Speech recognition and synthesis

Introduction

Two technologies are needed to make the HMM framework practical

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

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Dynamic programming

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 ε t i o n
ε e x e c u t i o n
```

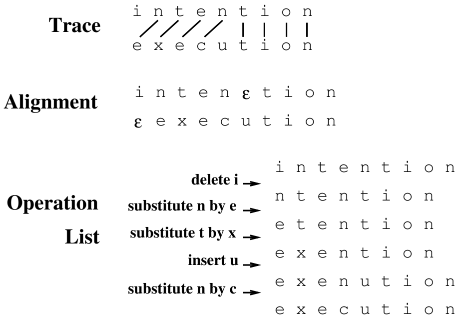
Operation List

```
                      i n t e n t i o n
delete i          →   n t e n t i o n
substitute n by e →   e t e n t i o n
substitute t by x →   e x e n t i o n
insert u          →   e x e n u t i o n
substitute n by c →   e x e c u t i o n
```

Look for best alignment: Minimum edit distance

- Delete
- Insert
- Substitute

Dynamic programming



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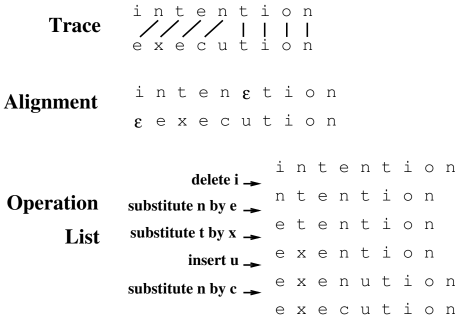

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function MIN-EDIT-DISTANCE(*target*, *source*) **returns** *min-distance*

$n \leftarrow$ LENGTH(*target*)
$m \leftarrow$ LENGTH(*source*)
Create a distance matrix *distance[n+1,m+1]*
distance[0,0] $\leftarrow 0$
for each column i **from** 0 **to** n **do**
  for each row j **from** 0 **to** m **do**
    $distance[i,j] \leftarrow \text{MIN}(\, distance[i-1,j] + \textit{ins-cost}(target_i),$
      $distance[i-1,j-1] + \textit{subst-cost}(source_j, \text{target}_i),$
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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$(source_j, target_i)$
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i	7	8	9	8	9	10	9	**8**	9	10
t	6	7	8	7	8	9	**8**	9	10	11
n	5	6	7	6	7	**8**	9	10	11	12
e	4	5	6	**5**	**6**	7	8	9	10	11
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n	2	3	**4**	5	6	7	8	8	10	11
i	1	**2**	3	4	5	6	7	8	9	10
#	**0**	1	2	3	4	5	6	7	8	9
	#	e	x	e	c	u	t	i	o	n

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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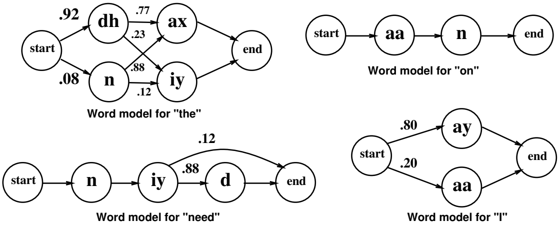

Simplified pronunciation networks [Jurafsky and Martin(2000)]

- Each word is modeled as a Finite State Machine
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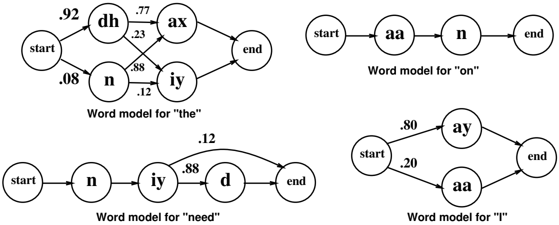

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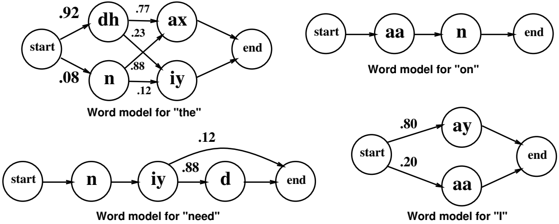

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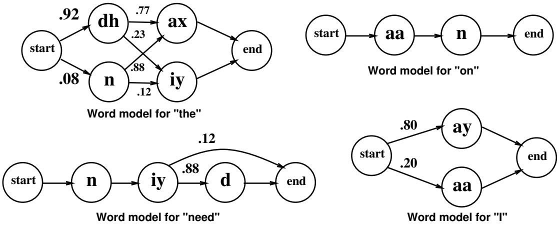

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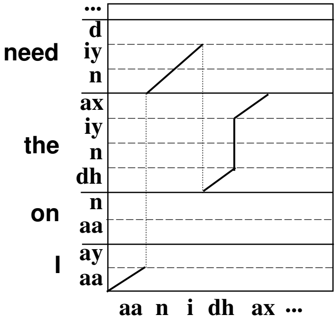

Viterbi algorithm result *"for I need a"* [Jurafsky and Martin(2000)]

- Whole sequence on **X** axis
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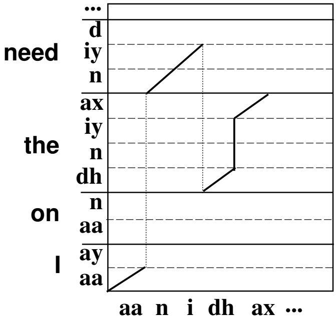

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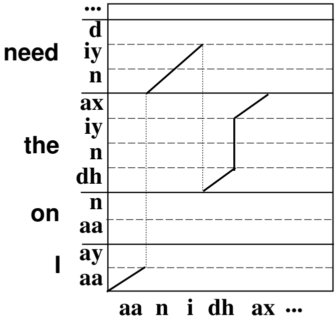

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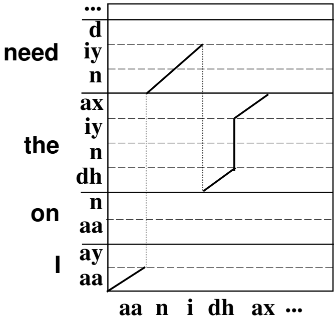

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I the	0.00018	need the	0.012	# The	0.016
I on	0.000047	need on	0.000047	# On	0.00077
I I	0.039	need I	0.000016	# I	0.079
the need	0.00051	on need	0.000055		
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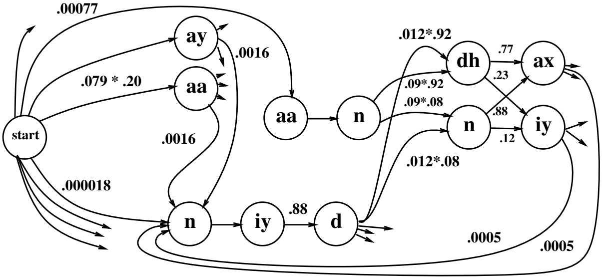

Single pronunciation automaton for *I*, *need*, *on*, and *the*

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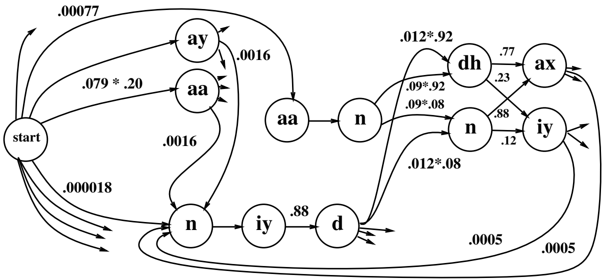

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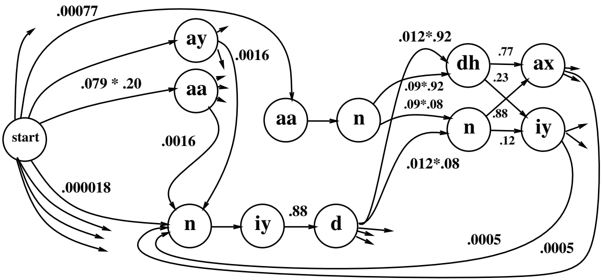

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function VITERBI(*observations* of len *T*,*state-graph*) **returns** *best-path*

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', $t+1$]))
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Extended version of the edit distance [Jurafsky and Martin(2000)]

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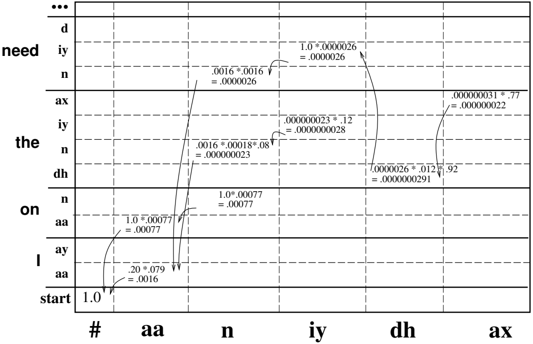

Individual state columns in Viterbi algorithm

[Jurafsky and Martin(2000)]

- The actual entries for the Automaton
- Note the problems for a 20,000 word dictionary

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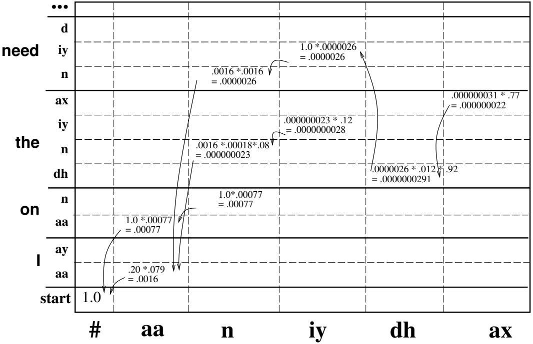

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Viterbi algorithm: Subphones revisited

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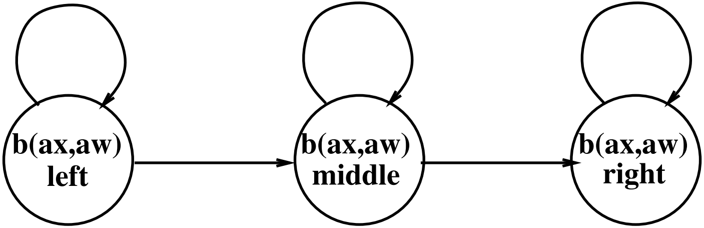

Use structured, context sensitive phone units

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

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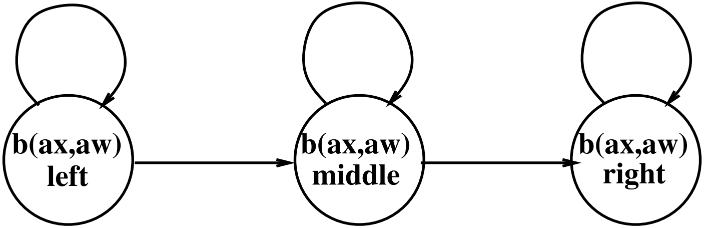

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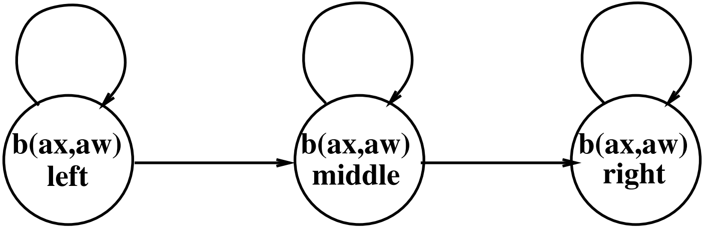

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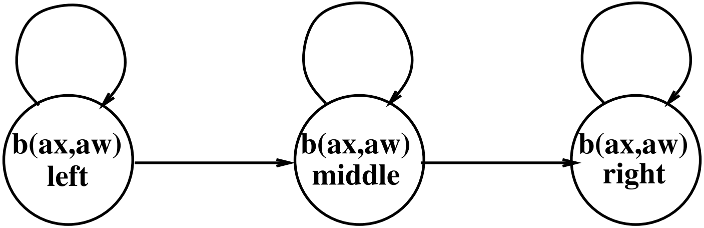

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Other approaches to decoding: Introduction

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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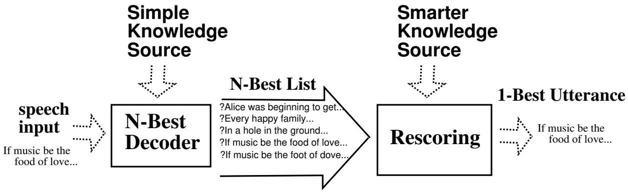

Two stage N-best decoding [Jurafsky and Martin(2000)]

- Keep N-best utterance list or word lattice
- Rescore the probabilities with the extra knowledge
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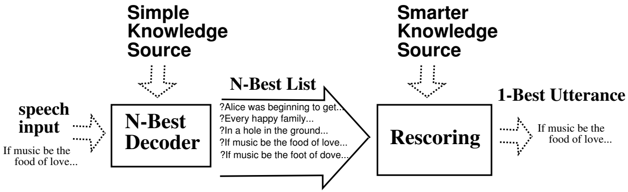

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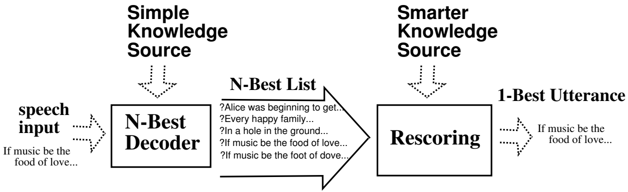

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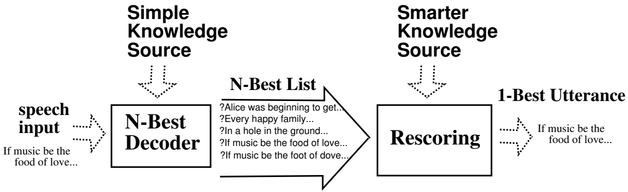

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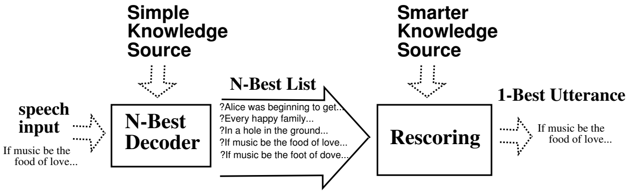

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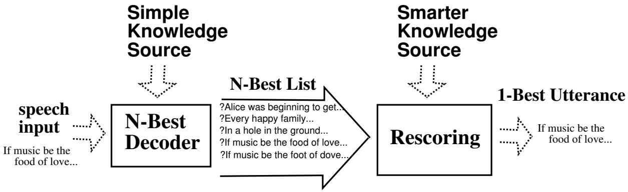

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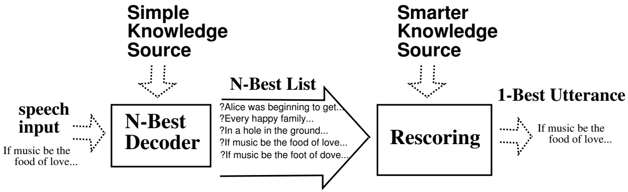

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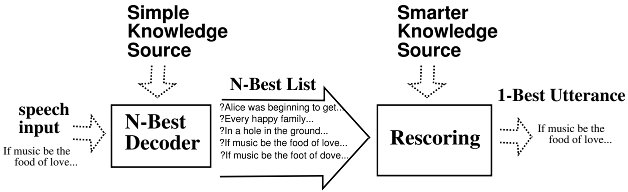

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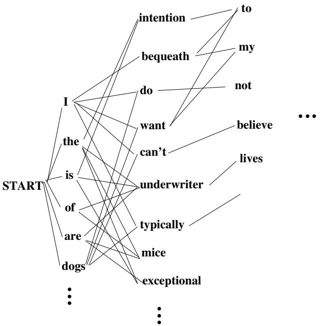

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- Viterbi uses best path upto position t to get to $t + 1$
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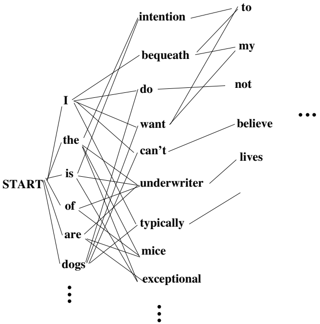

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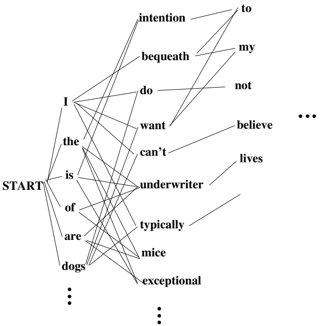

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Initialize the priority queue with a null sentence.
Pop the best (highest score) sentence s off the queue.
If (s is marked end-of-sentence (EOS)) output s and terminate.
Get list of candidate next words by doing fast matches.
For each candidate next word w:
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Stack decoding [Jurafsky and Martin(2000)]

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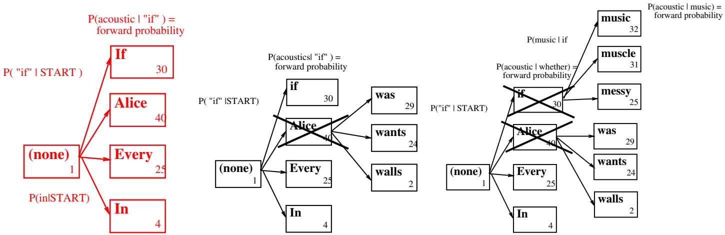

If music be the food of love [Jurafsky and Martin(2000)]

- *"Start Alice"* has highest score: 40
- *"Start if"* has highest score: 30
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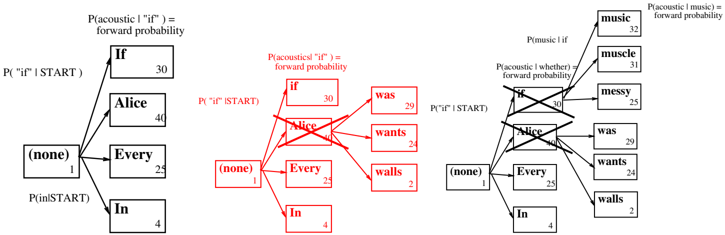

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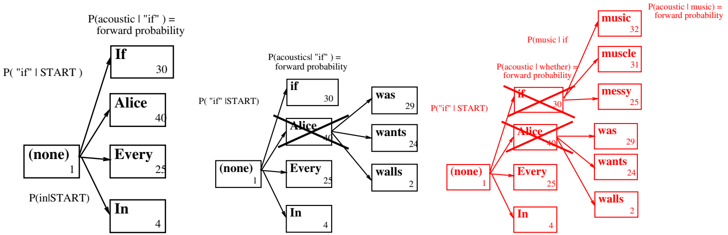

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- Use fast match heuristics for selecting next words
- Longer utterances have lower probabilities, score should correct for this
- A^* evaluation function: $f^*(p) = g(p) + h^*(p)$
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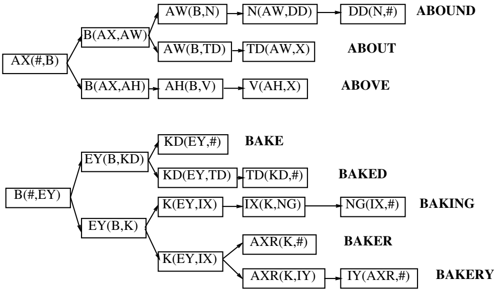

A tree structured lexicon from SPHINX

[Gouvêa()][Jurafsky and Martin(2000)]

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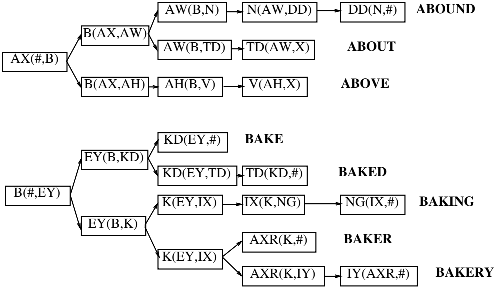

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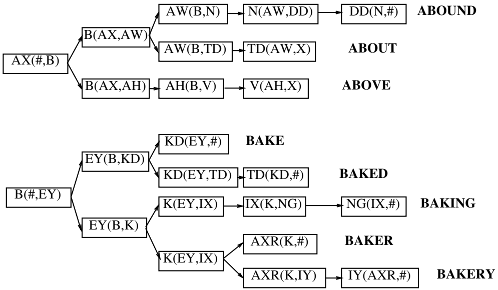

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Determine $P(Observation|Words)$, i.e. the transition probability between phone states a_{ij} and the acoustic likelihood of the speech vectors $b_j(o_k)$

- Large, "transcribed" speech corpus (on text level)
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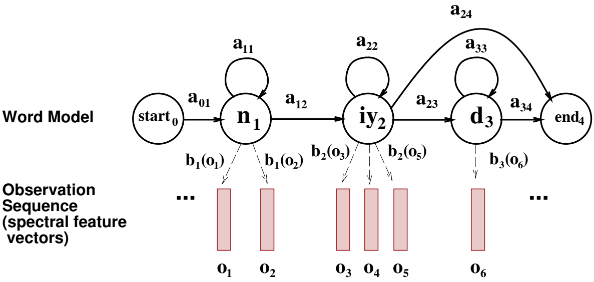

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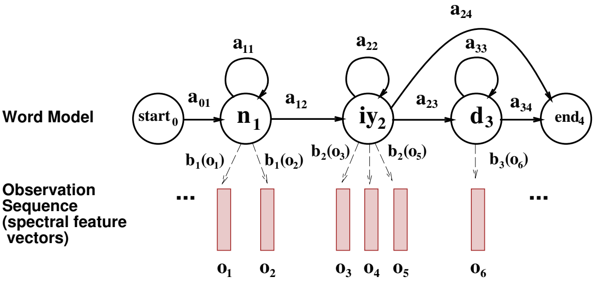

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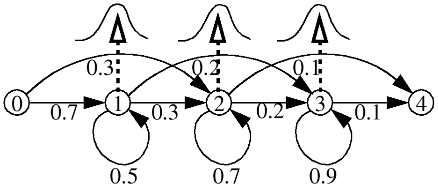

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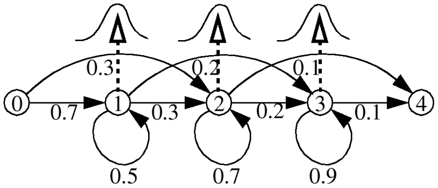

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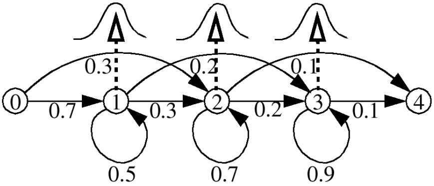

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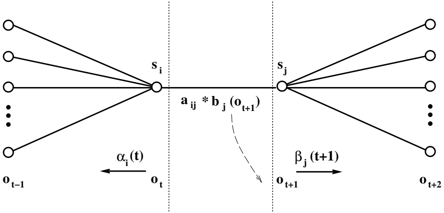

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App D [Jurafsky and Martin(2000)]

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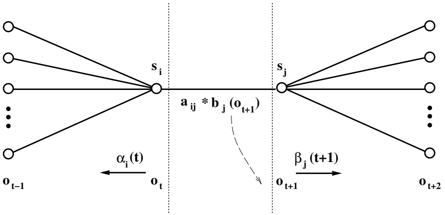

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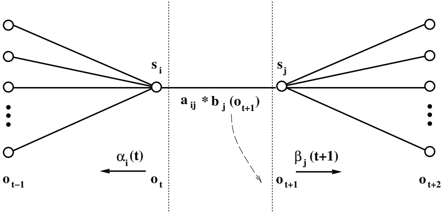

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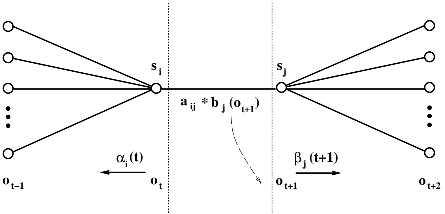

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- Open Mind Speech [Valin()]

FLOSS resources

Free and Open Source ASR systems

- SPHINX (CMU) [Gouvêa()] [Singh(2005)]
- CMU Statistical Language Modeling Toolkit [Rosenfeld()]
- CMU Pronouncing Dictionary [Lenzo()]
- Internet-Accessible Speech Recognition Technology project (ISIP, Mississippi State University) [ISIP(2004)]
- Open Mind Speech [Valin()]

Assignment: Week 8 Statistical Language Models

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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Appendix A

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The GNU General Public License IX

Appendix: How to Apply These Terms to Your New Programs

If you develop a new program, and you want it to be of the greatest possible use to the public, the best way to achieve this is to make it free software which everyone can redistribute and change under these terms.

To do so, attach the following notices to the program. It is safest to attach them to the start of each source file to most effectively convey the exclusion of warranty; and each file should have at least the "copyright" line and a pointer to where the full notice is found.

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You should also get your employer (if you work as a programmer) or your school, if any, to sign a "copyright disclaimer" for the program, if necessary. Here is a sample; alter the names:

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