Regulatory Documents via LDA - Documentation

Sebastian Knigge

18 8 2019

Contents

1 Setup

Following libraries are used in the code:

```
library(dplyr)
library(tidytext)
library(pdftools)
library(tidyr)
library(stringr)
library(tidytext)
library(udpipe)
library(topicmodels)
library(ggplot2)
library(wordcloud)
library(tm)
library(SnowballC)
library(RColorBrewer)
library(RCurl)
library(XML)
library(openxlsx)
library(keras)
library(foreach)
library(doParallel)
```

2 Import data

The Documents had to be preprocessed. For the documents wp2.5 all list of contents had to be deleted, because they were the same in each of these documents. No more adjustments had to be made.

In this code reulatory documents are red in and processed via LDA. This first part focusses on reading in the pdf documents.

```r
# getting the right order
setwd('..')
documents <- read.xlsx("Docs_classes.xlsx")[,2]
classes <- read.xlsx("Docs_classes.xlsx")[,c(1,3)]
documents <- paste0(documents,".pdf")
documents %>% as.data.frame() %>% stargazer(summary=FALSE,
                                            header = FALSE,
                                            title="Document Titles")
```

Table 1: Document Titles

	.
1	admin-wp1.1__analysis__legal__institutional__environment__final.pdf
2	admin-wp1.2__good__practices__final.pdf
3	admin-wp2.1__estimation__methods1.pdf
4	admin-wp2.2__estimation__methods2.pdf
5	admin-wp2.3-estimation__methods3.pdf
6	admin-wp2.4__examples.pdf
7	admin-wp2.5__alignment.pdf
8	admin-wp2.5__editing.pdf
9	admin-wp2.5__greg.pdf
10	admin-wp2.5__imputation.pdf
11	admin-wp2.5__macro__integration.pdf
12	admin-wp2.5__matching.pdf
13	admin-wp2.6__good__practices.pdf
14	admin-wp2.6__guidelines.pdf
15	admin-wp3.1__quality1.pdf
16	admin-wp3.2__quality2.pdf
17	admin-wp3.3__quality.pdf
18	admin-wp3.4__quality.pdf
19	admin-wp3.5__quality__measures.pdf
20	admin-wp3__coherence.pdf
21	admin-wp3__growth__rates.pdf
22	admin-wp3__suitability1.pdf
23	admin-wp3__suitability2.pdf
24	admin-wp3__suitability3.pdf
25	admin-wp3__uncertainty.pdf
26	admin-wp5__frames.pdf
27	admin-wp5__frames__examples.pdf
28	admin-wp5__frames__recommendation.pdf

```r
# getting the right directory
library(here)
setwd("../")
path <- getwd() %>%
  file.path("TextDocs")
```

```r
setwd(path)
```

Following functions are used to set up and analyze the pdfs. When cleaning up data, we have to take into account certain circumstances of the regulatory documents. For example, there are many formulas and technical abbreviations in the documents. Every variable, every estimator, and every index is included as a single word in the bag of words. These terms sometimes have a big influence on the documents, because they are very specific for individual documents and occur quite often. To avoid this, we exclude all mixed words with characters and numeric values, as well as all terms with special characters (e.g. Greek letters).

```r
read_pdf_clean <- function(document){
  # This function loads the document given per name
  # and excludes the stop words
  pdf1 <- pdf_text(file.path(path, document)) %>%
    strsplit(split = "\n") %>%
    do.call("c",.) %>%
    as_tibble() %>%
    unnest_tokens(word,value) %>%
    # also exclude all words which include numbers and special characters
    filter(grepl("^[a-z]+$", word))
  # load stopword library
  data(stop_words)
  # stop words are excluded via anti_join
  pdf1 %>%
    anti_join(stop_words)
}

plot_most_freq_words <- function(pdf, n=7){
  # plots a bar plot via ggplot
  pdf %>% count(word) %>% arrange(desc(n)) %>% head(n) %>%
    ggplot(aes(x=word,y=n)) +
    geom_bar(stat="identity")+
    # no labels for x and y scale
    theme(axis.title.y=element_blank(),
          axis.title.x=element_blank())
}
```

Now we can read in all documents using a for loop:

```r
setwd(path)
# inital set up for the corpus
pdf1 <- read_pdf_clean(documents[1])
corpus <- tibble(document=1, word=pdf1$word)
# adding the documents iteratively
for (i in 2:length(documents)){
  pdf_i <- read_pdf_clean(documents[i])
  corpus <- tibble(document=i, word=pdf_i$word) %>% bind_rows(corpus,.)
}
```

3 LDA

The LDA model is applied. First the document term matrix has to be set up.

```r
dtm <- corpus %>% count(document, word, sort = TRUE) %>%
  select(doc_id=document, term=word, freq=n) %>%
  document_term_matrix()
# dimensions
c(N,M) %<-% dim(dtm)
N; M
```

```
## [1] 28

## [1] 8254
```

We use term frequency 2 embedding because in the example with the Gutenberg Data, it turned out to be advantageous with regard to the "predictive power" of the LDA algorithm.

```
dtm_tf2 <- dtm %>%
    # reduce by low frequencies
    dtm_remove_lowfreq(minfreq = 2)
ncol(dtm_tf2 )
```

```
## [1] 5842
```

Using the function LDA sets up the model and prediction/evaluation is done via *predict*(). But first of all it shall be verified whether the Predict function actually delivers the same classification as the export of the gamma matrix directly from the LDA model. Therefore both gamma matrices of the single functions are compared. Table 2 displays the output of the gamma matrix received by the *predict*() function and Table 3 displays the gamma matrix returned by the LDA model itself.

```
tim1 <- Sys.time()
set.seed(123)
documents_lda <- LDA(dtm_tf2, method = "Gibbs",
                     k = 7, control = list(seed = 1234))
tim2 <- Sys.time()
u1 <- tim2 - tim1
```

```
prediction5 <- predict(documents_lda, newdata=dtm_tf2, type="topic")

prediction5 <- merge(prediction5, classes, by.x="doc_id", by.y="No")

prediction5 %>%
  select(doc_id,topic_001,topic_002,topic_003,topic_004,topic_005,
         topic_006, topic_007) %>%
  mutate_each(funs(as.numeric),
              doc_id,topic_001,topic_002,topic_003,topic_004,
              topic_005, topic_006, topic_007) %>%
  arrange(desc(-doc_id)) %>%
  round(2) %>%
  stargazer(summary=F, rownames = F, header = F,
            title="Gamma matrix for predict function", label="predict")
```

```
ext_gamma_matrix <- function(model=documents_lda){
  # get gamma matrix for chapter probabilities
  chapters_gamma <- tidy(model, matrix = "gamma")
  # get matrix with probabilities for each topic per chapter
  spreaded_gamma <- chapters_gamma %>% spread(topic, gamma)
  spreaded_gamma %>%
    mutate_each(funs(as.numeric), document,1,2,3,4,5,6,7) %>%
  arrange(desc(-document))
}
```

Table 2: Gamma matrix for predict function

doc_id	topic_001	topic_002	topic_003	topic_004	topic_005	topic_006	topic_007
1	0	0.950	0	0.030	0.010	0	0.010
2	0.010	0.760	0.010	0.160	0.030	0.030	0.010
3	0.160	0.020	0.060	0.030	0.630	0.050	0.050
4	0.180	0.010	0.030	0.020	0.710	0.020	0.040
5	0.720	0	0.080	0.010	0.160	0.020	0.010
6	0.600	0.010	0.230	0.030	0.120	0.010	0.010
7	0.830	0.010	0.080	0.010	0.040	0.020	0.020
8	0.760	0.020	0.030	0.010	0.130	0.030	0.020
9	0.750	0.010	0.090	0.030	0.060	0.030	0.030
10	0.900	0	0.030	0.010	0.050	0.010	0.010
11	0.690	0.010	0.170	0.010	0.100	0.020	0.010
12	0.800	0.010	0.030	0.010	0.120	0.030	0.010
13	0.010	0.080	0.010	0.410	0.470	0.020	0.010
14	0.170	0.010	0.030	0.030	0.730	0.020	0.010
15	0.010	0.020	0.010	0.020	0.180	0.750	0.010
16	0.010	0	0.770	0	0.120	0.080	0.010
17	0.010	0.010	0.100	0.030	0.050	0.040	0.760
18	0.010	0	0.770	0	0.130	0.080	0.010
19	0.060	0	0.450	0.010	0.100	0.320	0.060
20	0.030	0.010	0.040	0.020	0.040	0.840	0.020
21	0.010	0	0.940	0.010	0.020	0.010	0.010
22	0.010	0.010	0.910	0.020	0.030	0	0.010
23	0.010	0.010	0.820	0.030	0.040	0.050	0.050
24	0.010	0.010	0.860	0.010	0.080	0.010	0.010
25	0.130	0	0.820	0.010	0.010	0.020	0.010
26	0.010	0.010	0.010	0.100	0.160	0.060	0.650
27	0	0.100	0.010	0.690	0.020	0.010	0.180
28	0.010	0.060	0.010	0.670	0.020	0.180	0.050

```r
ext_gamma_matrix(documents_lda) %>%
  round(2) %>%
  stargazer(summary=F, rownames = F, header=F,
            title="Gamma matrix extracted from model",
            label="extract")
```

Table 3: Gamma matrix extracted from model

document	1	2	3	4	5	6	7
1	0	0.94	0	0.03	0.01	0	0.01
2	0.01	0.75	0	0.16	0.03	0.03	0.01
3	0.15	0.02	0.07	0.03	0.62	0.05	0.05
4	0.18	0.01	0.03	0.03	0.7	0.02	0.04
5	0.71	0.01	0.09	0	0.16	0.02	0.01
6	0.59	0.02	0.23	0.02	0.12	0.01	0.01
7	0.8	0.01	0.07	0.01	0.04	0.03	0.03
8	0.73	0.01	0.05	0.01	0.14	0.04	0.02
9	0.73	0.01	0.09	0.02	0.07	0.03	0.05
10	0.88	0	0.04	0.01	0.06	0	0.02
11	0.67	0.01	0.19	0.01	0.1	0.01	0.01
12	0.79	0.01	0.04	0.01	0.12	0.02	0.01
13	0.01	0.08	0.01	0.4	0.47	0.02	0.01
14	0.18	0.01	0.03	0.04	0.72	0.02	0.01
15	0.02	0.02	0.02	0.02	0.18	0.73	0.02
16	0.01	0.01	0.76	0.01	0.13	0.08	0.01
17	0.01	0.01	0.1	0.03	0.05	0.05	0.74
18	0.01	0	0.76	0	0.13	0.08	0.01
19	0.07	0.01	0.45	0.01	0.1	0.31	0.06
20	0.05	0.01	0.03	0.02	0.05	0.82	0.03
21	0.01	0	0.92	0.01	0.02	0.02	0.01
22	0.01	0	0.89	0.02	0.04	0.01	0.02
23	0.01	0.01	0.82	0.03	0.04	0.05	0.04
24	0.02	0.01	0.87	0.01	0.08	0.01	0.01
25	0.13	0.01	0.81	0.02	0.01	0.02	0.01
26	0.01	0.02	0.01	0.11	0.16	0.06	0.64
27	0.01	0.09	0.01	0.68	0.03	0.01	0.17
28	0.01	0.06	0.02	0.66	0.02	0.19	0.05

The tables below summarize which document refers to which topic, according to the LDA model (term frequency 2 embedding).

3.1 Wordclouds

To check what topics tackle which context, we produce wordclouds using the TFIDF and the TF itself.

```r
plot_wordcloud <- function(corpus, selection="ALL",
                           max.words=50, i, freq="tfidf",
                           scale=c(3,0.2)){
  # setting up a tibble which returns tfidf and tf and frequency for
  # the whole corpus
  tfidf <- corpus %>% count(document, word, sort = TRUE) %>%
    bind_tf_idf(word, document, n)
```

Table 4: Documents for Topic 1

Topic	doc_id	Group
1	10	4
1	11	4
1	12	4
1	5	2
1	6	3
1	7	4
1	8	4
1	9	4

Table 5: Documents for Topic 2

Topic	doc_id	Group
2	1	1
2	2	1

Table 6: Documents for Topic 3

Topic	doc_id	Group
3	16	5
3	18	5
3	19	5
3	21	6
3	22	6
3	23	6
3	24	6
3	25	6

Table 7: Documents for Topic 4

Topic	doc_id	Group
4	27	7
4	28	7

Table 8: Documents for Topic 5

Topic	doc_id	Group
5	13	3
5	14	4
5	3	2
5	4	2

Table 9: Documents for Topic 6

Topic	doc_id	Group
6	15	5
6	20	5

Table 10: Documents for Topic 7

Topic	doc_id	Group
7	17	5
7	26	7

```r
  # include all documents for selection if selection="ALL"
  if (all(selection=="ALL")) {
    selection <- corpus %>%
      select(document) %>%
      unique() %>%
      unlist() %>%
      sort()}
  # filter for all selected documents
  # use either ft or tfidf
  if (freq=="tfidf"){
    dtm_selected <- tfidf %>% filter(document%in%selection) %>%
      select(word, tf_idf) %>% count(word, wt=tf_idf, sort=TRUE)
  } else {
    dtm_selected <- tfidf %>% filter(document%in%selection) %>%
      select(word, tf) %>% count(word, wt=tf, sort=TRUE)
  }
  # plotting
  wordcloud(words = dtm_selected$word, freq = dtm_selected$n,
            min.freq = 1,max.words=max.words, random.order=FALSE,
            colors=brewer.pal(8, "Dark2"), scale=scale,
            main="Title", use.r.layout = TRUE)
  # set a title = document
  text(x=0.5, y=1, paste("Topic", i))
}
```

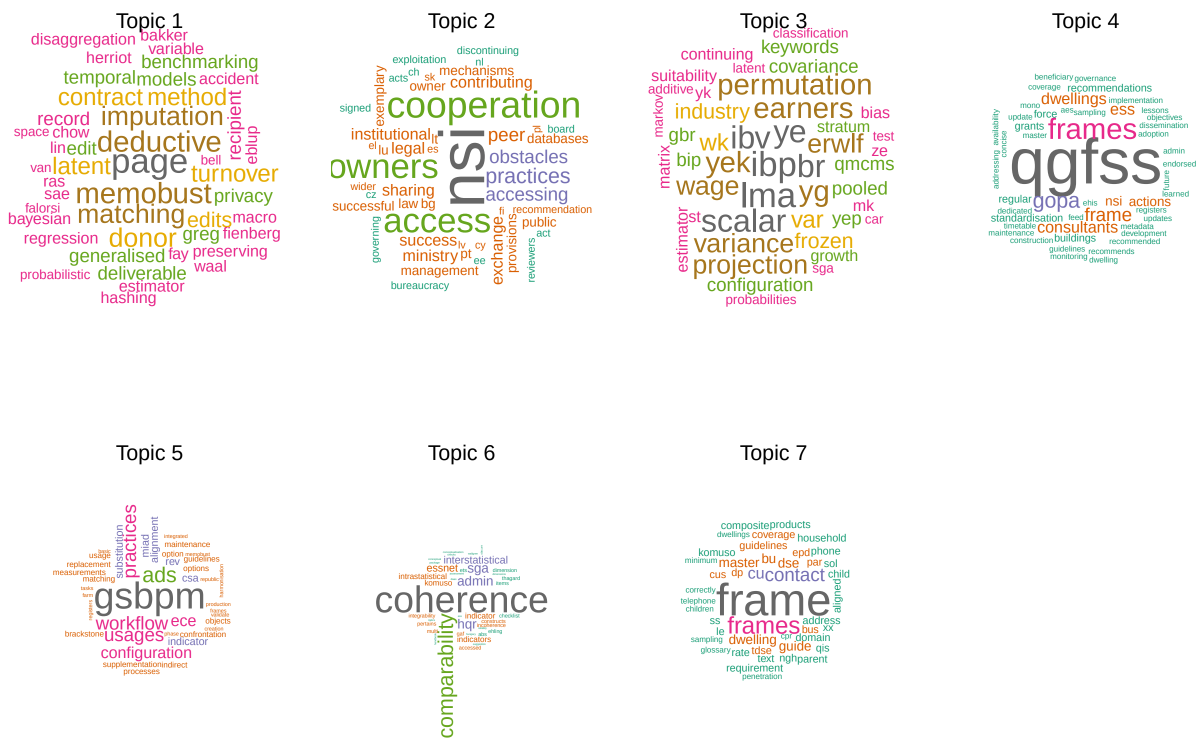
A second possibility is to extract the TFIDFs of the words linked to the topics directly. First you have to map the topics to the documents within the tidytext format. This is the only way the tfidf_tf matrix can be set up for the individual topics.

```r
plot_wordcloud_topic <- function(corpus, topic_select=1, prediction=prediction5,
                                 max.words=50,
                                 scale=c(3,0.2)){
  # get the correct topic mapping via the first two columns
  # of the prediction matrix
  new_corpus <- prediction %>%
    transmute(doc_id=as.numeric(doc_id), topic) %>%
    right_join(corpus, c("doc_id"="document"))
  # setting up a tibble which returns tfidf and tf and frequency for
  # the whole corpus
  tfidf <- new_corpus %>% count(topic, word, sort = TRUE) %>%
    bind_tf_idf(word, topic, n) %>%
    # filter for all selected topics
    # use either ft or tfidf
    filter(topic==topic_select)
  # plotting
  wordcloud(words = tfidf$word, freq = tfidf$tf_idf,
            min.freq = 1,max.words=max.words, random.order=FALSE,
            colors=brewer.pal(8, "Dark2"), scale=scale,
            main="Title", use.r.layout = TRUE)
  # set a title = document
  text(x=0.5, y=1, paste("Topic", topic_select))
}
```

3.1.1 Wordclouds using TFIDF

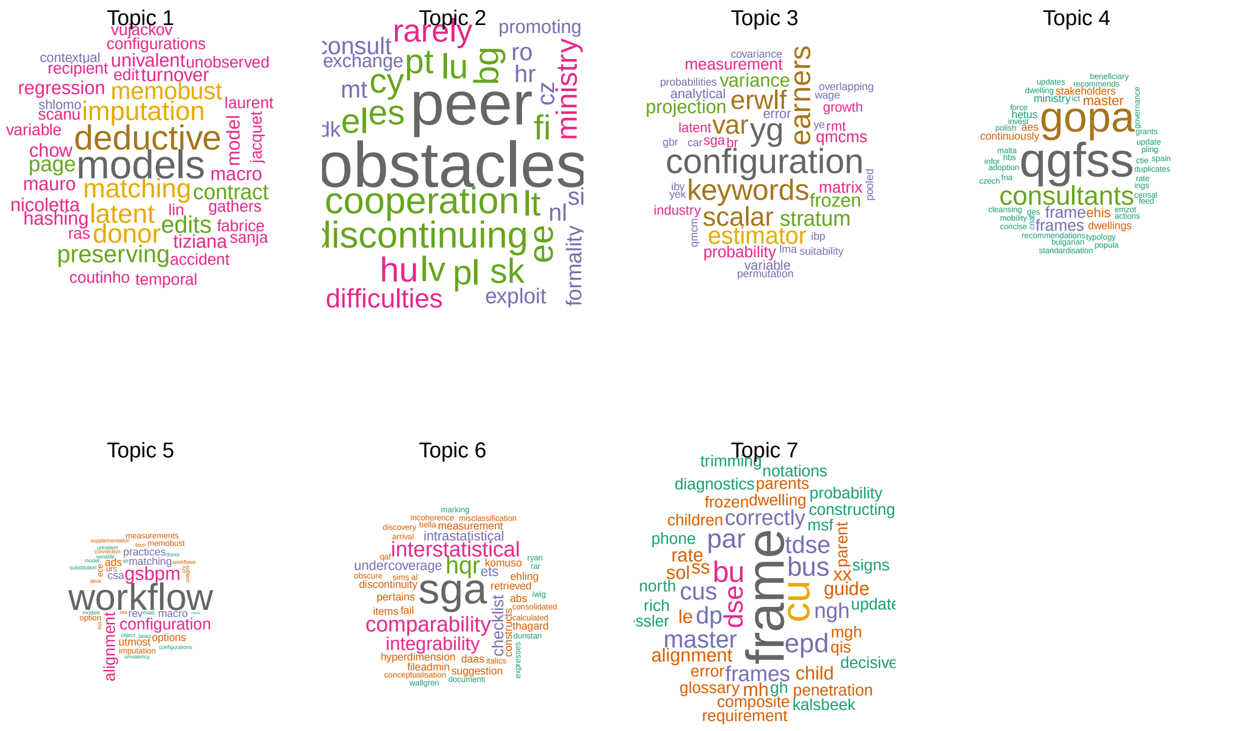
For getting specific and more individual words for each cloud, we use the TFIDF in the first step. Now there are two methods to create the word clouds for the TFIDF measure. Once by aggregating the individual TFIDFs of the documents, as it is done in the following.

```
par(mfrow=c(2,4))
par(mar=c(1,1,1,1))
set.seed(123)
plot_wordcloud(corpus, selection=ind1[,1], i=1, scale=c(1.7,0.001),
               max.words = 45)
plot_wordcloud(corpus, selection=ind2[,1], i=2)
plot_wordcloud(corpus, selection=ind3[,1], i=3, scale=c(1.6,0.005),
               max.words = 45)
plot_wordcloud(corpus, selection=ind4[,1], i=4)
plot_wordcloud(corpus, selection=ind5[,1], i=5, scale=c(1.8,0.001),
               max.words = 40)
plot_wordcloud(corpus, selection=ind6[,1], i=6, scale=c(1.8,0.001),
               max.words = 40)
plot_wordcloud(corpus, selection=ind7[,1], i=7, scale=c(2.1,0.3),
               max.words = 45)
```



Now using the second approach, when applying the TFIDF measure to the mapped corpus.

```
par(mfrow=c(2,4))
par(mar=c(1,1,1,1))
set.seed(123)
plot_wordcloud_topic(corpus, topic_select=1, scale=c(1.9,0.0006),
                max.words = 40)
plot_wordcloud_topic(corpus, topic_select=2)
plot_wordcloud_topic(corpus, topic_select=3, scale=c(1.6,0.005),
                max.words = 40)
plot_wordcloud_topic(corpus, topic_select=4, max.words = 50, scale=c(2.3, 0.2))
plot_wordcloud_topic(corpus, topic_select=5, scale=c(1.8,0.01),
                max.words = 40)
plot_wordcloud_topic(corpus, topic_select=6, scale=c(2,0.1),
                max.words = 45)
plot_wordcloud_topic(corpus, topic_select=7, scale=c(2.5,0.5),
                max.words = 50)
```

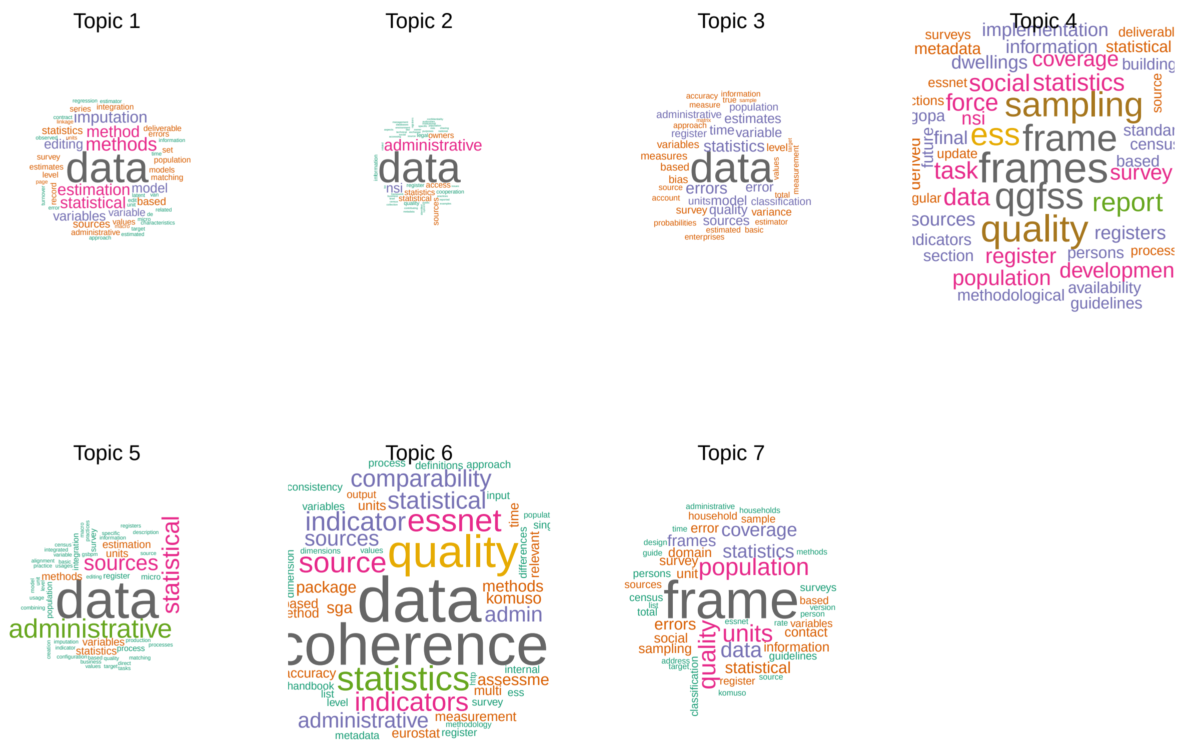


Although the second procedure, using TFIDF distributions for the individual topics, seems to be more intuitive, the two figures are surprisingly similar.

3.1.2 Wordclouds using TF

The same can be done using the regular term frequency.

```r
par(mfrow=c(2,4))
par(mar=c(1,1,0.5,1))
set.seed(123)
plot_wordcloud(corpus, selection=ind1[,1], i=1, freq="tf", scale=c(2,0.05))
plot_wordcloud(corpus, selection=ind2[,1], i=2, freq="tf", scale=c(2,0.05))
plot_wordcloud(corpus, selection=ind3[,1], i=3, freq="tf", scale=c(2,0.03),
               max.words = 40)
plot_wordcloud(corpus, selection=ind4[,1], i=4, freq="tf", scale=c(2,0.3))
plot_wordcloud(corpus, selection=ind5[,1], i=5, freq="tf", scale=c(2.5,0.1))
plot_wordcloud(corpus, selection=ind6[,1], i=6, freq="tf")
plot_wordcloud(corpus, selection=ind7[,1], i=7, freq="tf", scale=c(2.5,0.2),
               max.words = 45)
```



3.2 Embedding via TFIDF

Now it is interesting to see if embedding via TFIDF will cluster other groups or the same. So we will reduce the Document Term Matrix to 5717 words, which amounts to a reduction by 50%.

```r
tim1_tfidf <- Sys.time()
dtm_50 <- dtm %>% dtm_remove_tfidf(top=(0.5*M))
set.seed(123)
documents_lda_2 <- LDA(dtm_50, method="Gibbs",
                     k = 7, control = list(seed = 1234))
tim2_tfidf <- Sys.time()
u2 <- tim2_tfidf - tim1_tfidf
```

```r
prediction5_2 <- predict(documents_lda_2, newdata=dtm_50, type="topic")
prediction5_2 <- merge(prediction5_2, classes, by.x="doc_id", by.y="No")
# compare topic 1 with topic 2, 3, 4 and 5
ind1_2 <- prediction5_2 %>% filter(topic==1) %>% select(doc_id, Group)
ind2_2 <- prediction5_2 %>% filter(topic==2) %>% select(doc_id, Group)
ind3_2 <- prediction5_2 %>% filter(topic==3) %>% select(doc_id, Group)
ind4_2 <- prediction5_2 %>% filter(topic==4) %>% select(doc_id, Group)
ind5_2 <- prediction5_2 %>% filter(topic==5) %>% select(doc_id, Group)
ind6_2 <- prediction5_2 %>% filter(topic==6) %>% select(doc_id, Group)
ind7_2 <- prediction5_2 %>% filter(topic==7) %>% select(doc_id, Group)
```

```r
ext_gamma_matrix(documents_lda_2) %>%
  round(2) %>%
  stargazer(summary=F, rownames = F, header=F,
            title="Gamma matrix extracted from model for embedding with tfidf",
            label="extract2")
```

Table 11: Documents for Topic 1

Topic_embedding_0.8	doc_id	Group
1	10	4
1	11	4
1	12	4
1	5	2
1	6	3
1	7	4
1	8	4
1	9	4

Table 12: Documents for Topic 2

Topic_embedding_0.8	doc_id	Group
2	15	5
2	25	6

Table 13: Documents for Topic 3

Topic_embedding_0.8	doc_id	Group
3	13	3
3	14	4
3	3	2
3	4	2

Table 14: Documents for Topic 4

Topic_embedding_0.8	doc_id	Group
4	1	1
4	2	1

Table 15: Documents for Topic 5

Topic_embedding_0.8	doc_id	Group
5	16	5
5	18	5
5	19	5
5	21	6
5	22	6
5	23	6
5	24	6

Table 16: Documents for Topic 6

Topic_embedding_0.8	doc_id	Group
6	20	5
6	28	7

Table 17: Documents for Topic 7

Topic_embedding_0.8	doc_id	Group
7	17	5
7	26	7
7	27	7

Table 18: Gamma matrix extracted from model for embedding with tfidf

document	1	2	3	4	5	6	7
1	0	0	0	0.99	0	0	0
2	0.01	0.02	0.03	0.86	0.01	0.07	0.01
3	0.16	0.02	0.54	0.01	0.18	0.03	0.05
4	0.2	0.02	0.68	0.02	0.02	0.02	0.04
5	0.85	0.03	0.04	0.01	0.07	0.01	0.01
6	0.69	0	0.02	0.01	0.25	0.01	0.01
7	0.85	0.04	0.02	0.01	0.05	0.01	0.03
8	0.86	0.02	0.03	0.02	0.03	0.01	0.03
9	0.72	0.06	0.08	0.01	0.06	0.03	0.05
10	0.95	0	0.01	0	0.02	0.01	0
11	0.73	0.01	0.03	0.01	0.19	0.01	0.01
12	0.9	0.02	0.03	0.01	0.02	0.01	0.01
13	0.01	0.02	0.76	0.15	0	0.01	0.04
14	0.24	0.02	0.68	0.02	0.02	0.01	0.01
15	0.01	0.83	0.09	0.02	0.02	0.01	0.02
16	0.01	0.06	0.01	0.01	0.9	0.01	0.01
17	0.01	0.05	0.01	0.01	0.07	0.01	0.84
18	0.01	0.06	0.01	0	0.89	0.01	0.02
19	0.04	0.42	0.02	0.01	0.43	0.02	0.07
20	0.01	0.05	0.02	0.01	0.01	0.88	0.01
21	0.01	0.01	0.01	0.01	0.96	0.01	0.01
22	0.01	0.01	0.01	0.01	0.94	0.01	0.01
23	0	0.02	0.03	0.01	0.9	0	0.03
24	0.02	0.01	0.02	0.01	0.92	0.01	0.01
25	0.01	0.91	0.01	0.01	0.05	0.01	0.01
26	0.01	0.01	0.06	0.03	0.02	0.05	0.82
27	0.01	0.01	0.03	0.19	0	0.02	0.75
28	0.01	0.03	0.04	0.05	0.01	0.73	0.13

We want to give an overview over the clustered documents using the TFIDF embedding.

Table 19: Documents for Topic 1

Topic	doc_id	Group
1	10	4
1	11	4
1	12	4
1	5	2
1	6	3
1	7	4
1	8	4
1	9	4

Table 20: Documents for Topic 2

Topic	doc_id	Group
2	15	5
2	25	6

Table 21: Documents for Topic 3

Topic	doc_id	Group
3	13	3
3	14	4
3	3	2
3	4	2

Table 22: Documents for Topic 4

Topic	doc_id	Group
4	1	1
4	2	1

Table 23: Documents for Topic 5

Topic	doc_id	Group
5	16	5
5	18	5
5	19	5
5	21	6
5	22	6
5	23	6
5	24	6

We want to produce wordclouds again. This time using the TFIDF embedding for clustering via LDA. The first plot shows the aggregated TFIDFs.

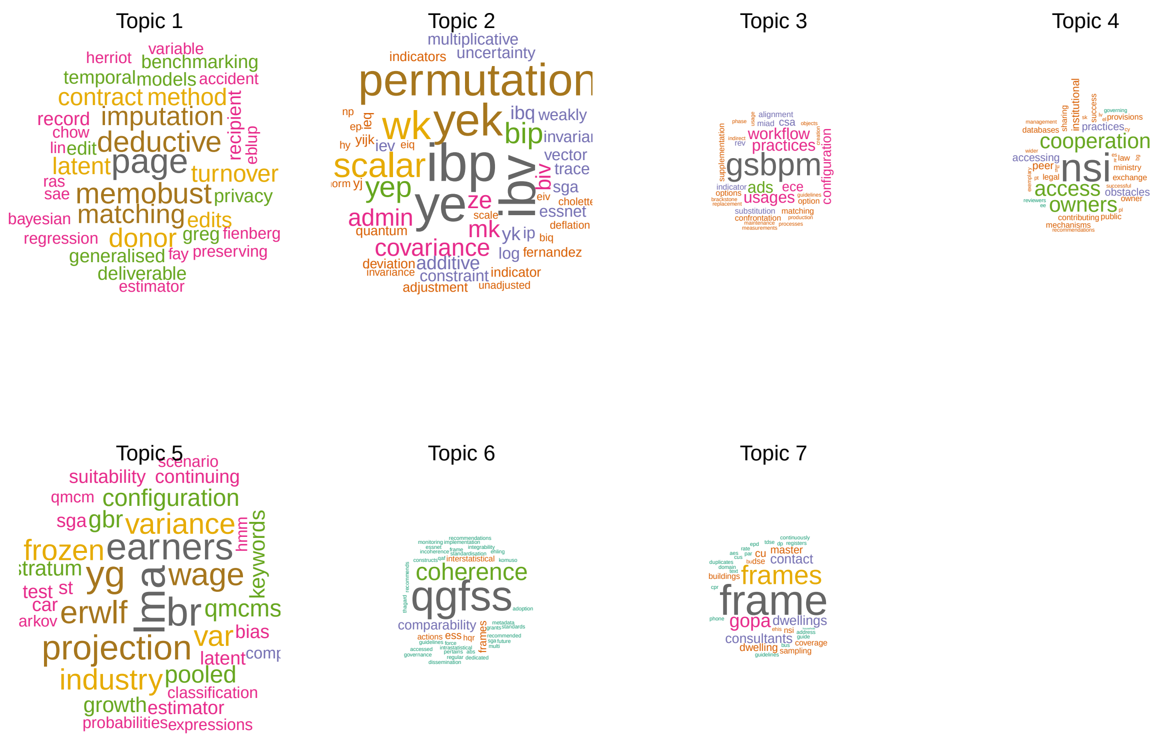
Table 24: Documents for Topic 6

Topic	doc_id	Group
6	20	5
6	28	7

Table 25: Documents for Topic 7

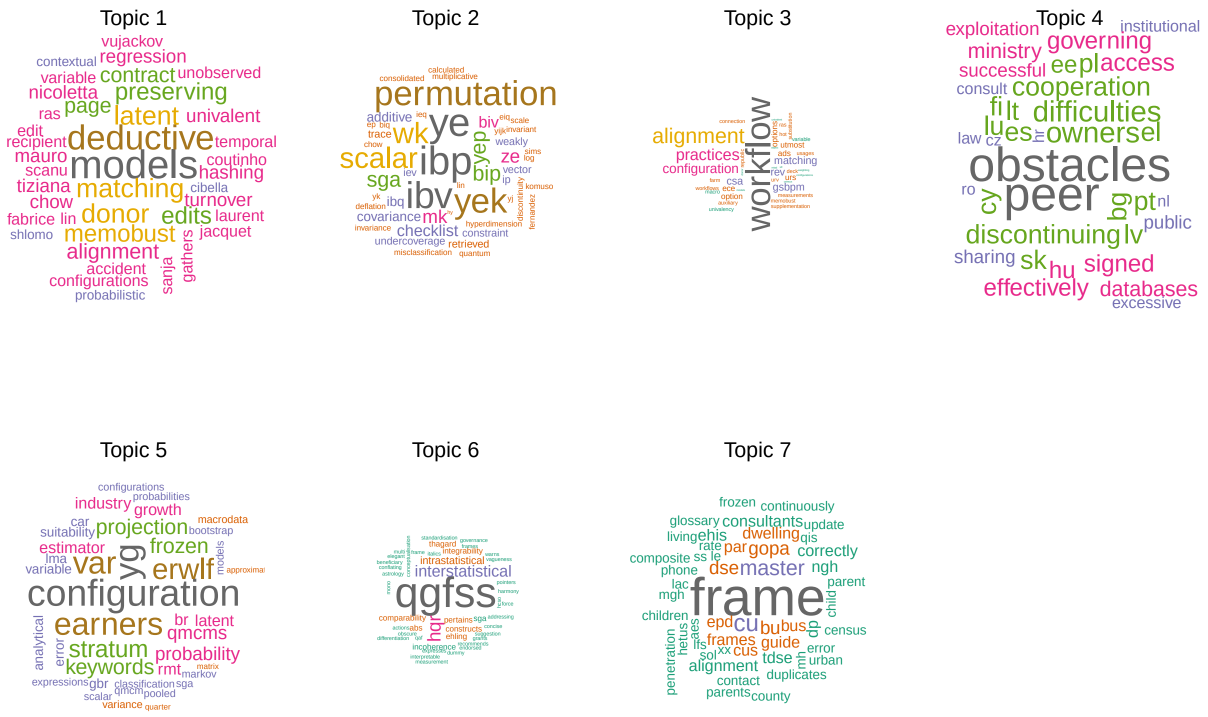
Topic	doc_id	Group
7	17	5
7	26	7
7	27	7

```r
par(mfrow=c(2,4))
par(mar=c(1,1,0.5,1))
set.seed(123)
plot_wordcloud(corpus, selection=ind1_2[,1], i=1, scale=c(1.7,0.002),
               max.words = 35)
plot_wordcloud(corpus, selection=ind2_2[,1], i=2, scale=c(2.5,0.1))
plot_wordcloud(corpus, selection=ind3_2[,1], i=3, scale=c(1.5,0.001),
               max.words = 30)
plot_wordcloud(corpus, selection=ind4_2[,1], i=4, scale=c(1.9,0.05),
               max.words = 40)
plot_wordcloud(corpus, selection=ind5_2[,1], i=5, scale=c(2,0.02),
               max.words = 35)
plot_wordcloud(corpus, selection=ind6_2[,1], i=6, scale=c(2,0.1),
               max.words = 40)
plot_wordcloud(corpus, selection=ind7_2[,1], i=7, scale=c(2,0.03),
               max.words = 35)
```



The second plot shows the TFIDFs for each individual topic.

```r
par(mfrow=c(2,4))
par(mar=c(1,1,1,1))
set.seed(123)
plot_wordcloud_topic(corpus, topic_select=1, scale=c(1.9,0.0006),
                max.words = 40, prediction=prediction5_2)
plot_wordcloud_topic(corpus, topic_select=2, prediction=prediction5_2,
                     scale=c(1.9,0.0006))
plot_wordcloud_topic(corpus, topic_select=3, scale=c(1.6,0.005),
                max.words = 40, prediction=prediction5_2)
plot_wordcloud_topic(corpus, topic_select=4, max.words = 40,
                     scale=c(2.3, 0.02), prediction=prediction5_2)
plot_wordcloud_topic(corpus, topic_select=5, scale=c(1.8,0.01),
                max.words = 40, prediction=prediction5_2)
plot_wordcloud_topic(corpus, topic_select=6, scale=c(2,0.1),
                max.words = 45, prediction=prediction5_2)
plot_wordcloud_topic(corpus, topic_select=7, scale=c(2.5,0.5),
                max.words = 50, prediction=prediction5_2)
```



3.3 Missclassification Rates

Now we use the validation measure we used for Example 1.

```r
validate_LDAclassification <- function(predict_table){
  # gamma_matrix ... an object of the function ext_gamma_matrix()
  # First we'd find the topic that was most associated with
  # each chapter
  conversion <- predict_table %>%
    select(Group, topic) %>%
    group_by(Group) %>%
    top_n(1,topic) %>%
    unique()

  consensus <- predict_table %>%
    left_join(conversion, by=c("topic"))
  consensus %>% filter(Group.x!=Group.y) %>%
    nrow()/nrow(consensus)
}
```

On both full bag of words and 50% embedding via TFIDF

```r
predict_table <- prediction5 %>% select(doc_id, topic) %>%
  merge( y=classes, by.x=1, by.y=1)

( misc.rate_embedding2 <- validate_LDAclassification(predict_table) )
```

```
## [1] 0.3421053
```

```r
predict_table2 <- prediction5_2 %>% select(doc_id, topic) %>%
  merge( y=classes, by.x=1, by.y=1)
```

```
( misc.rate_embedding_tfidf <- validate_LDAclassification(predict_table2))
```

```
## [1] 0.3589744
```

```
performance_matrix <- data.frame(freq2.embedding=c(misc.rate_embedding2, u1),
           tfidf.embedding=c(misc.rate_embedding_tfidf, u2))
rownames(performance_matrix) <- c("missc. rate", "time")
performance_matrix %>%  stargazer(summary=FALSE, header=F, title = "LDA via Gibbs Sampling")
```

Table 26: LDA via Gibbs Sampling

	freq2.embedding	tfidf.embedding
missc. rate	0.342	0.359
time	52.131	19.559

4 Optimal value of Reduction via tfidf

In this example we want to know if there is a better value for the reduction of tfidf than 50%. We will examine it using the same approach as for the Gutenberg examples.

```
evaluation_for_embedding <- function(word_counts, frac=0.1, M=8254) {
  # embedding 3
  chapters_dtm_tfidf <- dtm %>% dtm_remove_tfidf(top=(frac*M))
  # fitting
  tim1 <- Sys.time()
  chapters_lda_tfidf_Gibbs <- LDA(chapters_dtm_tfidf,  method="Gibbs",
                  k = 7, control = list(seed = 1234))
  tim2 <- Sys.time()
  u_tfidf_Gibbs <- tim2-tim1
  prediction5_2 <- predict(chapters_lda_tfidf_Gibbs,
                        newdata=chapters_dtm_tfidf, type="topic")
  prediction5_2 <- merge(prediction5_2, classes, by.x="doc_id", by.y="No")
  # calculating missclassification rate
  predict_table <- prediction5_2 %>% select(doc_id, topic) %>%
  merge( y=classes, by.x=1, by.y=1)

  misc.rate_tfidf_Gibbs <-validate_LDAclassification(predict_table)

  # function returns a vector including the misc. ratio and the fitting time
  return(c(misc.rate_tfidf_Gibbs,
             as.numeric(u_tfidf_Gibbs)))
}
```

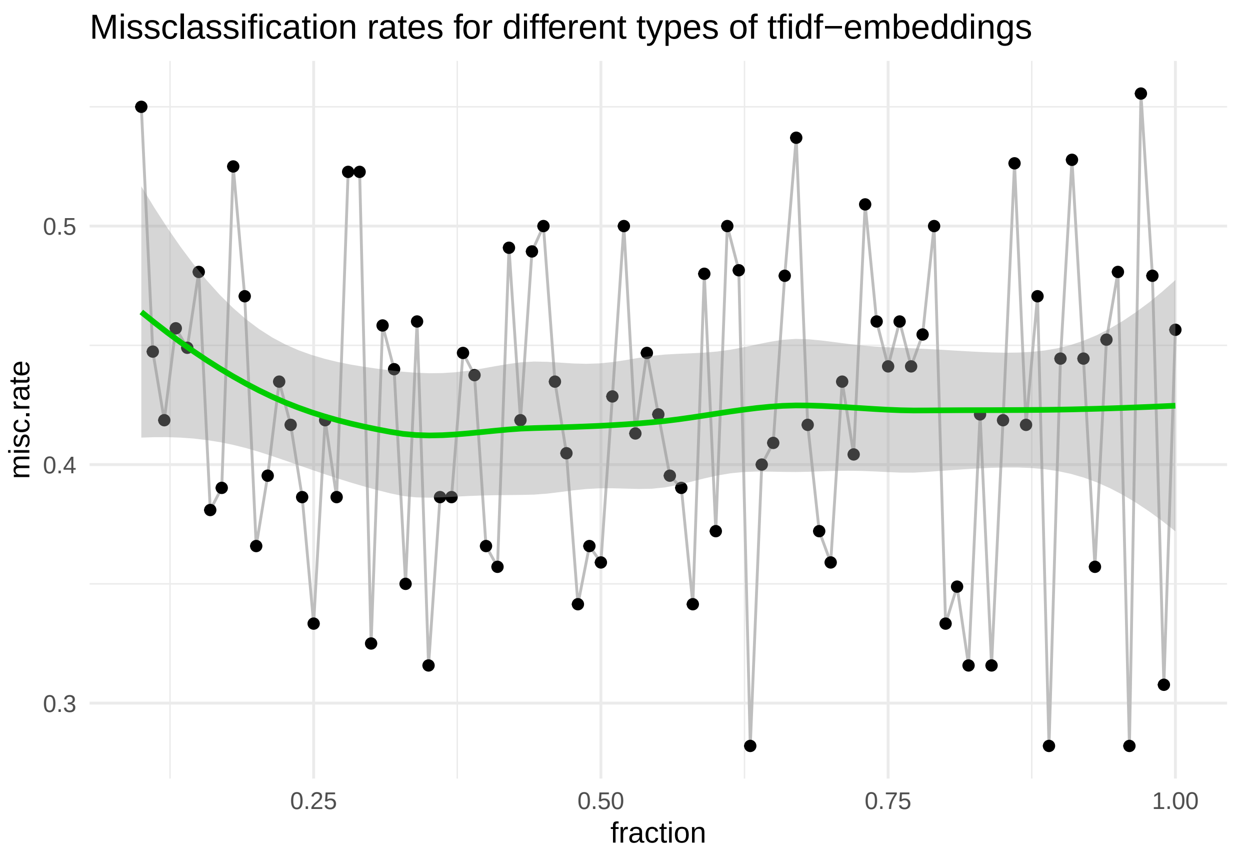
```
# set up the fractions we want to use
# we use 0.1, 0.2, ..., 1
fractions <- seq(0.1,1,0.01)

# Use parallelization
# setting up how many cores to be used
useable_cores <- parallel::detectCores() - 1
# registering cluster
```

```r
cl <- parallel::makeCluster(useable_cores)
doParallel::registerDoParallel(cl)
embedding_performance_matrix <- foreach(i = 1:length(fractions), .combine = 'rbind', .export = ls(.Glob


  evaluation_for_embedding(dtm, frac=fractions[i]) %>%
    c(.,fractions[i])


}
```

```
## Warning in e$fun(obj, substitute(ex), parent.frame(), e$data): already
## exporting variable(s): classes, dtm, evaluation_for_embedding, fractions,
## validate_LDAclassification
```

```r
parallel::stopCluster(cl)

# adjust the resulting matrix to a data frame for plotting
colnames(embedding_performance_matrix) <- c("misc.rate","time","fractions")
embedding_performance_matrix <- as.data.frame(embedding_performance_matrix)
```

```r
ggplot(data=embedding_performance_matrix,
       aes(x=fractions, y=misc.rate)) +
  geom_line(col="grey") +
  geom_point() +
  geom_smooth(col="green3", method="loess", span=0.7) +
  theme_minimal() +
  ggtitle("Missclassification rates for different types of tfidf-embeddings") +
  xlab("fraction")
```



We can find an optimal value for *fraction* at the value aroung 0.35, so it might be interesting to campare the results of a fit using this optimized value of fraction to the other embeddings.

```r
tim1_tfidf0.85 <- Sys.time()
dtm_0.85 <- dtm %>% dtm_remove_tfidf(top=(0.35*M))
set.seed(123)
documents_lda_0.85 <- LDA(dtm_0.85, method="Gibbs",
                     k = 7, control = list(seed = 1234))
tim2_tfidf0.85 <- Sys.time()
u0.85 <- tim2_tfidf0.85 - tim1_tfidf0.85
```

```r
prediction0.85 <- predict(documents_lda_0.85, newdata=dtm_0.85, type="topic")
prediction0.85 <- merge(prediction0.85, classes, by.x="doc_id", by.y="No")
```

```r
predict_table0.85 <- prediction0.85 %>% select(doc_id, topic) %>%
  merge( y=classes, by.x=1, by.y=1)

( misc.rate_embedding_0.85 <- validate_LDAclassification(predict_table0.85))
```

```
## [1] 0.3157895
```

In Table 27 you will find an overview of the performace of the different embedding methods including *tfidf* embedding of fraction 0.35.

```r
performance_matrix <- data.frame(freq2.embedding=c(misc.rate_embedding2, u1),
           tfidf_0.5.embedding=c(misc.rate_embedding_tfidf, u2),
           tfidf_0.85.embedding=c(misc.rate_embedding_0.85, u0.85))
rownames(performance_matrix) <- c("missc. rate", "time")
performance_matrix %>%  stargazer(summary=FALSE, header=F,
                              title = "LDA via Gibbs Sampling", label="comp0.85")
```

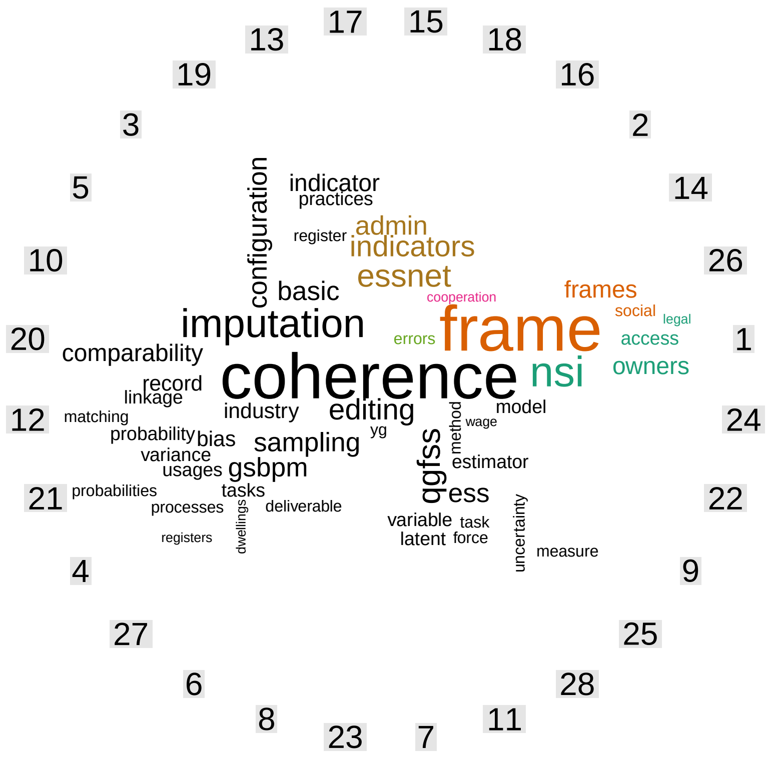
Table 27: LDA via Gibbs Sampling

	freq2.embedding	tfidf_0.5.embedding	tfidf_0.85.embedding
missc. rate	0.342	0.359	0.316
time	52.131	19.559	14.527

5 Coherence Cloud

```
dtm_50 %>% as.matrix() %>% t() %>% comparison.cloud(scale=c(2,.05),
                                                   max.words=50, title.size = 1)
```

```
## Warning in brewer.pal(max(3, ncol(term.matrix)), "Dark2"): n too large, allowed maximum for palette I
## Returning the palette you asked for with that many colors
```


configuration
indicator
practices
register
admin
indicators
essnet
basic
cooperation
frames
social
legal
imputation
errors
frame
access
comparability
coherence
nsi
owners
record
linkage
industry
editing
method
model
wage
matching
probability
bias
sampling
yg
variance
usages
gsbpm
qgfss
estimator
probabilities
tasks
ess
processes
deliverable
dwellings
variable
task
uncertainty
registers
latent
force
measure