Sentiment Analysis with R
Natural Language Processing for Semi-Automated Assessments of Qualitative Data

a Working Paper and Tutorial by Dennis Klinkhammer

Abstract
Sentiment analysis is a sub-discipline in the field of natural language processing and computational linguistics and can be used for automated or semi-automated analyses of text documents. One of the aims of these analyses is to recognize an expressed attitude as positive or negative as it can be contained in comments on social media platforms or political documents and speeches as well as fictional and nonfictional texts. Regarding analyses of comments on social media platforms, this is an extension of the previous tutorial on semi-automated screenings of social media network data. A longitudinal perspective regarding social media comments as well as cross-sectional perspectives regarding fictional and nonfictional texts, e.g. entire books and libraries, can lead to extensive text documents. Their analyses can be simplified and accelerated by using sentiment analysis with acceptable inter-rater reliability. Therefore, this tutorial introduces the basic functions for performing a sentiment analysis with R and explains how text documents can be analysed step by step - regardless of their underlying formatting. All prerequisites and steps are described in detail and associated codes are available on GitHub. A comparison of two political speeches illustrates a possible use case.

Keywords Sentiment Analysis, Natural Language Processing, Computational Linguistics, Qualitative Data

Introduction to Sentiment Analysis and this Tutorial
Sentiment analysis – as the name suggests - can be used to capture the sentiment in qualitative data, such as text documents. Text documents can contain different types of content and information, e.g. comments on social media platforms or political documents and speeches as well as fictional and nonfictional texts up to entire libraries. Usually, these text documents come in different formats, e.g. PDF format, HTML format and many more, depending on the medium the text is located. Since most formats can be converted into a simpler format, such as the TXT format, this tutorial uses the TXT format as default. For example, if someone wants to convert a text document from PDF format to TXT format, the copy and paste function would be sufficient for this tutorial.

Within this TXT format the polarity can be classified word by word as positive or negative and in some cases neutral via basic sentiment analysis. In addition, different types of emotional states can be classified via advanced sentiment analysis and by using the NRC Word-Emotion Association Lexicon, the first word-emotion lexicon with eight basic emotional states (Mohammad 2020). Despite positive and negative sentiments, anger, fear, anticipation, trust, surprise, sadness, joy, and disgust can be classified as well. Furthermore, a semi-automated sentiment analysis has a sufficient inter-rater-reliability with less time requirements. The inter-rater-reliability is a degree of agreement among independent observers who rate, code, or assess the same phenomenon within a text document. While scientist usually achieve an inter-rater-reliability up to 80% the semi-automated ones can achieve up to 70%. This appears to be an acceptable value, because even if different types of semi-automated sentiment analyses would agree up to 100%, research indicates that scientists would still disagree by 20% (Ogneva 2010). Therefore, sentiment analyses can be found in a broad application context, of which a few will be presented in this tutorial.

Since this is an addition to the previous tutorial on semi-automated screenings of social media network data (Klinkhammer 2020), the analysis of comments on social media platforms should not go unmentioned. Especially social media platforms offer several users a low-threshold opportunity to exchange opinions and experiences. For example, these opinions and experiences can affect various areas of society, such as political
and economical ones. From a methodological point of view, the question whether one technique is equally suitable for entire books as well as short comments on social media platforms seems relevant. Research indicates that, for example, comments on social media platforms can be used to capture social issues like radicalisation and extremism (Tanoli et al. 2022), sexuality (Wood et al. 2017), side effects of medication and drugs (Korkontzelos et al. 2016) as well as for the reflection of the offline political landscape (Tumasjan et al. 2010). A well known use-case is the political campaign of former U.S. president Barack Obama, who used sentiment analysis back in 2012. These methodological approaches hardly differ from the analyses of entire books. There are many possible use-cases, but also numerous challenges in the application of sentiment analysis. Accordingly, research in this area continues (Hamborg & Donnay 2021) and this tutorial refers to a semi-automated sentiment analysis rather than automated ones.

This contribution includes all software requirements, a full disclosure of codes for the R programming language, the entire process of accessing and pre-processing text documents and how to perform basic and advances sentiment analyses. This tutorial is mainly supposed to be a methodological tutorial for students, and researchers.

**Software Requirements**

Written in *R Markdown*, this tutorial refers to the R programming language. A free software environment for using R is available for Linux, macOS by Apple and Windows by Microsoft. The main purpose of R is statistical computing and it is both used for manual quantitative and qualitative analyses as well as automated or semi-automated analyses. When it comes to Big Data, R can also be used for unsupervised and supervised Machine Learning.

In detail, R is an object based programming language. Therefore, datasets, variables, cases, values as well as functions can be applied as a combination of objects. All commands, as combinations of functions, datasets, variables, cases, values and functions will be highlighted, so that they can be used as step by step tutorial. The commands have to be entered directly into the R terminal, which is available after downloading, installing and starting the R software environment.

**Preparations: Attaching necessary Packages**

This tutorial requires six additional packages in order to expand the range of basic R functions. All packages can be installed by using the `install(...)` command and attached via the `library(...)` command by typing the following commands directly into the R terminal.

Since the analysis of extensive text documents requires a focus on every single element that is to be analysed, it is necessary to break down the underlying data structure into manageable little pieces. A package that is specifically designed to do so is called *dplyr*. It can split, apply and combine data for further analytical steps (Wickham 2022). The package *dplyr* can be installed and attached as follows:

```r
install.packages("dplyr", dependencies=TRUE)
library(dplyr)
```

The second package is called *stringr*. Since qualitative data, like the text in social media comments, is represented by character variables in R, a package that can process and - if necessary - manipulate individual characters within the strings of a character variable is required (Wickham 2019); A string is marked either by single quote signs or double quote signs. In order to install and attach the *stringr* package, following commands can be typed in the R terminal:

```r
install.packages("stringr", dependencies=TRUE)
library(stringr)
```

Another necessary package is called *textdata*. It contains several words as references and sentiment libraries, such as the NRC Word-Emotion Association Lexicon. So it does not only needed to be installed by the `install.packages(...)` command and attached by the subsequent `library(...)` command, but the NRC Word-Emotion Association Lexicon must be installed for advanced sentiment analysis as well. In addition, a second
lexicon will be installed to implement basic sentiment analysis: The Bing Sentiment Lexicon. This can be done via the `get_sentiments(...)` command:

```r
install.packages("textdata", dependencies=TRUE)
library(textdata)
get_sentiments("nrc")
get_sentiment("bing")
```

Sentiment analysis is a text mining technique and the package `tidytext` is required in order to convert conventional text documents into tidy formats, such as single words without punctuation or spaces (De Queiroz et al. 2022). This allows scientists to focus on paragraphs or otherwise separated content word by word. As a result, the tidy text format lists and counts all words individually and assigns them a numbered line according to their paragraph or other used methods of content separation. Again, this package can be installed and attached as follows:

```r
install.packages("tidytext", dependencies=TRUE)
library(tidytext)
```

The package `tidytext` provides the connection between the packages `dplyr` and `ggplot2` by using their basic formulas and commands. The latter is responsible for the detailed visualisation of sentiments and other types of results, based on “The Grammar of Graphics” (Wickham et al. 2022). In particular, defining the details of a visualisation enables scientists to create informative as well as attractive plots. Therefore, the package `ggplot2` requires several dependencies in order to carry out this task:

```r
install.packages("ggplot2", dependencies=TRUE)
library(ggplot2)
```

Finally, the package `gridExtra` enables scientists to arrange multiple visualisations at once and to create dashboards for an intuitive display of relevant information (Auguie & Antonov 2017). Following commands must be typed in the R terminal in order to make the package `gridExtra` work:

```r
install.packages("gridExtra", dependencies=TRUE)
library(gridExtra)
```

Additional note: If not already pre-installed, the package `magrittr` is also required in order to make use of the forward-pipe operator for more elegant coding. It is possible that further packages have to be installed in the R environment. This will be automatically checked via the extension of the `install (...)` command with `dependencies = TRUE` that will install additional packages, if necessary. In a freshly created R environment (based upon version 4.1.2 of R), the six packages listed above have been running sufficient on Ubuntu 22.04 LTS (Linux Kernel 5.15.0-37), macOS Monterey (12.4) and Windows 11 (22000.708), each brought to application on RStudio.

**Data Pre-Processing: Getting and Cleaning Text Documents**

Data pre-processing is used to check datasets for irrelevant and redundant information present or noisy and unreliable data. In a first step, an external text document is imported into the R working environment by using the `read.delim(...)` command and saving this text document as a new object called `imported_text`. The external text document is TXT formatted and can be accessed by entering the associated directory and file name. In this case, a chapter from one of the Sherlock Holmes novels will be imported (thanks to the great work of Arthur Conan Doyle):

```r
imported_text <- read.delim("your_unformatted_document.txt", header=F, sep="\t")
```

The subsequent `dim(...)` command indicates the number of paragraphs within this text document, which is necessary for the next step, as well as the number of variables within the `imported_text`. As a result, 229 paragraphs and one Variable, named `V1`, can be processed further:
The next step creates tibbles out of the `imported_text`. Tibbles are data frames that are considered plain and simple. In fact, they are so plain and simple, that the number of lines needs to be entered manually in order to define the structure of the data frame. In this case, the number of lines within the tibble is supposed to be the exact number of paragraphs of the `imported_text`, hence 229. As a result, the `tibble(...)` command leads to a new object called `text_df` and the first six lines can be inspected by using the `head(...)` command:

```r
text_df <- tibble(line=1:229, text=imported_text$V1)
head(text_df)
```

```
## # A tibble: 6 x 2
##   line text
##  <int> <chr>
## 1     1 "To Sherlock Holmes she is always the woman. I have seldom heard him"
## 2     2 " mention her under any other name. In his eyes she eclipses and"
## 3     3 " predominates the whole of her sex. It was not that he felt any"
## 4     4 " emotion akin to love for Irene Adler. All emotions, and that one"
## 5     5 " particularly, were abhorrent to his cold, precise but admirably"
## 6     6 " balanced mind. He was, I take it, the most perfect reasoning and"
```

Although the object `text_df` is plain and simple formatted, it needs to be pre-processed further. Sentiment analysis requires a tidy data set, which can be generated by using the object `text_df` combined with the `unnest.tokens(...)` command. In this case, each word within the text has to be separated, indicated by `word` and `text`. For the first time in this tutorial the connection between an object and command will be established via the forward-pipe operator `%>%`. Later on, this technique allows to combine several commands regarding one object and - in this case - to generate the new object `text_tidy`:

```r
text_tidy <- text_df %>%
unnest_tokens(word, text)
```

This object is just a listing of all the words in the different paragraphs. This allows the sentiment analysis to be performed word by word and line by line. Since non-essential words may be included in this list, they can be eliminated by using the `stop_words` data via the `data(...)` command. Again, the forward-pipe operator combines the object `text_tidy` with the new command `anti_join(...)` in order to exclude the specified words:

```r
data(stop_words)
text_tidy <- text_tidy %>%
anti_join(stop_words)
```

```
## Joining, by = "word"
```

Now the object `text_tidy` is prepared for sentiment analysis. In addition, custom words can also be excluded from this object. They can be generated by using the `tibble(...)` command and repeating the previous step of the pre-processing.

```r
custom_stop_words <- c("custom_word")
custom_stop_words <- tibble(1:1, word=custom_stop_words)
```

Finally, the `head(...)` command generates an output of the first six lines of the pre-processed object `text_tidy`. This object includes only words that are relevant for an understanding of the original text document and the lines - respectively paragraphs - they have been mentioned within the text document:
head(text_tidy)

## A tibble: 6 x 2
## line word
## <int> <chr>
## 1 1 sherlock
## 2 1 holmes
## 3 1 woman
## 4 1 seldom
## 5 1 heard
## 6 2 mention

Analysis - 1: Identification of Common Words and their Sentiment

The first three analytical steps refer to the the NRC Word-Emotion Association Lexicon, which can be specified as criteria for sentiment analysis via the inner_join(...) command. Since the first analytical step of this tutorial relates to the frequency of the words used within the text document and their sentiments as well as the expressed emotional states, the count(...) command counts and sorts each word and its sentiment regarding the underlying object text_tidy. The result of this step will be saved as a new object nrc_word_counts:

```r
# Positive und negative Wörter auflisten
nrc_word_counts <- text_tidy %>%
  inner_join(get_sentiments("nrc")) %>%
  count(word, sentiment, sort = TRUE) %>%
  ungroup()
```

This new object can be converted into a corresponding graphic. The words shall be listed in descending order according to their frequency, where the minimum number is specified as n > 2 within the filter(...) command. Larger text documents can contain multiple repetitions of the same words, so that the minimum number has to be adapted accordingly. It is advisable to try different numbers if necessary. The order is specified by using the mutate(...) command and the ggplot(...) command combines the words to be highlighted with their sentiment and emotional state, where each is represented by an individual color, specified within the geom_col(...) command. Since the sentiments and emotional states are to be shown as horizontal bar charts, the command coord_flip is also used. The plot also requires a label that has to be assigned to the Y-axis. This is done by using the labs(...) command. A title will be added via the ggtitle(...) command:

```r
nrc_word_counts %>%
  filter(n > 2) %>%
  mutate(word = reorder(word, n)) %>%
  ggplot(aes(word, n, fill = sentiment)) +
  geom_col() +
  coord_flip() +
  labs(y = "sentiment (n)") +
  ggtitle("Common Words & Sentiments (Frequency)")
```
The result is a graphical representation of the most common words in descending order (Y-axis) and the frequency of associated sentiments and emotional states (X-axis). For example, the word *doubt* is the third most common word but it represents the emotional states trust, sadness and fear as well as a negative sentiment within different paragraphs of the text document.

**Analysis - 2: Distribution of Sentiments**

In the second step of the analysis the total number of each sentiment and emotional state within the text document shall be focused in order to highlight their distribution. Here the object *nrc_word_counts* is used again, which can be directly specified and plotted via the pipe-forward operator. This time the words will not be specified within the `ggplot(...)` command, but the sentiments and emotional states via *sentiment*:

```r
nrc_word_counts %>%
  inner_join(get_sentiments("nrc")) %>%
  count(word, sentiment) %>%
  ggplot(aes(sentiment, n, fill = sentiment)) +
  geom_col(show.legend = FALSE) +
  ggtitle("Sentiments (Distribution)") +
  coord_flip()
```

## Joining, by = c("word", "sentiment")
This output highlights the total number (X-axis) of each sentiment and emotional state (Y-axis) within the entire chapter of the Sherlock Holmes novel. Overall, the chapter is dominated by a positive sentiment. Furthermore, trust and anticipation outweigh fear, joy and sadness. Regular readers of Sherlock Holmes novels should recognise the basic elements that are inherent for the work of Arthur Conan Doyle.

**Analysis - 3: Intertemporal Use of Sentiments (Conditional Mean)**

While the first two analytical steps related to the sentiments and emotional states of words, the third step is about the conditional means of their use over time - as known as the intertemporal use of them. Therefore, the `count(…)` command needs to be adjusted in order to count every sentiment used in a line.

```r
nrc_word_counts <- text_tidy %>%
  inner_join(get_sentiments("nrc")) %>%
  count(line, sentiment, sort = TRUE) %>%
  ungroup()
```

## Joining, by = "word"

Subsequently, object `nrc_word_counts` is a tibble, indicating not only the sentiments and emotional states within a line but also the total number `n` of them and how often they are used within that line. For example, line 33 contains the sentiments negative and the emotional states fear and sadness. In total, three sentiments and emotional states are used in that line, but each of them appears only once. As a result, the mean value for line 33 would be 1. Each line can be inspected by using the `subset(…)` command:
In order to highlight the dynamics regarding the appearance of sentiments and emotional states over time, a smoothed slope will be plotted. Smoothed slopes do not represent the actual values, like mean values, but they do represent estimated values, in this case conditional means, to indicate the development. Thus, primarily the course of the slope should be interpreted and not individual data points. For example, line 133 contains a positive sentiment and three emotional states - trust, anticipation and joy - whereas two of them appear eight times. This paragraph (here: line) is about a narcissistic character, who is talking about himself and people he would like to meet. Hence, the high number of positive sentiments and emotional states. As a result, the mean value for line 133 should be much higher in respect to the mean value of line 33, but the plotted slope will not reach out to that specific mean value, it would only indicate a higher point in the course of the slope. The `subset(…)` command highlights line 133 before plotting the slope:

```r
subset(nrc_word_counts, line==133)
```

```markdown
## # A tibble: 4 x 3
##  line sentiment n
##  <int> <chr>     <int>
## 1 133 positive 8
## 2 133 trust    8
## 3 133 anticipation 2
## 4 133 joy      1
```

The intertemporal use of sentiments and emotional states can be plotted by using the `ggplot(…)` command, again. The `span` operator within the `geom_smooth(…)` command specifies the smoothness of the plotted slope and can be adjusted for a more detailed representation:

```r
ggplot(data = nrc_word_counts, mapping = aes(x = line, y = n)) +
  geom_smooth(method="loess", formula="y~x", span=0.2) +
  xlab("document (line)") +
  ylab("sentiment (conditional mean)") +
  ggtitle("Intertemporal Use of Sentiments (Conditional Mean)"
```
The plot indicates that fewer sentiments and emotional states (Y-axis) are used at the beginning, the center and the end of this chapter than in between (represented by lines on the X-axis). Other chapters of the Sherlock Holmes novel could be analysed accordingly. However, this plot just highlights the intertemporal use of sentiments and emotional states as conditional means, regardless of whether they are positive or negative. This aspect will be taken into account in the next step of this tutorial.

**Analysis - 4: Intertemporal Use of Sentiments (Score)**

Another way of analysing the intertemporal use of sentiments and emotional states is based upon scores. A sentiment score results from the sum of positive (1) and negative (-1) values in respect to the underlying sentiment. Since the NRC Word-Emotion Association Lexicon differentiates between positive and negative sentiments as well as eight emotional states, a lexicon is required that differentiates only between positive and negative sentiments: The Bing Sentiment Lexicon, written by distinguished professor Bing Liu from the department of computer science at the University of Illinois (Chicago), is suited for that task. By specifying his lexicon within the `inner_join` command, a new object called `bing_word_counts` can be generated and inspected by using the `head(...)` command:

```r
bing_word_counts <- bind_rows(
  text_tidy %>%
  inner_join(get_sentiments("bing")) %>%
  mutate(method = "Bing et al."))
```

## Joining, by = "word"
Within this object a sentiment is designated to each word and the `ifelse(...)` command assigns values of 1 and -1 accordingly. A few commands are required in order to generate a data frame that aggregates these values for each line. Therefore, after the `cbind(...)` command has focused the relevant variables but eliminated their labels, the lines will be labeled `var1` and the sum of the values `var2`. After transformation into a data frame by using the `as.data.frame(...)` command the `aggregate(...)` command generates the necessary object `sentiment_sum_df`, which can be sorted in respect to the lines within `var1`:

```r
sentiment_sum <- ifelse(bing_word_counts$sentiment == "positive", 1, -1)
sentiment_sum_df <- cbind(bing_word_counts$line, sentiment_sum)
colnames(sentiment_sum_df) <- c('var1', 'var2')
sentiment_sum_df <- as.data.frame(sentiment_sum_df)
sentiment_sum_df <- aggregate(sentiment_sum_df$var2, 
                              by=list(line=sentiment_sum_df$var1), FUN=sum)
```

The `head(...)` command provides insights into the data frame called `sentiment_sum_df`. For each line with sentiments the score of these sentiments (x) is assigned as sum of all positive (1) and negative (-1) sentiments:

```r
head(sentiment_sum_df)
##   line  x
## 1    4  1
## 2    5  1
## 3    6  2
## 4    7  1
## 5    8  0
## 6    9 -1
```

The related plot is called via the `ggplot(...)` command as in the previous steps of this tutorial. Again, the X-axis relates to the lines in the text document. This time, the Y-axis relates to the previously generated sentiment score. The result is an intertemporal representation of these scores line by line:

```r
ggplot(data = sentiment_sum_df, mapping = aes(x = line, y = x)) + 
  geom_smooth(method="loess", formula="y~x", span=0.2) + 
  xlab("document (line)") + 
  ylab("sentiment (score)") + 
  ggtitle("Intertemporal Use of Sentiments (Score)")
```
As a result, this Sherlock Holmes chapter seems to have positive sentiments at the beginning and an increasing sentiment at the end, while there appears to be a dramaturgical downscaling during the chapter to highlight the tensions in solving the crime.

**Application Example: Comparing Political Speeches**

The last chapter of this tutorial is about comparing two political speeches. For that purpose, English-language versions of two simultaneous speeches on a specific issue relating the war in Ukraine were selected. One speech is from Jens Stoltenberg (Secretary General of NATO) and the other speech - that is supposed to be an answer to the first one - is from Sergey Viktorovich Lavrov (Minister of Foreign Affairs, Russian Federation). Basic and advanced sentiment analyses enable a comparison of the linguistic composition of both speeches.

All commands can be used as in the previous steps of this tutorial. In order to systematically summarise the graphical findings, a dashboard with all four plots at once is generated by using the previously installed package gridExtra and the grid.arrange(...) command. This requires that all previous plots be created as new objects, for example: plot1 <- ggplot(...). The assignment arrow should always be on the first line of the commands that contain the ggplot(...) command and each new object should be the first word in that command. This makes it possible to display all plots from plot1 to plot4 in one dashboard:

```
grid.arrange(plot1, plot2, plot3, plot4)
```

The corresponding output for both speeches is plotted on the next page:
The dashboard regarding the speech of Jens Stoltenberg:

Frequency

| word            | sentiment |
|-----------------|-----------|
| alliance        |                       |
| including       |                       |
| readiness       |                       |
| military        |                       |
| agreed          |                       |
| civil           |                       |
| time            |                       |
| essential       |                       |
| defend          |                       |
| cooperation     |                       |
| committed       |                       |

Distribution

| sentiment | 0     | 10    | 20    | 30    | 40    | 50    |
|-----------|-------|-------|-------|-------|-------|-------|
| trust     | 5     | 15    | 25    | 35    | 45    | 55    |
| surprise  | 5     | 15    | 25    | 35    | 45    | 55    |
| sadness   | 5     | 15    | 25    | 35    | 45    | 55    |
| positive  | 5     | 15    | 25    | 35    | 45    | 55    |
| negative  | 5     | 15    | 25    | 35    | 45    | 55    |
| joy       | 5     | 15    | 25    | 35    | 45    | 55    |
| fear      | 5     | 15    | 25    | 35    | 45    | 55    |
| disgust   | 5     | 15    | 25    | 35    | 45    | 55    |
| anticipation | 5     | 15    | 25    | 35    | 45    | 55    |
| anger     | 5     | 15    | 25    | 35    | 45    | 55    |

In comparison, the dashboard regarding the speech of Sergey Viktorovich Lavrov:

Frequency

| word     | sentiment |
|----------|-----------|
| threat   |                       |
| president|                       |
| united   |                       |
| military |                       |
| time     |                       |
| defending|                       |

Distribution

| sentiment | 0     | 5     | 10    | 15    | 20    | 25    |
|-----------|-------|-------|-------|-------|-------|-------|
| trust     | 10    | 20    | 30    | 40    | 50    | 60    |
| surprise  | 10    | 20    | 30    | 40    | 50    | 60    |
| sadness   | 10    | 20    | 30    | 40    | 50    | 60    |
| positive  | 10    | 20    | 30    | 40    | 50    | 60    |
| negative  | 10    | 20    | 30    | 40    | 50    | 60    |
| joy       | 10    | 20    | 30    | 40    | 50    | 60    |
| fear      | 10    | 20    | 30    | 40    | 50    | 60    |
| disgust   | 10    | 20    | 30    | 40    | 50    | 60    |
| anticipation | 10    | 20    | 30    | 40    | 50    | 60    |
| anger     | 10    | 20    | 30    | 40    | 50    | 60    |
The plots above indicate that Jens Stoltenberg focuses the readiness and the alliance of NATO states by expressing trust and anticipation as emotional states (Frequency). There is also a strong use of positive sentiments within his speech (Distribution). Overall, his speech is characterised by an estimated use of three sentiments and emotional states per paragraph, while his speech begins with an estimate of only two sentiments and emotional states (Conditional Mean). The beginning of his speech can be characterised as negative, which changes to a positive sentiment score as the speech progresses (Score). Finally, his speech ends with a neutral sentiment score.

Sergey Viktorovich Lavrov, on the other hand, refers to a threat for the Russian Federation and his trust in the president of the Russian Federation (Frequency). The threat is expressed with the emotional states fear and anger, thus a negative sentiment is inherent. When it comes to the distribution of sentiments and emotional states, positive and negative sentiments seem to be equally used, while trust and anticipation counterbalance the emotional states fear and anger (Distribution). His speech begins with an estimate of four sentiments and emotional states but he seems to use fewer sentiments and emotional states at the end of his speech (Conditional Mean). In total, his sentiment score remains negative with a slight increase at the center of his speech (Score).

Based on such findings, it seems necessary to inspect the corresponding paragraphs (here: lines) which include the highlighted words, their sentiments and emotional states, but also the intertemporal use of them. For example, each turning point and saddle point of the slopes could be inspected line by line to validate these findings. Finally, this is primarily a technique in order to speed up the process of analysing text documents and qualitative data, rather than a possibility of reaching to final conclusions.

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All codes required for the basic and advanced Sentiment Analysis with R can be accessed on GitHub: https://github.com/statistical-thinking/sentiment-analysis