

# Title

*Name*

*date*

Let's take a look at a set of Dutch speeches in English from the EUSpeech dataset. Use `setwd()` to set the working directory to the folder that contains Dutch speeches in the file `speeches_nl.csv`. Read in the speeches and do some cleaning as follows:

```
Sys.setlocale(locale = "en_US.UTF-8")

## [1] "en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8"

library(foreign)
library(stringr)

## Warning: package 'stringr' was built under R version 3.5.2

library(quanteda)

## Warning: package 'quanteda' was built under R version 3.5.2

library(readtext)
library(topicmodels)

speeches <- read.csv(file = "speeches_nl.csv",
                     header = TRUE,
                     stringsAsFactors = FALSE,
                     sep = ",")

speeches$text <- str_replace_all(speeches$text, "<.+?>", "")

#we'll set the seed to get reproducible random starting values
set.seed(2)
```

- 1) Turn the speeches dataframe into a corpus, and then into a dfm object. Remove punctuation and numbers and stopwords, apply stemming, and lowercase the corpus

```
speeches <- corpus(speeches)

speeches.dfm <- dfm(speeches,
                    tolower = TRUE, stem = TRUE,
                    remove=stopwords("english"),
                    remove_punct=TRUE, ngrams = 1,
                    remove_numbers = TRUE)
```

- 2) Apply a Wordfish scaling model to these speeches.

```
speeches.wordfish <- textmodel_wordfish(speeches.dfm)
```

- 3) Locate the speeches with the highest score and lowest score on the underlying estimated dimension. Take a look at those two speeches. Do they span an ideological dimension? Write a few sentences on why yes or why no.

```
which.max(speeches.wordfish$theta)
```

```
## [1] 15
```

```
#memorial speech
```

```
which.min(speeches.wordfish$theta)
```

```
## [1] 81
```

```
#economic ties speech
```

- 4) Use the `textstat_simil()` function in `quanteda` to calculate the cosine similarity between these two speeches?

```
textstat_simil(speeches.dfm, c("text15"), method = "cosine", margin = "documents")
```

```
##           text15
## text1  0.13927728
## text2  0.13072112
## text3  0.34414870
## text4  0.22201959
## text5  0.29099036
## text6  0.18093995
## text7  0.40015703
## text8  0.34460402
## text9  0.13072112
## text10 0.25518273
## text11 0.28863072
## text12 0.23349140
## text13 0.27112135
## text14 0.12348792
## text15 1.00000000
## text16 0.07139148
## text17 0.14714689
## text18 0.11142718
## text19 0.11044737
## text20 0.07272779
## text21 0.20679943
## text22 0.20987207
## text23 0.17120957
## text24 0.25665700
## text25 0.16322446
## text26 0.12054864
## text27 0.14326172
## text28 0.08229814
## text29 0.13775969
## text30 0.21678997
## text31 0.09990782
## text32 0.18010420
## text33 0.19707649
## text34 0.36289827
## text35 0.18876833
## text36 0.15728174
## text37 0.12657248
## text38 0.15888920
## text39 0.14454321
## text40 0.12569364
## text41 0.12649225
```

## text42 0.25644485  
## text43 0.21346981  
## text44 0.13656491  
## text45 0.09447658  
## text46 0.14746377  
## text47 0.15741276  
## text48 0.16474265  
## text49 0.12219708  
## text50 0.18630890  
## text51 0.16163750  
## text52 0.11524287  
## text53 0.09355286  
## text54 0.10598550  
## text55 0.12917788  
## text56 0.07485618  
## text57 0.16036974  
## text58 0.08663201  
## text59 0.14729467  
## text60 0.05734113  
## text61 0.13114267  
## text62 0.13101173  
## text63 0.10188729  
## text64 0.14595128  
## text65 0.29031179  
## text66 0.27419999  
## text67 0.19511896  
## text68 0.16665317  
## text69 0.06167367  
## text70 0.15488555  
## text71 0.29089734  
## text72 0.18005628  
## text73 0.14236295  
## text74 0.15731239  
## text75 0.09577805  
## text76 0.12144177  
## text77 0.15411203  
## text78 0.16224808  
## text79 0.15778100  
## text80 0.16929781  
## text81 0.12715248  
## text82 0.12076147  
## text83 0.07707878  
## text84 0.25018304  
## text85 0.19819424  
## text86 0.23732223  
## text87 0.19613415  
## text88 0.22145109  
## text89 0.12076581  
## text90 0.12347602  
## text91 0.18674731  
## text92 0.10982504  
## text93 0.09677882  
## text94 0.18075725  
## text95 0.19735347

```
## text96 0.36768971
## text97 0.18465741
## text98 0.16029315
## text99 0.11503946
## text100 0.15605040
## text101 0.13218946
## text102 0.12649225
## text103 0.10063026
## text104 0.11876126
## text105 0.10535320
## text106 0.12980451
## text107 0.16068774
## text108 0.08697969
## text109 0.14692577
## text110 0.05798547
## text111 0.12739219
## text112 0.10317971
## text113 0.14965060
## text114 0.20178303
## text115 0.16516958
## text116 0.13240969
## text117 0.15447512
## text118 0.11787577
## text119 0.18713652
## text120 0.16224808
## text121 0.15732546
## text122 0.17738762
## text123 0.16929781
## text124 0.12715248
## text125 0.12715248
## text126 0.25018304
## text127 0.16650787
## text128 0.23108952
## text129 0.18175113
## text130 0.12059967
## text131 0.13569381
## text132 0.22434009
```

Let's turn to LDA topic models. First, take a sample of 15 speeches as a test set. The rest of our speeches will be our training set:

*#we have 132 speeches. let's divide them so that we have 117 speeches as our training set, and 15 as our test data.*

```
docvars(speeches.dfm, "id_numeric") <- 1:ndoc(speeches)
id_train <- sample(1:132, 117, replace = FALSE)

train.dfm <- dfm_subset(speeches.dfm, id_numeric %in% id_train)

#and the 15 remaining speeches as our test data.
test.dfm <- dfm_subset(speeches.dfm, !id_numeric %in% id_train)

#convert both dfms to the topic model library
train.lda.dfm <- convert(train.dfm, to = "topicmodels")
test.lda.dfm <- convert(test.dfm, to = "topicmodels")
```

- 5) Estimate a 2 topic, a 4 topic and a 6 topic LDA model on `train.dfm` using Gibbs sampling using the LDA function in the `topicmodels` library on a converted `quanteda` dfm object. Call the LDA output `speeches.lda.2`, `speeches.lda.4`, `speeches.lda.6` respectively.

```
speeches.lda.2 <- LDA(train.lda.dfm, method = "Gibbs", k = 2)
speeches.lda.4 <- LDA(train.lda.dfm, method = "Gibbs", k = 4)
speeches.lda.6 <- LDA(train.lda.dfm, method = "Gibbs", k = 6)
```

- 6) Calculate the perplexity score for each of the 3 models on the `test.lda.dfm` using the `perplexity()` function in the `topicmodels` library. This syntax of the `perplexity()` function is `perplexity(object, newdata)` where `object` is your lda model, and `newdata` your test set.

```
perplexity(object = speeches.lda.2, newdata = test.lda.dfm)
```

```
## [1] 2065.773
```

```
perplexity(object = speeches.lda.4, newdata = test.lda.dfm)
```

```
## [1] 1884.839
```

```
perplexity(object = speeches.lda.6, newdata = test.lda.dfm)
```

```
## [1] 1788.051
```

- 7) According to the perplexity criterion, which would be the most appropriate topic model?

```
#The 6 topic lda model, since it has the smallest perplexity on the test set
```

- 8) Inspect the 10 highest loading words on the 6 topic LDA model. How would you interpret each topic?  
[NB: no right or wrong here]

```
terms(speeches.lda.6, 10)
```

```
##      Topic 1      Topic 2      Topic 3      Topic 4      Topic 5
## [1,] "dutch"      "netherlands" "one"      "world"      "netherlands"
## [2,] "country"    "europe"     "freedom"  "international" "development"
## [3,] "netherlands" "us"         "today"    "security"    "year"
## [4,] "business"   "trade"      "year"     "country"     "un"
## [5,] "trade"      "economy"    "people"   "nation"      "women"
## [6,] "china"      "like"       "live"     "president"   "work"
## [7,] "indonesia"  "invest"     "netherlands" "right"      "governance"
## [8,] "can"        "together"   "world"    "also"        "achievement"
## [9,] "also"       "one"        "day"      "people"      "dutch"
## [10,] "man"       "make"       "victim"   "european"    "commitment"
##      Topic 6
## [1,] "can"
## [2,] "sustain"
## [3,] "like"
## [4,] "innovation"
## [5,] "need"
## [6,] "change"
## [7,] "new"
## [8,] "governance"
## [9,] "work"
## [10,] "climate"
```

- 9) Write a line of code to count the number of speeches for which topic 6 is the most prevalent topic.

```
sum(topics(speeches.lda.6, 1) == 6)
```

```
## [1] 17
```

10) Write a line of code to display the average topic proportion of each of the 6 topics over all 117 training speeches.

```
topic.proportions <- posterior(speeches.lda.6)$topics  
colMeans(topic.proportions)
```

```
##           1           2           3           4           5           6  
## 0.1974617 0.1603453 0.1830540 0.1497694 0.1431353 0.1662342
```