Multi-document Text Summarization

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Abstract

In this paper, we provide a description of our multi-document summarization system. The documents are parsed using several modules, the sentences of the documents are clustered and scored, and the scores of the sentences are used in conjunction with a pre-set word count threshold to produce summaries that are then analyzed by the ROUGE evaluation toolkit.

1 Introduction

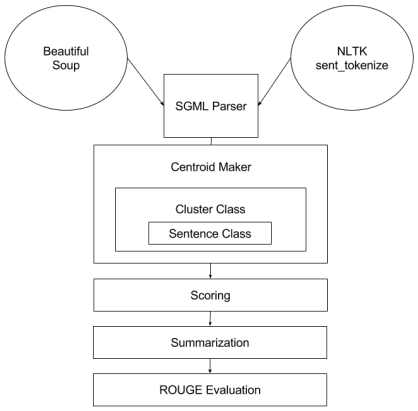
Multi-document summarization has become a burgeoning field in natural language processing where multiple documents are collected and parsed in order to provide a concise and readable summary. There have been many approaches constructed to tackle the problem, including graph models, rule-based methods using hidden Markov models, and statistical methods. One of the seminal approaches in multi-document summarization devised by researchers has been to use a centroid approach. This process, where the sentences closest to the centroids in topic clusters are extracted into the summary, was first described by Radev and other researchers in Radev, Jing, and Budzikowska (2000) and Radev, Jing, Stys, and Tam (2004). We applied this simple and effective approach to the AQUAINT data set provided by the National Institute of Standards and Technology (NIST). What follows is a description of this approach. Section 2 describes the general architecture of our system with a more detailed description in Section 3. The results of our system are described in Section 4 with a follow up discussion in Section 5.

2 System Overview

The system is comprised of three major parts: a Standard General Markup Language (SGML) parser that links the document IDs found in the guided summary file to the document SGML files in the corpus folders, a centroid-based algorithm that scores the sentences within each cluster, and a knapsack algorithm that chooses the highest scoring set of sentences constrained by the word count limit of the summary.

2.1 System Architecture

The following graph displays the architecture of our system:



3 Approach

3.1 Content Selection

The SGML parser uses Python's subprocess library to grep for each document ID found in the guided summary file. Once found, the exact file is read and parsed using BeautifulSoup and the Natural Language Toolkit (NLTK). This was done to avoid loading all 3,000 files in the corpus folder into memory before linking the document IDs from the summary files to the document files, thereby reducing the risk of running out of memory. The text of each document is retrieved using BeautifulSoup and pre-processed by removing extraneous tags, duplicate headlines, and the document IDs themselves from the text. The text is then tokenized into sentences using NLTK and

saved into a JSON object, where the keys are the topic IDs and the values consist of the tokenized documents along with the document headlines. This file is then loaded into the next program in the pipeline, where it is to be processed even further.

Next, the centroid-based algorithm loads the JSON file into memory and further processes the text with a series of regular expressions. The module parses the processed text to initialize a list of Cluster instances. Unlike the MEAD algorithm outlined by Radev et. al. (2004), our system does not automatically perform any clustering; since each cluster produces its own summary, we defined a cluster as a set of documents with the same topic ID. This allows our system to produce one summary per topic, avoiding multiple summaries for one topic ID.

Each Cluster object contains a list of instances of the Sentence class, which encapsulates all the data necessary to rank a sentence. The algorithm assigns three scores to each sentence: (1) centroid score, (2) position score, and (3) first sentence overlap score. In addition, a redundancy penalty is subtracted from the sum of these scores. More detail about the redundancy penalty follows after a discussion of the scoring mechanism.

Firstly, the centroid-based algorithm calculates TF*IDF for each of the terms in this cluster, using the "news" subset of the Brown corpus for inverse document frequency. To optimize the code, IDF scores for every term in the background corpus are calculated once and stored in a dictionary. Term frequency is defined as the average frequency of a term across the documents in the cluster. Rather than using a TF*IDF threshold like the MEAD system, the centroid size is selected by a system argument. A centroid size of 50, for example, saves the top 50 terms for the cluster, ranked by descending TF*IDF scores.

When building a centroid, the system preprocesses the text by tokenizing each sentence within the cluster, lowercasing every token, and removing punctuation-only tokens. A list of cleaned tokens is stored within every Sentence instance, allowing the centroid score for the aforementioned sentence to be easily calculated. For each token in the sentence, if the token appears in the centroid for this cluster, the token's TF*IDF score is added to the total centroid score for the sentence. This process ignores terms not appearing in the centroid, giving better scores to sentences with relevant terms.

Secondly, the system calculates the position score for every Sentence instance. The formula from Radev et. al. (2003) prefers first sentences, since the position score of the first sentence in every document equals the highest centroid score for that cluster. Every sentence after the first sentence gets penalized with the following formula, where *n* is the position of the sentence within the document and $c_(max)$ is the value of the highest centroid score for the cluster:

$$P_i = ((n - i + 1)/n) * C_(max)$$

Third, the system initializes the first sentence overlap score for each sentence, defined as the dot product between vectorized sentences. As a form of optimization, rather than vectorizing the text, every Sentence instance contains a dictionary of (word, count) pairs; the overlap between sentences can be quickly calculated by finding the intersection of keys between dictionaries. For every word shared by both sentences, the counts are multiplied and added to the first sentence overlap score.

Finally, a redundancy penalty is subtracted from the sum of the previous three scores. The original MEAD algorithm calculates redundancy pairwise, comparing the similarity between each sentence and the immediately preceding sentence, ranked by total score in descending order. We found this approach still had too much redundancy within the summaries, and opted for a revised approach. The redundancy penalty for our system is cumulative; that is, the overlap for each sentence is calculated using the intersection of the word types of the current sentence to the word types of all sentences with a higher total score.

$$R_s = 2 \times \frac{\#overlappingwords}{\#wordsinpreviussentence + \#wordsincurrentsentence}$$

After the total score of each sentence is calculated, the sentences are ordered by their total score, in descending order, and only the top N are considered to create the summary. In our experiment, we used N = 20.

In order to create the summary, we use the knapsack algorithm, which allows us to select a subset of the top N sentences such that the word count of the summary, equal to the sum of the word counts of the sentences in the subset, is less than or equal to a given threshold. The knapsack algorithm also selects a subset of the top N sentences that has the

highest total score, calculated as the summation of the total scores of each sentence in the subset. Per the assignment, the threshold for the summary word count limit is set as 100.

3.2 Information Ordering

Currently, our system does not do any information ordering, though the centroid-based summarization algorithm does have a tendency to choose the first sentence from each document in the cluster. Before we improved the redundancy penalty, this led to many summaries composed entirely of first sentences. The MEAD system mentions building centroids from chronologically-ordered documents, so this may be something we implement for the next deliverable, to improve information ordering.

3.3 Content Realization

Beyond penalizing redundancy, we have not implemented content realization. For the next deliverable, we may look at co-reference resolution and sentence merging.

4 Results

Reviewing the ROUGE scores, the ROUGE-1 scores are consistently the best for summaries produced by our system.

4.1 Base results

The following table displays the ROUGE-1, ROUGE-2, ROUGE-3, and ROUGE-4 recall values, in terms of percentage, for a few test cases:

Peer ID	ROUGE-1	ROUGE-2	ROUGE-3	ROUGE-4
08B6D95UEL	20.0	1.695	0.0	0.0
0FJXJNAWTW	22.388	6.061	0.0	0.0
0MW7JTXZ12	34.483	12.281	5.357	0.0

5 Discussion

For the third deliverable, we plan to implement a choice of background corpora, in the hopes that this will allow us to better tune the parameters of the overall system.

The recall values from the base results indicate that our system runs poorly, for the time being. One of the most salient results from the evaluation was that ROUGE-3 and ROUGE-4 consistently had scores of zero, ROUGE-4 more so than ROUGE-3. This is understandable: As n-gram size increases, each type of n-gram overall occurs less frequently. There are several ways that we could improve the scores of ROUGE-3 and ROUGE-4, one being increasing the summary word count threshold.

6 Conclusion

In conclusion, our multi-document summarization system pre-processes documents, clusters and scores the sentences, and uses the knapsack algorithm to create a summary, keeping in mind the highest scoring subset of sentences as well as the summary word count threshold. Moreover, the results are evaluated using the ROUGE evaluation toolkit. The results show that ROUGE-1 and ROUGE-2 consistently perform the best, although there is much improvement to be made, while ROUGE-3 and ROUGE-4 often produce scores of zero. This is easily explained by the fact that types of n-grams become less frequent as the n-gram size increases, and will be one of the topics of interest, among others, in future work regarding our system.

References

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