Speech recognition and synthesis

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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, ie, training

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

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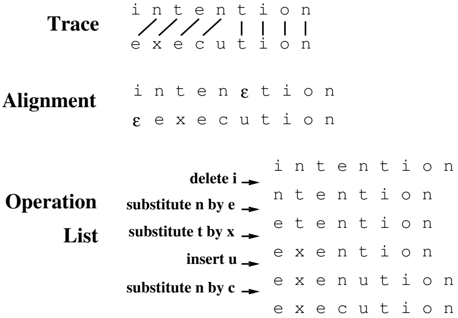

Look for best alignment: Minimum edit distance

- Delete
- Insert
- Substitute

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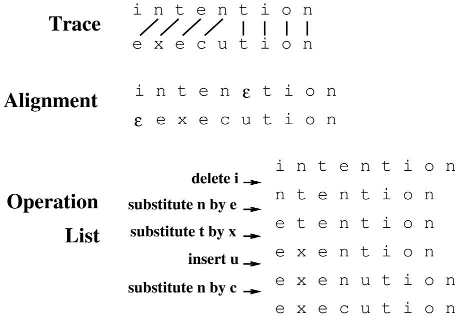

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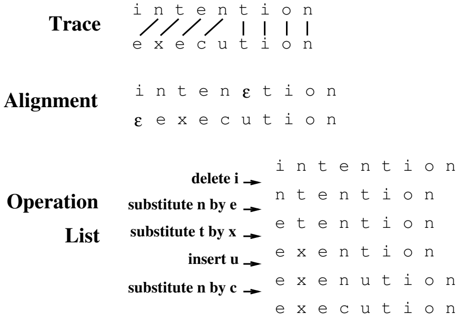

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function MIN-EDIT-DISTANCE(*target*, *source*) **returns** *min-distance*

$n \leftarrow$ 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

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o	8	9	10	9	10	11	10	9	**8**	9
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
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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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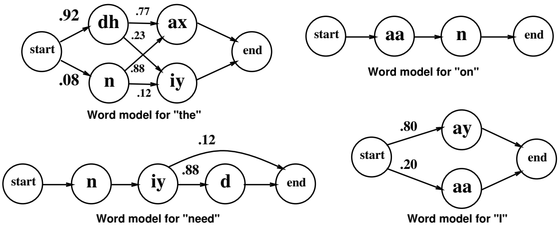

Simplified pronunciation networks [Jurafsky and Martin(2000)]

- Each word is modeled as a Finite State Machine
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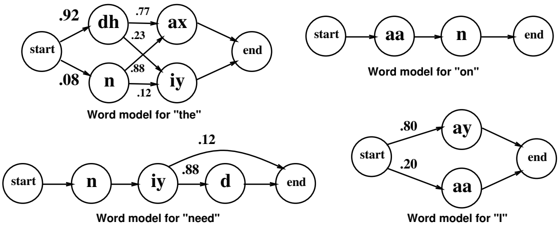

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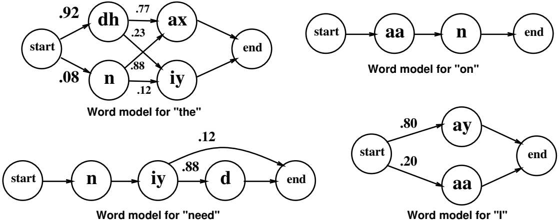

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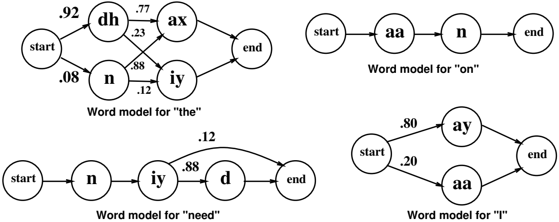

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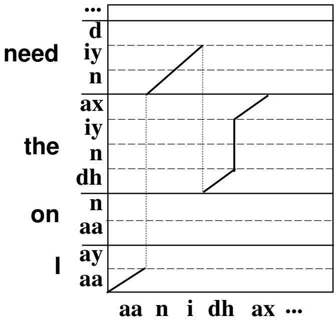

Viterbi algorithm result *"for I need a"* [Jurafsky and Martin(2000)]

- Whole sequence on **X** axis
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- Word switching cost based on the language model

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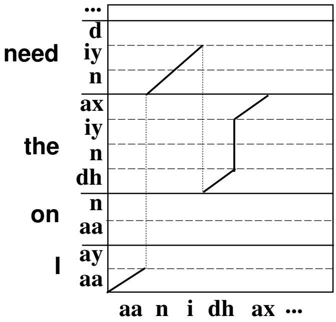

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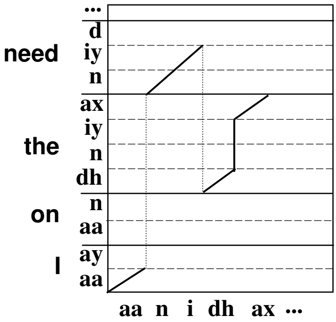

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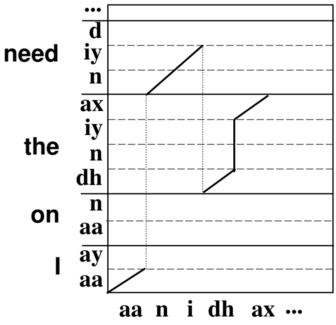

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I the	0.00018	need the	0.012	# The	0.016
I on	0.000047	need on	0.000047	# On	0.00077
I I	0.039	need I	0.000016	# I	0.079
the need	0.00051	on need	0.000055		
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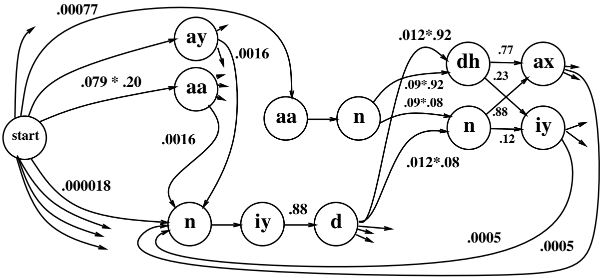

Single pronunciation automaton for *I*, *need*, *on*, and *the*

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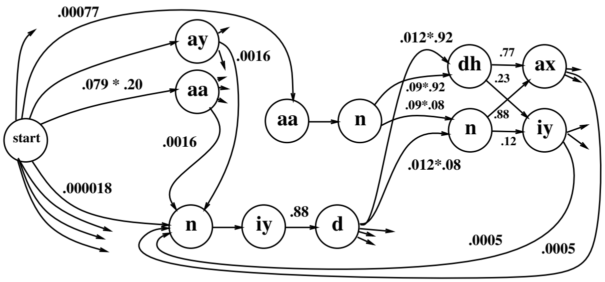

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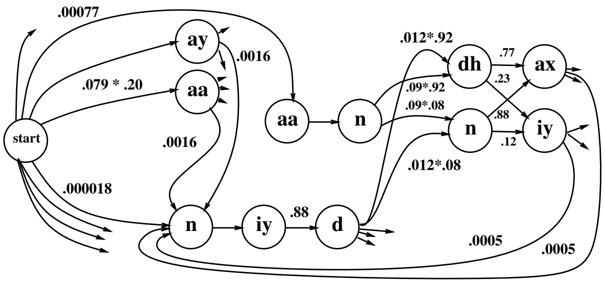

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num-states ← NUM-OF-STATES(*state-graph*)
Create a path probability matrix *viterbi[num-states+2,T+2]*
viterbi[0,0] ← 1.0
for each time step t **from** 0 **to** T **do**
  for each state s **from** 0 **to** *num-states* **do**
    for each transition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

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

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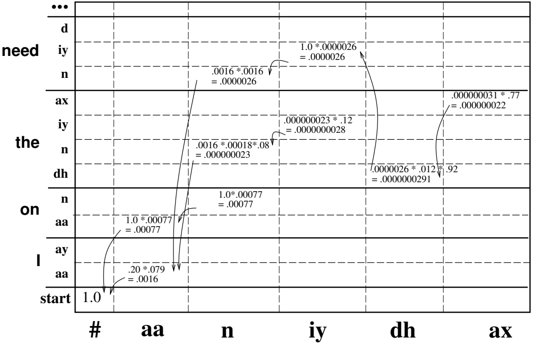

Individual state columns in Viterbi algorithm

[Jurafsky and Martin(2000)]

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

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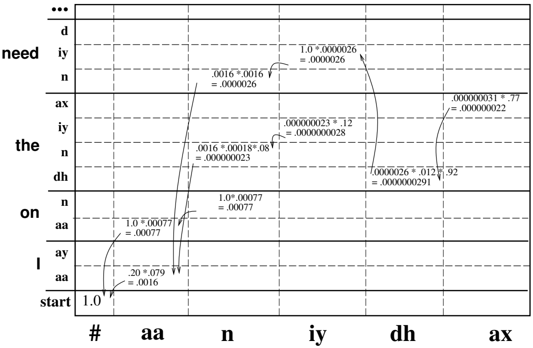

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Viterbi algorithm: Subphones revisited

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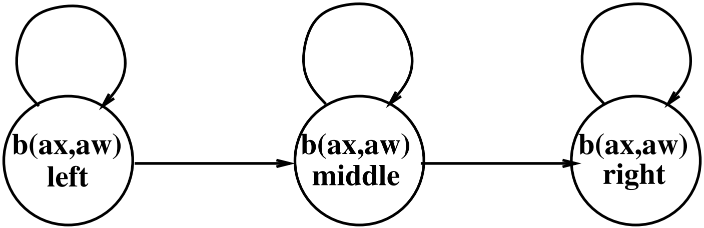

Use structured, context sensitive phone units

- 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

Viterbi algorithm: Subphones revisited
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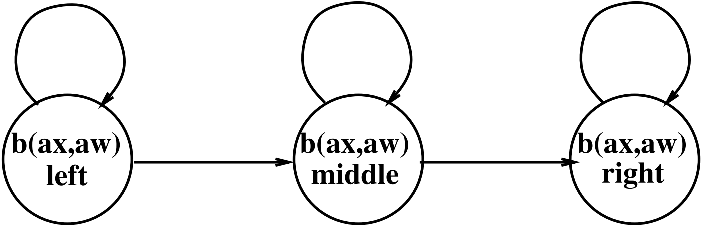

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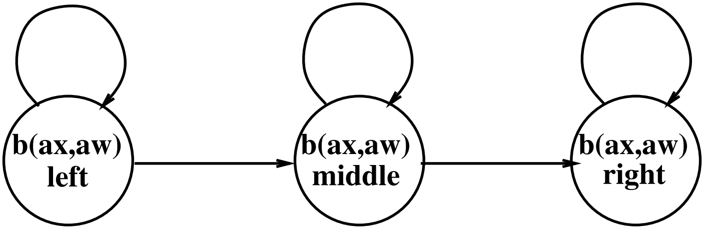

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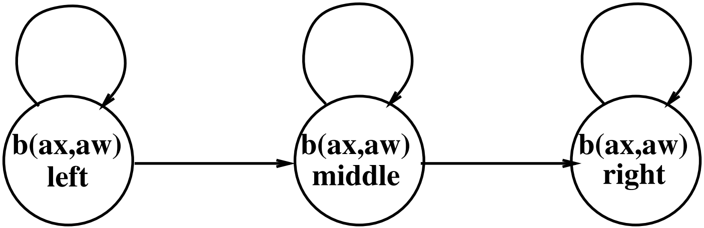

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Other approaches to decoding: Introduction

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
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    - Intonation
    - Semantics
    - Speaker identification
    - Expressive speech tags
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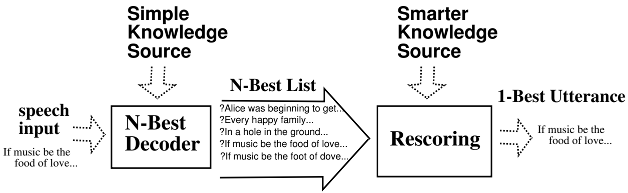

Two stage N-best decoding [Jurafsky and Martin(2000)]

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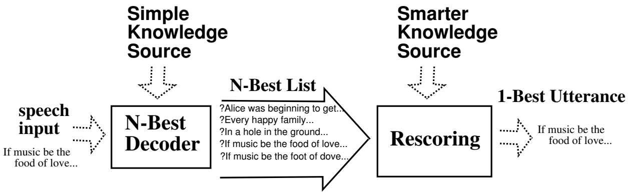

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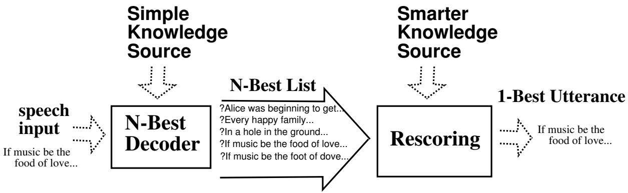

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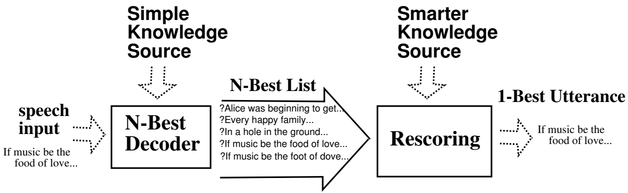

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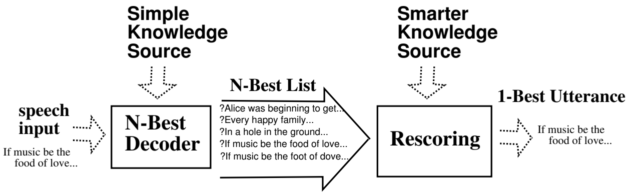

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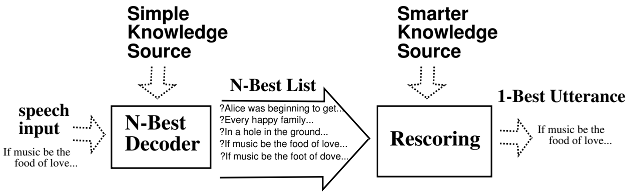

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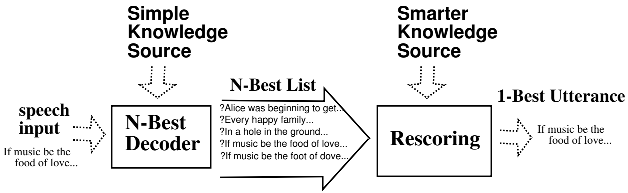

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Dynamic programming
Viterbi algorithm
Other approaches to decoding
Training acoustic models
FLOSS resources
Assignment
Bibliography

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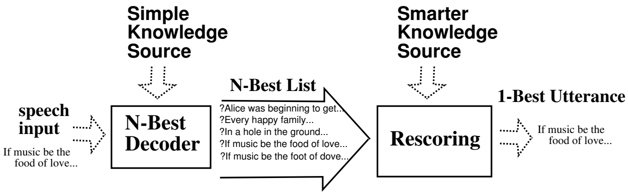

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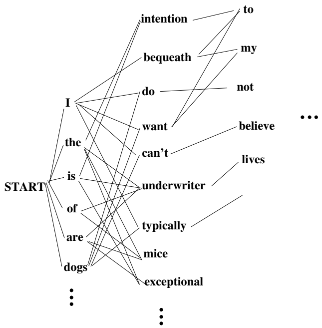

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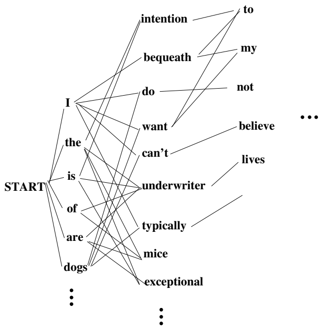

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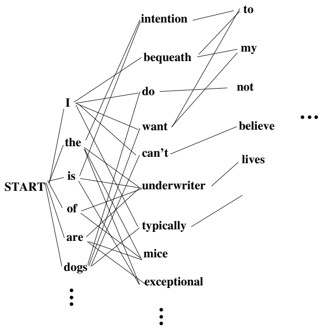

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function STACK-DECODING() **returns** *min-distance*

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 $s+w$.
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Stack decoding [Jurafsky and Martin(2000)]

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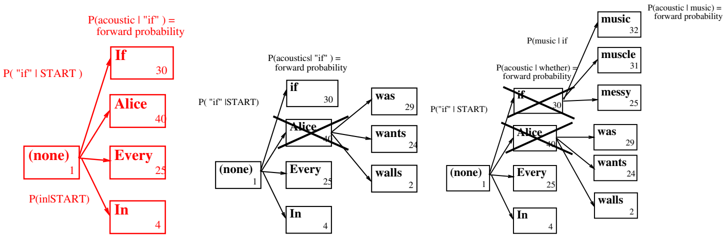

If music be the food of love [Jurafsky and Martin(2000)]

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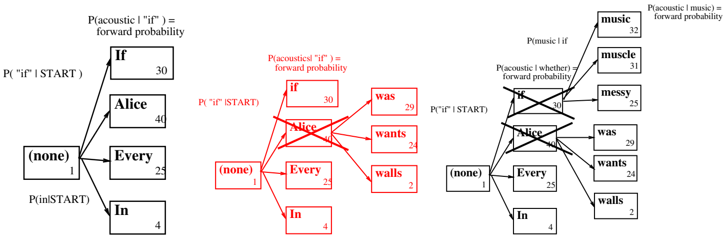

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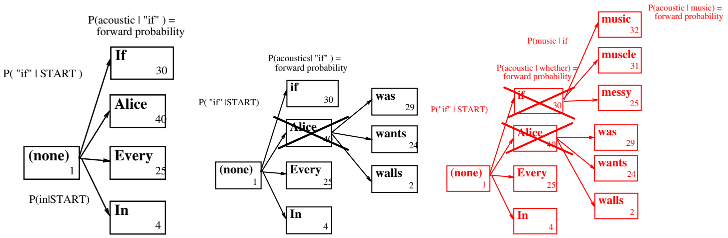

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- Use fast match heuristics for selecting next words
- Longer utterances have lower probabilities, score should correct for this
- A^* evaluation function: $f^*(p) = g(p) + h^*(p)$
- $g(partial\ path) = P(O|Words) \cdot P(Words)$, ie, the likelihood until now
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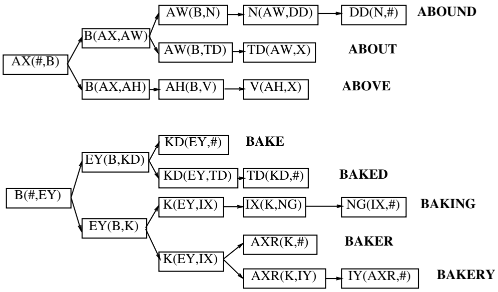

A tree structured lexicon from SPHINX

[Gouvêa()][Jurafsky and Martin(2000)]

- Need to get forward probabilities of potential continuations *fast*
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- Allows early pruning of search trees

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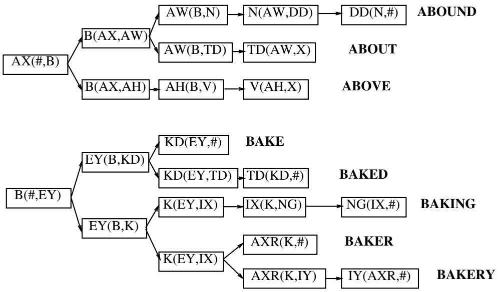

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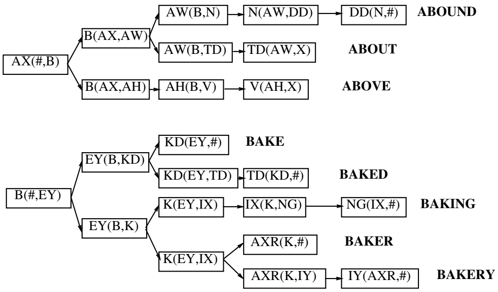

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Training acoustic models: Introduction

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
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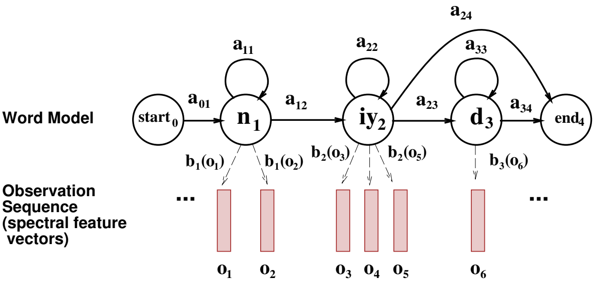

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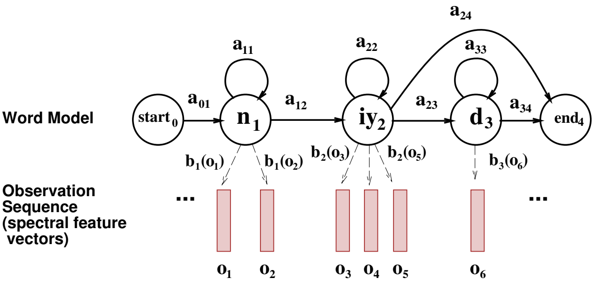

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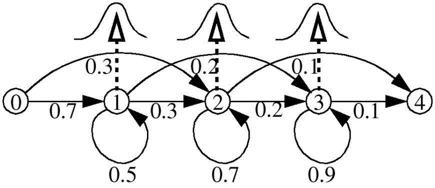

If observations are continuous vectors [SPH()]

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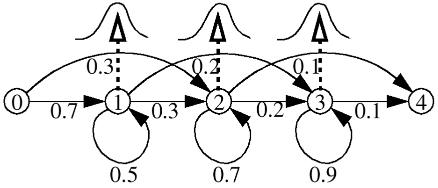

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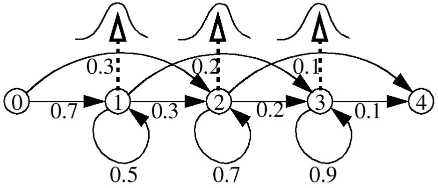

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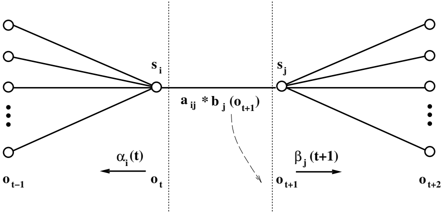

States have to be estimated. Use an iterative procedure

App D [Jurafsky and Martin(2000)]

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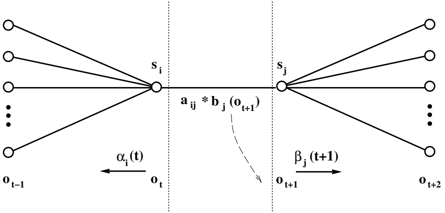

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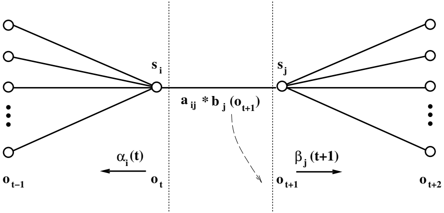

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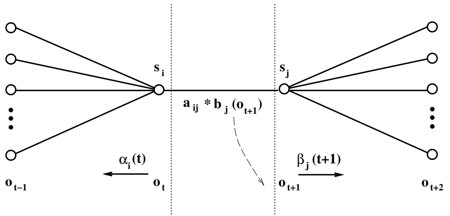

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FLOSS resources

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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

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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- Inspect the table files. What are the most frequent words and bigrams?
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Further Reading I

P. Boersma.
Praat, a system for doing phonetics by computer.
Glot International, 5:341–345, 2001.
URL http://www.Praat.org/.

P. Boersma and D. Weenink.
Praat 4.2: doing phonetics by computer.
Computer program: http://www.Praat.org/, 2004.
URL http://www.Praat.org/.

CSLU.
CSLU Toolkit.
Web.
URL http://cslu.cse.ogi.edu/toolkit/index.html.

FSF.
GNU General Public License.
Web, June 1991.
URL http://www.gnu.org/licenses/gpl.html.

Joshua T. Goodman.
A bit of progress in language modeling.
Computer Speech and Language, 15:403–434, 2001.
URL http://arxiv.org/abs/cs.CL/0108005.
URL is extended preprint.

E. Gouvêa.
The CMU Sphinx Group Open Source Speech Recognition Engines.
Web.
URL http://cmusphinx.sourceforge.net/html/cmusphinx.php.

Further Reading II

ISIP.
The Mississippi State ISIP public domain speech recognizer.
Web, August 2004.
URL http://www.cavs.msstate.edu/hse/ies/projects/speech/index.html.

Daniel Jurafsky and James H. Martin.
Speech and Language Processing.
Prentice-Hall, 2000.
ISBN 0-13-095069-6.
URL http://www.cs.colorado.edu/~martin/slp.html.

Kevin Lenzo.
The CMU Pronouncing Dictionary.
Web.
URL http://www.speech.cs.cmu.edu/SLM_info.html.

Project Gutenberg.
Project gutenberg free ebook library.
Web, 2005.
URL http://www.gutenberg.org/.

Roni Rosenfeld.
The CMU Statistical Language Modeling (SLM) Toolkit.
Web.
URL http://www.speech.cs.cmu.edu/SLM_info.html.

Further Reading III

Rita Singh.
Robust group's open source tutorial learning to use the cmu sphinx automatic speech recognition system.
Web, 2005.
URL http://www.cs.cmu.edu/~robust/Tutorial/opensource.html.

Manual for the Sphinx-III recognition system.
SPHINX-CMU.
URL http://fife.speech.cs.cmu.edu/sphinxman/.

Paul A. Taylor, S. King, S. D. Isard, and H. Wright.
Intonation and dialogue context as constraints for speech recognition.
Language and Speech, 41:493–512, 1998.
URL http://www.cstr.ed.ac.uk/downloads/publications/1998/Taylor_1998_b.pdf.

Jean-Marc Valin.
Open mind speech.
Web.
URL http://freespeech.sourceforge.net/.

Xue Wang.
incorporating knowledge on segmental duration in hmm-based continuous speech recognition.
PhD thesis, LOT Netherlands Graduate School of Linguistics, 04 1997.
URL http://www.fon.hum.uva.nl/wang/ThesisWangXue/TOCINDEX.html.

Appendix A

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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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