Adaptation and Environmental Robustness

DT2118 Speech and Speaker Recognition

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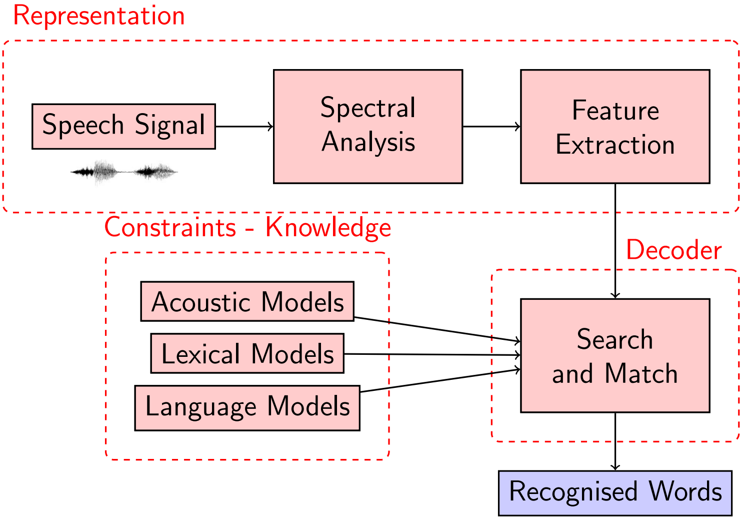
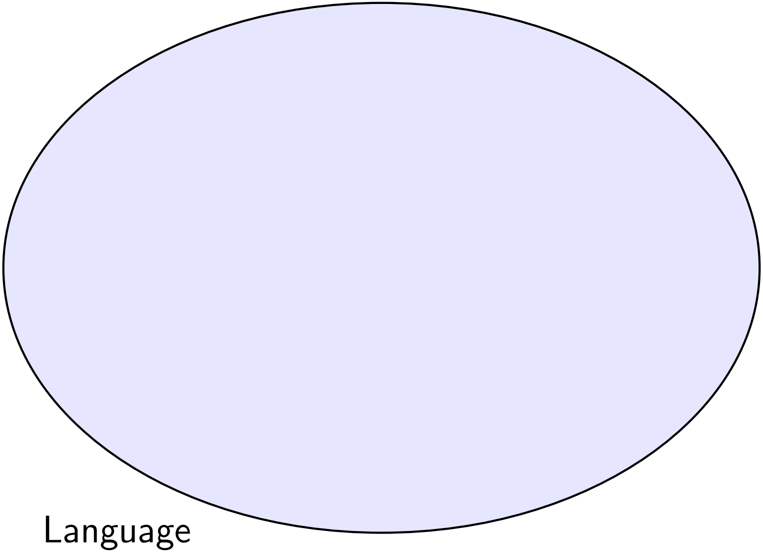
Components of ASR System



ASR seldom works out of the box!

Why is it so hard?



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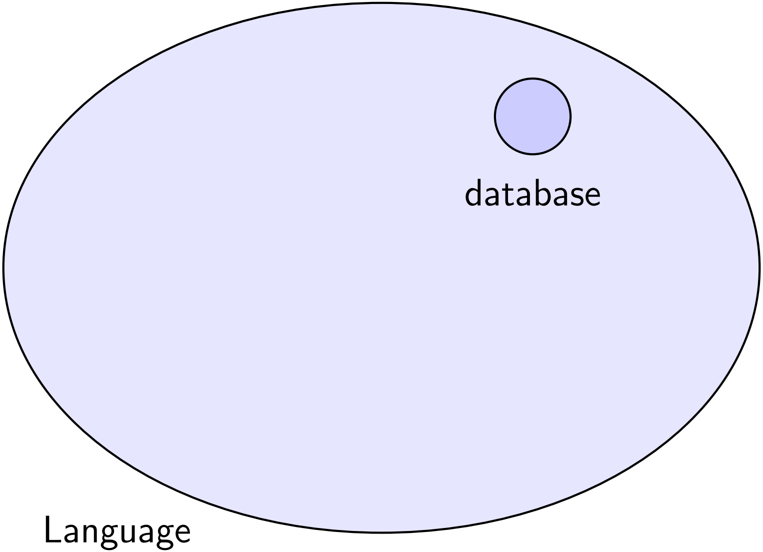

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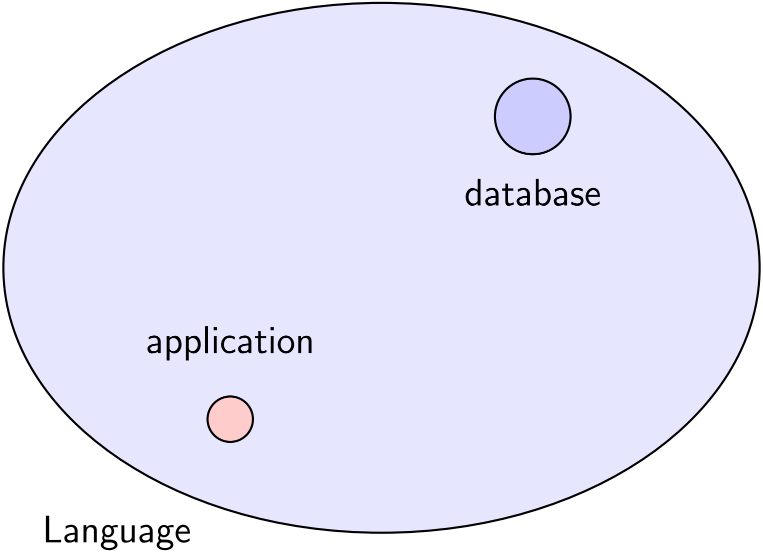
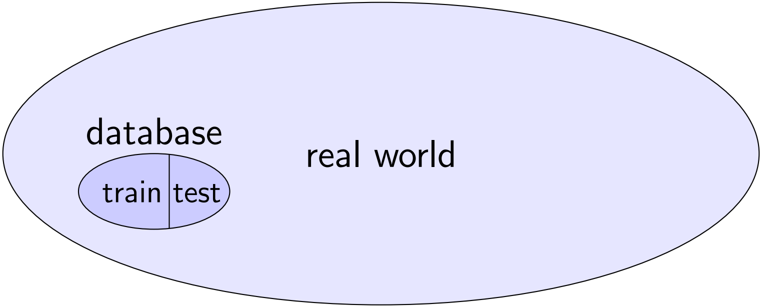


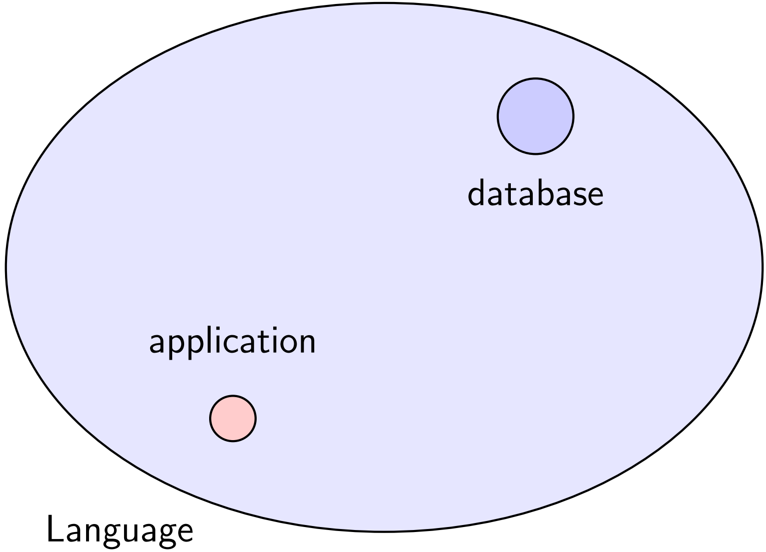
Misleading Training/Test Set



- mismatch between speakers
- unknown words or grammatical constructs
- environmental mismatch

How do we cope with variability?

Ideally: models that generalise



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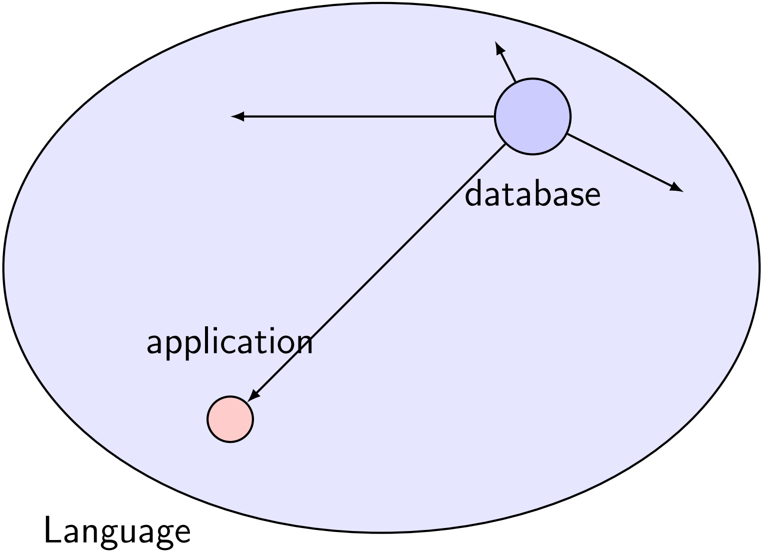
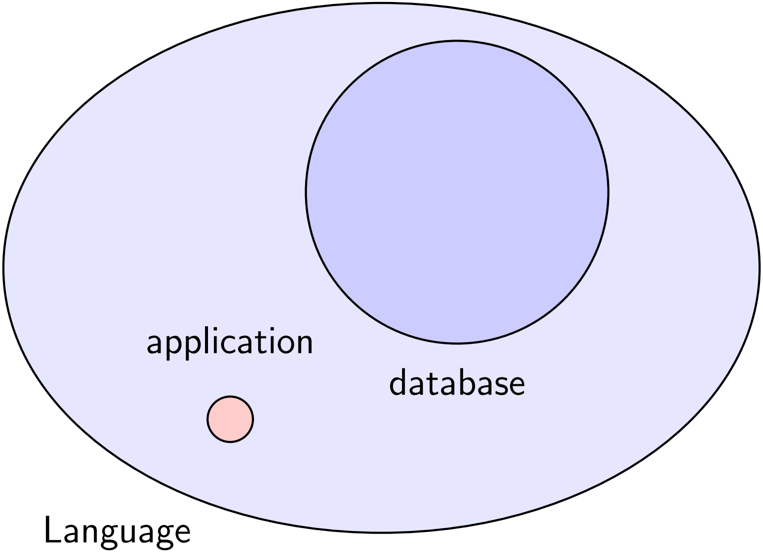


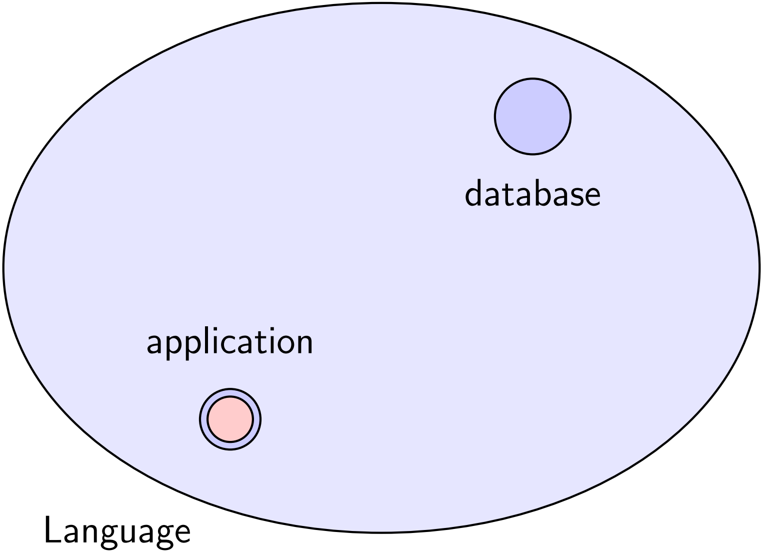
How do we cope with variability?

Large companies use insane quantities of data



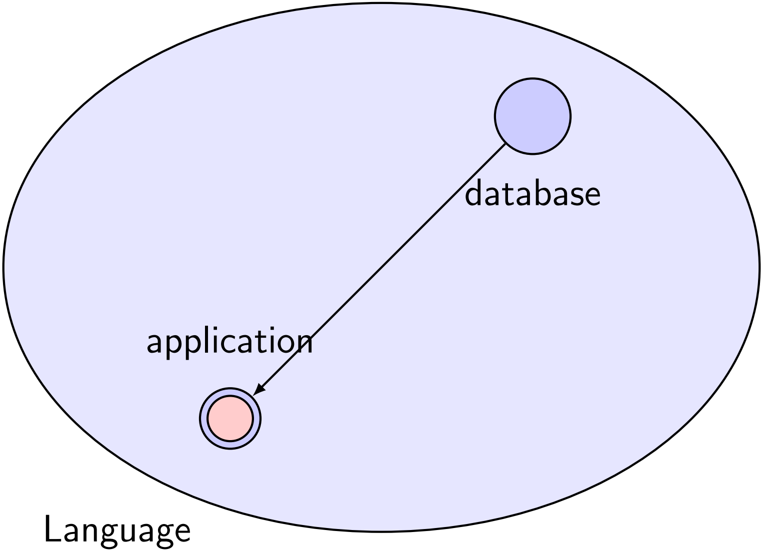
How do we cope with variability?

Adaptation



How do we cope with variability?

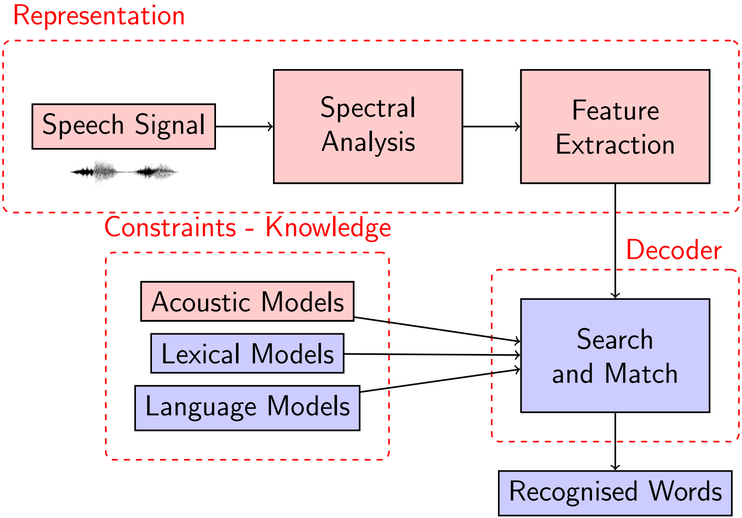
Adaptation



Adaptation

- adapt the acoustic features
- adapt the models (acoustic, language)

Components of ASR System



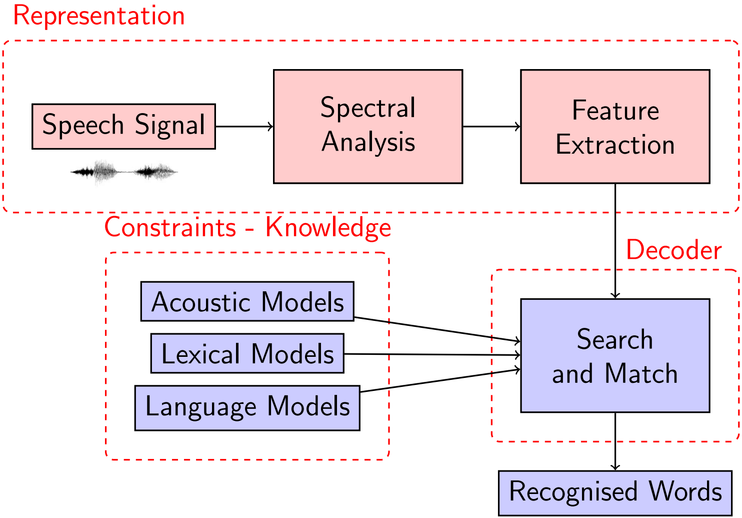
Outline

Outline

Adaptation and Speaker Characteristics

- anatomy, age, gender, dialect
- speaking style
- speaker adjustment to environment
- speaker adjustment to listener

Components of ASR System



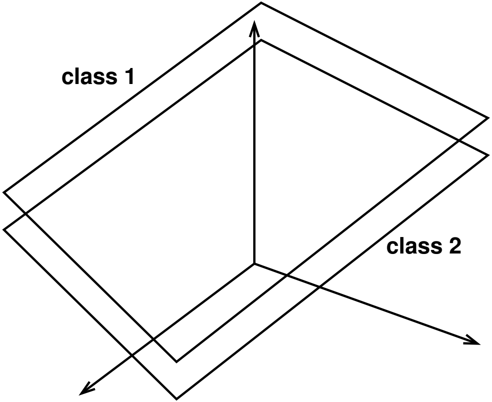
Feature Transformation

- general (PCA, LDA)
- explicit speaker modelling (VTLN)
- Speaker Specific (Statistical)

Principal Component Analysis (PCA)

- Aka Karhunen-Loewe transform
- Most used for dimensionality reduction
- new basis: ordered by data spread
- we can discard dimensions with small variation
- uncorrelated components

Problem with PCA



Linear Discriminant Analysis (LDA)

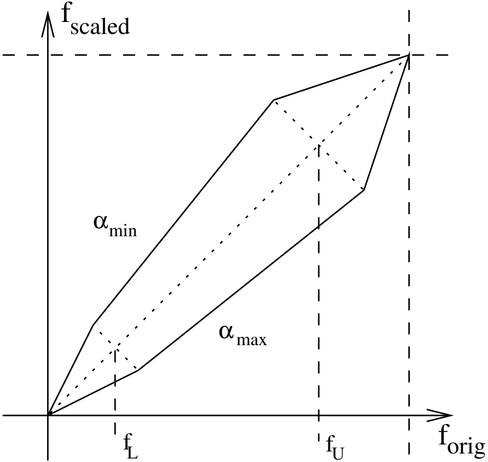
- supervised
- maximise ratio between:
    1. between class scatter matrix S_B
    2. within class scatter matrices S_W
- example: $J = \mathrm{tr}(S_W^{-1} S_B)$

Explicit Speaker Modelling

- focus on anatomy
- leave out all idiosyncrasies
- most salient parameter: Vocal Tract Length
- not correlated with body height
- possibly not correlated with formants [1]

[1] H. Hatano, T. Kitamura, H. Takemoto, P. Mokhtari, K. Honda, and S. Masaki. "Correlation between vocal tract length, body height, formant frequencies, and pitch frequency for the five Japanese vowels uttered by fifteen male speakers". In: *Proc. of Interspeech*. 2012

Vocal Tract Length Normalisation (VTLN)



VTLN factor

- vary factor α between α_{min} and α_{max} with regular steps
- run recogniser N times
- choose results with highest likelihood
- with adults α ranges between 0.8 and 1.25
- children to adults it ranges between 1.0 and 1.7

VTLN properties

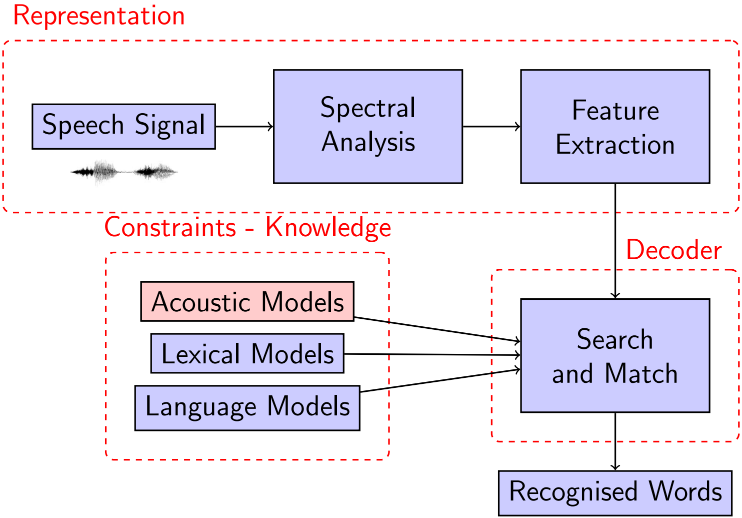
Advantages:

- no adaptation data needed
- simple transformation (one parameter)
- good improvements for children

Disadvantages:

- need to run recogniser N times
- phoneme dependent transforms (more parameters to tune)
- not powerful

Components of ASR System



Model Adaptation

- objective: adjust model parameters to new observations
- if plenty of data: retrain with Baum-Welch
- supervised vs unsupervised
- example: enrolment for dictation systems
- more often little data, no transcriptions
- use results from recogniser: risky

MAP Adaptation

- Maximum a Posteriori
- model parameters are stochastic variables
- define meaningful prior

$$\hat{\mu}_{ik} = \frac{\tau_{ik}\mu_{nw_{ik}} + \sum_{t=1}^{T} \zeta_t(i,k)x_t}{\tau_{ik} + \sum_{t=1}^{T} \zeta_t(i,k)}$$

MAP Problems

- need good prior
- all model parameters potentially updated
- need adaptation data to cover all phonetic classes

Maximum Likelihood Linear Regression (MLLR)

- constrained transformations
- reduce parameters to re-estimate
- linear regression:

$$\hat{\mu}_{ik} = A_c \mu_{ik} + b_c$$

- estimate A_c and b_c maximising likelihood
- one transform per regression class (example: for each phoneme)

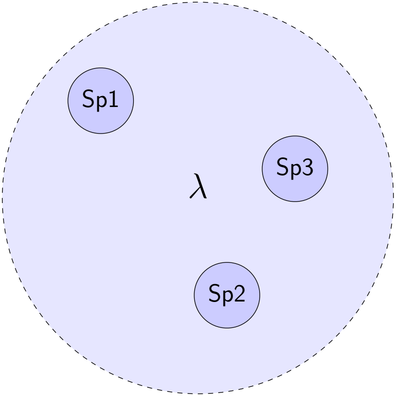
MLLR

if not enough data:

- use broader classes to be transformed
- for example one transform for fricatives, one for front vowels...

Speaker-Adaptive Training (SAT)

Conventional training



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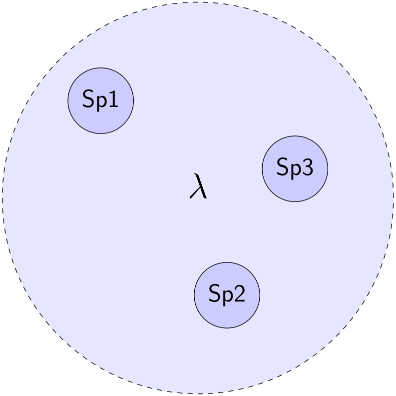
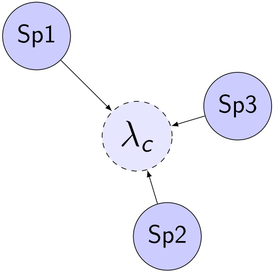
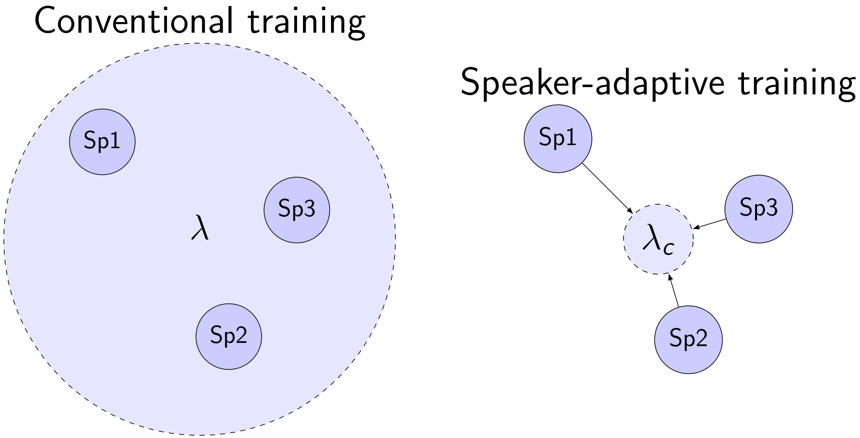


Speaker-adaptive training



Speaker-Adaptive Training (SAT)



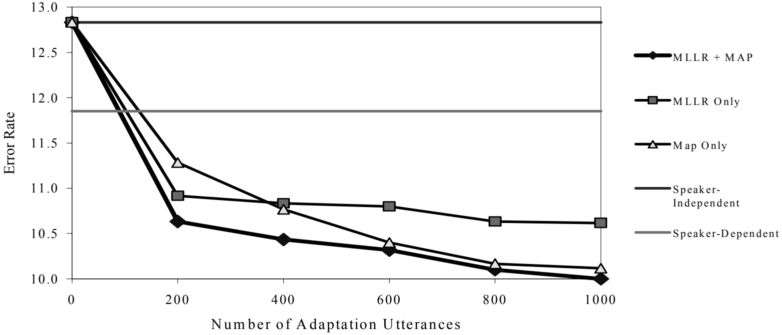
needs adaptation during recognition

Effects of Adaptation

Models	Relative Error Reduction (%)
CHMM	baseline
MLLR on mean only	12
MLLR on mean and variance	2
MLLR SAT	8

Here one regression class per phoneme was used (group all triphones with the same middle phoneme)

Combined MLLR and MAP

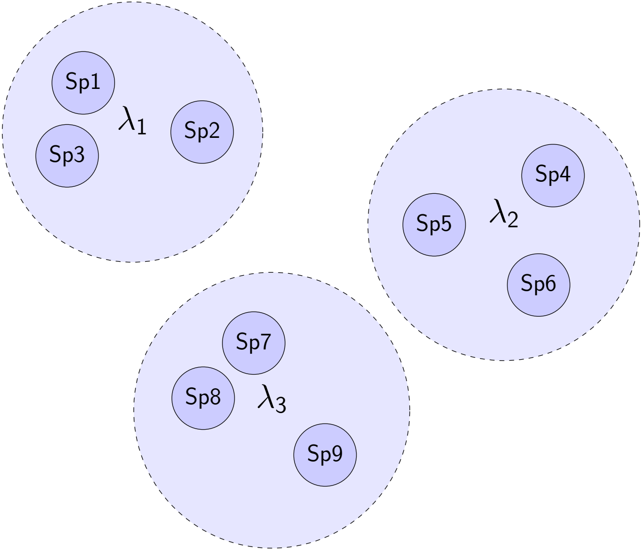


(from Huang, Acero and Hon)

Speaker Clustering

- MAP and MLLR require adaptation data
- not always available

Speaker Clustering



Speaker Clustering Variants

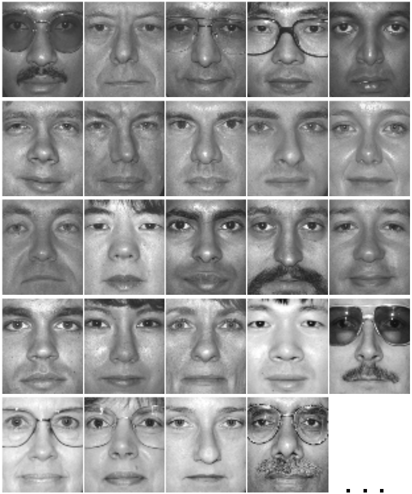
build models for each group

- at recognition time find best model
- can be integrated in search algorithm (pruning)
- combine with MLLR

use speaker dependent (SD) models and:

- represent each new speaker as linear combination of SD models
- eigenvoices

Eigenfaces



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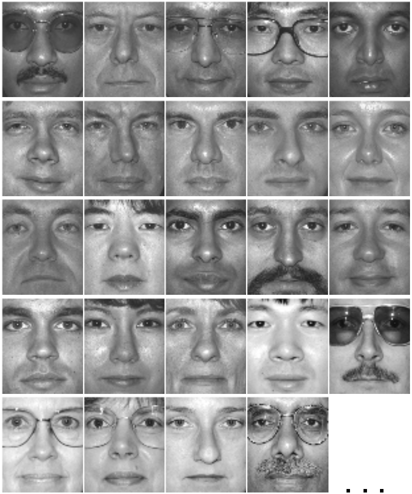
Faces from the FERET database

$$64 \times 73 \text{ pixels}$$
$$= 4672 \text{ dimensions!}$$

Eigenfaces



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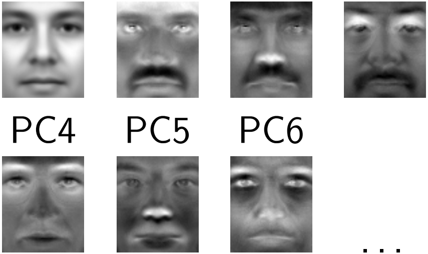
Faces from the FERET database

Eigenfaces

mean PC1 PC2 PC3

PC4 PC5 PC6



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from 4672 dimensions to a small basis

Eigenvoices

- each voice (face) represented by model parameters
- thousand of dimensions
- subtract mean and run PCA
- during recognition find new speaker in eigenvoice space
- very little adaptation data required

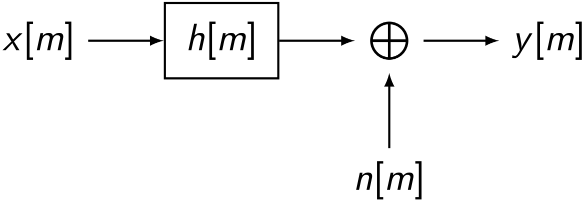
Outline

The Acoustical Environment

- additive noise
- reverberation (room)
- channel distortion (microphone, telephone line, codec)

A Model of the Environment

- A model of combined noise and reverberation effects



Additive Noise

- Stationary vs non-stationary
- White vs coloured (pink noise low frequency emphasis)

Additive Noise: Sources

Environment:

- air conditioner
- PC, keyboard
- cars
- other speakers (cocktail party effect)

The speaker:

- breath and puff noise
- lip smack
- mic and wire contacts

Additive Noise: Lombard Effect

- The speaker may change his voice when speaking in noise
- Reported recognition experiments are mainly performed in simulated noise
- do not capture this effect

Reverberation

- sound reflections from walls and objects in a room are added to the direct sound
- recognition systems are very sensitive to this effect
- strong sounds mask succeeding weak sounds
- reverberation radius: the distance from the sound source where the direct and the far sound fields are equal in amplitude

Typical office:

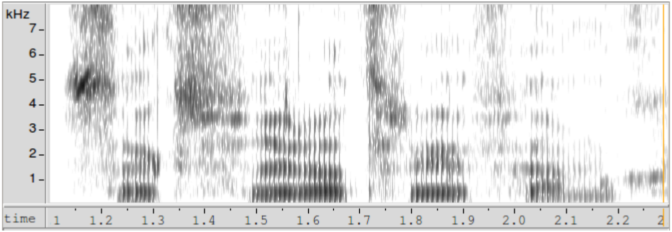
- reverberation time up to 100 ms
- reverberation radius 0.5 m

Acoustical Transducers

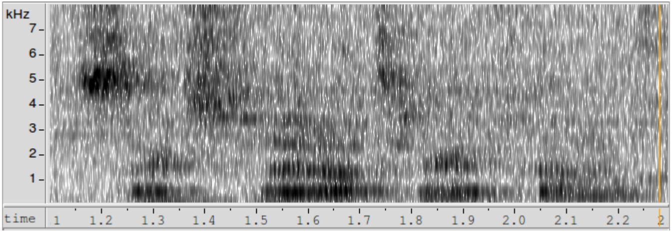
- Close-talk microphones
  - background noise is attenuated
  - sensitive to speaker non-speech sounds
  - positioning is critical
    - mouth corner recommended
    - plosive bursts may saturate the mic signal if right in front
- Far field microphones
  - pick up more background noise
  - positioning less critical
- Most popular type: condenser microphone
- Multimicrophones - Microphone Arrays
  - Adjustable directivity

Near and far distance microphones

Headset



2 m distance



Environment Compensation Pre-processing

Compensate with signal processing (feature extraction)

- Spectral Subtraction
- Cepstral Mean Normalisation (CMN)
- Real-time Cepstral Normalisation
- RASTA

Adaptive Echo Cancellation

- also used in voice over IP
- adjust parameters of a FIR filter online
- The Least Mean Squares (LMS) Algorithm

Multi-microphone Speech Enhancement

- Microphone Arrays (beam forming)
- Blind Source Separation

Spectral Subtraction

Assumption 1, noise additive:

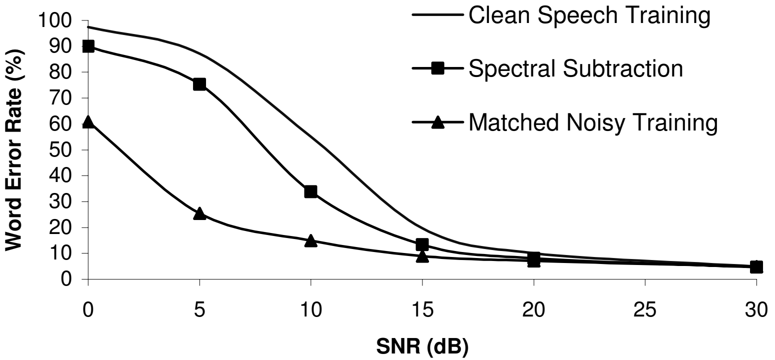
$$y[m] = x[m] + n[m]$$

Assumption 2, signal and noise decorrelated: In frequency domain

$$|Y(f)|^2 \approx |X(f)|^2 + |N(f)|^2$$

- estimate $|N(f)|^2$ in silent segments
- subtract $|N(f)|^2$ from $|Y(f)|^2$

Spectral Subtraction



(from Huang, Acero and Hon)

Cepstral Mean Normalisation (CMN)

- Subtract the average cepstrum over the utterance from each frame
- Compensates for different frequency characteristics

CMN Problem: Phonetic Information

The average cepstrum contains both channel and phonetic information

- The compensation will be different for different utterances, especially for short utterances ($<$ 2–4 sec)
- Still provides robustness against filtering operations
- For telephone recordings, 30% relative error reduction
- Some compensation also for differences in voice source spectra

Real Time CMN

Problem: Need whole utterance to computer average

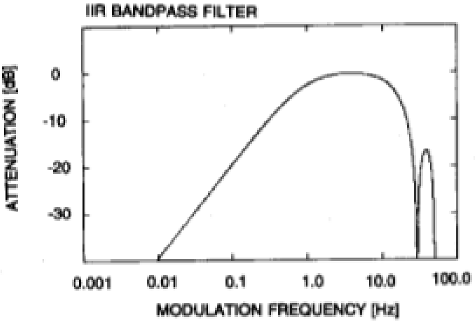
- Not suitable for live recognition
- use high-pass filter with about 5 sec time constant

$$\bar{x}_t = \alpha x_t + (1 - \alpha)\bar{x}_{t-1}$$

- other filters are also popular
- need good initialisation

RASTA: RelAtive SpecTrAl

- Hearing-inspired bandpass filtering of filterbank amplitude envelopes
- Removes long-term bias in the signal but leaves syllable rate modulation mainly unchanged



[2]

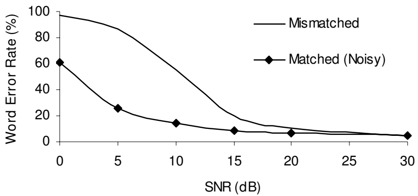
[2] H. Hermansky and N. Morgan. "RASTA Processing of Speech". In: *IEEE Trans. Speech Audio Process.* 2.4 (Oct. 1994), pp. 578–589

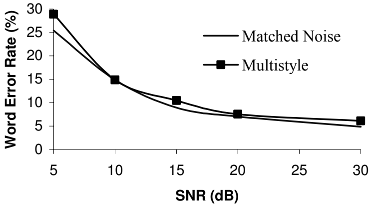
Environmental Model Adaptation

- Retraining on Corrupted Speech
- Model Adaptation
- Parallel Model Combination
- Retraining on Compensated Features

Retraining on Corrupted Speech

- If the distortion is known, then models can be trained by distorting the training data in this way (noise added, filtering)
- Several distortions can be used in parallel (multi-style training)
- Ignores the effect of the distortion on the speaker





Model Adaptation

- Same methods possible as for speaker adaptation (MAP and MLLR)
- MAP requires large adaptation data - impractical
- MLLR needs ca 1 min

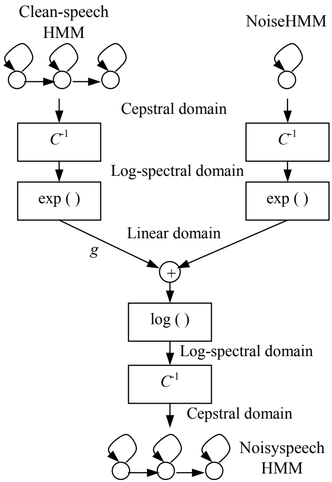
MLLR for Noise Adaptation

one regression class and only bias

- Combined speech recognition and MLLR estimation of the distortion
- Slightly better than CMN, especially for short utterances
- Slower than CMN since two-stage procedure and model adaptation as part of recognition

Parallel Model Combination

- Gaussian distribution converts into Non-Gaussian distribution
- No problem, a Gaussian mixture can model this
- Non-stationary noise can be modelled by having more than one state at the cost of multiplying the total number of states

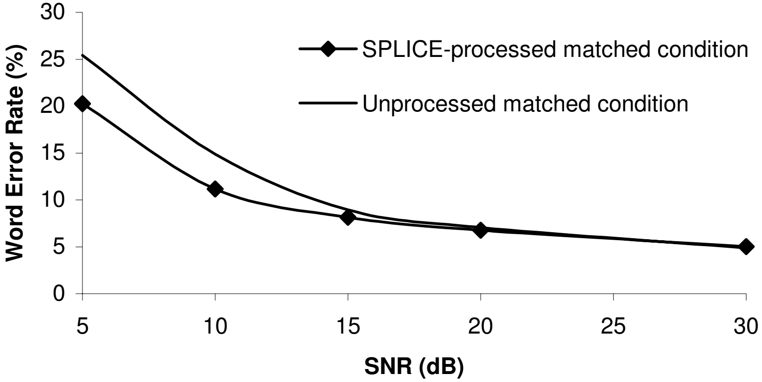


Environments

- Office - 200 speakers
  - at least 4 different rooms (close and far wall)
  - close talk, hands-free, medium distance (0.75 m), far distance (2 m)
- Public Place - 200 speakers
  - at least 2 locations: hall > 100 m^2 and outdoors
- Entertainment - 75 speakers
  - at least 3 different living rooms with radio on/off,
- Car - 75 speakers
  - middle or upper class car (VW Golf, Opel Astra, Mercedes A Class, Ford Mondeo, Mercedes C Class, Audi A6)
  - motor on/off, city 30-70, road 60-100, highway 90-130 km/h
- Children
  - 50 speakers (children's room)

Retraining on Compensated Features

- The algorithms for removing noise from noisy speech are not perfect
- Retraining can compensate for this



Modelling Non-stationary Noise

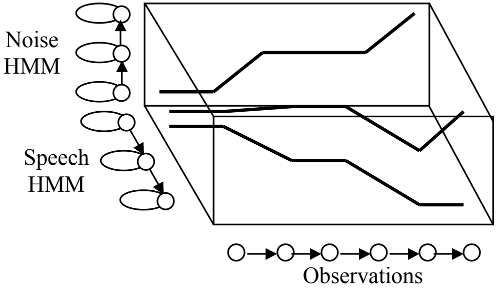
- speaker noise (clearing voice, breathing, lip smack)
- door slams, keyboard, other speakers
- can be between words or overlap with them

Approach 1: Explicit Noise Modelling

- Include non-speech labels in the training data
- Perform training
- Update the transcription with optional noise between words
- Retrain
- Problem when speech and noise overlap in time

Approach 2: Speech/noise decomposition

- During recognition
- 3-dimensional Viterbi
- Computationally complex



Outline

Confidence Measures

- errors are unavoidable
- in a larger system essential to diagnose errors
- dialogue system may be able to correct them

Confidence Measures

If accurate, $P(\text{words}|\text{sounds})$ best confidence measure
Problem: in

$$P(\text{words}|\text{sounds}) = \frac{P(\text{sounds}|\text{words})P(\text{words})}{P(\text{sounds})}$$

$P(\text{sounds})$ is usually not computed ($\arg\max$)
In general

$$P(\text{sounds}) = \sum_{\text{words}} P(\text{sounds}|\text{words})P(\text{words})$$

Filler models

$$P(\text{sounds}) = \sum_{\text{words}} P(\text{sounds}|\text{words})P(\text{words})$$

- General purpose recogniser
- should be able to "fill the holes" of the target recogniser
- often loop of phones
- any word sequence is allowed (including out of vocabulary)
- can be done word by word (segmentation from target recogniser)

Word Spotting

- do not recognise all the words
- only small number of keywords
- can build models of “antiwords”

Transformation Models

Use subword units in the confidence. If a word has N phones:

$$CS(\text{word}) = \sum_{i=1}^{N} f_i(CS(\text{phone}_i))$$

where

$$f_i(x) = a_i x + b_i$$

and can be optimised on the training data

Combination Models

use combination of several features:

- word stability when changing language model parameters
- average number of active hypothesis at word end
- acoustic score per frame within words normalised to active senones
- ...

A linear classifier works well