16 Text Summarization

Text summarization refers to the task of compressing a relatively large amount of text data or a long text article into a more concise form for easy digestion. It is obviously very important for text data access, where it can help users see the main content or points in the text data without having to read all the text. Summarization of search engine results is a good example of such an application. However, summarization can also be useful for text data analysis as it can help reduce the amount of text to be processed, thus improving the efficiency of any analysis algorithm.

However, summarization is a non-trivial task. Given a large document, how can we convey the important points in only a few sentences? And what do we mean by "document" and "important"? Although it is easy for a human to recognize a good summary, it is not as straightforward to define the process. In short, for any text summarization application, we'd like a semantic compression of text; that is, we would like to convey essentially the same amount of information in less space. The output should be fluent, readable language. In general, we need a purpose for summarization although it is often hard to define one. Once we know a purpose, we can start to formulate how to approach the task, and the problem itself becomes a little easier to evaluate.

In one concrete example, consider a news summary. If our input is a collection of news articles from one day, a potentially valid output is a list of headlines. Of course, this wouldn't be the entire list of headlines, but only those headlines that would interest a user. For a different angle, consider a news summarization task where the input is one text news article and the output should be one paragraph explaining what the article talks about in a readable format. Each task will require a different solution.

Summarizing retrieval results is also of particular interest. On a search engine result page, how can we help the user click on a relevant link? A common strategy is to highlight words matching the query in a short snippet. An alternative approach would be to take a few sentences to summarize each result and display the short

summaries on the results page. Using summaries in this way could give the user a better idea of what information the document contains before he or she decides to read it.

Opinion summarization is useful for both businesses and shoppers. Summarizing all reviews of a product lets the business know whether the buyers are satisfied (and why). The review summaries also let the shoppers make comparisons between different products when searching online. Reviews can be further broken down into summaries of positive reviews and summaries of negative reviews. An even more granular approach described in Wang et al. [2010] and Wang et al. [2011] and further discussed in Chapter 18 uses topic models to summarize product reviews relating to different aspects. For hotel reviews, this could correspond to service, location, price, and value. Although the output in these two works is not a human-readable summary, we could imagine a system that is able to summarize all the hotel reviews in English (or any other language) for the user.

In this chapter, we overview two main paradigms of summarization techniques and investigate their different applications.

16.1 Overview of Text Summarization Techniques

There are two main methods in text summarization. The first is **selection-based** or **extractive summarization**. With this method, a summary consists of a sequence of sentences selected from the original documents. No new sentences are written, hence the summary is *extracted*. The second method is **generation-based** or **abstractive summarization**. Here, a summary may contain new sentences not in any of the original documents. One method that we explore here is using a language model. Previously in this book, we've used language models to calculate the likelihood of some text; in this chapter, we will show how to use a language model in reverse to generate sentences. We also briefly touch on the field of **natural language generation** in our discussion of abstractive techniques.

Following the pattern of previous chapters, we then move on to evaluation of text summarization. The two methods each have evaluation metrics that are particularly focused towards their respective implementation, but it is possible to use (e.g.) an abstractive evaluation metric on a summary generated by an extractive algorithm. Finally, we look into some applications of text summarization and see how they are implemented in real-world systems.

Text summarization is a broad field and we only touch on the core concepts in this chapter. For further reading, we recommend that the reader start with Das and Martins [2007], which provides a systematic overview of the field and contains much of the content from this chapter in an expanded form.

16.2 Extractive Text Summarization

Information retrieval-based techniques use the notion of sentence vectors and similarity functions in order to create a summarization text. A sentence vector is equivalent in structure to a document vector, albeit based on a smaller number of words. Below, we will outline a basic information retrieval-based summarization system.

1. Split the document to be summarized into sections or passages.
2. For each passage, "compress" its sentences into a smaller number of relevant (yet not redundant) sentences.

This strategy retains coherency since the sentences in the summary are mostly in the same order as they were in the original document.

Step one is portrayed in Figure 16.1. The sentences in the document are traversed in order and a normalized, symmetric similarity measure (see Chapter 14) is applied on adjacent pairs of sentences. The plot on the right-hand side of the figure shows the change in similarity between the sentences. We can inspect these changes to segment the document into passages when the similarity is low, i.e., a shift in topic occurs. An alternative approach to this segmentation is to simply use paragraphs if the document being operated on contains that information, although most of the time this is not the case. This rudimentary partitioning strategy is a task in

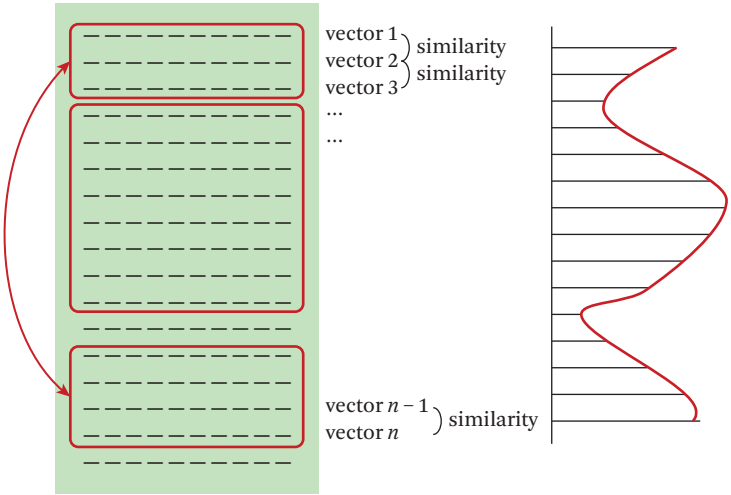

Figure 16.1 Segmenting a document into passages with a similarity-based discourse analysis.

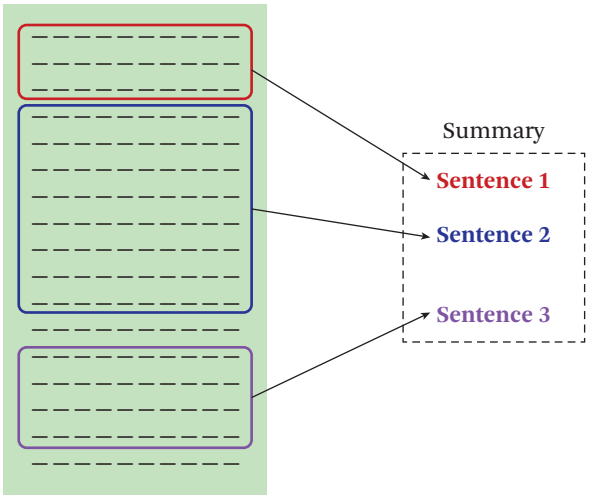

Figure 16.2 **Text summarization using maximum marginal relevance to select one sentence from each passage as a summary.**

discourse analysis (a subfield of NLP). Discourse analysis deals with sequences of sentences as opposed to only one sentence.

Now that we have our passages, how can we remove redundancy and increase diversity in the resulting summarization during step two? The technique **maximal marginal relevance** (MMR) reranking can be applied to our problem. Essentially, this algorithm greedily reranks each sentence in the current passage, outputting only the top few as a summary. Figure 16.2 shows the output of the algorithm when we only select one sentence from each passage.

The MMR algorithm is as follows. Assume we are given an original list R and a profile p to construct the set of selected sentences S (where $|S| \ll |R|$). R is a partitioned chunk of sentences in the document we wish to summarize. The profile p determines what is exactly meant by "relevance." Originally, the MMR formula was applied to documents returned from an information retrieval system (hence the term *reranking*). Documents were selected based on their marginal relevance to a query (which is our variable p) in addition to non-redundancy to already-selected documents. Since our task deals with sentence retrieval, p can be a user profile (text about the user), the entire document itself, or it could even be a query formulated by the user.

According to marginal relevance, the next sentence s_i to be added into the selected list S is defined as

$$s_i = \arg\max_{s \in R \setminus S} \left\{ (1-\lambda) \cdot \text{sim}_1(s, p) - \lambda \cdot \arg\max_{s_j \in S} \text{sim}_2(s, s_j) \right\}. \quad (16.1)$$

The $R \setminus S$ notation may be read as "R set minus S", i.e., all the elements in R that are not in S. The MMR formulation uses $\lambda \in [0, 1]$ to control relevance versus redundancy; the positive relevance score is discounted by the amount of redundancy (similarity) to the already-selected sentences. Again, the two similarity metrics may be any normalized, symmetric measures. The simplest instantiation for the similarity metric would be cosine similarity, and this is in fact the measure used in Carbonell and Goldstein [1998].

The algorithm may be terminated once an appropriate number of words or sentences is in S, or if the score $\text{sim}_1(s, p)$ is below some threshold. Furthermore, the similarity functions may be tweaked as well. Could you think of a way to include sentence position in the similarity function? That is, if a sentence is far away (dissimilar) from the candidate sentence, we could subtract from the similarity score. Even better, we could interpolate the two values into a new similarity score such as

$$\text{sim}(s, s') = \alpha \cdot \text{sim}_{\text{cosine}}(s, s') + (1-\alpha) \cdot \left(1 - \frac{d(s, s')}{\max d(s, \cdot)}\right), \quad (16.2)$$

where $\alpha \in [0, 1]$ controls the weight between the regular cosine similarity and the distance measure, and $d(\cdot, \cdot)$ is the number of sentences between the two parameters. Note the "one minus" in front of the distance calculation, since a smaller distance implies a greater similarity.

Of course, λ in the MMR formula is also able to be set. In fact, for multi-document summarization, Das and Martins [2007] suggests starting out with $\lambda = 0.3$ and then slowly increasing to $\lambda = 0.7$. The reasoning behind this is to first emphasize novelty and then default to relevance. This should remind you of the exploration-exploitation tradeoff discussed in Chapter 11.

16.3 Abstractive Text Summarization

An abstractive summary creates sentences that did not exist in the original document or documents. Instead of a document vector, we will use a language model to represent the original text. Unlike the document vector, our language model gives us a principled way in which to generate text. Imagine we tokenized our document with unigram words. In our language model, we would have a parameter representing the probability of each word occurring. To create our own text, we will draw words from this probability distribution.

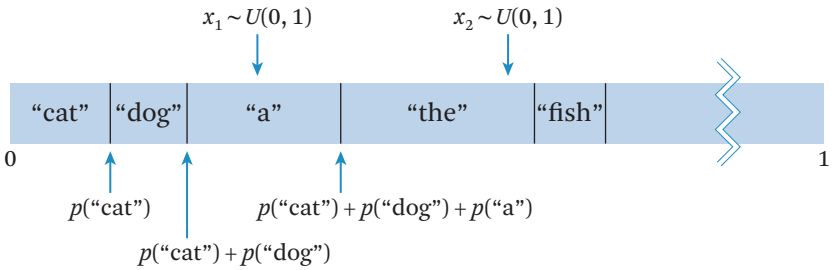

Figure 16.3 **Drawing words from a unigram language model.**

Say we have the unigram language model θ estimated on a document we wish to summarize. We wish to draw words $w_1, w_2, w_3, \ldots$ from θ that will comprise our summary. We want the word w_i to occur in our summary with about the same probability it occurred in the original document—this is how our generated text will approximate the longer document. Figure 16.3 depicts how we can accomplish this task. First, we create a list of all our parameters and incrementally sum their probabilities; this will allow us to use a random number on $[0, 1]$ to choose a word w_i. Simply, we get a uniform random floating point number between zero and one. Then, we iterate through the words in our vocabulary, summing their probabilities until we get to the random number. We output the term and repeat the process.

In the example, imagine we have the following values:

$p(\text{cat})$	0.010
$p(\text{cat}) + p(\text{dog})$	0.018
$p(\text{cat}) + p(\text{dog}) + p(\text{a})$	0.038
$\vdots$	$\vdots$
$p(\text{cat}) + p(\text{dog}) + p(\text{a}) + \cdots + p(\text{zap})$	1.0

Say we generate a random number x_1 using a uniform distribution on $[0, 1]$. This is denoted as $x_1 \sim \mathcal{U}(0, 1)$. Now imagine that $x_1 = 0.032$. We go to the cumulative point 0.032 in our distribution and output "a". We can repeat this process until our summary is of a certain length or until we generate an end-of-sentence token `</s>`.

At this point, you may be thinking that the text we generate will not make any sense—that is certainly true if we use a unigram language model since each word is generated independently without regard to its context. If more fluent language is required, we can use an n-gram language model, where $n > 1$. Instead of each word being independently generated, the new word will depend on the previous $n - 1$

words. The generation will work the same way as in the unigram case: say we have the word w_i and wish to generate w_{i+1} with a bigram language model. Our bigram language model gives us a distribution of words that occur after w_i and we draw the next word from there in the same way depicted in Figure 16.3.

The sentence generation from a bigram language model proceeds as follows: start with (e.g.) *The*. Then, pick from the distribution $p(w \mid \text{The})$ using the cumulative sum technique. The next selected word could be *cat*. Then, we use the distribution $p(w \mid \text{cat})$ to find the next w, and so on. While the unigram model only had one "sum table" (Figure 16.3), the bigram case needs V tables, one for each w' in $p(w \mid w')$.

Typically, the n-value will be around three to five depending on how much original data there is. We saw what happened when n is too small; we get a jumble of words that don't make sense together. But we have another problem if n is too large. Consider the extreme case where $n = 20$. Then, given 19 words, we wish to generate the next one using our 20-gram language model. It's very unlikely that those 19 words occurred more than once in our original document. That means there would only be one choice for the 20th word. Because of this, we would just be reproducing the original document, which is not a very good summary. In practice, we would like to choose an n-gram value that is large enough to produce coherent text yet small enough to not simply reproduce the corpus.

There is one major disadvantage to this abstractive summarization method. Due to its nature, a given word only depends on the n surrounding words. That is, there will be no long-range dependencies in our generated text. For example, consider the following sentence generated from a trigram language model:

They imposed a gradual smoking ban on virtually all corn seeds planted are hybrids.

All groups of three words make sense, but as a whole the sentence is incomprehensible; it seems the writer changed the topic from a smoking ban to hybrid crops mid-sentence. In special cases, when we restrict the length of a summary to a few words when summarizing highly redundant text, such a strategy appears to be effective as shown in the micropinion summarization method described in Ganesan et al. [2012].

16.3.1 Advanced Abstractive Methods

Some advanced abstractive methods rely more heavily on natural language processing to build a model of the document to summarize. **Named entity recognition** can be used to extract people, places, or businesses from the text. **Dependency parsers** and other syntactic techniques can be used to find the relation between the entities

and the actions they perform. Once these actors and roles are discovered, they are stored in some internal representation. To generate the actual text, some representations are chosen from the parsed collection, and English sentences are created based on them; this is called **realization**.

Such realization systems have much more fine-grained control over the generated text than the basic abstractive language model generator described above. A templated document structure may exist (such as intro→paragraph 1→paragraph 2→conclusion), and the structures are chosen to fill each spot. This control over text summarization and layout enables an easily-readable summary since it has a natural topical flow. In this environment, it would be possible to merge similar sentences with conjunctions such as *and* or *but*, depending on the context. To make the summary sound even more natural, pronouns can be used instead of entity names if the entity name has already been mentioned. Below are examples of these two operations:

> *Gold prices fell today. Silver prices fell today.* → *Gold and silver prices fell today.*
> *Company A lost* 9.43% *today. Company A was the biggest mover.* → *Company A lost* 9.43% *today. It was the biggest mover.*

Even better would be

> *Company A was today's biggest mover, losing* 9.43%.

These operations are possible since the entities are stored in a structured format. For more on advanced natural language generation, we suggest Reiter and Dale [2000], which has a focus on practicality and implementation.

16.4 Evaluation of Text Summarization

In extractive summarization, representative sentences were selected from passages in the text and output as a summary. This solution is modeled as an information retrieval problem, and we can evaluate it as such. Redundancy is a critical issue, and the MMR technique we discussed attempts to alleviate it. When doing our evaluation, we should consider redundant sentences to be irrelevant, since the user does not want to read the same information twice. For a more detailed explanation of IR evaluation measures, please consult Chapter 9.

For full output scoring, we should prefer IR evaluation metrics that do not take into account result position. Although our summary is generated by ranked sentences per passage, the entire output is not a ranked list since the original document is composed of multiple passages. Therefore we can use precision, recall, and F_1 score.

It is possible to rank the passage scoring retrieval function using position-dependent metrics such as average precision or NDCG, but with the final output this is not feasible. Thus we need to decide whether to evaluate the passage scoring or the entire output (or both). Entire output scoring is likely more useful for actual users, while passage scoring could be useful for researchers to fine-tune their methods.

In abstractive summarization, we can't use the IR measures since we don't have a fixed set of candidate sentences. How can we compute recall if we don't know the total number of relevant sentences? There is also no intermediate ranking stage, so we also can't use average precision or NDCG (and again, we don't even know the complete set of correct sentences).

A laborious yet accurate evaluation would have human annotators create a gold standard summary. This "perfect" summary would be compared with the generated one, and some measure (e.g., ROUGE) would be used to quantify the difference. For the comparison measure, we have many possibilities—any measure that can compare two groups of text would be potentially applicable. For example, we can use the cosine similarity between the gold standard and generated summary. Of course, this has the downside that fluency is completed ignored (using unigram words). An alternative means would be to learn an n-gram language model over the gold standard summary, and then calculate the log-likelihood of the generated summary. This can ensure a basic level of fluency at the n-gram level, while also producing an interpretable result. Other comparisons between two probability distributions would also be applicable, such as KL-divergence.

The overall effectiveness of a summary can be tested if users read a summary and then answer questions about the original text. Was the summary able to capture the important information that the evaluator needs? If the original text was an entire textbook chapter, could the user read a three-paragraph summary and obtain sufficient information to answer the provided exercises? This is the only metric that can be used for both extractive and abstractive measures. Using a language model to score an extractive summary vs. an abstractive one would likely be biased towards the extractive one since this method contains phrases directly from the original text, giving it a very high likelihood.

16.5 Applications of Text Summarization

At the beginning of the chapter, we've already touched on a few summarization applications; we mentioned news articles, retrieval results, and opinion summarization. Summarization saves users time from manually reading the entire corpus while simultaneously enhancing preexisting data with summary "annotations."

The aspect opinion analysis mentioned earlier segments portions of user reviews into speaking about a particular topic. We can use this topic analysis to collect passages of text into a large group of comments on one aspect. Instead of describing this aspect with sorted unigram words, we could run a summarizer on each topic, generating readable text as output. These two methods complement each other, since the first step finds what aspects the users are interested in, while the second step conveys the information.

A theme in this book is the union of both structured and unstructured data, mentioned much more in detail in Chapter 19. Summarization is an excellent example of this application. For example, consider a financial summarizer with text reports from the Securities and Exchange Commission (SEC) as well as raw stock market data. Summarizing both these data sources in one location would be very valuable for (e.g.) mutual fund managers or other financial workers. Being able to summarize (in text) a huge amount of structured trading data could reveal patterns that humans would otherwise be unaware of—this is an example of **knowledge discovery**.

E-discovery (electronic discovery) is the process of finding relevant information in litigation (lawsuits and court cases). Lawyers rely on e-discovery to sift through vast amounts of textual information to build their case. The Enron email dataset[1] is a well-known corpus in this field. Summarizing email correspondence between two people or a department lets investigators quickly decide whether they'd like to dig deeper in a particular area or try another approach. In this way, summarization and search are coupled; search allows a subset of data to be selected that is relevant to a query, and the summarization can take the search results and quickly explain them to the user. Finally, linking email correspondence together (from sender to receivers) is a structured complement to the unstructured text content of the email itself.

Perhaps of more interest to those reading this book is the ability to summarize research from a given field. Given proceedings from a conference, could we have a summarizer explain the main trends and common approaches? What was most novel compared to previous conferences? When writing your own paper, can you write everything except the introduction and related work? The introduction is an overview summary of your paper. Related work is mostly a summary of papers similar to yours.

1. https://www.cs.cmu.edu/~./enron/

Bibliographic Notes and Further Reading

As mentioned in this chapter, Das and Martins [2007] is a comprehensive survey on summarization techniques. Additionally, Nenkova and McKeown [2012] is a valuable read. For applications, latent aspect rating analysis [Wang et al. 2010], [Wang et al. 2011] is a form of summarization applied to product reviews. We mention this particular application in more detail in Chapter 18. A typical extractive summarizer is presented in Radev et al. [2004], a typical abstractive summarizer is presented in Ganesan et al. [2010], and evaluation suggestions are presented in Steinberger and Jezek [2009]. The MMR algorithm was originally described in Carbonell and Goldstein [1998]. For advanced NLG (natural language generation) techniques, a good starting point is Reiter and Dale [2000].

Exercises

16.1. Do you think one summarization method (extractive or abstractive) would perform better on a small dataset? How about a large dataset? Justify your reasoning.

16.2. Explain how you can improve the passage detection by looking beyond only the adjacent sentences. How would you implement this?

16.3. Write a basic passage segmenter in MeTA. As input, take a document and extract the sentences into a vector with a built-in tokenizer. Segment the vector into passages using a similarity algorithm.

16.4. Now that you have a document segmented into passages, use MeTA to set up a search engine over each passage, where you treat passages as individual documents. Ensure that you have enough sentences per passage. You many need to tweak your previous answer to achieve this.

16.5. With your passage search engine, find a representative sentence from each passage to create a summary for the original document.

16.6. Use MeTA's language model to learn a distribution of words over a document you wish to summarize.

16.7. Add a `generate` function to the language model. It should take a context ($n-1$ terms) and generate the n^{th} term. Use the calculation described in this chapter to generate the next word.

16.8. Summarize the input document using the generator. Experiment with different stopping criteria. Which seems to work the best?

16.9. Create some simple post-processing rules for natural language generation realization. The examples we gave in the text were sentence joining and pronoun insertion. What else can you think of?

16.10. Explain how we can combine text summarization and topic modeling to create a powerful exploratory text mining application.

16.11. What can we accomplish by interpolating a language model distribution for an abstractive summarizer with another probability distribution, perhaps from existing summaries?

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Index

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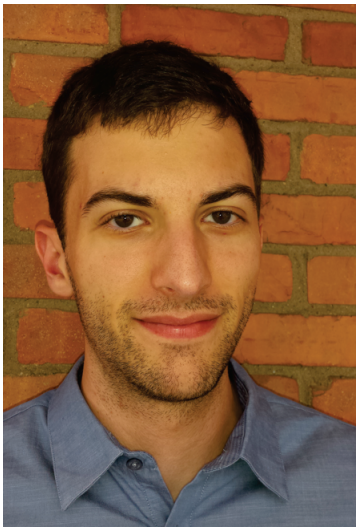
Sean Massung



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