Lecture 11:
ASR: Training & Systems

1. **Training HMMs**
2. **Language modeling**
3. **Discrimination & adaptation**

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Spring 2003

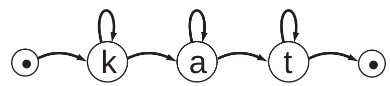
1 HMM review

- **HMM M_j is specified by:**

- states q^i

- transition probabilities a_{ij}

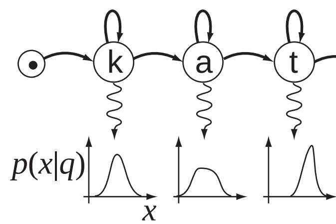
$$p(q_n^j | q_{n-1}^i) \equiv a_{ij}$$



	k	a	t	•
•	1.0	0.0	0.0	0.0
k	0.9	0.1	0.0	0.0
a	0.0	0.9	0.1	0.0
t	0.0	0.0	0.9	0.1

- emission distributions $b_i(x)$

$$p(x | q^i) \equiv b_i(x)$$



+ (initial state probabilities $p(q_1^i) \equiv \pi_i$)

- **See** e6820/papers/Rabiner89-hmm.pdf

HMM summary (1)

- **HMMs are a generative model:**
  recognition is inference of $p(M_j|X)$

- **During generation, behavior of model depends only on current state q_n:**
  - transition probabilities $p(q_{n+1} \mid q_n) = a_{ij}$
  - observation distributions $p(x_n \mid q_n) = b_i(x)$

- **Given states** $Q = \{q_1, q_2, \ldots, q_N\}$

  + observations $X = X_1^N = \{x_1, x_1, \ldots, x_N\}$

  Markov assumption makes

  $$p(X, Q|M) = \prod_n p(x_n|q_n) p(q_n|q_{n-1})$$

- **Given observed emissions X, can calculate:**

  $$p(X|M_j) = \sum_{\text{all } Q} p(X|Q, M) p(Q|M)$$

HMM summary (2)

- **Calculate $p(X|M)$ via forward recursion:**

$$p(X_1^n, q_n^j) = \alpha_n(j) = \left[\sum_{i=1}^{S} \alpha_{n-1}(i) a_{ij}\right] \cdot b_j(x_n)$$

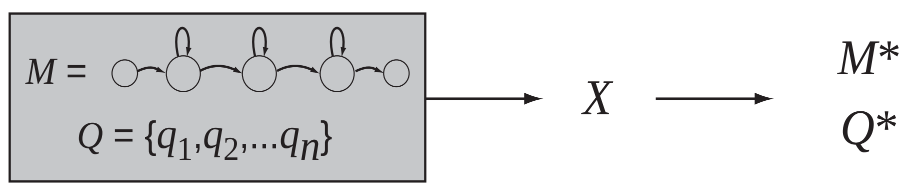
- **Viterbi (best path) approximation**

$$\alpha_n^*(j) = \left[\max_i \{\alpha_{n-1}^*(i) a_{ij}\}\right] \cdot b_j(x_n)$$

  - then backtrace...

$$Q^* = \underset{Q}{\operatorname{argmax}}\ p(X, Q|M)$$

- **Pictorially:**



assumed, hidden   observed   inferred

Outline

1. **Hidden Markov Model review**
2. **Training HMMs**
   - Viterbi training
   - EM for HMM parameters
   - Forward-backward (Baum-Welch)
3. **Language modeling**
4. **Discrimination & adaptation**

2 Training HMMs

- **Probabilistic foundation allows us to train HMMs to 'fit' training data**
  - i.e. estimate a_{ij}, $b_i(x)$ given data
  - better than DTW...
- **Algorithms to improve $p(M \mid X)$ are key to success of HMMs**
  - maximum-likelihood of models...
- **State alignments Q of training examples are generally unknown**
  - else estimating parameters would be easy

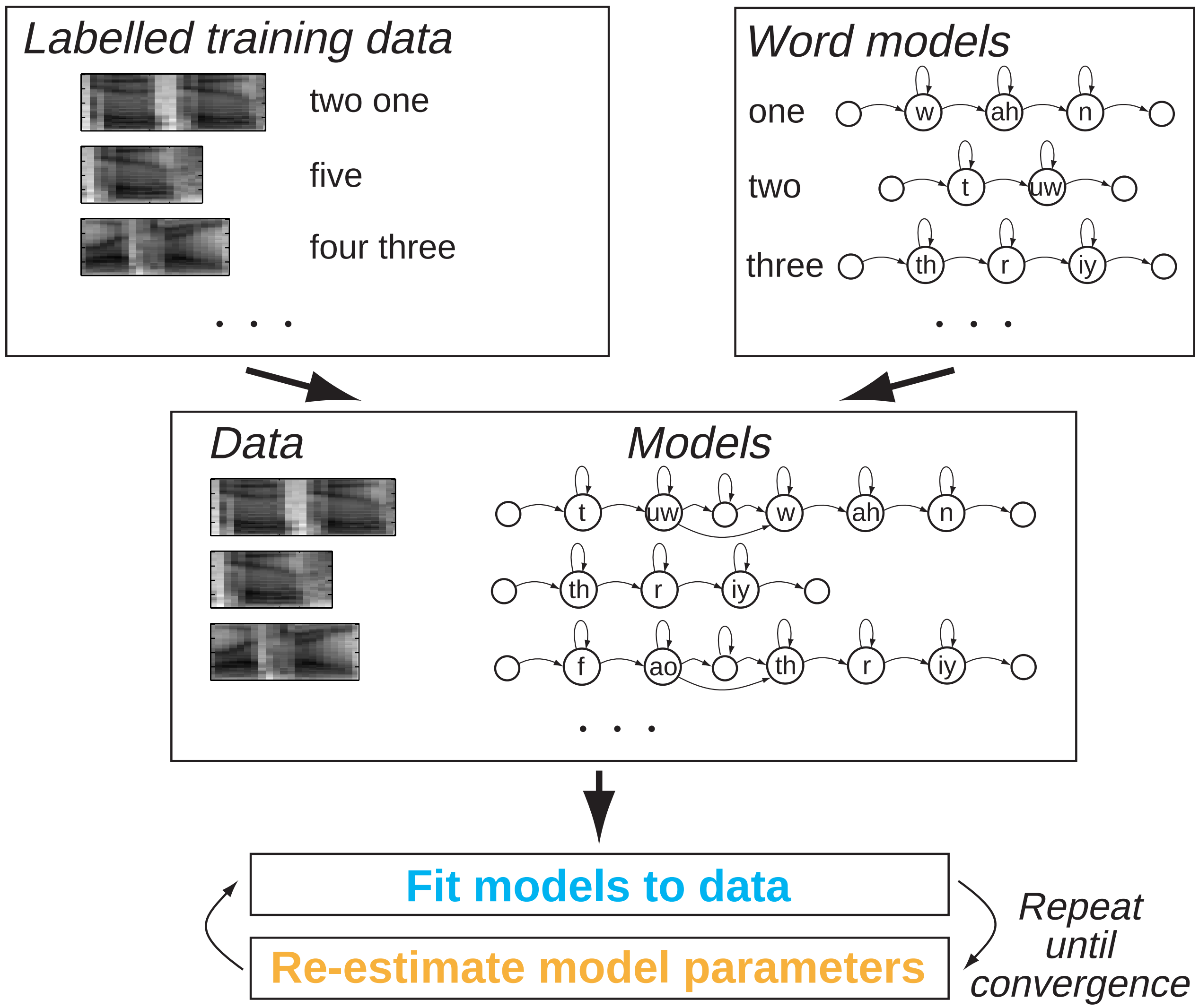
→ **Viterbi training**

- choose 'best' labels (heuristic)

→ **EM training**

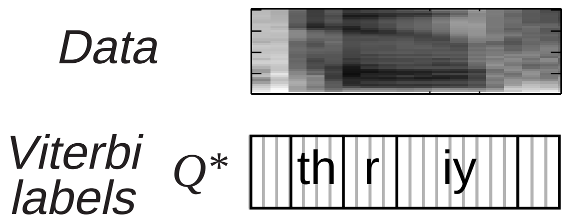
- 'fuzzy labels' (guaranteed local convergence)

Overall training procedure



Viterbi training

- "**Fit models to data**"
  = Viterbi best-path alignment



- "**Re-estimate model parameters**":

  pdf e.g. 1D Gauss: $\mu_i = \dfrac{\sum_{n \in q^i} x_n}{\#(q_n^i)}$

  count transitions: $a_{ij} = \dfrac{\#(q_{n-1}^i \rightarrow q_n^j)}{\#(q_n^i)}$

- **And repeat...**
- **But: converges only if good initialization**

EM for HMMs

- **Expectation-Maximization (EM): optimizes models with unknown parameters**
  - finds locally-optimal parameters Θ to maximize data likelihood $p(x_{train}|\Theta)$
  - makes sense for decision rules like $p(x|M_j) \cdot p(M_j)$

- **Principle: Adjust Θ to maximize expected log likelihood of known x & unknown u:**

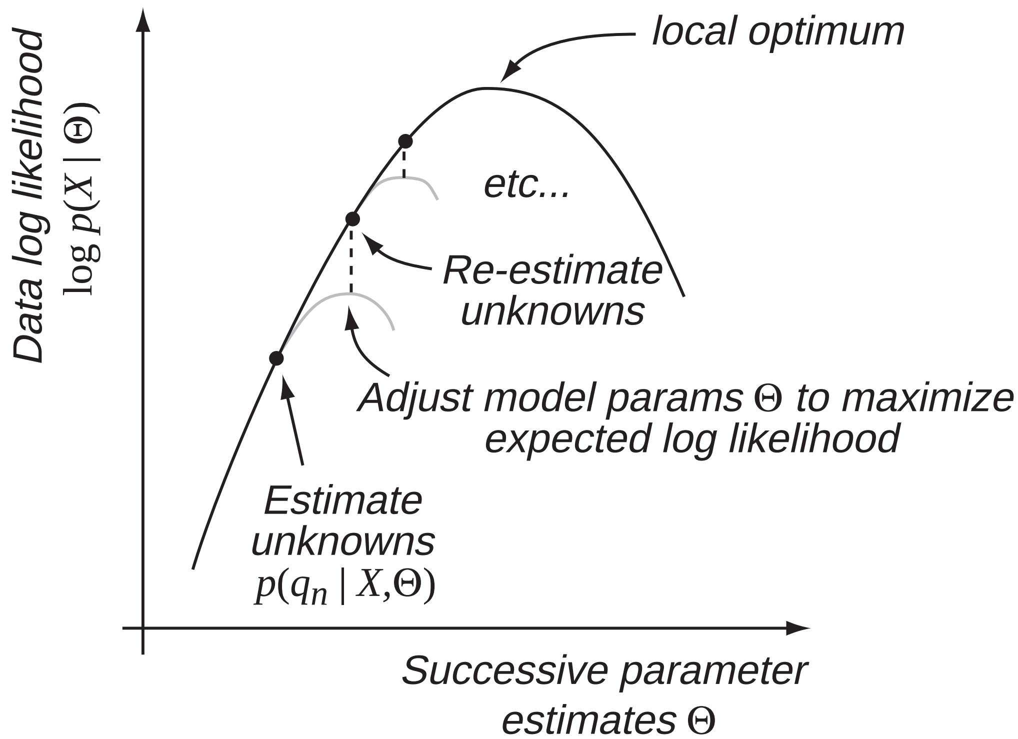
$$E[\log p(x,u|\Theta)] = \sum_u p(u|x,\Theta_{old}) \log[p(x|u,\Theta)p(u|\Theta)]$$

  - for GMMs, unknowns = mix assignments k
  - for HMMs, unknowns = hidden state q_n (take Θ to include M_j)

- **Interpretation: "fuzzy" values for unknowns**

What EM does

- **Maximize data likelihood**
  by repeatedly estimating unknowns
  and re-maximizing expected log likelihood:



EM for HMMs (2)

- **Expected log likelihood for HMM:**

$$\sum_{\text{all } Q_k} p(Q_k | X, \Theta_{\text{old}}) \log[p(X | Q_k, \Theta) p(Q_k | \Theta)]$$

$$= \sum_{\text{all } Q_k} p(Q_k | X, \Theta_{\text{old}}) \log\left[\prod_n p(x_n | q_n) \cdot p(q_n | q_{n-1})\right]$$

$$= \sum_{n=1}^{N} \sum_{i=1}^{S} p(q_n^i | X, \Theta_{\text{old}}) \log p(x_n | q_n^i, \Theta)$$

$$+ \sum_{i=1}^{S} p(q_1^i | X, \Theta_{\text{old}}) \log p(q_1^i | \Theta)$$

$$+ \sum_{n=2}^{N} \sum_{i=1}^{S} \sum_{j=1}^{S} p(q_{n-1}^i, q_n^j | X, \Theta_{\text{old}}) \log p(q_n^j | q_{n-1}^i, \Theta)$$

- closed-form maximization by differentiation etc.

EM update equations

- **For acoustic model (e.g. 1-D Gauss):**

$$\mu_i = \frac{\sum_n p(q_n^i | X, \Theta_{\text{old}}) \cdot x_n}{\sum_n p(q_n^i | X, \Theta_{\text{old}})}$$

- **For transition probabilities:**

$$p(q_n^j | q_{n-1}^i) = a_{ij}^{\text{new}} = \frac{\sum_n p(q_{n-1}^i, q_n^j | X, \Theta_{\text{old}})}{\sum_n p(q_{n-1}^i | X, \Theta_{\text{old}})}$$

- **Fuzzy versions of Viterbi training**
  - reduce to Viterbi if $p(q|X) = 1/0$

- **Require 'state occupancy probabilities',**

$$p(q_n^i | X_1^N, \Theta_{\text{old}})$$

The forward-backward algorithm

- **We need** $p(q_n^i | X_1^N)$ **for EM updates (**Θ **implied)**
- **Forward algorithm gives** $\alpha_n(i) = p(q_n^i, X_1^n)$
  - excludes influence of remaining data X_{n+1}^N
- **Hence, define** $\beta_n(i) = p(X_{n+1}^N | q_n^i, X_1^n)$

  so that $\alpha_n(i) \cdot \beta_n(i) = p(q_n^i, X_1^N)$

  then $p(q_n^i | X_1^N) = \dfrac{\alpha_n(i) \cdot \beta_n(i)}{\sum_j \alpha_n(j) \cdot \beta_n(j)}$
- Recursive **definition for** β**:**

  $\beta_n(i) = \sum_j \beta_{n+1}(j) a_{ij} b_j(x_{n+1})$
  - recurses backwards from final state N

Estimating a_{ij} from α & β

- **From EM equations:**

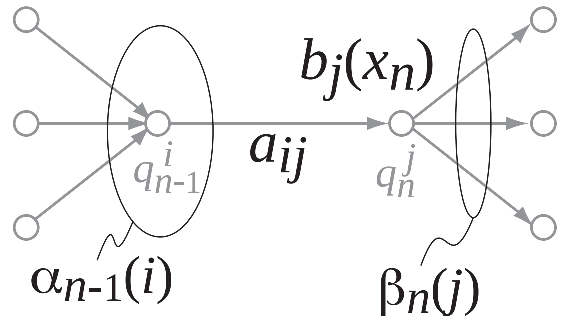
$$p(q_n^j | q_{n-1}^i) = a_{ij}^{\text{new}} = \frac{\sum_n p(q_{n-1}^i, q_n^j | X, \Theta_{\text{old}})}{\sum_n p(q_{n-1}^i | X, \Theta_{\text{old}})}$$

  - prob. of transition normalized by prob. in first

- **Obtain from** $p(q_{n-1}^i, q_n^j, X | \Theta_{\text{old}})$

$$= p(X_{n+1}^N | q_n^j) p(x_n | q_n^j) p(q_n^j | q_{n-1}^i) p(q_{n-1}^i, X_1^{n-1})$$

$$= \beta_n(j) \cdot b_j(x_n) \cdot a_{ij} \cdot \alpha_{n-1}(i)$$



GMM-HMMs in practice

- **GMMs as acoustic models: train by including mixture indices as unknowns**
  - just more complicated equations...

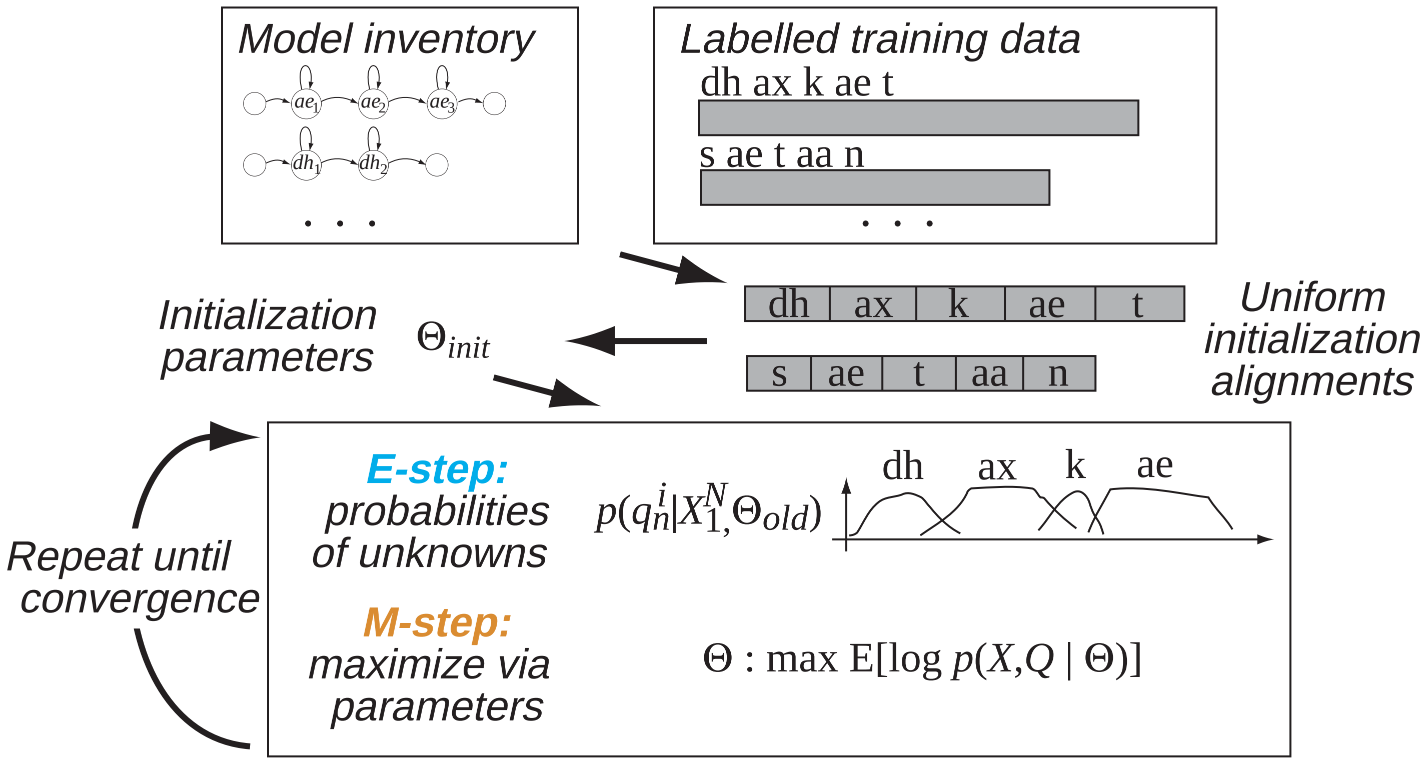
$$\mu_{ik} = \frac{\sum_n p(m_k | q^i, x_n, \Theta_{\text{old}}) p(q_n^i | X, \Theta_{\text{old}}) \cdot x_n}{\sum_n p(m_k | q^i, x_n, \Theta_{\text{old}}) p(q_n^i | X, \Theta_{\text{old}})}$$

- **Practical GMMs:**
  - 9 to 39 feature dimensions
  - 2 to 64 Gaussians per mixture depending on number of training examples
- **Lots of data → can model more classes**
  - e.g context-independent (CI): q^i = ***ae*** ***aa*** ***ax*** ...

  →context-dependent (CD): q^i = *b*-***ae***-*b* *b*-***ae***-*k* ...

HMM training in practice

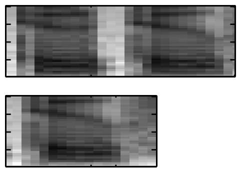
- **EM only finds local optimum**
  → critically dependent on initialization
  - approximate parameters / rough alignment



- **Applicable for more than just words...**

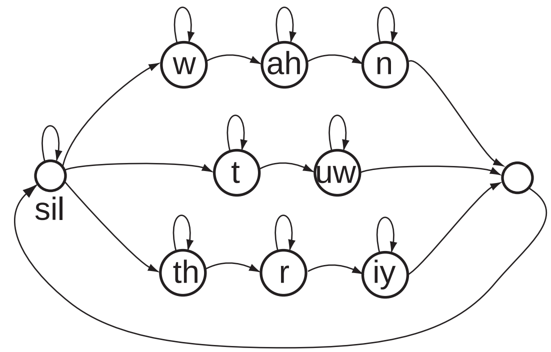
Training summary

- **Training data + basic model topologies**
  → derive fully-trained models



TWO ONE

FIVE



ONE = w ah n
TWO = t uw

  - alignment all handled implicitly

- **What do the states end up meaning?**
  - not necessarily what you intended;
    whatever locally maximizes data likelihood

- **What if the models or transcriptions are bad?**
  - slow convergence, poor discrimination in models

- **Other kinds of data, transcriptions**
  - less constrained initial models...

Outline

1. **Hidden Markov Models review**

2. **Training HMMs**

3. **Language modeling**
   - Pronunciation models
   - Grammars
   - Decoding

4. **Discrimination & adaptation**

3 Language models

- **Recall, MAP recognition criterion:**

$$M^* = \operatorname*{argmax}_{M_j} p(M_j|X, \Theta)$$

$$= \operatorname*{argmax}_{M_j} p(X|M_j, \Theta_A) p(M_j|\Theta_L)$$

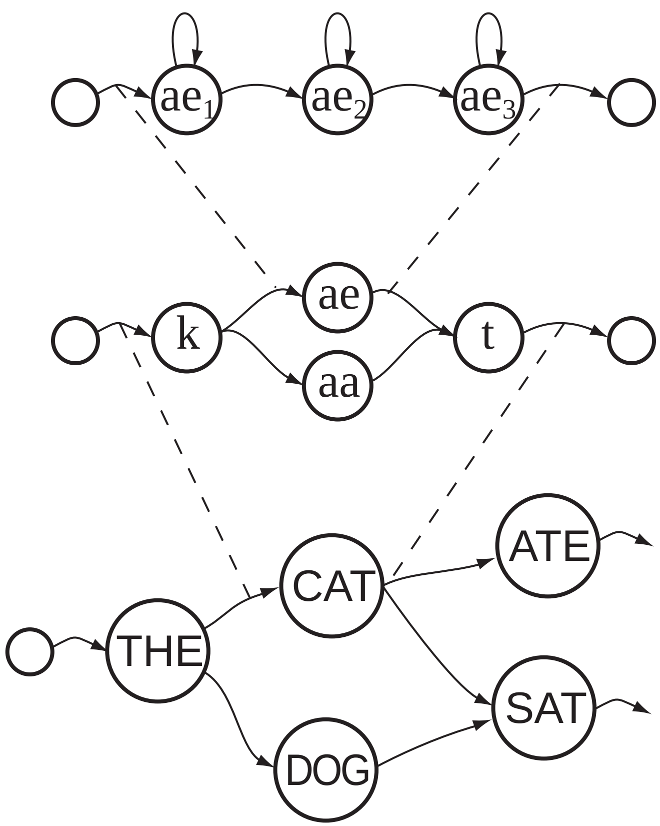
- **So far, looked at** $p(X|M_j, \Theta_A)$

- **What about** $p(M_j|\Theta_L)$ **?**
  - M_j is a particular word sequence
  - Θ_L are parameters related to the language

- **Two components:**
  - link state sequences to words $p(Q|w_i)$
  - priors on word sequences $p(w_i|M_j)$

HMM Hierarchy

- **HMMs support composition**
  - can handle time dilation, pronunciation, grammar all within the same framework



$$p(q|M) = p(q, \Phi, w|M)$$

$$= p(q|\phi) \cdot$$

$$p(\phi|w) \cdot$$

$$p(w_n|w_1^{n-1}, M)$$

Pronunciation models

- **Define states within each word** $p(Q|w_i)$
- **Can have unique states for each word ('whole-word' modeling), or ...**
- **Sharing (tying) subword units between words to reflect underlying phonology**
  - more training examples for each unit
  - generalizes to unseen words
  - (or can do it automatically...)
- **Start e.g. from pronouncing dictionary:**

```
ZERO(0.5)     z iy r ow
ZERO(0.5)     z ih r ow
ONE(1.0)      w ah n
TWO(1.0)      tcl t uw
...
```

Learning pronunciations

- **'Phone recognizer' transcribes training data as phones**
  - align to 'canonical' pronunciations

Baseform Phoneme String

`f ay v` `y iy r` `ow l d`

`f ah ay v y uh r ow l`

Surface Phone String

  - infer modification rules
  - predict other pronunciation variants

- **e.g. 'd deletion':**

  d → Ø / `l` _ [stop] p = 0.9

- **Generate pronunciation variants;**
  use forced alignment to find weights

Grammar

- **Account for different likelihoods of different words and word sequences** $p(w_i | M_j)$
- **'True' probabilities are very complex for LVCSR**
  - need parses, but speech often agrammatic

→ **Use n-grams:**

$$p(w_n | w_1^L) = p(w_n | w_{n-K}, \ldots, w_{n-1})$$

  - e.g. n-gram models of Shakespeare:

n=1 To him swallowed confess hear both. Which. Of save on ...

n=2 What means, sir. I confess she? then all sorts, he is trim, ...

n=3 Sweet prince, Falstaff shall die. Harry of Monmouth's grave...

n=4 King Henry. What! I will go seek the traitor Gloucester. ...

- **Big win in recognizer WER**
  - raw recognition results often highly ambiguous
  - grammar guides to 'reasonable' solutions

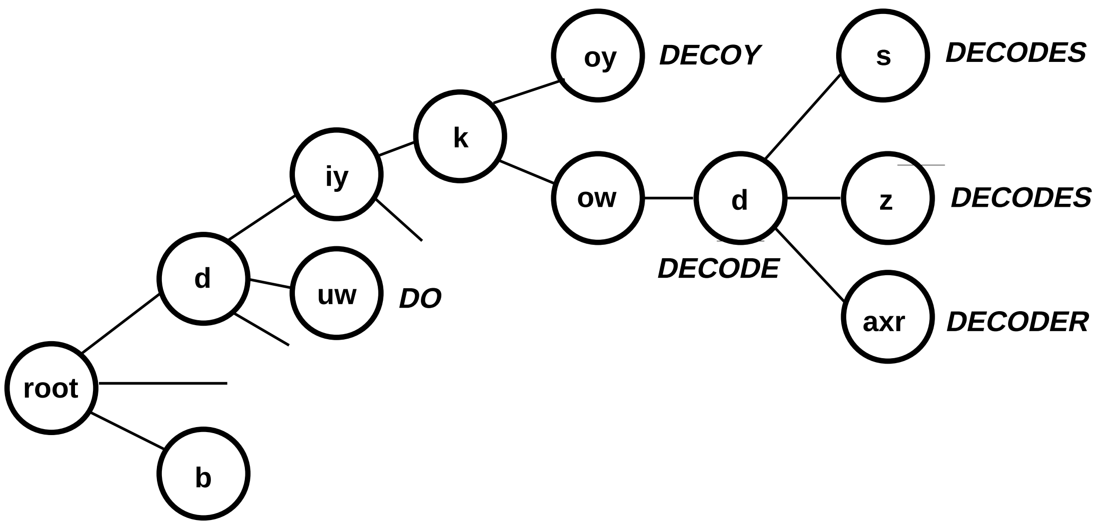
Smoothing LVCSR grammars

- **n-grams (n=3 or 4) are estimated from large text corpora**
  - 100M+ words
  - but: not like spoken language
- **100,000 word vocabulary $\rightarrow$ 10^{15} trigrams!**
  - never see enough examples
  - unobserved trigrams should NOT have Pr=0!
- **Backoff to bigrams, unigrams**
  - $p(w_n)$ as an approx to $p(w_n \mid w_{n\text{-}1})$ etc.
  - interpolate 1-gram, 2-gram, 3-gram with learned weights?
- **Lots of ideas e.g. category grammars**
  - e.g. $p(\text{ PLACE} \mid \text{“went”, “to”}) \cdot p(w_n \mid \text{PLACE})$
  - how to define categories?
  - how to tag words in training corpus?

Decoding

- **How to find the MAP word sequence?**
- **States, prons, words define one big HMM**
  - with 100,000+ individual states for LVCSR!

→ **Exploit hierarchic structure**
  - phone states independent of word
  - next word (semi) independent of word history



Decoder pruning

- **Searching 'all possible word sequences'?**
  - need to restrict search to most promising ones: beam search
  - sort by estimates of total probability
    = Pr(so far) + lower bound estimate of remains
  - trade search errors for speed
- **Start-synchronous algorithm:**
  - extract top hypothesis from queue:

$$[P_n, \{w_1, \ldots, w_k\}, n]$$

pr. so far *words* *next time frame*

  - find plausible words $\{w^i\}$ starting at time n
    $\rightarrow$ new hypotheses:

$$[P_n \cdot p(X_n^{n+N-1} | w^i) \cdot p(w^i | w_k \ldots), \{w_1, \ldots, w_k, w^i\}, n+N]$$

  - discard if too unlikely, or queue is too long
  - else re-insert into queue and repeat

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1. Hidden Markov Models review
2. Training HMMs
3. Language modeling
4. **Discrimination & adaptation**
    - Discriminant models
    - Neural net acoustic models
    - Model adaptation

4 Discriminant models

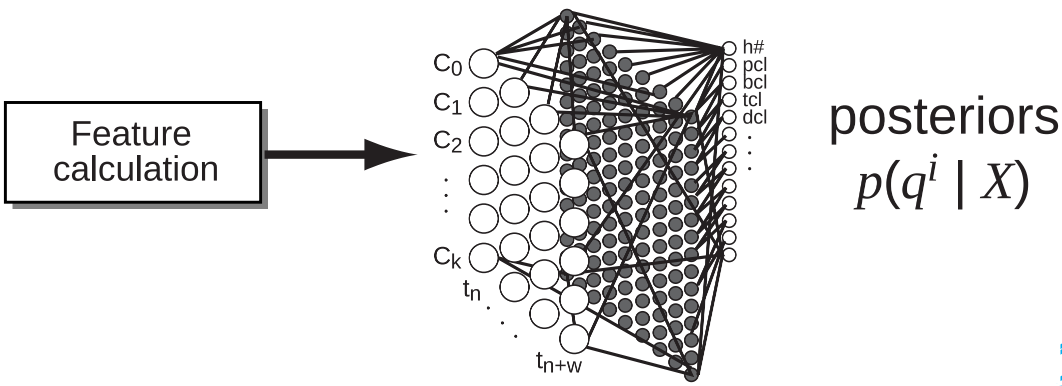
- **EM training of HMMs is maximum likelihood**
  - i.e. choose single Θ to $\max\ p(X_{trn} \mid \Theta)$
  - Bayesian approach: actually $p(\Theta \mid X_{trn})$
- **Decision rule is** $\max\ p(X \mid M) \cdot p(M)$
  - training will increase $p(X \mid M_{correct})$
  - may also increase $p(X \mid M_{wrong})$ ...as much?
- **Discriminant training tries directly to increase discrimination between right & wrong models**
  - e.g. Maximum Mutual Information (MMI)

$$I(M_j, X \mid \Theta) = \log \frac{p(M_j, X \mid \Theta)}{p(M_j \mid \Theta)\, p(X \mid \Theta)}$$

$$= \log \frac{p(X \mid M_j, \Theta)}{\sum p(X \mid M_k, \Theta)\, p(M_k \mid \Theta)}$$

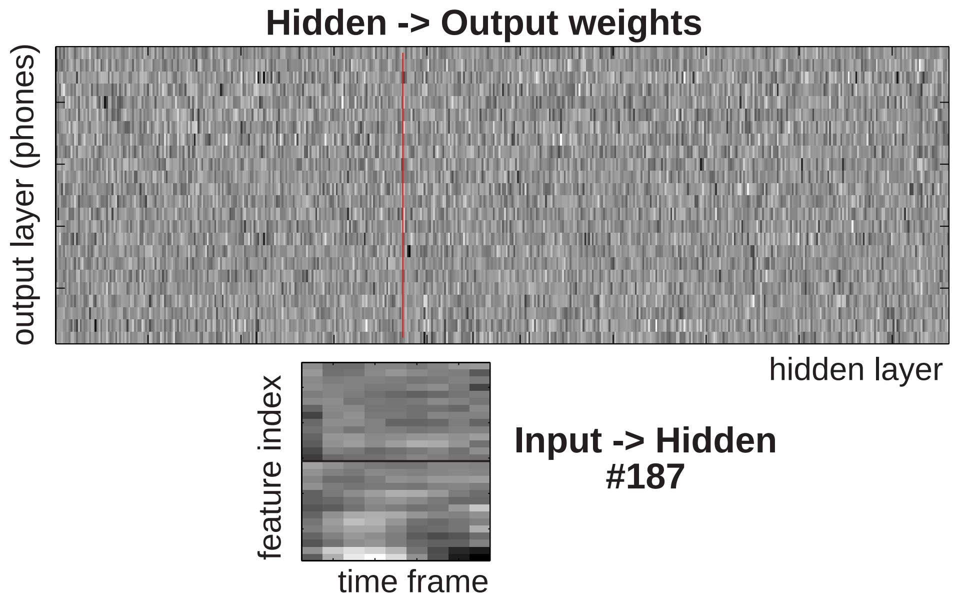
Neural Network Acoustic Models

- **Single model generates posteriors directly for all classes at once = frame-discriminant**
- **Use regular HMM decoder for recognition**
  - set $b_i(x_n) = p(x_n|q^i) \propto p(q^i|x_n) / p(q^i)$
- **Nets are less sensitive to input representation**
  - skewed feature distributions
  - correlated features
- **Can use temporal context window to let net 'see' feature dynamics:**



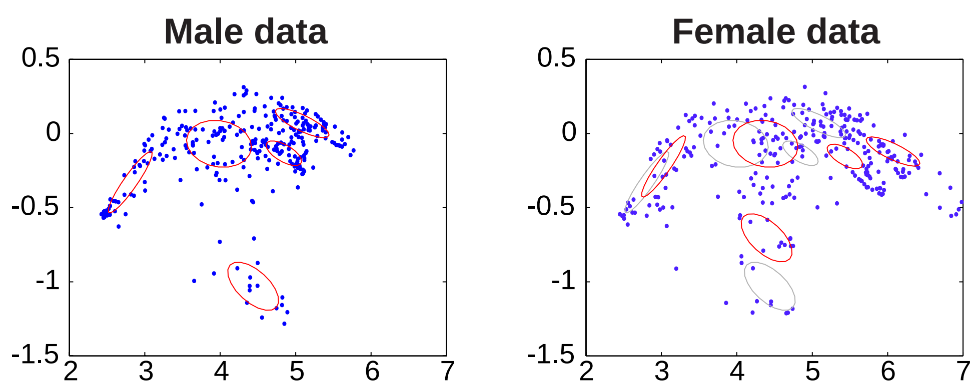
Neural nets: Practicalities

- **Typical net sizes:**
  - input layer: 9 frames x 9-40 features ~ 300 units
  - hidden layer: 100-8000 units, dep. train set size
  - output layer: 30-60 context-independent phones
- **Hard to make context dependent**
  - problems training many classes that are similar?
- **Representation is partially opaque:**

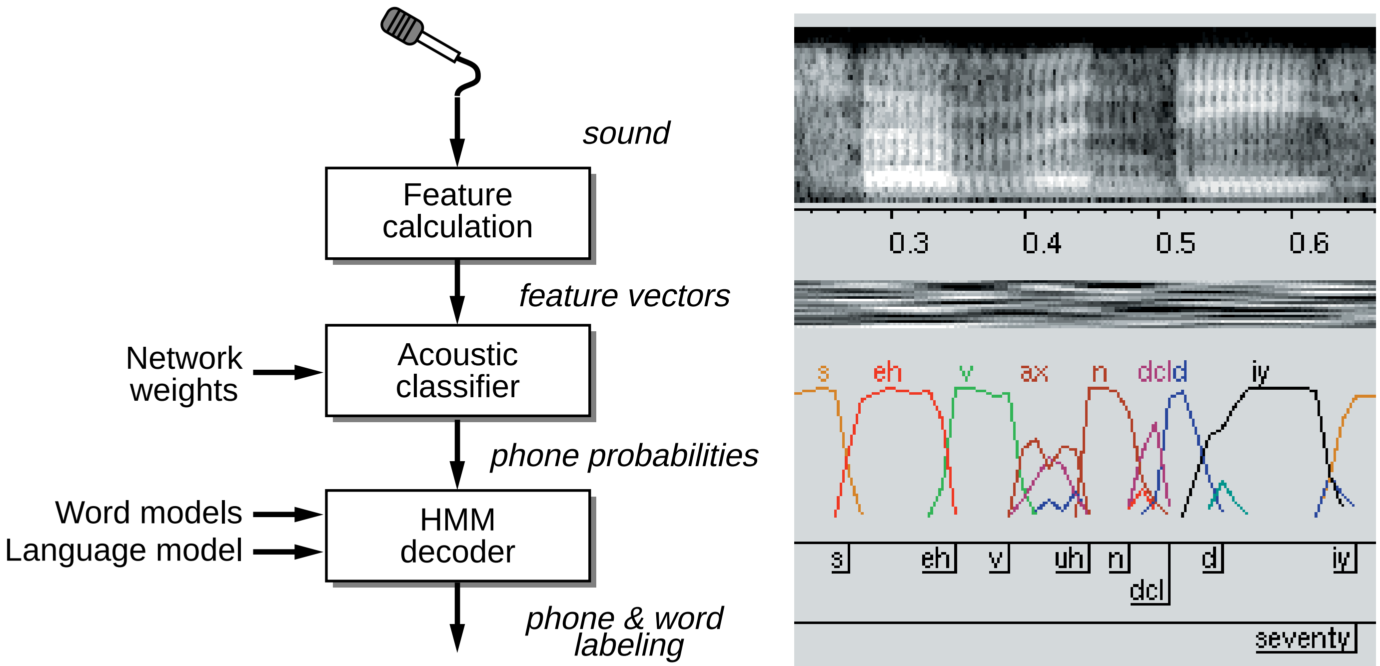


Model adaptation

- **Practical systems often suffer from mismatch**
  - test conditions are not like training data: accent, microphone, background noise ...
- **Desirable to continue tuning during recognition = adaptation**
  - but: no ‘ground truth’ labels or transcription
- **Assume that recognizer output is correct; Estimate a few parameters from those labels**
  - e.g. Maximum Likelihood Linear Regression (MLLR)



Recap: Recognizer Structure



- **Now we have it all!**

Summary

- **Hidden Markov Models**
    - state transitions and emission likelihoods in one
    - best path (Viterbi) performs recognition
- **HMMs can be trained**
    - Viterbi training makes intuitive sense
    - EM training is guaranteed to converge
    - acoustic models (e.g. GMMs) train at same time
- **Language modeling captures higher structure**
    - pronunciation, word sequences
    - fits directly into HMM state structure
    - need to 'prune' search space in decoding
- **Further improvements...**
    - discriminant training moves models 'apart'
    - adaptation adjusts models in new situations