Leibniz Institute for the Social Sciences

Automatic Sampling and Analysis of YouTube Data

Basic text analysis of user comments

Johannes Breuer, Annika Deubel, & M. Rohangis Mohseni

February 15th, 2023

Leibniz Association

Required Libraries for This Session

```
library(tidyverse)
library(lubridate)
library(tuber)
library(quanteda)
library(quanteda.textstats)
library(wordcloud)
```

We also need two libraries that are only available from *GitHub*. You can install them using the `install_github()` function from the `remotes` package.

```
library(remotes)
install_github("dill/emoGG")
install_github("hadley/emo")
library(emoGG)
library(emo)
```

Note: Emil Hvitfeldt has created the `emoji` package which is based on the `emo` package and also available via *CRAN*.

Get the Data

As in the last session, we will be working with the - now processed and cleaned - comments for the Emoji Movie Trailer. In case you have collected and saved the comments before, you can just load them at this point.

```
FormattedComments <- readRDS("./data/ParsedEmojiComments.rds")
```

Note: Depending on where you saved the data, how you named the file, and what your current working directory is, you might have to adjust the file path.

Repetition: Collecting Data

If you have not collected and parsed the comments before, you, of course, need to do that before you can analyse any data.

NB: To save time and your *YouTube* API quota limit you might not want to do this now.

Step 1: Collecting the comments

```
Comments <- get_all_comments(video_id="r8pJt4dK_s4") # takes a while
```

Repetition: Parsing the Comments

To run the following code the script `yt_parse.R` as well as the ones containing the helper functions (`CamelCase.R`, `ExtractEmoji.R`, and `ReplaceEmoji.R`) need to be in the working directory (you can find those files in the `scripts` folder in the workshop materials).

```
source("yt_parse.R")
FormattedComments <- yt_parse(Comments) # this will take a while
```

Note: As an alternative to sourcing the `yt_parse.R` file you could also "manually" run the code from the slides for the session on *Processing and Cleaning User Comments* on the collected comments.

Comments Over Time: Data Wrangling 🤠

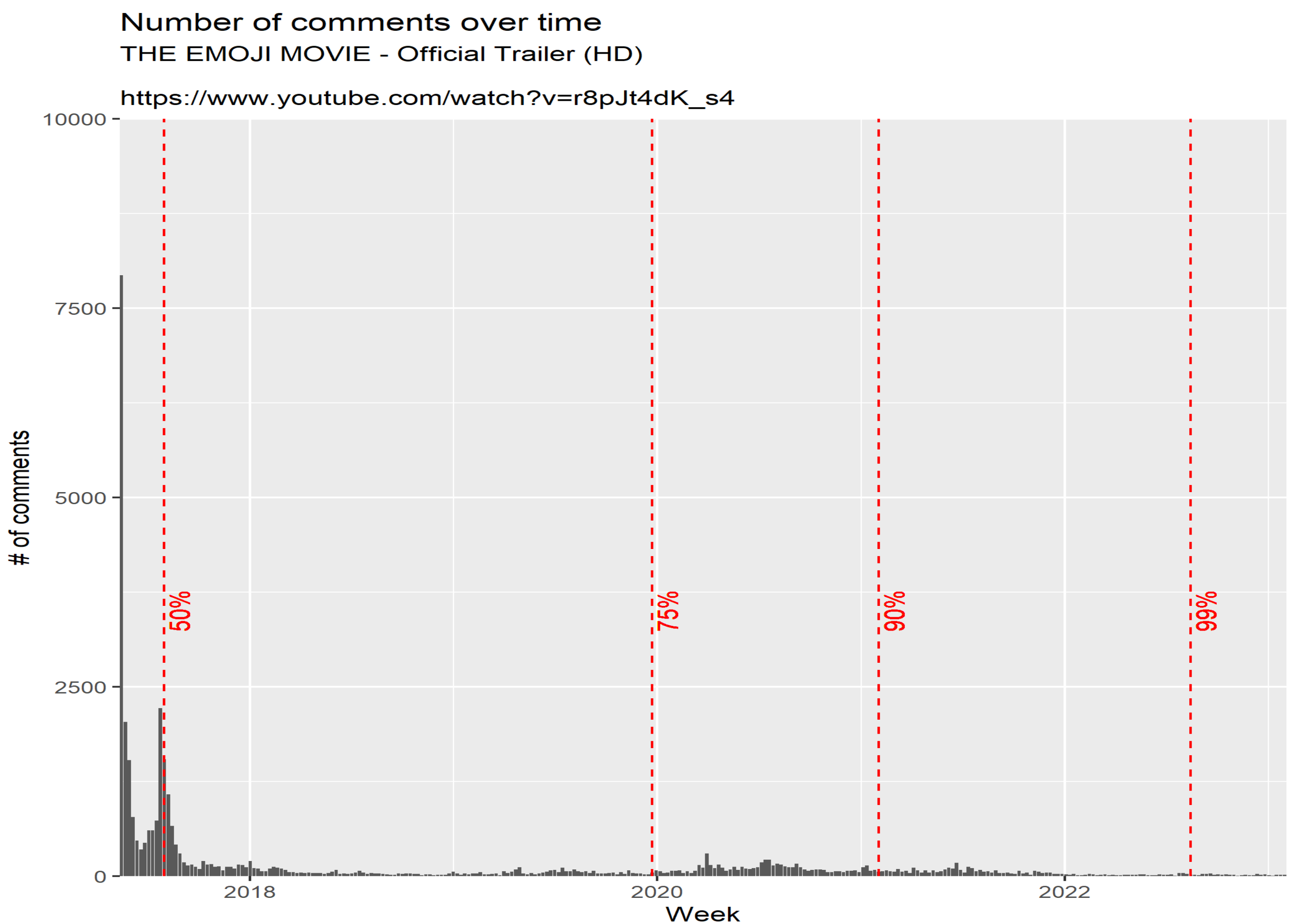
For a first exploratory plot, we want to plot the development of the number of comments per week over time and show until when 50%, 75%, 90%, and 99% of the comments had been posted. This requires some data wrangling.

```
FormattedComments <- FormattedComments %>%
  arrange(Published) %>%
  mutate(date = date(Published),
         week = floor_date(date,
                           unit = "week",
                           week_start = getOption("lubridate.week.start", 1)),
         counter = 1)

weekly_comments <- FormattedComments %>%
  count(week) %>%
  mutate(cumulative_count = cumsum(n))

PercTimes <- round(quantile(cumsum(FormattedComments$counter),
                            probs = c(0.5, 0.75, 0.9, 0.99)))
```

Comments Over Time: Plot

```
weekly_comments %>%
  ggplot(aes(x = week, y = n)) +
  geom_bar(stat = "identity") +
  scale_x_date(expand = c(0,0)) +
  scale_y_continuous(expand = c(0,0),
                     limits = c(0,10000)) +
  labs(title = "Number of comments over time",
       subtitle = "THE EMOJI MOVIE - Official Trailer (HD)
       \nhttps://www.youtube.com/watch?v=r8pJt4dK_s4",
       x = "Week",
       y = "# of comments") +
  geom_vline(xintercept = FormattedComments$week[PercTimes],linetype = "dashed",
  geom_text(aes(x = FormattedComments$week[PercTimes][1], label = "50%", y = 3500
            colour="red", angle=90, vjust = 1.2) +
  geom_text(aes(x = FormattedComments$week[PercTimes][2], label = "75%", y = 3500
            colour="red", angle=90, vjust = 1.2) +
  geom_text(aes(x = FormattedComments$week[PercTimes][3], label = "90%", y = 3500
            colour="red", angle=90, vjust = 1.2) +
  geom_text(aes(x = FormattedComments$week[PercTimes][4], label = "99%", y = 3500
            colour="red", angle=90, vjust = 1.2)
```

Number of Comments Over Time: Plot



gesis Leibniz Institute for the Social Sciences

Most Popular Comments

Which comments received the highest number of likes?

```
FormattedComments %>%
  arrange(-LikeCount) %>%
  head(10) %>%
  select(Text, LikeCount, Published)
```

```
##                                                                                                  Text LikeCount           Published
## 1                                                                  Will they show Snapchat nudes in the movie?      4287 2017-05-16 15:38:40
## 2                                                                                  The Meme Movie: Coming 2020      3260 2017-10-16 04:08:12
## 3                                                    Lmao the egg plant emoji never gets used? Do your research lmao      2952 2017-05-16 23:55:38
## 4                                                                 The book is so much better because it doesn’t exist.      2883 2020-10-30 15:08:17
## 5                                                              I believe everyone intentionally looked this up to dislike it      1802 2020-12-23 18:32:29
## 6                                                       This movie reeks of board room meetings on what kids find "cool".      1690 2017-05-16 22:40:13
## 7                                                                            The eggplant emoji never used? Suuuuuree.      1399 2017-05-17 03:10:34
## 8            So, this thing is still a thing? Ugh, I can't really still believe that you cancelled that Popeye movie...      1281 2017-05-16 15:32:41
## 9                                                                                          This is the best part 2:38      1109 2020-06-08 18:29:03
## 10 So apparently, the eggplant emoji is an emoji that never gets used? Shows how in touch the writers of this movie are.      1090 2021-05-02 14:35:05
```

Text Mining

An introduction to text mining and analysis (for social sciences) is beyond the scope of this workshop, but there are great introductions available (for free) online, e.g.

- Text Mining with R - A Tidy Approach by Julia Silge & David Robinson: A tidy(verse) approach
- Tutorials for the package `quanteda`
- Text mining for humanists and social scientists in R by Andreas Niekler & Gregor Wiedemann
- Text Mining in R by Jan Kirenz
- Computational Text Analysis by Theresa Gessler
- Automated Content Analysis by Chung-hong Chan

In the following, we will very briefly introduce some key terms and steps in text mining, and then go through some examples of exploring *YouTube* comments (text + emojis).

Popular Text Mining Packages

- tm: the first comprehensive text mining package for R
- tidytext: tidyverse tools & tidy data principles
- quanteda: very powerful text mining package with extensive documentation

Text as Data (in a 🌰)

Document = collection of text strings

Corpus = collection of documents (+ metadata about the documents)

Token = part of a text that is a meaningful unit of analysis (often individual words)

Vocabulary = list of all distinct words form a corpus (i.e., all types)

Document-term matrix (DTM) or **Document-feature matrix (DFM)** = matrix with n = # of documents rows and m = size of vocabulary columns where each cell contains the count of a particular word for a particular document

Preprocessing (in a 🌰)

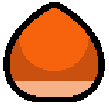
For our examples in this session, we will go through the following preprocessing steps:

1. Basic string operations:

- Transforming to lower case
- Detecting and removing certain patterns in strings (e.g., punctuation, numbers or URLs)

2. Tokenization: Splitting up strings into words (could also be combinations of multiple words: n-grams)

3. Stopword removal: Stopwords are very frequent words that appear in almost all texts (e.g., "a","but","it", "the") but have low informational value for most analyses (at least in the social sciences)

Preprocessing (in a )

NB:

- There are many other preprocessing options that we will not use for our examples, such as stemming, lemmatization or natural language processing pipelines (e.g., to detect and select specific word types, such as nouns and adjectives).
- Keep in mind that the choice and order of these preprocessing steps is important and should be informed by your research question.

Tokenization

Before we tokenize the comments, we want to remove newline commands from the strings.

```
FormattedComments <- FormattedComments %>%
  mutate(TextEmojiDeleted = str_replace_all(TextEmojiDeleted,
                                            pattern = "\\\n",
                                            replacement = " "))
```

Tokenization

Now we can tokenize the comments and remove punctuation, symbols, numbers, and URLs.

```
toks <- FormattedComments %>%
  pull(TextEmojiDeleted) %>%
  char_tolower() %>%
  tokens(remove_numbers = TRUE,
                remove_punct = TRUE,
                remove_separators = TRUE,
                remove_symbols = TRUE,
                split_hyphens = TRUE,
                remove_url = TRUE)
```

Document-Feature Matrix

With the tokens we can create a document-feature matrix (DFM) and remove stopwords.

```
commentsDfm <- dfm(toks,
                   remove = quanteda::stopwords("english"))
```

Most Frequent Words

```
TermFreq <- textstat_frequency(commentsDfm)
head(TermFreq, n = 20)
```

```
##     feature frequency rank docfreq group
## 1     movie     11706    1    8876   all
## 2     emoji      3191    2    2759   all
## 3      like      2816    3    2427   all
## 4      just      2486    4    2199   all
## 5       nom      2239    5       1   all
## 6    people      1541    6    1332   all
## 7      sony      1508    7    1397   all
## 8       bad      1395    8    1275   all
## 9      good      1312    9    1198   all
## 10      one      1227   10    1111   all
## 11     hate      1127   11    1019   all
## 12   emojis      1099   12     990   all
## 13      see      1047   13     927   all
## 14    watch      1030   14     948   all
## 15     make      1010   15     908   all
## 16    think       992   16     898   all
## 17     know       960   17     879   all
## 18   popeye       939   18     862   all
## 19 dislikes       912   19     895   all
## 20      can       886   20     772   all
```

Removing Tokens

We may want to remove additional words (that are not included in the stopwords list) if we consider them irrelevant for our analyses.

```
custom_stopwords <- c("nom", "just", "one")
commentsDfm <- dfm(toks, remove = c(quanteda::stopwords("english"),
                                    custom_stopwords))
TermFreq <- textstat_frequency(commentsDfm)
```

For more options for selecting or removing tokens, see the quanteda documentation.

Wordclouds

```
wordcloud(words = TermFreq$feature,
          freq = TermFreq$frequency,
          min.freq = 10,
          max.words = 50,
          random.order = FALSE,
          rot.per = 0.35,
          colors = brewer.pal(8, "Dark2"))
```

Note: You can adjust what is plotted by, e.g., changing the minimum frequency (`min.freq`) or the maximum # of words (`max.words`). Check `?wordcloud` for more customization options.

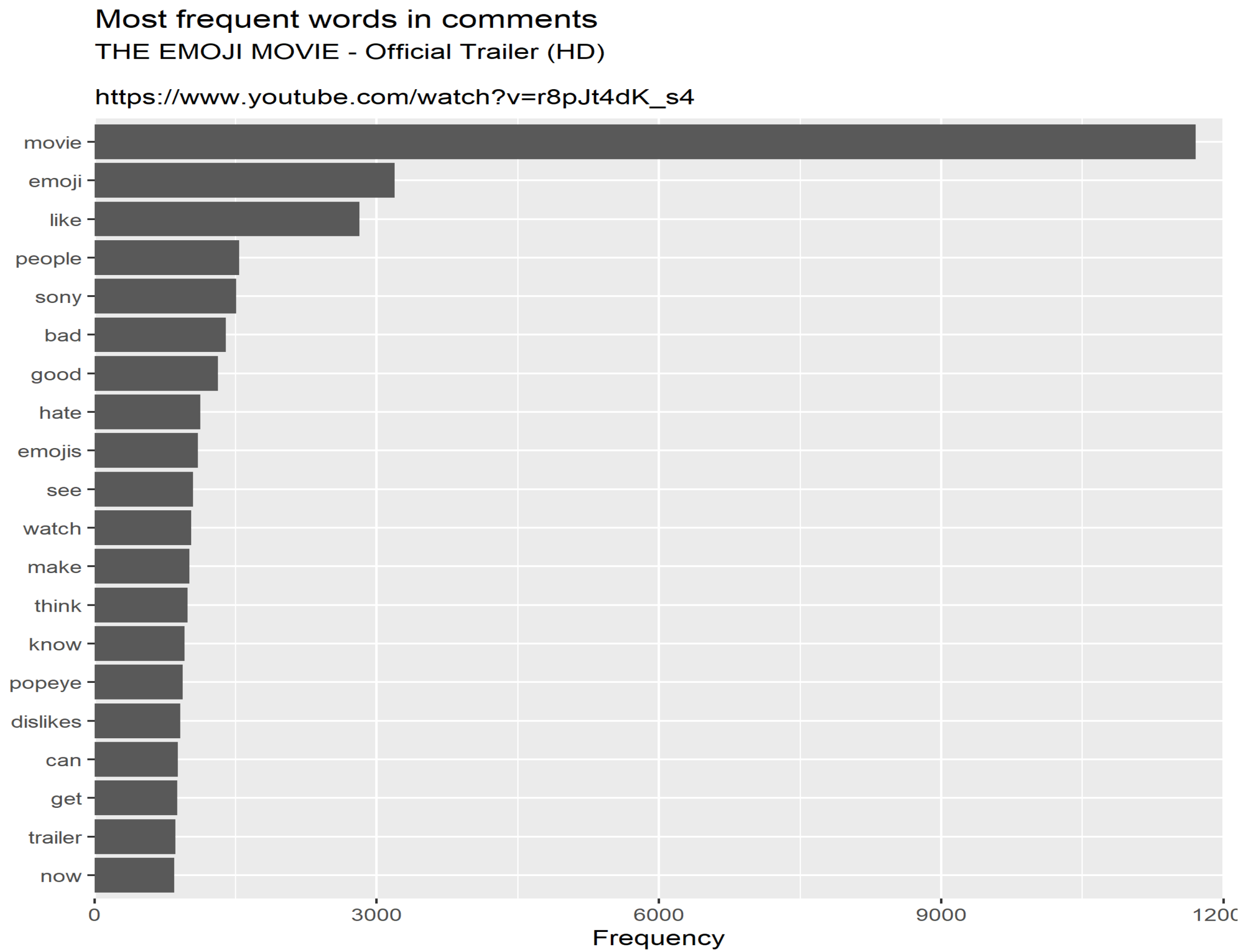
Wordclouds


movie
emoji
like
people
sony
bad
good
watch
kids
still
actually
film
big
inside
oh
ralph
want
money
trailer
see
cancer
can
well
fucking
emojis
really
made
cringe
wreck
much
dislikes
hate
looks
get
even
make
time
god
think
ever
now
love
lol
know
popeye
better
movies
dislike
going

Plot Most Frequent Words

```
TermFreq %>%
head(n = 20) %>%
  ggplot(aes(x = reorder(feature, frequency), y = frequency)) +
  geom_bar(stat="identity") +
  labs(title = "Most frequent words in comments",
       subtitle = "THE EMOJI MOVIE - Official Trailer (HD)
       \nhttps://www.youtube.com/watch?v=r8pJt4dK_s4",
       x = "",
       y = "Frequency") +
  scale_y_continuous(expand = c(0,0),
                     limits = c(0,12000)) +
  coord_flip()
```

Plot Most Frequent Words



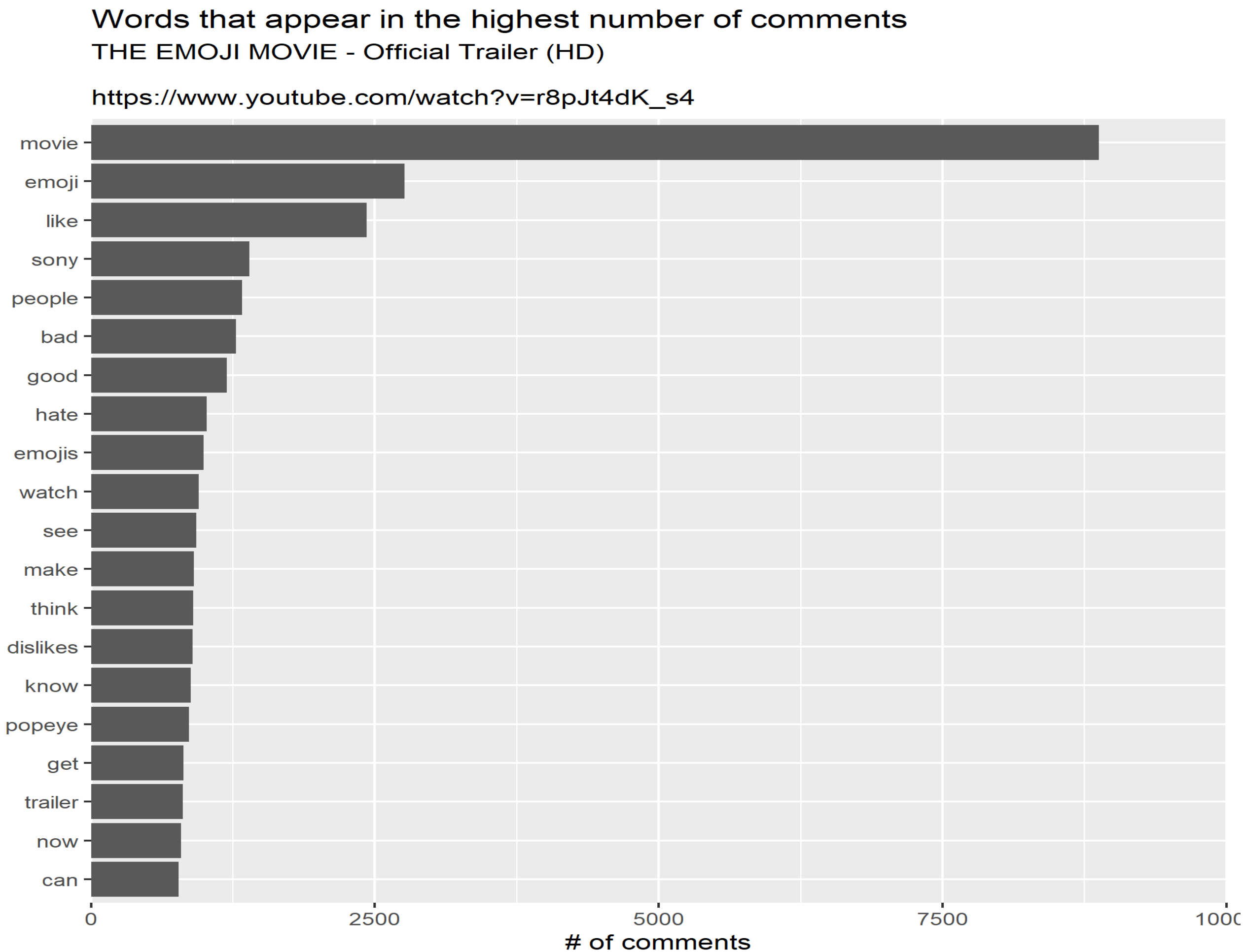
gesis Leibniz Institute for the Social Sciences

Plot Docfreq

Instead of the raw frequency of words we can also look at the number of comments that a particular word appears in. This metric takes into account that words might be used multiple times in the same comment.

```
TermFreq %>%
head(n = 20) %>%
  ggplot(aes(x = reorder(feature, docfreq), y = docfreq)) +
  geom_bar(stat="identity") +
  labs(title = "Words that appear in the highest number of comments",
       subtitle = "THE EMOJI MOVIE - Official Trailer (HD)
       \nhttps://www.youtube.com/watch?v=r8pJt4dK_s4",
       x = "",
       y = "# of comments") +
  scale_y_continuous(expand = c(0,0),
                     limits = c(0,10000)) +
  coord_flip()
```

Plot Docfreq



Emojis

In most of the research studying user-generated text from social media, emojis have, so far, been largely ignored. However, emojis convey emotions and meaning, and can, thus, provide additional information or context when working with textual data.

In the following, we will do some exploratory analysis of emoji frequencies in *YouTube* comments. Before we can start, we first need to do some data cleaning again, then tokenize the emojis as some comments include more than one emoji, and create an emoji DFM.

```
emoji_toks <- FormattedComments %>%
  mutate(Emoji = na_if(Emoji, "NA")) %>% # define missings
  mutate (Emoji = str_trim(Emoji)) %>% # remove spaces
  filter(!is.na(Emoji)) %>% # only keep comments with emojis
  pull(Emoji) %>% # pull out column cotaining emoji labels
  tokens(what = "fastestword") # tokenize emoji labels

EmojiDfm <- dfm(emoji_toks) # create DFM for emojis
```

Most Frequent Emojis

```
EmojiFreq <- textstat_frequency(EmojiDfm)
head(EmojiFreq, n = 10)
```

```
##                        feature frequency rank docfreq group
## 1              emoji_pileofpoo      3999    1     536   all
## 2               emoji_eggplant      3578    2     279   all
## 3      emoji_facewithtearsofjoy      2873    3     853   all
## 4           emoji_unamusedface      2488    4     677   all
## 5      emoji_bbutton(bloodtype)      1878    5     130   all
## 6           emoji_middlefinger      1866    6     298   all
## 7           emoji_grinningface      1562    7     374   all
## 8            emoji_flushedface      1239    8     256   all
## 9             emoji_thumbsdown      1157    9     264   all
## 10 emoji_facewithsymbolsonmouth       982   10     104   all
```

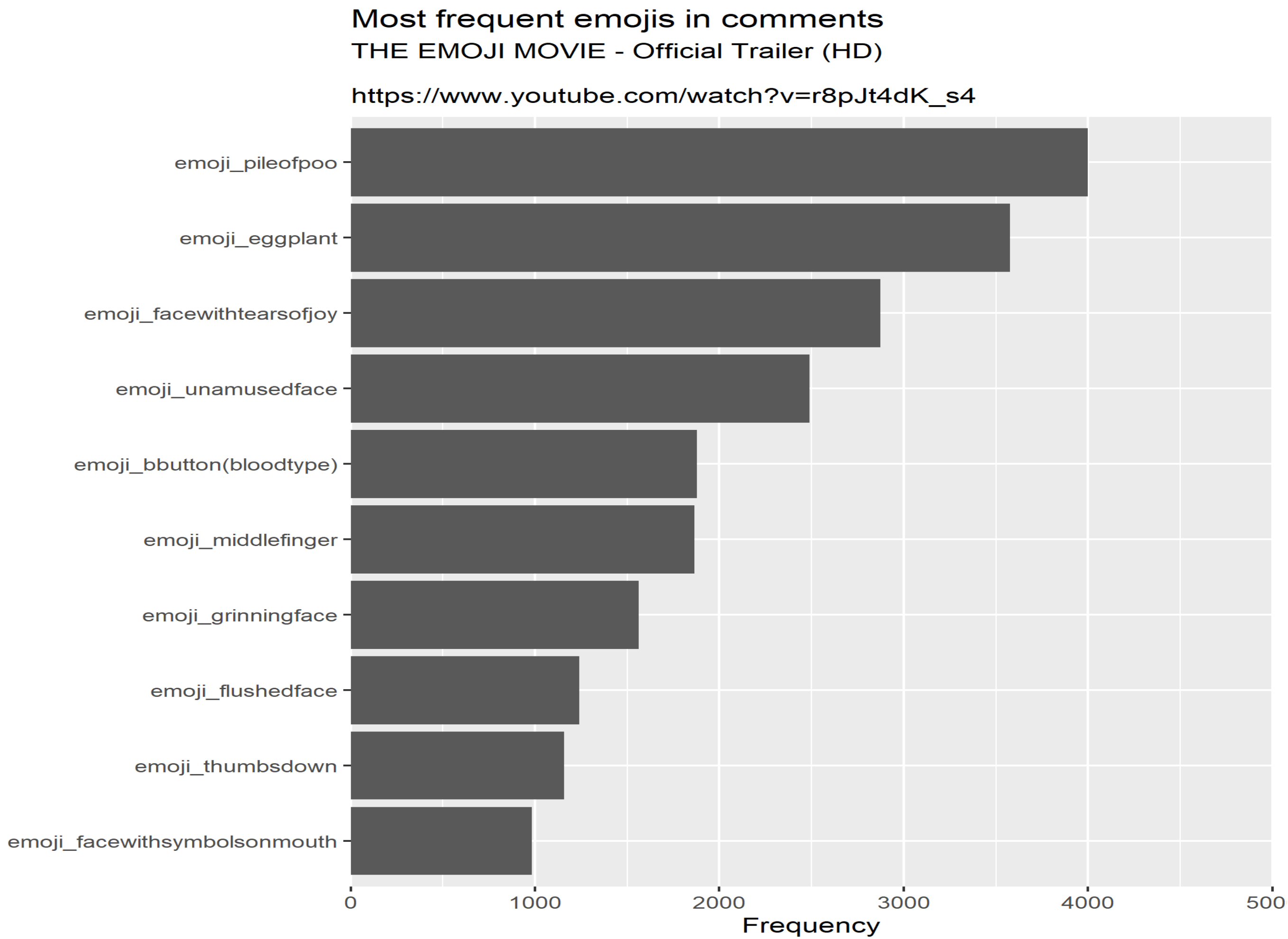
Plot Most Frequent Emojis

```
EmojiFreq %>%
head(n = 10) %>%
  ggplot(aes(x = reorder(feature, frequency), y = frequency)) +
  geom_bar(stat="identity") +
  labs(title = "Most frequent emojis in comments",
       subtitle = "THE EMOJI MOVIE - Official Trailer (HD)
       \nhttps://www.youtube.com/watch?v=r8pJt4dK_s4",
       x = "",
       y = "Frequency") +
  scale_y_continuous(expand = c(0,0),
                     limits = c(0,5000)) +
 coord_flip()
```

Note: Similar to what we did for the comment text before we could replace `frequency` with `docfreq` in the above code to create a plot with the emojis that appear in the highest number of comments.

gesis Leibniz Institute for the Social Sciences

Plot Most Frequent Emojis



Emoji Frequency Plot: Preparation (1)

The previous emoji frequency plot was a bit 😪. To make things prettier, we can use the actual emojis instead of the text labels in our plot. Doing this takes a bit of preparation.[1]

As a first step, we need an emoji lookup table in which the values in the name column have the same format as the labels in the feature column of our `EmojiFreq` object.

```
emoji_lookup <- jis %>%
  select(runes, name) %>%
  mutate(runes = str_to_lower(runes),
         name = str_to_lower(name)) %>%
  mutate(name = str_replace_all(name, " ", "")) %>%
  mutate(name = paste0("emoji_", name))
```

[1]For an alternative approach to using emojis in `ggplot2` see this blog post by Emil Hvitfeldt.

gesis Leibniz Institute for the Social Sciences

Emoji Frequency Plot: Preparation (2)

The second step of preparation for the nicer emoji frequency plot is creating mappings of emojis to data points so that we can use emojis instead of points in a scatter plot.[1]

```
top_emojis <- 1:10

for(i in top_emojis){
  name <- paste0("mapping", i)
  assign(name,
         do.call(geom_emoji,list(data = EmojiFreq[i,],
                                 emoji = gsub("^0{2}","", strsplit(tolower(emoji_
}
```

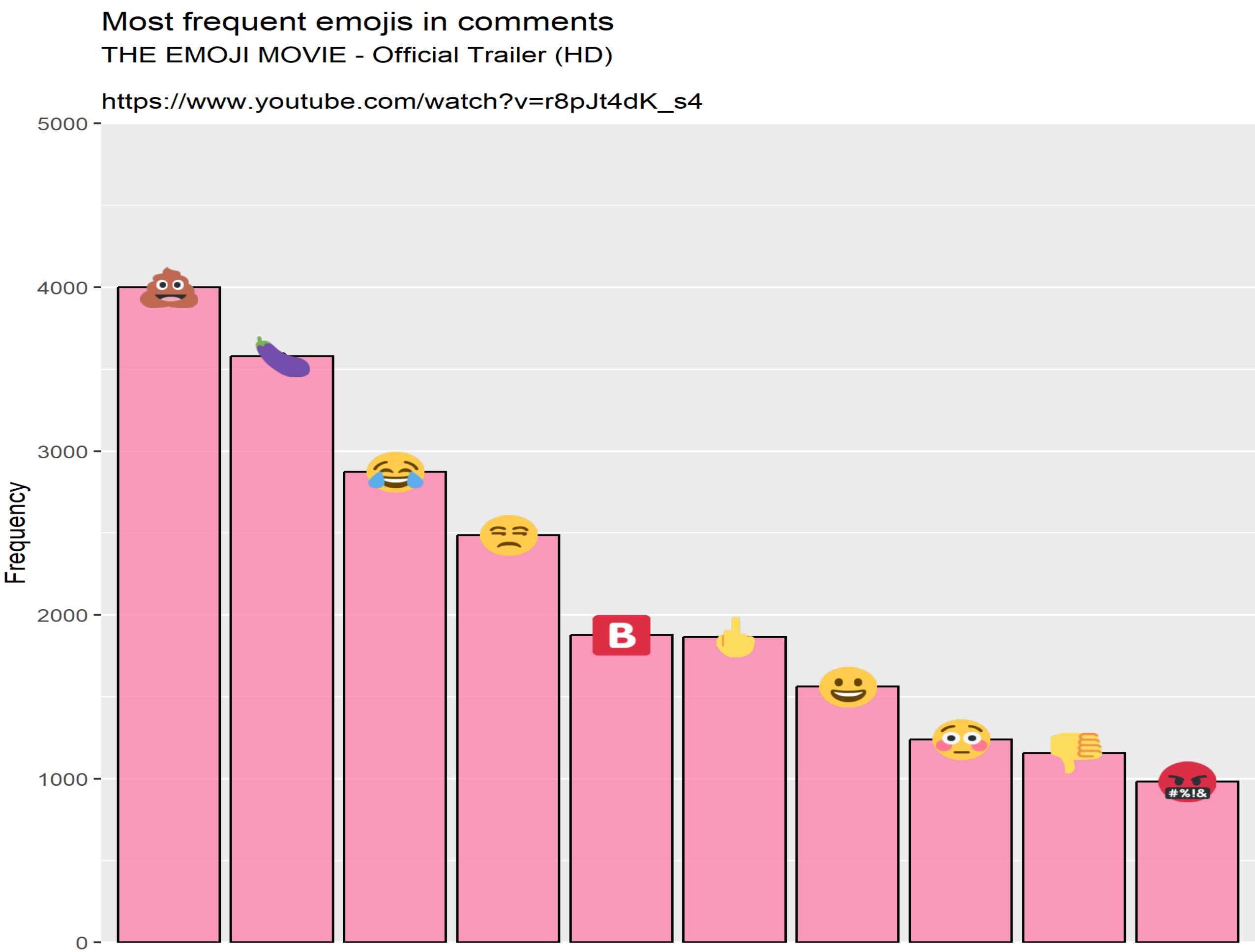
[1] Please note: this code has not been tested systematically. Depending on which emojis are most frequent for a video, this might not work because (a) one of the emojis is not included in the emoji lookup table (which uses the `jis` data frame from the `emo` package) or (b) the content in the `runes` column doesn't match the format/code that the `emoji` argument in the `geom_emoji` function from the emoGG

😎 Emoji Frequency Plot

```
EmojiFreq %>%
head(n = 10) %>%
  ggplot(aes(x = reorder(feature, -frequency), y = frequency)) +
  geom_bar(stat="identity",
           color = "black",
           fill = "#FF74A6",
           alpha = 0.7) +
  geom_point() +
  labs(title = "Most frequent emojis in comments",
       subtitle = "THE EMOJI MOVIE - Official Trailer (HD)
       \nhttps://www.youtube.com/watch?v=r8pJt4dK_s4",
       x = "",
       y = "Frequency") +
  scale_y_continuous(expand = c(0,0),
                     limits = c(0,5000)) +
  theme(panel.grid.major.x = element_blank(),
        axis.text.x = element_blank(),
        axis.ticks.x = element_blank()) +
  mapping1 +
  mapping2 +
  mapping3 +
  mapping4 +
  mapping5 +
  mapping6 +
  mapping7 +
  mapping8 +
  mapping9 +
  mapping10
```

gesis Leibniz Institute for the Social Sciences

😎 Emoji Frequency Plot



gesis Leibniz Institute for the Social Sciences

Exercise time 🏋️💪🏃🚴

Solutions