Information in Spoken Language
A quantitative approach

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LOT winterschool 2006
1 Symbolic Information in language

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

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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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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 Austen's 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
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- Diagonal terms are distance to Zipf distribution
- \( KL(q, p) = H(p) - H_X(q, p) \approx \) information difference per word
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- Multi-authored translations of Plato differ from novels
- All works differ more from each other than from Zipf's distr.
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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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\[ P(w_{i+1}|w_i) = \frac{P(w_{i+1}, w_i)}{P(w_i)} \]  \hspace{1cm} (1)

\[ P(w_1, \ldots, w_n) \approx \prod_{i=1}^{n} P(w_i|w_{i-N+1}, \ldots, w_{i-1}) \]  \hspace{1cm} (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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- 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 $P(S_i|S_{i-1})$
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[Jurafsky and Martin(2000)]
### Hidden Markov Models

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

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Construct phone state models for each word in the dictionary

- Possible pronunciations for each word have to be encoded in the dictionary
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- 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)

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Word Model

Observation Sequence (phone symbols) ...

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Phone models are concatenated into utterance networks

- Each word model is itself a Markov finite state network of phone models
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- **Accent assignment** [Pan and McKeown(1999)]

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- **Speech Understanding with Semantic HMMs**
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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
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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, e.g., articles, of roughly equal size
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CD = Kullback-Leibler distance between local context distribution and global word distribution

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Predictability from direct context

- Use a statistical predictor
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- Bag-of-words technique, eg, 10 word contexts
  - [Sproat and van Santen(1998)]
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Human word recognition

Basic aspects of word recognition

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

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- All matching words are activated
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- If there is only a single candidate left, chose it
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- Ganong effect: All candidates that fit an incomplete phoneme remain activated (eg, /ˈgɪɡət/ → Goat or Coat)
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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 (e.g., *cigaret* for */ʃɪɡərɛt/)
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- Combine Information theory with Human word recognition
- Words matching a phoneme onset with and without the new phoneme added
  \[ I(\text{phon}|\text{onset}) = H(W|\text{onset} + \ast) - H(W|\text{onset} + \text{phon}) \]
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- Use a large (automatically) transcribed corpus, eg, 350Mword Twente News Corpus [Ordelman(2002)]
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- But: Psychologically implausible?
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\[ I(\text{phon}|\text{onset}) = -\log_2 P(\text{phon}|\text{onset}) \]
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Information in phoneme given preceding onset

- Insensitive to vocabulary structure
- Can use smaller (≈ 30Mw) corpora
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Phonemic information: In-document frequency

\[ I'(phon|onset, w) = - \log_2 \frac{TokenCount(onset + phon) + D(w)}{TokenCount(onset + *) + D(w)} \]

\[ D(w) = (TF(w) \cdot IDF(w) - TF(w)) \cdot TotalCount \]

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
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\[ I''(phon|onset, w) = - \log_2 \frac{TokenCount(onset + phon) + D(w)}{TokenCount(onset + *) + D(w)} \]

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\[ CD(w) = KL(LocalDistr(w), GlobalDistr) \]
\[ TF(w): \text{Term frequency of } w \]

Focus on direct context of \( w \): \( LocalDistr(w) \)

- \( CD(w) \): Kullback-Leibler distance between local and global distribution
- Perceived frequency is \( TF(w) \cdot 2^{CD(w)} \)
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- Word tokens starting with /bo/: 67,710 (1,172 CELEX entries)
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- Strong decline after a few positions part of model
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