Information in Spoken Language

A quantitative approach

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LOT winterschool 2006

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1 Symbolic Information in language

- Introduction
- Information in the Lexicon
- Markov models
- Hidden Markov Models
- Predictability in context
- Human word recognition
- Phonemic information
- Bibliography

Introduction

Language is understood in symbolic form

- Speech is transcribed into phonemes and words
- Somehow, phonemes seem to matter for understanding
- What information is carried by a single phoneme?
- Answer depends on the information in words
- The predictability of words
- Word recognition by humans
- What does a single phoneme contribute?

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Information in the Lexicon

Content and function words

- A basic distinction
- Content words have an independent, lexical, meaning
- Function words have little, if any, lexical meaning, but chiefly indicate a grammatical relationship
- Function words form a closed class (around 1000 words)
- Content words belong to an open class
- Function words have a high frequency/low information content
- But how to treat the information content of words itself?

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Word frequencies follow a Zipf distribution

- 8 Jane Austens novels (1811-1817)
- 14,817 word forms on 801,183 words (tokens)
- Most frequent 10: *the to and of a her I in was it* (180,464 tokens)
- 4,571 words occur only once, 1,992 twice
- $H = 9.306$ bits/form
- Kullback-Leibler(Words, Zipfs dist) $= 0.173$ bits/form (average information difference)

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Author	N	Forms	H	KL(Zipf)
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Jane Austen	801,183	14,817	9.306	0.173
Brontë sisters	892,779	24,658	9.828	0.108
Plato (transl.)	1,445,372	21,095	9.173	0.129

Works of several authors 1750-1900?

- Large variation in number of distinct word forms (vocabulary)
- Information per word (H) roughly constant ($2^H \approx 890$)
- Difference with Zipf's distribution $\leq 2\%$

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Information in the Lexicon

	Fielding	Austen	Brontë	Plato
Henry Fielding	0.141	0.311	0.377	0.627
Jane Austen	0.323	0.173	0.326	0.767
Brontë sisters	0.323	0.270	0.108	0.712
Plato (transl.)	0.581	0.588	0.651	0.129

Kullback-Leibler divergence or Cross Entropy

- Diagonal terms are distance to Zipf distribution
- $KL(q,p) = H(p) - H_X(q,p) \approx$ information difference per word
- Averaged over one of the distributions
- Multi-authored translations of Plato differ from novels
- All works differ more from each other than from Zipf's distr.

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	Austen	Brontë	Plato
Henry Fielding	0.489	0.460	0.447
Jane Austen		0.526	0.536
Brontë sisters			0.470

Normalized Compression Distance (NCD)

- $NCD(x, y) = \frac{C(xy) - min(C(x), C(y))}{max(C(x), C(y))}$
- $C(x)$ is number of distinct word forms in text
- Half the words in the larger corpus do not appear in smaller corpus
- Jane Austen's works had the smallest "vocabulary" $\Rightarrow$ largest distances

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Markov models: Predictability

$$P(w_{i+1}|w_i) = \frac{P(w_{i+1}, w_i)}{P(w_i)} \tag{1}$$

$$P(w_1, \ldots, w_n) \approx \prod_{i=1}^{n} P(w_i|w_{i-N+1}, \ldots, w_{i-1}) \tag{2}$$

Extremely useful technology

- Probability of the next word, given the previous words
- Probability of a sentence (N-gram)
- Most likely sentence (eg, using Viterbi algorithm)
- Humans do not use anything like it

[Jurafsky and Martin(2000)]

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Hidden Markov Models

$$P(S_i|O_i, S_{i-1}) = P(O_i|S_i) \cdot P(S_i|S_{i-1})$$

HMM technology is extremely important for language (re-)search

- Split the problem in an Observation part and a Model part
- The "states", S_i, are not visible
- However, they can be estimated using the observation probabilities $P(O_i|S_i)$ and the transition probabilities $P(S_i|S_{i-1})$
- Standard in Automatic Speech Recognition (ASR)

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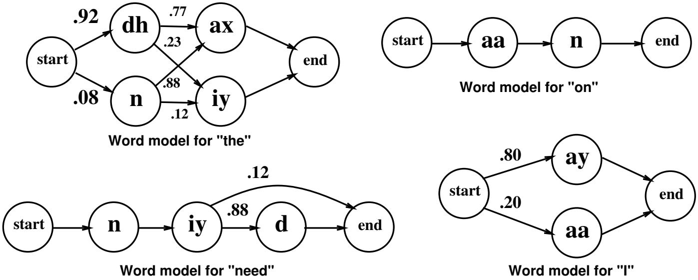
Hidden Markov Models: Pronunciation networks



Construct phone state models for each word in the dictionary

- Possible pronunciations for each word have to be encoded in the dictionary
- Transition probabilities are "trained" from the frequency of occurrence of the pronunciation in the corpus

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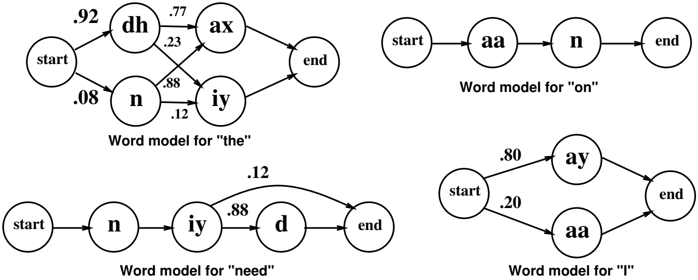

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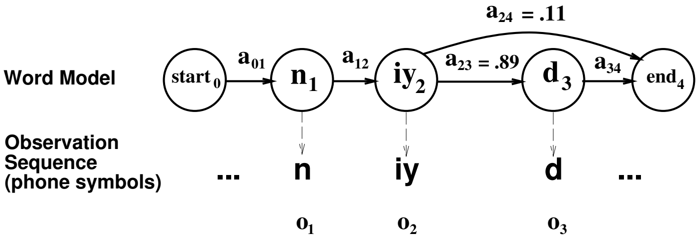

Word models: simple phone state model for *need*

- Each transition has a probability
- start and end are special states
- Each state *or* each transition has associated sound observations with a distinct probability density function (PDF)

[Jurafsky and Martin(2000)]

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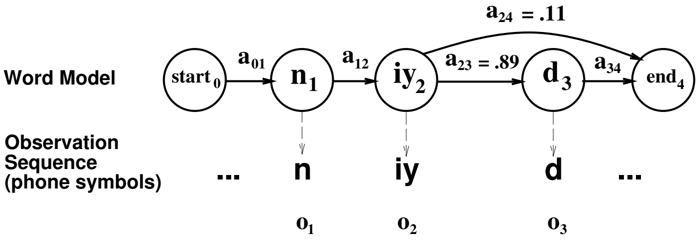

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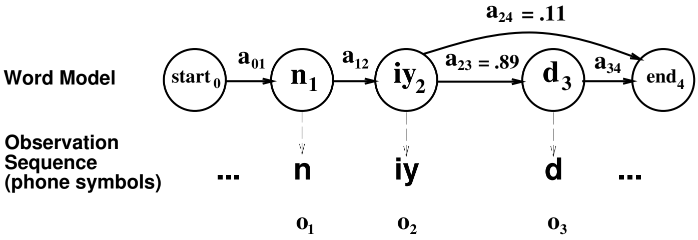

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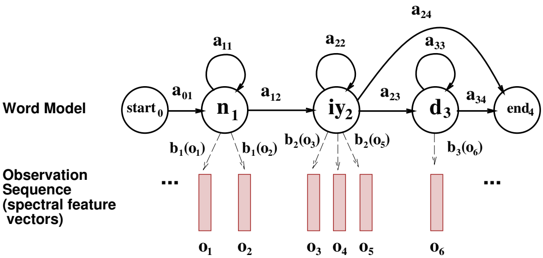

Observed are sound "spectra" for time "frames"

- Observation sequences have a probability
- Calculate this probability for each possible word
- Probabilities of observation O_i calculated from all possible underlying states
- Chose word *sequence* with the highest overall probability

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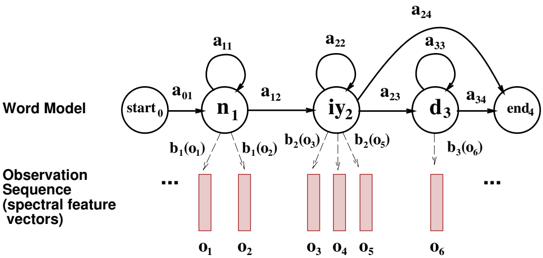

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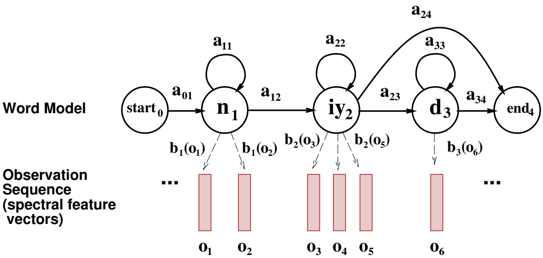

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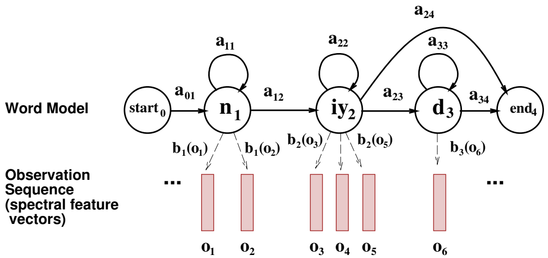

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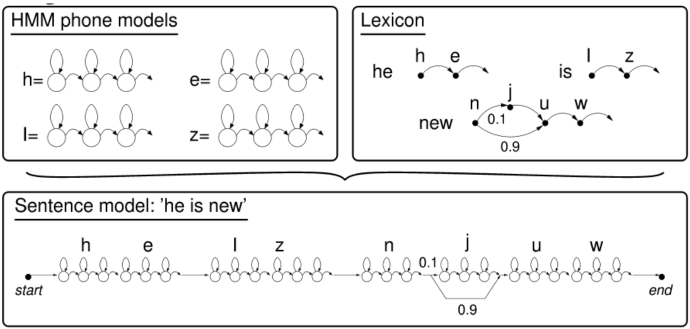

Phone models are concatenated into utterance networks

- Each word model is itself a Markov finite state network of phone models
- Phones and word are connected through the *start* and *end* states (not shown)

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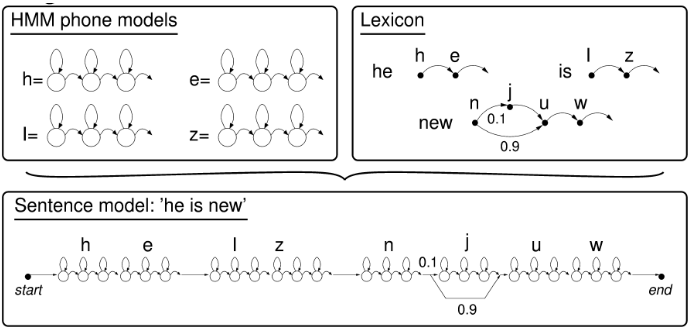

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Hidden Markov Models

Hidden Markov Models are very useful for:

- Automatic Speech Recognition
- Automatic POS tagging: $P(POS_i|Word_i, POS_{i-1}) = P(Word_i|POS_i) \cdot P(POS_i|POS_{i-1})$
- Accent assignment [Pan and McKeown(1999)]
- Automatic translation
- Speech Understanding with Semantic HMMs $P(Message_i|Words) = P(Words|Message_i) \cdot P(Message_i|Message_{i-1})$

  [Bühler et al.(2005)Bühler, Minker, and Elciyanti]
- Still, humans do not use (Hidden) Markov Models

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- Automatic POS tagging: $P(POS_i|Word_i, POS_{i-1}) = P(Word_i|POS_i) \cdot P(POS_i|POS_{i-1})$
- Accent assignment [Pan and McKeown(1999)]
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Predictability in context

Movies. . . pop-corn
Cats and. . . dogs
A stitch in time saves. . . nine
Good morning,. . . how are you

No real model of human grammar but there are regularities in human (re-)cognition

- Priming: people expect words given associates
- Semantic web: words in proximity tend to be cognates
- Words group in "documents"
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Predictability in context: In-document frequency

Distinguish global and local word frequencies: Term Frequency times Inverse Document Frequency (TF*IDF)

- Humans expect certain words based on topic, form, and style
- Break down corpus into small units, eg, articles, of roughly equal size
- Determine global word frequency
- Divide it by the fraction of documents the word is used in
- In-document frequency accounts statistically for both *priming* and *semantic webs*

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Predictability in context: Context distinctiveness

CD = Kullback-Leibler distance between local context distribution and global word distribution

[McDonald and Shillcock(2001)]

Predictability from direct context

- Use a statistical predictor
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- Bag-of-words technique, eg, 10 word contexts
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Human word recognition

Basic aspects of word recognition

- Prelexical: Sound $\longrightarrow$ Phonemic Symbols
- Postlexical:
- $\longrightarrow$ Activation
- $\longrightarrow$ Competition
- $\longrightarrow$ Selection

[Cutler(1997)] [Norris et al.(2000)Norris, McQueen, and Cutler] [McQueen et al.(2003)McQueen, Cutler, and Norris]

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Human word recognition: Postlexical stage - Activation

Phon.	ML Word	I(W)	Matching N	*Dutch*
b	bij	7.882	122,629	terms
boː	bovendien	11.658	5772	terms
boːm	bomen	14.831	798	terms

After recognizing a new phoneme, words are activated

- All matching words are activated
- Frequent words are activated more than rare words
- Non-matching phonemes decrease or end the activation of a word
- A word end is identified after an impossible continuation
- Word boundaries are also indicated by prosodic markers
- Simple model ignores morphological structure

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Words "compete" for activation

- Recognition is blocked as long as there are multiple candidates left
- Only when there is a single word left, is it recognized
- Words can occur inside other words
- $\Rightarrow$ wait for word boundary [Cutler(1997)]

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Human word recognition: Postlexical stage - Selection

Competition blocks selection

- If there is only a single candidate left, chose it
- If there is no single perfect candidate, chose the best (eg, *cigaret* for /ʃigərɛt/)
- Ganong effect: All candidates that fit an incomplete phoneme remain activated
  (eg, /(g/k)ot/ $\rightarrow$ *Goat* or *Coat*)
- Without enough phonetic "evidence", the most likely word is chosen $\rightarrow$ phonemic restoration
- People are only rarely aware of what *phonemes* have actually been spoken

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Phonemic information

What difference a phoneme makes?

- Combine Information theory with Human word recognition
- Words matching a phoneme onset with and without the new phoneme added
- $I(phon|onset) = H(W|onset + \star) - H(W|onset + phon)$
- $H(W|S)$: Entropy of words matching S
- Use a large (automatically) transcribed corpus, eg, 350*Mword Twente News Corpus* [Ordelman(2002)]
- Sensitive to vocabulary structure
- But: Psychologically implausible?
- Compound words, $>$ 1 million word-forms?
- No data available on this measure

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Phonemic information: Alternative

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\begin{aligned}
I(phon|onset) &= -\log_2 P(phon|onset) \\
&= -\log_2 \frac{TokenCount(onset + phon)}{TokenCount(onset + \star)}
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Information in phoneme given preceding onset

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Phonemic information: In-document frequency

$$I'(phon|onset, w) = -\log_2 \frac{TokenCount(onset + phon) + D(w)}{TokenCount(onset + \star) + D(w)}$$

$D(w) = (TF(w) \cdot IDF(w) - TF(w)) \cdot TotalCount$ $TF(w)$: Term frequency of w

Include statistical predictability of in-document frequency

- In the text, the correct word will be "predictable"
- Perceived "frequency" of the correct word, w, is the in-document frequency, $TF(w) \cdot IDF(w)$
- Assume only the correct word, w, is boosted
- Replace global frequency of w by in-document frequency

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$D(w) = (TF(w) \cdot IDF(w) - TF(w)) \cdot TotalCount$ $TF(w)$: Term frequency of w

Include statistical predictability of in-document frequency

- In the text, the correct word will be "predictable"
- Perceived "frequency" of the correct word, w, is the in-document frequency, $TF(w) \cdot IDF(w)$
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Focus on direct context of w: $LocalDistr(w)$

- $CD(w)$: Kullback-Leibler distance between local and global distribution
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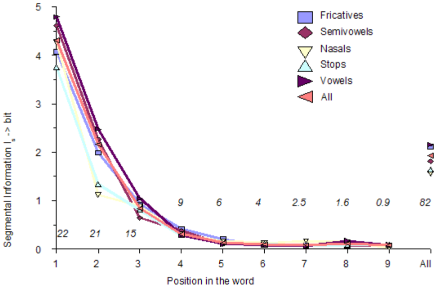

Segments (x1000)

$I''(phon|contex, w)$ versus the position in the word

- Only syllables without a /ə/
- Strong decline after a few positions part of model
- All manners of articulation carry the same information

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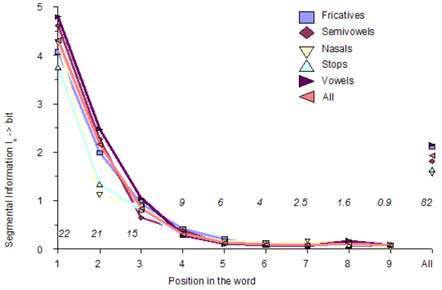

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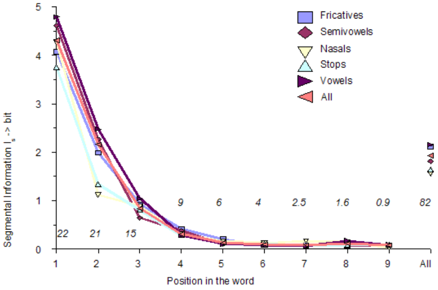
Phemic information



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No Warranty

Bibliography VIII

Appendix: How to Apply These Terms to Your New Programs

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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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