Multiple News Articles Summarization based on Event Reference Information

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Background

- Multiple News Articles Summarization
  - Text: Multiple news articles about particular events
  - Characteristics:Not a single document summarization
    - Redundant description
    - Important events might be referred several times in different articles

Objective

- Proposal of a method for Multiple News Articles Summarization based on Event Reference Information

Extraction of Events from a Sentence

- We apply Cabocha to obtain dependency analysis tree.
- We select verbs and nouns that have modification words as candidates of “Root" for events.
- We extract “Modifier” information from dependency analysis tree. At this time, we classify types of modifier by using POS tag and postpositional particle.
- When we can extract date information from the sentence, we set this date as “Date" for events that has dependency with date words.
- “ArticleDate" is obtained from article information.
- “Depth" and “Chunks" are calculated by comparing event information with the dependency analysis tree.

Event Reference

- Similar Events
  - Compare “Date” and “ArticleDate”
  - Compare “Root” and Corresponding element of “Root” and “Modifiers”

Important Sentence Extraction by using PageRank Algorithm

- PageRank : Calculate importance of pages by using link structure

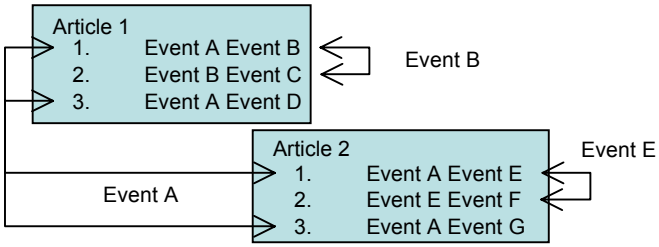
$$\vec{r}_{i+1} = M \times \vec{r}_i \qquad \vec{r}_\infty = \lim_{i \to \infty} \vec{r}_i$$

- Our algorithm
  - Node: a sentence
  - Link: a bidirectional link exists when two nodes shares same events or words
  - Transition matrix is calculated by a combination of event reference information and word reference information
    - Me: transition probability based on event reference biased with event importance.
    - Mw: transition probability based on word reference biased with IDF.

$$m_{ij} = \beta \times me_{ij} + (1-\beta) \times mw_{ij}$$

- Topic-Sensitive PageRank (Calculate importance of pages biased with initial importance vector)
  - Initial importance vector: Sentence position in an article

$$\vec{r}_{i+1} = (1-\alpha) * M \times \vec{r}_i + \alpha * \vec{v}$$



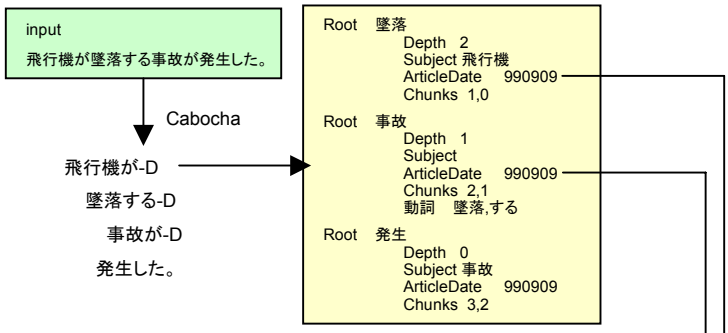
Link Structure based on Event Reference Information

Evaluation Results of Importance Sentence Extraction

		Short	Long
Event only	Coverage	0.325	0.313
	Precision	0.491	0.540
Event & Word	Coverage	0.323	0.341
	Precision	0.523	0.592
Word only	Coverage	0.313	0.344
	Precision	0.521	0.593

Event

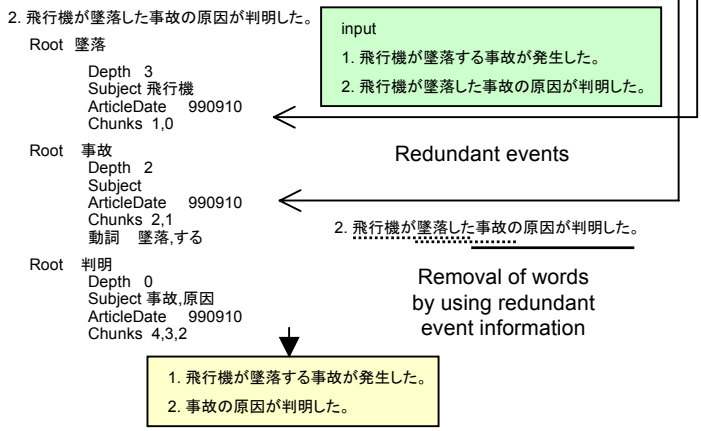
- Information that describes facts and related information on particular date.
  - Root is a word that dominates an event (verb that represents action or noun that represents subject or object)
  - Modifier is words that modify root word. Words are categorized into several groups, such as subject and object words for verbs and adjective and adnominal words for nouns.
  - Negative represents modality of expression.
  - Depth is a path length between Root of the event and root of the sentence in dependency analysis tree.
  - Date is a date that characterize the event. This slot is not a required slot to define an event.
  - ArticleDate is a date that the article was published.
  - Chunks represents list of word positions in a sentence.



An Example of Events Extraction from a Sentence

Text Reordering and Compaction by using Event Reference Information

- Keep sentence order in an article and chronological order of articles
  - When sentences comes from different articles in a same date, find similar sentence in its original article and set order based on it.
- Remove redundant event description from a sentence
  - An event that has similar events in the extracted event set is selected as a candidate one to remove.
  - Keep words, which is a “Root” element of an event and also belong to other non-redundant events.



An Example of Text Compaction

Evaluated Result

- Importance sentence extraction
  - Usage of event reference information only is not good compared with usage of word information.
- Abstraction
  - Positive
    - q00: Our method for removing redundant description works well.
    - q08,q02: Our sentence reordering methods works well.
    - q04: Our system tends to select most frequent description because of word reference information.
  - Negative
    - q01: Removal of redundant information is too naïve. We assume that usage of anaphoric word is necessary to solve this problem.
    - q10: Our method of removing words from a sentence is too naive