Evaluating Text Coherence Based on Semantic Similarity Graph

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Motivation

• Modeling coherence in linguistics theory into computational task (Barzilay & Lapata, 2008; Guinaudeau & Strube, 2013; Feng et al., 2014; Li and Hovy, 2014; Petersen et al., 2015, Nguyen and Joty, 2017)

• Approaches
  • Supervised – mostly
  • Unsupervised – infrequent
Coherence

- Coherent text is integrated as a whole, rather than a series of independent sentences (Bamberg, 1983; Garing, 2014)

- Every sentence in a coherent text has relation(s) to each other (Halliday and Hasan, 1976; Mann and Thompson, 1988; Grosz et al., 1995; Wolf and Gibson, 2005)

- Lexical and semantic (meaning) continuity are indispensable for coherent text (Feng et al., 2014)
Related Work: Entity Graph (1)

- Entity graph was introduced by Guinaudeau & Strube (2013)
- Text -> Bipartite Graph -> Projection Graphs
- Coherence is achieved by cohesion: considers repeated mention of entities and their syntactical role (weight)
Related Work: Entity Graph (2)

• Graph data structure can represent the structure of text and relations among sentences

• Coherence is achieved through lexical cohesion: repeated mention of entities.
  • Disadvantage: cannot capture the relation between related-yet-not identical entities (Li and Hovy, 2014; Petersen et al., 2015)
  • Solution: use distributed representation of words/sentences

• Relation between vertices in projection graph has to satisfy surface sequential ordering
  • Proposal: allows two directions (omit the constraint)
Proposed Method (1)

• Formally, text is a graph $G(V, E)$, where
  • $V$ is a set of vertices, $v_i$ represents $i$-th sentence.
  • $E$ is a set of edges, $e_{ij}$ represents relation (cohesion) from $i$-th to $j$-th sentence (weighted & directed).
  • Evaluate the coherence through cohesion

• Sentences are encoded into their meaning form
  Average of summation of word vectors (distributed representation of words)
  \[
  \tilde{s}_i = \frac{1}{M} \sum_{k=1}^{M} w_k
  \]
  • An edge represents cohesion among sentences
    Establishment of edge is decided as the operation of vectors representation of sentences
Proposed Method (2)

- Preceding Adjacent Vertex (PAV)
- Single Similar Vertex (SSV)
- Multiple Similar Vertex (MSV)
Proposed Method (3)

- An edge is established from the sentence vertex in question to the other vertex with the weight calculated by

\[
\text{weight}(e_{ij}) = \frac{\cos \text{sim}(s_i^T, s_j^T)}{|i - j|}
\]

- Text coherence measure (higher is better) is calculated by averaging the averaged weight of outgoing edges from every vertex in the graph as

\[
t_c = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{L_i} \sum_{k=1}^{L_i} \text{weight}(e_{ij})
\]
Evaluation

• Task 1: Discrimination (Barzilay and Lapata, 2008)
• Task 2: Insertion (Eisner and Charniak, 2011)

• Both tasks evaluate how well the methods in comparing coherence between texts
The goal is to compare original vs. permutated text.

Program is considered successful when giving greater score to the more coherent (original) text.

Dataset: 683 WSJ (LDC) texts, 13586 permutations (avg. 24 sentences, 521 tokens)
Result: Discrimination Task

- Difference of performance is statistically significant at $p < 0.05$

- PAV > MSV > Entity Graph
  Cohesion is not only about repeating mention of entities

- PAV – MSV pair shares 88.3% same judgement (largest).
  Local (adjacent) cohesion is possibly more important than long-distance cohesion

| Method     | Accuracy |
|------------|----------|
| PAV        | 0.774    |
| SSV        | 0.676    |
| MSV        | 0.741    |
| Entity Graph | 0.725  |
Evaluation: Insertion Task

• Insertion task is more important than discrimination task

• It was proposed by Eisner and Charniak (2011):
  • Given a text, take out a sentence (randomly), then place it into other positions
  • Program is considered successful if it prefers to insert take-out-sentence at its original position rather than arbitrary (distorted) positions

• Our Proposal: use TOEFL iBT insertion-type questions
TOEFL iBT Insertion-type Question

- A text is coherent even without the insertion sentence.
- Preservation of coherence is achieved when the question-sentence is inserted in the correct place but disrupt coherence otherwise.
- 104 questions (avg. 7 sentences, 139 tokens)

Question: Insert the following sentence into one of (A)-(D) question sentence = "This economic reliance on livestock in certain regions makes large tracts of land susceptible to overgrazing."

(A) The raising of livestock is a major economic activity in semiarid lands, where grasses are generally the dominant type of natural vegetation.
(B) The consequences of an excessive number of livestock grazing in an area are the reduction of the vegetation cover and trampling and pulverization of the soil. (C) This is usually followed by the drying of the soil and accelerated erosion. (D)

Correct answer = B
Result: Insertion Task

- Difference in every pair of methods is not statistically significant at $p < 0.05$

| Method      | Accuracy |
|-------------|----------|
| PAV         | 0.356    |
| SSV         | 0.346    |
| MSV         | 0.327    |
| Entity Graph| 0.260    |

- 14 questions are answered incorrectly by PAV, but correctly by SSV.
- In these questions, SSV tends to establish the relationship between distance sentences ($\text{dist} = 2.8$). For example, exemplification text
Conclusion and Future Work

• Coherence can be achieved through cohesion (lexical and semantic continuity)

• Local cohesion is more important than long-distance cohesion in evaluating coherence, but long-distance cohesion can also contribute as well
  • (PAV > {SSV, MSV})
  • We need to introduce a more refined mechanism for incorporating distant sentence relations.

• The representation of sentences and method to establish edges would be direct targets of the refinement
### Discrimination Task

| Method     | Accuracy |
|------------|----------|
| PAV        | 0.774    |
| SSV        | 0.676    |
| MSV        | 0.741    |
| Entity Grid| **0.845**|
| Entity Graph| 0.725   |

### Insertion Task

| Method     | Accuracy |
|------------|----------|
| PAV        | **0.356**|
| SSV        | 0.346    |
| MSV        | 0.327    |
| Entity Grid| 0.346    |
| Entity Graph| 0.260   |
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