Statistical NLP
Spring 2009

University of California
CALNLP
Berkeley

Lecture 10: Acoustic Models

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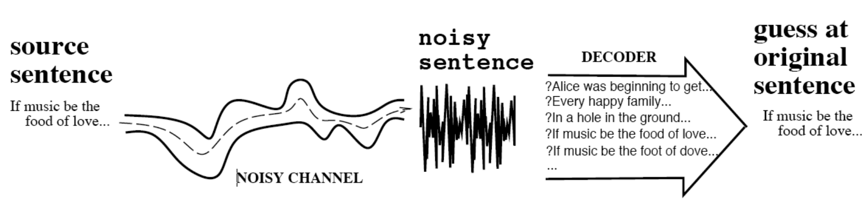
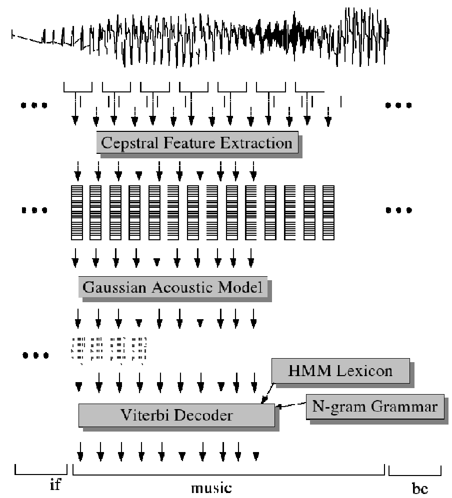
The Noisy Channel Model

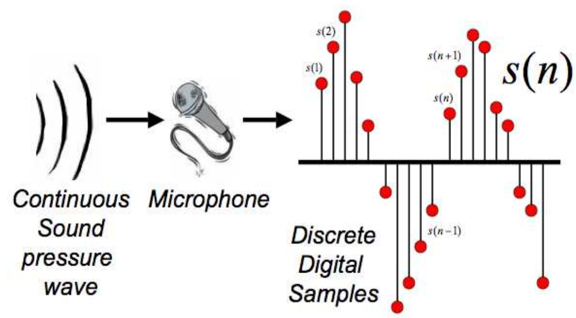


- Search through space of all possible sentences.
- Pick the one that is most probable given the waveform.

Speech Recognition Architecture



Digitizing Speech



Thanks to Bryan Pellom for this slide!

Frame Extraction

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

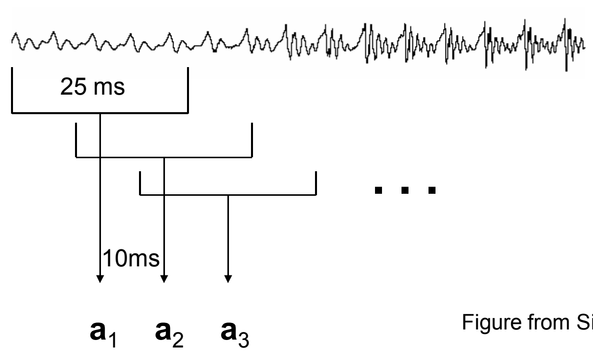


Figure from Simon Arnfield

Mel Freq. Cepstral Coefficients

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

Final Feature Vector

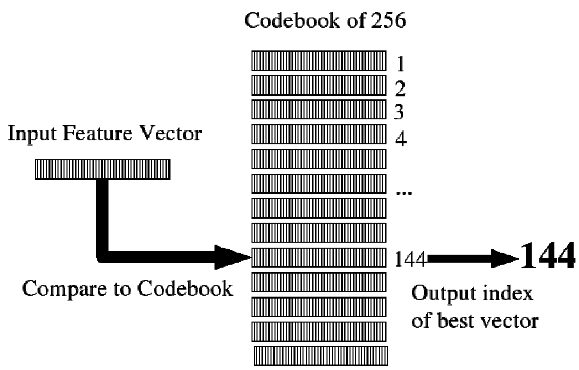
- 39 (real) features per 10 ms frame:
  - 12 MFCC features
  - 12 Delta MFCC features
  - 12 Delta-Delta MFCC features
  - 1 (log) frame energy
  - 1 Delta (log) frame energy
  - 1 Delta-Delta (log frame energy)
- So each frame is represented by a 39D vector

HMMs for Continuous Observations?

- Before: discrete, finite set of observations
- Now: spectral feature vectors are real-valued!
- Solution 1: discretization
- Solution 2: continuous emissions models
  - 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
- Useful to consider as a starting point



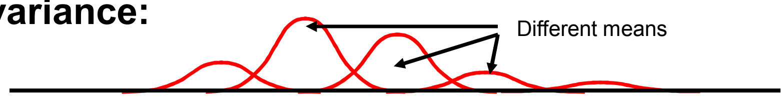
Gaussian Emissions

- VQ is insufficient for real ASR
- Instead: Assume the possible values of the observation vectors are normally distributed.
- Represent the observation likelihood function as a Gaussian with mean μ_j and variance σ_j^2

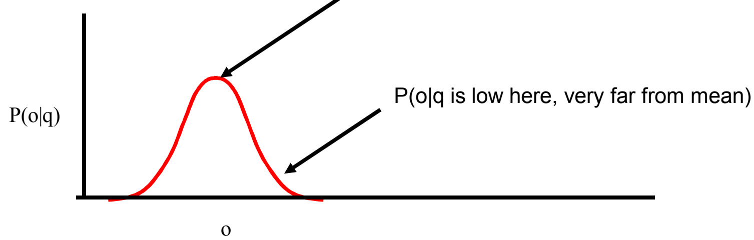
$$f(x \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

Gaussians for Acoustic Modeling

A Gaussian is parameterized by a mean and a variance:



- P(o|q):



Multivariate Gaussians

- Instead of a single mean μ and variance σ:

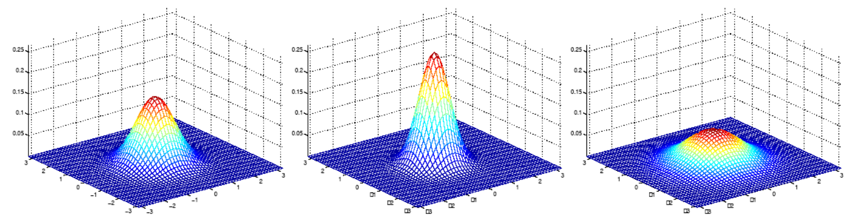
$$f(x \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

- Vector of means μ and covariance matrix Σ

$$f(x \mid \mu, \Sigma) = \frac{1}{(2\pi)^{n/2} \left|\Sigma\right|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^T \Sigma^{-1} (x-\mu)\right)$$

- Usually assume diagonal covariance
  - This isn't very true for FFT features, but is fine for MFCC features

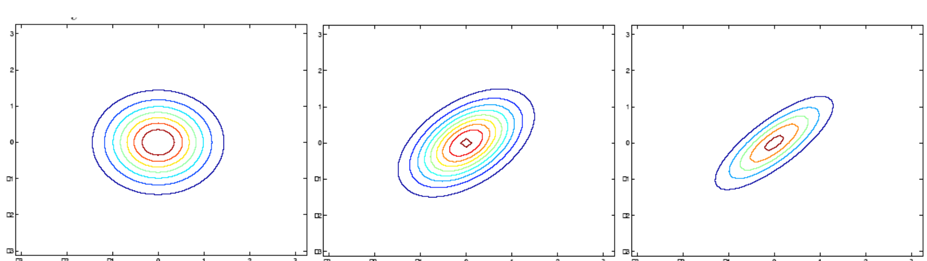
Gaussian Intuitions: Size of Σ



- 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's lecture notes for CS229

Gaussians: Off-Diagonal



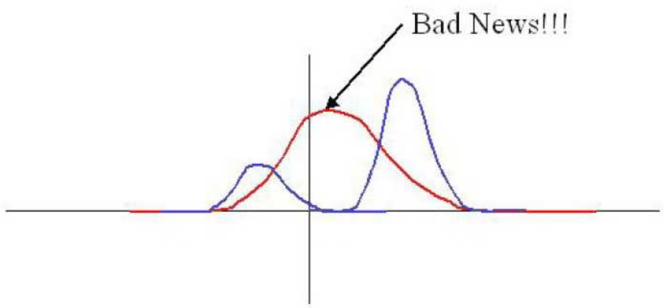
$$\Sigma = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}; \quad \Sigma = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}; \quad .\Sigma = \begin{bmatrix} 1 & 0.8 \\ 0.8 & 1 \end{bmatrix}$$

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

Text and figures from Andrew Ng's lecture notes for CS229

But we're not there yet

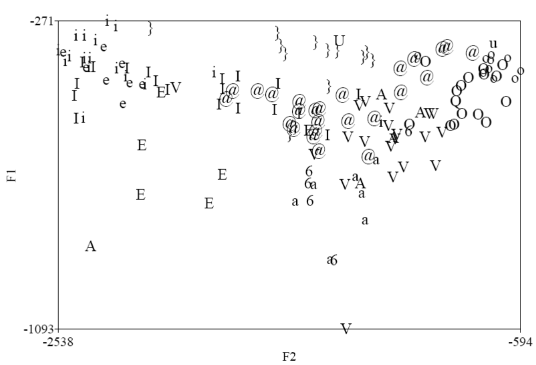
- Single Gaussian may do a bad job of modeling distribution in any dimension:

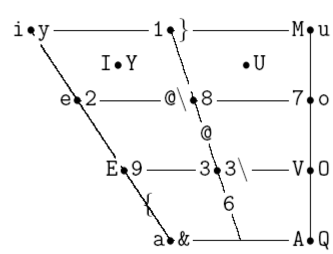


- Solution: Mixtures of Gaussians

Figure from Chen, Picheney et al slides

Scatter Plots





Mixtures of Gaussians

- M mixtures of Gaussians:

$$f(x \mid \mu_{jk}, \Sigma_{jk}) = \sum_{k=1}^{M} c_{jk} N(x, \mu_{jk}, \Sigma_{jk})$$

$$b_j(o_t) = \sum_{k=1}^{M} c_{jk} N(o_t, \mu_{jk}, \Sigma_{jk})$$

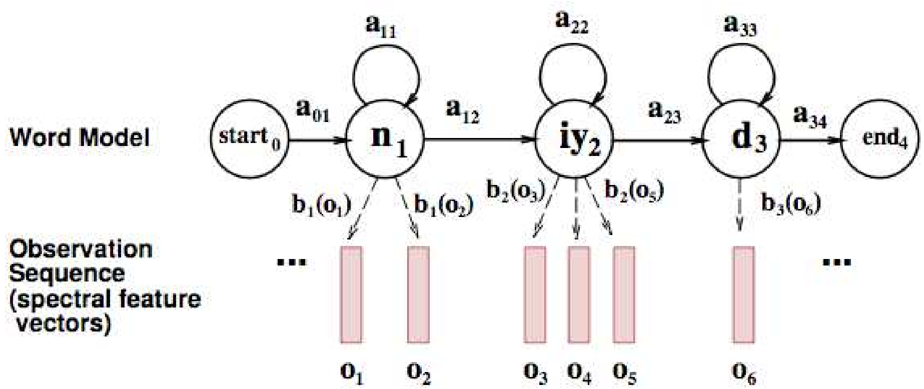
- For diagonal covariance:

$$b_j(o_t) = \sum_{k=1}^{M} \frac{c_{jk}}{2\pi^{D/2} \prod_{d=1}^{D} \sigma_{jkd}^{2}} \exp\left(-\frac{1}{2} \sum_{d=1}^{D} \frac{(x_{jkd} - \mu_{jkd})^2}{\sigma_{jkd}^{2}}\right)$$

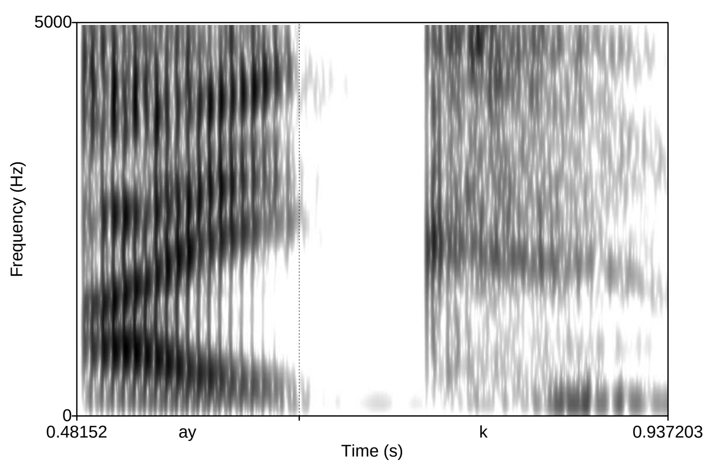
GMMs

- Summary: each state has a likelihood function parameterized by:
  - M mixture weights
  - M mean vectors of dimensionality D
  - Either
    - M covariance matrices of DxD
  - Or often
    - M diagonal covariance matrices of DxD
      which is equivalent to
    - M variance vectors of dimensionality D

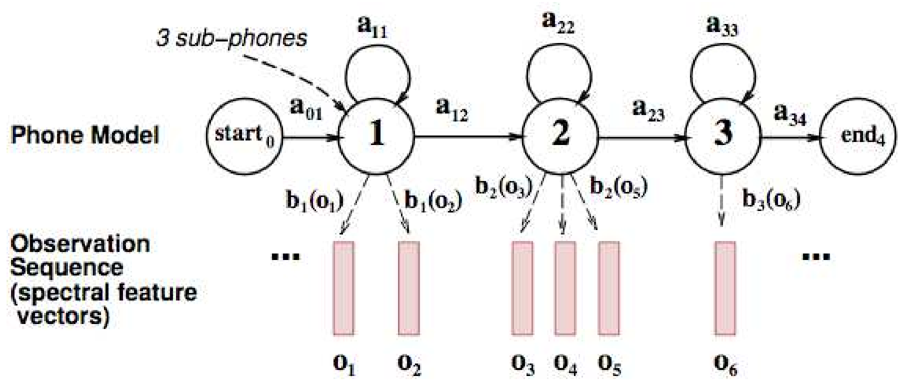
HMMs for Speech



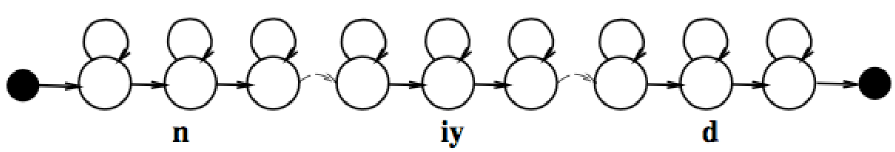
Phones Aren't Homogeneous



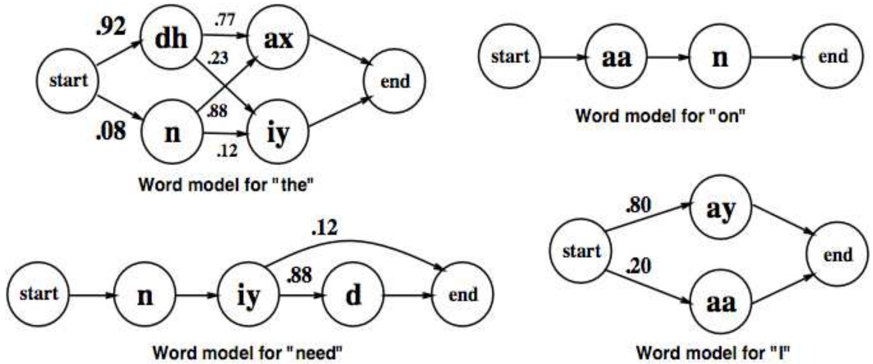
Need to Use Subphones



A Word with Subphones



ASR Lexicon: Markov Models



Markov Process with Bigrams

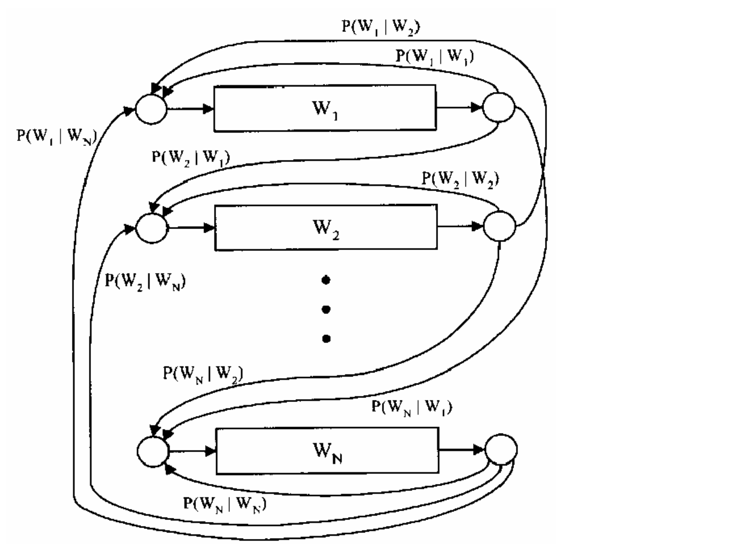
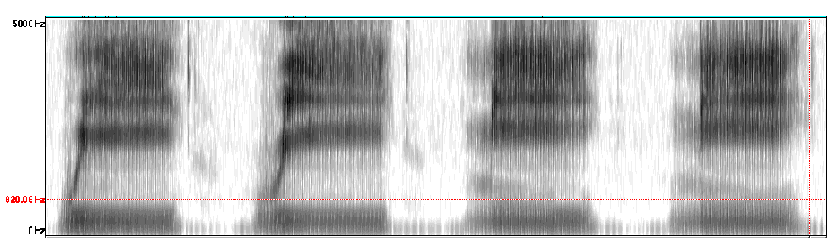


Figure from Huang et al page 618

Training Mixture Models

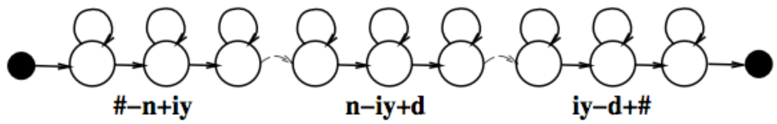
- Forced Alignment
  - Computing the "Viterbi path" over the training data (where the transcription is known) is called "forced alignment"
  - We know which word string to assign to each observation sequence.
  - We just don't know the state sequence.
  - So we constrain the path to go through the correct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

Modeling phonetic context



W iy r iy m iy n iy

“Need” with triphone models

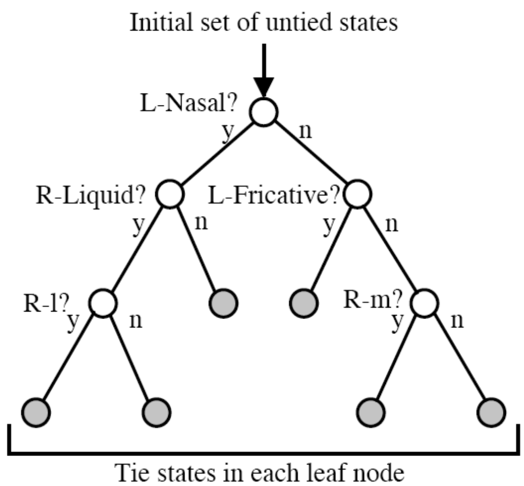


Implications of Cross-Word Triphones

- 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
  - But in training data only 22,800 triphones occur!
- Need to generalize models.

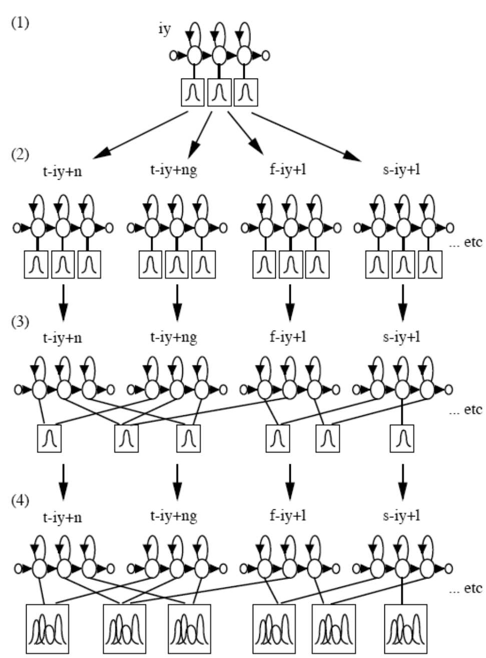
State Tying / Clustering

- [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

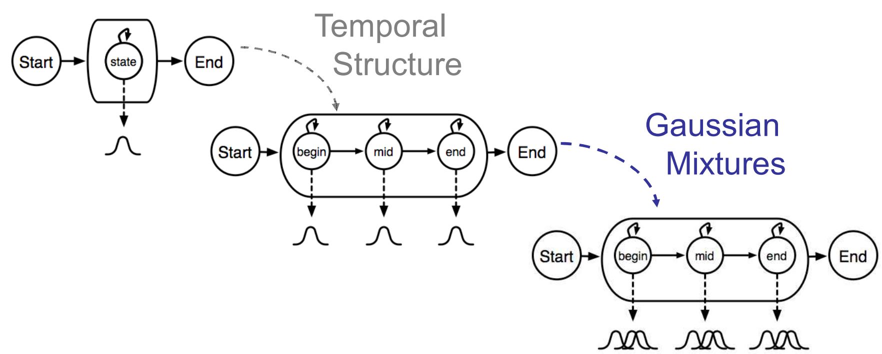


State Tying

- Creating CD phones:
  - Start with monophone, do EM training
  - Clone Gaussians into triphones
  - Build decision tree and cluster Gaussians
  - Clone and train mixtures (GMMs

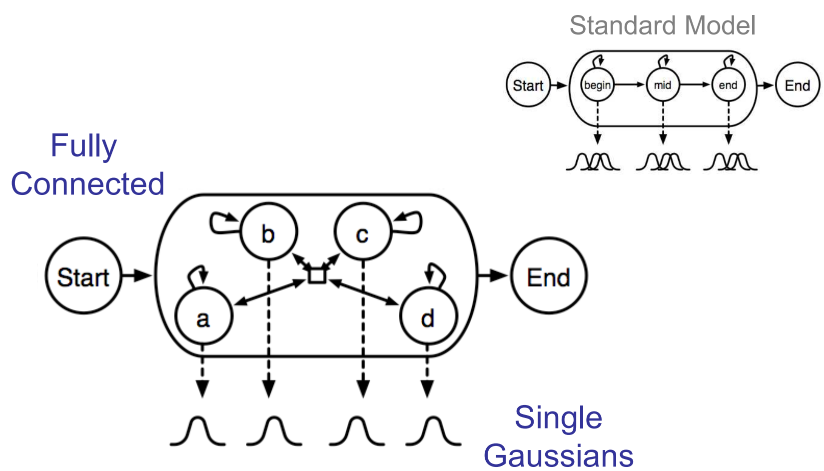


Standard subphone/mixture HMM

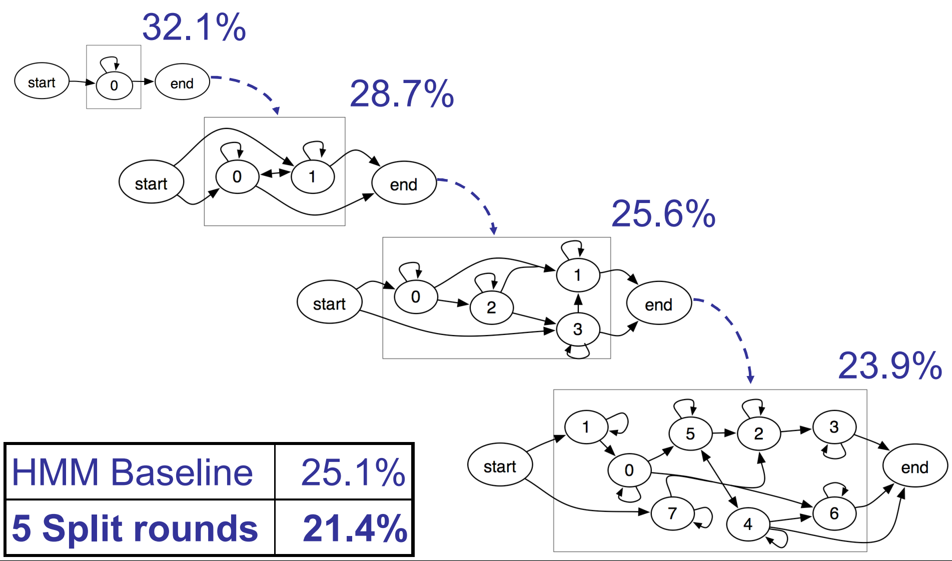


Model	Error rate
HMM Baseline	**25.1%**

Our Model

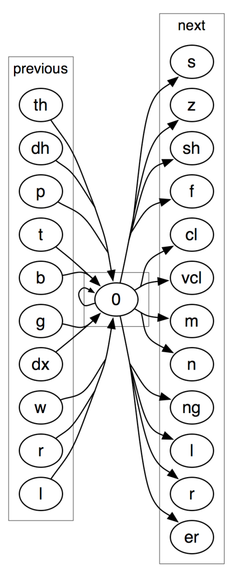


Hierarchical Baum-Welch Training

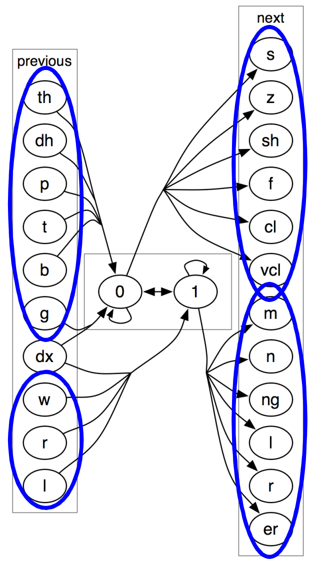


HMM Baseline	25.1%
5 Split rounds	**21.4%**

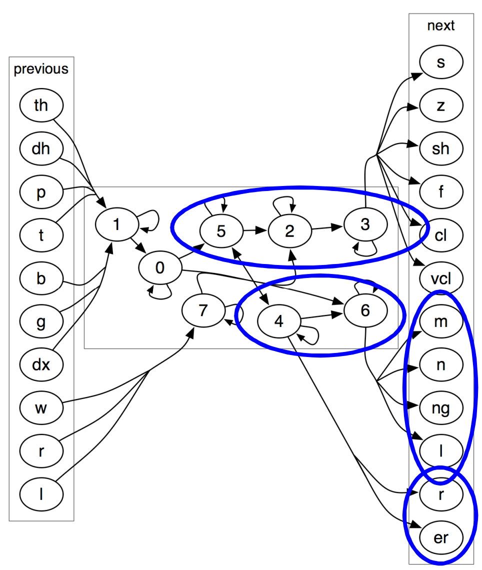
Refinement of the /ih/-phone



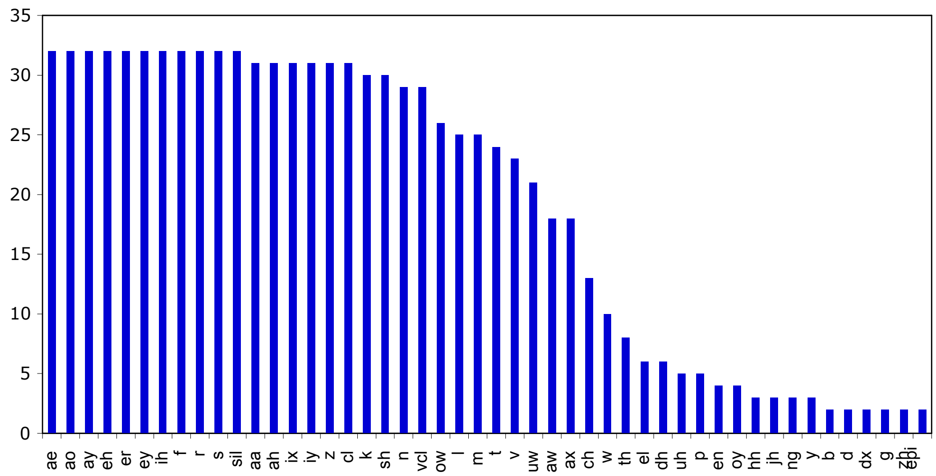
Refinement of the /ih/-phone



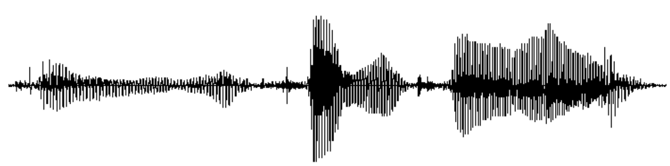
Refinement of the /ih/-phone



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

- Phone sequence:

  d - d - d -d -ae - ae - ae - ae - d - d -d - d - d

- Transcription

  d - ae - d

Viterbi

Variational

???