More about ASR

- Introduction
- Dynamic programming
- Viterbi algorithm
- Other approaches to decoding
- Training acoustic models
- FLOSS resources
- Assignment
- Bibliography
Two technologies are needed to make the HMM framework practical

- Decoder technology to find the
  \[
  \arg\max_{Words} \ P(Observation|Words) \cdot P(Words)
  \]
- Determining the stochastic parameters of the HMM state automaton, i.e., training

Many pictures (and their copyrights) are from [Jurafsky and Martin(2000)]
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Dynamic programming

Consider the following example:

**Trace**

```
i n t e n t i o n
e x e c u t i o n
```

**Alignment**

```
i n t e n t i o n
e x e c u t i o n
```

**Operation**

- Delete i
- Substitute n by e
- Substitute t by x
- Insert u
- Substitute n by c

**List**

```
i n t e n t i o n
e x e c u t i o n
```

Look for best alignment: Minimum edit distance

- Delete
- Insert
- Substitute
Dynamic programming

Trace

```
intention

///   /   \\
execution
```

Alignment

```
intention

ε execution
```

Operation

```
delete i
substitute n by e
substitute t by x
insert u
substitute n by c
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Look for best alignment: Minimum edit distance

- Delete
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Dynamic programming

<table>
<thead>
<tr>
<th>Trace</th>
<th>intention</th>
<th>execution</th>
</tr>
</thead>
<tbody>
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<td>Alignment</td>
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- delete i  
- substitute n by e  
- substitute t by x  
- insert u  
- substitute n by c

Look for best alignment: Minimum edit distance

- Delete
- Insert
- Substitute
Dynamic programming

```
function MIN-EDIT-DISTANCE(target, source) returns min-distance

n ← LENGTH(target)
m ← LENGTH(source)
Create a distance matrix distance[n+1,m+1]
distance[0,0] ← 0
for each column i from 0 to n do
    for each row j from 0 to m do
        distance[i,j] ← MIN( distance[i−1,j] + ins-cost(target_i),
            distance[i−1,j−1] + subst-cost(source_j,target_i),
            distance[i,j−1] + del-cost(source_j))
```

Fill a matrix with cumulative edit distances,
`distance[i,j] = min of`

- `distance[i − 1, j] + insert-cost(target_i)`
- `distance[i − 1, j − 1] + substitution-cost(source_j, target_i)`
- `distance[i, j − 1] + deletion-cost(source_j)`
Dynamic programming

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Fill a matrix with cumulative edit distances,
\[ distance[i,j] = \min \text{ of} \]
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**Dynamic programming**

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Dynamic programming

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Trace back the choices of the minimal distance (bold numbers)

- This finds the globally minimal cost path
- Full search unwieldy for large and complex matrices
- In general, searches are pruned to exclude paths that deviate far from the diagonal: Beam search
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Viterbi algorithm

Simplified pronunciation networks [Jurafsky and Martin(2000)]

- Each word is modeled as a Finite State Machine
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Viterbi algorithm result “for I need a” [Jurafsky and Martin(2000)]

- Whole sequence on X axis
- All word models on the other axis
- Switch to (any) new word after reaching the end of the current word
- Word switching cost based on the language model
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### Viterbi algorithm

<table>
<thead>
<tr>
<th>I need</th>
<th>0.0016</th>
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<td>I the</td>
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</tr>
<tr>
<td># I</td>
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</table>

| the on     | 0.00031 |
| on I       | 0.00085 |

### Bigram probabilities [Jurafsky and Martin(2000)]

- Word switching in Viterbi searches uses probabilities
- Switch to a new word with bigram probability cost
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*Note: The table above lists bigram probabilities, which are used to calculate the likelihood of transitioning from one word to another in a Viterbi search.*

---

**Other approaches to decoding**

- Training acoustic models
- FLOSS resources
- Assignment
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Single pronunciation automaton for *I, need, on, and the*

[Jurafsky and Martin(2000)]

- Bigram probabilities connect the word models
- Merge *start* and *end* states of connected words
- Need for *pruning* is apparent
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[Jurafsky and Martin(2000)]
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function VITERBI(observations of len T, state-graph) returns best-path

num-states ← NUM-OF-STATES(state-graph)
Create a path probability matrix viterbi[num-states+2,T+2]
viterbi[0,0] ← 1.0
for each time step t from 0 to T do
    for each state s from 0 to num-states do
        for each transition s' from s specified by state-graph
            new-score ← viterbi[s, t] * a[s,s'] * b_s'(o_t)
            if ((viterbi[s',t+1] = 0) || (new-score > viterbi[s',t+1]))
                then
                    viterbi[s',t+1] ← new-score
                    back-pointer[s',t+1] ← s
        Backtrace from highest probability state in the final column of viterbi[] and return path

Extended version of the edit distance [Jurafsky and Martin(2000)]

- \( a[s, s'] = P(s \rightarrow s') \)
- \( b_{s'}(o_t) = P(o_t | s') \)
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Individual state columns in Viterbi algorithm

[Jurafsky and Martin (2000)]

- The actual entries for the Automaton
- Note the problems for a 20,000 word dictionary
Individual state columns in Viterbi algorithm

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Use structured, context sensitive phone units

- Single phone units perform bad due to coarticulation
- *Begin* differs from *End* (e.g., */d*/)
- 60 context dependent triphones $\Rightarrow 60^3 = 216000$ models
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- Cluster contexts, e.g., on manner and place of articulation
Use structured, context sensitive phone units

- Single phone units perform bad due to coarticulation
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Other approaches to decoding: Introduction

The standard HMM model has limitations

- Viterbi decoder penalizes multiple pronunciations
- Viterbi decoder does not work for anything more complex than bigram
- It is not possible to include other linguistic knowledge
  - Phoneme duration (HMM have a Poison distribution)
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Two stage N-best decoding [Jurafsky and Martin(2000)]

- Keep N-best utterance list or word lattice
- Rescore the probabilities with the extra knowledge
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Other approaches to decoding: $A^*$

Stack, or $A^*$, decoding [Jurafsky and Martin (2000)]

- Viterbi uses **best** path upto position $t$ to get to $t + 1$
- $A^*$ uses complete forward algorithm (exact likelihoods)
- $A^*$ searches potential utterances best-first
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```plaintext
function STACK-DECODING() returns 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
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Stack decoding [Jurafsky and Martin(2000)]

- At each point, the $A^*$ looks for the most likely next word
- Acoustic likelihood is part the criterium
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If music be the food of love  [Jurafsky and Martin(2000)]

- “Start Alice” has highest score: 40
- “Start if” has highest score: 30
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Remarks

- Use fast match heuristics for selecting next words
- Longer utterances have lower probabilities, score should correct for this
- $A^*$ evaluation function: $f^*(p) = g(p) + h^*(p)$
- $g(\text{partial path}) = P(O|\text{Words}) \cdot P(\text{Words})$, ie, the likelihood until now
- $h^*(p)$ something that correlates with number of words in the rest of the utterance
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Other approaches to decoding: \( A^* \) fast match

A tree structured lexicon from SPHINX

- Need to get forward probabilities of potential continuations \( \textit{fast} \)
- Tree lexicon shares forward probabilities between words
- Allows early pruning of search trees

\[ \begin{align*}
&\text{AX}\,(#,\text{B}) &\text{B}(\text{AX},\text{AW}) &\text{AW}(\text{B},\text{N}) &\text{N}(\text{AW},\text{DD}) &\text{DD}(\text{N},\#) &\text{ABOUND} \\
&\text{B}(\text{AX},\text{AH}) &\text{AH}(\text{B},\text{V}) &\text{V}(\text{AH},\text{X}) &\text{ABOUT} \\
&\text{B}(\text{#,EY}) &\text{EY}(\text{B},\text{KD}) &\text{KD}(\text{EY},\#) &\text{BAKE} \\
&\text{EY}(\text{#,K}) &\text{K}(\text{EY},\text{IX}) &\text{IX}(\text{K},\text{NG}) &\text{BAKED} \\
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- [Gouvêa()](some resource) [Jurafsky and Martin(2000)]

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Determine \( P(Observation|Words) \), ie, the transition probability between phone states \( a_{ij} \) and the acoustic likelihood of the speech vectors \( b_j(o_k) \)

- Large, “transcribed” speech corpus (on text level)
- Coverage of speakers and language types
- Recorded under the same conditions as intended use, eg, over the phone or in a driving car
- Use the same microphone etc.
- Using a simulated task (Wizard of Oz or Green curtain) to elicit the same kind of speech
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If all states were known [Jurafsky and Martin(2000)]

- \( a_{ij} = \frac{\#S_{ij}}{\#S_i} \) (count transitions and states)
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If observations are continuous vectors

\( b_i(O_t) \Rightarrow N\{\hat{\mu}_i, \hat{\Sigma}_i\} \)

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States have to be estimated. Use an iterative procedure

App D [Jurafsky and Martin(2000)]

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Construct your own language model

- Download texts from the internet, eg, [Project Gutenberg(2005)]
- Use a single author or a single genre
- Use --help to see instructions of the programs
- Construct unigram and bigram word tables with Ngramcount.pl
  http://www.fon.hum.uva.nl/rob/Courses/Taaltechnologien/Ngramcount.pl
- perl Ngramcount.pl 1 <filename1> <filename2> ... > unigramtable.txt
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- Construct unigram and bigram word tables with `Ngramcount.pl` [http://www.fon.hum.uva.nl/rob/Courses/Taaltechnologien/Ngramcount.pl](http://www.fon.hum.uva.nl/rob/Courses/Taaltechnologien/Ngramcount.pl)
  - `perl Ngramcount.pl 1 <filename1> <filename2> ... > unigramtable.txt`
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- Inspect the table files. What are the most frequent words and bigrams?
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  - `perl ngramprobability.pl --count 5 --verbose bigramtable.txt "<sentence>"`
- Enter some sentences and inspect the resulting probabilities
- Experiment with the `--count` option. Try `--count -1` on a sentence that contains unknown word combinations
Assignment: Week 8

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A bit of progress in language modeling.  
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E. Gouvêa.  
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Paul A. Taylor, S. King, S. D. Isard, and H. Wright.
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Xue Wang.
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