Search and Decoding

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Automatic Speech Recognition— ASR Lecture 10
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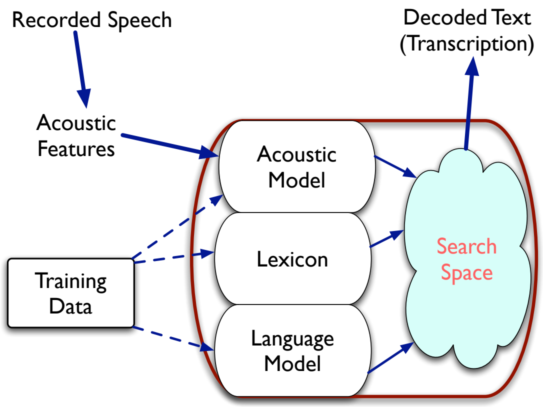
Overview

Today's lecture

- Search in (large vocabulary) speech recognition
- Viterbi decoding
- Approximate search

HMM Speech Recognition



The Search Problem in ASR (1)

- Find the most probable word sequence $\hat{W} = w_1, w_2, \ldots, w_M$ given the acoustic observations $\mathbf{X} = \mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n$:

$$\begin{aligned}\hat{W} &= \arg\max_W P(W|\mathbf{X}) \\ &= \arg\max_W \underbrace{p(\mathbf{X} \mid W)}_{\text{acoustic model}} \underbrace{P(W)}_{\text{language model}}\end{aligned}$$

- Words are composed of state sequences so we may express this criterion by summing over all state sequences $Q = q_1, q_2, \ldots, q_n$:

$$\hat{W} = \arg\max_W P(W) \sum_Q P(Q \mid W) P(X \mid Q)$$

The Search Problem in ASR (2)

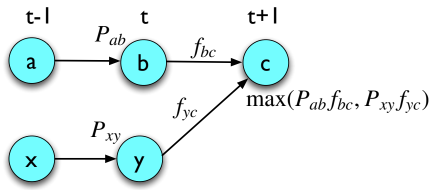
- Viterbi criterion: approximate the sum over all state sequences by using the most probable state sequence:

$$\hat{W} = \arg\max_{W} P(W) \max_{Q \in \mathcal{Q}_W} P(Q \mid W) P(X \mid Q)$$

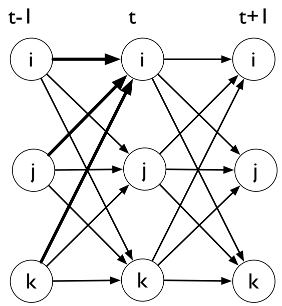
  $\mathcal{Q}_W$ is the set of all state sequences corresponding to word sequence W
- The task of the search (or decoding) algorithm is to determine $\hat{W}$ using the above equation given the acoustic, pronunciation and language models
- In a large vocabulary task evaluating all possible word sequences in infeasible (even using an efficient exact algorithm)
  - Reduce the size of the search space through pruning unlikely hypotheses
  - Eliminate repeated computations

Viterbi Decoding

- Naive exhaustive search: with a vocabulary size V, and a sequence of M words, there are V^M different alternatives to consider!
- Viterbi decoding (forward dynamic programming) is an efficient, recursive algorithm that performs an optimal exhaustive search
- For HMM-based speech recognition, the Viterbi algorithm is used to find the most probable path through a probabilistically scored time/state lattice
- Exploits first-order Markov property—only need to keep the most probable path at each state:

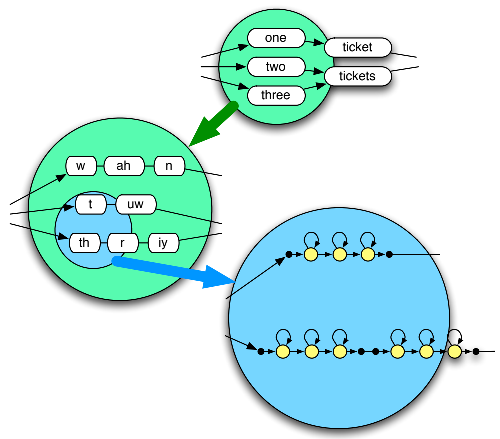


Time-state trellis



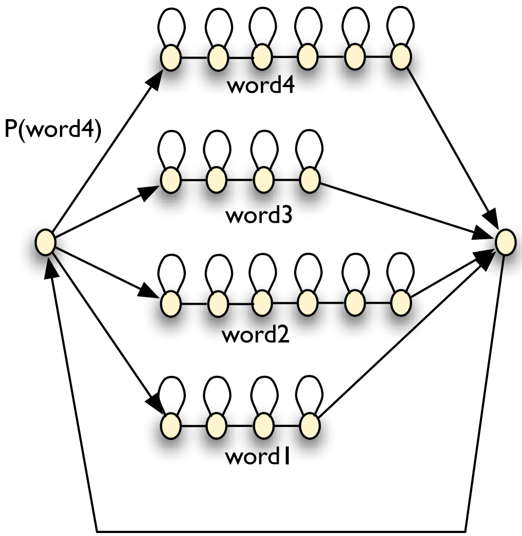
- Set up the problem as a trellis of states and times
- Use the Viterbi approximation
- At each state-time point keep the single most probable path, discard the rest
- The most probable path is the one at the end state at the final time
- Typically use log probabilities

Compiling a Recognition Network

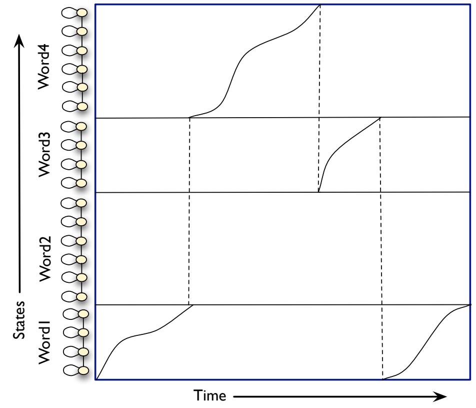


Build a network of HMM states from a network of phones from a network of words

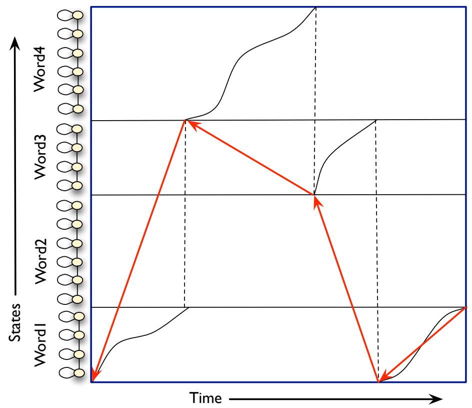
Connected Word Recognition



Time Alignment Path

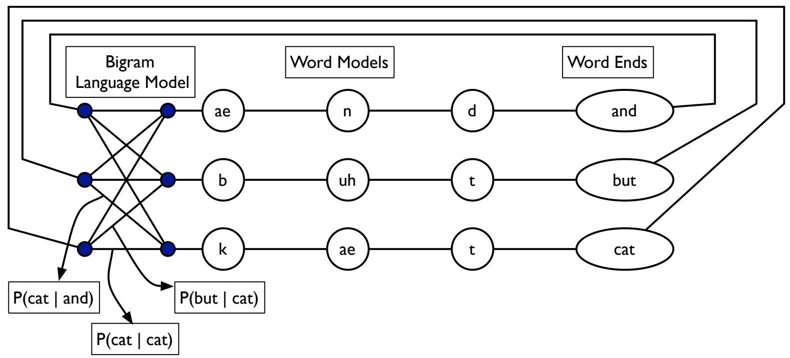


Backtrace to Obtain Word Sequence



- Backpointer array keeps track of word sequence for a path:
  backpointer[word][wordStartFrame] = (prevWord, prevWordStartFrame)
- Backtrace through backpointer array to obtain the word sequence for a path

Incorporating a bigram language model



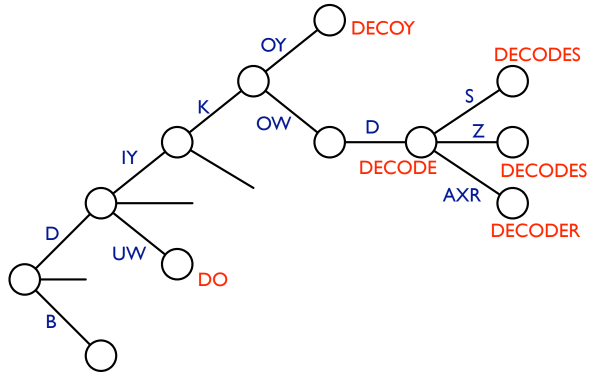
Trigram or longer span models require a word history.

Computational Issues

- Viterbi decoding performs an exact search in an efficient manner
- Exact search is not possible for large vocabulary tasks. If the vocab size is V:
  - Word boundaries are not known: V words may potentially start at each frame
  - Cross-word triphones need to be handled carefully since the acoustic score of a word-final phone depends on the initial phone of the next word
  - Long-span language models (eg trigrams) greatly increase the size of the search space
- Solutions:
  - Beam search (prune low probability hypotheses)
  - Dynamic search structures
  - Multipass search
  - Best-first search
  - Weighted Finite State Transducer (WFST) approaches

Sharing Computation: Prefix Pronunciation Tree

- Need to build an HMM for each word in the vocabulary
- Individual HMM for each word results in phone models duplicated in different words
- Share computation by arranging the lexicon as a tree



Beam Search

- Basic idea: Prune search paths which are unlikely to succeed
- Remove nodes in the time-state trellis whose path probability is more than a factor δ less probable then the best path (only consider paths in the beam)
- Both language model and acoustic model can contribute to pruning
- Pronunciation tree can limit pruning since the language model probabilities are only known at word ends: each internal node can keep a list of words it contributes to
- Search errors: errors arising due to the fact that the most probable hypothesis was incorrectly pruned
- Need to balance search errors with speed

Multipass Search

- Rather than compute the single best hypothesis the decoder can output alternative hypotheses
- N-best list: list of the N most probable hypotheses
- Word Graph/Word Lattice:
  - Nodes correspond to time (frame)
  - Arcs correspond to word hypotheses (with associated acoustic and language model probabilities)
- Multipass search using progressively more detailed models
  - Eg: use bigram language model on first pass, trigram on second pass
  - Transmit information between passes as word graphs
  - Later passes rescore word graphs produced by earlier passes

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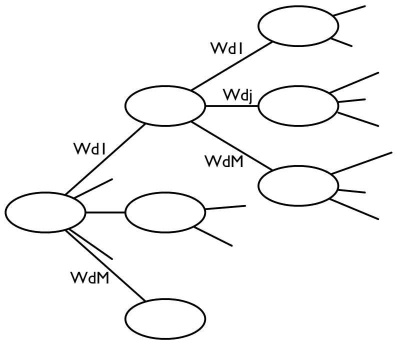
Word Search Tree



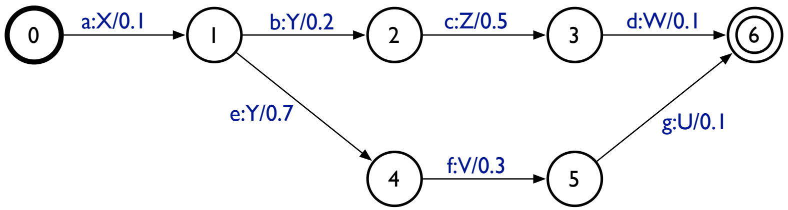
- View recognition search as searching a tree
- Viterbi decoding is breadth-first search — time-synchronous
- Pruning deactivates part of the search tree
- Also possible to use best first search (stack decoding) — time asynchronous

Static and dynamic networks

- Previous approaches constructed the search space *dynamically*: less probable paths are not explored.
- Dynamic search is resource-efficient but results in
  - complex software
  - tight interactions between pruning algorithms and data structures
- Static networks are efficient for smaller vocabularies, but not immediately applicable to large vocabularies
- Efficient static networks would enable
  - Application of network optimization algorithms in advance
  - Decoupling of search network construction and decoding

Weighted Finite State Transducers

- Finite state automaton that transduces an input sequence to an output sequence
- States connected by transitions. Each transition has
  - input label
  - output label
  - weight



WFST Algorithms

Composition Used to combine transducers at different levels. For example if G is a finite state grammar and P is a pronunciation dictionary then D transduces a phone string to any word string, whereas $P \circ G$ transduces a phone string to word strings allowed by the grammar

Determinisation removes non-determinancy from the network by ensuring that each state has no more than a single output transition for a given input label

Minimisation transforms a transducer to an equivalent transducer with the fewest possible states and transitions

Several libraries for WFSTs eg:

- Open FST: `http://www.openfst.org/`
- MIT: `http://people.csail.mit.edu/ilh/fst/`
- AT&T: `http://www.research.att.com/~fsmtools/fsm/`

WFST-based decoding

- Represent the following components as WFSTs
  - Context-dependent acoustic models (C)
  - Pronunciation dictionary (D)
  - n-gram language model (L)
- The decoding network is defined by their composition: $C \circ D \circ L$
- Successively determinize and combine the component transducers, then minimize the final network
- Problem: although the final network may be of manageable size, the construction process may be very memory intensive, particularly with 4-gram language models or vocabularies of over 50,000 words
- Used successfully in several systems

Summary

- Search in speech recognition
- Viterbi decoding
- Connected word recognition
- Incorporating the language model
- Pruning
- Prefix pronunciation trees
- Weighted finite state transducers
- Evaluation

References

- Aubert (2002) - review of decoding techniques
- Mohri et al (2002) - WFSTs applied to speech recognition
- Moore et al (2006) - Juicer (example of a WFST-based decoder)