Lecture 25: Discourse, coherence, cohesion

Henry S. Thompson
(Based in part on slides by Johanna Moore and Bonnie Webber)
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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 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
3. Identifying sub-topics/segmenting discourse

The goal is to delimit coherent sub-sequences of sentences

By division

- Look for cohesion discontinuities

By (generative) modelling

- Find the 'best' explanation

Relevant 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

Three steps:

1. Preprocess: tokenise, filter and partition
2. Score: pairwise cohesion
3. Locate: threshold 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. Reduce 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
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 symmetrical window of width $s$ around each gap

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 at each gap is then given by $(y_{i-1} - y_i) + (y_{i+1} - y_i)$

Larger depth scores correspond to deeper 'valleys'

Scores larger than some threshold are taken to mark topic boundaries

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

Liberal
  $s - \sigma$

Conservative
  $s - \frac{\sigma}{2}$

8. Evaluating segmentation

How well does TextTiling work?

• Here's an illustration from an early Hearst paper
• The curve is smoothed depth score, the vertical bars are consensus topic boundaries from human readers
• How can we quantify this?

Just classifying every possibly boundary as correct (Y+Y or N+N) vs. incorrect (Y+N or N+Y) doesn't work

• Segment boundaries are relatively rare
  ◦ So N+N is very common
  ◦ The "block of wood" can do very well by always saying "no"

Counting just Y+Y seems too strict
• Missing by one or two positions should get some credit

9. Evaluation, cont'd

The WindowDiff metric, which counts only misses (Y+N or N+Y) within a window attempts to address this

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

• Slide a window of size $k$ over Hyp and Ref
• Compare the number of boundaries within the window at each possible position $i$ in Ref ($r_i$) with those in Hyp ($h_i$)

• That is, $|r_i - h_i|$
  ◦ Count 0 if the result is 0 (correct)
  ◦ Count 1 if the result is > 0 (incorrect)

Based on Figure 21.2 from Jurafsky and Martin 2009
• Sum for all possible $i$, and normalise by the number of possible positions, $N - k$
0 is the best result
• No misses
10. 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


11. Topic is not the only divider

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