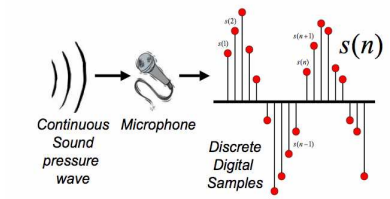
Statistical NLP
Spring 2008

Lecture 10: Acoustic Models

Dan Klein – UC Berkeley

Digitizing Speech



Thanks to Bryan Pellom for this slide!

Frame Extraction

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

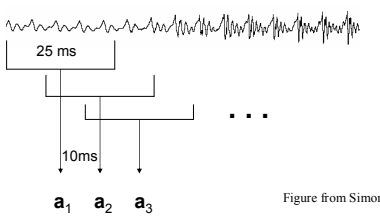


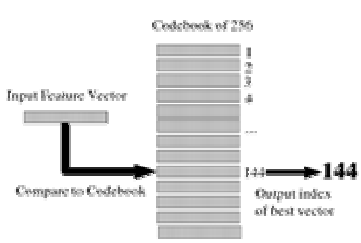
Figure from Simon Arnfield

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



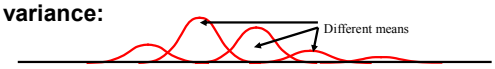
Gaussian Emissions

- 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

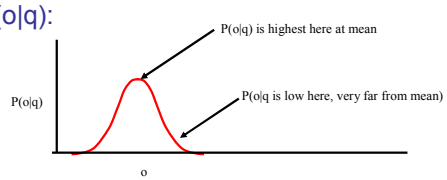
$$f(x \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

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:

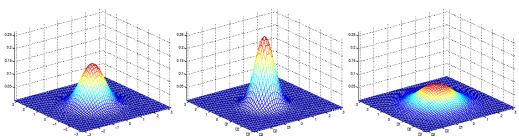
$$f(x \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

- Vector of means μ and covariance matrix Σ

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

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

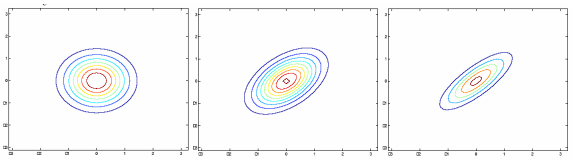
Gaussian Intuitions: Size of Σ



- 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

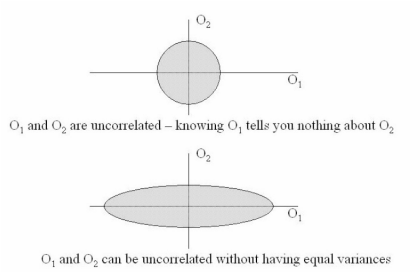


$$\Sigma = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}; \quad \Sigma = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}; \quad .\Sigma = \begin{bmatrix} 1 & 0.8 \\ 0.8 & 1 \end{bmatrix}$$

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

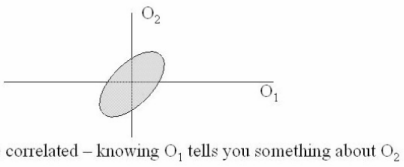
Text and figures from Andrew Ng's lecture notes for CS229

In two dimensions



From Chen, Picheny et al lecture slides

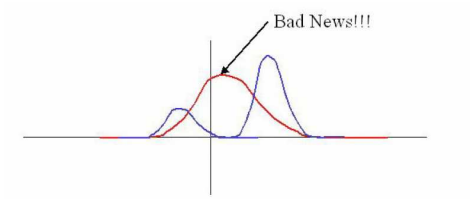
In two dimensions



From Chen, Picheny et al lecture slides

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

Mixtures of Gaussians

- M mixtures of Gaussians:

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

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

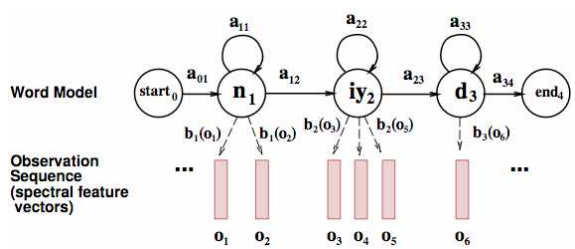
- For diagonal covariance:

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

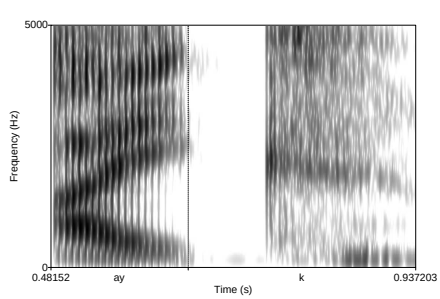
GMMs

- 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

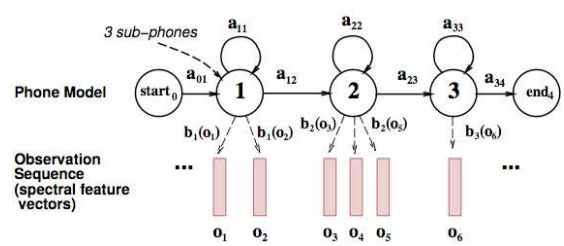
HMMs for Speech



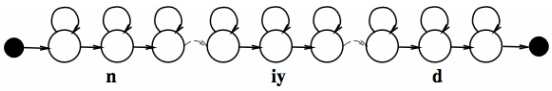
Phones Aren't Homogeneous



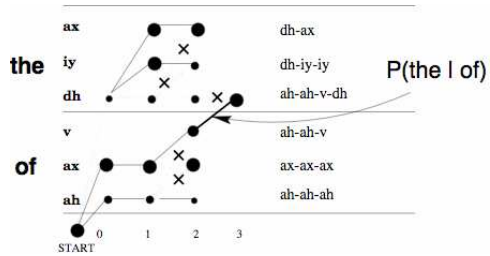
Need to Use Subphones



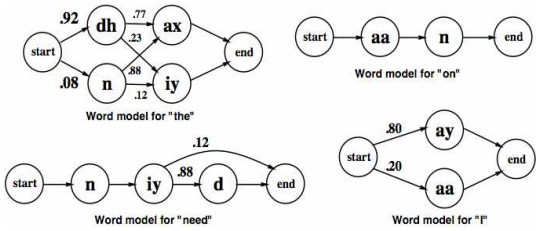
A Word with Subphones



Viterbi Decoding



ASR Lexicon: Markov Models



Markov Process with Bigrams

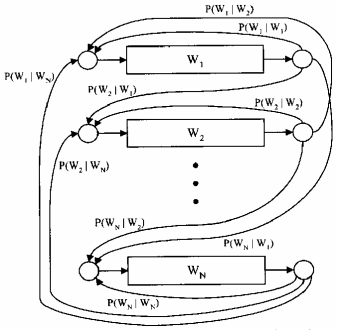
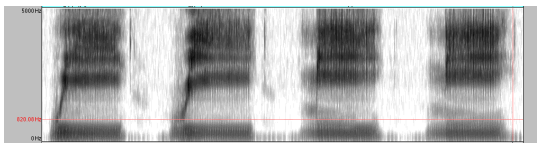


Figure from Huang et al page 618

Training Mixture Models

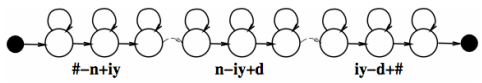
- Forced Alignment
  - Computing the "Viterbi path" over the training data is called "forced alignment"
  - We know which word string to assign to each observation sequence.
  - We just don't know the state sequence.
  - So we constrain the path to go through the correct words
  - And otherwise do normal Viterbi
- Result: state sequence!

Modeling phonetic context



W iy r iy m iy n iy

“Need” with triphone models

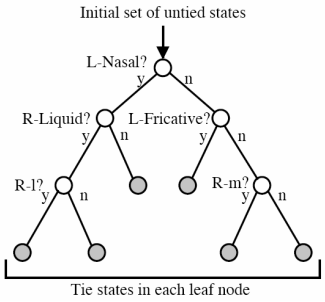


Implications of Cross-Word Triphones

- 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.

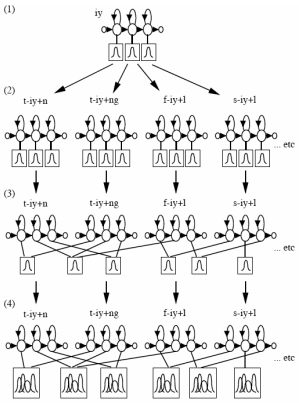
State Tying / Clustering

- [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

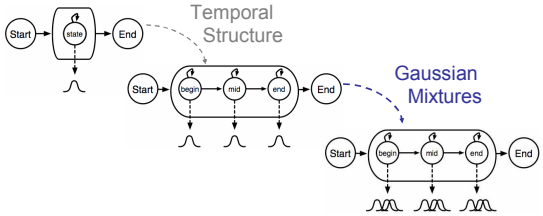


State Tying

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

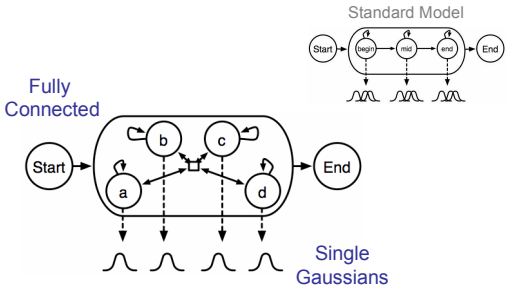


Standard subphone/mixture HMM

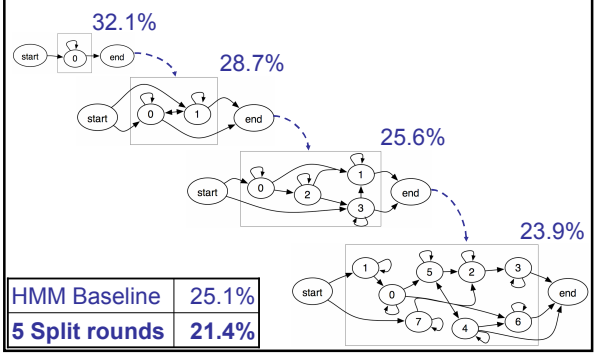


Model	Error rate
HMM Baseline	**25.1%**

Our Model

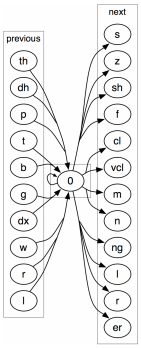


Hierarchical Baum-Welch Training



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

Refinement of the /ih/-phone



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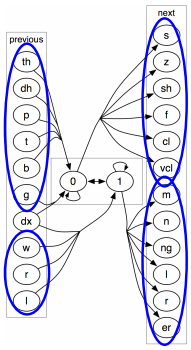
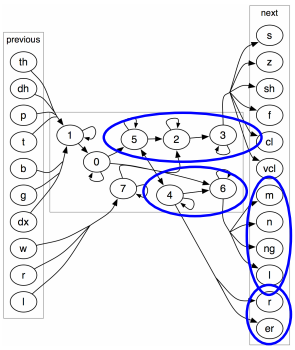
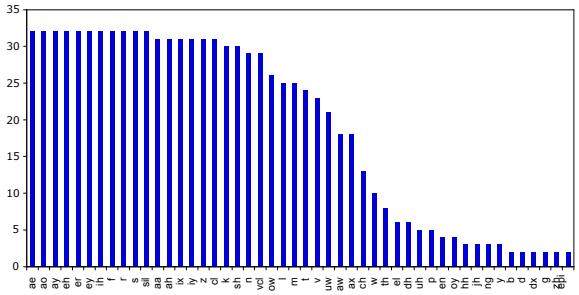


Refinement of the /ih/-phone



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

???