Speech recognition and synthesis

1. More about ASR
   - Introduction
   - Dynamic programming
   - Viterbi algorithm
   - Other approaches to decoding
   - Training acoustic models
   - FLOSS resources
   - Assignment
   - Bibliography

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

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

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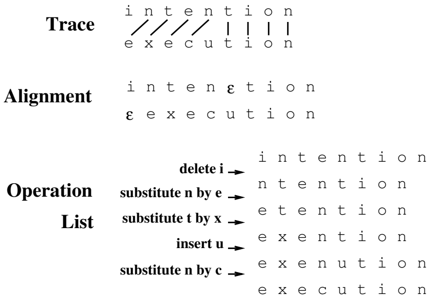

Look for best alignment: Minimum edit distance

- Delete
- Insert
- Substitute

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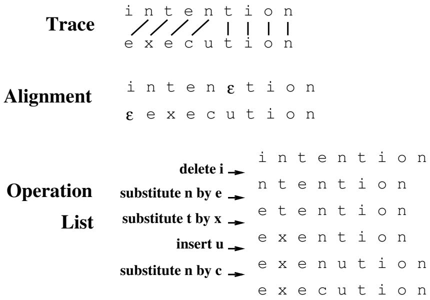

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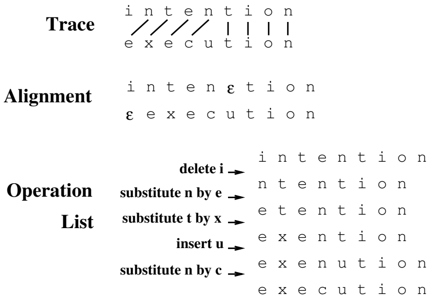

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function MIN-EDIT-DISTANCE(target, source) returns min-distance

  n ← LENGTH(target)
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  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),
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#	**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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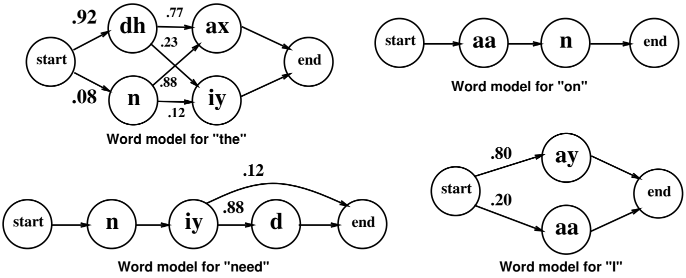

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- Each word is modeled as a Finite State Machine
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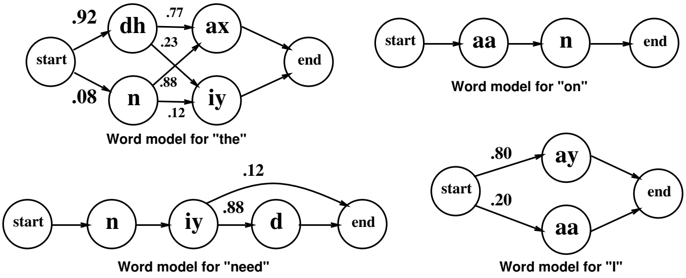

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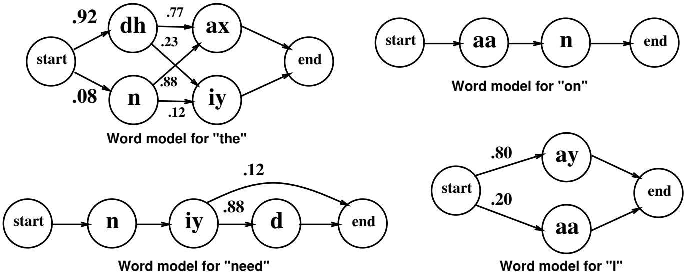

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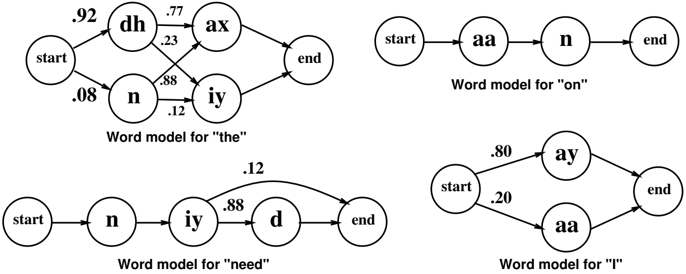

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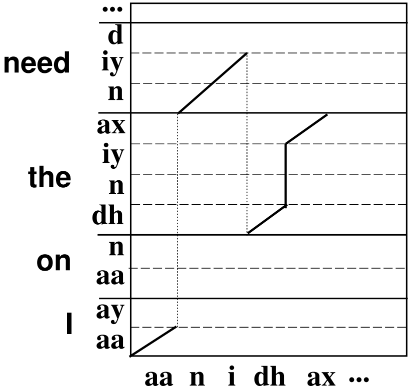

Viterbi algorithm result *"for I need a"* [Jurafsky and Martin(2000)]

- Whole sequence on **X** axis
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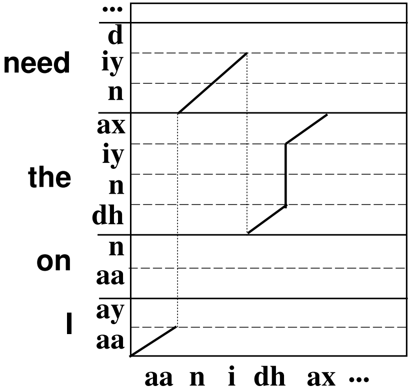

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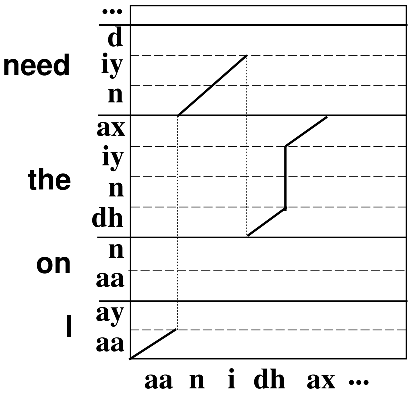

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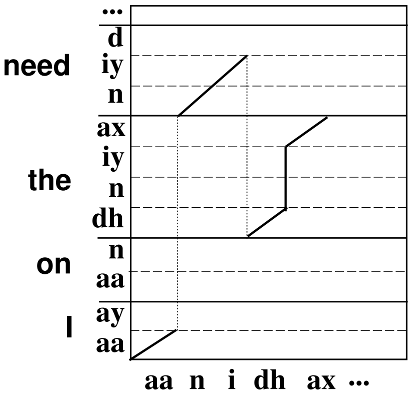

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I the	0.00018	need the	0.012	# The	0.016
I on	0.000047	need on	0.000047	# On	0.00077
I I	0.039	need I	0.000016	# I	0.079
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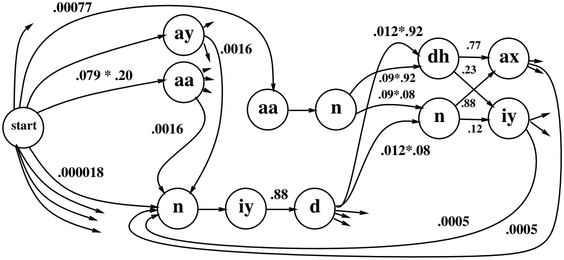

Single pronunciation automaton for *I*, *need*, *on*, and *the*

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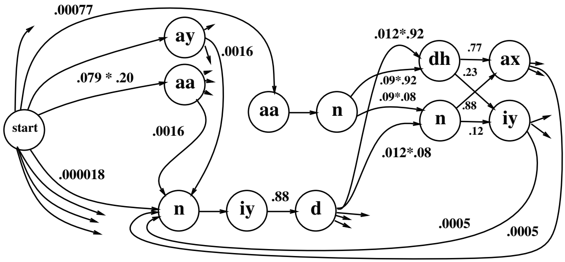

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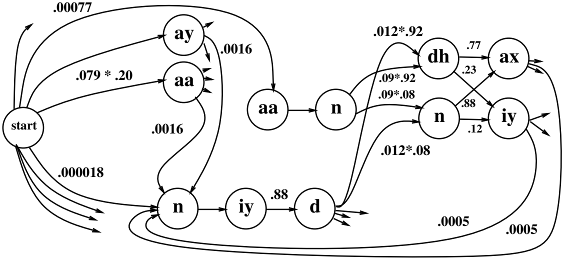

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function VITERBI(*observations* of len *T*,*state-graph*) **returns** *best-path*

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] * $a[s,s']$ * $b_{s'}(o_t)$
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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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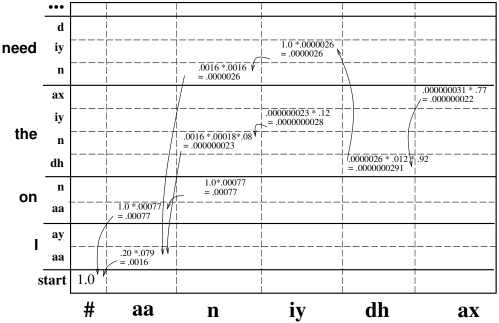

Individual state columns in Viterbi algorithm [Jurafsky and Martin(2000)]

- The actual entries for the Automaton
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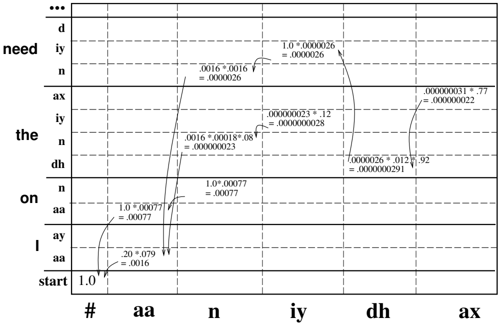

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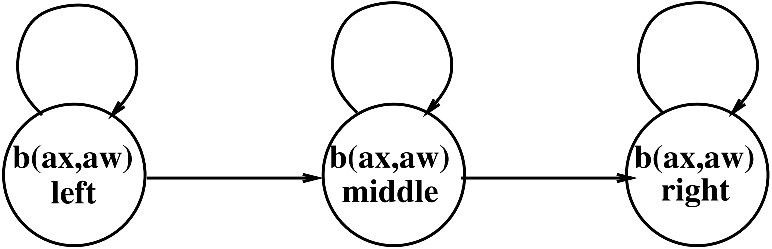

Use structured, context sensitive phone units

- Single phone units perform bad due to coarticulation
- *Begin* differs from *End* (eg, /d/)
- 60 context dependent triphones ⇒ $60^3 = 216000$ models
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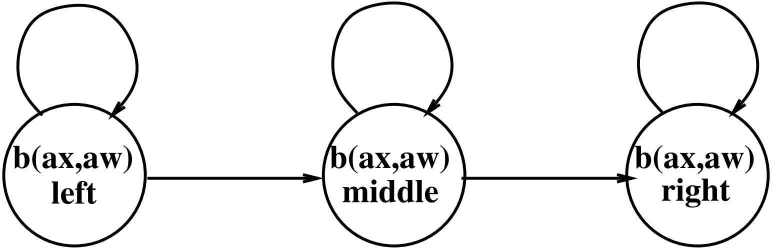

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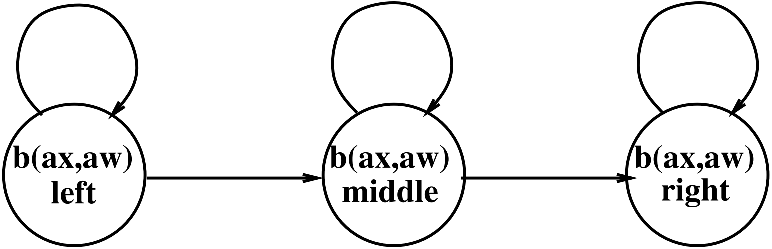

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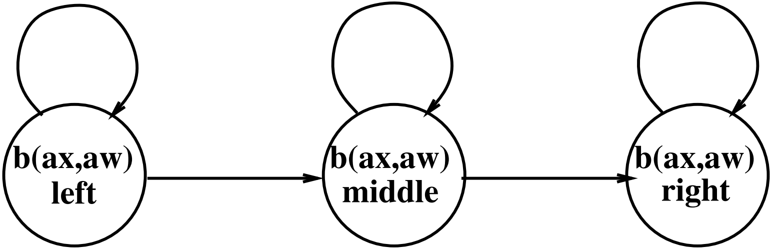

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Other approaches to decoding: Introduction

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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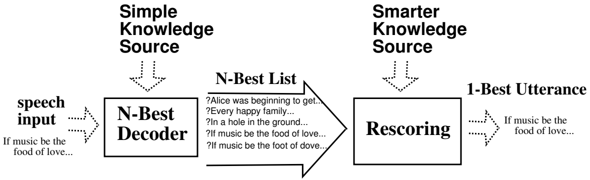
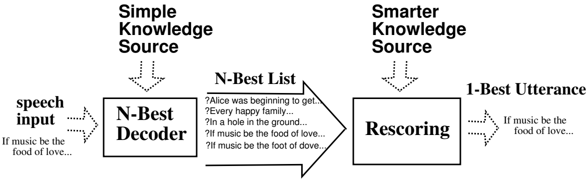


Two stage N-best decoding [Jurafsky and Martin(2000)]

- Keep N-best utterance list or word lattice
- Rescore the probabilities with the extra knowledge
  - A trigram or higher grammar
  - Phoneme duration probability Chapt 7 [Wang(1997)]
  - Parallel Intonation and Accent detector (HMM) example without N-best [Taylor et al.(1998)Taylor, King, Isard, and Wright]
  - Include semantic or task related knowledge
  - Multiple speakers and expressive speech tags
- Look up best path through rescored word lattice

Other approaches to decoding



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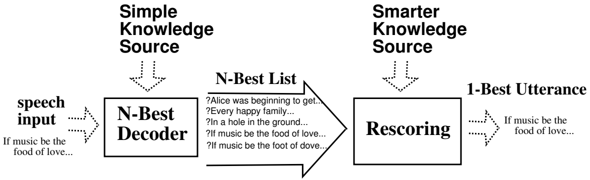

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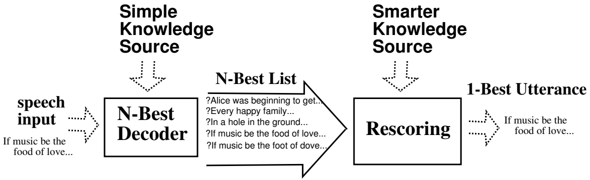

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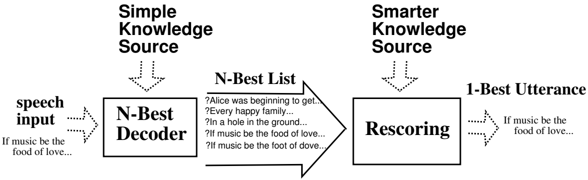

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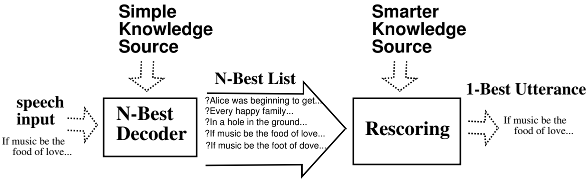

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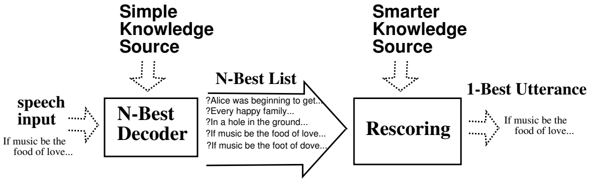

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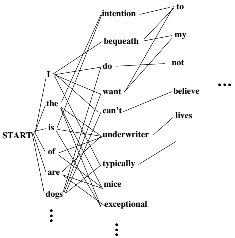
Other approaches to decoding: A^*



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)
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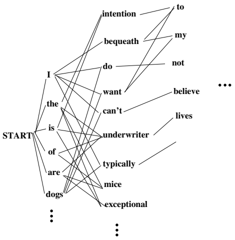

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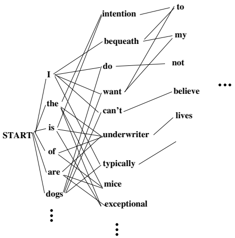

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function STACK-DECODING() **returns** *min-distance*

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)]

- At each point, the A^* looks for the most likely next word
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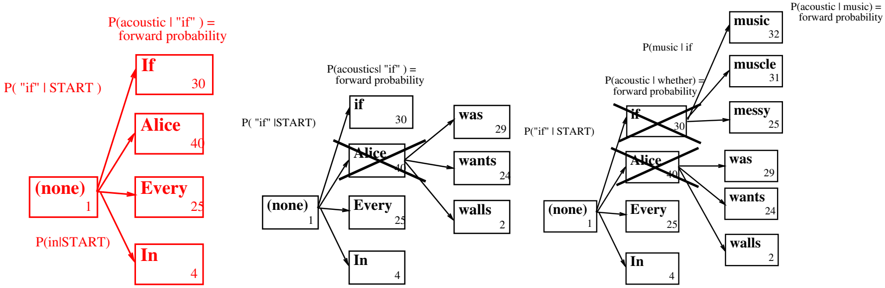
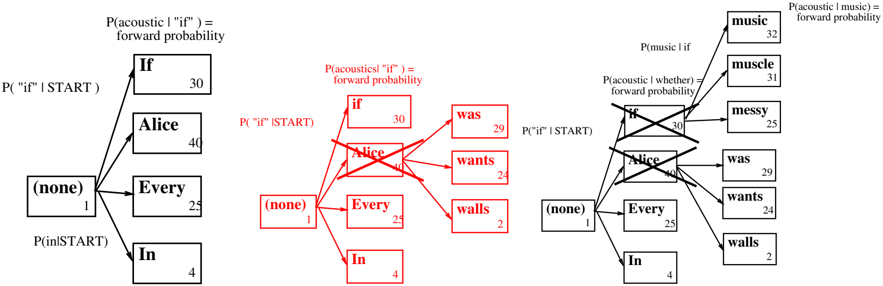


If music be the food of love [Jurafsky and Martin(2000)]

- *"Start Alice"* has highest score: 40
- *"Start if"* has highest score: 30
- *"Start if music"* has highest score: 32

Other approaches to decoding: A^*



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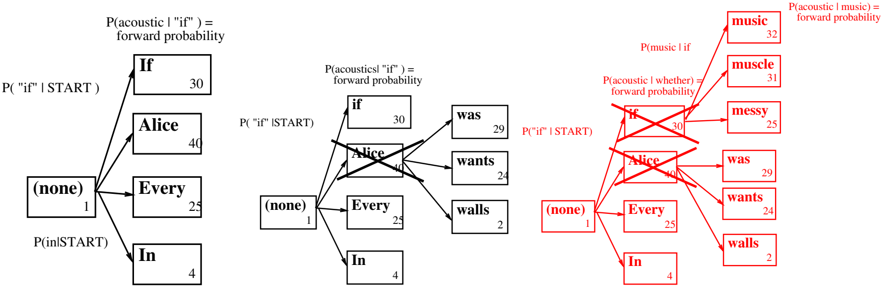

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Remarks

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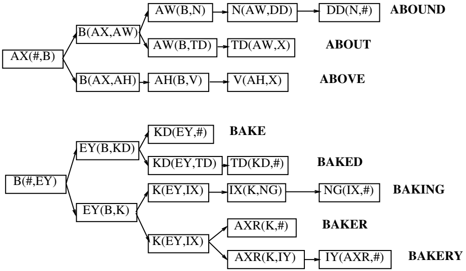
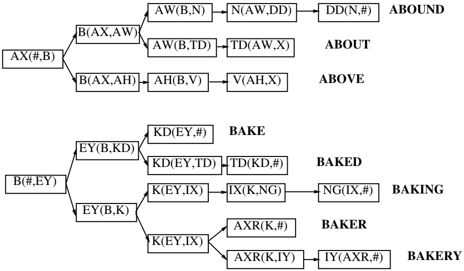
Other approaches to decoding: A^* fast match



A tree structured lexicon from SPHINX [Gouvêa()][Jurafsky and Martin(2000)]

- Need to get forward probabilities of potential continuations *fast*
- Tree lexicon shares forward probabilities between words
- Allows early pruning of search trees

Other approaches to decoding: A^* fast match



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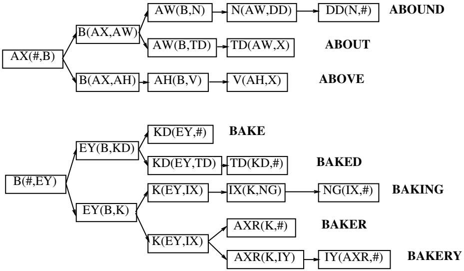

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Determine $P(Observation|Words)$, i.e. the transition probability between phone states a_{ij} and the acoustic likelihood of the speech vectors $b_j(o_k)$

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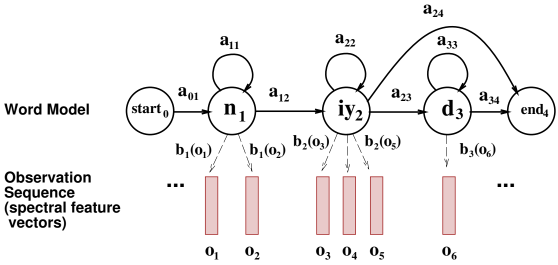

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- $a_{ij} = \frac{\#S_{ij}}{\#S_{i*}}$ (count transitions and states)
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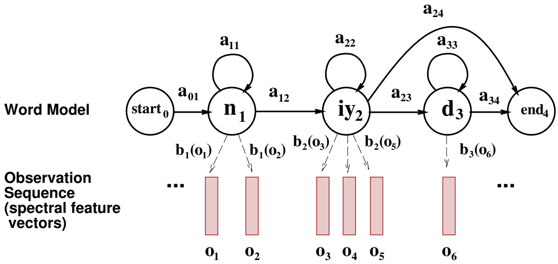

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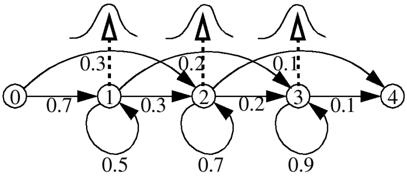

If observations are continuous vectors [SPH()]

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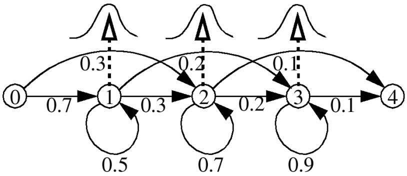

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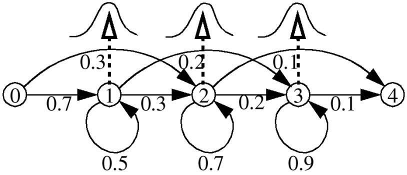

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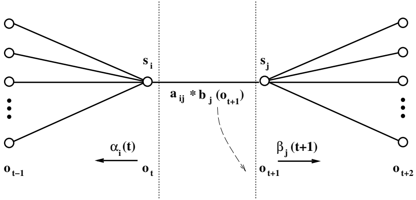

States have to be estimated. Use an iterative procedure App D [Jurafsky and Martin(2000)]

- Run the recognizer on the corpus with the known words
- Calculate $\hat{a}_{ij} = \frac{expected\ \#S_i \rightarrow S_j}{expected\ \#S_i \rightarrow S_*}$
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- Update all values and start again

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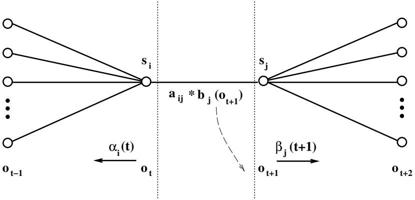

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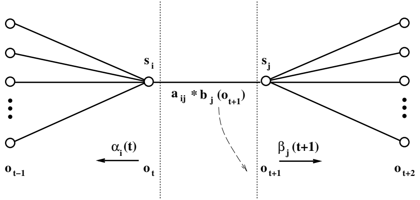

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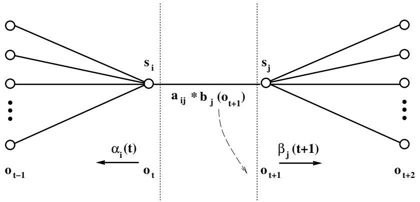

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FLOSS resources

Free and Open Source ASR systems

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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
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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.

Further Reading II

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

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.
Updates at http://www.cs.colorado.edu/

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/.

Further Reading III

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

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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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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Also add information on how to contact you by electronic and paper mail.

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The hypothetical commands `show w` and `show c` should show the appropriate parts of the General Public License. Of course, the commands you use may be called something other than `show w` and `show c`; they could even be mouse-clicks or menu items—whatever suits your program.
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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