

Resources for Evaluation of Summarization Techniques

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Abstract

We report on two corpora to be used in the evaluation of component systems for the tasks of (1) linear segmentation of text and (2) summary-directed sentence extraction. We present characteristics of the corpora, methods used in the collection of user judgments, and an overview of the application of the corpora to evaluating the component system. Finally, we discuss the problems and issues with construction of the test set which apply broadly to the construction of evaluation resources for language technologies.

2. Description of Resources

1. Application Context

We report on two corpora to be used in the evaluation of component systems for the tasks of (1) linear segmentation of text and (2) summary-directed sentence extraction.

Any development of a natural language processing (NLP) application requires systematic testing and evaluation. In the course of our ongoing development of a robust, domain-independent summarization system at Columbia University, we have followed this procedure of incremental testing and evaluation¹. However, we found that the resources that were necessary for the evaluation of our particular system components did not exist in the NLP community. Thus, we built a set of evaluation resources which we present in this paper. Our goal in this paper is to describe the resources and to discuss both theoretical and practical issues that arise in the development of such resources. All evaluation resources are publicly available, and we welcome collaboration on use and improvements.

The two resources discussed in this paper were utilized in the initial evaluation of a text analysis module. In the larger context, the analysis module serves as the initial steps for a complete system for summarization by analysis and reformulation, rather than solely by sentence extraction. Analysis components provide strategic conceptual information in the form of segments which are high in information content, and in which similar or different; this information provides input to subsequent processing, including reasoning about a single document or set of documents, followed by summary generation using language generation techniques (McKeown and Radev 1995, Radev and McKeown 1997).

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We detail these two evaluation corpora, both comprised of a corpus of human judgments, fashioned to accurately test the two technologies currently implemented in the text analysis module: namely, *linear segmentation* of text and *sentence extraction*.

2.1. Evaluation Resource for Segmentation

The segmentation task is motivated by the observation that longer texts benefit from automatic chunking of cohesive sections. Even though newspaper text appears to be segmented by paragraph and by headers, this segmentation is often driven by arbitrary page layout and length considerations rather than by discourse logic. For other kinds of text, such as transcripts, prior segmentation may not exist. Thus, our goal is to segment these texts by logical rhetorical considerations.

In this section, we discuss the development of the evaluation corpus for the task of segmentation. This task involves breaking input text into segments that represent some meaningful grouping of contiguous portions of the text.

In our formulation of the segmentation task, we examined the specifics of a linear multi-paragraph segmentation of the input text, "linear" in that we seek a sequential relation between the chunks, as opposed to "hierarchical" segmentation (Marcu 1997). "Multiple paragraph" refers to the size of the units to be grouped, as opposed to sentences or words. We believe that this simple type of segmentation yields useful information for summarization. Within the context of the text analysis module, segmentation is the first step in the identification of key areas of documents.

Segmentation is followed by an identification component to label segments according to function and importance within the document. This labeling then permits reasoning and filtering over labeled and ranked segments. In the current implementation, segments are labeled according to centrality vis à vis the overall document.

2.1.1. Segmentation Corpus

To evaluate our segmentation algorithm's effectiveness, we needed to test our algorithm on a varied set of articles. We first utilized the publicly available *Wall Street Journal* (WSJ) corpus provided by the Linguistic Data Consortium. Many of these articles are very short, i.e. 8 to 10 sen-

tences, but segmentation is more meaningful in the context of longer articles; thus, we screened for articles as close as possible to 50 sentences. Additionally, we controlled our selection of articles for the absence of section headers within the article itself, to guarantee that articles were not written to fit section headers. This is not to say that an evaluation cannot be done with articles with headers, but rather that an initial evaluation was performed without this complicating factor.

We arrived at a set of 15 newspaper articles from the WSJ corpus. We supplemented these by 5 articles from the on-line version of *The Economist* magazine, following the same restrictions, to protect against biasing our results to reflect WSJ style. Although WSJ articles were approximately 50 sentences in length; the *Economist* articles were slightly longer, ranging from 50 to 75 sentences. Average paragraph length of the WSJ articles was 2 to 3 sentences, which is typical of newspaper paragraphing, and 3 to 4 for the *Economist*. Documents were domain independent but genre specific in general terms, i.e. current events (any topic) but journalistic writing, since this is the initial focus of our summarization project.

2.1.2. Task

The goal of the task was to collect a set of user judgments on what is a meaningful segment with the hypothesis that what users perceive to be a meaningful unit will be useful data in evaluating the effectiveness of our system. The goal of our system is to identify segment boundaries and rank according to meaningfulness. The data could be used both to evaluate our algorithm, or in later stages, as part of training data for supervised learning.

To construct the evaluation corpus, subjects were asked to divide an average of six selected articles into meaningful topical units at paragraph boundaries. The definition of segment was purposefully left vague in order to assess the user’s interpretation of the notion “meaningful unit.” Subjects were also encouraged to give subjective strengths of the segments, if they wanted to. Subjects were not told how the segments would be used for later processing, nor informed of the number of segment breaks to produce, and were given no further criteria for choice. Finally, subjects were not constrained by time restrictions; however, subjects were given the tester’s time estimate on task completion time of 10 minutes per article (for both reading the article and determining segment boundaries). In total, 13 volunteers produced results, all graduate students or people with advanced degrees. A total of 19 articles were segmented by a minimum of four, and often five, subjects. All 13 subjects segmented the one remaining single article.

2.1.3. Analysis of Results of Human Segmentation

The variation in segmentation style produced results ranging from very few segments (1-2 per document) to over 15 for the longer documents. As shown in Table 1, the number of segments varied according to the length of the article and specific article in question. Most subjects completed the task within the time we had initially estimated.

Subjects were found to be consistent in behavior: if they segmented one article with fewer segments than the aver-

age, then the other articles segmented by the subject were often also segmented with fewer breaks. For example, Subject 4 displays “lumping” behavior, whereas Subject 6 is a “splitter”. This points to an individual’s notion of *granularity*, which is further discussed below in section 2.1.5.

	Article br7854 <i>P</i> = 20	Article am3332 <i>P</i> = 10	Article 0085 <i>P</i> = 19	Article 0090 <i>P</i> = 24
Subject 1	6	4	7	7
Subject 2	7	5	8	7
Subject 3	10	4	11	9

	Article fn6703 <i>P</i> = 10	Article mo0414 <i>P</i> = 10	Article 0071 <i>P</i> = 19
Subject 4	2	2	5
Subject 5	5	4	5
Subject 6	9	7	16

Table 1: Lumpers and Splitters problem on Segmentation Evaluation Corpora (where *P* = number of paragraph breaks in article)

2.1.4. Use

To compile the gold standard we used majority opinion, as advocated by Gale et al, 1992, i.e. if the majority indicated a break at the same spot, then that location was deemed a segment boundary. We compiled the judgments into a database for use in optimal parameterization of a set of constraints for weighting groups of lexical and phrasal term occurrences. We calculated a high level of interjudge reliability using Cochran’s *Q*, significant to the 1% level for all but 2 articles which were significant to the 5% level. See Kan et al, 1998 for further discussion of the use of data in evaluating the segmentation algorithm.

2.1.5. Issues

The segmentation task is subject to interpretation, just like many natural language tasks which involve drawing subjective boundaries. Since the directions were open-ended, responses can be divided into “the lumpers” and “the splitters”, to use the terminology applied to lexicographers when building dictionary definitions. In the case of dictionary construction, lumpers tend to write more terse, condensed definitions which consist of several possible uses in one definition, whereas splitters will divide definitions into a larger number of definitions, each of which may cover only one aspect or one usage of the word. For segmentation, the way this tendency expressed itself is that the lumpers tended to mark very few boundaries, whereas the splitters marked numerous boundaries. In fact, as mentioned above, some splitters marked over 15 segments for longer articles, which is over 85% of all possible paragraph breaks, on average.

For this reason, in determining what type of data to extract from the evaluation corpus, we took only the majority segments for training and testing; the result is that lumpers end up determining the majority.

2.1.6. Future Work on the Segmentation Resource

For future work, we would like to extend the resource to include a range of genres (such as journal articles, documentation) as well as expand the range of sources to include additional news articles (i.e. LDC's North American News Text Corpus). Also, we plan to extend our collection to other languages since there is little research on applicability of general techniques, such as segmentation based on terms and local maxima, across languages for multilingual analysis tasks. We are also considering analyzing articles with section headers, to see whether they follow the segment boundaries and if so, how they can be utilized for expanding an evaluation resource.

In addition to expanding the corpus by genre, we also plan to collect information for the segment labeling task. In this stage, segments are labeled for their function within the document. In addition, this resource will be useful in providing information on the function of the first (or lead) segments. In journalistic prose, the lead segment can often be used as a summary due to stylized rules prescribing that the most important information must be first. However, the lead can also be an anecdotal lead, i.e. material that grabs the reader's attention and leads into the article. Thus, we plan to perform a formal analysis of how human subjects characterize anecdotal leads.

2.1.7. Availability

The segmentation evaluation data is publicly available by request to the third author. Inquiries for the textual data that the evaluation corpus is based on should be directed to the respective owners of the materials.

2.2. Evaluation Resource for Sentence Extraction

In this section, we describe the collection of judgments to create the evaluation resource used to test summary-directed sentence extraction. One method to produce a "summary" of a text is by performing sentence extraction. In this approach a small set of informative sentences are chosen to represent the full text and presented to the user as a summary. Although computationally appealing, this approach falls prey to at least two major disadvantages: (1) missing key information and (2) disfluencies in the extracted text.

Our approach takes steps to handle both of these problems and thus changes what we mean by the sentence extraction task. The majority of systems use sentence extraction as a complete approach to summarization in that the sentences extracted from the text are, in fact, the summary presented to the user. In the context of our system, we use the sentence extraction component to choose a larger set of sentences than required for the intended summary length. All these sentences are then further analyzed for the generation component that will synthesize only the key information needed in a summary. The synthesis procedure will eliminate some clauses and possibly some whole sentences as well, resulting in a reformulated summary of the intended length. Thus, the goals of our "sentence extraction for generation" task differ from "sentence extraction as summarization" in that we seek high recall of key infor-

mation.

2.2.1. Extraction Corpus

We used newswire text, available on the World-Wide Web from Reuters. In examining random articles available at the time of testing, we found that the number of sentences per article were short: 18, on average. Short paragraphs were also a characteristic of the corpus, similar to the corpus used for the segmentation evaluation: 1 to 3 sentences per paragraph on average. These shorter texts enabled us to analyze more articles than in the segmentation evaluation. As a result we were able to double the number of articles used for testing; we selected 40 articles, with titles, taken from this on-line version.

2.2.2. Task

Naïve readers were asked to select sentences with high information content. Instructions were kept general, to let subjects form their own interpretation of "informativeness", similar to the segmentation experiment. A minimum of one sentence was required, but no maximum number was set. All 15 subjects were volunteers, consisting of graduate students and professors from different fields. Subjects were grouped at random into 5 reading groups of 3 subjects each such that an evaluation based on majority opinion would be possible. Each reading group analyzed 8 articles, which covered the entire 40 article set. Articles were provided in full with titles.

2.2.3. Analysis of Results of Human Sentence Extraction

As expected with newswire and other journalistic text, many individuals chose the first sentence. Although some subjects just took only the first sentence for each article as a summary, the majority picked several sentences, usually including the first sentence. Subjects implicitly followed the guidelines to pick whole sentences; no readers selected phrases or sentence fragments. Subjects indicated that this was not a difficult task, unlike the segmentation task.

2.2.4. Use

To establish the evaluation gold standard, we again applied the majority method, which resulted in choosing all sentences that were selected by at least 2 of 3 judges as "informative". The data was used for the automatic evaluation of an algorithm developed at Columbia, which exploits both symbolic and statistical techniques. The sentence extraction algorithm we have developed uses ranked weighting for information from a number of well established statistical heuristics from the information retrieval community, such as TF*IDF, combined with output from term identification, segmentation, and segment function modules discussed in the first part of the paper. Additional weight is given to sentences containing title words. Furthermore, several experimental symbolic techniques were incorporated as factors in the sentence selection weighting process: such as looking for verbs of communication (Klavans and Kan, 1998, to appear).

An informal examination of the data revealed high level of consistency among very important sentences, but a lower level of consistency when important detail was given. We

suspect that the reason may be due to the equivalency and redundancy of certain sentences.

2.2.5. Issues

	Article 02 <i>S</i> = 20	Article 18 <i>S</i> = 20	Article 22 <i>S</i> = 26
Subject 1	1	2	1
Subject 2	1	2	1
Subject 3	1	2	1
	Article 03 <i>S</i> = 26	Article 10 <i>S</i> = 15	Article 11 <i>S</i> = 17
Subject 4	4	4	4
Subject 5	3	2	2
Subject 6	1	1	1

Table 2: Verbose and Terse extracters phenomenon in Sentence Extraction Evaluation Corpora (where *S* = number of sentences in article)

As mentioned in the first section, the project which this resource was collected for consists of extraction of key sentences from text, and reformulation of a subset of these sentences into a coherent and concise summary. As such, our task is to extract more sentences than would be explicitly needed for a summary.

The primary challenge in building this resource is analogous to the lumpers versus splitters difference discussed in Section 2.1.5. For extraction, the issue is embodied in the verbose versus terse extractors, i.e. the number of sentences selected by subjects had a wide range. Some subjects consistently picked very few or just one sentence per article, whereas others consistently picked many more. This is shown in Table 2, where for example, subject 1 picked one or two sentences from each article over 20 sentences or more; whereas both subjects 2 and 3 picked an average of five sentences from the same article. Similarly, subject 6 consistently picked only one sentence, but subject 4 picked four sentences. This phenomenon, coupled with the use of a majority method evaluation biases results for high precision rather than high recall. Thus, there is a mismatch between what we asked people to do and what the program was to produce. We believe that our compiled resource may be even better suited for an evaluation of a summarization approach based purely on sentence extraction, although it is still useful for our evaluation.

2.2.6. Future Work on the Extraction Resource

We could compensate for the mismatch in task and algorithm above in two ways. One is in the way instructions are given; we could ask subjects to pick all of the sentences that could be considered of high information content, or we could give a number of sentences we would like them to pick for each article. For the very verbose, we could place an upper bound on the number of selected sentences. This could be done simply as some function of article length, logarithmic or linear. In the current collection, we found that some readers thought nearly every sentence was important, and this affected precision in the final evaluation task. Some constraints would push our results towards the more

verbose, and eliminate both the terse subject and the excessively verbose. Another approach is to relax the constraints for calculating the gold standard. As mentioned above, the majority method in conjunction with the lumpers versus splitters phenomenon biases results for high precision. In future work, we will investigate other methods for culling an evaluation corpus for “correct” answers, such as fractional recall and precision (Hatzivassiloglou and McKeown 93).

2.2.7. Availability

The sentence extraction corpora is also publicly available; send any requests to the first author. Again, inquiries for the textual data that the evaluation corpus is based on should be directed to the respective owners of the materials.

3. Conclusion

We have created two corpus resources to be used as a gold standard in the evaluation of two modules in the analysis stage of a summarization system. We have discussed several fundamental issues that must be considered in the effective construction of evaluation resources. With an increasing number of publicly available evaluation resources such as these, we contribute to the goals of the collective sharing of resources and techniques to enable the NLP community to improve the quality of our future work.

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