HW3

Lingyi Zhang

4/30/2018

```r
# Clear Global Environment and Set working directory
rm(list = ls())
#getwd()
setwd("/Users/Lingyi/TAD/HW3")
set.seed(8888)

#import needed libraries
libraries <- c("geometry","rsvd","Rtsne","tidyverse","stringr","stm","quanteda.corpora",
               "quanteda","lsa","NLP","tm","RTextTools","tidytext","topicmodels",
               "ldatuning","stringi","ggplot2","proxy","bursts","readtext")
lapply(libraries, require, character.only=TRUE)
```

1. Applying topicmodels to the news corpus:

(a) To decrease the time it takes to fit a topic model, we will limit our analysis to a subset of the immigration corpus. Create a subset of data corpus immigrationnews that only contains articles from the 4 news sources with the most documents in the immigration news corpus. Create a table that shows how many documents are associated with each newspaper.

```r
data <- data_corpus_immigrationnews
papername <- data$documents$paperName
freq_table <- as.data.frame(table(papername))
#check number of documents of each newspaper
freq_table[with(freq_table, order(Freq)), ]
```

```
##               papername Freq
## 8 the-sunday-telegraph   33
## 2                   ft  207
## 6                  sun  277
## 4          independent  324
## 1              express  325
## 9                times  352
## 3             guardian  392
## 5                 mail  412
## 7            telegraph  511
```

Top 4 are telegraph, mail, guardian, times.

```r
data_4 <- corpus_subset(data, subset=data$documents$paperName %in% c(
  "telegraph", "mail", "guardian", "times"))
```

(b) Create a document term matrix with your new immigration corpus in which punctuation is removed and words are set to lower case. Also, remove a custom set of stopwords custom stopwords (available on GitHub) that is relevant to this particular data set. Finally, use quanteda's "dfm trim" to remove words that occur fewer than 30 times or in fewer than 20 documents. Report the remaining number of features and the total number of documents in the DFM.

```
load("custom_stopwords.RData")
dfm4 <- dfm(data_4, tolower=TRUE, remove=custom_stopwords, remove_punct = TRUE)
dfm4 <- dfm_trim(dfm4, min_count=30, min_docfreq=20)
print(paste0("Total number of documents : ", ndoc(dfm4)))
```

```
## [1] "Total number of documents : 1667"
```

```
print(paste0("Remaining number of features : ", length(dfm4@Dimnames$features)))
```

```
## [1] "Remaining number of features : 3645"
```

(c) Preprocessing decisions can have substantive impacts on the topics created by topic model algorithms. Make a brief (1 paragraph) argument for or against removing rare terms from a dfm on which you plan to fit a topic model.

In this case of analyzing immigration news corpus, I think removing rare terms is a good choice. First, as immigration news are all long articles, removing rare terms won't lose major information and might even be helpful for reducing data noise. Second, some algorithms are very time-consuming. Removing rare terms can reduce time on computing.

(d) Fit a topic model with 30 topics using LDA(), with method = "Gibbs". Increase the number of iterations to 3000 to ensure that the model describes the underlying data well and set the seed to 10012 so that you can replicate your results. Report the @loglikelihood of your topic model object.

```
k <- 30
fitted <- LDA(dfm4, k=k, method="Gibbs", num_iter=3000, control=list(seed=10012))
print(paste0("Loglikelihood : ", logLik(fitted)))
```

```
## [1] "Loglikelihood : -2748468.25213177"
```

(e) Examine the top 10 words that contribute the most to each topic using get terms(). Report these words. Label each of the 5 topics that have the most articles in the corpus associated with them. Explain your choice of labels. You should save the top 10 words over all 30 topics, for later use.

```
imm_topics <- tidy(fitted, matrix="beta")
imm_top_terms <- imm_topics %>% group_by(topic) %>% top_n(10, beta) %>%
  ungroup() %>% arrange(topic, -beta)

get_terms(fitted, k=10)
```

```
##       Topic 1       Topic 2  Topic 3    Topic 4    Topic 5
##  [1,] "tax"         "show"   "family"   "housing"  "labour"
##  [2,] "money"       "2014"   "children" "economy"  "cameron"
```

```
##  [3,] "government" "street" "life"     "economic" "tory"
##  [4,] "pounds"     "series" "years"    "house"    "party"
##  [5,] "pay"        "film"   "father"   "market"   "miliband"
##  [6,] "public"     "tv"     "mother"   "growth"   "election"
##  [7,] "work"       "music"  "parents"  "prices"   "minister"
##  [8,] "benefit"    "play"   "wife"     "bank"     "david"
##  [9,] "benefits"   "4"      "friends"  "osborne"  "ed"
## [10,] "state"      "radio"  "marriage" "property" "conservative"
##       Topic 6      Topic 7        Topic 8         Topic 9  Topic 10
##  [1,] "eu"         "scotland"     "ukip"          "women"  "migration"
##  [2,] "european"   "english"      "voters"        "men"    "net"
##  [3,] "europe"     "scottish"     "party"         "mail"   "year"
##  [4,] "cameron"    "independence" "labour"        "man"    "number"
##  [5,] "britain"    "interview"    "vote"          "told"   "figures"
##  [6,] "referendum" "uk"           "tories"        "police" "government"
##  [7,] "union"      "group"        "parties"       "day"    "thousands"
##  [8,] "merkel"     "asked"        "elections"     "died"   "target"
##  [9,] "brussels"   "policy"       "conservatives" "woman"  "eu"
## [10,] "parliament" "id"           "support"       "found"  "britain"
##       Topic 11     Topic 12     Topic 13      Topic 14    Topic 15
##  [1,] "bbc"        "business"   "british"     "ukip"      "uk"
##  [2,] "mail"       "uk"         "workers"     "farage"    "britain"
##  [3,] "mp"         "government" "minister"    "party"     "migrants"
##  [4,] "culture"    "company"    "labour"      "racist"    "work"
##  [5,] "secretary"  "companies"  "foreign"     "nigel"     "countries"
##  [6,] "public"     "2014"       "secretary"   "european"  "2014"
##  [7,] "made"       "group"      "brokenshire" "campaign"  "country"
##  [8,] "newspapers" "visa"       "jobs"        "leader"    "eu"
##  [9,] "job"        "policy"     "home"        "political" "mail"
## [10,] "lord"       "services"   "elite"       "british"   "year"
##       Topic 16    Topic 17    Topic 18 Topic 19    Topic 20   Topic 21
##  [1,] "2014"      "britain"   "food"   "police"    "farage"   "english"
##  [2,] "media"     "political" "days"   "home"      "clegg"    "language"
##  [3,] "newspaper" "country"   "made"   "border"    "debate"   "care"
##  [4,] "march"     "social"    "time"   "office"    "nick"     "test"
##  [5,] "english"   "british"   "world"  "2014"      "leader"   "health"
##  [6,] "prince"    "politics"  "wine"   "crime"     "nigel"    "home"
##  [7,] "questions" "nation"    "spent"  "officials" "lib"      "mail"
##  [8,] "bill"      "world"     "town"   "mail"      "european" "speak"
##  [9,] "1"         "left"      "back"   "online"    "dem"      "nhs"
## [10,] "dt"        "public"    "peter"  "uk"        "ukip"     "dr"
##       Topic 22   Topic 23    Topic 24 Topic 25      Topic 26
##  [1,] "book"     "local"     "good"   "it’s"        "court"
##  [2,] "war"      "council"   "things" "don’t"       "human"
##  [3,] "world"    "page"      "didnt"  "online"      "justice"
##  [4,] "life"     "year"      "thing"  "i’m"         "law"
##  [5,] "history"  "smith"     "feel"   "time"        "years"
##  [6,] "great"    "newspaper" "back"   "that’s"      "judge"
##  [7,] "years"    "april"     "time"   "thetimescouk" "home"
##  [8,] "british"  "1"         "hes"    "make"        "legal"
##  [9,] "story"    "15"        "point"  "timeuk"      "year"
## [10,] "thatcher" "months"    "ive"    "can’t"       "act"
##       Topic 27     Topic 28       Topic 29   Topic 30
##  [1,] "cent"       "home"         "london"   "school"
```

```
##  [2,] "ethnic"     "2014"         "english"  "schools"
##  [3,] "white"      "media"        "england"  "students"
##  [4,] "minority"   "case"         "city"     "education"
##  [5,] "groups"     "office"       "2014"     "children"
##  [6,] "population" "news"         "country"  "places"
##  [7,] "report"     "guardiancouk" "east"     "year"
##  [8,] "research"   "newspaper"    "national" "2014"
##  [9,] "2014"       "uk"           "church"   "number"
## [10,] "study"      "back"         "part"     "choice"
```

```r
#distribution of topics over documents
doc_topics <- fitted@gamma
doc_topics <- t(doc_topics)
max <- apply(doc_topics, 2, which.max)
#find and extract the top5
tops <- sort(table(max), decreasing=TRUE)[1:5]
top5 <- imm_top_terms[imm_top_terms$topic %in% names(tops),]
top5 %>% group_by(topic) %>% summarise(terms = toString(term))
```

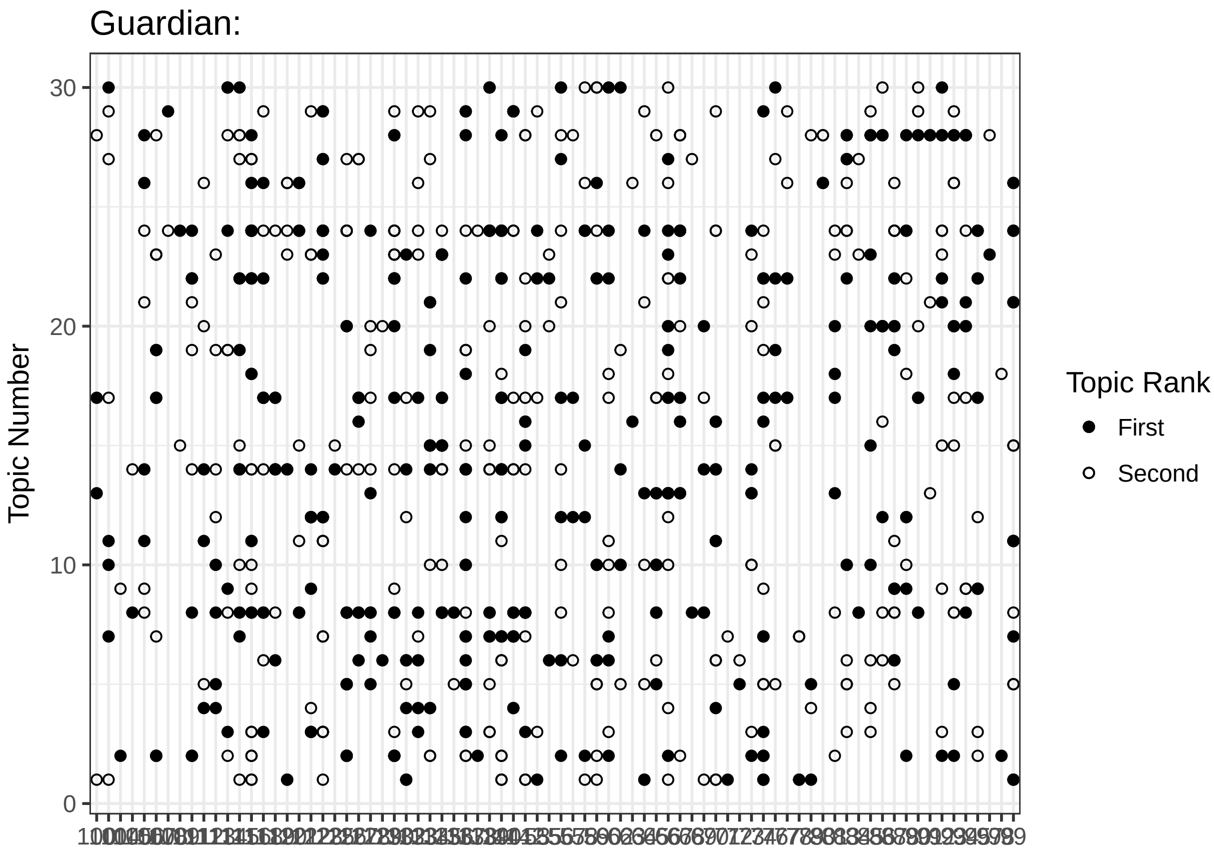
```
## # A tibble: 5 x 2
##   topic terms
##   <int> <chr>
## 1     2 show, 2014, street, series, film, tv, music, play, 4, radio
## 2     5 labour, cameron, tory, party, miliband, election, minister, david~
## 3     8 ukip, voters, party, labour, vote, tories, parties, elections, co~
## 4    13 british, workers, minister, labour, foreign, secretary, brokenshi~
## 5    14 ukip, farage, party, racist, nigel, european, campaign, leader, p~
```

- Topic 2: recreation. Most of them are for medium for entertaining.
- Topic 5: party. This is about political parties.
- Topic 8: vote/election. This is about which party to support.
- Topic 13: job/class. This is related to discussion about social classes.
- Topic 14: race. This is related to campaign against racist?

(f) Examine the topics that contribute the most to each document, using the code from Recitation 11 to visualize the top two topics per document for the Guardian and the Telegraph with separate graphs for each newspaper. Make sure that the documents are sorted by day of publication (the "day" variable in the data corpus immigrationnews corpus). Discuss your findings.

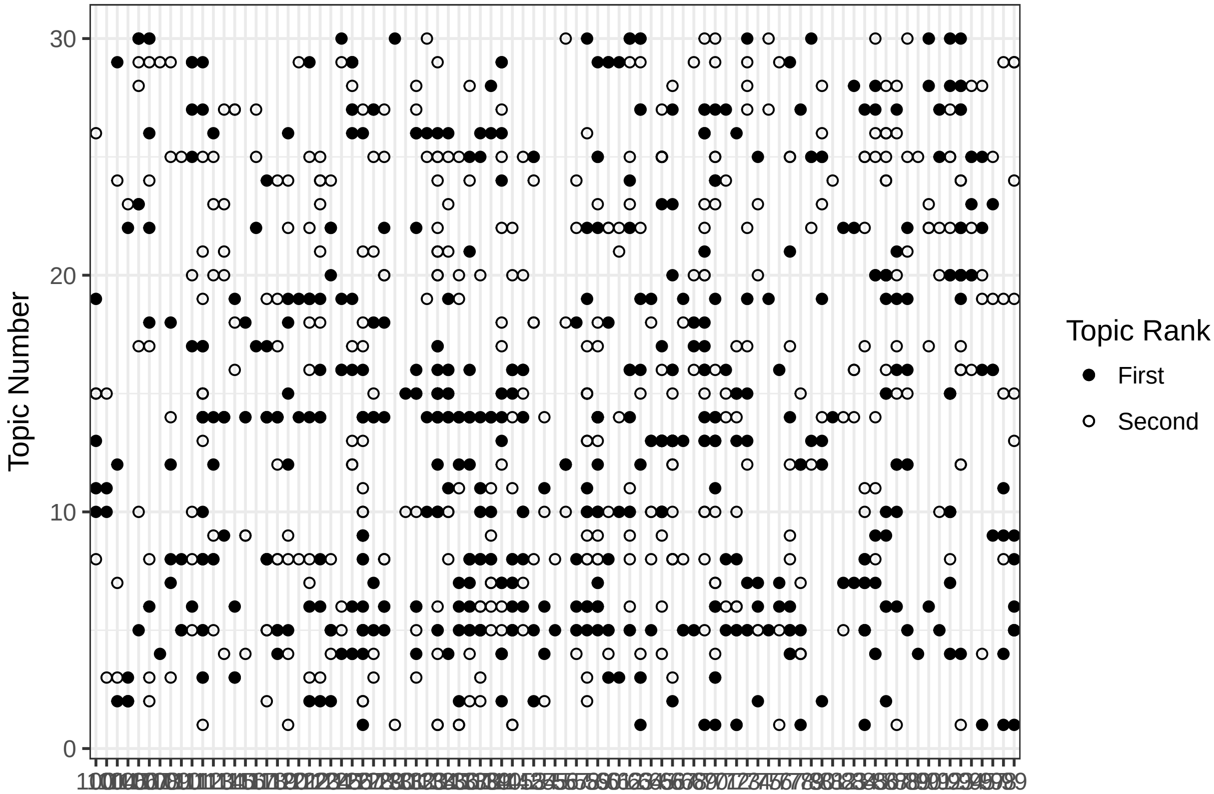
```r
which.max2 <- function(x){
  which(x == sort(x,partial=(k-1))[k-1])
}

max2 <- apply(doc_topics, 2, which.max2)
max2 <- sapply(max2, max)
top2 <- data.frame(top_topic=max, second_topic=max2,
                   paper=dfm4@docvars$paperName, date=dfm4@docvars$day)

df_g <- top2[top2$paper == "guardian",]
df_t <- top2[top2$paper == "telegraph",]
#sort by day
df_g <- df_g[with(df_g, order(as.numeric(df_g$date), decreasing=FALSE)) ,]
df_t <- df_t[with(df_t, order(as.numeric(df_t$date), decreasing=FALSE)) ,]
```

```
theplot <- ggplot(df_g, aes(x=date, y=top_topic, pch="First"))
theplot + geom_point(aes(x=date, y=second_topic, pch="Second")) + theme_bw() +
  ylab("Topic Number") + ggtitle("Guardian:") + geom_point() +
  xlab(NULL) + scale_shape_manual(values=c(19, 1), name = "Topic Rank")
```




```
theplot <- ggplot(df_t, aes(x=date, y=top_topic, pch="First"))
theplot + geom_point(aes(x=date, y=second_topic, pch="Second")) + theme_bw() +
  ylab("Topic Number") + ggtitle("Telegraph:") + geom_point() +
  xlab(NULL) + scale_shape_manual(values=c(19, 1), name = "Topic Rank")
```

Telegraph:



Findings: Sometimes the newspaper discusses a certain topic several days in a row, which showed in the graph as continuous points of one topic over days.

(g) Finally, we can find the average contribution of a topic to an article from a particular newspaper, and compare newspapers on particular topics. For each of the 5 topics you've named, see how their prevalence varies among the different newspapers. To do so, estimate the mean contribution of each topic over each newspaper. Report the contribution of each of the top 5 topics to each of the 4 newspapers. Discuss your findings.

```
df <- data.frame(posterior(fitted, dfm4)$topics)
names(df) <- seq(1:ncol(df))
df<- df[, names(df) %in% unique(top5$topic)]
df$paper <- top2$paper

#average contribution
average <- aggregate(
  cbind(df$`2`, df$`5`, df$`8`, df$`13`, df$`14`) ~ paper, data=df, FUN=mean)
colnames(average) <- c('paper','recreation','party','election','class','race')
average
```

```
##       paper recreation      party   election      class       race
## 1  guardian 0.04383112 0.03059087 0.05396193 0.03018634 0.03929631
## 2      mail 0.03790102 0.03409226 0.03666712 0.03351095 0.04811421
## 3 telegraph 0.02557639 0.05257118 0.04353489 0.04398273 0.04578744
## 4     times 0.03254079 0.04565643 0.04376410 0.03842645 0.04468599
```

- for recreation, guardian talked the most, while telegraph least;

- for party, telegraph talked the most, while guardian least;
- for election, guardian talked the most, while mail the least;
- for class, telegraph talked the most, while guardian the least;
- for race, theses four papers are pretty similar.

2. Topic stability: We want to see how stable these topics are, under two different sets of pre-processings.

(a) Re-run the model from question 1 with a different seed. Report the @loglikelihood of your topic model object.

```
k <- 30
fitted_new <- LDA(dfm4, k=k, method="Gibbs",
                  num_iter=3000, control=list(seed=07302))
print(paste0("Loglikelihood : ", logLik(fitted_new)))
```

```
## [1] "Loglikelihood : -2748102.69102845"
```

(b) For each topic in the new model, find the topic that is the closest match in the original run in terms of cosine similarity of the topic distribution over words. Your answer should be a table.

```
beta_old <- as.matrix(fitted@beta)
beta_new <- as.matrix(fitted_new@beta)
simi_result <- as.data.frame.matrix(simil(
  beta_new, beta_old, method="cosine", diag=TRUE))

names(simi_result) <- seq(1:ncol(simi_result))
rownames(simi_result) <- seq(1:nrow(simi_result))
simi_result$closest_match <- colnames(simi_result)[apply(simi_result, 1, which.max)]
match_table <- setNames(data.frame(
  cbind(rownames(simi_result), simi_result$closest_match)), c("old", "new"))
t(match_table)
```

```
##     [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13]
## old "1"  "2"  "3"  "4"  "5"  "6"  "7"  "8"  "9"  "10"  "11"  "12"  "13"
## new "14" "5"  "3"  "7"  "21" "9"  "13" "30" "16" "26"  "20"  "17"  "27"
##     [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22] [,23] [,24]
## old "14"  "15"  "16"  "17"  "18"  "19"  "20"  "21"  "22"  "23"  "24"
## new "27"  "12"  "7"   "15"  "2"   "16"  "8"   "18"  "19"  "21"  "28"
##     [,25] [,26] [,27] [,28] [,29] [,30]
## old "25"  "26"  "27"  "28"  "29"  "30"
## new "29"  "10"  "25"  "6"   "24"  "4"
```

(c) Calculate the average number of words in the top 10 words shared by each matched topic pair. Your answer should be a table.

```
fitted_tops <- tidy(fitted, matrix="beta")
fitted_topsnew <- tidy(fitted_new, matrix = "beta")
```

```r
fitted_terms <- fitted_tops %>% group_by(topic) %>% top_n(10, beta) %>%
  ungroup() %>% arrange(topic, -beta) %>% data.frame()
fitted_termsnew <- fitted_topsnew %>% group_by(topic) %>%
  top_n(10, beta) %>% ungroup() %>% arrange(topic, -beta) %>% data.frame()

for (i in 1:nrow(match_table)) {
  word_old <- fitted_terms[fitted_terms['topic'] == as.numeric(match_table$old[i]),]
  word_old <- word_old$term
  word_new <- fitted_termsnew[
    fitted_termsnew['topic'] == as.numeric(match_table$new[i]),]
  word_new <- word_new$term
  #find the num of words that match
  match_table$share_num[i] <- length(intersect(word_old, word_new))
}

t(match_table)
```

```
##           [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12]
## old       "1"  "2"  "3"  "4"  "5"  "6"  "7"  "8"  "9"  "10"  "11"  "12"
## new       "14" "5"  "3"  "7"  "21" "9"  "13" "30" "16" "26"  "20"  "17"
## share_num "0"  "2"  "0"  "0"  "0"  "0"  "1"  "0"  "0"  "1"   "0"   "0"
##           [,13] [,14] [,15] [,16] [,17] [,18] [,19] [,20] [,21] [,22]
## old       "13"  "14"  "15"  "16"  "17"  "18"  "19"  "20"  "21"  "22"
## new       "27"  "27"  "12"  "7"   "15"  "2"   "16"  "8"   "18"  "19"
## share_num "0"   "0"   "0"   "0"   "0"   "0"   "1"   "0"   "0"   "1"
##           [,23] [,24] [,25] [,26] [,27] [,28] [,29] [,30]
## old       "23"  "24"  "25"  "26"  "27"  "28"  "29"  "30"
## new       "21"  "28"  "29"  "10"  "25"  "6"   "24"  "4"
## share_num "0"   "0"   "1"   "0"   "0"   "3"   "1"   "1"
```

(d) Now run two more models, but this time, use only 5 topics. Again, find the average number of words in the top ten shared by each matched topic pair. How stable are the models with 5 topics compared to the models with 30 topics?

```r
k <- 5
#models with k=5
fitted<-LDA(dfm4, k = k, method = "Gibbs", num_iter=3000, control = list(seed = 11012))
fitted_new<-LDA(dfm4, k = k, method = "Gibbs",
                num_iter=3000, control = list(seed = 07302))

#repeat anlaysis above
beta_old <- as.matrix(fitted@beta)
beta_new <- as.matrix(fitted_new@beta)
simi_result <- as.data.frame.matrix(simil(
  beta_new, beta_old, method="cosine", diag=TRUE))

names(simi_result) <- seq(1:ncol(simi_result))
rownames(simi_result) <- seq(1:nrow(simi_result))
simi_result$closest_match <- colnames(simi_result)[apply(simi_result,1,which.max)]

match_table <- setNames(data.frame(
  cbind(seq(1:nrow(simi_result)), simi_result$closest_match)), c("old", "new"))
```

```r
fitted_tops <- tidy(fitted, matrix = "beta")
fitted_topsnew <- tidy(fitted_new, matrix = "beta")
fitted_terms <- fitted_tops %>% group_by(topic) %>% top_n(10, beta) %>%
  ungroup() %>% arrange(topic, -beta) %>% data.frame()
fitted_termsnew <- fitted_topsnew %>% group_by(topic) %>%
  top_n(10, beta) %>% ungroup() %>% arrange(topic, -beta) %>% data.frame()

for (i in 1:nrow(match_table)) {
  word_old <- fitted_terms[fitted_terms['topic'] == as.numeric(match_table$old[i]),]
  word_old <- word_old$term
  word_new <- fitted_termsnew[
    fitted_termsnew['topic'] == as.numeric(match_table$new[i]),]
  word_new <- word_new$term
  #find the num of words that match
  match_table$share_num[i] <- length(intersect(word_old, word_new))
}

match_table
```

```
##   old new share_num
## 1   1   3         1
## 2   2   1         2
## 3   3   4         0
## 4   4   5         1
## 5   5   2         0
```

3. Topic Models with covariates: The Structural Topic Model (STM) is designed to incorporate document-level variables into a standard topic model. Since, we have information about both the newspaper and the date of the articles, we can use an STM (from the stm package) to model the effects of these covariates directly.

(a) Using only articles from the Guardian and Telegraph, construct a numeric date variable from the "day" variable in the immigration news corpus. Use what preprocessing you believe to be appropriate for this problem. Discuss your preprocessing choice.

```r
data <- data_corpus_immigrationnews
data_GT <- corpus_subset(
  data, subset=data$documents$paperName %in% c("guardian", "telegraph"))

df <- tibble(
  name = data_GT$documents$paperName,
  day = as.numeric(data_GT$documents$day),
  content = data_GT$documents$texts
)

dfm_GT <- dfm(df$content, remove_punct=TRUE,
              tolower=TRUE, remove=stopwords("english"), stem=TRUE, verbose=FALSE)
```

I removed punctuation as it's not relevant to topic models. I also used lowercase and stem, removed stopwords, so that the dfm will be less sparse.

(b) Fit an STM model where the topic content varies according to this binary variable, and where the prevalence varies according to both this binary variable and the spline of the date variable you've created. Be sure to use the spectral initialization and set k=0, which will allow the STM function to automatically select a number of topics using the spectral learning method. Keep in mind that this function is computationally demanding, so start with the minimum threshold document frequency threshold set to 10; if your computer takes an unreasonably long time to fit the STM model with this threshold, you can raise it to as high as 30.

Report the number of topics selected in the fitted model. Also report the number of iterations completed before the model converged.

```
dfm_GT <- dfm_trim(dfm_GT, min_count=30, min_docfreq=10, verbose=FALSE)
stm_GT <- stm(dfm_GT, K=0, init.type='Spectral', seed=8888,
              prevalence =~name + s(day), data=df)
```

```
## Beginning Spectral Initialization
##   Calculating the gram matrix...
##   Finding anchor words...
##           Initializing tSNE with PCA...
##           Using tSNE to project to a low-dimensional space...
##           Calculating exact convex hull...
##
##   Recovering initialization...
##      .....................
## Initialization complete.
## ...............................................................................................
## Completed E-Step (3 seconds).
## Completed M-Step.
## Completing Iteration 1 (approx. per word bound = -6.745)
## ...............................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 2 (approx. per word bound = -6.631, relative change = 1.694e-02)
## ...............................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 3 (approx. per word bound = -6.573, relative change = 8.754e-03)
## ...............................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 4 (approx. per word bound = -6.540, relative change = 4.997e-03)
## ...............................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 5 (approx. per word bound = -6.520, relative change = 3.041e-03)
## Topic 1: migrat, net, immigr, year, number
##  Topic 2: telegraph, daili, 2014, immigr, ltd
##  Topic 3: compani, contract, custom, sale, agent
##  Topic 4: mail, complaint, expert, airlin, time
##  Topic 5: english, say, jew, jewish, ami
##  Topic 6: applic, said, visa, uk, year
##  Topic 7: right, home, deport, human, year
##  Topic 8: home, deport, said, case, yashika
##  Topic 9: book, prize, orwel, biographi, write
```

```
##  Topic 10: march, read, telegraph, twitter, 2014
##  Topic 11: eu, europ, european, britain, peopl
##  Topic 12: immigr, brokenshir, minist, will, worker
##  Topic 13: guardian, guardiancouk, media, news, c
##  Topic 14: peopl, christian, church, countri, say
##  Topic 15: mr, farag, telegraph, ukip, parti
##  Topic 16: gay, 2014, marriag, attack, guardian
##  Topic 17: london, citi, new, countri, capit
##  Topic 18: tax, labour, osborn, said, power
##  Topic 19: say, one, think, like, go
##  Topic 20: one, time, can, london, newspap
##  Topic 21: tori, will, cameron, parti, conserv
##  Topic 22: travel, offic, provid, passeng, can
##  Topic 23: uk, busi, world, economi, countri
##  Topic 24: muslim, polic, street, women, said
##  Topic 25: hous, price, languag, peopl, use
##  Topic 26: guardian, just, im, dont, peopl
##  Topic 27: ukip, parti, racist, farag, said
##  Topic 28: farag, clegg, debat, said, ukip
##  Topic 29: bbc, pound, broadcast, year, one
##  Topic 30: cameron, minist, prime, said, british
##  Topic 31: ukip, parti, elect, local, labour
##  Topic 32: immigr, migrant, benefit, claim, uk
##  Topic 33: migrat, report, job, immigr, said
##  Topic 34: one, book, life, like, mother
##  Topic 35: peopl, elit, worker, immigr, ordinari
##  Topic 36: minor, ethnic, voter, labour, white
##  Topic 37: per, cent, britain, countri, year
##  Topic 38: princ, charl, comment, russian, said
##  Topic 39: eu, britain, will, merkel, putin
##  Topic 40: peopl, group, increas, per, ethnic
##  Topic 41: said, telegraph, border, immigr, get
##  Topic 42: garden, can, best, place, year
##  Topic 43: romanian, said, bulgarian, peopl, work
##  Topic 44: parti, mep, european, polit, ukip
##  Topic 45: school, children, place, educ, said
##  Topic 46: guardian, page, copyright, reserv, grdn
##  Topic 47: scotland, scottish, independ, vote, uk
##  Topic 48: student, univers, uk, studi, intern
##  Topic 49: said, radio, miller, bbc, interview
##  Topic 50: ukip, parti, elect, farag, said
##  Topic 51: telegraph, daili, group, ltd, 2014
##  Topic 52: ten, minist, bill, committe, debat
##  Topic 53: parti, tori, ukip, vote, conserv
##  Topic 54: film, play, music, game, new
##  Topic 55: war, uniform, work, one, pictur
##  Topic 56: wine, visit, restaur, visitor, day
##  Topic 57: much, hous, peopl, can, might
##  Topic 58: will, guardian, elect, labour, ukip
##  Topic 59: labour, class, working-class, parti, voter
## ....................................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 6 (approx. per word bound = -6.507, relative change = 1.942e-03)
```

```
## ....................................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 7 (approx. per word bound = -6.499, relative change = 1.294e-03)
## ....................................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 8 (approx. per word bound = -6.493, relative change = 9.240e-04)
## ....................................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 9 (approx. per word bound = -6.488, relative change = 7.023e-04)
## ....................................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 10 (approx. per word bound = -6.484, relative change = 5.799e-04)
## Topic 1: migrat, net, immigr, year, number
##  Topic 2: telegraph, daili, 2014, dt, immigr
##  Topic 3: compani, contract, agent, custom, serco
##  Topic 4: mail, stori, report, claim, complaint
##  Topic 5: english, say, jew, england, jewish
##  Topic 6: applic, visa, said, uk, year
##  Topic 7: right, deport, home, human, said
##  Topic 8: home, deport, said, case, yashika
##  Topic 9: book, prize, orwel, read, biographi
##  Topic 10: march, read, april, 3, twitter
##  Topic 11: eu, europ, european, britain, will
##  Topic 12: immigr, brokenshir, will, minist, employ
##  Topic 13: guardian, guardiancouk, media, news, 2014
##  Topic 14: peopl, christian, church, countri, britain
##  Topic 15: mr, farag, ukip, parti, telegraph
##  Topic 16: gay, crime, victim, 2014, polic
##  Topic 17: london, citi, new, countri, capit
##  Topic 18: tax, labour, osborn, said, rate
##  Topic 19: say, think, one, go, like
##  Topic 20: one, newspap, time, can, london
##  Topic 21: tori, will, parti, cameron, conserv
##  Topic 22: travel, offic, home, provid, polici
##  Topic 23: uk, busi, world, economi, will
##  Topic 24: muslim, polic, women, street, said
##  Topic 25: hous, price, peopl, london, languag
##  Topic 26: just, dont, im, know, say
##  Topic 27: ukip, parti, racist, farag, said
##  Topic 28: farag, clegg, debat, said, ukip
##  Topic 29: bbc, pound, broadcast, one, year
##  Topic 30: cameron, minist, said, prime, david
##  Topic 31: ukip, parti, elect, local, councillor
##  Topic 32: immigr, migrant, benefit, uk, claim
##  Topic 33: migrat, report, immigr, worker, job
##  Topic 34: one, book, life, mother, like
##  Topic 35: peopl, immigr, ordinari, think, elit
##  Topic 36: minor, ethnic, voter, labour, vote
##  Topic 37: per, cent, britain, countri, year
##  Topic 38: princ, charl, russian, said, comment
```

```
##  Topic 39: eu, britain, will, merkel, putin
##  Topic 40: peopl, group, increas, ethnic, per
##  Topic 41: said, border, telegraph, immigr, illeg
##  Topic 42: garden, can, best, place, free
##  Topic 43: romanian, said, bulgarian, racist, peopl
##  Topic 44: parti, mep, european, ukip, polit
##  Topic 45: school, place, children, educ, said
##  Topic 46: guardian, page, copyright, reserv, grdn
##  Topic 47: scotland, scottish, independ, vote, uk
##  Topic 48: student, univers, uk, studi, intern
##  Topic 49: said, radio, miller, bbc, think
##  Topic 50: ukip, farag, parti, elect, said
##  Topic 51: telegraph, onlin, ltd, group, 2014
##  Topic 52: ten, lord, bill, committe, debat
##  Topic 53: parti, labour, tori, ukip, vote
##  Topic 54: film, play, music, game, new
##  Topic 55: war, uniform, work, one, pictur
##  Topic 56: wine, restaur, visitor, peter, tast
##  Topic 57: peopl, much, can, time, work
##  Topic 58: will, ukip, elect, immigr, eu
##  Topic 59: labour, class, voter, parti, ukip
## ...........................................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 11 (approx. per word bound = -6.481, relative change = 4.640e-04)
## ...........................................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 12 (approx. per word bound = -6.479, relative change = 3.822e-04)
## ...........................................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 13 (approx. per word bound = -6.477, relative change = 3.564e-04)
## ...........................................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 14 (approx. per word bound = -6.475, relative change = 2.971e-04)
## ...........................................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 15 (approx. per word bound = -6.473, relative change = 2.586e-04)
## Topic 1: migrat, net, immigr, year, number
##  Topic 2: telegraph, daili, 2014, dt, nation
##  Topic 3: compani, contract, agent, serco, custom
##  Topic 4: mail, stori, report, claim, time
##  Topic 5: english, say, england, british, jew
##  Topic 6: applic, visa, said, uk, year
##  Topic 7: right, deport, home, said, year
##  Topic 8: home, said, case, deport, yashika
##  Topic 9: book, prize, orwel, read, biographi
##  Topic 10: march, april, discuss, read, 3
##  Topic 11: eu, europ, european, britain, will
##  Topic 12: immigr, brokenshir, will, minist, employ
##  Topic 13: guardian, guardiancouk, media, news, 2014
```

```
##  Topic 14: peopl, christian, church, countri, britain
##  Topic 15: mr, farag, ukip, parti, miliband
##  Topic 16: crime, gay, polic, victim, attack
##  Topic 17: london, citi, new, capit, countri
##  Topic 18: tax, labour, osborn, said, rate
##  Topic 19: say, think, back, go, one
##  Topic 20: one, newspap, time, can, nation
##  Topic 21: tori, will, parti, cameron, conserv
##  Topic 22: offic, travel, home, polici, can
##  Topic 23: uk, busi, economi, world, countri
##  Topic 24: muslim, polic, women, street, said
##  Topic 25: hous, price, london, market, peopl
##  Topic 26: say, just, dont, know, im
##  Topic 27: ukip, parti, racist, farag, said
##  Topic 28: farag, clegg, debat, nick, peopl
##  Topic 29: bbc, broadcast, pound, one, licenc
##  Topic 30: cameron, minist, said, prime, david
##  Topic 31: ukip, parti, local, elect, councillor
##  Topic 32: immigr, migrant, benefit, uk, claim
##  Topic 33: migrat, report, immigr, worker, job
##  Topic 34: one, book, life, mother, like
##  Topic 35: peopl, immigr, ordinari, one, think
##  Topic 36: minor, ethnic, voter, vote, labour
##  Topic 37: per, cent, britain, countri, year
##  Topic 38: princ, charl, said, russian, comment
##  Topic 39: britain, eu, will, cameron, merkel
##  Topic 40: peopl, group, increas, ethnic, white
##  Topic 41: said, border, immigr, illeg, telegraph
##  Topic 42: garden, can, best, place, free
##  Topic 43: romanian, said, farag, racist, bulgarian
##  Topic 44: parti, mep, ukip, european, parliament
##  Topic 45: school, place, children, educ, said
##  Topic 46: guardian, page, copyright, reserv, grdn
##  Topic 47: scotland, scottish, independ, vote, uk
##  Topic 48: student, univers, uk, studi, intern
##  Topic 49: said, radio, miller, bbc, think
##  Topic 50: ukip, farag, parti, elect, said
##  Topic 51: telegraph, onlin, ltd, 2014, group
##  Topic 52: ten, lord, bill, committe, debat
##  Topic 53: labour, parti, tori, ukip, vote
##  Topic 54: film, play, music, game, new
##  Topic 55: war, work, uniform, one, pictur
##  Topic 56: wine, restaur, visitor, peter, tast
##  Topic 57: peopl, much, can, time, work
##  Topic 58: will, ukip, elect, immigr, eu
##  Topic 59: ukip, class, voter, parti, labour
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 16 (approx. per word bound = -6.472, relative change = 2.187e-04)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 17 (approx. per word bound = -6.470, relative change = 2.284e-04)
```

```
## .....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 18 (approx. per word bound = -6.469, relative change = 1.931e-04)
## .....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 19 (approx. per word bound = -6.468, relative change = 1.757e-04)
## .....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 20 (approx. per word bound = -6.467, relative change = 1.441e-04)
## Topic 1: migrat, net, immigr, number, year
##  Topic 2: telegraph, daili, 2014, nation, dt
##  Topic 3: compani, contract, agent, serco, prison
##  Topic 4: stori, mail, report, claim, time
##  Topic 5: english, say, england, british, peopl
##  Topic 6: applic, visa, said, uk, year
##  Topic 7: right, deport, year, human, said
##  Topic 8: said, case, home, deport, yashika
##  Topic 9: book, orwel, prize, read, biographi
##  Topic 10: march, discuss, april, 3, twitter
##  Topic 11: eu, europ, european, britain, will
##  Topic 12: immigr, brokenshir, will, minist, employ
##  Topic 13: guardian, guardiancouk, media, news, 2014
##  Topic 14: peopl, christian, church, britain, countri
##  Topic 15: mr, farag, ukip, parti, said
##  Topic 16: crime, polic, victim, attack, peopl
##  Topic 17: london, citi, new, capit, countri
##  Topic 18: tax, said, osborn, labour, rate
##  Topic 19: say, back, go, think, one
##  Topic 20: one, newspap, can, nation, time
##  Topic 21: tori, parti, will, cameron, conserv
##  Topic 22: offic, travel, home, polici, can
##  Topic 23: uk, busi, economi, world, countri
##  Topic 24: muslim, women, polic, street, said
##  Topic 25: hous, price, london, market, peopl
##  Topic 26: say, just, know, dont, one
##  Topic 27: ukip, parti, racist, farag, said
##  Topic 28: farag, clegg, debat, nick, peopl
##  Topic 29: bbc, broadcast, pound, one, licenc
##  Topic 30: cameron, minist, said, prime, david
##  Topic 31: ukip, parti, local, elect, councillor
##  Topic 32: immigr, migrant, benefit, uk, claim
##  Topic 33: migrat, report, immigr, worker, job
##  Topic 34: one, book, life, mother, like
##  Topic 35: peopl, ordinari, think, one, immigr
##  Topic 36: minor, ethnic, voter, vote, labour
##  Topic 37: per, cent, britain, countri, year
##  Topic 38: princ, charl, said, russian, comment
##  Topic 39: britain, eu, will, cameron, merkel
##  Topic 40: peopl, group, increas, ethnic, research
##  Topic 41: said, border, immigr, illeg, use
##  Topic 42: garden, can, place, best, free
```

```
##  Topic 43: romanian, said, farag, ukip, racist
##  Topic 44: parti, mep, ukip, european, parliament
##  Topic 45: school, place, children, educ, choic
##  Topic 46: guardian, page, copyright, reserv, right
##  Topic 47: scotland, scottish, independ, vote, salmond
##  Topic 48: student, univers, uk, studi, said
##  Topic 49: said, radio, miller, bbc, think
##  Topic 50: ukip, farag, parti, elect, said
##  Topic 51: telegraph, onlin, ltd, 2014, group
##  Topic 52: ten, bill, lord, committe, debat
##  Topic 53: labour, parti, tori, ukip, vote
##  Topic 54: film, play, music, game, work
##  Topic 55: war, work, uniform, one, new
##  Topic 56: wine, restaur, visitor, peter, tast
##  Topic 57: peopl, much, can, time, work
##  Topic 58: ukip, will, elect, immigr, european
##  Topic 59: ukip, voter, parti, class, labour
## ..........................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 21 (approx. per word bound = -6.466, relative change = 1.632e-04)
## ..........................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 22 (approx. per word bound = -6.465, relative change = 1.390e-04)
## ..........................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 23 (approx. per word bound = -6.464, relative change = 1.283e-04)
## ..........................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 24 (approx. per word bound = -6.463, relative change = 1.232e-04)
## ..........................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 25 (approx. per word bound = -6.462, relative change = 1.197e-04)
## Topic 1: migrat, net, number, immigr, year
##  Topic 2: telegraph, daili, 2014, nation, dt
##  Topic 3: compani, contract, agent, prison, serco
##  Topic 4: stori, mail, report, claim, time
##  Topic 5: english, england, say, british, peopl
##  Topic 6: applic, visa, said, uk, year
##  Topic 7: right, deport, year, human, said
##  Topic 8: said, case, home, deport, yashika
##  Topic 9: book, orwel, prize, read, biographi
##  Topic 10: march, discuss, april, twitter, 3
##  Topic 11: eu, europ, european, britain, will
##  Topic 12: immigr, brokenshir, will, employ, labour
##  Topic 13: guardian, guardiancouk, media, 2014, news
##  Topic 14: peopl, christian, church, britain, countri
##  Topic 15: mr, farag, ukip, parti, said
##  Topic 16: crime, polic, victim, attack, peopl
##  Topic 17: london, citi, new, capit, countri
```

```
##  Topic 18: tax, said, osborn, labour, rate
##  Topic 19: say, back, go, first, think
##  Topic 20: one, newspap, nation, young, need
##  Topic 21: tori, cameron, parti, will, conserv
##  Topic 22: offic, polici, can, home, provid
##  Topic 23: uk, busi, economi, world, countri
##  Topic 24: muslim, women, polic, street, said
##  Topic 25: hous, price, london, market, hitler
##  Topic 26: say, just, know, one, go
##  Topic 27: ukip, parti, racist, farag, said
##  Topic 28: farag, clegg, debat, nick, peopl
##  Topic 29: bbc, broadcast, pound, one, licenc
##  Topic 30: cameron, minist, said, prime, david
##  Topic 31: ukip, parti, local, elect, councillor
##  Topic 32: immigr, benefit, migrant, will, uk
##  Topic 33: migrat, report, immigr, worker, job
##  Topic 34: one, book, life, mother, like
##  Topic 35: peopl, think, one, ordinari, immigr
##  Topic 36: minor, ethnic, voter, vote, labour
##  Topic 37: per, cent, britain, year, countri
##  Topic 38: princ, charl, said, russian, comment
##  Topic 39: britain, eu, will, cameron, merkel
##  Topic 40: peopl, group, increas, ethnic, research
##  Topic 41: said, border, immigr, use, airport
##  Topic 42: garden, can, place, best, year
##  Topic 43: romanian, farag, said, ukip, racist
##  Topic 44: parti, mep, ukip, european, parliament
##  Topic 45: school, place, children, educ, choic
##  Topic 46: guardian, page, 2014, right, reserv
##  Topic 47: scotland, scottish, independ, vote, salmond
##  Topic 48: student, univers, uk, studi, said
##  Topic 49: said, radio, miller, bbc, think
##  Topic 50: ukip, farag, parti, elect, said
##  Topic 51: telegraph, onlin, 2014, ltd, group
##  Topic 52: ten, bill, lord, committe, debat
##  Topic 53: labour, parti, tori, ukip, conserv
##  Topic 54: film, play, music, game, work
##  Topic 55: war, work, uniform, new, one
##  Topic 56: wine, restaur, visitor, peter, tast
##  Topic 57: peopl, much, can, time, work
##  Topic 58: ukip, elect, will, immigr, european
##  Topic 59: ukip, voter, parti, class, labour
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 26 (approx. per word bound = -6.462, relative change = 1.119e-04)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 27 (approx. per word bound = -6.461, relative change = 1.046e-04)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 28 (approx. per word bound = -6.460, relative change = 9.719e-05)
```

```
## ........................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 29 (approx. per word bound = -6.460, relative change = 9.036e-05)
## ........................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 30 (approx. per word bound = -6.459, relative change = 8.383e-05)
## Topic 1: migrat, net, number, immigr, year
##  Topic 2: telegraph, daili, 2014, nation, dt
##  Topic 3: compani, contract, prison, agent, serco
##  Topic 4: stori, mail, report, claim, time
##  Topic 5: english, england, british, say, peopl
##  Topic 6: applic, visa, said, uk, year
##  Topic 7: right, deport, human, year, law
##  Topic 8: said, case, home, deport, yashika
##  Topic 9: book, prize, orwel, read, biographi
##  Topic 10: discuss, march, april, twitter, 3
##  Topic 11: eu, europ, european, britain, polit
##  Topic 12: immigr, brokenshir, will, employ, labour
##  Topic 13: guardian, guardiancouk, media, 2014, news
##  Topic 14: peopl, christian, church, britain, countri
##  Topic 15: mr, farag, ukip, said, parti
##  Topic 16: crime, polic, said, victim, attack
##  Topic 17: london, citi, new, capit, countri
##  Topic 18: tax, said, osborn, labour, rate
##  Topic 19: say, back, first, go, think
##  Topic 20: one, newspap, young, need, children
##  Topic 21: tori, cameron, parti, will, conserv
##  Topic 22: can, polici, provid, busi, data
##  Topic 23: uk, busi, economi, world, countri
##  Topic 24: muslim, women, polic, street, said
##  Topic 25: hous, price, london, market, hitler
##  Topic 26: say, just, know, one, go
##  Topic 27: ukip, parti, racist, farag, said
##  Topic 28: farag, clegg, debat, nick, nigel
##  Topic 29: bbc, pound, broadcast, one, licenc
##  Topic 30: cameron, minist, said, prime, david
##  Topic 31: ukip, parti, local, elect, councillor
##  Topic 32: immigr, benefit, migrant, will, work
##  Topic 33: migrat, report, immigr, worker, job
##  Topic 34: one, book, life, mother, like
##  Topic 35: peopl, think, one, ordinari, can
##  Topic 36: minor, ethnic, voter, vote, labour
##  Topic 37: per, cent, year, britain, countri
##  Topic 38: princ, charl, said, russian, comment
##  Topic 39: britain, eu, cameron, will, merkel
##  Topic 40: peopl, group, increas, ethnic, research
##  Topic 41: said, border, immigr, travel, use
##  Topic 42: garden, can, place, free, best
##  Topic 43: romanian, farag, said, ukip, racist
##  Topic 44: parti, mep, ukip, european, parliament
##  Topic 45: school, place, children, educ, choic
##  Topic 46: guardian, page, 2014, right, reserv
```

```
##  Topic 47: scotland, scottish, independ, vote, salmond
##  Topic 48: student, univers, uk, studi, said
##  Topic 49: said, miller, bbc, think, radio
##  Topic 50: ukip, farag, parti, elect, said
##  Topic 51: telegraph, onlin, 2014, ltd, group
##  Topic 52: ten, bill, lord, committe, debat
##  Topic 53: labour, parti, tori, ukip, conserv
##  Topic 54: film, play, music, game, work
##  Topic 55: war, work, uniform, new, first
##  Topic 56: wine, restaur, visitor, peter, tast
##  Topic 57: peopl, time, much, can, work
##  Topic 58: ukip, elect, will, european, immigr
##  Topic 59: ukip, voter, parti, class, labour
## ...........................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 31 (approx. per word bound = -6.459, relative change = 7.822e-05)
## ...........................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 32 (approx. per word bound = -6.458, relative change = 7.329e-05)
## ...........................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 33 (approx. per word bound = -6.458, relative change = 4.628e-05)
## ...........................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 34 (approx. per word bound = -6.458, relative change = 8.520e-05)
## ...........................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 35 (approx. per word bound = -6.457, relative change = 1.351e-05)
## Topic 1: migrat, net, number, year, immigr
##  Topic 2: telegraph, daili, 2014, nation, dt
##  Topic 3: compani, contract, prison, agent, custom
##  Topic 4: stori, mail, report, claim, time
##  Topic 5: english, england, british, say, peopl
##  Topic 6: applic, visa, said, uk, year
##  Topic 7: right, deport, human, year, law
##  Topic 8: said, case, home, deport, yashika
##  Topic 9: book, prize, orwel, read, biographi
##  Topic 10: radio, discuss, march, twitter, april
##  Topic 11: eu, europ, european, britain, polit
##  Topic 12: immigr, brokenshir, will, employ, labour
##  Topic 13: guardian, guardiancouk, media, 2014, news
##  Topic 14: peopl, christian, church, britain, countri
##  Topic 15: mr, farag, ukip, said, parti
##  Topic 16: crime, polic, said, victim, peopl
##  Topic 17: london, citi, new, capit, countri
##  Topic 18: tax, said, osborn, labour, rate
##  Topic 19: say, back, first, think, one
##  Topic 20: one, newspap, young, need, children
##  Topic 21: tori, cameron, parti, will, conserv
```

```
##  Topic 22: can, polici, provid, busi, data
##  Topic 23: uk, busi, economi, world, countri
##  Topic 24: muslim, women, polic, street, said
##  Topic 25: hous, price, london, market, hitler
##  Topic 26: say, just, go, know, one
##  Topic 27: ukip, parti, racist, farag, said
##  Topic 28: farag, clegg, debat, nick, nigel
##  Topic 29: bbc, pound, broadcast, one, licenc
##  Topic 30: cameron, said, minist, prime, david
##  Topic 31: ukip, parti, local, elect, councillor
##  Topic 32: immigr, benefit, migrant, will, work
##  Topic 33: migrat, report, immigr, worker, job
##  Topic 34: one, book, life, mother, like
##  Topic 35: peopl, think, one, ordinari, can
##  Topic 36: minor, ethnic, voter, vote, labour
##  Topic 37: per, cent, year, britain, countri
##  Topic 38: princ, charl, said, russian, comment
##  Topic 39: britain, eu, cameron, will, merkel
##  Topic 40: peopl, group, increas, ethnic, research
##  Topic 41: said, border, travel, immigr, offic
##  Topic 42: garden, can, place, free, year
##  Topic 43: romanian, farag, said, ukip, racist
##  Topic 44: parti, mep, ukip, parliament, european
##  Topic 45: school, place, children, educ, choic
##  Topic 46: guardian, 2014, page, right, reserv
##  Topic 47: scotland, scottish, independ, vote, salmond
##  Topic 48: student, univers, uk, studi, said
##  Topic 49: said, miller, think, bbc, mps
##  Topic 50: ukip, farag, parti, elect, said
##  Topic 51: telegraph, onlin, 2014, group, ltd
##  Topic 52: ten, bill, committe, lord, debat
##  Topic 53: labour, parti, tori, ukip, conserv
##  Topic 54: film, play, music, game, work
##  Topic 55: war, work, uniform, new, first
##  Topic 56: wine, restaur, visitor, peter, tast
##  Topic 57: peopl, time, work, much, can
##  Topic 58: ukip, elect, will, european, immigr
##  Topic 59: ukip, voter, parti, class, polit
## ...........................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 36 (approx. per word bound = -6.457, relative change = 9.381e-05)
## ...........................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 37 (approx. per word bound = -6.456, relative change = 5.124e-05)
## ...........................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 38 (approx. per word bound = -6.456, relative change = 4.909e-05)
## ...........................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 39 (approx. per word bound = -6.456, relative change = 4.537e-05)
```

```
## ........................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 40 (approx. per word bound = -6.456, relative change = 4.374e-05)
## Topic 1: migrat, net, number, year, figur
##  Topic 2: telegraph, daili, 2014, nation, dt
##  Topic 3: compani, contract, prison, agent, custom
##  Topic 4: stori, mail, report, claim, time
##  Topic 5: english, england, british, say, peopl
##  Topic 6: applic, visa, said, uk, year
##  Topic 7: right, deport, human, law, year
##  Topic 8: said, case, home, deport, yashika
##  Topic 9: book, prize, orwel, read, biographi
##  Topic 10: radio, discuss, march, twitter, 3
##  Topic 11: eu, europ, european, britain, polit
##  Topic 12: immigr, brokenshir, will, employ, labour
##  Topic 13: guardian, guardiancouk, media, 2014, news
##  Topic 14: peopl, christian, church, britain, countri
##  Topic 15: mr, farag, ukip, said, parti
##  Topic 16: crime, polic, said, peopl, victim
##  Topic 17: london, citi, new, capit, countri
##  Topic 18: tax, said, osborn, labour, rate
##  Topic 19: say, back, one, first, think
##  Topic 20: one, newspap, young, need, children
##  Topic 21: tori, cameron, parti, will, conserv
##  Topic 22: can, polici, provid, busi, data
##  Topic 23: uk, busi, economi, world, countri
##  Topic 24: muslim, women, polic, street, said
##  Topic 25: hous, price, london, market, peopl
##  Topic 26: say, go, just, know, dont
##  Topic 27: ukip, parti, racist, farag, said
##  Topic 28: farag, clegg, debat, nick, nigel
##  Topic 29: bbc, pound, broadcast, one, licenc
##  Topic 30: cameron, said, minist, prime, david
##  Topic 31: ukip, parti, local, elect, councillor
##  Topic 32: immigr, benefit, migrant, work, will
##  Topic 33: migrat, report, immigr, worker, british
##  Topic 34: one, book, life, mother, like
##  Topic 35: peopl, think, one, can, ordinari
##  Topic 36: minor, ethnic, voter, vote, labour
##  Topic 37: per, cent, year, britain, countri
##  Topic 38: princ, charl, said, russian, comment
##  Topic 39: britain, eu, cameron, will, merkel
##  Topic 40: peopl, group, increas, ethnic, live
##  Topic 41: said, border, travel, immigr, offic
##  Topic 42: garden, can, place, free, peopl
##  Topic 43: romanian, farag, said, ukip, racist
##  Topic 44: parti, mep, ukip, parliament, european
##  Topic 45: school, place, children, educ, choic
##  Topic 46: guardian, 2014, page, right, reserv
##  Topic 47: scotland, scottish, independ, vote, salmond
##  Topic 48: student, univers, uk, studi, said
##  Topic 49: said, miller, think, mps, bbc
##  Topic 50: ukip, farag, parti, elect, said
```

```
##  Topic 51: telegraph, onlin, 2014, group, ltd
##  Topic 52: ten, bill, committe, lord, debat
##  Topic 53: labour, parti, tori, ukip, vote
##  Topic 54: film, play, music, game, work
##  Topic 55: war, work, uniform, new, first
##  Topic 56: wine, restaur, visitor, peter, tast
##  Topic 57: peopl, time, work, addict, much
##  Topic 58: ukip, elect, will, european, peopl
##  Topic 59: ukip, voter, parti, class, polit
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 41 (approx. per word bound = -6.455, relative change = 2.359e-05)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 42 (approx. per word bound = -6.455, relative change = 6.069e-05)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 43 (approx. per word bound = -6.455, relative change = 4.108e-05)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 44 (approx. per word bound = -6.455, relative change = 3.832e-05)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 45 (approx. per word bound = -6.454, relative change = 4.027e-05)
## Topic 1: migrat, net, number, year, figur
##  Topic 2: telegraph, daili, 2014, nation, dt
##  Topic 3: compani, prison, contract, agent, custom
##  Topic 4: stori, mail, report, claim, time
##  Topic 5: english, england, british, say, peopl
##  Topic 6: applic, visa, said, uk, year
##  Topic 7: right, deport, human, law, year
##  Topic 8: said, case, home, deport, yashika
##  Topic 9: book, prize, orwel, read, biographi
##  Topic 10: radio, discuss, march, twitter, 3
##  Topic 11: eu, europ, european, polit, britain
##  Topic 12: immigr, brokenshir, will, labour, employ
##  Topic 13: guardian, media, guardiancouk, 2014, news
##  Topic 14: peopl, christian, church, britain, countri
##  Topic 15: mr, farag, ukip, said, parti
##  Topic 16: crime, polic, said, peopl, victim
##  Topic 17: london, citi, new, capit, countri
##  Topic 18: tax, said, osborn, rate, labour
##  Topic 19: say, back, one, first, think
##  Topic 20: one, newspap, young, need, children
##  Topic 21: tori, cameron, parti, will, conserv
##  Topic 22: can, polici, provid, busi, data
##  Topic 23: uk, busi, economi, world, countri
##  Topic 24: muslim, women, polic, street, said
##  Topic 25: hous, price, london, market, peopl
```

```
##  Topic 26: say, go, just, dont, know
##  Topic 27: ukip, parti, racist, farag, said
##  Topic 28: farag, clegg, debat, nick, nigel
##  Topic 29: bbc, pound, broadcast, one, licenc
##  Topic 30: cameron, said, minist, prime, david
##  Topic 31: ukip, parti, local, elect, councillor
##  Topic 32: immigr, benefit, migrant, work, will
##  Topic 33: migrat, report, immigr, worker, british
##  Topic 34: one, book, life, novel, like
##  Topic 35: peopl, think, one, can, say
##  Topic 36: minor, ethnic, voter, vote, labour
##  Topic 37: per, cent, year, britain, countri
##  Topic 38: princ, said, charl, russian, comment
##  Topic 39: britain, eu, cameron, will, merkel
##  Topic 40: peopl, increas, group, ethnic, live
##  Topic 41: said, border, travel, offic, home
##  Topic 42: garden, can, place, peopl, year
##  Topic 43: romanian, farag, said, ukip, racist
##  Topic 44: parti, mep, ukip, parliament, european
##  Topic 45: school, place, children, educ, choic
##  Topic 46: guardian, 2014, page, right, reserv
##  Topic 47: scotland, scottish, independ, vote, salmond
##  Topic 48: student, univers, uk, studi, said
##  Topic 49: said, miller, mps, think, bbc
##  Topic 50: ukip, farag, parti, elect, said
##  Topic 51: telegraph, onlin, 2014, group, ltd
##  Topic 52: ten, bill, committe, lord, debat
##  Topic 53: labour, parti, tori, vote, ukip
##  Topic 54: film, play, music, game, work
##  Topic 55: war, work, uniform, new, first
##  Topic 56: wine, restaur, visitor, peter, tast
##  Topic 57: peopl, time, work, addict, think
##  Topic 58: ukip, elect, will, european, peopl
##  Topic 59: ukip, voter, parti, class, polit
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 46 (approx. per word bound = -6.454, relative change = 4.056e-05)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 47 (approx. per word bound = -6.454, relative change = 1.513e-05)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 48 (approx. per word bound = -6.454, relative change = 6.362e-05)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 49 (approx. per word bound = -6.453, relative change = 3.430e-05)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 50 (approx. per word bound = -6.453, relative change = 3.538e-05)
```

```
## Topic 1: migrat, net, number, year, figur
##  Topic 2: telegraph, daili, 2014, nation, dt
##  Topic 3: compani, prison, contract, agent, custom
##  Topic 4: stori, mail, report, claim, time
##  Topic 5: english, england, british, say, nation
##  Topic 6: applic, visa, said, uk, year
##  Topic 7: right, deport, law, human, year
##  Topic 8: said, case, home, deport, yashika
##  Topic 9: book, prize, orwel, read, biographi
##  Topic 10: radio, discuss, march, twitter, 3
##  Topic 11: eu, europ, european, polit, britain
##  Topic 12: immigr, brokenshir, will, labour, employ
##  Topic 13: guardian, media, guardiancouk, 2014, news
##  Topic 14: peopl, christian, church, britain, countri
##  Topic 15: mr, farag, said, ukip, miliband
##  Topic 16: crime, polic, said, peopl, victim
##  Topic 17: london, citi, new, capit, countri
##  Topic 18: tax, osborn, said, rate, labour
##  Topic 19: say, back, one, day, first
##  Topic 20: one, newspap, young, need, said
##  Topic 21: tori, parti, cameron, conserv, will
##  Topic 22: can, polici, provid, busi, data
##  Topic 23: uk, busi, economi, world, countri
##  Topic 24: muslim, women, polic, street, said
##  Topic 25: hous, price, london, market, peopl
##  Topic 26: say, go, just, dont, one
##  Topic 27: ukip, parti, racist, farag, said
##  Topic 28: clegg, farag, debat, nick, nigel
##  Topic 29: bbc, pound, broadcast, one, licenc
##  Topic 30: cameron, said, minist, prime, david
##  Topic 31: ukip, parti, local, elect, councillor
##  Topic 32: immigr, benefit, migrant, work, will
##  Topic 33: migrat, report, immigr, worker, migrant
##  Topic 34: book, one, life, novel, like
##  Topic 35: peopl, one, think, can, say
##  Topic 36: minor, ethnic, voter, vote, labour
##  Topic 37: per, cent, year, britain, countri
##  Topic 38: princ, said, charl, russian, comment
##  Topic 39: britain, eu, cameron, will, merkel
##  Topic 40: peopl, increas, group, ethnic, live
##  Topic 41: said, border, offic, home, travel
##  Topic 42: garden, can, place, peopl, year
##  Topic 43: romanian, farag, said, ukip, peopl
##  Topic 44: parti, mep, ukip, parliament, european
##  Topic 45: school, place, children, educ, choic
##  Topic 46: guardian, 2014, page, right, reserv
##  Topic 47: scotland, scottish, independ, vote, salmond
##  Topic 48: student, univers, uk, studi, intern
##  Topic 49: said, miller, mps, think, bbc
##  Topic 50: ukip, farag, parti, elect, said
##  Topic 51: telegraph, onlin, 2014, group, ltd
##  Topic 52: ten, bill, committe, lord, debat
##  Topic 53: labour, parti, tori, vote, conserv
##  Topic 54: film, play, music, game, work
```

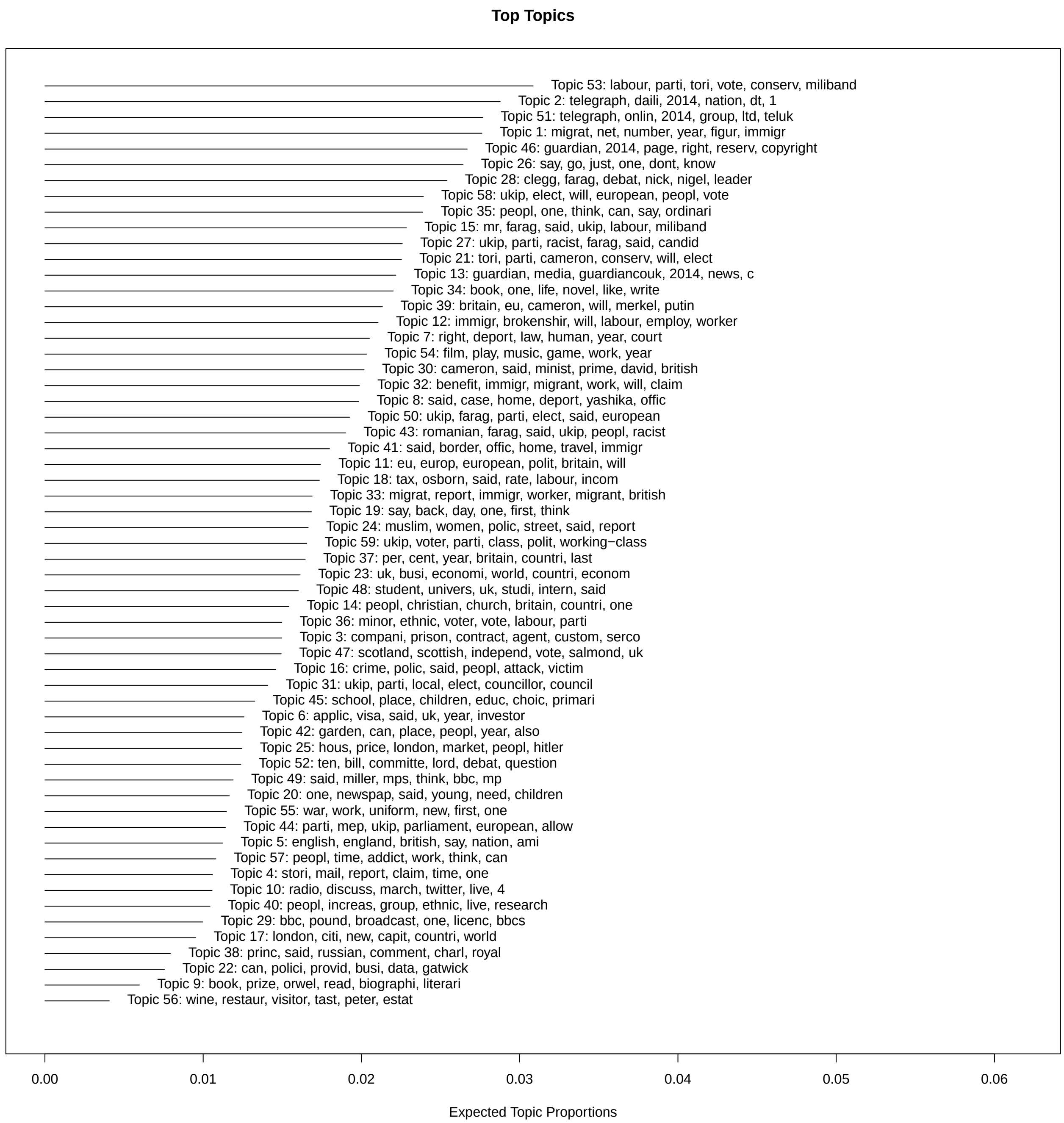
```
##  Topic 55: war, work, uniform, new, first
##  Topic 56: wine, restaur, visitor, peter, tast
##  Topic 57: peopl, time, addict, work, think
##  Topic 58: ukip, elect, will, european, peopl
##  Topic 59: ukip, voter, parti, class, polit
## ....................................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 51 (approx. per word bound = -6.453, relative change = 3.594e-05)
## ....................................................................................................
## Completed E-Step (2 seconds).
## Completed M-Step.
## Completing Iteration 52 (approx. per word bound = -6.453, relative change = 3.193e-05)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 53 (approx. per word bound = -6.452, relative change = 3.679e-05)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Completing Iteration 54 (approx. per word bound = -6.452, relative change = 3.156e-05)
## ....................................................................................................
## Completed E-Step (1 seconds).
## Completed M-Step.
## Model Converged
```

The model gives back 59 topics. And 54 Iterations before model converged.

(c) Identify and name each of the 5 topics that occur in the highest proportion of documents using the following code:

```r
plot(fit.stm, type = "summary")
```

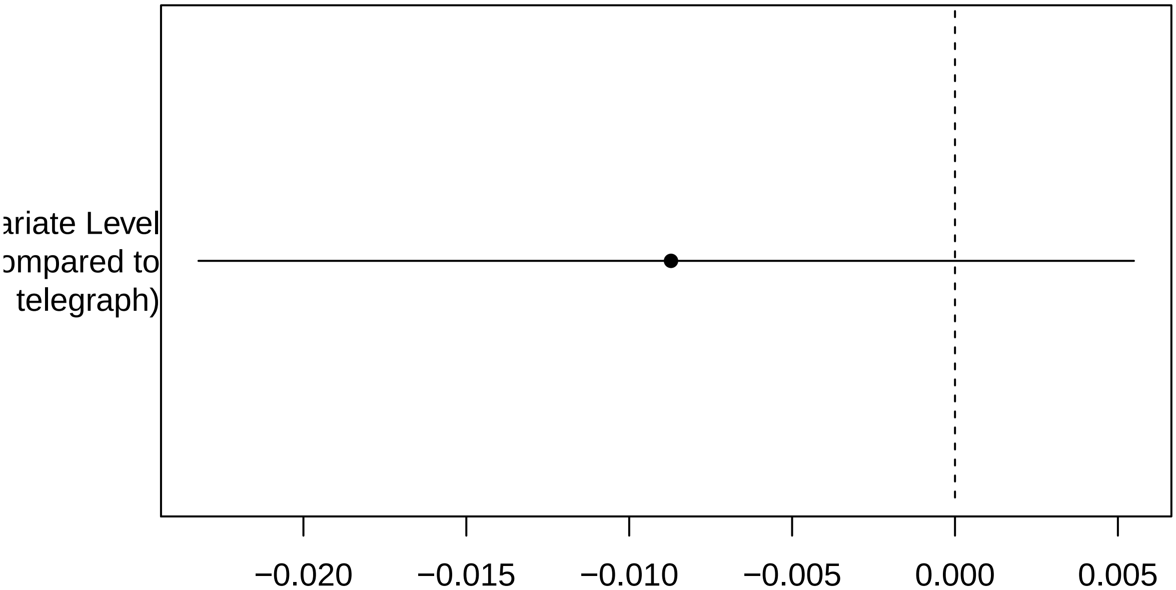
```r
plot(stm_GT, type="summary", n=6)
```



The topic with the highest expected topic proportions is about "party".

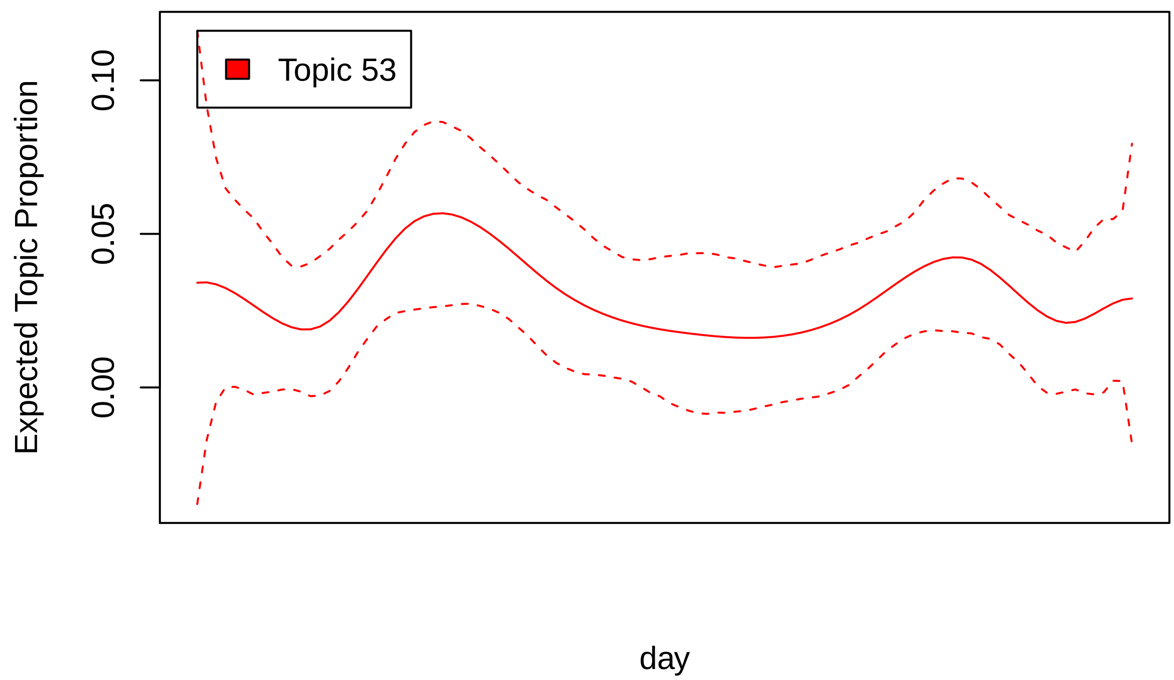
(d) Using the visualization commands in the stm package, discuss one of these top 5 topics. How does the content vary with the paper discussing that topic? How does the prevalence change over time?

```
prep <- estimateEffect(c(53) ~ name, stm_GT, meta=df)
plot(prep, "name", model=stm_GT,
     method="difference",cov.value1="guardian",cov.value2="telegraph")
```



The guardian talked the topic of “party” less than the telegraph.

```
prep <- estimateEffect(c(53) ~ name + s(day), stm_GT, meta=df)
plot(prep, "day", model=stm_GT, topics=c(53),
     method="continuous",xaxt="n",xlab="day")
```



For this topic 53 “party”, the whole trend experienced two major fluctuations around the expected topic proportion of 0.4.

4. Non-Parametric Scaling - Wordfish: Recall that the Wordfish algorithm allows us to scale political texts by a latent dimension. We will apply this function to analyze the inaugural addresses.

(a) First, create a corpus that is the subset of the data corpus inaugural that contains only speeches that occurred after 1900.

```
data <- data_corpus_sotu
data_sub <- corpus_subset(data, as.numeric(substring(data$documents$Date,1,4))>1900)
```

(b) Wordfish requires that we select anchors that lie at the extremes of the latent dimension; in this case, we are looking to estimate the latent left-right ideological dimension. Use Obama's 2009 speech and Ronald Reagan's 1981 speech as our anchors for a Wordfish model.

```
df <- tibble(
  President = data_sub$documents$President,
  year = as.numeric(substring(data_sub$documents$Date,1,4)),
  content = data_sub$documents$texts
)

obama <- which(df$President=="Obama" & df$year=="2012")
reagan <- which(df$President=="Reagan" & df$year=="1981")
sotu_dfm <- dfm(df$content, remove_punct=TRUE, tolower=TRUE, remove=stopwords("english"))
sotu_fish <- textmodel_wordfish(sotu_dfm, dir=c(obama, reagan))
```

(c) Which of the documents is the most left wing? Which is the most right-wing? Are these results surprising? Why or why not?

```
df <- mutate(df, fish_theta=sotu_fish$theta)
df[which.max(df$fish_theta),c(1:2,4)]
```

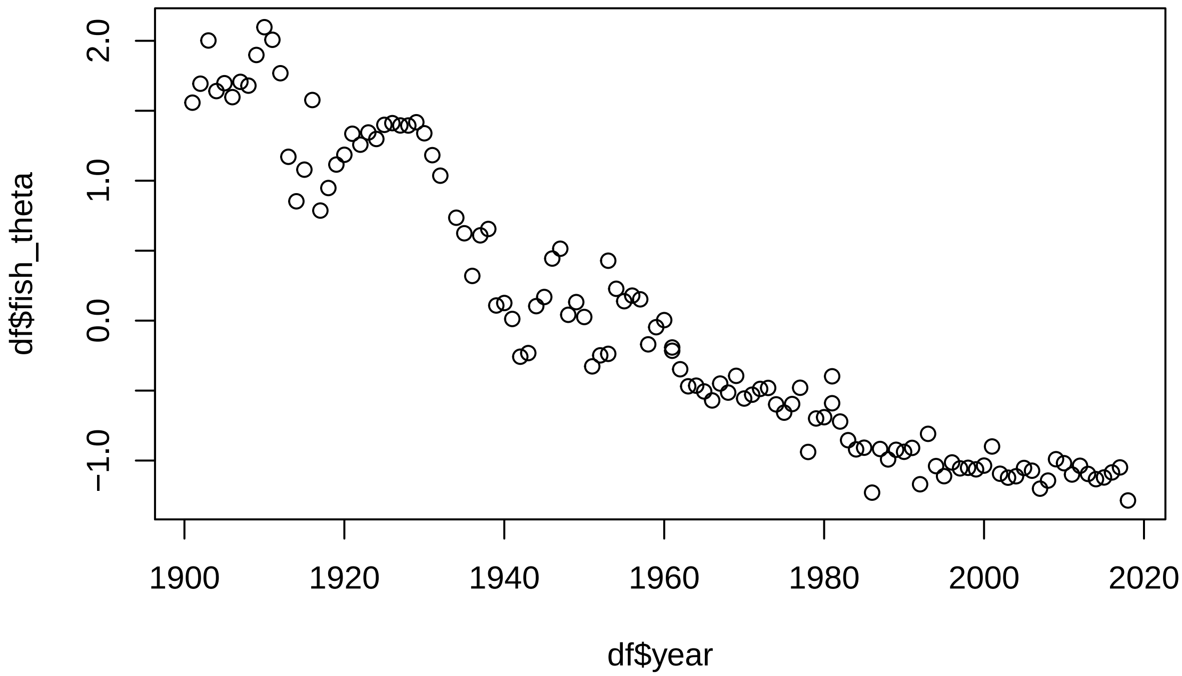
```
## # A tibble: 1 x 3
##   President  year fish_theta
##   <chr>     <dbl>      <dbl>
## 1 Taft       1910       2.10
```

```
df[which.min(df$fish_theta),c(1:2,4)]
```

```
## # A tibble: 1 x 3
##   President  year fish_theta
##   <chr>     <dbl>      <dbl>
## 1 Trump      2018      -1.29
```

Considering the Obama's 2009 speech and Ronald Reagan's 1981 as left and right anchor, the most left-wing speech is Trump2018 and the most right-wing speech is Taft1910. This is not very surprising after seeing the plot below which shows that there is an obvious decline trend in regards of wordfish score. I think the reason is that how and what those speeches were delivered is changing over time so that the anchor documents captured this difference rather than the ideology difference.

```
plot(df$year, df$fish_theta)
```



(d) Re-create the "guitar plot" from Recitation 9. Describe the parameters estimated by Wordfish that lie on the axes of the plot.

```
words<-sotu_fish$psi
weights<-sotu_fish$beta
names(words) <- sotu_fish$features
sort(words)[1:50]
```

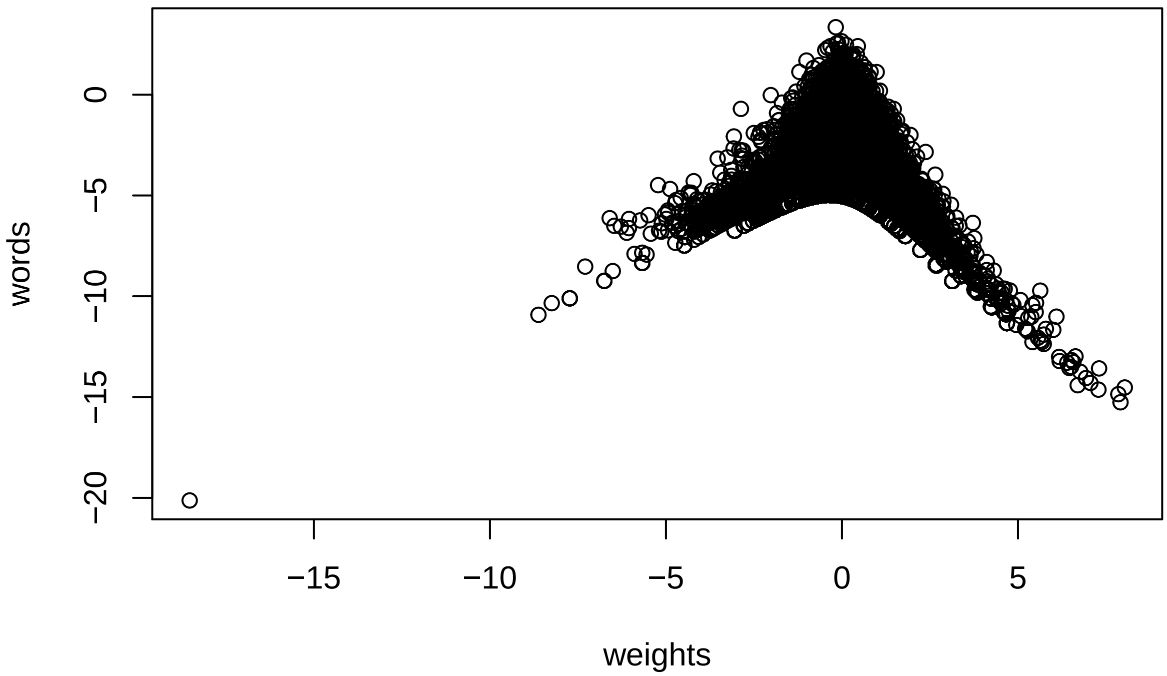
```
##              applause              decree                1910
##             -20.12994           -15.26146           -14.85872
##               douglas                1911       10,634,122.63
##             -14.63265           -14.52675           -14.41319
##                 wools           colombian            enjoined
##             -14.30037           -14.05868           -13.74606
##                  wool             adviser         prohibitory
##             -13.58095           -13.55884           -13.50069
##                  riot             granada          montenegro
##             -13.29530           -13.27539           -13.21709
##           dissolution             scoured                1903
##             -13.16373           -13.00965           -12.98425
##         ratifications         trade-marks            portland
##             -12.36775           -12.27409           -12.26972
##               ensuing             hukuang              zelaya
##             -12.19669           -12.06062           -11.90344
##                grease            telegram               opium
##             -11.74292           -11.67270           -11.66554
##             argentine                1885      correspondence
##             -11.61475           -11.60285           -11.42200
##               identic            circular            portugal
##             -11.33250           -11.33250           -11.33250
## internationalization           mediators        conciliatory
```

```
##          -11.33250          -11.33250          -11.33250
##             ottawa     630,494,013.12           auditing
##          -11.33250          -11.33250          -11.33250
##         disbursing      13,169,679.70      28,232,465.00
##          -11.33250          -11.33250          -11.33250
##      12,844,122.00       1,695,690.00               1856
##          -11.33250          -11.33250          -11.07941
##      incorporation               1909       stipulations
##          -11.02276          -11.01266          -10.98921
##                 cj         monopolize
##          -10.91983          -10.89282
```

```r
sort(words, decreasing=T)[1:50]
```

```
##       will        can       must     people   congress      world
##   3.347395   2.653329   2.580973   2.532463   2.474318   2.405953
## government        new       year        now   american         us
##   2.405773   2.323381   2.257129   2.228774   2.221174   2.212746
##      years        one        war     states      great     nation
##   2.135347   2.077097   2.022412   2.011663   1.986243   1.971244
##       time    country     united       work      every       make
##   1.960055   1.959141   1.952857   1.909660   1.896113   1.867856
##   national      peace    nations    federal       many       also
##   1.840246   1.824741   1.808186   1.791916   1.740136   1.708503
##    america   economic       last       made       need      first
##   1.692845   1.626815   1.610648   1.592060   1.569443   1.529804
##      power   security    program     system       free       good
##   1.474831   1.464267   1.463609   1.449741   1.430845   1.389278
##        men     public      state        act     future    economy
##   1.366859   1.363472   1.348168   1.340714   1.330796   1.328942
##       help      shall
##   1.321858   1.315922
```

```r
plot(weights, words)
```



Words lie on the top of this "tower" are common words shared by both sides, while words lie on the two bottoms of this "tower" make a difference.

(e) Optional: Estimate a linear regression with the Wordfish score as the dependent vari- able and binary variable indicating whether or not a President was a Democrat as an independent variable. Include a binary control variable for each president. If we use being a Democrat as a proxy for liberal ideology, how well did our Wordfish model do at capturing latent ideology?

```
df <- mutate(df, party=ifelse(data_sub$documents$party=='Democratic', 1, 0))
fit <- lm(fish_theta ~ party, data=df)
summary(fit)
```

```
##
## Call:
## lm(formula = fish_theta ~ party, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4660 -0.8430 -0.1859  0.9903  1.9164
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.1807     0.1242   1.455   0.1482
## party        -0.3805     0.1802  -2.112   0.0368 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9858 on 118 degrees of freedom
## Multiple R-squared:  0.03641,    Adjusted R-squared:  0.02824
## F-statistic: 4.459 on 1 and 118 DF,  p-value: 0.03683
```

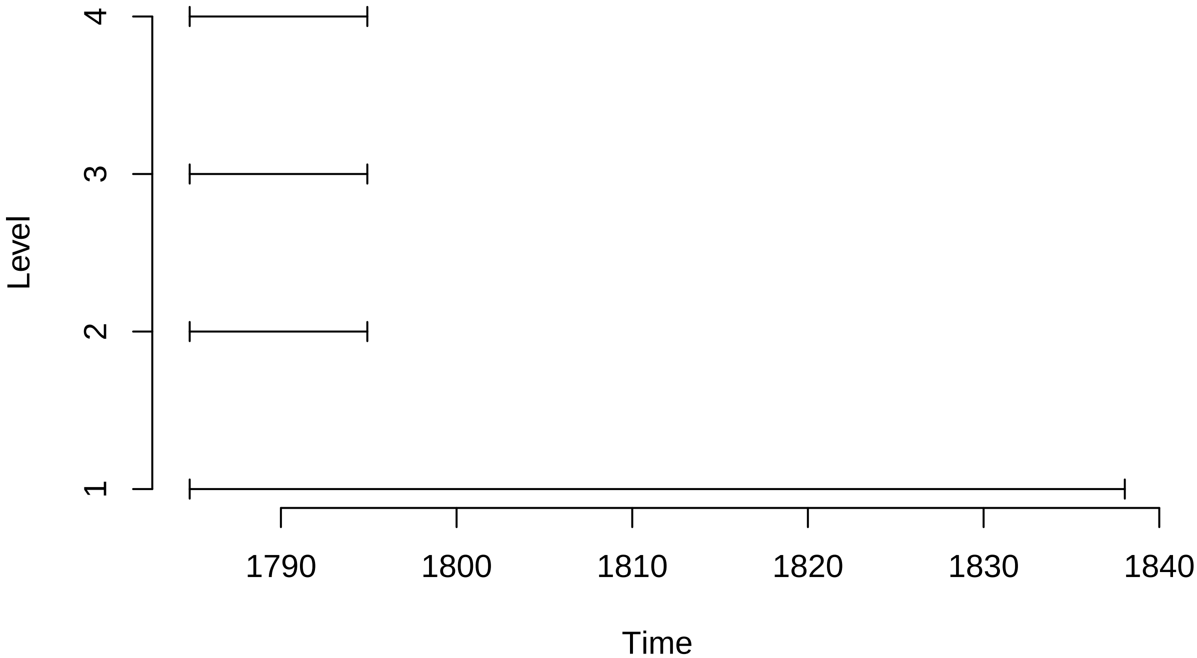
The p-value=0.0368 which significant at a 5% level. But the R-squared is low, which means the model is not a good fit.

5. Burstiness: Here we evaluate the burstiness of several words using Arthur's corpus of treaties between Native American tribes and the U.S. government. To evaluate burstiness we will use the bursts package and the user-written function bursty from Recitation 12 that visualizes the results. You can download the treaty data from GitHub.

(a) Create a corpus from the treaties using the readtext command. For each of the words "Oneidas", "and", and "peaceably" use the bursty function to visualize the burst period(s) and levels. Also, for each of the plots include a brief interpretation about what the timing and level of the burst indicates about groups and events associated with the treaties.

Hint: Look at the events and parties affected by the Indian Removal Act of 1830. You can use the following synopsis as a reference: Indian Treaties and the Removal Act of 1830

```r
bursty<-function(word="oneidas",DTM, date){
  word.vec <- DTM[,which(colnames(DTM) == word)]
  if(length(word.vec) == 0){
    print(word, " does not exist in this corpus.")
  } else{
    word.times <- c(0,which(as.vector(word.vec)>0))
    kl <- kleinberg(word.times, gamma=.5)
    kl$start <- date[kl$start+1]
    kl$end <- date[kl$end]
    max_level <- max(kl$level)
    plot(c(kl$start[1], kl$end[1]), c(1,max_level),
         type = "n", xlab = "Time", ylab = "Level", bty = "n",
         xlim = c(kl$start[1], kl$end[1]), ylim = c(1, max_level),
         yaxt = "n")
    axis(2, at = 1:max_level)
    for(i in 1:nrow(kl)){
      if(kl$start[i] != kl$end[i]){
        arrows(kl$start[i], kl$level[i], kl$end[i], kl$level[i], code = 3, angle = 90,
               length = 0.05)
      } else{
        points(kl$start[i], kl$level[i])
      }
    }
    print(kl)
  }
    #note deviation from standard defaults bec don't have that much data
}

treaties <- readtext("treaties/*.txt", docvarsfrom=c("filenames"))
treaties_corpus <- corpus(treaties)
cases <- read.csv("treaties/universecases.csv")
date <- as.Date(as.character(cases$Date[1:365]), "%m-%d-%Y")
docvars(treaties_corpus)$Date <- date

treaties_dtm <- dfm(treaties_corpus)
bursty("oneidas", treaties_dtm, date)
```

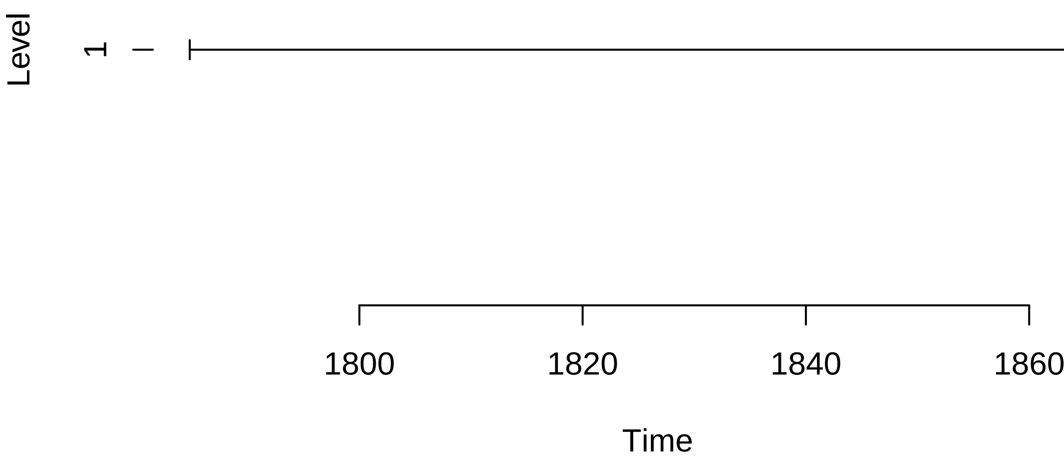



```
##   level      start        end
## 1     1 1784-10-22 1838-01-15
## 2     2 1784-10-22 1794-12-02
## 3     3 1784-10-22 1794-12-02
## 4     4 1784-10-22 1794-12-02
```

The Treaty of Fort Stanwix, the first treaty between the Oneida and the United States, was signed under the Articles of Confederation in 1784.[1]

[1] Oneida Treaties and Treaty Rights. Retrieved from: http://www.mpm.edu/content/wirp/ICW-106.html

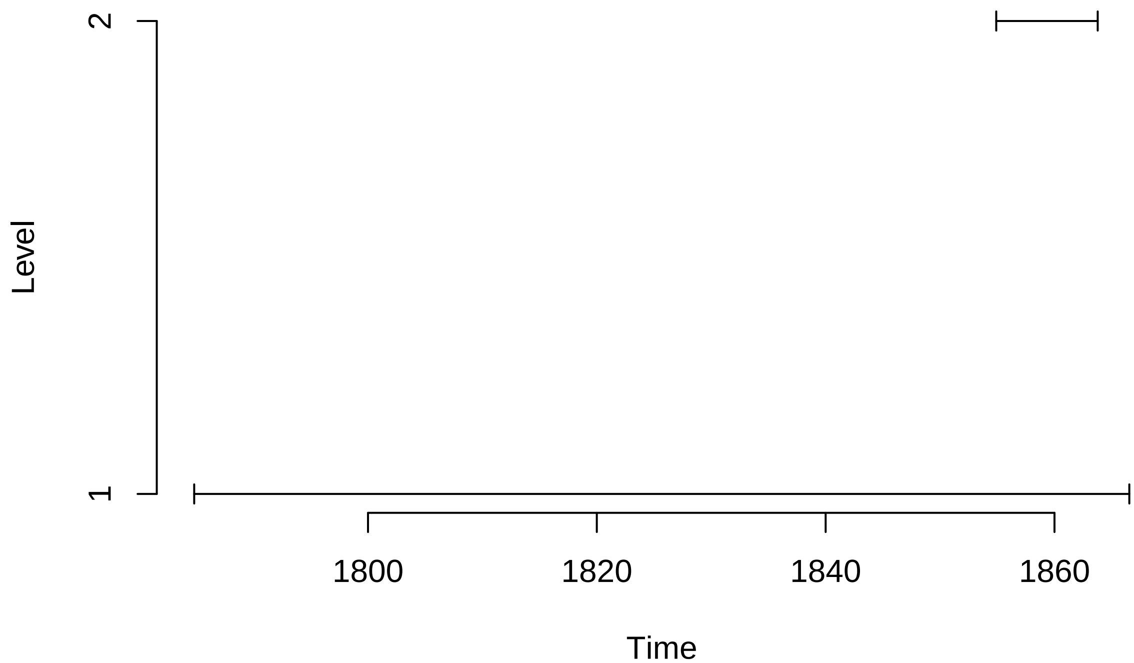
```r
bursty("and", treaties_dtm, date)
```




```
##   level      start        end
## 1     1 1784-10-22 1868-08-13
```

“and” is a common word in all documents, so that the burst period covered the whole time range.

```r
bursty("peaceably", treaties_dtm, date)
```




```
##   level      start        end
## 1     1 1784-10-22 1866-07-17
## 2     2 1854-11-29 1863-10-12
```

In 1851 the U.S. government held a conference with several local Indian tribes and established the Treaty of Fort Laramie. But this peaceful accord between the U.S. government and the Native American tribes did not last long.[2]

[2] Native American Tribes & U.S. Government. Retrieved from: http://www.victoriana.com/history/nativeamericans.html