HMM Theory and Practice

Multimodal Interaction Lab

EE4R Automatic Spoken Language Processing

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Objectives

- To understand how to apply HMMs
- To understand the basic HMM algorithms
- *Notes: pp 46 - 55*

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Training & Recognition

- Major advantage of HMMs is the availability of a ‘toolkit’ of powerful, well-founded mathematical methods for HMM manipulation
- The **Baum-Welch** algorithm is used to train the parameters of a set of HMMs given a set of training data
- **Viterbi Decoding** is used to classify an unknown speech pattern in terms of the sequence of HMMs which is most likely to have produced it

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The Recognition Problem

- Given a sequence of acoustic feature vectors
  $Y = \{y_1,...,y_T\}$
  we want to find the sequence of words
  $W = \{w_1,...,w_L\}$
  such that the probability
  $P(W \mid Y)$
  is maximized.
- If $M = \{M_1,...,M_K\}$ is the sequence of HMMs which represents W, then $P(W \mid Y) = P(M \mid Y)$

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Bayes' Theorem

- Computation of the probability $P(M \mid Y)$ is made possible using **Bayes' Theorem**

$$P(W \mid Y) = \frac{p(Y \mid W)P(W)}{p(Y)}$$

- *P(W)* is the "language model probability"
- $p(Y \mid W)$ is the "acoustic model probability"
- Bayes Theorem has been referred to as the "fundamental theorem of speech recognition"!

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The Baum-Welch Algorithm

- The Baum-Welch algorithm is the method which is normally used for HMM parameter estimation
- Given a set of HMMs M_0 and a set of speech patterns Y, Baum's theorem defines how to produce a new model set M_1 such that

$$P(Y \mid M_1) \geq P(Y \mid M_0)$$

- Baum-Welch algorithm applies this method repeatedly until a HMM M_n is found which (locally) maximizes $P(Y \mid M)$
- Baum's theorem only valid for particular classes of state output PDF

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Notes on B-W Reestimation

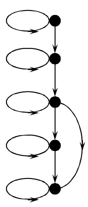
- The Baum-Welch algorithm is only guaranteed to find a **locally** optimal HMM set - hence choice of M_0 can be important
- Baum-Welch is a **supervised** training algorithm which requires labelled speech data
- The labelling need **not** be at the same level as the HMM set - phoneme level HMMs can be trained using data labelled orthographically at the phrase or sentence level
- For large applications B-W reestimation can be **very** computationally expensive

Viterbi Decoding

- Viterbi Decoding is the algorithm which is used to find the sequence of HMMs which is most likely to have generated a given speech pattern
- Based on **Dynamic Programming**
- Viterbi Decoding illustrates the type of computation typically done with HMMs

Viterbi Decoding (1)

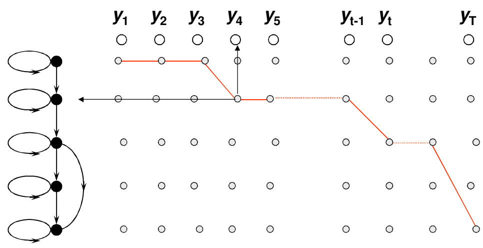
$y_1 \quad y_2 \quad y_3 \quad y_4 \quad y_5 \quad\quad y_{t-1} \quad y_t \quad\quad y_T$



Q: How can *M* have generated *Y*?

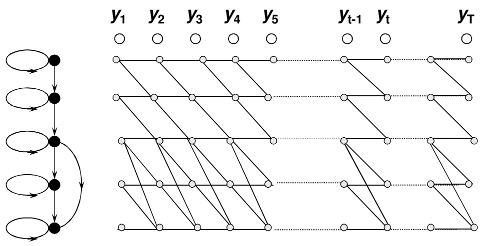
A: Via a state sequence of length T

Function of State Sequence



Viterbi Decoding (2)

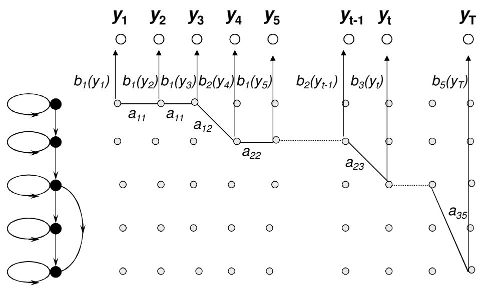
- **Construction of 'state-time trellis'**



Constructing the State-Time Trellis

- Simple Rule:
  - Connect node (i,t) of the trellis to node $(j,t+1)$ if and only if there is a transition between state i and state j in the HMM with probability a_{ij} greater than zero

Basic Probability Calculation



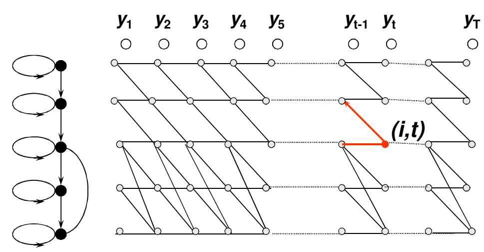
Viterbi Decoding (3)

- Let $X = \{x_1,...,x_T\}$ be a state sequence of length T
- The joint probability of Y and X is given by:

$$p(Y,X) = b_{x_1}(y_1)\prod_{t=2}^{T} a_{x_{t-1}x_t} b_{x_t}(y_t)$$

- i.e. the product of the state-output and state transition probabilities along the state sequence
- The optimal state sequence is the sequence X such that $p(Y,X)$ is maximized
- $p(Y)$ is the sum of $P(Y,X)$ over all sequences X

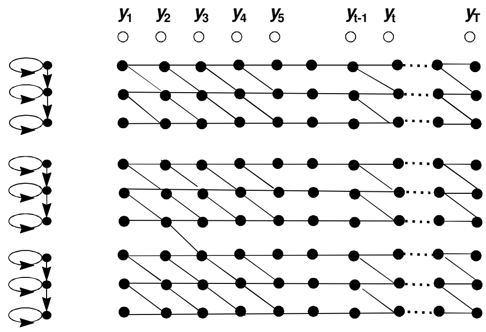
Viterbi Decoding (4)



$p_t(i)$ = Prob($y_1,...,y_t$, opt sequence to (i,t))

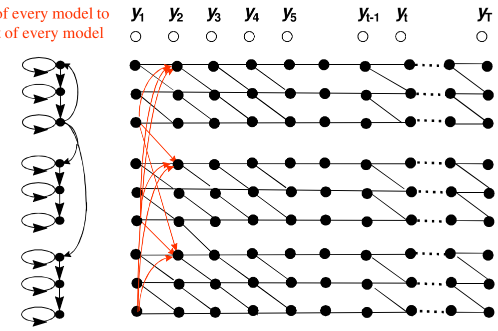
$p_t(i) = \max\{p_{t-1}(i-1)a_{i-1,i} ,\ p_{t-1}(i)a_{i,i}\}b_i(y_t)$

Isolated Speech Recognition

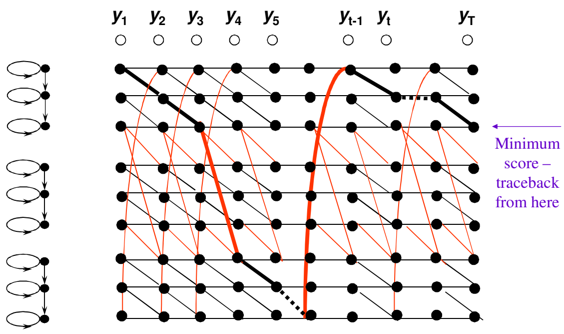


Connected Speech Recognition

New transitions connect end of every model to start of every model



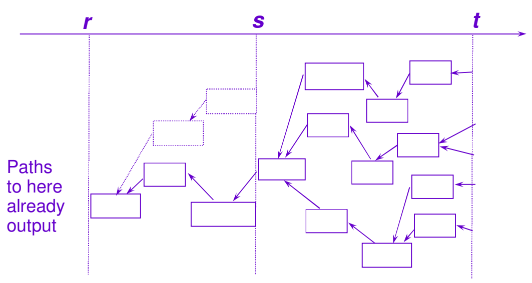
Connected Speech Recognition



Partial Traceback (1)

- In continuous speech recognition, cannot trace-back from the end of the utterance (there is no end!)
- Instead **partial traceback** operates as follows:
  - For each time t and state i a *word link record* describes the sequence of words on the best path to (t,i).
  - At regular intervals all active paths are traced back to see if they converge at some time s in the past
  - If so, the best path up to time s cannot change, and the sequence of words up to s can be output

Partial Traceback (2)



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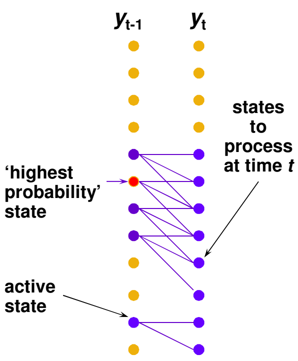
Beam Pruning

- Choose threshold T
- The active states at time $t-1$ are those whose partial path scores are within T of the best path score at time $t-1$
- At time t, only process those states which link back to an active state



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Partial Traceback, Beam Pruning & Recognition 'Speed'

- Partial traceback introduces a 'lag' into recognition process - **not** due to inadequate processor speed
- Lag worse when models are poor
- Beam Pruning less effective for ambiguous input
- Severe Beam Pruning will degrade performance
- Proper management of Partial Traceback and Beam Pruning is essential for optimal performance

Summary

- HMM Theory and Practice
- HMM Training
  - The Baum-Welch algorithm
- Recognition
  - Viterbi decoding
  - Beam pruning
  - Partial traceback