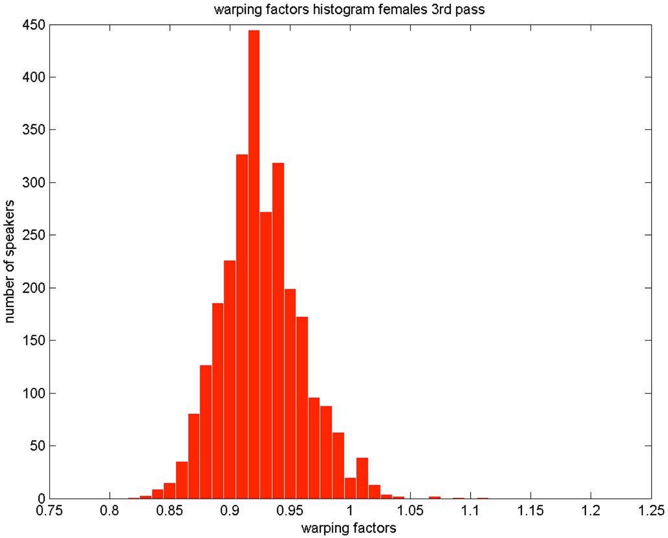
VTLN: Warp factor estimation, females, pass 1



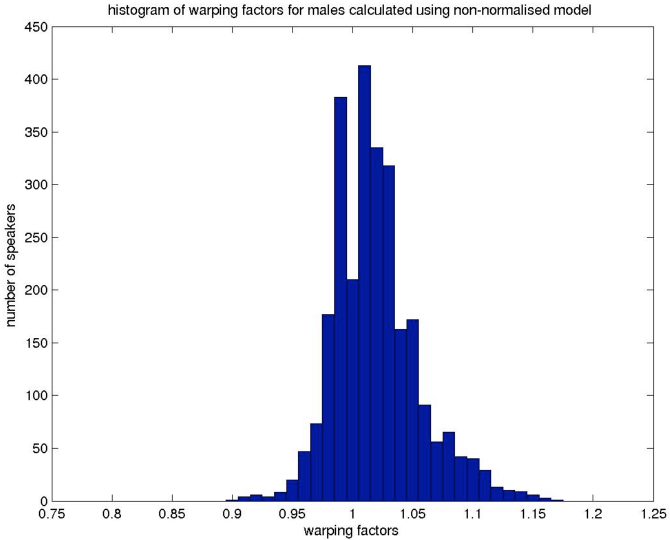
VTLN: Warp factor estimation, females, pass 2



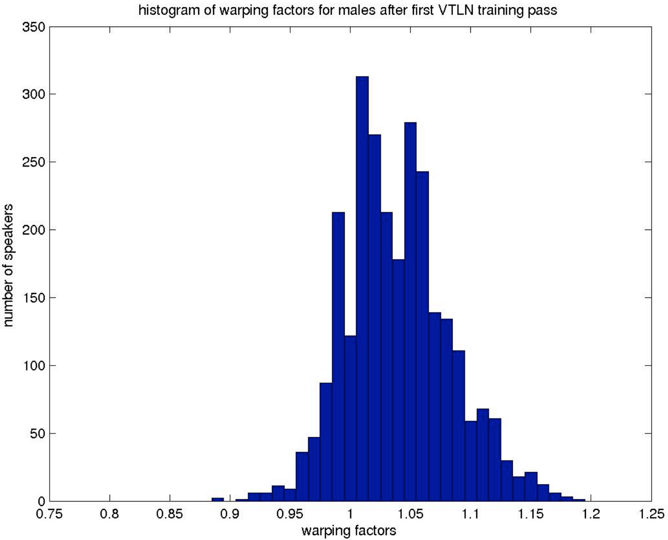
VTLN: Warp factor estimation, females, pass 3



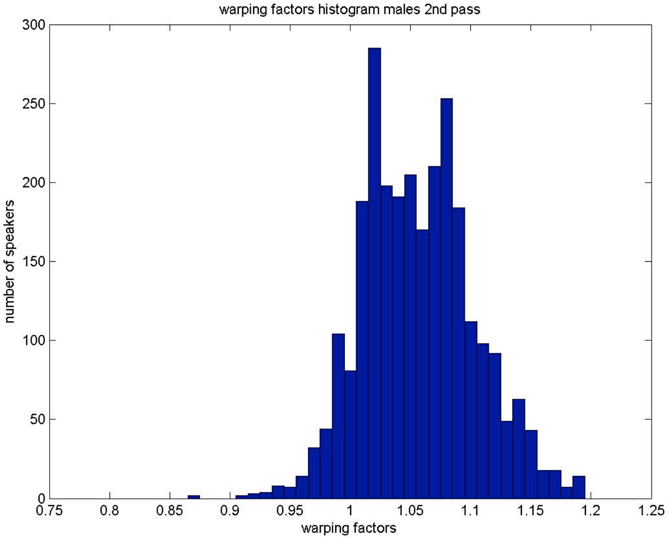
VTLN: Warp factor estimation, males, non-normalized



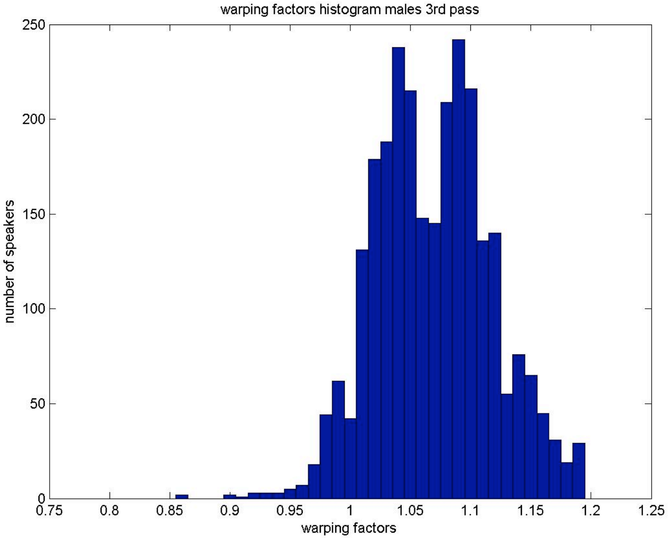
VTLN: Warp factor estimation, males, pass 1



VTLN: Warp factor estimation, males, pass 2



VTLN: Warp factor estimation, males, pass 3



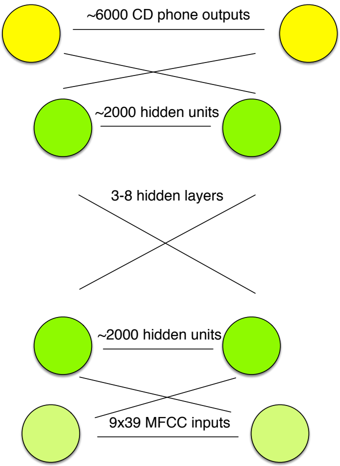
Speaker adaptation in hybrid HMM/NN systems: CMLLR feature transformation

- Basic idea: If HMM/GMM system is used to estimate a single constrained MLLR adaptation transform, this can be viewed as a feature space transform
- Use the HMM/GMM system with the same tied state space to estimate a single CMLLR transform for a given speaker, and use this to transform the input speech to the DNN for the target speaker
- Can operate unsupervised (since the GMM system estimates the transform)
- Limited to a single transform (regression class)

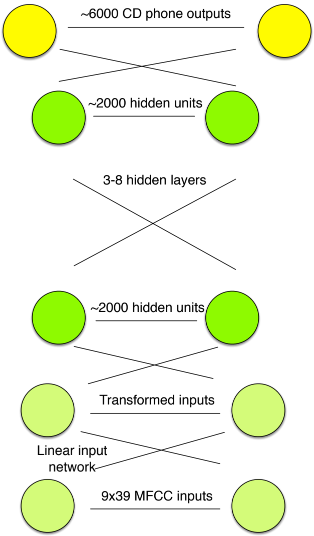
Speaker adaptation in hybrid HMM/NN systems: LIN

- Basic idea: single linear input layer trained to map input speaker-dependent speech to speaker-independent network
- Training: linear input network (LIN) can either be fixed as the identity or (adaptive training) be trained along with the other parameters
- Testing: freeze the main (speaker-independent) network and propagate gradients for speech from the target speaker to the LIN, which is updated — linear transform learned for each speaker
- Requires supervised training data

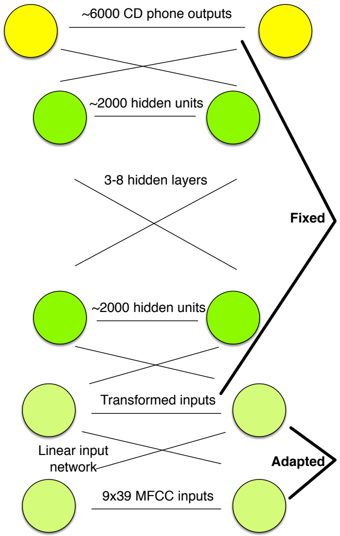
LIN


~6000 CD phone outputs
~2000 hidden units
3-8 hidden layers
~2000 hidden units
9x39 MFCC inputs

LIN

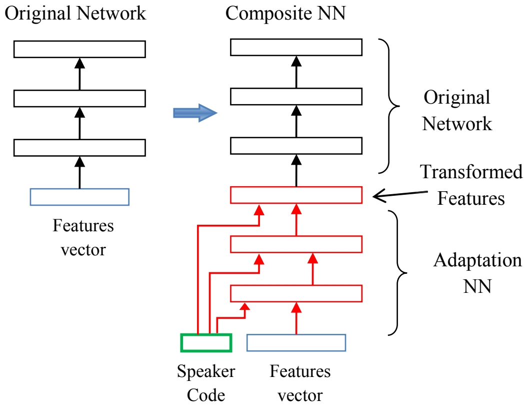

~6000 CD phone outputs
~2000 hidden units
3-8 hidden layers
~2000 hidden units
Transformed inputs
Linear input
network
9x39 MFCC inputs

LIN


~6000 CD phone outputs
~2000 hidden units
3-8 hidden layers
Fixed
~2000 hidden units
Transformed inputs
Linear input network
Adapted
9x39 MFCC inputs

Speaker adaptation in hybrid HMM/NN systems: Speaker codes

- Basic idea: Learn a short speaker code vector for each talker



Summary

Speaker Adaptation

- One of the most intensive areas of speech recognition research since the early 1990s
- HMM/GMM
  - 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
- HMM/NN
  - Open research topic
  - GMM-based feature space transforms somewhat effective
  - Direct weight adaptation less effective

Reading

- HMM/GMM
  - Gales and Young (2007), The Application of Hidden Markov Models in Speech Recognition, *Foundations and Trends in Signal Processing*, **1** (3), 195–304: section 5.
  - Woodland (2001), Speaker adaptation for continuous density HMMs: A review, ISCA ITRW on Adaptation Methods for Speech Recognition.
  - Gales (1998), Maximum likelihood linear transformations for HMM-based speech recognition, *Computer Speech and Language*, **12**:75–98.
- HMM/DNN
  - Liao (2013), Speaker adaptation of context dependent deep neural networks, Proc IEEE ICASSP
  - Abdel-Hamid and Jiang (2013), Fast speaker adaptation of hybrid NN/HMM model for speech recognition based on discriminative learning of speaker code, Proc IEEE ICASSP