Chapter6_exercises

Anna Wohlmann

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1) Go to the website polidoc and download manifestos of your choice in one language. Create a dfm and run a wordfish model.

Download the data of your choice and create a dfm: We chose manifestos from Austria from 2017 from polidoc.

```
datadir <- "./data_exercises"

library(readtext)
library(quanteda) #read in necessary packages

## Warning: Paket 'quanteda' wurde unter R Version 4.2.3 erstellt

## Package version: 3.3.1
## Unicode version: 13.0
## ICU version: 69.1

## Parallel computing: 12 of 12 threads used.

## See https://quanteda.io for tutorials and examples.

manifestos_df<- readtext(paste0(datadir,"/austria_manifestos"), encoding=
"UTF-8") #read in data from folder
country <- c("Austria", "Austria", "Austria", "Austria", "Austria") #add a
country variable
party <- c("Die Grünen", "KPÖ","SPÖ", "FPÖ", "NEOS") #party of manifesto
variable - same order as in folder!
year <- c("2017", "2017", "2017", "2017", "2017") #year of manifesto variable
manifestos_df$country <- country
manifestos_df$year <- year
manifestos_df$party <- party #add additional variables to data frame

corpus_manifestos <- corpus(manifestos_df) #turn dataframe into corpus
summary(corpus_manifestos) #print corpus summary

## Corpus consisting of 5 documents, showing 5 documents:
##
##                    Text Types Tokens Sentences country year      party
##  42110.000.2017.1.1.txt  5707  21000       677 Austria 2017 Die Grünen
##  42220.000.2017.1.1.txt  1605   4376       181 Austria 2017        KPÖ
##  42320.000.2017.1.1.txt 10076  57291      2958 Austria 2017        SPÖ
##  42420.000.2017.1.1.txt  2786   8601       289 Austria 2017        FPÖ
##  42450.000.2017.1.1.txt  8856  37117      1649 Austria 2017       NEOS

dfm_aus <-
  quanteda::dfm(corpus_manifestos %>%
```

```
                  quanteda::tokens(
                    remove_punct = TRUE,
                    remove_numbers = TRUE,
                    remove_symbols = TRUE,
                    remove_url = TRUE)) %>%
    quanteda::dfm_remove(stopwords("de")) %>%
  quanteda::dfm_wordstem(language = "de")
head(dfm_aus)
```

```
## Document-feature matrix of: 5 documents, 13,193 features (68.79% sparse)
and 3 docvars.
##                          features
## docs                      grun wahlprogramm nationalratswahl lieb leserin
les
##   42110.000.2017.1.1.txt   70            3                1    2       1
1
##   42220.000.2017.1.1.txt    0            3                2    1       0
0
##   42320.000.2017.1.1.txt    0            0                1    7       0
6
##   42420.000.2017.1.1.txt    1            2                1    0       0
0
##   42450.000.2017.1.1.txt    4            0                0    2       0
2
##                          features
## docs                      osterreich europa steh gross
##   42110.000.2017.1.1.txt        112     46   12    30
##   42220.000.2017.1.1.txt         16      2    2     5
##   42320.000.2017.1.1.txt        322     69   28    64
##   42420.000.2017.1.1.txt        112     15    7     5
##   42450.000.2017.1.1.txt        196    108   21    33
## [ reached max_nfeat ... 13,183 more features ]
```

Run Wordfish: We need to rank two texts. Here, we make the justifiable statement that Die Grünen are left of FPÖ.

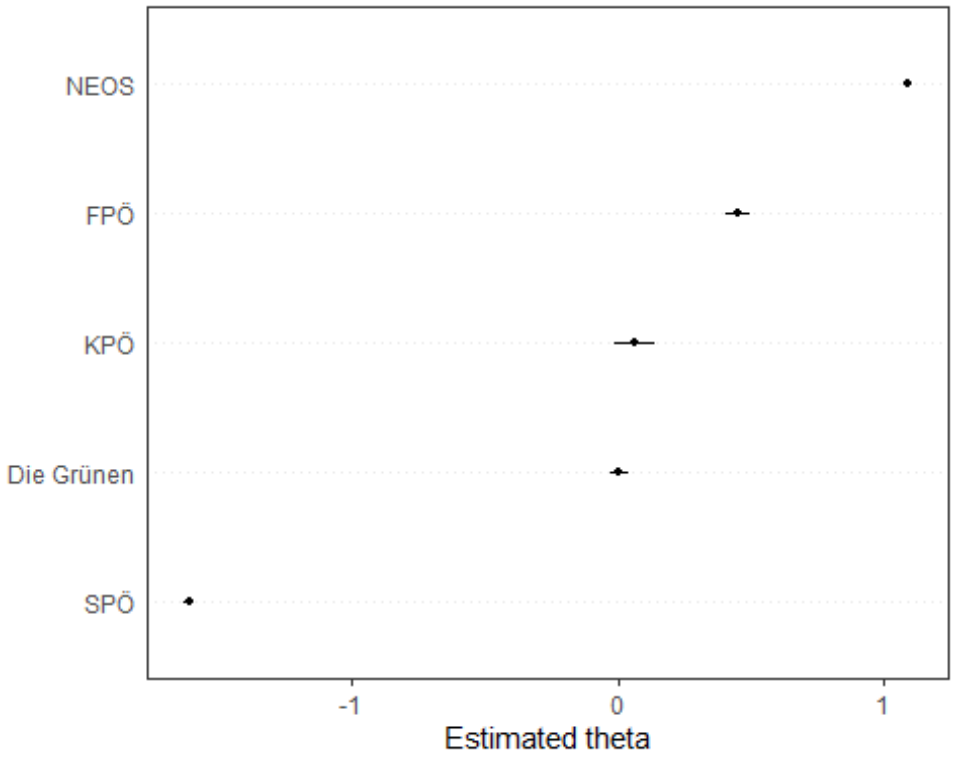
```
library(quanteda.textmodels)
library(quanteda.textplots)
fish_aus <- textmodel_wordfish(dfm_aus, dir = c(1,4)) #1 = Die Grünen, 4 =
FPÖ
summary(fish_aus, n = 5)
```

```
##
## Call:
## textmodel_wordfish.dfm(x = dfm_aus, dir = c(1, 4))
##
## Estimated Document Positions:
##                            theta       se
## 42110.000.2017.1.1.txt  0.006585 0.017813
## 42220.000.2017.1.1.txt  0.061448 0.039101
## 42320.000.2017.1.1.txt -1.611993 0.009437
## 42420.000.2017.1.1.txt  0.451237 0.022944
```

```
## 42450.000.2017.1.1.txt  1.092724 0.007745
##
## Estimated Feature Scores:
##        grun wahlprogramm nationalratswahl    lieb leserin
## beta 0.1791       0.2392         -0.04765 -0.4833  0.1127
## psi  2.4639       0.2198         -0.25955  0.4065 -1.8517
```

You can visualize the results:

```
textplot_scale1d(fish_aus, doclabels=fish_aus$x@docvars$party)
```



2) Replicate the code in the k-means section for the word2vec model on the data used here, or choose another text dataset of your choice. You will keep using this model for Exercise 2 of Chapter 7.

To correct your replication, you can check the chapter again. We do it here quickly:

```
datadir <- "./data_exercises"
load(paste0(datadir, "\\supercorpus_unstemmed_V4.RData")) #load where you
saved it
library(word2vec)

## Warning: Paket 'word2vec' wurde unter R Version 4.2.3 erstellt

clean_doc <- txt_clean_word2vec(corpus_unstemmed[["documents"]][["texts"]],
ascii = TRUE, alpha = TRUE, tolower = TRUE, trim = TRUE)
library(stopwords)
set.seed(45) #same results every run
model_w2v <- word2vec(clean_doc, stopwords = stopwords("en")) #run model
```

a) Find out what the six nearest neighbours, meaning most similar words, are to the word “ideology”.

```
set.seed(5)
predict(model_w2v, "ideology", type = "nearest", top_n = 6)
```

```
## $ideology
##      term1        term2 similarity rank
## 1 ideology   ideologies  0.9010481    1
## 2 ideology   intolerant  0.8998477    2
## 3 ideology    dogmatism  0.8844938    3
## 4 ideology    perverted  0.8769405    4
## 5 ideology sectarianism  0.8753314    5
## 6 ideology   liberalism  0.8701701    6
```

In this dataset, intolerance, dogmatism, obsession, and fanaticism are closely related to ideology.

b) Choose your own word and find the words closest to it based on the speeches dataset.

```
set.seed(5)
predict(model_w2v, "racism", type = "nearest", top_n = 1)
```

```
## $racism
##    term1      term2 similarity rank
## 1 racism xenophobia  0.9503211    1
```

For racism, the nearest neighbor is xenophobia.

c) Find the embedding vector for the word “speech”. Hint: word2vec has documentation that you can access online.

The documentation on CRAN shows that we can use the predict function again:

```
??word2vec::predict

## starte den http Server für die Hilfe fertig

set.seed(5)
predict(model_w2v, "speech", type = "embedding")
```

```
##              [,1]     [,2]       [,3]       [,4]       [,5]    [,6]
[,7]
## speech -0.2161069 1.434303 -0.1087207 -0.9055808 -0.4051178 1.99464 -
1.301896
##             [,8]       [,9]     [,10]      [,11]       [,12]      [,13]
## speech 0.3186335 -0.3486725 -1.859534 -0.3497184 -0.01728884 -0.3574432
##            [,14]       [,15]      [,16]    [,17]      [,18]    [,19]
[,20]
## speech 0.3285038 -0.02338453 -0.6958435 0.599277 -0.7498181 1.425376 -
1.485081
##           [,21]      [,22]    [,23]     [,24]     [,25]     [,26]
[,27]
```

```
## speech 1.104491 -0.3240533 1.065067 -1.257822 0.2602832 0.4577345
0.5264484
##            [,28]     [,29]      [,30]     [,31]    [,32]      [,33]
[,34]
## speech 0.7548172 -1.156543 -0.6036345 -1.950491 1.362632 -0.8856723
0.7299964
##             [,35]     [,36]     [,37]    [,38]      [,39]     [,40]
[,41]
## speech -0.3035209 0.5556855 -1.050442 1.495407 -0.5547905 -1.035912
1.692212
##            [,42]     [,43]     [,44]     [,45]      [,46]    [,47]
[,48]
## speech 0.9947924 0.9015331 -2.063983 0.2032624 -0.6872873 1.271068
0.3267138
##             [,49]     [,50]
## speech -0.6684237 0.9837236
```

3) Use the data from Exercise 1. Replicate the LDA analysis from this chapter, finding out how much the chosen parties talk about renewable energy and unemployment. You will keep using this model in Exercise 3 of Chapter 7.

In exercise 1, we worked on the whole document; here, we are interested in individual sentences. Therefore, we need to reshape the corpus and then create a dtm:

```
corpus_sent <- corpus_reshape(corpus_manifestos, to = "sentences") #transform
into sentence corpus

dfm_sent_aus <-
  quanteda::dfm(corpus_sent %>%
                  quanteda::tokens(
                    remove_punct = TRUE,
                    remove_numbers = TRUE,
                    remove_symbols = TRUE,
                    remove_url = TRUE)) %>%
    quanteda::dfm_remove(stopwords("de")) %>%
  quanteda::dfm_wordstem(language = "de")
head(dfm_sent_aus)
```

```
## Document-feature matrix of: 6 documents, 13,193 features (99.93% sparse)
and 3 docvars.
##                            features
## docs                        grun wahlprogramm nationalratswahl lieb leserin
les
##   42110.000.2017.1.1.txt.1    1            0                0    0       0
0
##   42110.000.2017.1.1.txt.2    1            1                1    2       1
1
##   42110.000.2017.1.1.txt.3    0            0                0    0       0
0
##   42110.000.2017.1.1.txt.4    0            0                0    0       0
0
```

```
##   42110.000.2017.1.1.txt.5    0            0                0    0       0
0
##   42110.000.2017.1.1.txt.6    1            0                0    0       0
0
##                            features
## docs                        osterreich europa steh gross
##   42110.000.2017.1.1.txt.1          0      0    0     0
##   42110.000.2017.1.1.txt.2          0      0    0     0
##   42110.000.2017.1.1.txt.3          1      1    1     1
##   42110.000.2017.1.1.txt.4          0      0    0     0
##   42110.000.2017.1.1.txt.5          0      1    0     0
##   42110.000.2017.1.1.txt.6          0      0    0     0
## [ reached max_nfeat ... 13,183 more features ]
```

Save dfm for chapter 7: NOT WORKING

```
saveRDS(dfm_sent_aus,file = "dfm_sentences_austria.rds")
```

For LDA, we need a DTM:

```
dtm_aus <- convert(dfm_sent_aus, to = "topicmodels")
```

Finding k: We use the ldatuning package to decide on k.

```
library("ldatuning") #install this package if you haven't yet, then use
library
```

```
## Warning: Paket 'ldatuning' wurde unter R Version 4.2.3 erstellt
```

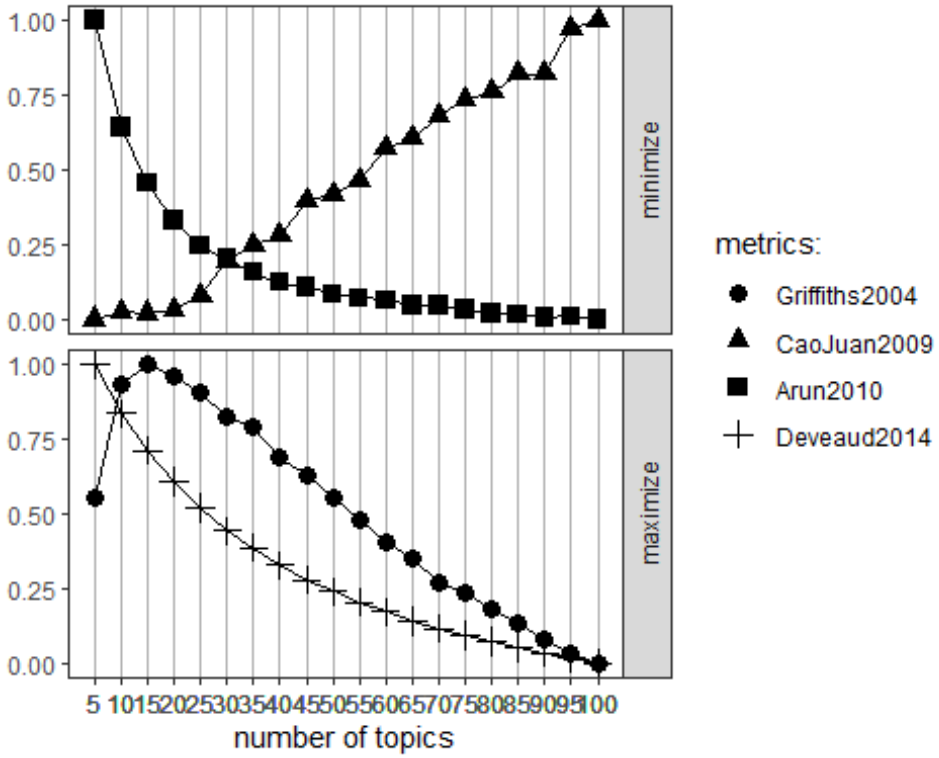
```
result_aus <- FindTopicsNumber(
  dtm_aus, #pass dtm
  topics = seq(from = 5, to = 100, by = 5), #calculated amount of topics
  metrics = c("Griffiths2004", "CaoJuan2009", "Arun2010", "Deveaud2014"),
#the algorithms
  method = "Gibbs", #the sampling algorithm
  control = list(seed = 77), #same result if code is run again
  verbose = TRUE #so R tells you what it is working on right now
)
```

```
## fit models... done.
## calculate metrics:
##   Griffiths2004... done.
##   CaoJuan2009... done.
##   Arun2010... done.
##   Deveaud2014... done.
```

```
FindTopicsNumber_plot(result_aus)
```

```
## Warning: The `<scale>` argument of `guides()` cannot be `FALSE`. Use
"none" instead as
## of ggplot2 3.3.4.
## ℹ The deprecated feature was likely used in the ldatuning package.
##   Please report the issue at <]8;;https://github.com/nikita-
```

```
moor/ldatuning/issueshttps://github.com/nikita-moor/ldatuning/issues]8;;>.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```



Looking at the maximum of Griffiths, I choose 15 here.

Fit the LDA model: We use the topicmodels package and the k from above.

```
library(topicmodels) #Load

## Warning: Paket 'topicmodels' wurde unter R Version 4.2.3 erstellt

set.seed(50)  #same result if you run the code again
model_aus <- topicmodels::LDA(dtm_aus, k = 15, method = "Gibbs", control =
list(alpha = 0.5, burnin = 1000, iter =3000)) #burnin and iter will be
improved in exercise 3 of chapter 7
```

Let's look at the terms to find renewable energy and unemployment:

```
terms(model_aus, 20)

##       Topic 1      Topic 2        Topic 3      Topic 4      Topic 5
##  [1,] "kind"       "uns"          "massnahm"   "euro"       "offent"
##  [2,] "ausbau"     "gesellschaft" "ziel"       "prozent"    "mehr"
##  [3,] "bess"       "herausforder" "klar"       "jahr"       "sowi"
##  [4,] "bereich"    "sich"         "plan"       "osterreich" "investition"
##  [5,] "recht"      "muss"         "dah"        "pro"        "forder"
##  [6,] "famili"     "land"         "osterreich" "rund"       "hoh"
##  [7,] "pfleg"      "beitrag"      "braucht"    "derzeit"    "privat"
```

```
##  [8,] "zugang"     "gross"        "verantwort" "million"    "sozial"
##  [9,] "ab"         "zukunft"      "a"          "jahrlich"   "ausbau"
## [10,] "unabhang"   "wichtig"      "konkret"    "monat"      "neu"
## [11,] "ermog"      "stell"        "bring"      "zwei"       "wohn"
## [12,] "lang"       "sozial"       "setz"       "milliard"   "geld"
## [13,] "etc"        "leist"        "umsetz"     "mehr"       "energi"
## [14,] "finanziell" "gerecht"      "kunst-"     "drei"       "leistbar"
## [15,] "versorg"    "wirtschaft"   "gut"        "davon"      "langfrist"
## [16,] "angebot"    "zeit"         "kultur"     "hoh"
"infrastruktur"
## [17,] "sowi"       "interess"     "kunst"      "liegt"      "einfuhr"
## [18,] "betreu"     "wohlstand"    "form"       "steu"       "mittel"
## [19,] "ausreich"   "gemeinsam"    "notwend"    "kost"       "arbeitsplatz"
## [20,] "gleichzeit" "fair"         "land"       "etwa"       "erneuerbar"
##       Topic 6      Topic 7          Topic 8         Topic 9
##  [1,] "dass"       "europa"         "entwickl"      "mensch"
##  [2,] "osterreich" "polit"          "forschung"     "leb"
##  [3,] "uns"        "stark"          "bereich"       "alt"
##  [4,] "bereich"    "osterreich"     "international" "viel"
##  [5,] "imm"        "staat"          "schaff"        "gut"
##  [6,] "dafur"      "eu"             "osterreich"    "aufgrund"
##  [7,] "dah"        "gemeinsam"      "neu"           "recht"
##  [8,] "sorg"       "aufgab"         "universitat"   "jung"
##  [9,] "schutz"     "demokrati"      "unternehm"     "person"
## [10,] "vier"       "aktiv"          "wirtschaft"    "oft"
## [11,] "muss"       "statt"          "hochschul"     "gesellschaft"
## [12,] "fairness"   "braucht"        "unterstutz"    "mehr"
## [13,] "beseit"     "menschenrecht"  "rahmenbeding"  "imm"
## [14,] "verdi"      "union"          "bereit"        "eig"
## [15,] "unfair"     "eben"           "studier"       "freiheit"
## [16,] "gegenub"    "militar"        "stark"         "behinder"
## [17,] "staat"      "sich"           "insbesond"     "seh"
## [18,] "weiterhin"  "zusammenarbeit" "innovation"    "darf"
## [19,] "sich"       "sinn"           "forder"        "gerad"
## [20,] "aufgab"     "neu"            "wettbewerb"    "folg"
##       Topic 10         Topic 11     Topic 12          Topic 13
##  [1,] "osterreich"     "schul"      "muss"            "moglich"
##  [2,] "nachhalt"       "soll"       "gesetz"          "soll"
##  [3,] "erhalt"         "ausbild"    "verpflicht"      "land"
##  [4,] "wirtschaft"     "mehr"       "moglich"         "entsprech"
##  [5,] "landwirtschaft" "chanc"      "mehr"            "einfach"
##  [6,] "besond"         "neu"        "dass"            "gibt"
##  [7,] "raum"           "bildung"    "gilt"            "transparent"
##  [8,] "umwelt"         "kind"       "unternehm"       "bund"
##  [9,] "natur"          "digital"    "anspruch"        "einzeln"
## [10,] "gesund"         "lehrling"   "regel"           "offent"
## [11,] "klein"          "schulerinn" "bzw"             "gemeind"
## [12,] "produkt"        "betrieb"    "kommt"           "zustand"
## [13,] "regional"       "den"        "arbeitnehmerinn" "derzeit"
## [14,] "forder"         "ford"       "darub"           "b"
## [15,] "einsatz"        "dabei"      "soll"            "neu"
```

```
## [16,] "landlich"       "gefordert"  "arbeitszeit"     "steht"
## [17,] "ressourc"       "kindergart" "durf"            "verwalt"
## [18,] "konzern"        "zeit"       "hinaus"          "wesent"
## [19,] "international"  "dafur"      "steh"            "verfug"
## [20,] "ford"           "gemeinsam"  "schnell"         "zukunft"
##       Topic 14      Topic 15
##  [1,] "jahr"        "frau"
##  [2,] "seit"        "arbeit"
##  [3,] "wurd"        "wenig"
##  [4,] "geht"        "gleich"
##  [5,] "grun"        "viel"
##  [6,] "osterreich"  "imm"
##  [7,] "schon"       "gibt"
##  [8,] "bereit"      "leistung"
##  [9,] "letzt"       "einkomm"
## [10,] "viel"        "mann"
## [11,] "unterschied" "dass"
## [12,] "stark"       "gering"
## [13,] "weit"        "sozial"
## [14,] "erst"        "arbeitslos"
## [15,] "land"        "lang"
## [16,] "gross"       "arbeitsmarkt"
## [17,] "mehr"        "betroff"
## [18,] "macht"       "tatig"
## [19,] "heut"        "hoch"
## [20,] "wien"        "lohn"
```

Topic 15 contains “arbeitslos” meaning unemployed. Topic 10 discusses nature, but renewable energy is not highly influential on the topic. You can go deeper into the sentences and their topics to find more information:

```
a_doc_topic <- data.frame(topics(model_aus))
head(a_doc_topic, 5) #just showing the beginning of the table

##                          topics.model_aus.
## 42110.000.2017.1.1.txt.1                14
## 42110.000.2017.1.1.txt.2                12
## 42110.000.2017.1.1.txt.3                 2
## 42110.000.2017.1.1.txt.4                 2
## 42110.000.2017.1.1.txt.5                 7
```

We use the corpus on a sentence basis to get a dataframe and merge it with the topics:

```
df_aus_sent <- convert(corpus_sent, to = "data.frame")

a_doc_topic$doc_id <- rownames(a_doc_topic)
aus_topics <- merge(df_aus_sent, a_doc_topic, by= "doc_id")
View(aus_topics)

env_topic <- aus_topics[which(aus_topics$topics.model_aus.=="10"),]
head(env_topic$text)
```

```
## [1] "Die Schwerpunkte der Sicherheitspolitik tragen dem täglichen Risiko,
im Verkehr zu schaden zu kommen, nicht angemessen Rechnung."
## [2] "Nicht umgekehrt."
## [3] "Tätigkeiten (Kfz- und Flugverkehr) sollen höher als saubere Energien
besteuert werden, weil damit jene belohnt werden, die einen Beitrag zu einer
sauberen Umwelt leisten. im Gegenzug sollen der Faktor Arbeit entlastet und
durch die ökosoziale Steuerreform neue Arbeitsplätze geschaffen werden."
## [4] "Der sogenannte Regress wird häufig durch rechtzeitiges weitergeben
von Vermögen umgangen.  -   eine kluge Klimapolitik muss zur gerechten
lastenverteilung beitragen, einen Ausgleich zwischen industrie- und
Entwicklungsländern ermöglichen und nachfolgenden Generationen einen
lebenswerten Planeten erhalten."
## [5] "Mit dem Beschluss des Pariser Klimaabkommens im Dezember 2015 ist
klar: Die Dekarbonisierung unserer Weltwirtschaft – also der globale Ausstieg
aus der Nutzung von Erdöl, Kohle und Erdgas – wird notwendig sein, um die
internationalen Klimaziele zu erreichen."
## [6] "Besonders wenig geht insbesondere in Österreich beim Problemsektor
Nr. 1, dem Verkehr, weiter."
```

```
unemp_topic <- aus_topics[which(aus_topics$topics.model_aus.=="15"),]
head(unemp_topic$text)
```

```
## [1] "Von der tarifreform 2015/16 haben Besserverdienende viel stärker
profitiert als Niedrigverdienende, unter welchen zudem besonders viele Frauen
sind."
## [2] "Nach wie vor sind Frauen zahlreichen Diskriminierungen am
Arbeitsmarkt ausgesetzt."
## [3] "Die Arbeit von Frauen wird grundsätzlich minderbewertet, zudem
arbeiten Frauen sehr oft in Teilzeit (48 Prozent) und drittens sind sie
überproportional häufig in Niedriglohnsektoren tätig. all diese Faktoren
führen dazu, dass Frauen im Schnitt ein um 38 Prozent geringeres Einkommen
haben als Männer."
## [4] "Niedrige und mittlere Einkommen sollen profitieren."
## [5] "Für viele wohnungssuchende sind „marktkonforme“ Mieten kaum mehr
leistbar, gerade in den Ballungszentren."
## [6] "Von Arbeit leben zu können, wird häufig immer schwieriger."
```

A closer look at the sentences shows again that it is difficult to expect a specific topic; here, general environmental and work-related discrimination issues are discussed.

Now, we want to know how much the different parties talk about renewable energy and unemployment. We check the length of the topics with nrow and the length of the whole manifesto with the sentences variable in the corpus:

```
summary(corpus_manifestos) #check length
```

```
## Corpus consisting of 5 documents, showing 5 documents:
##
##                     Text Types Tokens Sentences country year      party
##  42110.000.2017.1.1.txt  5707  21000       677 Austria 2017 Die Grünen
##  42220.000.2017.1.1.txt  1605   4376       181 Austria 2017        KPÖ
##  42320.000.2017.1.1.txt 10076  57291      2958 Austria 2017        SPÖ
```

```
##  42420.000.2017.1.1.txt  2786   8601       289 Austria 2017        FPÖ
##  42450.000.2017.1.1.txt  8856  37117      1649 Austria 2017       NEOS
```

```
(nrow(env_topic[ env_topic$party == "Die Grünen",])/677)*100
```

```
## [1] 7.090103
```

```
(nrow(env_topic[ env_topic$party == "KPÖ",])/181)*100
```

```
## [1] 3.867403
```

```
(nrow(env_topic[ env_topic$party == "SPÖ",])/2958)*100
```

```
## [1] 3.076403
```

```
(nrow(env_topic[ env_topic$party == "FPÖ",])/289)*100
```

```
## [1] 6.920415
```

```
(nrow(env_topic[env_topic$party == "NEOS",])/1649)*100
```

```
## [1] 6.852638
```

As expected, in relation to the manifesto length, the environment/renewable energy topic is most discussed by the Green Party followed by FPÖ and NEOS.

```
(nrow(unemp_topic[unemp_topic$party == "Die Grünen",])/677)*100
```

```
## [1] 4.874446
```

```
(nrow(unemp_topic[unemp_topic$party == "KPÖ",])/181)*100
```

```
## [1] 5.524862
```

```
(nrow(unemp_topic[unemp_topic$party == "SPÖ",])/2958)*100
```

```
## [1] 5.30764
```

```
(nrow(unemp_topic[ unemp_topic$party == "FPÖ",])/289)*100
```

```
## [1] 4.49827
```

```
(nrow(unemp_topic[unemp_topic$party == "NEOS",])/1649)*100
```

```
## [1] 4.487568
```

KPÖ and SPÖ discuss the unemployment topic the most. Be careful with the interpretation and keep the discussed shortcomings in mind.