Automatic Speech Recognition (CS753)
Lecture 19: Search, Decoding and Lattices

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Recap: Static and Dynamic Networks

- **Static network:** Build compact decoding graph using WFST optimisation techniques.

- **Dynamic networks:**
  - Dynamically build the graph with active states on the fly
  - On-the-fly composition with the language model acceptor G
Static Network Decoding

• Expand the whole network prior to decoding.

• The individual transducers $H$, $C$, $L$ and $G$ are combined using composition to build a static decoding graph.

• The graph is further optimised by weighted determinization and minimisation.

\[ D = \pi_\varepsilon(\min(\det(\tilde{H} \circ \det(\tilde{C} \circ \det(\tilde{L} \circ G)))))) \]

• The final optimised network is typically 3-5 times larger than the language model $G$

• Becomes impractical for very large vocabularies
Searching the graph

- Two main decoding algorithms adopted in ASR systems:
  1. Viterbi beam search decoder
  2. A* stack decoder
Viterbi beam search decoder

- Time-synchronous search algorithm:
  - For time $t$, each state is updated by the best score from all states in time $t-1$
  - Beam search prunes unpromising states at every time step.
  - At each time-step $t$, only retain those nodes in the time-state trellis that are within a fixed threshold $\delta$ (beam width) of the score of the best hypothesis.
Trellis with full Viterbi & beam search

No beam search

With beam search
Beam search algorithm

Initialization: \textit{current states} := \textit{initial state}

while (\textit{current states} do not contain the \textit{goal state}) do:

\begin{itemize}
  \item \textit{successor states} := NEXT(\textit{current states})
    where NEXT is next state function
  \item score the \textit{successor states}
  \item set \textit{current states} to a pruned set of \textit{successor states} using beam width \(\delta\)
    only retain those \textit{successor states} that are within \(\delta\) times the best path weight
\end{itemize}
A* stack decoder

• So far, we considered a time-synchronous search algorithm that moves through the observation sequence step-by-step

• A* stack decoding is a time-asynchronous algorithm that proceeds by extending one or more hypotheses word by word (i.e. no constraint on hypotheses ending at the same time)

• Running hypotheses are handled using a stack which is a priority queue sorted on scores. Two problems to be addressed:

  1. Which hypotheses should be extended? (Use A*)

  2. How to choose the next word used in the extensions? (fast-match)
Recall A* algorithm

- To find the best path from a node to a goal node within a weighted graph,
  - A* maintains a tree of paths until one of them terminates in a goal node
  - A* expands a path that minimises $f(n) = g(n) + h(n)$ where $n$ is the final node on the path, $g(n)$ is the cost from the start node to $n$ and $h(n)$ is a heuristic determining the cost from $n$ to the goal node
  - $h(n)$ must be admissible i.e. it shouldn’t overestimate the true cost to the nearest goal node
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Which hypotheses should be extended?

- A* maintains a priority queue of partial paths and chooses the one with the highest score to be extended.

- Score should be related to probability: For a word sequence $W$ given an acoustic sequence $O$, score $\propto \Pr(O|W)\Pr(W)$.

- But not exactly this score because this will be biased towards shorter paths.

- A* evaluation function based on $f(p) = g(p) + h(p)$ for a partial path $p$ where $g(p) =$ score from the beginning of the utterance to the end of $p$ and $h(p) =$ estimate of best scoring extension from $p$ to end of the utterance.

- An example of $h(p)$: Compute some average probability $prob$ per frame (over a training corpus). Then $h(p) = prob \times (T-t)$ where $t$ is the end time of the hypothesis and $T$ is the length of the utterance.
A* stack decoder

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Fast-match

• Fast-match: Algorithm to quickly find words in the lexicon that are a good match to a portion of the acoustic input

• Acoustics are split into a front part, $A$, (accounted by the word string so far, $W$) and the remaining part $A'$. Fast-match is to find a small subset of words that best match the beginning of $A'$.

• Many techniques exist: 1) Rapidly find $Pr(A'|w)$ for all $w$ in the vocabulary and choose words that exceed a threshold 2) Vocabulary is pre-clustered into subsets of acoustically similar words. Each cluster is associated with a centroid. Match $A'$ against the centroids and choose subsets having centroids whose match exceeds a threshold

[B et al.]: Bahl et al., Fast match for continuous speech recognition using allophonic models, 1992
function \textsc{Stack-Decoding}() \textbf{returns} \textit{min-distance}

Initialize the priority queue with a null sentence.
Pop the best (highest score) sentence \(s\) off the queue.
If \((s\) is marked end-of-sentence (EOS)) output \(s\) and terminate.
Get list of candidate next words by doing fast matches.
For each candidate next word \(w\):
    Create a new candidate sentence \(s + w\).
    Use forward algorithm to compute acoustic likelihood \(L\) of \(s + w\)
    Compute language model probability \(P\) of extended sentence \(s + w\)
    Compute “score” for \(s + w\) (a function of \(L, P\), and ???)
    if (end-of-sentence) set EOS flag for \(s + w\).
    Insert \(s + w\) into the queue together with its score and EOS flag.
Example (1)

P(acoustic | "if") = forward probability

P("if" | START)

P("if" | START) = 30

Alice

Alice = 40

If

In

P(in | START) = 1

Every

Every = 25

In

In = 4

Figure 10.8

The beginning of the search for the sentence "If music be the food of love".

At this early stage Alice is the most likely hypothesis. (It has a higher score than the other hypotheses.)

Figure 10.9

The next steps of the search for the sentence "If music be the food of love". In (a) we've now expanded the Alice node and added three extensions which have a relatively high score; the highest-scoring node is START if, which is not on the START Alice path at all. In (b) we've expanded the if node. The hypothesis START if music then has the highest score.

If we used probability as the score, the A* decoding algorithm would get stuck on the single-word hypotheses. Instead, we use the A* evaluation function (Nilsson, 1980; Pearl, 1984) $f^*(p)$, given a partial path $p$:

$$f^*(p) = g(p) + h^*(p)$$

$f^*(p)$ is the estimated score of the best complete path (complete sentence) which starts with the partial path $p$. In other words, it is an estimate of how well this path would do if we let it continue through the sentence. The A* algorithm builds this string itself (e.g., $P(START the . . . ) will be greater than $P(START the book))$. Thus if we used probability as the score, the A* decoding algorithm would get stuck on the single-word hypotheses.
Example (2)

P(acoustic | "if") = forward probability

P("if" | START)

Alice

Every

In

(none)

was

wants

walls

P(acoustic | "if") = forward probability

P( "if" |START) =

music

muscle

messy

was

wants

walls

P(acoustic | music) = forward probability

P(acoustic | whether) = forward probability

P("if" | START) =

If music be the food of love

At this early stage Alice is the most likely hypothesis. (It has a higher score than the other hypotheses.)

Figure 10.8 The beginning of the search for the sentence If music be the food of love.

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Image from [JM]: Jurafsky & Martin, SLP 2nd edition, Chapter 10
A* vs Beam search

- Nowadays Viterbi beam search is the more popular paradigm for ASR tasks
- A* is used to search through lattices
- How are lattices generated?
Lattice Generation

• Say we want to decode an utterance, U, of T frames.

• Construct a sausage acceptor for this utterance, X, with T+1 states and arcs for each context-dependent HMM state at each time-step

• Search the following composed machine for the best word sequence corresponding to U:

\[ D = X \circ HCLG \]
Lattice Generation

- For all practical applications, we have to use beam pruning over D such that only a subset of states/arcs in D are visited. Call this resulting pruned machine, B.

- Word lattice, say L, is a further pruned version of B defined by a lattice beam, $\beta$. L satisfies the following requirements:
  - L should have a path for every word sequence within $\beta$ of the best-scoring path in B
  - All scores and alignments in L correspond to actual paths through B
  - L does not contain duplicate paths with the same word sequence
Word Confusion Networks

Word confusion networks are normalised word lattices that provide alignments for a fraction of word sequences in the word lattice.

(a) Word Lattice

(b) Confusion Network

Image from [GY08]: Gales & Young, Application of HMMs in speech recognition, NOW book, 2008
Constructing word confusion network

- Links of a confusion network are grouped into confusion sets and every path contains exactly one link from each set.

- This clustering is done in two stages:
  
  1. Links that correspond to the same word and overlap in time are combined.
  
  2. Links corresponding to different words are clustered into confusion sets. Clustering algorithm is based on phonetic similarity, time overlap and word posteriors. More details in [LBS00].

Image from [LBS00]: L. Mangu et al., “Finding consensus in speech recognition”, Computer Speech & Lang, 2000