

Analysing Social Media Network Data with R

Semi-Automated Screening of Users, Comments and Communication Patterns

a Working Paper and Tutorial by Dennis Klinkhammer

Abstract

Communication on social media platforms is not only culturally and politically relevant, it is also increasingly widespread across societies. Users not only communicate via social media platforms, but also search specifically for information, disseminate it or post information themselves. However, fake news, hate speech and even radicalizing elements are part of this modern form of communication: Sometimes with far-reaching effects on individuals and societies. A basic understanding of these mechanisms and communication patterns could help to counteract negative forms of communication, e.g. bullying among children or extreme political points of view. To this end, a method will be presented in order to break down the underlying communication patterns, to trace individual users and to inspect their comments and range on social media platforms; Or to contrast them later on via qualitative research. This approach can identify particularly active users with an accuracy of 100 percent, if the framing social networks as well as the topics are taken into account. However, methodological as well as counteracting approaches must be even more dynamic and flexible to ensure sensitivity and specificity regarding users who spread hate speech, fake news and radicalizing elements.

Keywords Social Media Analysis, Social Networks, Communication Patterns, Network Data Screening

Relevance of Social Media Networks

Forecasts assume that in the year 2021 the number of contributions of active social media users will increase to 3.02 billion per month worldwide (Pereira-Kohatsu et al. 2019). The importance of such contributions for forming a political opinion was especially set in scene by the 45th President of the United States of America, Donald Trump. He used social media platforms frequently for sharing and commenting his political actions; Sometimes by using aggressive, inappropriate, misleading, racist and / or otherwise disparaging comments (Ott 2016). In addition, social media platforms can shape the cultural habitus of parts of societies and contribute to the transfer of knowledge.

But fake news, hate speech as well as radicalizing elements show an increasing number on social media platforms, as well (Reichelmann et al. 2020). However, such social media elements - often on seemingly harmless social media platforms like YouTube and accessible to children (Machackova et al. 2020) - can also be used to investigate communications patterns inside social networks, to focus the role of individual users and what influence the content of their comments and actions might have on the underlying structures of a social network. Giving as well as withholding likes and replies on social media platforms, for example, are actions that can be analysed on a quantitative basis. These are individual phenomena occurring en masse, of which some seem more relevant than others when it comes to generating and distributing fake news, hate speech and radicalizing elements.

YouTube, for example, had 2.1 billion active users in 2020 and represents one of the most frequently used social media platforms worldwide (Clement 2020). Along with videos on cultural, political and even private content, there is a large number of comments, likes and replies. Some of these comments include fake news, hate speech and radicalizing elements, that need to be assessed critically (Awan 2017). However, focusing individual aspects of social networks manually, e.g. for getting deeper insights or contrasting analyses, tends to be very time-consuming for researchers from various scientific disciplines. Both, qualitative and quantitative analyses, are faced with a very large and continuously growing number of users and contributions; Each of them bringing an influential dynamic that needs to be considered in every methodological approach.

Therefore, this contribution presents how singular social media contributions can be identified throughout a mass of contributions, how individual users and their activities can be traced and, furthermore, how important it is to consider different communication patterns, depending on the content. One of the results is a graphic representation of individual users and the range of their contributions on social media platforms. Another result can be considered the basis for creating automated screening methods - in addition to this semi-automated approach - and how to generate qualitative datasets out of social media data for further research.

This contribution includes all software requirements, a full disclosure of codes for the R programming language, the entire process of accessing and pre-processing social media based datasets and how to analyse and visualize the included variables. As a result, this working paper is mainly supposed to be a methodological tutorial for students, researchers and users of social media platforms.

Software Requirements

This working paper is written in *R Markdown*, so it uses 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 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, as it is necessary for Analysing Social Media Network Data. All commands, as combinations of functions, datasets, variables, cases, values and functions will be highlighted within this working paper, 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 - 1: Attaching necessary Packages

The Analysis of Social Media Network Data requires four additional packages in order to expand the range of basic R functions. All packages can be installed by using the *install(...)* command and can be attached via the *library(...)* command by typing the following commands directly into the R terminal.

Since the Analysis of Social Media Network Data can be described as a huge process regarding the underlying data structure, it is necessary to break down this process and its 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 analysis (Wickham 2020). The package *dplyr* can be installed and attached as follows:

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

Variables regarding the social network structures on social media platforms can easily be accessed by using the *vosonSML* package. It expands the range of basic R functions in order to collect data from popular social media platforms like YouTube, Twitter or Reddit (Graham et al. 2020). This package will provide access to comments, likes, replies and additional information regarding the social network structures on these social media platforms. These commands will install and attach the *vosonSML* package:

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

For keeping the necessary R commands tidy and structured, the package *magrittr* can be used. It provides a forward-pipe operator that allows for chaining several commands (Bache/Wickham 2020). As a result, complementary commands for a single analysis step can be called up together. The package *magrittr* can also be installed and attached by using the *install(...)* and *library(...)* commands:

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

The final package is called *stringr*. Since text, like 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); And 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:

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

Additional note: 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 4.0.3 of R), the four packages listed above have been running sufficient on Ubuntu 20.04 LTS (Linux Kernel 5.9.11), macOS Big Sur (11.0) and Windows 10 (20H2), each brought to application on RStudio.

Preparations - 2: Requesting an Application Programming Interface

In order to perform an Analysis of Social Media Network Data, analytical access to social media platforms and its underlying variables is required. This can be achieved via an Application Programming Interface (API). An API is a set of functions and procedures allowing the creation of applications that access the features or data of an operating system, application, or other services like social media platforms (Fielding 2000). In short: It lets the *vosonSML* package in R communicate with YouTube, Twitter and Reddit as social media platforms.

For scientific purpose APIs can be used to generate datasets with a variety of variables regarding the users of social media platforms and their behavior on these platforms. How an API can be included in the R commands for performing an Analysis of Social Media Network Data is presented below. This is an example for the social media platform YouTube, that can be easily adapted for similar application with Twitter and Reddit:

```
my_apiKeyYoutube<-"ENTER YOUR APPLICATION PROGRAMMING INTERFACE HERE"
apiKeyYoutube<-Authenticate("youtube", apiKey=my_apiKeyYoutube)
```

Since YouTube belongs to Google, a Google Developers Account is necessary in order to request an API. Each API will be assigned to a specific project, such as e.g. "Social Media Analysis". Creating an account, logging in and starting a new project with an specific API is possible within the Google Developers console: <https://console.developers.google.com/project/>.

There are similar procedures for requesting an API for Twitter or Reddit. Twitter offers a developers program, similar to YouTube; Reddit provides an *wiki* on requesting an API.

Accessing Data - 1: Selecting Content

Once a social media platform has been selected for an Analysis of Social Media Network Data, an access point must be determined. In this context, for example, access points can be relevant content on social media platforms. Sticking to the example with YouTube, one would not only pick a video as access point, but one with content relevant to current affairs, created by a specific person or on a specific topic. In most scientific cases, the research interest will determine the relevance of the access point.

Each access point can be directly addressed via an unique identification number, which is clearly assigned to each content on social media platforms. On YouTube these identification numbers are combinations of letters and digits at the end of each link to a video, separated by an equals sign. The combination of letters from a-z, A-Z and digits from 0-9 provides a unique identification number than can be entered in the R terminal as follows:

```
videoIDs=c("ENTER IDENTIFICATION NUMBER OF SOCIAL MEDIA CONTENT HERE")
```

Referring to the presidential election 2020 in the U.S. for example, YouTube provides a news video called *US Elections: Trump's Statement in Full - BBC News*, identified by the unique identification number *KtNZV7qezMM*. This news video has been watched more than 200.000 times within two days and several users have generated comments, likes and replies below this video, which reflects a moment of current affairs. The Analysis of Social Media Network Data provides methods for an quick identification of particularly active users, their comments and the underlying communication patterns within that social media content.

Twitter and Reddit provide similar access points and it is possible to combine several access points, separated by a comma between the unique identification numbers within the above presented R command.

Accessing Data - 2: Generating a Dataset

This step uses the *Collect(...)* command of the *vosonSML* package and refers to the generated objects *apiKeyYoutube* and *videoIDs* of the previous steps in order to access YouTube. In addition, the commands *writeToFile=TRUE* and *verbose=TRUE* not only allow to write the collected data to a file, but also to collect additional information on the process of data gathering, if necessary. Furthermore, the maximum number of collected comments is most relevant to the Analysis of Social Media Network Data, since the size could influence the results, e.g. when the relevance of a topic changes over a period of time or the public opinion tends to change. This example uses the command *maxComments=200* and therefore collects the latest 200 comments and all replies to these comments, without counting the replies as one of the latest 200 comments. As a result, more than 200 comments can be collected by typing the following command into the R terminal:

```
myYoutubeData<-Collect(apiKeyYoutube, videoIDs,  
  writeToFile=TRUE, verbose=TRUE, maxComments=200)
```

Hence, a new dataset *myYoutubeData* will be generated. The *str(...)* command and *head(...)* command would provide first insights into this initial dataset, but before doing so the dataset will be pre-processed in order to get a tidy dataset.

Data Pre-Processing - 1: Inspecting the Variables

Data pre-processing is used to check datasets for irrelevant and redundant information present or noisy and unreliable data. Targeted research questions with a firm theoretical background also allow focusing the most relevant variables. For an thorough Analysis of Social Media Network Data the authors of social media comments would be relevant, the sentences they have written, how often someone replied to their comments and how many likes they got for their comments. Focusing the relevant variables provides a tidy dataset as result of data pre-processing. The variables mentioned can be transferred to a first tidy dataset to start with and be labeled accordingly by using the following command:

```
easy_dataset <- data.frame(myYoutubeData$AuthorDisplayName,  
  myYoutubeData$Comment, myYoutubeData$ReplyCount, myYoutubeData$LikeCount)  
colnames(easy_dataset) <- c("author", "sentence", "replies", "likes")
```

This command leads to a dataset called *easy_dataset* with four variables: *author*, *sentence*, *replies* and *likes*. A first insight can be called via the *summary(...)* command applied on the *easy_dataset* in the R terminal:

```
summary(easy_dataset)
```

The output should look like this in order to focus the number of cases and the type of the variables:

```
##      author      sentence      replies      likes  
## Length:252      Length:252      Length:252      Length:252  
## Class :character Class :character Class :character Class :character  
## Mode  :character Mode  :character Mode  :character Mode  :character
```

As a result of this command, the four variables and the type of these variables are shown. All four variables are currently shown as character variables. However, this would only be true if all variables included letters. The names of the authors of the comments as well as their written sentences will most likely include letters, so the variables *author* and *sentence* should remain character variables; At least for the moment. Since the variables *replies* and *likes* contain numbers and not letters, simply by counting the number of replies and likes, they should therefore be converted into numeric variables:

```
easy_dataset$likes <- as.numeric(as.character(easy_dataset$likes))
easy_dataset$replies <- as.numeric(as.character(easy_dataset$replies))
easy_dataset$sentence <- as.character(easy_dataset$sentence)
easy_dataset$author <- as.character(easy_dataset$author)
```

The results of this procedure can be checked by repeating the *summary(...)* command in the R terminal:

```
summary(easy_dataset)
```

However, this output is not only a snapshot and may have developed further in a later step of this analysis, but may also vary due to the parameter in the *maxComments* setting while generating the initial dataset:

```
##      author      sentence      replies      likes
## Length:252      Length:252      Min.   : 0.0000      Min.   : 0.000
## Class :character Class :character 1st Qu.: 0.0000      1st Qu.: 0.000
## Mode  :character Mode  :character Median : 0.0000      Median : 0.000
##                                     Mean  : 0.2063      Mean  : 1.401
##                                     3rd Qu.: 0.0000      3rd Qu.: 1.000
##                                     Max.   :10.0000      Max.   :52.000
```

Now the minimum, mean and maximum number of replies and likes for the variables *replies* and *likes* can be taken directly from the output and they can be interpreted as numeric variables. For example, there seems to be at least one author of social media comments who got a maximum of 10 replies and at least another one - or the same one, since that can not be determined before further analysis - got a maximum of 52 likes.

There is also a way for generating numeric variables on basis of character variables. However, this requires a methodical approach on dealing with duplicate cases. Therefore, in the next section, a corresponding procedure is presented without affecting the informative value of the dataset by focusing the cases.

Data Pre-Processing - 2: Inspecting the Cases

By counting the number of comments of an user via the variable *author* a new variable *comments* can be generated. Same procedure is applicable on the number of words within the variable *sentence*. Numeric variables on basis of character variables can be generated like this:

```
comments <- count(easy_dataset$author)
comments <- comments$freq
```

The command above simply counts the number of *comments* by each author of a social media comment. This number will be used later on to generate a new variable *comments*. In order to generate the number of words and to generate a new variable *words*, every sentence in a comment must be broken down into its components, known as words. R provides the *strsplit(...)* command in order to generate the new variable *words*:

```
temp <- strsplit(easy_dataset$sentence, split=" ")
easy_dataset$words <- sapply(temp, length)
```

Only now and as one of the final steps of data pre-processing, the double cases can be identified and have to be merged. This is necessary, because some authors of social media comments have posted several comments. Accordingly, the amounts of their numeric variables should be summed up: If someone gets two likes for his first comment and three likes for his second comment, he gets a total of five likes. This can be done by using the *ddply(...)* command in the R terminal:

```
easy_dataset <- ddply(easy_dataset, "easy_dataset$author", numcolwise(sum))
```

Now it is possible to assign the correct number of comments for each author of social media comments and to create a new variable *comments* inside the *easy_dataset*. This can be achieved by applying the following command:

```
easy_dataset$comments <- comments
colnames(easy_dataset) <- c("author", "replies", "likes", "words", "comments")
```

This new and extended dataset, including two new generated numeric variables, is suitable for further analyses. Since the variable *sentence* with all the qualitative data can not be summed up, it is automatically excluded from the dataset by the previous commands. However, it can be accessed any time before aggregating the double cases and later on by using the initial dataset *myYoutubeData*. Finally, the *head(...)* command provides insights into this tidy dataset, that still carries the designation *easy_dataset*. This time only the quantitative variables will be focused, which can be addressed by focusing the 2nd to 5th column of the dataset:

```
head(easy_dataset[2:5])
```

```
##   replies likes words comments
## 1      0     0   13         2
## 2      0     7   21         4
## 3      1     2   58         1
## 4      0     0    5         1
## 5      0     2   11         1
## 6      0     0   13         1
```

The first six - and at this moment only disordered - cases can now easily be inspected. For example, the second case reports 0 replies, 7 likes, 21 words and 4 comments in total.

All collected 200 cases will be the basis for further steps in the Analysis of Social Media Network Data. Within the next chapter, not only the methodological approach for ordering the cases systematically and identifying single authors of social media comments will be presented, but also how to access their original comments in the previous dataset for performing qualitative - and quantitative - analyses, if necessary.

Analysis - 1: Identification of Cases and Comments

Using the dataset *easy_dataset* makes it possible to identify particularly active users within the social media network. This is done via the quantitative variables presented above. Since not all users of social media networks get replies and likes, a first parameter for identification could be a predefined minimum of at least one reply and one like. This is probably the case, when they have written more than one word, e.g. ten words; Therefore they must have written at least one comment. The identification parameters can be specified in the R terminal as follows:

```
identification <- subset(easy_dataset, replies>="1" & likes>="1"
  & words>="10" & comments>="1")
head(identification)
```

```
##           author replies likes words comments
## 3 anonymized username      1     2   58         1
## 10 anonymized username      1     6   36         1
## 13 anonymized username      1    15   19         1
## 16 anonymized username     10    58   58         4
## 17 anonymized username      2     6   31         2
## 19 anonymized username      3    14   48         1
```

The result is a list of six particularly active users and their number of replies, likes, words and comments. This provides a first insight into the top-down communication patterns within the social media network

across several identification parameters. Since each user can be addressed by his username (in this working paper anonymized) within the variable *author*, a user with a particular behavior can be analysed individually. It is also possible to identify users by addressing only one identification parameter:

```
most_replies <- easy_dataset[order(-easy_dataset$replies),]
most_likes <- easy_dataset[order(-easy_dataset$likes),]
most_words <- easy_dataset[order(-easy_dataset$words),]
most_comments <- easy_dataset[order(-easy_dataset$comments),]
```

With the presented command above, the dataset *easy_dataset* will be ordered top-down, beginning with the maximum number of replies, likes, words or comments. Each ranking can be addressed directly by its designation, e.g. *most_likes*. If someone is interested in the user with the current maximum of likes, the username of this user will be on top of that ranking:

```
head(most_likes)
```

```
##               author replies likes words comments
## 16  anonymized username         10    58    58         4
## 71  anonymized username          1    39     6         1
## 180 anonymized username          0    26     8         1
## 144 anonymized username          1    21     9         1
## 122 anonymized username          2    17    17         2
## 13  anonymized username          1    15    19         1
```

Furthermore, the username within the variable *author* provides access to the sentences that were originally written by that user. This can be done with recourse to the dataset *myYoutubeData* and the *subset(...)* command:

```
sentences <- subset(myYoutubeData[c(1:2)], AuthorDisplayName=="ENTER USERNAME HERE")
sentences[c(1), 1]
```

Therefore, this example will focus the 16th case, again displayed as “anonymized username”, since all usernames have been anonymized for this working paper. This user not only got the highest number on likes, but also wrote more comments than other users and collected several replies. Therefore, his example clarifies the output in R for each single sentence, which can be directly addressed by changing the second number within the command. Hence, this is the first sentence of this specific user:

```
## # A tibble: 1 x 1
##   Comment
##   <chr>
## 1 Being a sore loser isn't grounds for a lawsuit.
```

By accessing the sentences, there are a lot of things that can be analysed from here on. Sentiment analysis and semantic analysis of sentences are only two examples. Furthermore a simple word cloud could be generated by using R, in order to focus on keywords used within the social media network.

However, this techniques will be highlighted in a separate paper, because after this demonstration on how individual cases and comments can be identified and addressed among several hundreds or thousands of cases. How easy it can be to identify users as conversation partners of a specific user will be highlighted in the chapter about the visualization of social networks. Next aim is to gain a general understanding of the communication patterns within specific contents on social media platforms.

Analysis - 2: Identification of Communication Patterns

A social network is characterized by active and less active users. In particular, active users tend to shape the communication patterns of social networks more likely than their lesser-active counterparts. In theory, some of these active users seem to reach out to others in order to share their opinion; That is what makes

them relevant for Analysing Social Media Network Data. Therefore, the above-average active users and the below-average active users are identified by using the *summary(...)* command first:

```
summary(easy_dataset[c(2:5)])
```

In the following output, the mean values will be used to differentiate between above-average active users and below-average active users:

```
##      replies      likes      words      comments
## Min.   : 0.0000   Min.   : 0.000   Min.    : 1.00   Min.    :1.000
## 1st Qu.: 0.0000   1st Qu.: 0.000   1st Qu.: 6.00   1st Qu.:1.000
## Median : 0.0000   Median : 0.000   Median : 12.00   Median :1.000
## Mean   : 0.2574   Mean   : 1.748   Mean    : 27.12   Mean    :1.248
## 3rd Qu.: 0.0000   3rd Qu.: 1.000   3rd Qu.: 25.75   3rd Qu.:1.000
## Max.   :10.0000   Max.   :58.000   Max.    :561.00   Max.    :7.000
```

The mean values can then be implemented in the *ifelse(...)* command in the R terminal in order to create a new variable *relevant*.

```
easy_dataset$relevant <- ifelse(easy_dataset$replies>=0.25 & easy_dataset$likes>=1.74
& easy_dataset$words>=27.12 & easy_dataset$comments>=1.24, 1,0)
```

Again, the result can be inspected by using the *summary(...)* command:

```
summary(easy_dataset[c(6)])
```

Presented below is the output of the new variable *relevant*, which can be found in the six column of the dataset. This variable has been generated as binary variable, which means that above-average active users can be identified as 1 and below-average active users as 0:

```
##      relevant
## Min.   :0.0000
## 1st Qu.:0.0000
## Median :0.0000
## Mean   :0.0198
## 3rd Qu.:0.0000
## Max.   :1.0000
```

It is also possible to convert the remaining variables into binary variables. This has the advantage that all variables have a uniform scale level. Based on a uniform scale level, the next step is to set up an analysis model to identify the communication patterns. First, however, the command for converting the predictors into binary variables will be presented:

```
easy_dataset$replies <- ifelse(easy_dataset$replies>=0.25,1,0)
easy_dataset$likes <- ifelse(easy_dataset$likes>=1.74,1,0)
easy_dataset$words <- ifelse(easy_dataset$words>=27.12,1,0)
easy_dataset$comments <- ifelse(easy_dataset$comments>1.24,1,0)
```

These binary variables can also be inspected via the *summary(...)* command in the R terminal:

```
summary(easy_dataset[c(2:5)])
```

As a result, all predictors vary between a minimum of zero and a maximum of one. The predictors can now be used to predict whether a user shows relevant behavior inside a social network, or not:

```
##      replies      likes      words      comments
## Min.   :0.0000   Min.   :0.000   Min.    :0.0000   Min.    :0.0000
## 1st Qu.:0.0000   1st Qu.:0.000   1st Qu.:0.0000   1st Qu.:0.0000
## Median :0.0000   Median :0.000   Median :0.0000   Median :0.0000
## Mean   :0.1386   Mean    :0.203   Mean    :0.2327   Mean    :0.1634
```



```
## 3rd Qu.:0.0000 3rd Qu.:0.000 3rd Qu.:0.0000 3rd Qu.:0.0000
## Max. :1.0000 Max. :1.000 Max. :1.0000 Max. :1.0000
```

An adequate model would examine whether users who have the value 1 for the predictors also have a value of 1 for the variable *relevant*. Then the weight of the predictors can be calculated, which are representative for the communication patterns of any specific social network. A model using binary variables can be called with the *glm (...)* command with reference to *family=binomial()* in the R terminal:

```
glm.fit <- glm(data=easy_dataset, relevant~replies+likes+words+comments,
  family=binomial())
glm.fit
```

A logistic regression model with the weights of the predictors is shown in the output. The weights can be found directly below the predictors, indicated by the names of the variables, and they vary between a minimum weight of 41.44 and a maximum weight of 42.61. The procedure using such a model is also often referred to as Artificial Neural Network (ANN), however, in this instance only on a very simple basis:

```
##
## Call: glm(formula = relevant ~ replies + likes + words + comments,
##          family = binomial(), data = easy_dataset)
##
## Coefficients:
## (Intercept)      replies          likes          words          comments
##      -147.84         42.51         41.44         42.27         42.61
##
## Degrees of Freedom: 201 Total (i.e. Null); 197 Residual
## Null Deviance:      39.3
## Residual Deviance: 1.622e-08 AIC: 10
```

This slight difference can be considered a ranking of all variables in order to describe the communication pattern within this specific social network. Therefore, the variable *comments* is more important for being an above-average active user than the variables *replies*, *words* and *likes* (in descending order). These results tend to vary, depending on the size of the network, the activity of the users as well as the content of the access point. Therefore, social networks referring to political content have different communication patterns than those referring to sports, music or other contents, as will be highlighted later on via graphical representation.

Instead of using a uniform method for analysing users of social media platforms, a content- and network-specific approach is recommended. Only an interplay of sensitivity and specificity enables the identification of particularly active - and relevant - users, their comments and unique patterns via the predictors used in this statistical analysis. This makes it possible to identify opinion leaders, polarizing content and heated debates more quickly, compared to manual inspections of all users. In addition, one can see whether the users stand out in particular because they write a lot of comments, use a lot of words, get a lot of likes or how often they receive replies.

If necessary, a list of identified cases can be called by using the *which(...)* command in R, subsequent after computing the predictions of the logistic regression model with the *predict(...)* command and assigning the specification parameters 0 and 1 within the *ifelse(...)* command. In this instance, cases 16, 17, 30 and 35 can be identified as relevant users that frame a hot spot of communication within the social network. In addition, the predictions can be compared with the actual values of the variable *relevant*, which in this case results in an accuracy of 100 percent. The complete list of required commands is presented below:

```
probabilities <- glm.fit %>% predict(easy_dataset, type = "response")
predicted.classes <- ifelse(probabilities > 0.5, "1", "0")
which(predicted.classes=="1")
mean(predicted.classes == easy_dataset$relevant)
```

In contrast to what is shown in this example, by using mainly mean values, the relevant cases can also be designated manually on basis of qualitative inspection of the comments. With this method, for example, the

communication patterns of polarizing and appeasing users could easily be compared with one another, even if it can be assumed that the accuracy will then be slightly lower. This example, however, has focused mainly the above-average users for demonstration purpose only.

Analysis - 3: Visualization of Social Networks

The identification of cases and comments as well as a basic understanding of communication patterns on social media platforms are necessary for visualizing social networks. Thereby, relevant users as well as individual topics and the dissemination of these topics can be made clear throughout the comments and replies of a social network. In order to do so, the initial dataset *myYoutubeData* will be transformed into a dataset ready for visualization that focuses the activity within the network via the *Create(...)* command. Activity networks are based upon the comments, represented by nodes within each network and edges represent the direction of these comments, either to the social media content itself or to other comments. The result is a Graph-object, stored as *activityGraph*:

```
activityNetwork <- myYoutubeData %>% Create("activity") %>% AddText(myYoutubeData)
activityGraph <- activityNetwork %>% Graph(writeToFile = TRUE)
```

Since Graph-objects as well as the underlying dataset on the activity network differ from common datasets in terms of datastructure, the package *iGraph* is needed - which, at this step in Analysing Social Media Network Data, should be already installed via the previous commands - in order to process them:

```
library(igraph)
```

The difference to a normal dataset leads to a different way of writing the commands. For instance, the names of the authors of the comments are now stored inside the sixth column of the variable *nodes* of the *activityNetwork*, whereas in a common dataset the columns represent only one variable. If one wants to put the focus back on the already identified user “anonymized username”, his name needs to be added to the following command:

```
which(activityNetwork$nodes[6]=="ENTER USERNAME HERE")
```

```
## [1] 134 230 235 236
```

The result is the specific number of cases the user commented on YouTube. Since within a Graph-object the number of cases are the comments and not the authors of the comments, this specific number is needed in order to identify users afterwards within the activity network. Any user can be identified within an activity network by his *author_id*, which is usually represented by a random and anonymized number, but the specific case number enables direct access to this random and anonymized number:

```
(V(activityGraph)$author_id[ENTER CASE NUMBER HERE])
```

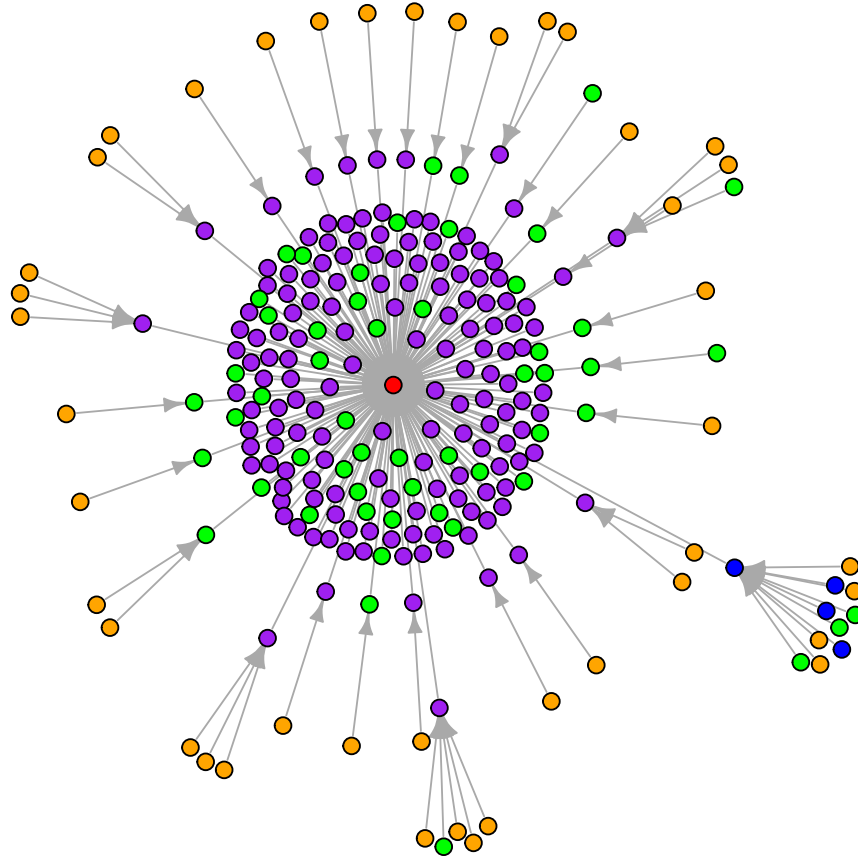
```
## [1] "UCtICekaZ9ptKjKHPBJxBSbA"
```

It is also possible to reverse this technique in order to identify the conversation partners of a specific user by their usernames. To identify recipients of a comment one has to subtract 1 from the particular case number of interest and in order to identify replies to that comment one can add a consecutive series of numbers, starting with 1. This is due to the fact that a comment can only be addressed to one other user, but several users can refer to one comment. A corresponding command would look like this in R:

```
activityNetwork$nodes[ENTER CASE NUMBER HERE, 6]
```

This could also be used to call up the comments of these users - as previously shown - and their positions as conversation partners in the social network. Therefore it is possible to highlight relevant elements in color:

Activity Network (N=200)



For example, the video itself is highlighted in red, each comment is highlighted in purple, focusing the 16th case can be done by referring to his random and anonymized *author_id* and assigning him blue as color and it is also possible to highlight each comment that contains a predefined list of buzzwords, such as “Donald Trump”, “President” or “White House”. One can add any number of buzzwords that either have to occur together, represented by a \mathcal{E} sign, or can also occur individually, represented by a / sign. As a result, the distribution of these buzzwords can be visualized throughout the entire social network. All remaining comments are replies and will be plotted in orange, as assigned by the following command:

```
V(activityGraph)$color <- "orange"
V(activityGraph)$color[which(V(activityGraph)
  $node_type=="video")] <- "red"
V(activityGraph)$color[which(V(activityGraph)
  $node_type=="comment")] <- "purple"
V(activityGraph)$color[which(V(activityGraph)
```

```

$author_id=="ENTER AUTHOR ID HERE")] <- "blue"
marker <- grep("ENTER BUZZWORDS HERE",
  tolower(V(activityGraph)$vosonTxt_comment))
V(activityGraph)$color[marker] <- "green"

```

The standard *plot(...)* command of R can also be specified in terms of the sizes of each element within the plot, but the setting presented below should enable a readable plot for most cases, as presented before:

```

plot(activityGraph, vertex.label="", vertex.size=4,
  edge.arrow.size=0.6, main="Activity Network (N=200)")

```

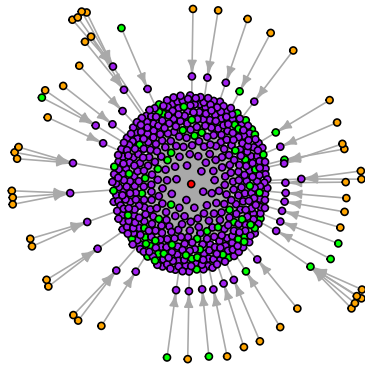
In summary, this activity network visualizes the Youtube video in the center of the social network, surrounded by a number of comments directed towards it. These comments are thereby initial comments. Comments referring to the initial comments can be identified by a larger distance to the video and by referring to other comments and not to the video itself. Regardless of their proximity to the center of the social network, ordinary comments are shown in purple, as predefined before. Non-ordinary comments, e.g. when containing some of the predefined buzzwords, are highlighted in green. And the comments of the 16th case with an “anonymized username” are plotted in blue, so that it is possible to assess the role of specific users and buzzwords when it comes to the dynamics within social networks. Further application examples follow in the next section, in order to highlight the different types of dynamics by the topic of a social network.

Application Examples and Comparison of Communication Patterns

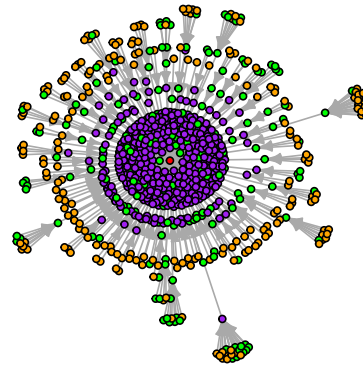
In a final step, four application examples are to be compared with one another: Music, sports, politics and games. All data is collected on YouTube via specific access points that are representative for all four different topics, are frequently watched on YouTube and strongly commented on.

As a first result, comparable topics, with the same number of comments to be analysed, tend to generate social networks with a similar structure when it comes to the distribution of comments and replies, as well as the scattering of buzzwords throughout the social network. Buzzwords, for example, are not only more often used when talking about sports and politics, they also seem to have a greater range in these social networks. The range can be addressed by counting the number of outer rings of the social network, which represent replies to previous replies or comments. Within these social networks, the topics seem to run through several levels of discussion, contrary to the social networks regarding music or games.

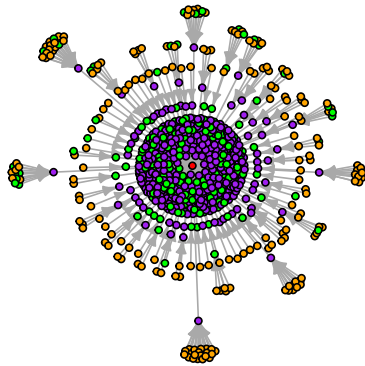
Music (N=500)



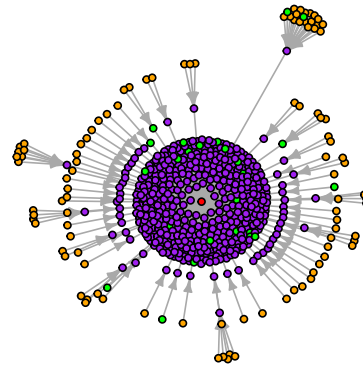
Sports (N=500)



Politics (N=500)



Games (N=500)



As a second result, further variables could be generated, based on the properties of each social network (e.g. by counting the appearances of buzzwords or the number of outer rings). This not only makes it possible to identify individual users and their specific role within a social network more sensitive, but to increase the specificity of the search for relevant users by taking these different types of social network structures into account. Furthermore, the scattering of buzzwords can be compared on an inter-topic level and be combined with sentiment analysis, semantic analysis and qualitative content analysis by identifying the position of each comment within a social network and the reactions it created.

Closing Remarks

A methodological approach based on the R programming language was presented, so that social media platforms like YouTube, Twitter or Reddit can be analysed in few and reproducible steps.

In a first step, an initial dataset based upon the social media platform YouTube has been converted into accessible variables via *vosonSML* and pre-processed in order to generate a dataset which is easy to understand,

in a few steps to modify and comprehensible to analyse. In a second step, it was presented how further quantitative variables can be generated on the basis of qualitative variables. This setting of quantitative variables has been used in order to identify particularly active users within a social network.

Furthermore, as a third step, since the comments of particularly active users could contain relevant content, e.g. from a scientific point of view or in order to identify fake news, hate speech and radicalizing elements, a method was shown how to access these comments among an often confusing large number of other comments, so that they can be inspected individually or compared among others. This assessment is subject to the scientists or analysing persons themselves.

After the content has been classified as relevant, the fourth step broke down the underlying communication patterns. As a result, the same users of social media platforms could be highlighted in the output, that already have been identified within the third step. A method for classification using the mean values of the variables was presented in order to do so; The accuracy was 100 percent. Other approaches are also conceivable, provided they can be theoretically justified and tested afterwards. The overlap between identified users in these two steps confirm this procedure. Based on the communication patterns, indicated mainly by focusing the weight of the variables *likes*, *replies*, *words* and *comments*, the impact and the systematics of active users within a social network could be pinpointed.

It must be taken into account, that every social network, depending on its users and topics, can have its own dynamics and thus different weights for these variables. This makes uniform identification approaches more difficult, if not impossible. The influence of these dynamics, which seems to emanate mainly from the topics discussed within a social network, can also be highlighted graphically. Examples have been provided by focusing social networks on music, sports, politics and gaming as primary topics. All social networks differ in terms of density, their range and the distribution of the topic within the comments. However, different social networks on a similar topic are more alike than social networks with a different topic.

This indicates that the general communication pattern should first be identified before the particularities of individual users can be highlighted. With this temporary result, the working paper, which is also a tutorial on the R programming language in terms of Analysing Social Media Network Data, provides a basis for further research and a methodological approach for several scientific disciplines. All codes are also available on GitHub.

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All codes required for an Analysis of Social Media Network Data with R can be accessed on GitHub: <https://github.com/statistical-thinking/social-media-analysis>