Phrase Mining

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ABSTRACT

Extracting frequent words from a collection of texts is performed on a great scale in many subjects. Extracting phrases, on the other hand, is not commonly done due to inherent complications when extracting phrases, the most significant complication being that of double-counting, where words or phrases are counted when they appear inside longer phrases that themselves are also counted.

Several papers have been written on phrase mining that describe solutions to this issue; however, they either require a list of so-called quality phrases to be available to the extracting process, or they require human interaction to identify those quality phrases during the process.

We present a method that eliminates double-counting without the need to identify lists of quality phrases. In the context of a set of texts, we define a principal phrase as a phrase that does not cross punctuation marks, does not start with a stop word, with the exception of the stop words “not” and “no”, does not end with a stop word, is frequent within those texts without being double counted, and is meaningful to the user. Our method can identify such principal phrases independently without human input, and enables their extraction from any texts.

An R package called phm has been developed that implements this method.
1. Introduction

Definition: A document is a text together with additional information, called meta data, such as the name of the text, its author, the date it was created, etc.

Definition: A corpus (plural corpora) is a collection of documents that are related, together with additional data, called corpus-level meta data, such as the name of the collection, the relationship between the documents, the date they were combined, etc.

In text mining we wish to investigate and analyze the information provided in texts without actually having to read those texts. In particular, we may wish to obtain relevant information for the documents in a corpus, so we can make better choices as to which document we may actually wish to investigate further and read its text.

With the currently available methods, we can select the most frequent words in each text of documents within a corpus. We can do this using the R text mining package tm (Feinerer, Introduction to the tm Package. Text Mining in R, 2017) (Feinerer, An Introduction to Text Mining in R, 2008) (Feinerer, Hornik, & Meyer, Text Mining Infrastructure in R, 2008). This information can indeed be used to provide information about the context of each text without having to read the full text.

However, as useful as frequencies of words can be, it would be even more useful to be able to select common phrases with their frequencies, as they can provide more specific information. But extracting phrases from texts brings with it certain complications that do not occur when we extract words from texts; the most significant of these complications is the issue of double-counting.

Definition: Double-counting occurs when words or phrases are counted when they appear inside longer phrases that are also counted. For example, when the phrase “severe cardiovascular disease” results in one count of the phrase “severe cardiovascular disease” as well as one count of “severe cardiovascular” and one count of “cardiovascular disease”.
Definition: A stop word is a trivial word such as “a”, “and”, “of”, “the”, “we”, i.e., a word that does not provide useful information.

Definition: A principal phrase is a phrase that occurs in a text, a set of texts, or a corpus of texts within documents, does not cross punctuation marks, does not start with a stop word with the exception of the stop words “not” and “no”, does not end with a stop word, is frequent within those texts without having been double counted, and is meaningful to the user.

Here we present a technique for extracting principal phrases from texts.

An R package called phm has been created that implements this technique and can be used to extract principal phrases either from collections of texts or from corpora with documents.

### 1.1. Phrase Mining Complications

When we extract words from texts, we usually prepare the texts first. Some of those preparations involve converting everything to lower case, remove punctuation, and remove stop words.

Definition: An n-gram is any consecutive set of n words, as it appears in a text.

It is not difficult to expand the extraction from words to n-grams. However, this would result in multiple problems, described in detail by (Liu, Shang, & Han, 2017):

- If we continue to exclude stop words, then for example, the phrase “cats and dogs” would turn into the meaningless phrase “cats dogs”. But if we include stop words, it could result in other meaningless phrases such as “and this disease” and “attack of”. Note also that the words “not” and “no” are stop words, but ones that will change the meaning of a word or phrase significantly if they occur right before it.

- Some phrases are inherently meaningless to researchers such as the phrase “here we are”, which may still occur frequently. In addition, many meaningless phrases are subject dependent. For example, if
we obtained a set of texts related to the omicron variant of the coronavirus, the phrase “omicron variant” itself may not be meaningful to the investigator since it will appear in all texts.

- If we remove punctuation marks before extracting phrases, we would be selecting n-grams that cross those punctuation marks, resulting in meaningless phrases.

- Most importantly, we would have double-counting issues.

Note that if we were to allow double-counting, then one word or group of words may be counted in multiple phrases. This would result in meaningless subsets of phrases being presented as frequent phrases together with their meaningful super phrases since they would occur with the same frequency. If we were to cluster the results this would likely cause these phrases to be clustered together, and the meaningless sub phrase would provide no useful additional information to the cluster that wasn’t already provided by its super phrase. As an example, consider the phrases “severe cardiovascular disease” and “severe cardiovascular”, the former meaningful, the latter meaningless. Since the latter always occurs inside the former, its frequency would be the same, and even if the phrase “severe cardiovascular” never occurred on its own, it would still be presented as a phrase as frequent as “severe cardiovascular disease”. If we were to display the most common phrases in a corpus, the phrase “severe cardiovascular disease” would appear right next to the phrase “severe cardiovascular” since its frequency would be the same.

In addition, some meaningful phrases such as “cardiovascular disease” would have their frequency exaggerated since the frequencies of “severe cardiovascular disease” would be added to its stand-alone occurrences. This would cause any sub phrase such as “cardiovascular disease” to appear to always be more common than its super phrase.
There are several papers that suggest solutions to these problems. However, most of the current methods for extracting phrases are not fully automated and require human experts to design rules or label phrases. (Liu, Shang, & Han, 2017) suggest a technique called phrasal segmentation which requires a set of quality phrases to be supplied before the phrases can be extracted. Their method needs domain experts to first carefully select hundreds of varying quality phrases from millions of candidates. (Shang, et al., 2018) discuss using a method called AutoPhrase, which needs a general knowledge base (e.g., Wikipedia) in the required language, and benefits from a POS tagger. This method, like most other methods, also seeks to keep a list of so-called quality phrases, which it then compares to the contents of a collection of texts. The difference with this particular method being that it obtains this list from a general knowledge base rather than domain experts or the investigators themselves.

We developed an automated method that avoids the issues described, is remarkably simple, does not require human effort to label phrases nor a general knowledge base, is highly efficient, and extracts principal phrases only from texts. Phrases of any range of number of words can be extracted, including those consisting of just one word. It is able to do this without any human input.

Our method is based on the idea that phrases consisting of many words that are frequent are likely to be important phrases, and are given priority over phrases consisting of less words.

2. Method

The method we propose starts with a collection of texts or a corpus with documents, each of which containing a text.

We split each text in blocks, which are determined by the placement of punctuation marks in the texts. For a specific range of n, we extract all n-grams from each block, but exclude those that start with a stop
word not equal to either “not” or “no”, those that end in a stop word, and those that are part of a list of phrases that should be excluded.

For each n-gram that makes the cut, we store its location, i.e., the text, block, and position within the block.

Once all n-grams have been extracted, they will go through a rectification process to remove all double-counting. This rectification process works as follows:

All n-grams will be ordered by number of words (n) and their frequency within the collection of texts. Each n-gram will then be evaluated in that order. If its frequency is high enough, it will be considered a principal phrase. At that point, using its location, we reduce the frequency of each n-gram that starts and/or ends within the principal phrase.

The end result will be a selection of principal phrases with their frequencies in each text.

2.1. Example

Let’s consider the sentence “The authors wrote abstract phrase mining papers.” as part of a larger text. The question is, what are the principal phrases in this sentence?

First, we find all the n-grams with n greater than or equal to 2. Since we will not have our n-grams cross punctuation marks, n is at most 7. However, “the” is a stop word, and thus no n-gram can start with it. As such the largest n-gram has n=6, and the 6-gram is “authors wrote abstract phrase mining papers”.

We have the following n-grams in the sentence:
Each of these n-grams will be assigned frequency 1 due to our sentence.

We see that this one short sentence gives rise to 15 n-grams, most of which do not appear to be meaningful phrases.

Which ones will be selected as principal phrases depends on the frequency of the same n-grams in other parts of the text.

Let’s assume that the minimum frequency for principal phrases is 3, and that the only n-grams that made the frequency requirement in the sentence “The authors wrote abstract phrase mining papers” are the following:

| n-grams                      | frequency |
|------------------------------|-----------|
| abstract phrase              | 10        |
| phrase mining                | 18        |
| Phrase                          | Frequency |
|--------------------------------|-----------|
| mining papers                  | 5         |
| authors wrote abstract         | 3         |
| abstract phrase mining         | 10        |
| phrase mining papers           | 5         |

Note that the frequency of these phrases are the frequencies collected from the entire collection of texts under consideration.

The largest $n$ here is 3, so we look for the 3-gram with the highest frequency. That is the phrase “abstract phrase mining”. We designate this as a principal phrase.

Then we look for any $n$-grams whose words started or ended in one of the occurrences of this phrase.

The $n$-gram “abstract phrase” occurs in each, so its frequency is reduced by 10. This causes it to be eliminated; it is NOT a principal phrase.

The $n$-gram “phrase mining” also wholly occurs in “abstract phrase mining”, so this $n$-gram also loses 10 frequencies. In this case, however, 8 more frequencies are left.

In our sentence, “mining papers” starts in our principal phrase, so it would lose one frequency for that occurrence. There may be additional such occurrences in the remaining blocks and/or texts, let’s say there are 3 of those. So “mining papers” ends up with a frequency below 3 and would be eliminated.

Similarly, “authors wrote abstract” ended inside the principal phrase “abstract phrase mining” for our sentence. As such it loses at least one frequency and is eliminated.

Finally, “phrase mining papers” also starts in our principal phrase in our sentence, so that one also loses at least one frequency. If there are more such cases, it may also end up below 3 and be eliminated.

In the end, all that is left besides “abstract phrase mining”, is “phrase mining” with a frequency of 8. If its frequencies stay above 3 when all other principal phrases consisting of 3 words, and all principal
phrases consisting of 2 words with a greater frequency, have been processed, it will also be designated as a principal phrase.

Note that the only two n-grams left from our sentence are meaningful ones. Also note that “phrase mining” ended up with a lower frequency than its super phrase “abstract phrase mining”.

3. Results

As an example, on March 31, 2022 we selected all publications in PubMed related to the Omicron variant of the Coronavirus, and extracted all principal phrases with a minimum of two and a maximum of 8 words from their abstracts. The size of the file obtained from PubMed was 6207 KB and took a little over 1 second to read into a data table in R. Using this data table, we extracted 1375 principal phrases from the abstracts of 1531 documents in 16 seconds. The 10 most common phrases with their frequencies within this collection of texts were the following:

| Principal Phrase                                    | Frequency |
|-----------------------------------------------------|-----------|
| omicron variant                                     | 451       |
| 95% ci                                              | 153       |
| delta variant                                       | 132       |
| spike protein                                       | 131       |
| sars-cov-2 variants                                 | 117       |
| variants of concern                                 | 105       |
| severe acute respiratory syndrome coronavirus       | 94        |
| sars-cov-2 infection                                | 91        |
| sars-cov-2 omicron variant                          | 87        |
Upon inspection of the first abstract in the collection, we found it contained the following principal phrases and frequencies in this abstract:

| Principal Phrases for PMID: 34982466 | Frequency |
|--------------------------------------|-----------|
| amino acid                          | 1         |
| covid-19 vaccines                   | 1         |
| mutations in the spike protein       | 2         |
| new variant                         | 1         |
| new variant of sars-cov-2           | 1         |
| november 2021                       | 1         |
| omicron variant                     | 2         |
| previous variants                   | 1         |
| previously infected                 | 1         |
| receptor-binding domain             | 2         |
| sars-cov-2 variants                 | 2         |
| south africa                        | 1         |
| spike protein                       | 1         |
| transmissibility and immune          | 1         |
| vaccinated individuals               | 1         |
| variant of concern                  | 1         |
| world health organization           | 1         |
It is clear that the principal phrases are mostly meaningful. In the case that certain of the phrases are not considered meaningful, such as, for example, the phrase “transmissibility and immune”, they can be excluded from the process, either at the start when the principal phrases are extracted, or afterwards. (Small, Cabrera, & Kostis, 2020) describe an application that extracts principal phrases from PubMed files and allows phrases that are not meaningful to the user to be removed. The application is created using the functionality described here implemented via the phm R package.

4. Conclusion

Strengths:

We envisage a wealth of applications for this method; any application that currently extracts words from texts can be improved by selecting principal phrases instead; the information provided that way will be more specific and useful. In addition, sentiments of words that are preceded by “not” or “no” are no longer incorrectly identified.

In comparison to currently existing methods for extracting phrases from texts, there is no need to provide a list of quality phrases. As such, it is not possible for any important frequent phrases to be missed, which, using any of the existing methods, may be the case for new phrases, or phrases in a different language, or any other phrases not present on their provided lists of quality phrases.

Limitations:

Unlike existing methods for extracting phrases, this method may on occasion return a phrase that is not particularly meaningful. However, it is possible to remove such meaningless phrases once they have been identified.
When words are extracted from texts, we are able to use several lexicons to determine the sentiment of those words, and so we are able to determine the sentiment of each text as well as the complete collection. Since there are no such lexicons for phrases, this would be a disadvantage of our method. However, it may be possible in the future to establish a lexicon with sentiments for phrases. Certain phrases may be very similar, such as, for example, “previous variant” and “previous variants”, and it could be argued that they should be combined. This issue can be resolved by stemming the words in the texts first before extracting principal phrases, but it could also be a future enhancement to the process to combine like phrases.

In conclusion, we have developed a method that will extract principal phrases from a collection of texts or a corpus of documents, where a principal phrase is a phrase that occurs in this collection of texts, does not cross punctuation marks, does not start with a stop word with the exception of the stop words “not” and “no”, does not end with a stop word, is frequent within those texts without having been double counted, and is meaningful to the user.

The method is implemented in the R-language via a package called phm, where the function phraseDoc will extract the principal phrases. This package also contains several other functions in order to easily obtain information from those texts utilizing the principal phrases. A vignette called phm-intro has been included to explain the process and functions in this package.
5. References

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