Topic Modelling & Latent Dirichlet Allocation (LDA)

STQD 6114: Unstructured Data Analytics

What is topic modelling?

- a statistical model to discover the topics that occur in a collection of documents
- method for finding a group of words (ie topics) from a collection of document that best represents the info in the collection
- it is a form of text mining

Why?

- Data exploration
- Rough idea on what is the structure/pattern/category of your text data
- Allow us to answer big picture questions quickly, & without human interventions

Example

% of Gazette	Most likely words in a topic in order of likelihood	Human-added topic label
5.6	away reward servant named feet jacket high paid hair coat run inches master...	*Runaways*
5.1	state government constitution law united power citizen people public congress...	*Government*
4.6	good house acre sold land meadow mile premise plantation stone mill dwelling...	*Real Estate*
3.9	silk cotton ditto white black linen cloth women blue worsted men fine thread...	*Cloth*

Example

- Topic modeling as
  - Qualitative Social Evidence
    - angry speech and patriotism over time
    - similar trend
  - Literary Theoretical Springboard
    - study on poem
    - the opaque features in a poem harden the machine’s task; in which human assessment is still needed
    - novel/book genre

More examples

- Suppose you have these statements:
  - I love father
  - Mommy plays with sister
  - My hamster is cute
  - Sister likes rabbit
- Latent Dirichlet Allocation: a method to automatically discovering topics for a set of statements
- Referring to the example, and if you asked for 2 topics, LDA might produce the following results:
  - Sentences 1 and 2: 100% Topic A
  - Sentence 3: 100% Topic B
  - Sentence 4: 50% Topic A & 50% Topic B

The LDA model - How?

- LDA represents documents as mixtures of topics that contains words with certain probabilities
- Assume that the document is produced based on this process:
  - The number of words, N is decided; and distributed as Poisson (example)
  - Choose a topic mixture (according to Dirichlet distribution over a fixed set of K topics): for example; 2/3 on family and 1/3 on pet

- for each word, use the topic to generate the word; based on multinomial distribution. For example; with topic family, we might generate “mommy” with 30% probability, daddy 40% and so on
- then, LDA will try to backtrack this process to find a set of topics that are likely to have generated the collection
- hence, topic modeling is a way of extrapolating backward from a collection of documents to infer the topics that could have generated them

Example

- Say that we pick 4 to be the number of words in our document
- Then, we decide that D will be ½ about family and ½ about pet
- Pick the first word from the family topic; → mommy
- Pick the second word from the pet topic; → hamster
- Pick the third word from the family topic; → sister
- Pick the fourth word from the pet topic; → rabbit
- Hence, the document generated will consists of these words: mommy-hamster-sister-rabbit

Gentle intro to Bayesian modelling

- LDA is a Bayesian hierarchical model (3 layer)!
- Bayes theorem?
- Posterior, likelihood, prior?
- Gibbs sampling?
- Further reading:

http://www.jmlr.org/papers/volume3/blei03a/blei03a.pdf

Expected output from LDA

- List of terms in each topic

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
1	work	question	chang	system	project
2	practic	map	organ	data	manag
3	mani	time	consult	model	approach

List of the document to the (primary) topic

Document	Topic
BeyondEntitiesAndRelationships.txt	4
bigdata.txt	4
ConditionsOverCauses.txt	5
EmergentDesignInEnterpriseIT.txt	4
FromInformationToKnowledge.txt	2
FromTheCoalface.txt	1

- Topic probabilities by documents

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
BeyondEn	0.071	0.064	0.024	**0.741**	0.1
bigdata.	0.182	**0.221**	0.182	0.26	0.156
Conditio	0.144	0.109	0.048	0.205	**0.494**
Emergent	0.121	0.226	0.204	**0.236**	0.213
FromInfo	0.096	**0.643**	0.026	0.169	0.066

Cross validation of a model

- perplexity
  - to validate a model & to determine the optimum number of topics
  - low value of perplexity is preferable
- Topic coherence

LDA in R

- Data source & R code:

https://cran.r-project.org/web/packages/topicmodels/vignettes/topicmodels.pdf

https://eight2late.wordpress.com/2015/09/29/a-gentle-introduction-to-topic-modeling-using-r/

https://www.tidytextmining.com/topicmodeling.html

Example in R – topicmodels package

- prepping the data: transform to lower case, remove symbols, punctuations, general errors (different versions of English, stopwords
- create a document term matrix
- frequency of each word

Example in R – topicmodels package

```
#load topic models library
library(topicmodels)
```

```
#Set parameters for Gibbs sampling
burnin <- 4000
iter <- 2000
thin <- 500
seed <-list(2003,5,63,100001,765)
nstart <- 5
best <- TRUE
```

```
#Number of topics
k <- 5
```

```
#Run LDA using Gibbs sampling
ldaOut <-LDA(dtm,k, method="Gibbs", control=list(nstart=nstart, seed = seed, best=best,
burnin = burnin, iter = iter, thin=thin))
```

```
#write out results
#docs to topics
ldaOut.topics <- as.matrix(topics(ldaOut))
write.csv(ldaOut.topics,file=paste("LDAGibbs",k,"DocsToTopics.csv"))
```

```
#top 6 terms in each topic
ldaOut.terms <- as.matrix(terms(ldaOut,6))
write.csv(ldaOut.terms,file=paste("LDAGibbs",k,"TopicsToTerms.csv"))
```

```
#probabilities associated with each topic assignment
topicProbabilities <- as.data.frame(ldaOut@gamma)
write.csv(topicProbabilities,file=paste("LDAGibbs",k,"TopicProbabilities.csv"))
```

```
#Find relative importance of top 2 topics
topic1ToTopic2 <- lapply(1:nrow(dtm),function(x)
sort(topicProbabilities[x,])[k]/sort(topicProbabilities[x,])[k-1])
```

```
#Find relative importance of second and third most important topics
topic2ToTopic3 <- lapply(1:nrow(dtm),function(x)
sort(topicProbabilities[x,])[k-1]/sort(topicProbabilities[x,])[k-2])
```

```
#write to file
write.csv(topic1ToTopic2,file=paste("LDAGibbs",k,"Topic1ToTopic2.csv"))
write.csv(topic2ToTopic3,file=paste("LDAGibbs",k,"Topic2ToTopic3.csv"))
```

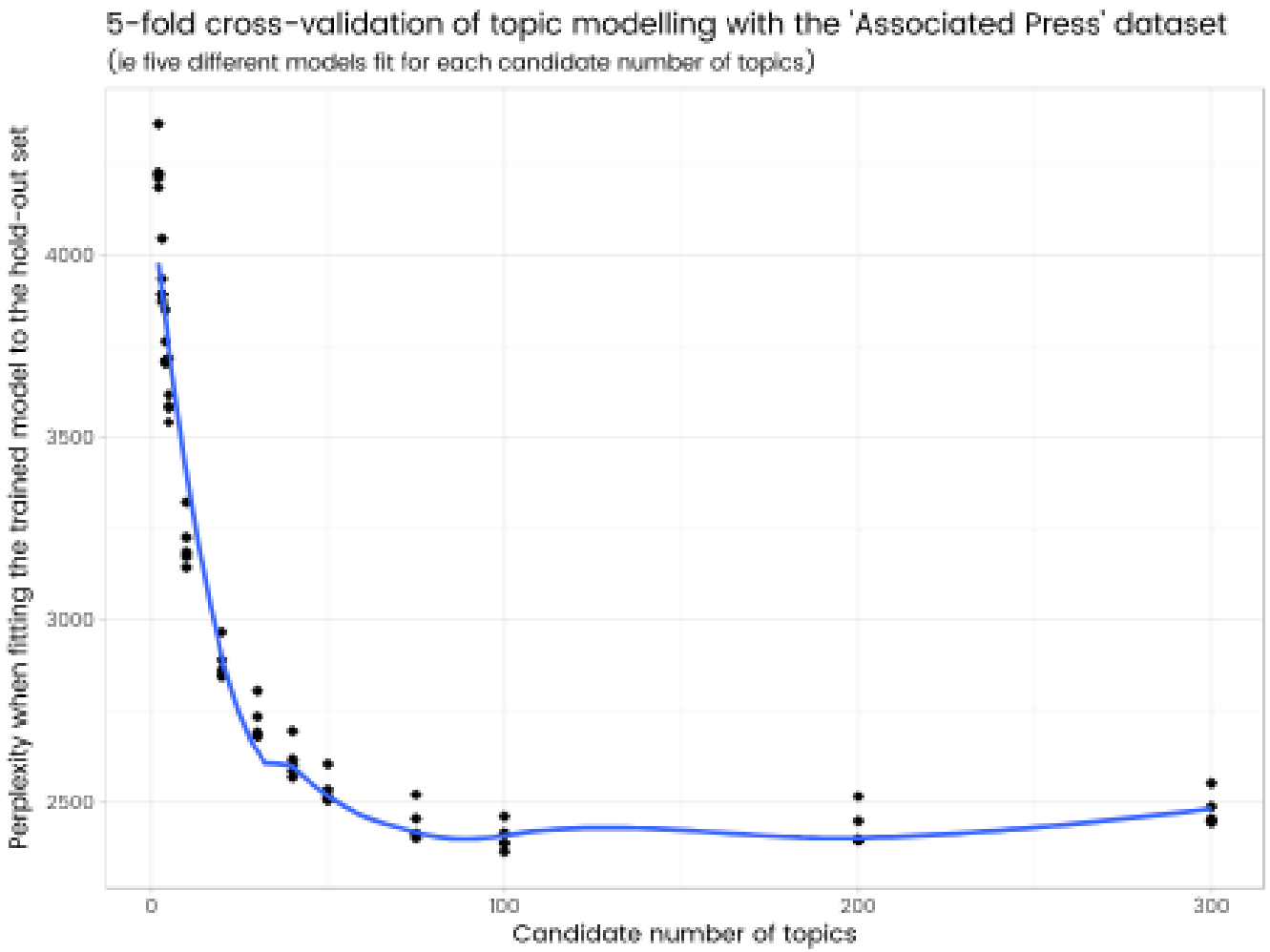
```
library(topicmodels)
library(doParallel)
library(ggplot2)
library(scales)

data("AssociatedPress", package =
"topicmodels")

burnin = 1000
iter = 1000
keep = 50

# define our "full data" - during
development I pretend the full dataset is
# just the first 500 AP articles, which is
enough for a reasonable test while not
taking
# forever to run.  When I ran the final
model, I came back and removed the "1:500"
from below
full_data  <- AssociatedPress[1:500 , ]
n <- nrow(full_data)
```

```
#----------validation--------
k <- 5 # number of topics

splitter <- sample(1:n, round(n * 0.75))
train_set <- full_data[splitter, ]
valid_set <- full_data[-splitter, ]

fitted <- LDA(train_set, k = k, method =
"Gibbs",
                          control =
list(burnin = burnin, iter = iter, keep =
keep) )
perplexity(fitted, newdata = train_set)
perplexity(fitted, newdata = valid_set)
```

```
#----------------5-fold cross-validation,
different numbers of topics---------------
cluster <- makeCluster(detectCores(logical =
TRUE) - 1) # leave one CPU spare...
registerDoParallel(cluster)

clusterEvalQ(cluster, {
   library(topicmodels)
})

folds <- 5
splitfolds <- sample(1:folds, n, replace =
TRUE)
candidate_k <- c(2, 3, 4, 5, 10, 20, 30, 40,
50, 75, 100, 200, 300) # candidates for how
many topics
clusterExport(cluster, c("full_data",
"burnin", "iter", "keep", "splitfolds",
"folds", "candidate_k"))
```

```
# we parallelize by the different number of
topics.  A processor is allocated a value
# of k, and does the cross-validation
serially.  This is because it is assumed
there
# are more candidate values of k than there
are cross-validation folds, hence it
# will be more efficient to parallelise
system.time({
results <- foreach(j =
1:length(candidate_k), .combine = rbind)
%dopar%{
   k <- candidate_k[j]
   results_1k <- matrix(0, nrow = folds,
ncol = 2)
   colnames(results_1k) <- c("k",
"perplexity")
   for(i in 1:folds){
      train_set <- full_data[splitfolds != i
, ]
      valid_set <- full_data[splitfolds ==
i, ]
```

```
      fitted <- LDA(train_set, k = k, method
= "Gibbs",
                    control = list(burnin =
burnin, iter = iter, keep = keep) )
      results_1k[i,] <- c(k,
perplexity(fitted, newdata = valid_set))
   }
   return(results_1k)
}
})
stopCluster(cluster)

results_df <- as.data.frame(results)

ggplot(results_df, aes(x = k, y =
perplexity)) +
   geom_point() +
   geom_smooth(se = FALSE) +
   ggtitle("5-fold cross-validation of topic
modelling with the 'Associated Press'
dataset",
           "(ie five different models fit
for each candidate number of topics)") +
   labs(x = "Candidate number of topics", y
= "Perplexity when fitting the trained model
to the hold-out set")
```



- alternatively: use ‘ldatuning’package
- coherence score can be computed using FitLdaModel in textmineR package

Example in R – exploring and interpreting using ‘tidytext’ package

```
library(topicmodels)


data("AssociatedPress")
AssociatedPress
```

```
## <<DocumentTermMatrix (documents: 2246, terms: 10473)>>
## Non-/sparse entries: 302031/23220327
## Sparsity           : 99%
## Maximal term length: 18
## Weighting          : term frequency (tf)
```

```r
# set a seed so that the output of the model is predictable
ap_lda <- LDA(AssociatedPress, k = 2, control = list(seed = 1234))
ap_lda
```

```
## A LDA_VEM topic model with 2 topics.
```

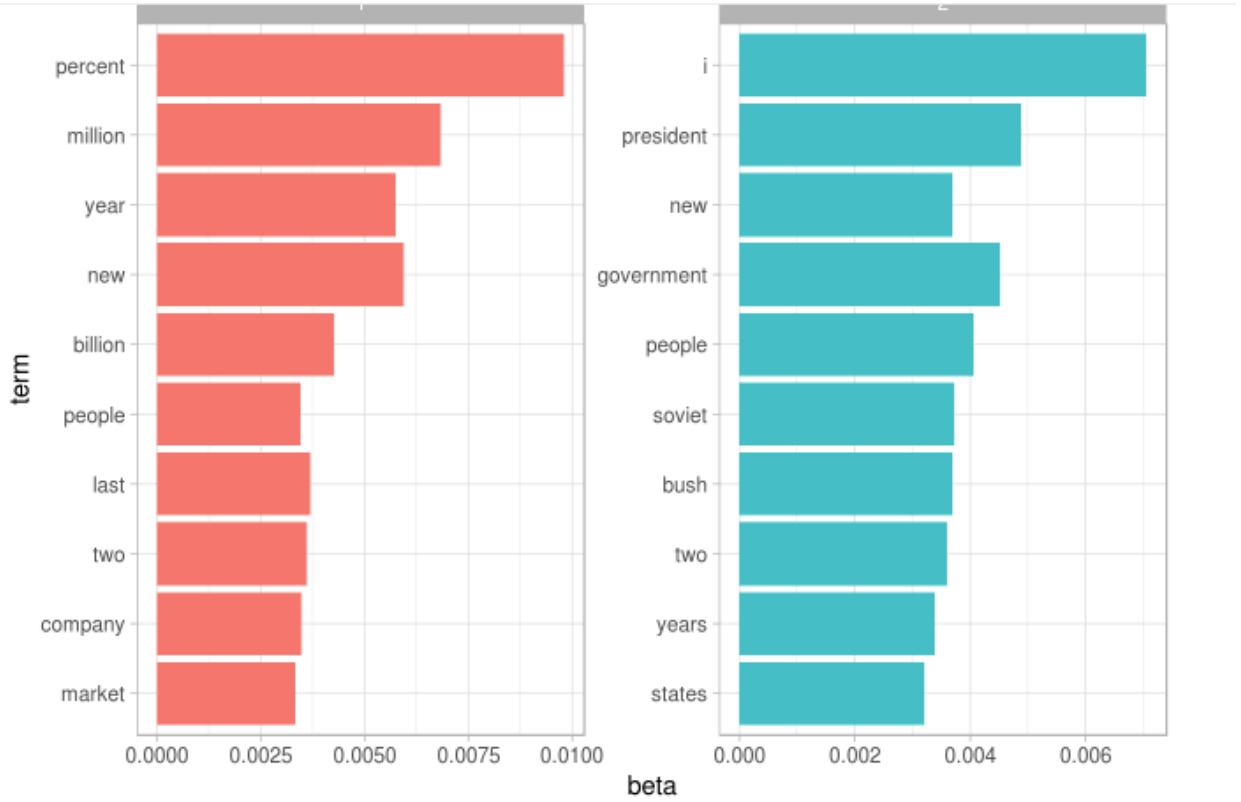
```
library(tidytext)


ap_topics <- tidy(ap_lda, matrix = "beta")
ap_topics
```

```
## # A tibble: 20,946 x 3
##    topic term           beta
##    <int> <chr>         <dbl>
##  1     1 aaron      1.69e-12
##  2     2 aaron      3.90e- 5
##  3     1 abandon    2.65e- 5
##  4     2 abandon    3.99e- 5
##  5     1 abandoned  1.39e- 4
##  6     2 abandoned  5.88e- 5
##  7     1 abandoning 2.45e-33
```

extracting the per-topic-per-word probabilities

```r
library(ggplot2)
library(dplyr)

ap_top_terms <- ap_topics %>%
  group_by(topic) %>%
  top_n(10, beta) %>%
  ungroup() %>%
  arrange(topic, -beta)

ap_top_terms %>%
  mutate(term = reorder(term, beta)) %>%
  ggplot(aes(term, beta, fill = factor(topic))) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~ topic, scales = "free") +
  coord_flip()
```

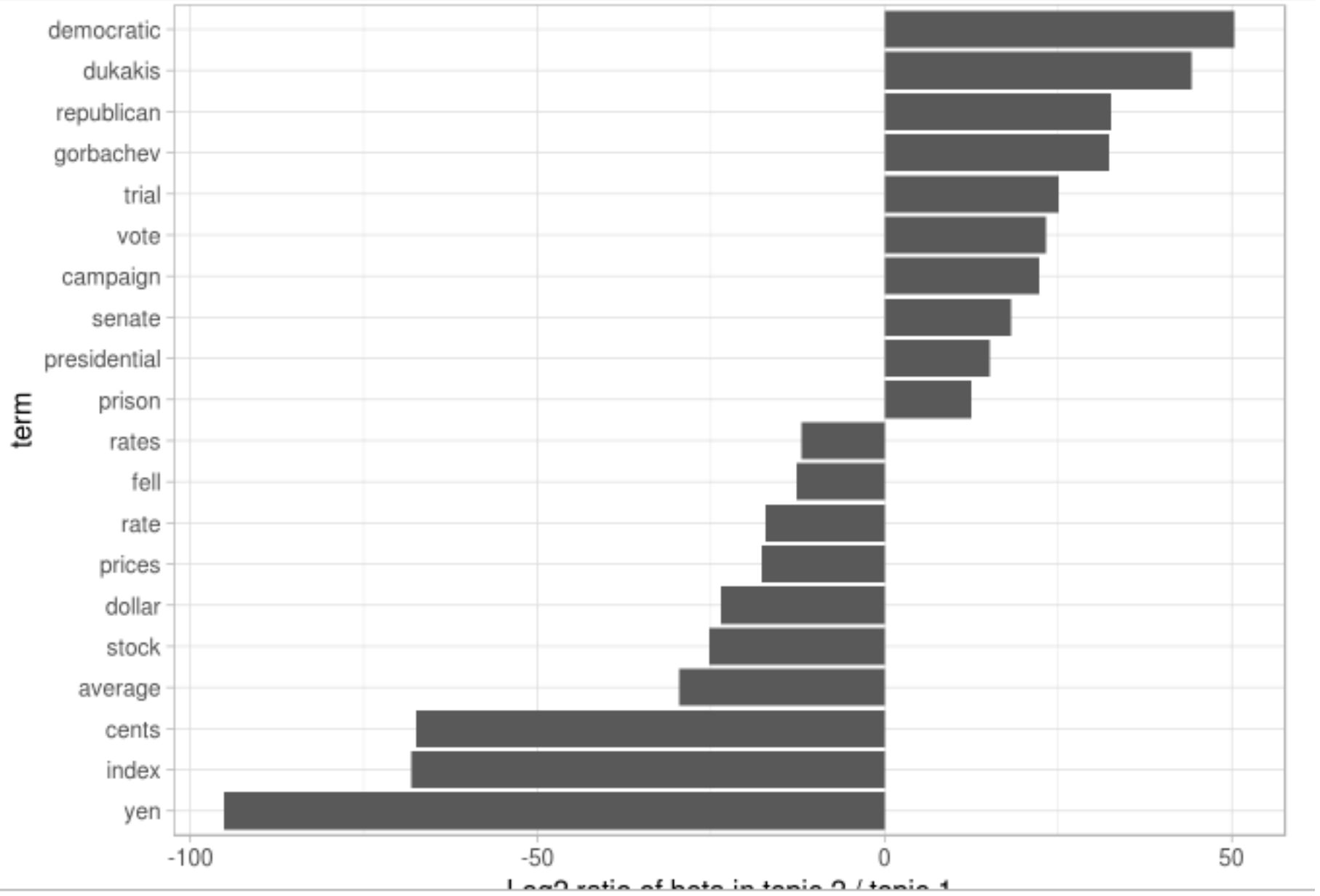
find the 10 terms that are most common within each topic



This visualization lets us understand the two topics that were extracted from the articles. The most common words in topic 1 include “percent”, “million”, “billion”, and “company”, which suggests it may represent business or financial news. Those most common in topic 2 include “president”, “government”, and “soviet”, suggesting that this topic represents political news. One important observation about the words in each topic is that some words, such as “new” and “people”, are common within both topics. This is an advantage of topic modeling as opposed to “hard clustering” methods: topics used in natural language could have some overlap in terms of words

the terms that had the greatest difference in
β between topic 1 and topic 2. This can be estimated based on the log ratio of the two:
log (β2/β1). A log ratio is useful because it makes the difference symmetrical:
β2 being twice as large leads to a log ratio of 1, while β1 being twice as large results in -1). To constrain it to a set of especially relevant words, we can filter for rel ve a β greater than 1/1000 in

```
library(tidyr)


beta_spread <- ap_topics %>%
  mutate(topic = paste0("topic", topic)) %>%
  spread(topic, beta) %>%
  filter(topic1 > .001 | topic2 > .001) %>%
  mutate(log_ratio = log2(topic2 / topic1))


beta_spread
```


democratic
dukakis
republican
gorbachev
trial
vote
campaign
senate
presidential
prison
rates
fell
rate
prices
dollar
stock
average
cents
index
yen
term
-100
-50
0
50

```
ap_documents <- tidy(ap_lda, matrix = "gamma")
ap_documents
```

```
## # A tibble: 4,492 x 3
##    document topic    gamma
##       <int> <int>    <dbl>
##  1        1     1 0.248
##  2        2     1 0.362
```

document-topic probabilities

```r
tidy(AssociatedPress) %>%
  filter(document == 6) %>%
  arrange(desc(count))
```

```
## # A tibble: 287 x 3
##    document term           count
##       <int> <chr>          <dbl>
##  1        6 noriega           16
##  2        6 panama            12
##  3        6 jackson            6
##  4        6 powell             6
##  5        6 administration     5
##  6        6 economic           5
```

list of words for a specific document

Summary

Overall, the process in performing the topic modelling analysis consists of the following steps:

- Pre-processing data
- Tokenizing – decide to use single words, bigram or trigram
- Transforming into data form that can be used: corpus, dtm
- Fitting the model
- Visualization and interpretation

Exercise

- Perform the LDA analysis to your own choice of data. Interpret the results.