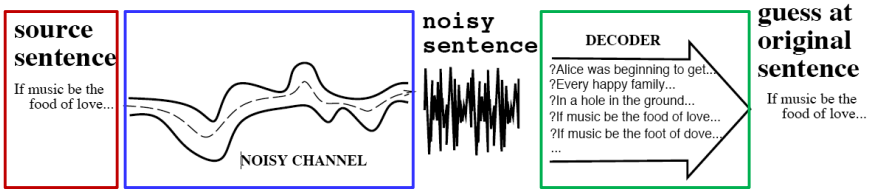
Statistical NLP
Spring 2010

Lecture 9: Acoustic Models

Dan Klein – UC Berkeley

The Noisy Channel Model

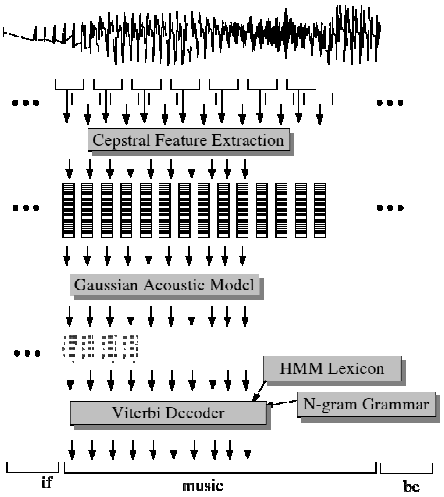


$$w^* = \arg\max_w P(w|a)$$
$$\propto \arg\max_w P(a|w)P(w)$$

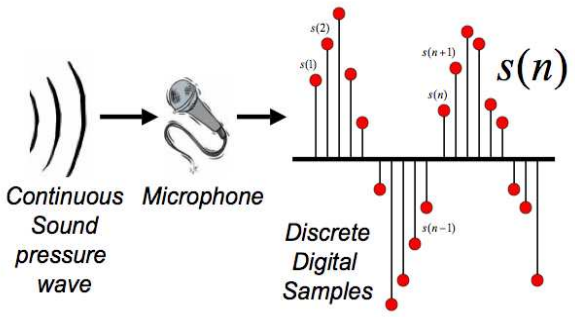
Acoustic model: HMMs over word positions with mixtures of Gaussians as emissions

Language model: Distributions over sequences of words (sentences)

Speech Recognition Architecture



Digitizing Speech



Thanks to Bryan Pellom for this slide!

Frame Extraction

- A frame (25 ms wide) extracted every 10 ms

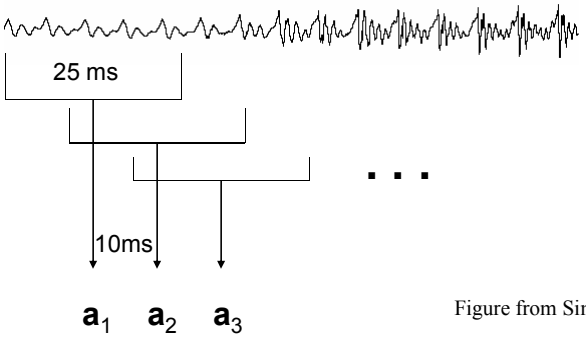
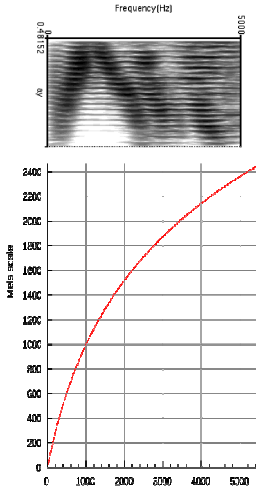


Figure from Simon Arnfield

Mel Freq. Cepstral Coefficients

- Do FFT to get spectral information
  - Like the spectrogram/spectrum we saw earlier
- Apply Mel scaling
  - Models human ear; more sensitivity in lower freqs
  - Approx linear below 1kHz, log above, equal samples above and below 1kHz
- Plus discrete cosine transform



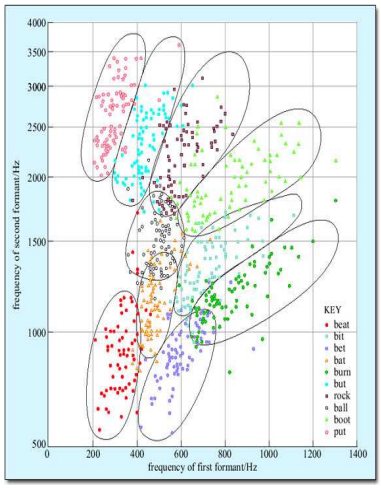
[Graph from Wikipedia]

Final Feature Vector

- 39 (real) features per 10 ms frame:
  - 12 MFCC features
  - 12 delta MFCC features
  - 12 delta-delta MFCC features
  - 1 (log) frame energy
  - 1 delta (log) frame energy
  - 1 delta-delta (log frame energy)
- So each frame is represented by a 39D vector

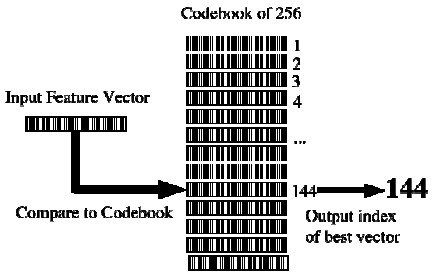
HMMs for Continuous Observations

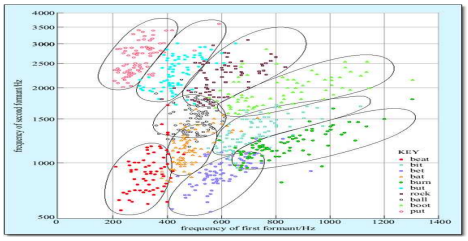
- Before: discrete set of observations
- Now: feature vectors are real-valued
- Solution 1: discretization
- Solution 2: continuous emissions
  - Gaussians
  - Multivariate Gaussians
  - Mixtures of multivariate Gaussians
- A state is progressively
  - Context independent subphone (~3 per phone)
  - Context dependent phone (triphones)
  - State tying of CD phone



Vector Quantization

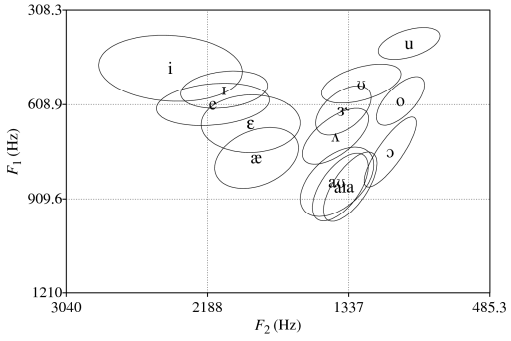
- Idea: discretization
  - Map MFCC vectors onto discrete symbols
  - Compute probabilities just by counting
- This is called vector quantization or VQ
- Not used for ASR any more; too simple
- But: useful to consider as a starting point





Gaussian Emissions

- VQ is insufficient for real ASR
  - Hard to cover high-dimensional space with codebook
  - What about our perception of low-dimensional phonemes?
- Instead: assume the possible values of the observation vectors are normally distributed.
  - Represent the observation likelihood function as a Gaussian?



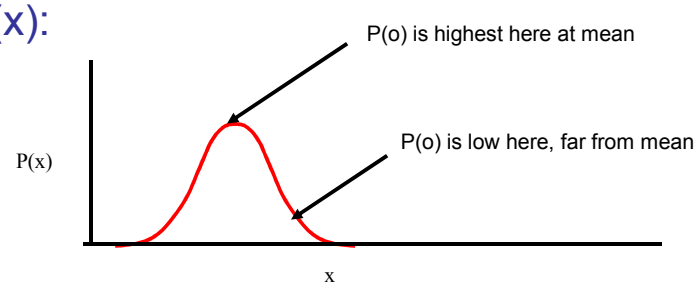
From bartus.org/akustyk

Gaussians for Acoustic Modeling

A Gaussian is parameterized by a mean and a variance:

$$P(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

- P(x):



Multivariate Gaussians

- Instead of a single mean μ and variance σ^2:

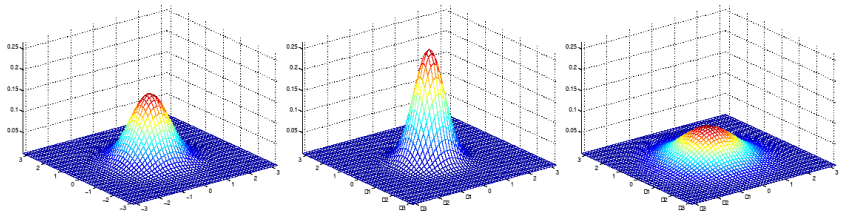
$$P(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

- Vector of means μ and covariance matrix Σ

$$P(x|\mu,\Sigma) = \frac{1}{(2\pi)^{k/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^\top \Sigma^{-1}(x-\mu)\right)$$

- Usually assume diagonal covariance (!)
  - This isn't very true for FFT features, but is often OK for MFCC features

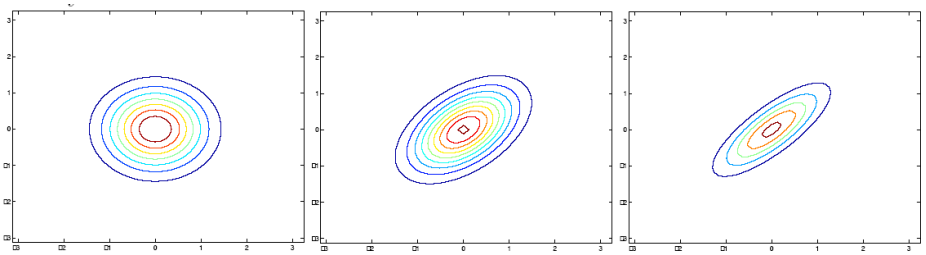
Gaussians: Size of Σ



- μ = [0 0] μ = [0 0] μ = [0 0]
- Σ = I Σ = 0.6I Σ = 2I
- As Σ becomes larger, Gaussian becomes more spread out; as Σ becomes smaller, Gaussian more compressed

Text and figures from Andrew Ng

Gaussians: Shape of Σ



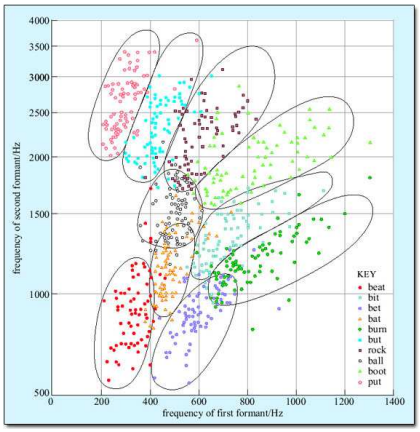
$$\Sigma = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}; \quad \Sigma = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}; \quad .\Sigma = \begin{bmatrix} 1 & 0.8 \\ 0.8 & 1 \end{bmatrix}$$

- As we increase the off diagonal entries, more correlation between value of x and value of y

Text and figures from Andrew Ng

But we're not there yet

- Single Gaussians may do a bad job of modeling a complex distribution in any dimension
- Even worse for diagonal covariances
- Solution: mixtures of Gaussians



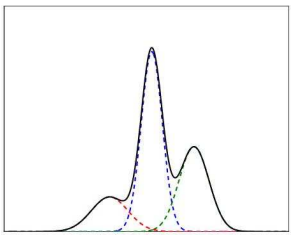
From openlearn.open.ac.uk

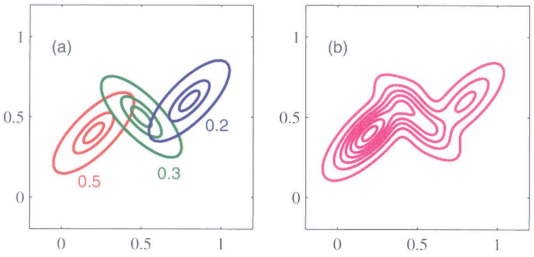
Mixtures of Gaussians

- M mixtures of Gaussians:

$$P(x|\mu_i, \Sigma_i) = \frac{1}{(2\pi)^{k/2}|\Sigma_i|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu_i)^\top \Sigma_i^{-1}(x-\mu_i)\right)$$

$$P(x|\mu, \mathbf{\Sigma}, \mathbf{c}) = \sum_i c_i P(x|\mu_i, \Sigma_i)$$



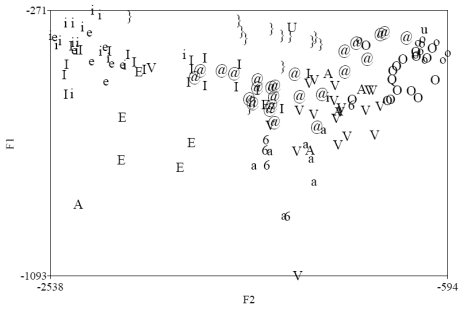


From robots.ox.ac.uk

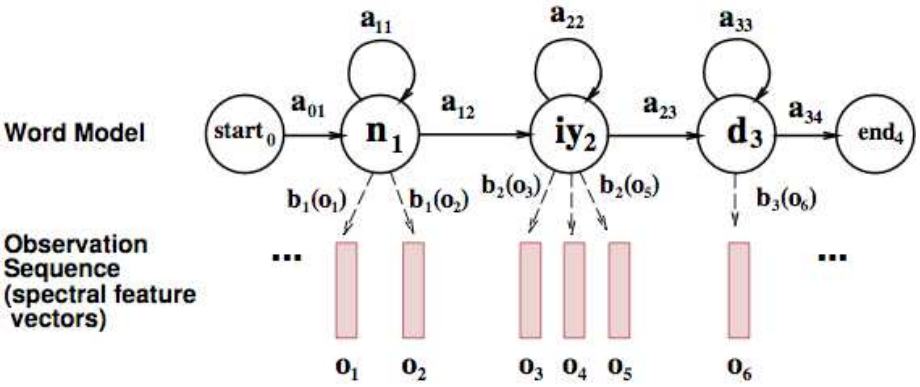
http://www.itee.uq.edu.au/~comp4702

GMMs

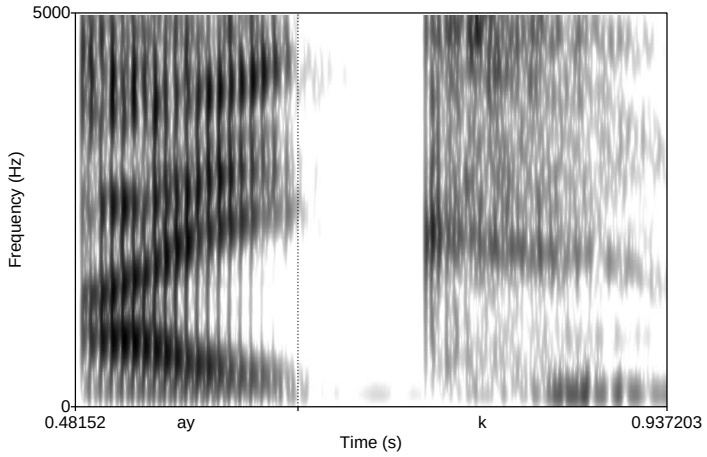
- Summary: each state has an emission distribution P(x|s) (likelihood function) parameterized by:
  - M mixture weights
  - M mean vectors of dimensionality D
  - Either M covariance matrices of DxD or M Dx1 diagonal variance vectors



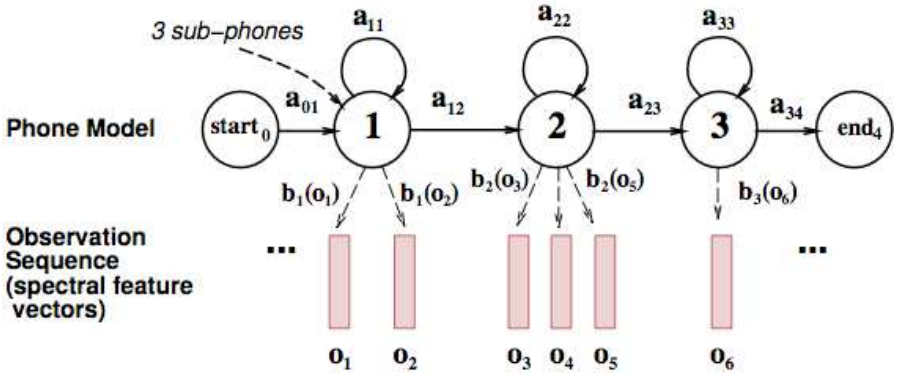
HMMs for Speech



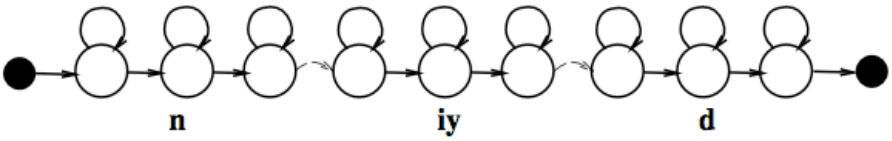
Phones Aren't Homogeneous



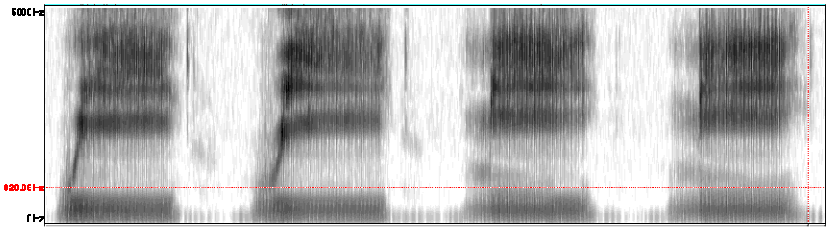
Need to Use Subphones



A Word with Subphones

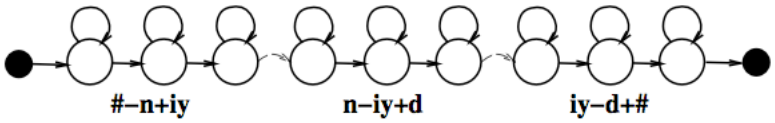


Modeling phonetic context

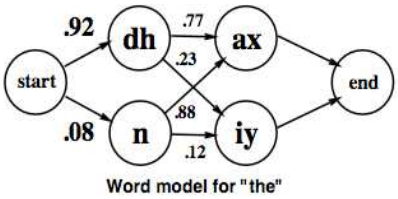


w iy r iy m iy n iy

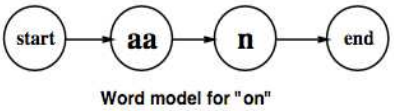
“Need” with triphone models



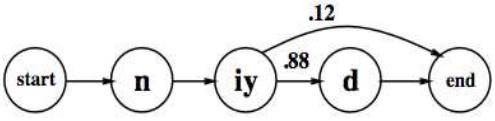
ASR Lexicon: Markov Models



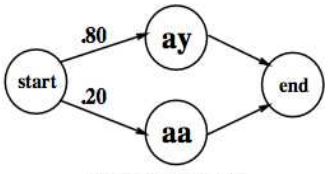
Word model for "the"



Word model for "on"



Word model for "need"



Word model for "I"

Markov Process with Bigrams

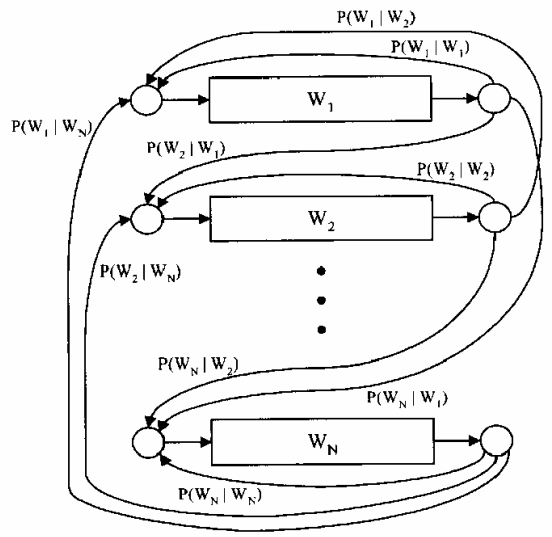


Figure from Huang et al page 618

Training Mixture Models

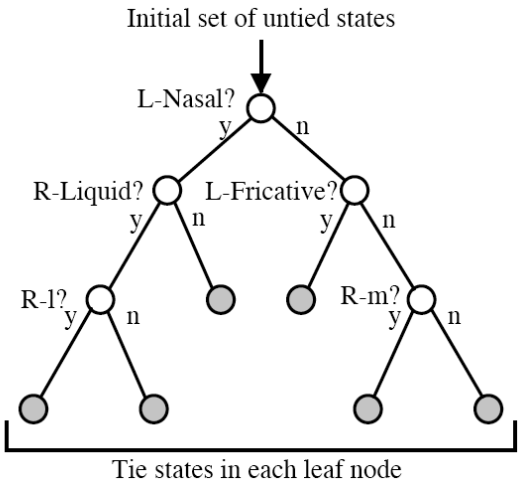
- Input: wav files with unaligned transcriptions
- Forced alignment
  - Computing the "Viterbi path" over the training data (where the transcription is known) is called "forced alignment"
  - We know which word string to assign to each observation sequence.
  - We just don't know the state sequence.
  - So we constrain the path to go through the correct words (by using a special example-specific language model)
  - And otherwise run the Viterbi algorithm
- Result: aligned state sequence

Lots of Triphones

- Possible triphones: 50x50x50=125,000
- How many triphone types actually occur?
- 20K word WSJ Task (from Bryan Pellom)
  - Word internal models: need 14,300 triphones
  - Cross word models: need 54,400 triphones
- Need to generalize models, tie triphones

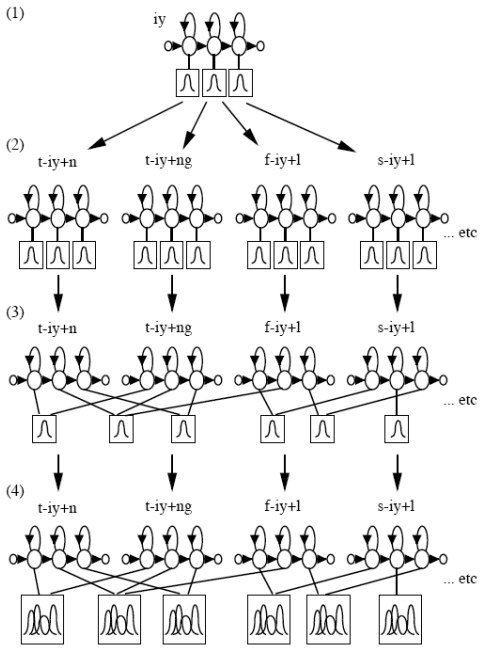
State Tying / Clustering

- [Young, Odell, Woodland 1994]
- How do we decide which triphones to cluster together?
- Use phonetic features (or 'broad phonetic classes')
  - Stop
  - Nasal
  - Fricative
  - Sibilant
  - Vowel
  - lateral

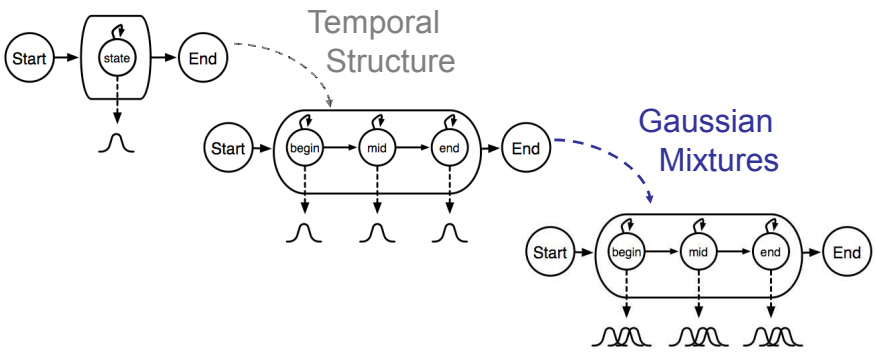


State Tying

- Creating CD phones:
  - Start with monophone, do EM training
  - Clone Gaussians into triphones
  - Build decision tree and cluster Gaussians
  - Clone and train mixtures (GMMs)
- General idea:
  - Introduce complexity gradually
  - Interleave constraint with flexibility

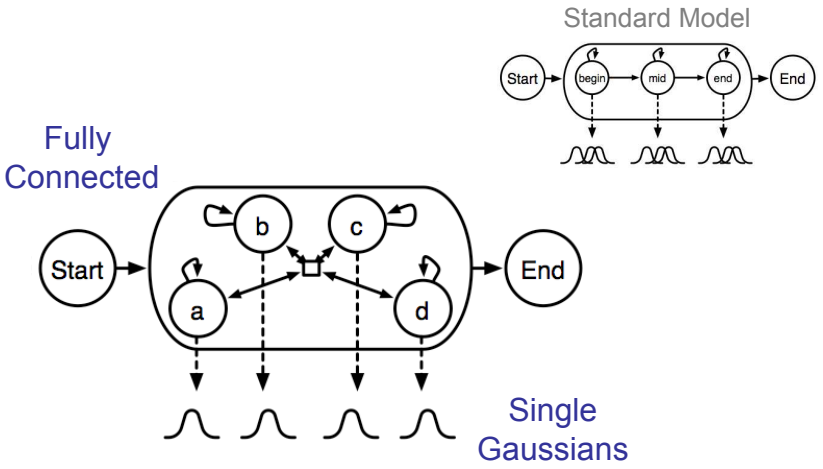


Standard subphone/mixture HMM



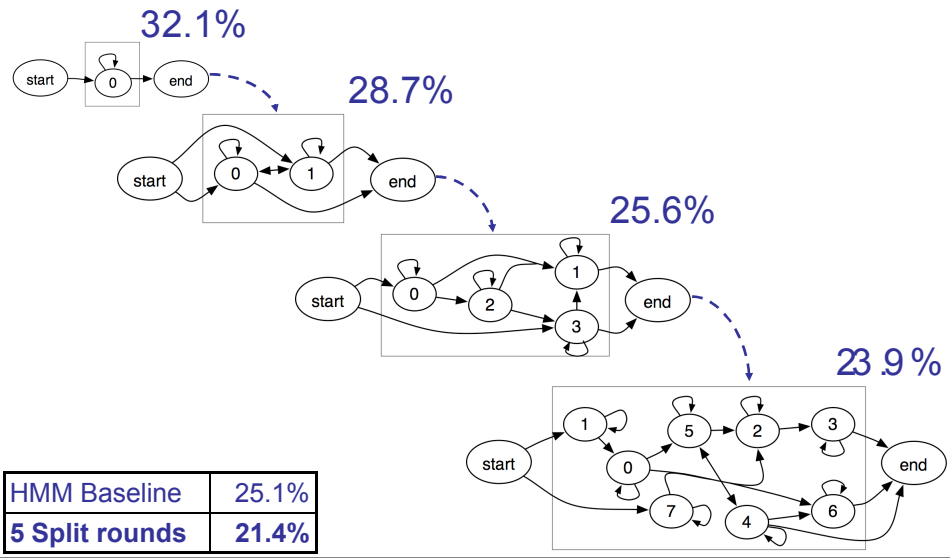
Model	Error rate
HMM Baseline	**25.1%**

An Induced Model



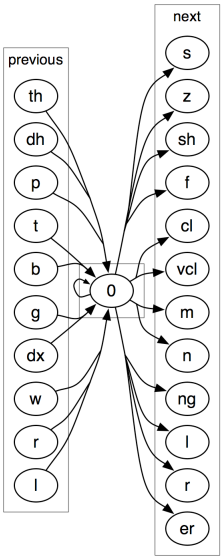
[Petrov, Pauls, and Klein, 07]

Hierarchical Split Training with EM

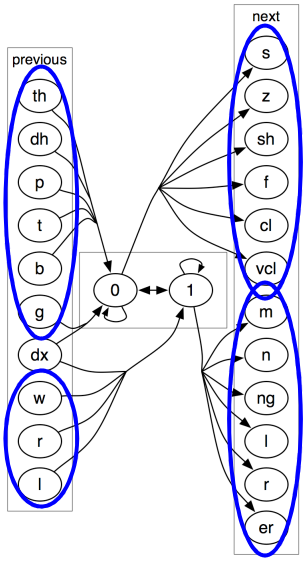


HMM Baseline	25.1%
5 Split rounds	**21.4%**

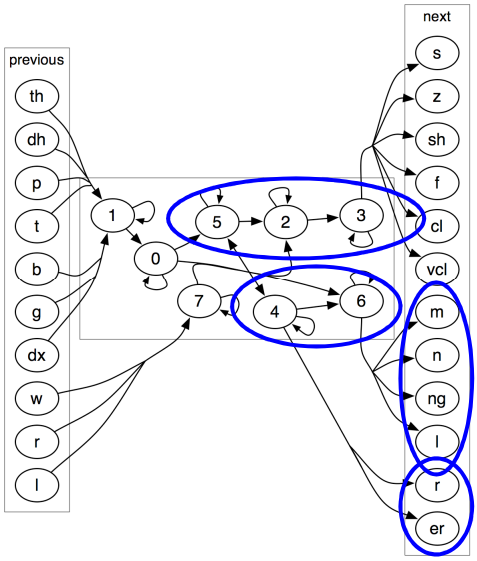
Refinement of the /ih/-phone



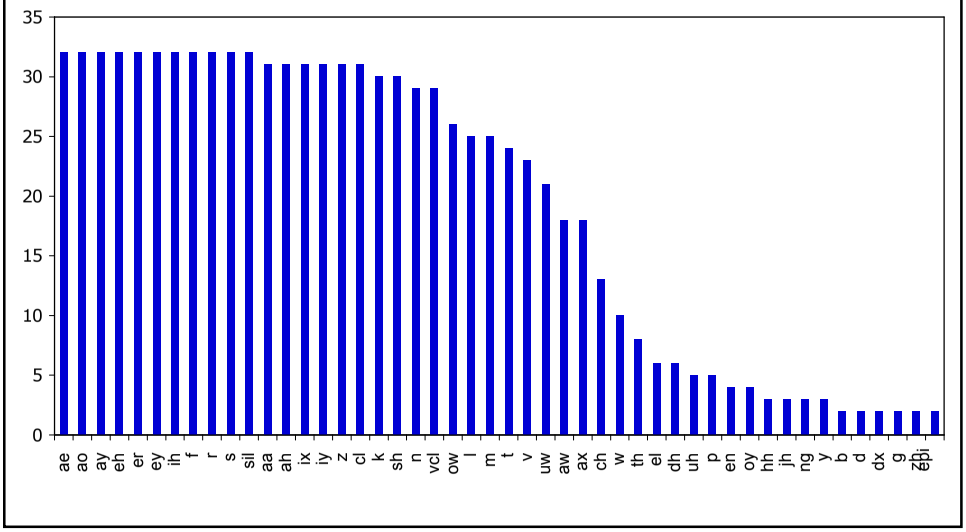
Refinement of the /ih/-phone



Refinement of the /ih/-phone



HMM states per phone



Inference

- State sequence:
  d_1-d_6-d_6-d_4-ae_5-ae_2-ae_3-ae_0-d_2-d_2-d_3-d_7-d_5

  Viterbi
- Phone sequence:
  d - d - d -d -ae - ae - ae - ae - d - d -d - d - d

  Variational
- Transcription
  d - ae - d

  ???