Abstract

We propose a method for segmentation of expository texts based on hierarchical agglomerative clustering. The method uses paragraphs as the basic segments for identifying hierarchical discourse structure in the text, applying lexical similarity between them as the proximity test. Linear segmentation can be induced from the identified structure through application of two simple rules. However, the hierarchy can be used also for intelligent exploration of the text. The proposed segmentation algorithm is evaluated against an accepted linear segmentation method and shows comparable results.

Introduction

The interest in expository texts comes, among others, from their widespread use as online information resources. Information retrieval gives us methods for scoring document collections based on their relevance to a query. However once we are about to browse a document, or extract some specific information from it, an interest arises for deeper analysis of the text.

The kind and depth of the analysis depends on the reader. In the case of text extraction, the “reader” is the text understanding system, which implies a need for rather deep semantic analysis (Iwanska & al. 91; Soderland & Lehner 94; Hahn 91). However, for (human) browsing and reading in free expository texts, we can suffice with delineating the structure of the text and provide easy access to the discovered substructures. This kind of discourse segmentation is thus a critical task for exploratory reading of the retrieved text.

This article presents an approach for discovering discourse structure in free expository texts. The identified structure can be used in various tasks such as text browsing and summarization. Section 1 surveys other approaches to discourse segmentation, in particular those based on lexical cohesion metrics. Section 2 details the proposed method for identifying a hierarchical discourse structure in the text, based on the hierarchical agglomerative clustering method, while using common lexical cohesion metrics. We show how, through application of two simple rules, linear discourse segmentation can be recognized in the discovered structure. The output of the algorithm is analyzed and evaluated in section 3. Finally, section 4 concludes the paper and outlines future work.

1 Discourse Segmentation Methods

Two main approaches can be seen in discourse segmentation of free text: the multiple-source approach where multiple kinds of evidence are used to determine discourse boundaries and relations, and the lexical cohesion approach, where lexical cohesion (or lexical similarity) is the sole criteria for boundary detection. These two approaches are discussed in the following subsections.

1.1 Multiple Source Methods

With the dominant discourse analysis theories of today (Grosz & Sidner 86; Mann & Thompson 87; Grosz et al. 93), there is no simple computational way to determine the detailed discourse structure from the free text. Detailed structure may include participants intentions, coherent discourse segments, their functions and inter-relations.

To reach this level of understanding, researchers are forced to use multiple sources of evidence and apply it in some adaptive manner. A good example is in (Litman & Passoneau 94) which uses prosodic features, cue phrases, and NP references, and applies machine learning methods for the analysis of verbal discourse. Another approach (Kurohashi & Nagao 94; Miike et al. 94) is to identify inter-sentential discourse relationships using sources of evidence like cue phrases, topic words/phrases, and grammatical and lexical similarity between sentences. A complex decision rule sets was developed to map cue word patterns to
potential discourse functions or relationships.

1.2 Lexical Cohesion Methods

When the source text is truly free text, methods that attempt to identify detailed discourse structure tend to be brittle. Researchers then turn to simpler but reliable evidence, in particular, lexical cohesion.

Lexical cohesion between two discourse segments is an indicator of textual coherence, and is achieved when the segments contain words which are similar or semantically related (Halliday & Hasan 76). We will say that a discourse boundary exists between the two segments if the lexical cohesion between them, as computed by some similarity metrics, for example using the cosine distance between the term vectors (Salton 89), falls below some threshold.

Two related methods (Kozima 93; Hearst 94) use a concept of text window, within which they compute a lexical cohesion function. By moving the window \( W \) over the text, they form a linear plot of the lexical cohesion as a function of the word position, \( w_i \) (where the window is centered). A discourse boundary is assigned to \( w_i \) if that value falls below a threshold. Kozima uses a semantic network with words at the nodes and edges indicating their semantic relation as computed from a MRD. The lexical cohesion function computes \( w_i \) by spreading activation on the semantic network for each word in the window \( W \) and summing the output at \( w_i \). Here, then, the lexical cohesion takes into account the similarity of the words based on their definition in a dictionary. Hearst splits the window \( W \) to two halves, the one to the left of \( w_i \), and the one to its right, and determines the term vector of each. Term vectors consist simply the counts of each open class words in the window. She then computes the lexical cohesion function at \( w_i \) by evaluating the similarity between the two terms vector using the cosine distance formula.

While the above methods produce linear segmentation, some attempts have been made to identify a more elaborated structure. The lexical chaining method (Morris & Hirst 91) attempts to determine the hierarchical intention structure (Grosz & Sidner 86) by identifying lexical chains that run through the text. The lexical cohesion between words in a chain is determined using various relations defined over the Roget thesaurus, however the algorithm is only implemented manually. A more practical approach is to build, from the text, a graph with paragraphs at the nodes, and their lexical similarity at the edges (Salton & Allan 94). By setting a threshold we can than identify strongly-connected subgraphs which correspond to inter-related paragraphs. This structure can be used both to improve text retrieval and for identifying themes for text browsing.

2 Segmentation By Hierarchical Agglomerative Clustering

The proposed segmentation process consists of three main phases:

1. Morphological analysis.
2. Hierarchical agglomerative clustering of text segments.
3. Boundary detection.

2.1 Morphological Analysis

The purpose of this phase is to determine the terms to be used as content words in the following phase. The phase consists of the following steps:

1. Tokenization. Convert the raw text, through regular expression recognizer, to streams of tokens: words, numbers and special symbols.
2. Perform part-of-speech tagging (Brill 94). This step filters open class words, adjectives, verbs, adverbs, and nouns, to the next step.
3. Determine the general significance of each word \( i \), \( Gsig_i \). In this experiment we use IDF as the measure for general significance, using frequency-in-files information from the BNC corpus (Leech 92):

   \[
   Gsig_i = IDF_i = \log \frac{N}{N_i} \tag{1}
   \]

   where \( N \) is the number of files in the corpus and \( N_i \) is the number of files containing word \( i \).
4. Stemming. Replace each word by its stem, \( r_i \) (Porter’s algorithm is used here (Porter 80)). The general significance \( Gsig_i \), associated with \( r_i \), is the minimum \( Gsig_j \) over all words \( j \) having this stem: \( Gsig_i = \min_{j, r_j = r_i} Gsig_j \). This has the effect of counting all instances of a given stem as a single concept.
2.2 Hierarchical agglomerative clustering of text segments

The main motivation behind the proposed algorithm is discovering a structure in text. The bottom-up Hierarchical Agglomerative Clustering (HAC) algorithm is a widely used clustering method in information retrieval (Everitt 80), psychology (Milligan & Sokol 80), linguistics (Kessler 94), and elsewhere.

When applying hierarchical agglomerative clustering on text segments the algorithm successively grows areas of coherence at the most appropriate place, thus forming a text structure. A similar approach (Maarek & Wecker 94) uses HAC to determine a hierarchical bookshelf from a given set of documents.

The HAC algorithm for discourse segmentation, based on paragraphs as the elementary segments, is shown in Figure 1.

**Partition** the text to elementary segments (=paragraphs).

**While** more than one segment left do

**Apply** a proximity test to find the two most similar consecutive segments, $s_i, s_{i+1}$.

**Merge** $s_i, s_{i+1}$ into one segment.

**End while**

Figure 1: Hierarchical agglomerative clustering of text segments

Figure 2 shows the result of the algorithm for the *Stargazers* text (Hearst 94), in a dendrogram representation. Figure 3 shows the corresponding outline representation, which plots the depth of the nesting of the paragraphs in the dendrogram, that is, the path length from the paragraph node to the dendrogram root. The gray dashed vertical lines both plots indicate the segment boundaries. Determination of these boundaries is discussed in the next section.

The algorithm successively grows “coherent” segments by appending lexically related paragraphs, or by merging larger segments. The result is hierarchical structure, called dendrogram, where text segments correspond to its subtrees.

We propose that the dendrogram represents the internal hierarchy of the text discourse, similar to an intention structure (Grosz & Sidner 86).

Using paragraphs as the elementary segments for the algorithm makes sense for a number of reasons. The paragraph is a universal linguistic structure, representing a coherent textual segment (Chafe 79; Longacre 79; Kieras 82). Allowing a boundary in the middle of the paragraph is thus counter to the author’s intention. In addition, the size of a paragraph, unlike a sentence, contains sufficient lexical information for the proximity test.

Note that unlike general HAC applications, where at each stage we compute the proximity of the newly merged object to all other available segments, in our case we compute only the proximity of the segment to its two neighbors. This is because we require that the linear order in the text will be preserved in the structure. The implication on complexity is that while general HAC algorithm takes an order of $O(N^2)$ steps, ours takes only $O(N)$.

The proximity test selects the closest pair of segments. The test is based on repetition of words, a well-recognized indicator for lexical cohesion (see Hearst 94 for more references). The test computes the cosine between the representative term vectors of the segments (Salton & Buckley 88):

$$
Proximity(s_i, s_{i+1}) = \sum_{k=1}^{n} \frac{w_{k,i} \cdot w_{k,i+1}}{|s_i| \cdot |s_{i+1}|}
$$

(2)

Where $s_i$ is the term vector representing segment $i$, $|s_i|$ is its length, $\sqrt{\sum_{k=1}^{n} w_{k,i}^2}$, and $w_{k,i}$ is the weight of word $k$ in segment $i$.

$$
w_{k,i} = f_{k,i} \cdot \frac{f_i}{f_{max}} \cdot Gsig_i
$$

(3)

The word weight $w_{k,i}$ is the product of three factors - $f_{k,i}$, the frequency of the word in the segment, serves as the in-segment factor, $f_{max}$, the relative frequency of word $i$ in the text, is an in-text factor, and $Gsig_i$ is the general word significance.

2.3 Boundary Detection

The algorithm for boundary detection in the dendrogram makes use of size and depth attributes of a segment. As indicated above, a segment corresponds to a subtree in the resulting dendrogram tree. The segment size is defined as the number of leaves, i.e., paragraphs, it contains. Its depth is defined as the longest path in the subtree from
Figure 2: Paragraph dendrogram of the *Stargazers* article. The leaves in the dendrogram are paragraphs shown as a sequence of equal-length vertical lines - the paragraph’s sentences. The scale below the X axis shows sentence numbers and the one above paragraph numbers (placed at end of the respective paragraphs). Gray dashed vertical lines show the computed boundaries.

Figure 3: Outline of the *Stargazers* article. The graph plots the depth of each paragraph in the dendrogram, i.e., its path length to the dendrogram root. The notches indicate the depth of the merge points. Gray dashed vertical lines are segment boundaries. Paragraphs marks are shown above the X scale, sentence marks below it.
the root to the leaves. Thus, a size 1 segment is a single paragraph.

With these definitions, the algorithm for boundary detection is stated in Figure 4.

For each node in the dendrogram tree $T$ do

Let $S_1$ and $S_2$ be the two segments being merged at the node, such that $size(S_1) \geq size(S_2)$.

Set a boundary between the two segments if one of the following two rules holds:

- **The notch rule:**
  \[
  size(S_1) > n \land size(S_2) > n
  \]

- **The cliff rule:**
  \[
  size(S_1) > n \land size(S_2) \leq n \land depth(S_1) - depth(S_2) > m
  \]

End for each

Figure 4: Algorithm for identifying boundaries in a dendrogram

The algorithm defines two rules to identify boundaries. The notch rule constrains segments across boundaries to be of a significant size. We found that $n = 1$ gives maximum boundary information without adding false boundaries, that is, it allows a paragraph that is cohesive with its neighbor to be merged with it without creating a boundary between them. The cliff rule relaxes the notch rule, allowing one of the segments to be smaller than $n$ if the difference between their depths is larger than a threshold $m$. Such boundaries indicate remotely related segments and are seen as high cliffs in the outline plot. The minimum for $m$ was set experimentally to $depth(T)/5$.

Cases of the notch rule are seen, as the name implies, as deep notches (deeper than 1 ($= n$), in our case) in the outline view. See, for example, Figure 3, between paragraphs 11 and 12. Cases of the cliff rule may indicate a setting (or introduction) segment at the beginning of a larger text segment, or a summary segment at its end. These setting and summary segments consist of paragraphs, each discussing a different topic. This creates a build-up effect (in case of setting) or a fall-off effect (in case of summary). Cliff boundaries happen less frequently than notches. For example, in Figure 3 they appear between paragraph 3 and 4, and between paragraphs 18 and 19. In the last case, paragraphs 19, 20 and 21 can be regarded as a conclusion section for the whole article. While the bulk of the article talks about the special case of the earth and the moon, and their life-enabling conditions, the last paragraphs summarize the conditions for life existence in a solar system and future research directions to be undertaken by astronomers.

3 Evaluation

We have used the Stargazers article, discussed in the previous section, as the test bench for evaluation. Stargazers is an expository text that discusses the conditions for evolution of life in solar systems. What makes it particularly useful is that segmentation data is available both as produced by Hearst’s TextTiling algorithm, which is robust and gives good results, and as produced by human judges [Hearst 94].

Comparing the results of TextTiling and Hierarchical Agglomerative Clustering for boundary detection shows impressive matching. Table 1 compares the results of the two algorithms against those of the human judges. The boundaries for the human judges are those with agreement of 3 or more among the 7 judges, and are considered the correct boundary set. The P and R columns give the precision and recall relative to that correct set. These results, while not yet very extensive, are encouraging. The reason for the good match between boundaries determined by the two algorithms is that in both cases boundaries are set when they separate segments of low lexical cohesion. The main difference is the way these segments are determined - fixed size in case of TextTiling, versus variable size in case of HAC.

| Boundaries | P | R |
|------------|---|---|
| Human judges | 100 | 100 |
| TextTiling | 69 | 56 |
| HAC | 87 | 78 |

Table 1: Performance of discourse segmentation algorithms
subsegment \{17...18\} is about their low probability. Similarly we can deduce that the segment \{12,13\} is more lexically-related to \{10,11\} than to \{14,15,16\}. Another example is the typical build-up of a setting and fall-off of a summary, seen in coherent texts (see Figs. 3 and 5). This information may help us later in constructing a table-of-content visual representation of the text.

Figure 3 presents an outline of a case of “non-coherent” text. The article is not about any specific subject but rather a survey of special events in genetic engineering during 1995. The outline shows deep notches, following paragraphs 13, 22, 31, 35, and 49. These are the exact boundaries between the main articles in the text. Unlike the former examples, here there is no fall-off summary at the end. This is expected since the ending paragraphs are, in fact, a series of three tiny independent articles, following paragraphs 55, 57 and 60.

4 Conclusions and Future Work
The main topic for research in the HAC algorithm is the proximity test. At the moment it is a rather simple lexical similarity test, so some modifications are possible in the way words are weighted (see Equations 1 and 3). A more radical approach is using concept vectors like in WordSpace \[\text{(Schutze 93)}\]. Other sources of information can be used to complement lexical similarity. In particular, evidence involving cue phrases and part-of-speech patterns can be processed, using previously-trained decision trees, to augment the lexical similarity function \[\text{(Litman \& Passoneau 94)}\].

Another research direction is table-of-content production. The clustering produced by the HAC algorithm provides the necessary structure information. The main task here, and a major research topic, is identification of topics, or titles, for the segments.

Finally, while the comparison with the TTextTiling algorithm and the human judges is promising, a methodical evaluation of additional texts is required.

References
[Brill 94] (Brill 94) E. Brill. Some advances in rule-based part of speech tagging. In Proceedings of Twelfth National Conference on Artificial Intelligence, Seattle, WA, 1994.

[Chafe 79] (Chafe 79) W.L. Chafe. The flow of thought and the flow of language. In T. Giv´on, editor, Syntax and Semantics: Discourse and Syntax, volume 12, pages 159–182. Academic Press, 1979.

[Everitt 80] (Everitt 80) B. Everitt. Clustering Analysis. Halsted Press (John Wiley & Sons), New York, 1980.

[Grosz & Sidner 86] (Grosz & Sidner 86) B.J. Grosz and C.L. Sidner. Attention, intentions and the structure of discourse. Computational Linguistics., 12(3):175–204, 1986.

[Grosz et al. 95] (Grosz et al. 95) B.J. Grosz, A.K. Joshi, and S. Weinstein. Centering: A framework for modeling the local coherence of discourse. Computational Linguistics., 21(2):203–225, 1995.

[Hahn 90] (Hahn 90) U. Hahn. Topic parsing: Accounting for text macro structures in full-text analysis. Information Processing and Management, 26(1):135–170, 1990.

[Halliday & Hasan 76] (Halliday & Hasan 76) M.A.K. Halliday and R. Hasan. Cohesion in English. New York: Longman Group, 1976.

[Hearst 94] (Hearst 94) M.A. Hearst. Multi-paragraph segmentation of expository texts. In Proceedings of 32nd Annual meeting of ACL, 1994.

[Iwanska & al. 91] (Iwanska & al. 91) L.M. Iwanska and al. Computational aspects of discourse in the context of muc-3. In Proceedings of MUC-5, pages 256–282, 1991.

[Kessler 94] (Kessler 94) B. Kessler. Computational dialectology in irish gaelic. In Proceedings of EACL, pages 66–66, 1994.

[Kiersa 82] (Kiersa 82) D.E. Kiersa. A model of reader strategy for abstracting main ideas from simple technical prose. Text, 2(1–3):47–81, 1982.

[Kozima 93] (Kozima 93) K. Kozima. Text segmentation based on similarity between words. In Proceedings of ACL, pages 286–288, Columbus, OH, 1993.

[Kurohashi & Nagao 94] (Kurohashi & Nagao 94) K Kurohashi and M. Nagao. Automatic detection of discourse structure by checking surface information in sentences. In Proceedings of COLING, pages 1123–1127, Kyoto, Japan, 1994.

[Leech 92] (Leech 92) G. Leech. 100 million words of english: the british national corpus. Language Research, 28(1):1–13, 1992.

[Litman & Passoneau 94] (Litman & Passoneau 94) D.J. Litman and R.J. Passoneau. Combining multiple knowledge sources for discourse segmentation. In Proceedings of ACL, pages 108–115, 1994.

[Maarek & Wecker 94] (Maarek & Wecker 94) Y.S. Maarek and A.J. Wecker. The librarian’s asistant: Automatically organizing online books into dynamic bookshelves. In Proceedings of RIAO, pages 233–247, 1994.

[Maarek & Wecker 95] (Maarek & Wecker 95) Y.S. Maarek and A.J. Wecker. The librarian’s assistant: Automatically organizing online books into dynamic bookshelves. In Proceedings of RIAO, pages 233–247, 1994.

[Mann & Thompson 87] (Mann & Thompson 87) W.C. Mann and S.A. Thompson. Rhethorical structure theory: A theory of text organization. Technical Report ISI/RS-87-190, ISI, 1987.

[Miike et al. 94] (Miike et al. 94) S. Miike, E. Itoh, K. Ono, and K. Sumita. A full text retrieval system. In Proceedings of SIGIR, pages 152–161, Dublin, Ireland, 1994.

[Milligan & Sokol 80] (Milligan & Sokol 80) G.W. Milligan and L. Sokol. A two stage clustering algorithm with robust recovery characteristics. Educational and Psychological Measurement, 40:755–759, 1980.

[Morris & Hirst 91] (Morris & Hirst 91) J. Morris and G. Hirst. Lexical coherence computed by thesaurial relations as an indicator of the structure of text. Computational Linguistics., 17(1):21–42, 1991.

[Porter 80] (Porter 80) M.F. Porter. An algorithm for suffix stripping. Program, 14:130–137, 1980.

[Porter 89] (Porter 89) M.F. Porter. An algorithm for suffix stripping. Program, 14:130–137, 1980.

[Salton & Allan 94] (Salton & Allan 94) G. Salton and M. Allan. Automatic text decomposition and structuring. In Proceedings of RIAO, pages 6–29, New York, NY, 1994.

[Salton & Buckley 88] (Salton & Buckley 88) G. Salton and C. Buckley. Term weighting approaches in automatic text retrieval. Information Processing and Management, 24(5):513–523, 1988.

[Salton 89] (Salton 89) G. Salton. Automatic Text Processing - The Transformation Analysis and Retrieval in Full Text Information Systems. Addison Wesley, Reading, MA, 1989.
Figure 5: Outline of “How to Make a Desert”, Discover Magazine, 2/96

Figure 6: Outline of “Special issue: The Year in Science – Genetics”, Discover Magazine, 1/96

[Schutze 93] (Schutze 93) H. Schutze. Word space. In S.J., Hanson and al., editors, Advances in Neural Information Processing Systems, volume 5. Morgan Kaufmann, San Mateo, CA., 1993.

[Soderland & Lehnert 94] (Soderland & Lehnert 94) S. Soderland and W. Lehnert. Corpus-driven knowledge acquisition for discourse analysis. In Proceedings of Twelfth National Conference on Artificial Intelligence, Seattle, WA, 1994.