Welbers, K., Van Atteveldt, W., & Benoit, K. (2017). Text Analysis in R. *Communication Methods and Measures*, *11*(4), 245-265. http://www.tandfonline.com/doi/10.1080/19312458.2017.1387238

Text Analysis in R

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Abstract

Computational text analysis has become an exciting research field with many applications in communication research. It can be a difficult method to apply, however, because it requires knowledge of various techniques, and the software required to perform most of these techniques is not readily available in common statistical software packages. In this teacher's corner, we address these barriers by providing an overview of general steps and operations in a computational text analysis project, and demonstrate how each step can be performed using the R statistical software. As a popular open-source platform, R has an extensive user community that develops and maintains a wide range of text analysis packages. We show that these packages make it easy to perform advanced text analytics.

With the increasing importance of computational text analysis in communication research (Boumans & Trilling, 2016; Grimmer & Stewart, 2013), many researchers face the challenge of learning how to use advanced software that enables this type of analysis. Currently, one of the most popular environments for computational methods and the emerging field of "data science" [1] is the R statistical software (R Core Team, 2017). However, for researchers that are not well-versed in programming, learning how to use R can be a challenge, and performing text analysis in particular can seem daunting. In this teacher's corner, we show that performing text analysis in R is not as hard as some might fear. We provide a step-by-step introduction into the use of common techniques, with the aim of helping researchers get acquainted with computational text analysis in general, as well as getting a start at performing advanced text analysis studies in R.

R is a free, open-source, cross-platform programming environment. In contrast to most programming languages, R was specifically designed for statistical analysis, which makes it highly suitable for data science applications. Although the learning curve for programming with R can be steep, especially for people without prior programming experience, the tools now available for carrying out text analysis in R make it easy to perform powerful, cutting-edge text analytics using only a few simple commands. One of the keys to

R's explosive growth (Fox & Leanage, 2016; TIOBE, 2017) has been its densely populated collection of extension software libraries, known in R terminology as *packages*, supplied and maintained by R's extensive user community. Each package extends the functionality of the base R language and core packages, and in addition to functions and data must include documentation and examples, often in the form of vignettes demonstrating the use of the package. The best-known package repository, the Comprehensive R Archive Network (CRAN), currently has over 10,000 packages that are published, and which have gone through an extensive screening for procedural conformity and cross-platform compatibility before being accepted by the archive.[2] R thus features a wide range of inter-compatible packages, maintained and continuously updated by scholars, practitioners, and projects such as RStudio and rOpenSci. Furthermore, these packages may be installed easily and safely from within the R environment using a single command. R thus provides a solid bridge for developers and users of new analysis tools to meet, making it a very suitable programming environment for scientific collaboration.

Text analysis in particular has become well established in R. There is a vast collection of dedicated text processing and text analysis packages, from low-level string operations (Gagolewski, 2017) to advanced text modeling techniques such as fitting Latent Dirichlet Allocation models (Blei, Ng, & Jordan, 2003; Roberts et al., 2014)—nearly 50 packages in total at our last count. Furthermore, there is an increasing effort among developers to cooperate and coordinate, such as the rOpenSci special interest group.[3] One of the main advantages of performing text analysis in R is that it is often possible, and relatively easy, to switch between different packages or to combine them. Recent efforts among the R text analysis developers' community are designed to promote this interoperability to maximize flexibility and choice among users.[4] As a result, learning the basics for text analysis in R provides access to a wide range of advanced text analysis features.

Structure of this Teacher's Corner

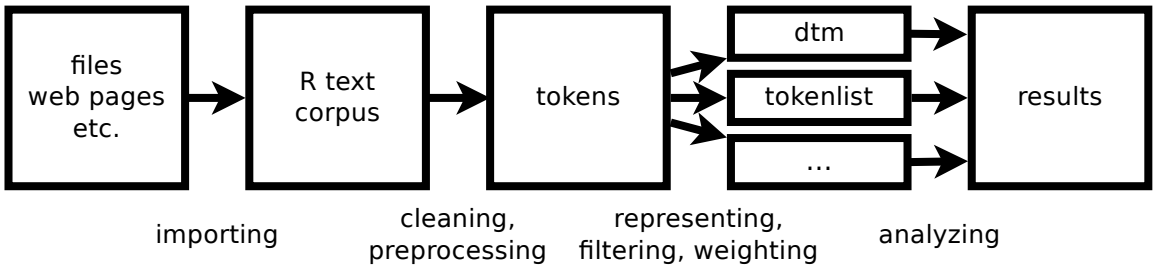
This teacher's corner covers the most common steps for performing text analysis in R, from data preparation to analysis, and provides easy to replicate example code to perform each step. The example code is also digitally available in our online appendix, which is updated over time.[5] We focus primarily on bag-of-words text analysis approaches, meaning that only the frequencies of words per text are used and word positions are ignored. Although this drastically simplifies text content, research and many real-world applications show that word frequencies alone contain sufficient information for many types of analysis (Grimmer & Stewart, 2013).

Table 1 presents an overview of the text analysis operations that we address, categorized in three sections. In the *data preparation* section we discuss five steps to prepare texts for analysis. The first step, *importing text*, covers the functions for reading texts from various types of file formats (e.g., txt, csv, pdf) into a *raw text corpus* in R. The steps *string operations* and *preprocessing* cover techniques for manipulating raw texts and processing them into *tokens* (i.e., units of text, such as words or word stems). The tokens are then used for creating the *document-term matrix* (DTM), which is a common format for representing a bag-of-words type corpus, that is used by many R text analysis packages. Other non-bag-of-words formats, such as the tokenlist, are briefly touched upon in the *advanced topics* section. Finally, it is a common step to *filter and weight* the terms in the DTM. These

Table 1
An overview of text analysis operations, with the R packages used in this teacher's corner

Operation	**R packages**	
	example	alternatives
Data preparation		
importing text	readtext	jsonlite, XML, antiword, readxl, pdftools
string operations	stringi	stringr
preprocessing	quanteda	stringi, tokenizers, snowballC, tm, etc.
document-term matrix (DTM)	quanteda	tm, tidytext, Matrix
filtering and weighting	quanteda	tm, tidytext, Matrix
Analysis		
dictionary	quanteda	tm, tidytext, koRpus, corpustools
supervised machine learning	quanteda	RTextTools, kerasR, austin
unsupervised machine learning	topicmodels	quanteda, stm, austin, text2vec
text statistics	quanteda	koRpus, corpustools, textreuse
Advanced topics		
advanced NLP	spacyr	coreNLP, cleanNLP, koRpus
word positions and syntax	corpustools	quanteda, tidytext, koRpus

Figure 1. Order of text analysis operations for data preparation and analysis.



steps are generally performed in the presented sequential order (see Figure 1 for conceptual illustration). As we will show, there are R packages that provide convenient functions that manage multiple data preparation steps in a single line of code. Still, we first discuss and demonstrate each step separately to provide a basic understanding of the purpose of each step, the choices that can be made and the pitfalls to watch out for.

The *analysis* section discusses four text analysis methods that have become popular in communication research (Boumans & Trilling, 2016) and that can be performed with a DTM as input. Rather than being competing approaches, these methods have different advantages and disadvantages, so choosing the best method for a study depends largely on the research question, and sometimes different methods can be used complementarily (Grimmer & Stewart, 2013). Accordingly, our recommendation is to become familiar with each type of method. To demonstrate the general idea of each type of method, we provide code for typical analysis examples. Furthermore, It is important to note that different types of analysis can also have different implications for how the data should be prepared. For each type of analysis we therefore address general considerations for data preparation.

Finally, the additional *advanced topics* section discusses alternatives for data prepara-

tion and analysis that require external software modules or that go beyond the bag-of-words assumption, using word positions and syntactic relations. The purpose of this section is to provide a glimpse of alternatives that are possible in R, but might be more difficult to use.

Within each category we distinguish several groups of operations, and for each operation we demonstrate how they can be implemented in R. To provide parsimonious and easy to replicate examples, we have chosen a specific selection of packages that are easy to use and broadly applicable. However, there are many alternative packages in R that can perform the same or similar operations. Due to the open-source nature of R, different people from often different disciplines have worked on similar problems, creating some duplication in functionality across different packages. This also offers a range of choice, however, providing alternatives to suit a user's needs and tastes. Depending on the research project, as well as personal preference, other packages might be better suited to different readers. While a fully comprehensive review and comparison of text analysis packages for R is beyond our scope here—especially given that existing and new packages are constantly being developed—we have tried to cover, or at least mention, a variety of alternative packages for each text analysis operation.[6] In general, these packages often use the same standards for data formats, and thus are easy to substitute or combine with the other packages discussed in this teacher's corner.

Data preparation

Data preparation is the starting point for any data analysis. Not only is computational text analysis no different in this regard, but also frequently presents special challenges for data preparation that can be daunting for novice and advanced practitioners alike. Furthermore, preparing texts for analysis requires making choices that can affect the accuracy, validity, and findings of a text analysis study as much as the techniques used for the analysis (Crone, Lessmann, & Stahlbock, 2006; Günther & Quandt, 2016; Leopold & Kindermann, 2002). Here we distinguish five general steps: importing text, string operations, preprocessing, creating a document-term matrix (DTM), and filtering and weighting the DTM.

Importing text

Getting text into R is the first step in any R-based text analytic project. Textual data can be stored in a wide variety of file formats. R natively supports reading regular flat text files such as CSV and TXT, but additional packages are required for processing formatted text files such as JSON (Ooms, 2014), HTML, and XML (Lang & the CRAN Team, 2017), and for reading complex file formats such as Word (Ooms, 2017a), Excel (Wickham & Bryan, 2017) and PDF (Ooms, 2017b). Working with these different packages and their different interfaces and output can be challenging, especially if different file formats are used together in the same project. A convenient solution for this problem is the `readtext` package(Benoit & Obeng, 2017), that wraps various import packages together to offer a single catch-all function for importing many types of data in a uniform format. The following lines of code illustrate how to read a CSV file with the `readtext` function, by providing the path to the file as the main argument (the path can also be an URL, as used in our example). An online appendix with copyable code available from `https://github.com/kasperwelbers/text_analysis_in_R`.

```
install.packages("readtext")
library(readtext)

# url to Inaugural Address demo data that is provided by the readtext package
filepath <- "http://bit.ly/2uhqjJE?.csv"

rt <- readtext(filepath, text_field = "texts")
rt
```

```
readtext object consisting of 5 documents and 3 docvars.
# data.frame [5 x 5]
          doc_id                text  Year  President FirstName
           <chr>               <chr> <int>      <chr>     <chr>
1 2uhqjJE?.csv.1 "\"Fellow-Cit\"..."  1789 Washington    George
2 2uhqjJE?.csv.2 "\"Fellow cit\"..."  1793 Washington    George
3 2uhqjJE?.csv.3 "\"When it wa\"..."  1797      Adams      John
4 2uhqjJE?.csv.4 "\"Friends an\"..."  1801  Jefferson    Thomas
5 2uhqjJE?.csv.5 "\"Proceeding\"..."  1805  Jefferson    Thomas
```

The same function can be used for importing all formats mentioned above, and the path can also reference a (zip) folder to read all files within. In most cases, the only thing that has to be specified is the name of the field that contains the texts. Not only can multiple files be references using simple, "glob"-style pattern matches, such as `/myfiles/*.txt`, but also the same command will recurse through sub-directories to locate these files. Each file is automatically imported according to its format, making it very easy to import and work with data from different input file types.

Another important consideration is that texts can be represented with different character encodings. Digital text requires binary code to be mapped to semantically meaningful characters, but many different such mappings exist, with widely different methods of encoding "extended" characters, including letters with diacritical marks, special symbols, and emoji. In order to be able to map all known characters to a single scheme, the Unicode standard was proposed, although it also requires a digital encoding format (such as the UTF-8 format, but also UTF-16 or UTF-32). Our recommendation is simple: in R, ensure that all texts are encoded as UTF-8, either by reading in UTF-8 texts, or converting them from a known encoding upon import. If the encoding is unknown, readtext's encoding function can be used to guess the encoding. readtext can convert most known encodings (such as ISO-8859-2 for Central and Eastern European languages, or Windows-1250 for Cyrillic—although there are hundreds of others) into the common UTF-8 standard. R also offers additional low-level tools for converting character encodings, such as a bundled version of the GNU libiconv library, or conversion though the stringi package.

String operations

One of the core requirements of a framework for computational text analysis is the ability to manipulate digital texts. Digital text is represented as a sequence of characters, called a string. In R, strings are represented as objects called "character" types, which are vectors of strings. The group of string operations refers to the low-level operations for working with textual data. The most common string operations are joining, splitting,

and extracting parts of strings (collectively referred to as *parsing*) and the use of *regular expressions* to find or replace patterns.

Although R has numerous built-in functions for working with character objects, we recommend using the stringi package (Gagolewski, 2017) instead. Most importantly, because stringi uses the International Components for Unicode (ICU) library for proper Unicode support, such as implementing Unicode character categories (such as punctuation or spacing) and Unicode-defined rules for case conversion that work correctly in all languages. An alternative is the stringr package (Wickham, 2017), which uses stringi as a backend, but has a simpler syntax that many end users will find sufficient for their needs.

It is often unnecessary to perform manual, low-level string operations, because the most important applications of string operations for text analysis are built into common text analysis packages. Nevertheless, access to low-level string operations provides a great deal of versatility, which can be crucial when standardized solutions are not an option for a specific use case. The following example shows how to perform some basic cleaning with stringi functions: removing boilerplate content in the form of markup tags, stripping extraneous whitespace, and converting to lower case.

```
install.packages("stringi")
library(stringi)
x <- c("The first string", ' The <font size="6">second string</font>')

x <- stri_replace_all(x, "", regex = "<.*?>")   # remove html tags
x <- stri_trim(x)                               # strip surrounding whitespace
x <- stri_trans_tolower(x)                      # transform to lower case
x
```

```
[1] "the first string"  "the second string"
```

As with most functions in R, stringi operations are *vectorized*, meaning they apply to each element of a vector. Manipulation of vectors of strings is the recommended approach in R, since looping over each element and processing it separately in R is very inefficient.

Preprocessing

For most computational text analysis methods, full texts must be *tokenized* into smaller, more specific text features, such as words or word combinations. Also, the computational performance and accuracy of many text analysis techniques can be improved by normalizing features, or by removing "stopwords": words designated in advance to be of no interest, and which are therefore discarded prior to analysis. Taken together, these preparatory steps are commonly referred to as "preprocessing". Here we first discuss several of the most common preprocessing techniques, and show how to perform each technique with the quanteda package.

In practice, all of these preprocessing techniques can be applied in one function when creating a document-term matrix, as we will demonstrate in the *DTM* section. Here, we show each step separately to illustrate what each technique does.

Tokenization. Tokenization is the process of splitting a text into tokens. This is crucial for computational text analysis, because full texts are too specific to perform any

meaningful computations with. Most often tokens are words, because these are the most common semantically meaningful components of texts.

For many languages, splitting texts by words can mostly be done with low-level string processing due to clear indicators of word boundaries, such as white spaces, dots and commas. A good tokenizer, however, must also be able to handle certain exceptions, such as the period in the title "Dr.", which can be confused for a sentence boundary. Furthermore, tokenization is more difficult for languages where words are not clearly separated by white spaces, such as Chinese and Japanese. To deal with these cases, some tokenizers include dictionaries of patterns for splitting texts. In R, the stringi package is often used for sentence and word disambiguation, for which it leverages dictionaries from the ICU library. There is also a dedicated package for text tokenization, called tokenizers (Mullen, 2016b).

The following code uses quanteda's (Benoit et al., 2017) tokens function to split a single sentence into words. The tokens function returns a list whose elements each contain the tokens of the input texts as a character vector.

```
install.packages("quanteda")
library(quanteda)

text <- "An example of preprocessing techniques"
toks <- tokens(text)  # tokenize into unigrams
toks
```

```
tokens from 1 document.
text1 :
[1] "An"            "example"       "of"            "preprocessing"
[5] "techniques"
```

Normalization: Lowercasing and stemming. The process of normalization broadly refers to the transformation of words into a more uniform form. This can be important if for a certain analysis a computer has to recognize when two words have (roughly) the same meaning, even if they are written slightly differently. Another advantage is that it reduces the size of the vocabulary (i.e., the full range of features used in the analysis). A simple but important normalization techniques is to make all text lower case. If we do not perform this transformation, then a computer will not recognize that two words are identical if one of them was capitalized because it occurred at the start of a sentence.

Another argument for normalization is that a base word might have different morphological variations, such as the suffixes from conjugating a verb, or making a noun plural. For purposes of analysis, we might wish to consider these variations as equivalent because of their close semantic relation, and because reducing the feature space is generally desirable when multiple features are in fact closely related. A technique for achieving this is *stemming*, which is essentially a rule-based algorithm that converts inflected forms of words into their base forms (stems). A more advanced technique is *lemmatization*, which uses a dictionary to replace words with their morphological root form. However, lemmatization in R requires external software modules (see the *advanced preprocessing* section for instructions) and for weakly inflected languages such as modern English, stemming is often sufficient. In R, the SnowballC package (Bouchet-Valat, 2014; Porter, 2001) is used in many text analysis packages (such as quanteda and tm) to implement stemming, and currently

supports 15 different languages. Lowercasing and stemming of character, tokens, or feature vectors can be performed in quanteda with the `_tolower` and `_wordstem` functions, such as `char_tolower` to convert character objects to lower case, or `tokens_wordstem` to stem tokens.

```
toks <- tokens_tolower(toks)
toks <- tokens_wordstem(toks)
toks
```

```
tokens from 1 document.
text1 :
[1] "an"         "exampl"     "of"         "preprocess" "techniqu"
```

In this example we see that the difference between "an" and "An" is eliminated due to lowercasing. The words "example" and "techniques" are reduced to "exampl" and "techniqu", such that any distinction between singular and plural forms is removed.

Removing stopwords. Common words such as "the" in the English language are rarely informative about the content of a text. Filtering these words out has the benefit of reducing the size of the data, reducing computational load, and in some cases also improving accuracy. To remove these words beforehand, they are matched to predefined lists of "stop words" and deleted. Several text analysis packages provide stopword lists for various languages, that can be used to manually filter out stopwords. In quanteda, the `stopwords` function returns a character vector of stopwords for a given language. A total of 17 languages are currently supported.

```
sw <- stopwords("english")   # get character vector of stopwords
head(sw)                     # show head (first 6) stopwords
```

```
[1] "i"      "me"     "my"     "myself" "we"     "our"
```

```
tokens_remove(toks, sw)
```

```
tokens from 1 document.
text1 :
[1] "exampl"     "preprocess" "techniqu"
```

Care should be taken to perform some preprocessing steps in the correct order, for instance removing stopwords prior to stemming, otherwise "during" will be stemmed into "dure" and not matched to a stopword "during". Case conversion may also create sequencing issues, although the default stopword matching used by quanteda is case-insensitive.

Conveniently, the preprocessing steps discussed above can all be performed with a single function that will automatically apply the correct order of operations. We will demonstrate this in the next section.

Document-term matrix

The document term matrix (DTM) is one of the most common formats for representing a text corpus (i.e. a collection of texts) in a bag-of-words format. A DTM is a matrix

in which rows are documents, columns are terms, and cells indicate how often each term occurred in each document. The advantage of this representation is that it allows the data to be analyzed with vector and matrix algebra, effectively moving from text to numbers. Furthermore, with the use of special matrix formats for sparse matrices, text data in a DTM format is very memory efficient and can be analyzed with highly optimized operations.

Two of the most established text analysis packages in R that provide dedicated DTM classes are tm and quanteda. Of the two, the venerable tm package is the more commonly used, with a user base of almost 10 years (Meyer, Hornik, & Feinerer, 2008) and several other R packages using its DTM classes (*DocumentTermMatrix* and *TermDocumentMatrix*) as inputs for their analytic functions. The quanteda package is a more recently developed package, built by a team supported by an ERC grant to provide state-of-the-art, high performance text analysis. Its sparse DTM class, known as a `dfm` or *document-feature matrix*, is based on the powerful Matrix package (Bates & Maechler, 2015) as a backend, but includes functions to convert to nearly every other sparse document-term matrix used in other R packages (including the tm formats). The performance and flexibility of quanteda's `dfm` format lends us to recommend it over the tm equivalent.

Another notable alternative is the tidytext package (Silge & Robinson, 2016). This is a text analysis package that is part of the *Tidyverse*[7]—a collection of R packages with a common philosophy and format. Central to the Tidyverse philosophy is that all data is arranged as a table, where (1) "each variable forms a column", (2) "each observation forms a row", and (3) "each type of observational unit forms a table" (Wickham et al., 2014, 4). As such, tidytext does not strictly use a document term matrix, but instead represents the same data in a long format, where each (non-zero) value of the DTM is a row with the columns document, term, and count (note that this is essentially a triplet format for sparse matrices, with the columns specifying the row, column and value). This format can be less memory efficient and make matrix algebra less easily applicable, but has the advantage of being able to add more variables (e.g., a sentiment score) and enables the use of the entire Tidyverse arsenal. Thus, for users that prefer the tidy data philosophy, tidytext can be a good alternative package to quanteda or tm, although these packages can also be used together quite nicely depending on the particular operations desired.

Consistent with the other examples in this teacher's corner, we demonstrate the creation of DTMs using the quanteda package. Its `dfm` function provides a single line solution for creating a DTM from raw text, that also integrates the preprocessing techniques discussed above. These may also be built up through a sequence of lower-level functions, but many users find it convenient to go straight from a text or corpus to a DTM using this single function.

```
text <-  c(d1 = "An example of preprocessing techniques",
           d2 = "An additional example",
           d3 = "A third example")
dtm <- dfm(text,                            # input text
           tolower = TRUE, stem = TRUE,     # set lowercasing and stemming to TRUE
           remove = stopwords("english"))  # provide the stopwords for deletion
dtm
```

```
Document-feature matrix of: 3 documents, 5 features (53.3% sparse).
3 x 5 sparse Matrix of class "dfmSparse"
    features
docs exampl preprocess techniqu addit third
  d1      1          1        1     0     0
  d2      1          0        0     1     0
  d3      1          0        0     0     1
```

The DTM can also be created from a quanteda corpus object, which stores text and associated meta-data, including document-level variables. When a corpus is tokenized or converted into a DTM, these document-level variables are saved in the object, which can be very useful later when the documents in the DTM need to be used as covariates in supervised machine learning. The stored document variables also make it possible to aggregate quanteda objects by groups, which is extremely useful when texts are stored in small units—like Tweets—but need to be aggregated in a DTM by grouping variables such as users, dates, or combinations of these.

Because quanteda is compatible with the pkgreadtext package, creating a corpus from texts on disk takes only a single additional step. In the following example we create a DTM from the readtext data as imported above.

```
fulltext <- corpus(rt)                                # create quanteda corpus
dtm <- dfm(fulltext, tolower = TRUE, stem = TRUE,   # create dtm with preprocessing
           remove_punct = TRUE,remove = stopwords("english"))
dtm
```

```
Document-feature matrix of: 5 documents, 1,405 features (67.9% sparse).
```

Filtering and weighting

Not all terms are equally informative for text analysis. One way to deal with this is to remove these terms from the DTM. We have already discussed the use of stopword lists to remove very common terms, but there are likely still other common words and this will be different between corpora. Furthermore, it can be useful to remove very rare terms for tasks such as category prediction (Yang & Pedersen, 1997) or topic modeling (Griffiths & Steyvers, 2004). This is especially useful for improving efficiency, because it can greatly reduce the size of the vocabulary (i.e., the number of unique terms), but it can also improve accuracy. A simple but effective method is to filter on document frequencies (the number of documents in which a term occurs), using a threshold for minimum and maximum number (or proportion) of documents (Griffiths & Steyvers, 2004; Yang & Pedersen, 1997).

Instead of removing less informative terms, an alternative approach is assign them variable weights. Many text analysis techniques perform better if terms are weighted to take an estimated information value into account, rather than directly using their occurrence frequency. Given a sufficiently large corpus, we can use information about the distribution of terms in the corpus to estimate this information value. A popular weighting scheme that does so is term frequency-inverse document frequency (*tf-idf*), which down-weights that occur in many documents in the corpus.

Using a document frequency threshold and weighting can easily be performed on a DTM. quanteda includes the functions `docfreq`, `tf`, and `tfidf`, for obtaining document frequency, term frequency, and *tf-idf* respectively. Each function has numerous options for implementing the SMART weighting scheme (Manning et al., 2008). As a high-level wrapper to these, quanteda also provides the `dfm_weight` function. In the example below, the word "senat[e]" has a higher weight than the less informative term "among", which both occur once in the first document.

```
doc_freq <- docfreq(dtm)         # document frequency per term (column)
dtm <- dtm[, doc_freq >= 2]      # select terms with doc_freq >= 2
dtm <- dfm_weight(dtm, "tfidf")  # weight the features using tf-idf
head(dtm)
```

```
Document-feature matrix of: 5 documents, 6 features (40% sparse).
5 x 6 sparse Matrix of class "dfmSparse"
       features
docs    fellow-citizen   senat    hous    repres      among       life
  text1      0.2218487 0.39794 0.79588 0.4436975 0.09691001 0.09691001
  text2      0         0       0       0         0          0
  text3      0.6655462 0.39794 1.19382 0.6655462 0.38764005 0.19382003
  text4      0.4436975 0       0       0.2218487 0.09691001 0.09691001
  text5      0         0       0       0         0.67837009 0.19382003
```

Analysis

For an overview of text analysis approaches we build on the classification proposed by Boumans and Trilling (2016) in which three approaches are distinguished: *counting and dictionary* methods, *supervised machine learning*, and *unsupervised machine learning*. They position these approaches, in this order, on a dimension from most deductive to most inductive. Deductive, in this scenario, refers to the use of an *a priori* defined coding scheme. In other words, the researchers know beforehand what they are looking for, and only seek to automate this analysis. The relation to the concept of deductive reasoning is that the researcher assumes that certain rules, or premises, are true (e.g., a list of words that indicates positive sentiment) and thus can be applied to draw conclusions about texts. Inductive, in contrast, means here that instead of using an a priori coding scheme, the computer algorithm itself somehow extracts meaningful codes from texts. For example, by looking for patterns in the co-occurrence of words and finding latent factors (e.g., topics, frames, authors) that explain these patterns—at least mathematically. In terms of inductive reasoning, it can be said that the algorithm creates broad generalizations based on specific observations.

In addition to these three categories, we also consider a *statistics* category, encompassing all techniques for describing a text or corpus in numbers. Like unsupervised learning, these techniques are inductive in the sense that no a priori coding scheme is used, but they do not use machine learning.

For the example code for each type of analysis, we use the Inaugural Addresses of US presidents (N = 58) that is included in the quanteda package.

```
dtm <- dfm(data_corpus_inaugural, stem = TRUE, remove = stopwords("english"),
           remove_punct = TRUE)
dtm
```

```
## Document-feature matrix of: 58 documents, 5,405 features (89.2% sparse).
```

Counting and dictionary

The dictionary approach broadly refers to the use of patterns—from simple keywords to complex Boolean queries and regular expressions—to count how often certain concepts occur in texts. This is a deductive approach, because the dictionary defines a priori what codes are measured and how, and this is not affected by the data.[8] Using dictionaries is a computationally simple but powerful approach. It has been used to study subjects such as media attention for political actors (Schuck, Xezonakis, Elenbaas, Banducci, & De Vreese, 2011; Vliegenthart, Boomgaarden, & Van Spanje, 2012) and framing in corporate news (Schultz, Kleinnijenhuis, Oegema, Utz, & Van Atteveldt, 2012). Dictionaries are also a popular approach for measuring sentiment (De Smedt & Daelemans, 2012; Mostafa, 2013; Taboada, Brooke, Tofiloski, Voll, & Stede, 2011) as well as other dimensions of subjective language (Tausczik & Pennebaker, 2010). By combining this type of analysis with information from advanced NLP techniques for identifying syntactic clauses, it also becomes possible to perform more fine-grained analyses, such as sentiment expressions attributed to specific actors (Van Atteveldt, 2008), or actions and affections from one actor directed to another (Van Atteveldt, Sheafer, Shenhav, & Fogel-Dror, 2017).

The following example shows how to apply a dictionary to a quanteda DTM. The first step is to create a dictionary object (here called `myDict`), using the dictionary function. For simplicity our example uses a very simple dictionary, but it is is also possible to import large, pre-made dictionaries, including files in other text analysis dictionary formats such as LIWC, Wordstat, and Lexicoder. Dictionaries can also be written and imported from YAML files, and can include patterns of fixed matches, regular expressions, or the simpler "glob" pattern match (using just * and ? for wildcard characters) common in many dictionary formats. With the `dfm_lookup` function, the dictionary object can then be applied on a DTM to create a new DTM in which columns represent the dictionary codes.

```
myDict <- dictionary(list(terror = c("terror*"),
                          economy = c("job*", "business*", "econom*")))
dict_dtm <- dfm_lookup(dtm, myDict, nomatch = "_unmatched")
tail(dict_dtm)
```

```
Document-feature matrix of: 6 documents, 3 features (16.7% sparse).
6 x 3 sparse Matrix of class "dfmSparse"
             features
docs          terror economy _unmatched
  1997-Clinton      2       3       1125
  2001-Bush         0       2        782
  2005-Bush         0       1       1040
  2009-Obama        1       7       1165
  2013-Obama        0       6       1030
  2017-Trump        1       5        709
```

Supervised machine learning

The supervised machine learning approach refers to all classes of techniques in which an algorithm learns patterns from an annotated set of training data. The intuitive idea is that these algorithms can learn how to code texts if we give them enough examples of how they should be coded. A straightforward example is sentiment analysis, using a set of texts that are manually coded as *positive*, *neutral*, or *negative*, based on which the algorithm can learn which features (words or word combinations) are more likely to occur in positive or negative texts. Given an unseen text (from which the algorithm was not trained), the sentiment of the text can then be estimated based on the presence of these features. The deductive part is that the researchers provide the training data, which contains good examples representing the categories that the researchers are attempting to predict or measure. However, the researchers do not provide explicit rules for how to look for these codes. The inductive part is that the supervised machine learning algorithm learns these rules from the training data. To paraphrase a classic syllogism: if the training data is a list of people that are either mortal or immortal, then the algorithm will learn that all men are extremely likely to be mortal, and thus would estimate that Socrates is mortal as well.

To demonstrate this, we train a model to predict whether an Inaugural Address was given before World War II—which we expect because prominent issues shift over time, and after wars in particular. Some dedicated packages for supervised machine learning are RTextTools (Jurka, Collingwood, Boydstun, Grossman, & Van Atteveldt, 2014) and kerasR (Arnold, 2017b). For this example, however, we use a classifier that is included in quanteda. Before we start, we set a custom seed for R's random number generator so that the results of the random parts of the code are always the same. To prepare the data, we add the document (meta) variable `is_prewar` to the DTM that indicates which documents predate 1945. This is the variable that our model will try to predict. We then split the DTM into training (`train_dtm`) and test (`test_dtm`) data, using a random sample of 40 documents for training and the remaining 18 documents for testing. The training data is used to train a multinomial Naive Bayes classifier (Manning et al., 2008, Ch. 13) which we assign to `nb_model`. To test how well this model predicts whether an Inaugural Address predates the war, we predict the code for the test data, and make a table in which the rows show the prediction and the columns show the actual value of the `is_prewar` variable.

```
set.seed(2)
# create a document variable indicating pre or post war
docvars(dtm, "is_prewar") <- docvars(dtm, "Year") < 1945

# sample 40 documents for the training set and use remaining (18) for testing
train_dtm <- dfm_sample(dtm, size = 40)
test_dtm <- dtm[setdiff(docnames(dtm), docnames(train_dtm)), ]

# fit a Naive Bayes multinomial model and use it to predict the test data
nb_model <- textmodel_NB(train_dtm, y = docvars(train_dtm, "is_prewar"))
pred_nb <- predict(nb_model, newdata = test_dtm)

# compare prediction (rows) and actual is_prewar value (columns) in a table
table(prediction = pred_nb$nb.predicted, is_prewar = docvars(test_dtm, "is_prewar"))
```

```
          is_prewar
prediction FALSE TRUE
     FALSE     8    0
     TRUE      0   10
```

The results show that the predictions are perfect. Of the eight times that FALSE (i.e. Inaugural Address does not predate the war) was predicted, and the 10 times that TRUE was predicted, this was actually the case.

Unsupervised machine learning

In unsupervised machine learning approaches, no coding rules are specified and no annotated training data is provided. Instead, an algorithm comes up with a model by identifying certain patterns in text. The only influence of the researcher is the specification of certain parameters, such as the number of categories into which documents are classified. Popular examples are topic modeling for automatically classifying documents based on an underlying topical structure (Blei et al., 2003; Roberts et al., 2014) and the "Wordfish" parametric factor model (Proksch & Slapin, 2009) for scaling documents on a single underlying dimension, such as left-right ideology.

Grimmer and Stewart (2013) argue that supervised and unsupervised machine learning are not competitor methods, but fulfill different purposes and can very well be used to complement each other. Supervised methods are the most suitable approach if documents need to be placed in predetermined categories, because it is unlikely that an unsupervised method will yield a categorization that reflects these categories and how the researcher interprets them. The advantage of the somewhat unpredictable nature of unsupervised methods is that it can come up with categories that the researchers had not considered. (Conversely, this may also present challenges for post-hoc interpretation when results are unclear.)

To demonstrate the essence of unsupervised learning, the example below shows how to fit a topic model in R using the topicmodels package (Grun & Hornik, 2011). To focus more specifically on topics within the inaugural addresses, and to increase the number of texts to model, we first split the texts by paragraph and create a new DTM. From this DTM we remove terms with a document frequency of five and lower to reduce the size of the vocabulary (less important for current example) and use quanteda's convert function to convert the DTM to the format used by topicmodels. We then train a vanilla LDA topic model(Blei et al., 2003) with five topics—using a fixed seed to make the results reproducible, since LDA is non-deterministic.

```
install.packages("topicmodels")
library(topicmodels)

texts = corpus_reshape(data_corpus_inaugural, to = "paragraphs")

par_dtm <- dfm(texts, stem = TRUE,              # create a document-term matrix
               remove_punct = TRUE, remove = stopwords("english"))
par_dtm <- dfm_trim(par_dtm, min_count = 5)     # remove rare terms
par_dtm <- convert(par_dtm, to = "topicmodels") # convert to topicmodels format

set.seed(1)
lda_model <- topicmodels::LDA(par_dtm, method = "Gibbs", k = 5)
terms(lda_model, 5)
```

```
     Topic 1     Topic 2  Topic 3   Topic 4    Topic 5
[1,] "govern"    "nation" "great"   "us"       "shall"
[2,] "state"     "can"    "war"     "world"    "citizen"
[3,] "power"     "must"   "secur"   "new"      "peopl"
[4,] "constitut" "peopl"  "countri" "american" "duti"
[5,] "law"       "everi"  "unit"    "america"  "countri"
```

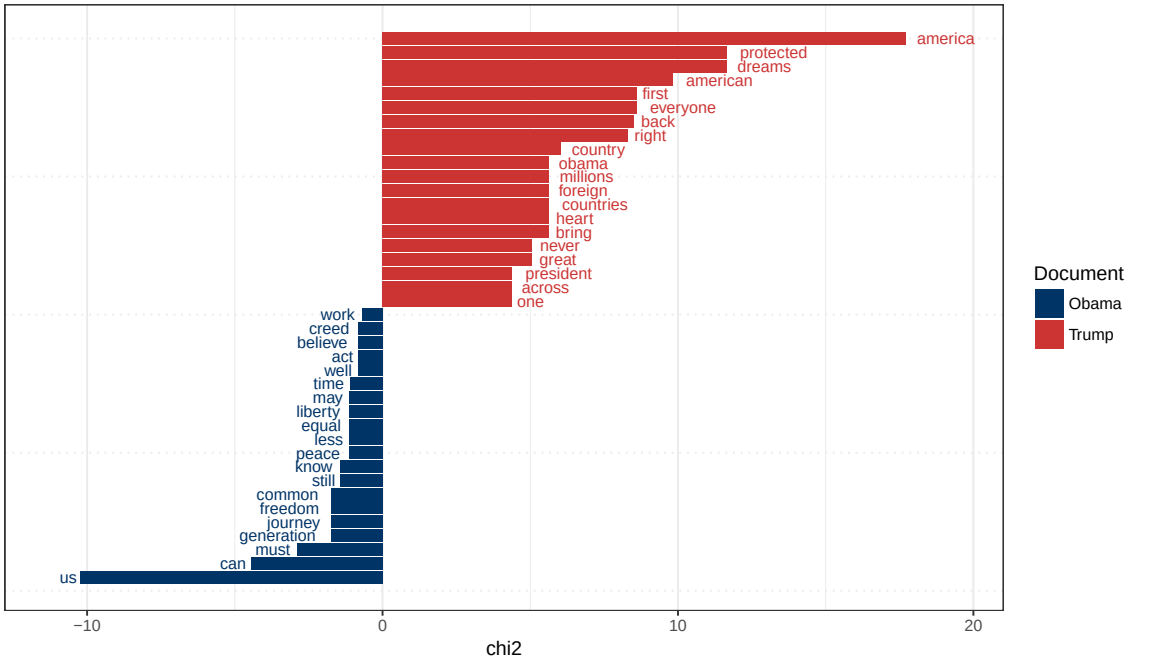
The results show the first five terms of the five topics. Although this is a basic example, the idea of "topics" being found bottom-up from the data can be seen in the semantic coherence of terms within the same topic. In particular, topic one seems to revolve around governance, with the terms "govern[ance]", "power", "state", "constitut[ion]", and "law".

Statistics

Various statistics can be used to describe, explore and analyze a text corpus. An example of a popular technique is to rank the information value of words inside a corpus and then visualize the most informative words as a word cloud to get a quick indication of what a corpus is about. Text statistics (e.g., average word and sentence length, word and syllable counts) are also commonly used as an operationalization of concepts such as readability (Flesch, 1948) or lexical diversity (McCarthy & Jarvis, 2010). A wide range of such measures is available in R with the koRpus package (Michalke, 2017). Furthermore, there are many useful applications of calculating term and document similarities (which are often based on the inner product of a DTM or transposed DTM), such as analyzing semantic relations between words or concepts and measuring content homogeneity. Both techniques are supported in quanteda, corpustools (Welbers & Van Atteveldt, 2016), or dedicated packages such as textreuse (Mullen, 2016a) for text overlap.

A particularly useful technique is to compare the term frequencies of two corpora, or between two subsets of the same corpus. For instance, to see which words are more likely to occur in documents about a certain topic. In addition to providing a way to quickly explore how this topic is discussed in the corpus, this can provide input for developing better queries. In the following example we show how to perform this technique in quanteda (results in Figure 2).

Figure 2. Keyness plot comparing relative word frequencies for Trump and Obama.




```
# create DTM that contains Trump and Obama speeches
corpus_pres = corpus_subset(data_corpus_inaugural,
                            President %in% c("Obama", "Trump"))
dtm_pres = dfm(corpus_pres, groups = "President",
               remove = stopwords("english"), remove_punct = TRUE)

# compare target (in this case Trump) to rest of DTM (in this case only Obama).
keyness = textstat_keyness(dtm_pres, target = "Trump")
textplot_keyness(keyness)
```

```
output in Figure 2.
```

Here, the signed χ^2 measure of association indicates that "america", "american", and "first" were used with far greater frequency by Trump than Obama, while "us", "can", "freedom", "peace", and "liberty" were among the words much more likely to be used by Obama than by Trump.

Advanced topics

The data preparation and bag-of-words analysis techniques discussed above are the basis for the majority of the text analysis approaches that are currently used in communication research. For certain types of analyses, however, techniques might be required that rely on external software modules, are more computationally demanding, or that are more complicated to use. In this section we briefly elaborate on some of these advanced approaches that are worth taking note of.

Advanced NLP

In addition to the preprocessing techniques discussed in the data preparation section, there are powerful preprocessing techniques that rely on more advanced natural language processing (NLP). At present, these techniques are not available in native R, but rely on external software modules that often have to be installed outside of R. Many of the advanced NLP techniques are also much more computationally demanding, thus taking more time to perform. Another complication is that these techniques are language specific, and often only available for English and a few other big languages.

Several R packages provide interfaces for external NLP modules, so that once these modules have been installed, they can easily be used from within R. The coreNLP package (Arnold & Tilton, 2016) provides bindings for Stanford CoreNLP java library (Manning et al., 2014), which is a full NLP parser for English, that also supports (albeit with limitations) Arabic, Chinese, French, German, and Spanish. The spacyr package (Benoit & Matsuo, 2017) provides an interface for the spaCy module for Python, which is comparable to CoreNLP but is faster, and supports English and (again with some limitations) German and French. A third package, cleanNLP (Arnold, 2017a), conveniently wraps both CoreNLP and spaCy, and also includes a minimal back-end that does not rely on external dependencies. This way it can be used as a swiss army knife, choosing the approach that best suits the occasion and for which the back-end is available, but with standardized output and methods.

Advanced NLP parsers generally perform all techniques in one go. In the following example we use the spacyr package to parse a sentence, that will be used to illustrate four advanced NLP techniques: lemmatization, part-of-speech (POS) tagging, named entity recognition (NER) and dependency parsing.

```
install.packages("spacyr")
library(spacyr)
spacy_initialize()

d <- spacy_parse("Bob Smith gave Alice his login information.", dependency = TRUE)
d[, -c(1,2)]
```

```
  token_id       token       lemma   pos head_token_id  dep_rel   entity
1        1         Bob         bob PROPN             2 compound PERSON_B
2        2       Smith       smith PROPN             3    nsubj PERSON_I
3        3        gave        give  VERB             3     ROOT
4        4       Alice       alice PROPN             3   dative PERSON_B
5        5         his      -PRON-   ADJ             7     poss
6        6       login       login  NOUN             7 compound
7        7 information information  NOUN             3     dobj
8        8           .           . PUNCT             3    punct
```

Lemmatization. Lemmatization fulfills a similar purpose as stemming, but instead of cutting off the ends of terms to normalize them, a dictionary is used to replace terms with their lemma. The main advantage of this approach is that it can more accurately normalize different verb forms—such as “gave” and “give” in the example—which is particularly important for heavily inflected languages such as Dutch or German.

Part-of-speech tagging. POS tags are morpho-syntactic categories for words, such as nouns, verbs, articles and adjectives. In the example we see three proper nouns (PROPN), a verb (VERB) an adjective (ADJ), two nouns (NOUN), and punctuation (PUNCT). This information can be used to focus an analysis on certain types of grammar categories, for example, using nouns and proper names to measure similar events in news items (Welbers, Van Atteveldt, Kleinnijenhuis, & Ruigrok, 2016), or using adjectives to focus on subjective language (De Smedt & Daelemans, 2012). Similarly, it is a good approach for filtering out certain types of words, such as articles or pronouns.

Named entity recognition. Named entity recognition is a technique for identifying whether a word or sequence of words represents an entity and what type of entity, such as a person or organization. Both "Bob Smith" and "Alice" are recognized as persons. Ideally, named entity recognition is paired with co-reference resolution. This is a technique for grouping different references to the same entity, such as anaphora (e.g., he, she, the president). In the example sentence, the word "his" refers to "Bob Smith". Co-reference resolution is currently only supported by Stanford CoreNLP, but discussion on the spaCy GitHub page suggests that this feature is on the agenda.

Dependency parsing. Dependency parsing provides the syntactic relations between tokens, which can be used to analyze texts at the level of syntactic clauses (Van Atteveldt, 2008). In the `spacyr` output this information is given in the `head_token_i` and `dep_rel` columns, where the former indicates to what token a token is related and the latter indicates the type of relation. For example, we see that "Bob" is related to "Smith" (`head_token_i` 2) as a compound, thus recognizing "Bob Smith" as a single entity. Also, since "Smith" is the nominal subject (nsubj) of the verb "gave", and Alice is the dative case (dative) we know that "Bob Smith" is the one who gives to "Alice". This type of information can for instance be used to analyze who is attacking whom in news coverage about the Gaza war (Van Atteveldt et al., 2017).

Word positions and syntax

As discussed above, the bag-of-words representation of texts is memory-efficient and convenient for various types of analyses, and this often outweighs the disadvantage of losing information by dropping the word positions. For some analyses, however, the order of words and syntactical properties can be highly beneficial if not crucial. In this section we address some text representations and analysis techniques where word positions are maintained.

A simple but potentially powerful solution is to use higher order n-grams. That is, instead of tokenizing texts into single words (n = 1; *unigrams*), sequences of two words (n = 2; *bigrams*), three words (n = 3; *trigrams*) or more are used.[9] The use of higher order n-grams is often optional in tokenization functions. `quanteda` makes it possible to form n-grams when tokenizing, or to form n-grams from tokens already formed. Other options include the formation of "skip-grams", or n-grams from words with variable windows of adjacency. Such non-adjacent collocations form the basis for counting weighted proximity vectors, used in vector-space network-based models built on deep learning techniques (Mikolov, Chen, Corrado, & Dean, 2013; Selivanov, 2016). Below, we illustrate how to form both tri-grams and skipgrams of size three using a vector of both 0 and 1 skips.

```
text <- "an example of preprocessing techniques"
tokens(text, ngrams = 3, skip = 0:1)
```

```
tokens from 1 document.
text1 :
[1] "an_example_of"                    "an_example_preprocessing"
[3] "an_of_preprocessing"              "an_of_techniques"
[5] "example_of_preprocessing"         "example_of_techniques"
[7] "example_preprocessing_techniques" "of_preprocessing_techniques"
```

The advantage of this approach is that these n-grams can be used in the same way as unigrams: we can make a DTM with n-grams, and perform all the types of analyses discussed above. Functions for creating a DTM in R from raw text therefore often allow the use of n-grams other than unigrams. For some analysis this can improve performance. Consider, for instance, the importance of negations and amplifiers in sentiment analysis, such as "not good" and "very bad" (Aue & Gamon, 2005). An important disadvantage, however, is that using n-grams is more computationally demanding, since there are many more unique sequences of words than individual words. This also means that more data is required to get a good estimate of the distribution of n-grams.

Another approach is to preserve the word positions after tokenization. This has three main advantages. First, the order and distance of tokens can be taken into account in analyses, enabling analyses such as the co-occurrence of words within a word window. Second, the data can be transformed into both a fulltext corpus (by pasting together the tokens) and a DTM (by dropping the token positions). This also enables the results of some text analysis techniques to be visualized in the text, such as coloring words based on a word scale model (Slapin & Proksch, 2008) or to produce browsers for topic models (Gardner et al., 2010). Third, each token can be annotated with token specific information, such as obtained from advanced NLP techniques. This enables, for instance, the use of dependency parsing to perform an analysis at the level of syntactic clauses (Van Atteveldt et al., 2017). The main disadvantage of preserving positions is that it is very memory inefficient, especially if all tokens are kept and annotations are added.

A common way to represent tokens with positions maintained is a data frame in which rows represent tokens, ordered by their position, and columns represent different variables pertaining to the token, such as the literal text, its lemma form and its POS tag. An example of this type of representation was shown above in the advanced NLP section, in the spacyr token output. Several R packages provide dedicated classes for tokens in this format. One is the koRpus package (Michalke, 2017), which specializes in various types of text statistics, in particular lexical diversity and readability. Another is corpustools (Welbers & Van Atteveldt, 2016), which focuses on managing and querying annotated tokens, and on reconstructing texts to visualize quantitative text analysis results in the original text content for qualitative investigation. A third option is tidytext (Silge & Robinson, 2016), which does not focus on this format of annotated tokens, but provides a framework for working with tokenized text in data frames.

For a brief demonstration of utilizing word positions, we perform a dictionary search with the corpustools package, that supports searching for words within a given word distance. The results are then viewed in key word in context (KWIC) listings. In the example, we look for the queries "freedom" and "americ*" within a distance of five words, using the

State of the Union speeches from George W. Bush and Barack Obama.

```
install.packages("corpustools")
library(corpustools)

tc <- create_tcorpus(sotu_texts, doc_column = "id")
hits <- tc$search_features('"freedom americ*"~5')
## created index for "token" column
kwic <- tc$kwic(hits, ntokens = 3)
head(kwic$kwic, 3)
```

```
[1] "...making progress toward <freedom> will find <America> is their friend..."
[2] "...friends, and <freedom> in Iraq will make <America> safer for generations..."
[3] "...men who despise <freedom>, despise <America>, and aim..."
```

Conclusion

R is a powerful platform for computational text analysis, that can be a valuable tool for communication research. First, its well developed packages provide easy access to cutting edge text analysis techniques. As shown here, not only are most common text analysis techniques implemented, but in most cases, multiple packages offer users choice when selecting tools to implement them. Many of these packages have been developed by and for scholars, and provide established procedures for data preparation and analysis. Second, R's open source nature and excellent system for handling packages make it a convenient platform for bridging the gap between research and tool development, which is paramount to establishing a strong computational methods paradigm in communication research. New algorithms do not have to be confined to abstract and complex explanations in journal articles aimed at methodology experts, or made available through arcane code that many interested parties would not know what to do with. As an R package, algorithms can be made readily available in a standardized and familiar format.

For new users, however, choosing from the wide range of text analysis packages in R can also be daunting. With various alternatives for most techniques, it can be difficult to determine which packages are worth investing the effort to learn. The primary goal of this teacher's corner, therefore, has been to provide a starting point for scholars looking for ways to incorporate computational text analysis in their research. Our selection of packages is based on our experience as both users and developers of text analysis packages in R, and should cover the most common use cases. In particular, we advise users to become familiar with at least one established and well-maintained package that handles data preparation and management, such as quanteda, tidytext or tm. From here, it is often a small step to convert data to formats that are compatible with most of the available text analysis packages.

It should be emphasized that the selection of packages presented in this teacher's corner is not exhaustive, and does not represent which packages are the most suitable for the associated functionalities. Often, the best package for the job depends largely on specific features and problem specific priorities such as speed, memory efficiency and accuracy. Furthermore, when it comes to establishing a productive workflow, the importance

of personal preference and experience should not be underestimated. A good example is the workflow of the tidytext package (Silge & Robinson, 2016), which could be preferred by people that are familiar with the tidyverse philosophy (Wickham et al., 2014). Accordingly, the packages recommended in this teacher's corner provide a good starting point, and for many users could be all they need, but there are many other great package out there. For a more complete list of packages, a good starting point is the CRAN Task View for Natural Language Processing (Wild, 2017).

Marshall McLuhan famously stated that "we shape our tools, and thereafter our tools shape us", and in science the same can be said for how tools shape our findings. We thus argue that the establishment of a strong computational methods paradigm in communication research goes hand-in-hand with embracing open-source tool development as an inherent part of scientific practice. As such, we conclude with a call for researchers to cite R packages similar to how one would cite other scientific work.[10] This gives due credit to developers, and thereby provides a just incentive for developers to publish and maintain new code, including proper testing and documentation to facilitate the correct use of code by others. Citing packages is also paramount for the transparency of research, which is especially important when using new computational techniques, where results might vary depending on implementation choices and where the absence of bugs is often not guaranteed. Just as our theories are shaped through collaboration, transparency and peer feedback, so should we shape our tools.

Footnotes

[1]The term "data science" is a popular buzzword related to "data-driven research" and "big data" (Provost & Fawcett, 2013).

[2]Other programming environments have similar archives, such as pip for python. However, CRAN excels in how it is strictly maintained, with elaborate checks that packages need to pass before they will be accepted.

[3]The London School of Economics and Political Science recently hosted a workshop (http://textworkshop17.ropensci.org/), forming the beginnings of an rOpenSci special interest group for text analysis.

[4]For example, the tif (Text Interchange Formats) package (rOpenSci Text Workshop, 2017) describes and validates standards for common text data formats.

[5]`https://github.com/kasperwelbers/text_analysis_in_R`.

[6]For a list that includes more packages, and that is also maintained over time, a good source is the CRAN Task View for Natural Language Processing (Wild, 2017). CRAN Task Views are expert curated and maintained lists of R packages on the Comprehensive R Archive Network, and are available for various major methodological topics.

[7]`http://www.tidyverse.org/`.

[8]Notably, there are techniques for automatically expanding a dictionary based on the semantic space of a text corpus (Watanabe, 2017). This can be said to add an inductive layer to the approach, because the coding rules (i.e., the dictionary) are to some extent learned from the data.

[9]The term n-grams can be used more broadly to refer to sequences, and is also often used for sequences of individual characters. In this teacher's corner we strictly use n-grams to refer to sequences of words.

[10]To view how to cite a package, the citation function can be used—e.g., citation("quanteda") for citing quanteda, or citation() for citing the R project. This either provides the citation details provided by the package developer or auto-generated details.

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