ANLP 2016

Lecture 28: Discourse, coherence, cohesion

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1. "If we do not hang together

> then surely we must hang separately" (Benjamin Franklin)

Not just any collection of sentences makes a discourse.

- A proper discourse is **coherent**
- It makes sense as a unit
  - Possibly with sub-structure
- The linguistic cues to coherence are called **cohesion**

The difference?

Cohesion
: The (linguistic) clues *that* sentences belong to the same discourse

Coherence
: The underlying (semantic) way in which it *makes sense* that they belong together

2. Linking together

Cohesive discourse often uses **lexical chains**

- That is, sets of the same or related words (synonyms, antonyms, hyponyms, meronyms, etc.) that appear in consecutive sentences

Longer texts usually contain several **discourse segments**

- Sub-topics within the overall coherence of the discourse

Intuition: When the topic shifts, different words will be used

- We can try to detect this automatically

But, the presence of cohesion does not guarantee coherence

> John found some firm ripe apples and dropped them in a wooden bucket filled with water
> Newton is said to have discovered gravity when hit on the head by an apple that dropped from a tree.

There are four lexical chains in the above mini-discourse, indicated by the words in red.

- *But* the two sentences don't actually cohere particularly well.

3. Automatically identifying sub-topics/segmenting discourse

Discourse-level NLP can sometimes profit from working with coherent sub-discourses

- So we need an automatic approach to delimiting coherent sub-sequences of sentences

There are several alternative approaches available:

- Segmentation:
  - Look for cohesion discontinuities
- (generative) modelling

    - Find the 'best' explanation

Useful for

- Information retrieval
- Search more generally, in
    - lectures
    - news
    - meeting records
- Summarisation
    - Did we miss anything?
- Information extraction
    - Template filling
    - Question answering

4. Finding discontinuities: TextTiling

An unsupervised approach based on lexical chains

- Developed by Marti Hearst

Originally developed and tested using a corpus of scientific papers

- That is, quite lengthy texts, compared to the trivial examples seen in these lectures

Three steps:

1. Preprocess: tokenise, filter and partition
2. Score: pairwise cohesion
3. Locate: threshhold discontinuities

5. TextTiling: Preprocessing

In order to focus on what is assumed to matter

- That is, content words

Moderately aggressive preprocessing is done:

- Segment at whitespace
- Down-case
- Throw out stop-words
- Reduce inflected/derived forms to their base
    - Also known as **stemming**
- Group the results into 20-word 'pseudo-sentences'
    - Hearst calls these **token sequences**

6. TextTiling: Scoring

Compute a score for the gap between each adjacent pair of token sequences, as follows

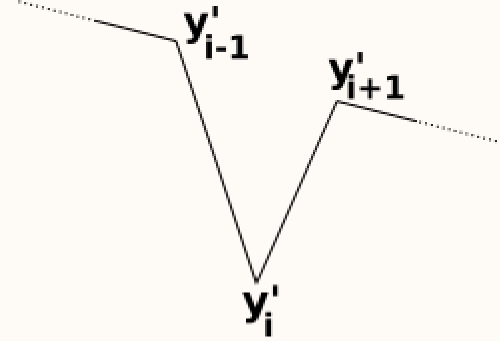
1. Merge blocks of *k* pseudo-sentences on either side of the gap to a **bag of words**
    - That is, a vector of counts
    - With one position for every 'word' in the whole text
    - Hearst used k=6
2. Compute the normalised dot product of the two vectors
    - The cosine distance
3. Smooth the resulting score sequence by averaging the scores in a window of width *w*
    - Hearst used w=3
    - That is, for a distance y_i Hearst used $y_i' = \frac{y_{i-1}+y_i+y_{i+1}}{3}$ for the smoothed distance

7. TextTiling: Locate

We're looking for discontinuities

- Where the score drops
- Indicating a lack of cohesion between two blocks

That is, something like this:



The **depth score** (*s*) at each gap is then given by $s=(y_{i-1}'-y_i')+(y_{i+1}'-y_i')$

Larger depth scores correspond to deeper 'valleys'

Scores larger than some threshhold are taken to mark topic boundaries

- Hearst evaluated several possible threshhold values
- Based on the mean and standard deviation of all the depth scores in the document

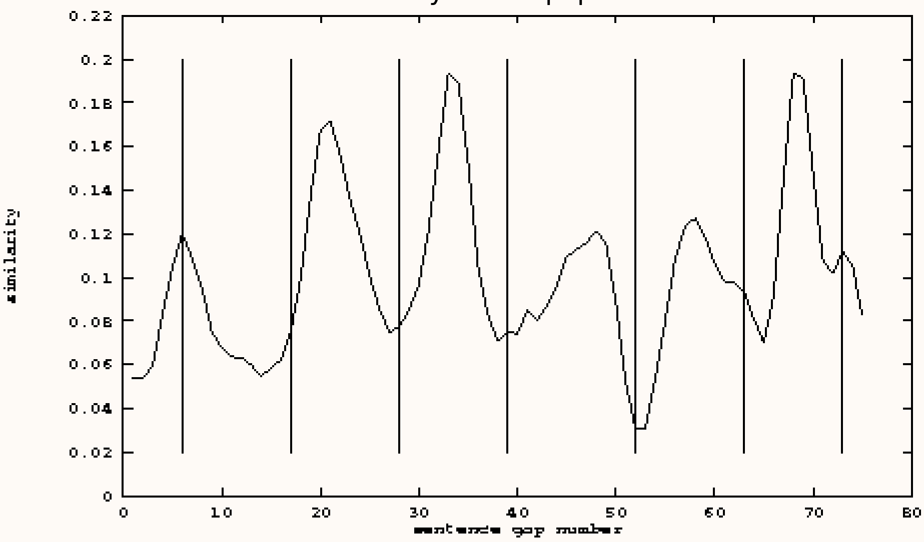
Liberal
: $\bar{s}-\sigma$

Conservative
: $\bar{s}-\sigma2$

8. Evaluating segmentation

How well does TextTiling work?

- Here's an illustration from an early Hearst paper



From [Hearst, M. A. and C. Plaunt 1993 "Subtopic structuring for full-length document access", in *Proceedings of SIGIR 16*]

- The curve is (smoothed) similarity (*y*'), the vertical bars are consensus topic boundaries from human readers
- How can we quantify this?

Treating this as a two-way forced-choice classification task

- That is, each gap is either a boundary or it isn't

And scoring every gap as correctly or incorrectly classified doesn't work

- Segment boundaries are relatively rare
  - So it's too easy to score well for correctly labelling non-boundary gaps, just by being biased against boundaries
  - The 'block of wood' would do very well by always saying "no"

But counting just correctly labelled boundary gaps seems too strict

- Missing by one or two positions should get *some* credit

9. Evaluation, cont'd

The **WindowDiff** metric, which counts only **misses** (incorrect classifications) *within a window* attempts to address both problems

- It doesn't give too much credit for correct non-boundary labelling

- It allows certain amount of mis-placing of boundary labels

Specifically, to compare boundaries in a gold standard reference (**Ref**) with those in a hypothesis (**Hyp)**:

- Each a vector with 1 for a boundary and 0 for non-boundary

We will slide a window of size *k* over **Hyp** and **Ref** comparing the number of boundaries in each

- Define a windowed boundary count r_i in **Ref** for window size *k* as $\sum_{j=i}^{i+k-1}$**Ref**$_j$
- And similarly for h_i in **Hyp**

Then we compare the boundary counts for each possible window position

- That is, $|r_i-h_i|$ for each *i*
  - This will be 0 if the two agree, positive otherwise
    - We count 0 if the result is 0 (correct)
    - And count 1 if the result is > 0 (incorrect)

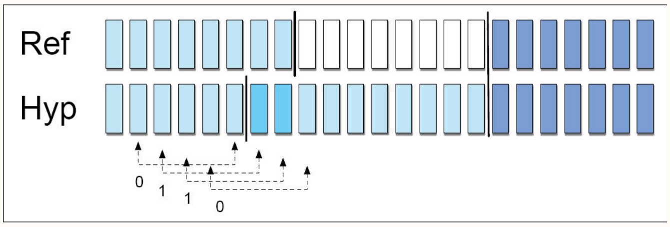
Sum for all possible window positions, and normalise by the number of such positions: $\frac{1}{N-k}\sum_{i=1}^{N-k}|r_i-h_i| \neq 0$

- 0 is the best result
  - No misses
- 1 is the worst
  - Misses at every possible window position

10. Evaluation example

An example from J&M with

- k=4 (half the mean width of the gold-standard segments)
- N=23
- a total of 4 misses



Based on Figure 21.2 from Jurafsky and Martin 2009

(The colouring of the rectangles in the bottom row is misleading, I think)

- The resulting score is $\frac{4}{23-4}=0.21$

The block of wood always guessing "no" would score $\frac{8}{23-4}=0.42$

- Whereas if we simply counted misses without windowing, both scores would be $\frac{2}{22}=0.09$

Note that this approach to evaluation is appropriate for *any* segmentation task where the ratio of candidate segmentation points to actual segments is high

- Sentences in unpunctuated text
- Tone groups in continuous speech
- ...

11. Machine learning?

More recently, (semi-)supervised machine learning approaches to uncovering topic structure have been explored

Over-simplifying, you can think of the problem as similar to POS-tagging

So you can even use Hidden Markov Models to learn and label:

- There are transitions between topics
- And each topic is characterised by an output probability distribution

But now the distribution governs the whole space of (substantive) lexical choice within a topic

- Modelling not just one word choice
- but the whole bag of words

See [Purver, M. 2011, "Topic Segmentation", in Tur, G. and de Mori, R. *Spoken Language Understanding*] for a more detailed introduction

12. Topic is not the only dimension of discourse change

Topic/sub-topic is not the only structuring principle we find in discourse

- Different genres may mean different kinds of structure

Some common patterns, by genre

Expository
: Topic/sub-topic

Task-oriented
: Function/precondition

Narrative
: Cause/effect, sequence/sub-sequence, state/event

But note that some of this is not necessarily universal

- Different scholarly communities may have different structural conventions
- Different cultures have different narrative conventions

Cohesion sometimes manifests itself *differently* for different genres

13. Functional Segmentation

Texts within a given genre

- News reports
- Scientific papers
- Legal judgements
- Laws

generally share a similar structure, independent of topic

- sports, politics, disasters
- molecular biology, radio astronomy, cognitive psychology

That is, their structure

- reflects the function played by their parts
- in a *conventionalised* way

14. Example: news stories

The conventional structure is so 'obvious' that you hardly notice it

- Known as the **inverted pyramid**

In decreasing order of importance

- Headline
- Lead paragraph
  - Who, what, when, where, maybe why and how
- Body paragraphs, more on why and how
- Tail, the least important
  - And available for cutting if space requires it

15. Example: Scientific journal papers

Individual disciplines typically report on experiments in highly conventionalised ways

- Your paper *will not* be published in a leading e.g. psychology research journal if it doesn't look like this

Front matter
: Title, Abstract

Body
: - Introduction (or Objective), including background
  - Methods
  - Results
  - Discussion

  (or, mnemonically, **IMRAD**)

Back matter
Acknowledgements, References

The major divisions (IMRAD) will usually be typographically distinct and explicitly labelled

- Less immediately distinctive, more equivocal, cues give evidence for finer grained internal structure

16. Richer structure

Discourse structure is not (always) just ODTAA

- That is, it's not flat
- "One Damn Thing After Another"

Sometimes detecting this structure really matters

Welcome to word processing$_i$
- That$_i$'s using a computer to type letters and reports
- Make a typo$_j$?
  - No problem
  - Just back up, type over the mistake$_j$, and it$_j$'s gone
  - *And, it$_j$ eliminates retyping
- And, it$_i$ eliminates retyping