Tutorial 1: Processing of textual data

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2020-07-03

Contents

In this tutorial, we demonstrate how to read text data in R, tokenize texts and create a document-term matrix.

1. Reading various file formats with the `readtext` package,
2. From text to a corpus,
3. Create a document-term matrix and investigate Zipf's law

First, let's create a new R Project (File -> New Project -> Existing directory) in the provided tutorial folder. Then we create a new R File (File -> New File -> R script) and save it as "Tutorial_1.R".

Reading txt, pdf, html, docx, . . .

In case you have already a collection of document files on your disk, you can import them into R in a very convenient way provided by the `readtext` package. The package depends on some other programs or libraries in your system, e.g. to provide extraction of text from Word- and PDF-documents.

Hence, some persons encountered hurdles to install the package due to missing libraries. In this case, carefully read error messages and install the missing libraries.

For demonstration purpose, we provide in `data/documents` a random selection of documents in various file formats. First, we request a list of files in the directory to extract text from.

```
data_files <- list.files(path = "data/documents", full.names = T, recursive = T)

# View first file paths
head(data_files, 3)
```

```
## [1] "data/documents/bundestag/17_16_580-F_neu.pdf"
## [2] "data/documents/bundestag/prot_17_95.pdf"
## [3] "data/documents/bundestag/stellungnahme---buendnis-buergerenergie-e--v--data.pdf"
```

The `readtext` function from the package with the same name, detects automatically file formats of the given files list and extracts the content into a `data.frame`. The parameter `docvarsfrom` allows you to set metadata variables by splitting path names. In our example, `docvar3` contains a source type variable derived from the sub folder name.

```r
require(readtext)

extracted_texts <- readtext(data_files, docvarsfrom = "filepaths", dvsep = "/")

# View first rows of the extracted texts
head(extracted_texts)

# View beginning of the second extracted text
cat(substr(extracted_texts$text[2] , 0, 300))
```

Again, the `extracted_texts` can be written by `write.csv2` to disk for later use.

```r
write.csv2(extracted_texts, file = "data/text_extracts.csv", fileEncoding = "UTF-8")
```

We choose CSV as a convenient text column based format for easy import and export in R and other programs. Also our example data for the rest of the tutorials is provided as CSV file. Windows users: Take care of setting UTF-8 file encoding explicitly when writing text data to the hard drive.

From text to a corpus object

Set global options at the beginning of each script! When working with textual data strings, it is recommended to turn R's automatic conversion of strings into factors off.

```r
# Global options
options(stringsAsFactors = FALSE)
```

The `read.csv` command reads a **CSV** (Comma Separated Value) file from disk. Such files represent a table whose rows are represented by single lines in the files and columns are marked by a *separator* character within lines. Arguments of the command can be set to specify whether the CSV file contains a line with column names (header = `TRUE` or `FALSE`) and the character set.

We read a CSV containing 233 "State of the Union" addresses of the presidents of the United States. The texts are freely available from http://stateoftheunion.onetwothree.net.

Our CSV file has the format: `"doc_id";"speech_type";"president";"date";"text"`. Text is encapsulated into quotes (`"`). Since sepration is marked by `;` instead of `,`, we need to specify the separator char.

```r
# read csv into a data.frame
textdata <- read.csv("data/sotu.csv", header = TRUE, sep = ";", encoding = "UTF-8")
```

The texts are now available in a `data.frame` together with some metadata (document id, speech type, president). Let us first see how many documents and metadata we have read.

```r
# dimensions of the data frame
dim(textdata)
```

```
## [1] 233   5
```

```r
# column names of text and metadata
colnames(textdata)
```

```
## [1] "doc_id"      "speech_type" "president"   "date"        "text"
```

How many speeches do we have per president? This can easily be counted with the command `table`, which can be used to create a cross table of different values. If we apply it to a column, e.g. *president* of our data frame, we get the counts of the unique *president* values.

```r
table(textdata[, "president"])
```

```
##
##      Abraham Lincoln        Andrew Jackson        Andrew Johnson
##                    4                     8                     4
##         Barack Obama     Benjamin Harrison       Calvin Coolidge
##                    8                     4                     6
##     Chester A. Arthur       Donald J. Trump  Dwight D. Eisenhower
##                    4                     3                     9
## Franklin D. Roosevelt       Franklin Pierce       George H.W. Bush
##                   12                     4                     4
```

Now we want to transfer the loaded text source into a **corpus object** of the `quanteda`-package. Quanteda provides a large number of highly efficient convenience functions to process text in R [1]. First we load the package.

```r
require(quanteda)
```

A corpus object is created with the `corpus` command. As parameter, the command gets the fulltext of the documents. In our case, this is the `text`-column of the `textdata`-data.frame. The docnames-parameter of the corpus function defines which unique identifier is given to each text example in the input (values from other columns of the data frame could be imported as metadata to each document but we will not use them in this tutorial).

```r
sotu_corpus <- corpus(textdata$text, docnames = textdata$doc_id)
# have a look on the new corpus object
summary(sotu_corpus)
```

```
## Corpus consisting of 233 documents, showing 100 documents:
##
##  Text Types Tokens Sentences
##     1   460   1167        24
##     2   593   1504        40
##     3   816   2476        60
##     4   772   2287        61
##     5   803   2121        56
```

```
##      6  1137   3197            79
##      7   821   2154            53
##      8  1005   3095            78
##      9   732   2236            58
##     10   833   2368            54
##     11   597   1624            35
##     12   562   1489            40
##     13  1098   3493            90
##     14   823   2397            62
##     15   837   2463            48
##     16   746   2286            50
##     17   984   3171            78
##     18   969   3113            76
##     19   858   2606            62
##     20   956   2921            72
##     21   699   1950            40
##     22   893   2615            61
##     23   829   2439            46
##     24  1126   3495            87
##     25  1074   3521            67
##     26   831   2282            50
##     27  1050   3389            59
##     28  1086   3614            72
##     29  1222   4814           122
##     30  1243   4728           114
##     31  1196   5091           131
##     32  1070   3762            84
##     33  1319   6323           149
##     34  1265   5145           117
##     35  1593   6926           184
##     36  1750   9175           247
##     37  2147   9798           212
##     38  1817   8406           172
##     39  1819   7578           165
##     40  1832   7937           195
##     41  2356  11408           299
##     42  2767  16271           391
##     43  1792   7716           165
##     44  1916   8476           199
##     45  1741   8494           181
##     46  2581  14454           318
##     47  2240  11567           239
##     48  2421  13212           294
##     49  2368  12341           281
##     50  2388  12426           264
##     51  2638  14498           341
##     52  2153   9700           182
##     53  2002   8836           197
##     54  2037   9018           205
##     55  1958   8635           193
##     56  2115  10019           267
##     57  2689  17517           446
##     58  2782  19849           476
##     59  2687  17782           440
```

```
##     60  3289  23273         597
##     61  1863   8222         210
##     62  2061   9004         232
##     63  2696  14328         351
##     64  2379  10705         284
##     65  2292  10375         231
##     66  2427  10985         267
##     67  2458  12581         274
##     68  2325  11379         255
##     69  2575  14929         406
##     70  2912  17828         518
##     71  2453  13596         396
##     72  2638  15360         484
##     73  1872   7651         213
##     74  2061   9367         319
##     75  1719   6643         200
##     76  1755   6585         207
##     77  2153  10077         276
##     78  1871   7790         202
##     79  2668  13156         381
##     80  2352  10846         281
##     81  1924   8481         247
##     82  2173   9577         266
##     83  1758   7016         211
##     84  1162   4336         112
##     85  2377  11007         292
##     86  2143  10074         273
##     87  2574  13397         347
##     88  1787   7429         192
##     89  1965   8706         218
##     90  2040   8641         237
##     91  2443  12643         313
##     92  1768   7209         191
##     93  1351   4095         118
##     94  1062   3295          92
##     95  1315   4079         108
##     96  2355   9667         288
##     97  3813  21377         559
##     98  3110  16350         416
##     99  1394   5722         123
##    100  2402   9794         239
```

A corpus is an extension of R list objects. With the `[[]]` brackets, we can access single list elements, here documents, within a corpus. We print the text of the first element of the corpus using the `texts` command.

```r
# getting a single text documents content
cat(texts(sotu_corpus[1]))
```

```
## Fellow-Citizens of the Senate and House of Representatives:
##
## I embrace with great satisfaction the opportunity which now presents itself
## of congratulating ...
```

The command `cat` prints a given character vector with correct line breaks (compare the difference of the output with the `print` method instead).

Success!!! We now have 233 speeches for further analysis available in a convenient tm corpus object!

Text statistics

A further aim of this exercise is to learn about statistical characteristics of text data. At the moment, our texts are represented as long character strings wrapped in document objects of a corpus. To analyze which word forms the texts contain, they must be **tokenized**. This means that all the words in the texts need to be identified and separated. Only in this way it is possible to count the frequency of individual word forms. A word form is also called **"type"**. The occurrence of a type in a text is a **"token"**.

For text mining, texts are further transformed into a numeric representation. The basic idea is that the texts can be represented as statistics about the contained words (or other content fragments such as sequences of two words). The list of every distinct word form in the entire corpus forms the **vocabulary** of a corpus.

For each document, we can count how often each word of the vocabulary occurs in it. By this, we get a term **frequency vector** for each document. The dimensionality of this term vector corresponds to the size of the vocabulary. Hence, the word vectors have the same form for each document in a corpus. Consequently, multiple term vectors representing different documents can be combined into a matrix. This data structure is called **document-term matrix** (DTM).

The function `dfm` (Document-Feature-Matrix; Quanteda treats words as features of a text-based dataset) of the `quanteda` package creates such a DTM. If this command is called without further parameters, the individual word forms are identified by using the tokenizer of quanteda as the word separator (see `help(tokens)`for details). Quanteda has 3 different word separation methods. The standard and smartest way uses word boundaries and punctuations to separate the text sources. The other methods rely on whitespace information an work significantly faster but not as accurate.

```r
# Create a DTM (may take a while)
DTM <- dfm(sotu_corpus)
# Show some information
DTM
```

```
## Document-feature matrix of: 233 documents, 30,358 features (94.3% sparse).
##     features
## docs fellow-citizens  of the senate and house representatives :  i embrace
##    1               1  69  97      2  41     3               3 3 11       1
##    2               1  89 122      2  45     3               3 3  8       0
##    3               1 159 242      3  73     3               3 4  6       0
##    4               1 139 195      2  56     3               3 3 21       0
##    5               1 132 180      2  49     3               3 3 12       0
##    6               1 187 273      2  86     4               3 3 18       0
## [ reached max_ndoc ... 227 more documents, reached max_nfeat ... 30,348 more features ]
```

```r
# Dimensionality of the DTM
dim(DTM)
```

```
## [1]   233 30358
```

The dimensions of the DTM, 233 rows and 30358 columns, match the number of documents in the corpus and the number of different word forms (types) of the vocabulary.

A first impression of text statistics we can get from a word list. Such a word list represents the frequency counts of all words in all documents. We can get that information easily from the DTM by summing all of its column vectors.

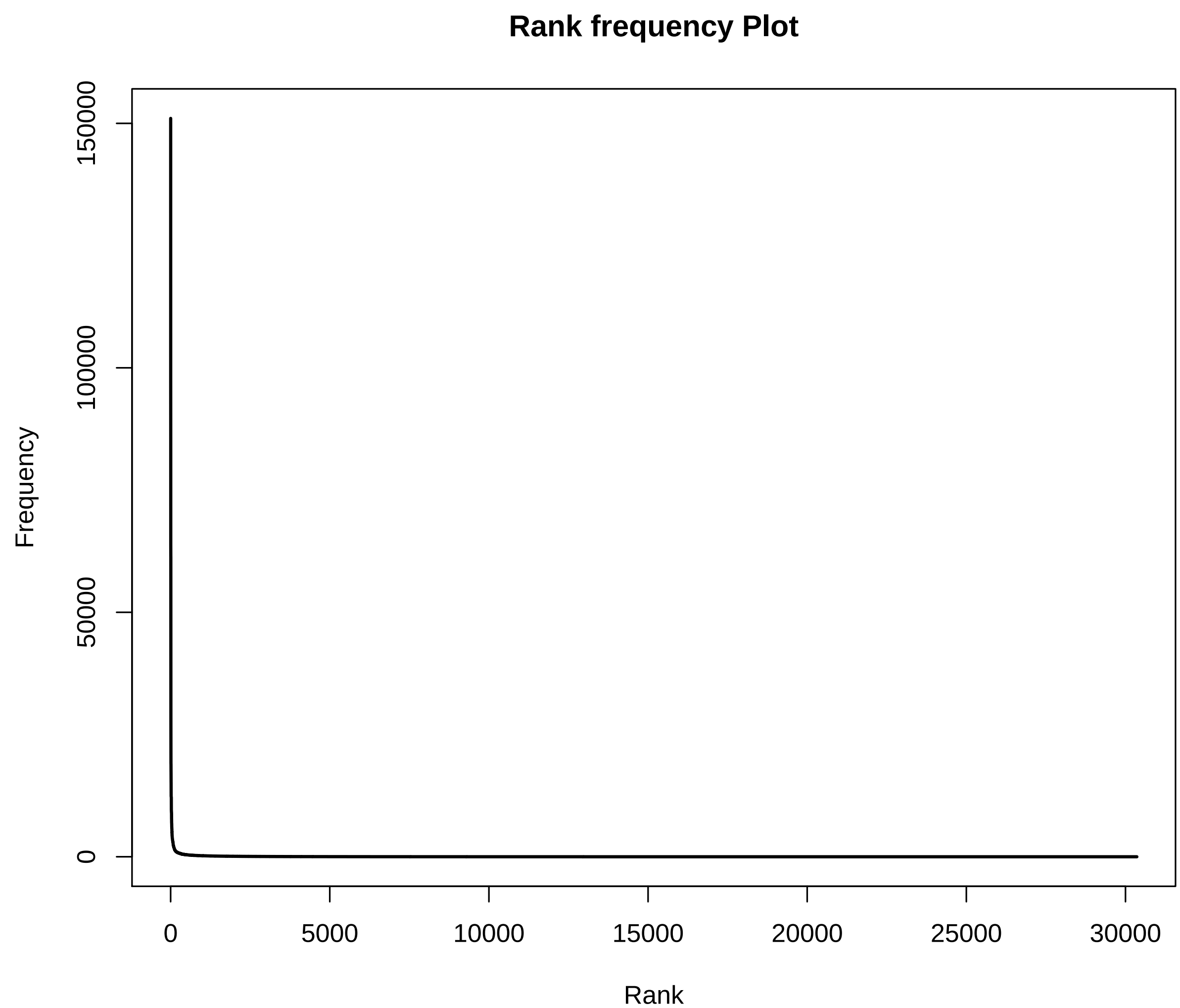
A so-called **sparse matrix** data structure is used for the document term matrix in the quanteda package (quanteda inherits the `Matrix` package for sparse matrices). Since most entries in a document term vector are 0, it would be very inefficient to actually store all these values. A sparse data structure instead stores only those values of a vector/matrix different from zero. The *Matrix* package provides arithmetic operations on sparse DTMs.

```
# sum columns for word counts
freqs <- colSums(DTM)
# get vocabulary vector
words <- colnames(DTM)
# combine words and their frequencies in a data frame
wordlist <- data.frame(words, freqs)
# re-order the wordlist by decreasing frequency
wordIndexes <- order(wordlist[, "freqs"], decreasing = TRUE)
wordlist <- wordlist[wordIndexes, ]
# show the most frequent words
head(wordlist, 25)
```

```
##        words  freqs
## the      the 151018
## of        of  97395
## ,          ,  85384
## .          .  63784
## and      and  61565
## to        to  61304
## in        in  38980
## a          a  28351
## that    that  21960
## for      for  19183
## be        be  18787
## our      our  17678
## is        is  17197
## it        it  15321
## by        by  15074
## we        we  12377
## which which  12354
## as        as  12277
## this    this  12215
## have    have  12172
## with    with  12119
## will    will   9615
## on        on   9520
## i          i   9372
## has      has   9104
```

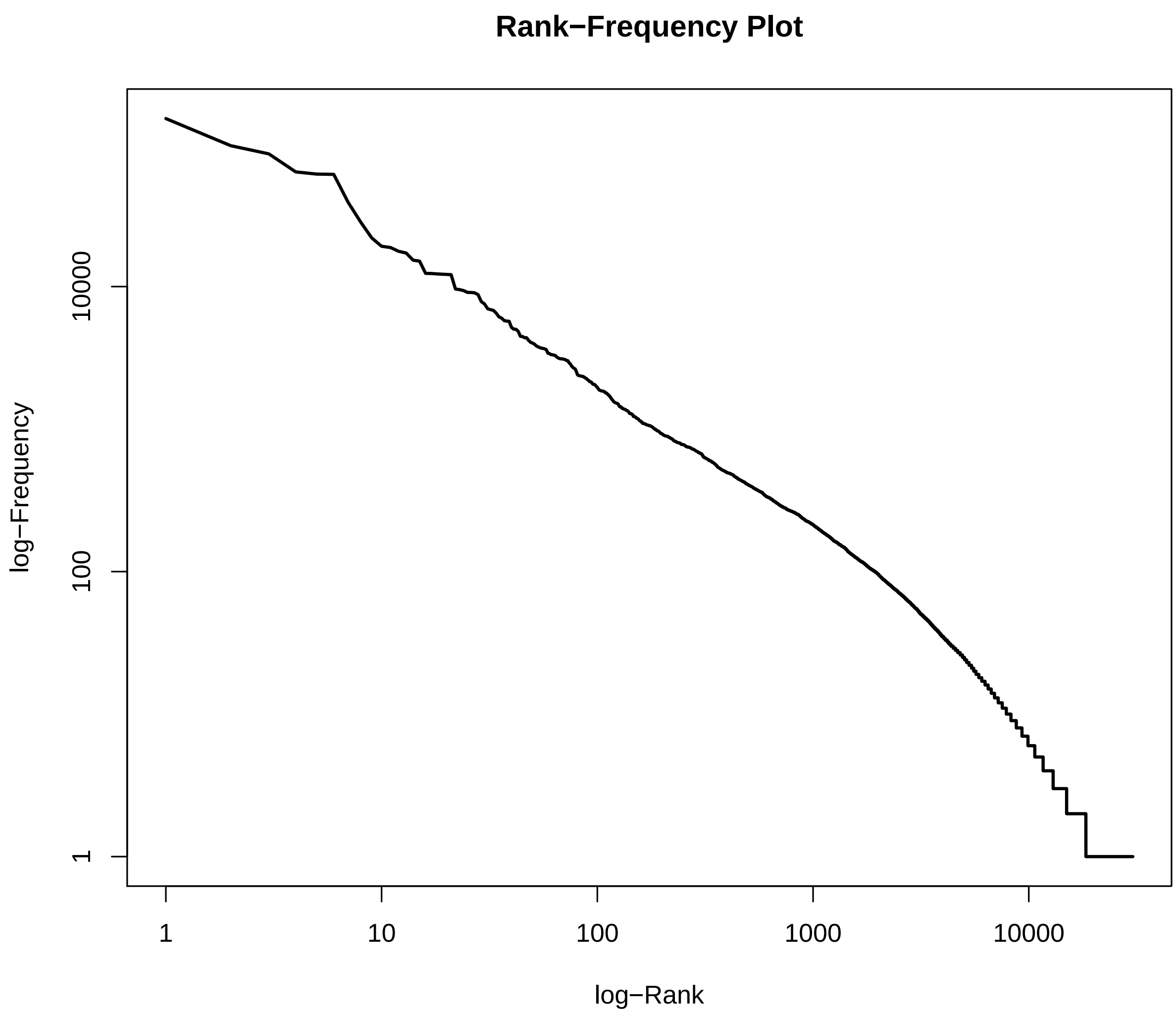
The words in this sorted list have a ranking depending on the position in this list. If the word ranks are plotted on the x axis and all frequencies on the y axis, then the Zipf distribution is obtained. This is a typical property of language data and its distribution is similar for all languages.

```r
plot(wordlist$freqs , type = "l", lwd=2, main = "Rank frequency Plot", xlab="Rank", ylab ="Frequency")
```



The distribution follows an extreme power law distribution (very few words occur very often, very many words occur very rare). The Zipf law says that the frequency of a word is reciprocal to its rank (1 / r). To make the plot more readable, the axes can be logarithmized.

```r
plot(wordlist$freqs , type = "l", log="xy", lwd=2, main = "Rank-Frequency Plot", xlab="log-Rank", ylab =
```



In the plot, two extreme ranges can be determined. Words in ranks between ca. 10,000 and 30358 can be observed only 10 times or less. Words below rank 100 can be oberved more than 1000 times in the documents. The goal of text mining is to automatically find structures in documents. Both mentioned extreme ranges of the vocabulary often are not suitable for this. Words which occur rarely, on very few documents, and words which occur extremely often, in almost every document, do not contribute much to the meaning of a text.

Hence, ignoring very rare / frequent words has many advantages:

- reducing the dimensionality of the vocabulary (saves memory)
- processing speed up
- better identification of meaningful structures.

To illustrate the range of ranks best to be used for analysis, we augment information in the rank frequency plot. First, we mark so-called **stop words**. These are words of a language that normally do not contribute to semantic information about a text. In addition, all words in the word list are identified which occur less than 10 times.

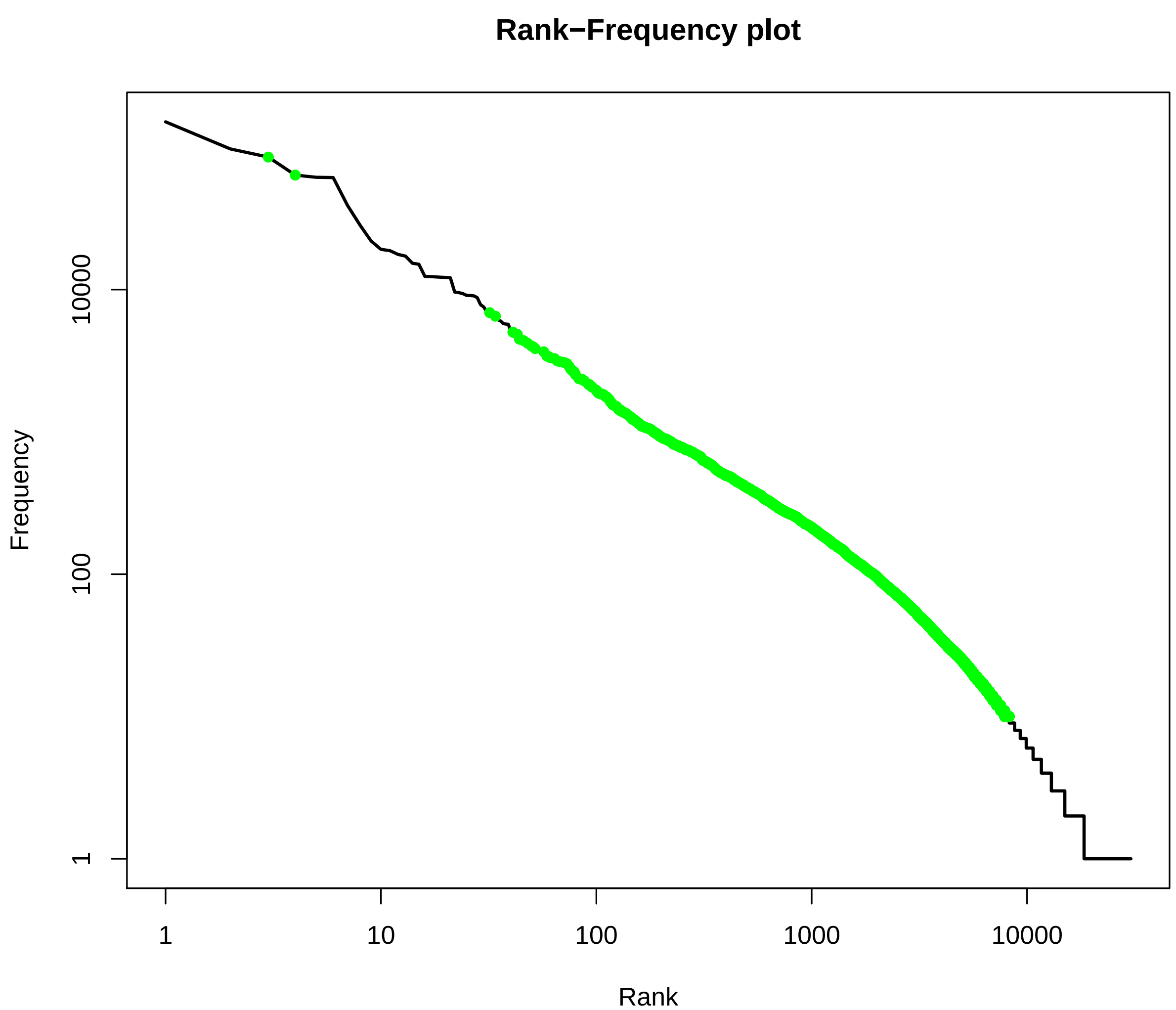
The `%in%` operator can be used to compare which elements of the first vector are contained in the second vector. At this point, we compare the words in the word list with a loaded stopword list (retrieved by the function stopwords of the tm package) . The result of the %in% operator is a boolean vector which contains TRUE or FALSE values.

A boolean value (or a vector of boolean values) can be inverted with the ! operator (TRUE gets FALSE and vice versa). The which command returns the indices of entries in a boolean vector which contain the value TRUE.

We also compute indices of words, which occur less than 10 times. With a union set operation, we combine both index lists. With a setdiff operation, we reduce a vector of all indices (the sequence 1:nrow(wordlist)) by removing the stopword indices and the low freuent word indices.

With the command "lines" the range of the remining indices can be drawn into the plot.

```
plot(wordlist$freqs, type = "l", log="xy",lwd=2, main = "Rank-Frequency plot", xlab="Rank", ylab = "Freq
englishStopwords <- stopwords("en")
stopwords_idx <- which(wordlist$words %in% englishStopwords)
low_frequent_idx <- which(wordlist$freqs < 10)
insignificant_idx <- union(stopwords_idx, low_frequent_idx)
meaningful_range_idx <- setdiff(1:nrow(wordlist), insignificant_idx)
lines(meaningful_range_idx, wordlist$freqs[meaningful_range_idx], col = "green", lwd=2, type="p", pch=20
```



The green range marks the range of meaningful terms for the collection.

Optional exercises

1. Print out the word list without stop words and low frequent words.

```
##                 words freqs
## ,                   , 85384
## .                   . 63784
## government government  6884
## states         states  6502
## congress     congress  5023
## united         united  4847
## ;                   ;  4478
## can               can  4378
## -                   -  4196
## people         people  4014
## upon             upon  3958
## year             year  3850
## $                   $  3659
## may               may  3408
## country       country  3390
## must             must  3329
## great           great  3275
## made             made  3151
## now               now  3110
## public         public  3074
## new               new  3020
## time             time  2865
## war               war  2767
## one               one  2713
## american     american  2668
```

2. If you look at the result, are there any corpus specific terms that should also be considered as stop word?
3. What is the share of terms regarding the entire vocabulary which occur only once in the corpus?

```
## [1] 0.39413
```

4. Compute the type-token ratio (TTR) of the corpus. the TTR is the fraction of the number of tokens divided by the number of types.

```
## [1] 0.01551821
```

References

1. Welbers, K., van Atteveldt, W., Benoit, K.: Text analysis in r. Communication Methods and Measures. 11, 245–265 (2017).