DSBA 5122: Visual Analytics

Class 8: Text-as-Data

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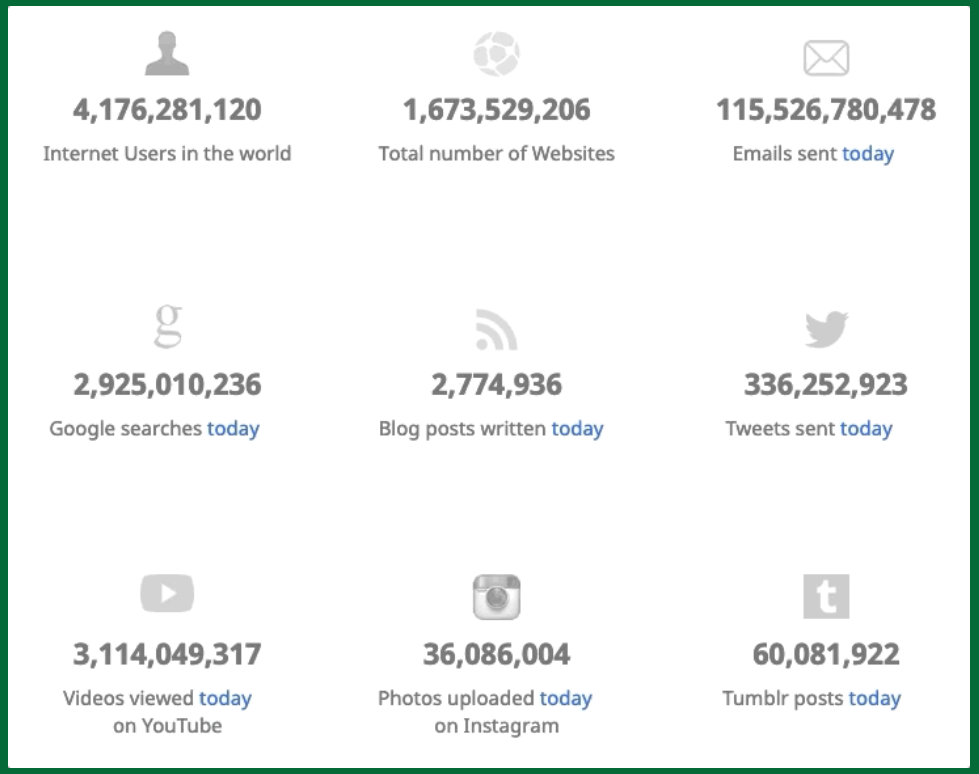
March 18, 2019

Introduction to Text-as-Data



High dimensionality of text

High dimensionality of text

High dimensionality of text

High dimensionality of text

# of Combinations = 1000 ^ 30 =~ # of Atoms in the Universe

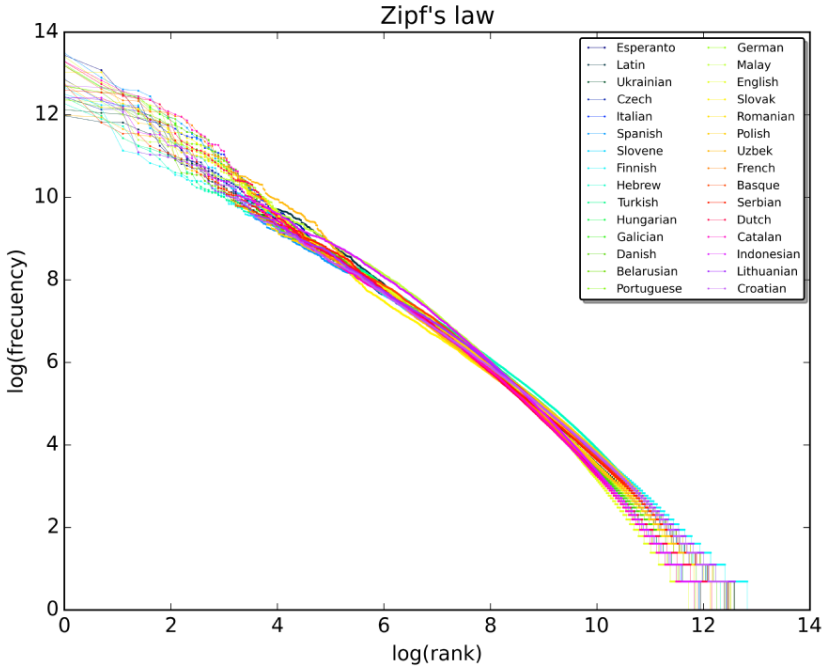
"A sample of 30-word Twitter messages that use only the 1,000 most common words in the English language ... has roughly as many dimensions as there are **atoms in the universe**." "Text as Data", 2017

Weird world of Text:

2353998352	1130101293	946294559	863581738	706982856
684761013	580256321	480926559	456126097	441438735
399042774	369017665	342269528	334036059	325737726
315443303	273974507	236570857	228023789	218485649
214844562	214763612	212806925	209752718	206977286
205533735	203881512	186956891	182196299	181076438
178890269	175721468	168824899	166759773	164714238
158607215	158594713	153211676	152999718	151850852
140045964	137955669	135804137	134732045	132704679
126375434	124635518	124298019	121705956	116298949
113376649	111255484	106959799	103674275	101213111
101113423	100809913	100766261	96714588	95234214
94049412	92699191	91813197	91235208	90418407
88990659	88879775	88487122	85461362	85374746
81379853	80145246	79985376	78995313	78819006

Key Properties about Text

Zipf's Law



VSauce video on Zipf's Law

Bag of Words

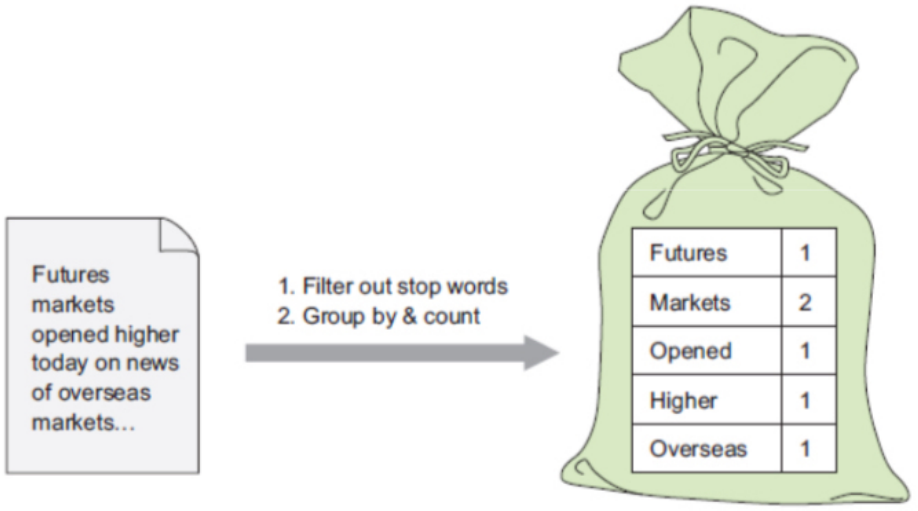
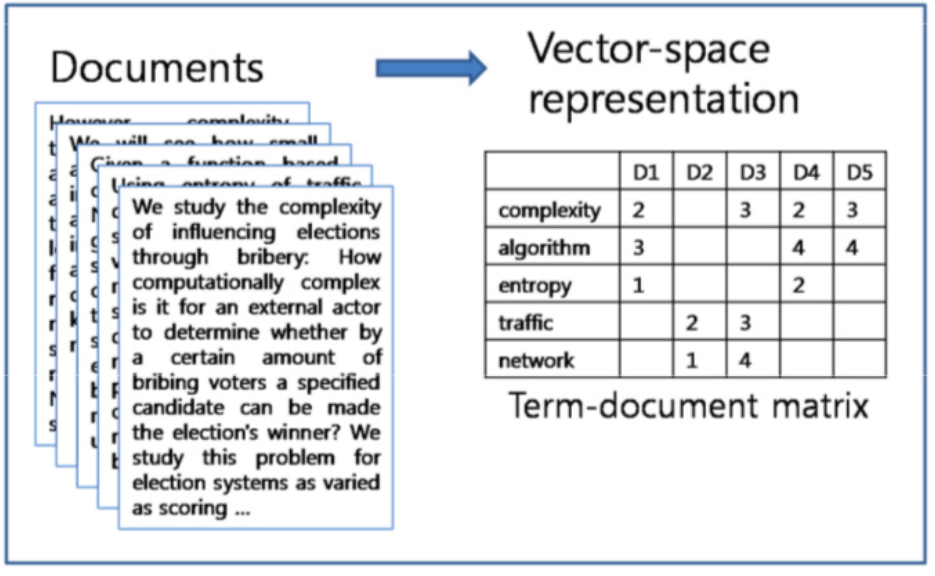


Figure 7.6 Bag of words representation of a document.

Document Term Matrix



	D1	D2	D3	D4	D5
complexity	2		3	2	3
algorithm	3			4	4
entropy	1			2	
traffic		2	3		
network		1	4		

Term-document matrix

Corpus

```
library(quanteda)
tweets <- read_csv("../data/CharlotteTweets20Sample.csv")

# create corpus
twcorpus <- corpus(tweets$body)

summary(twcorpus, n = 10)
```

```
## Corpus consisting of 47274 documents, showing 10 documents:
##
##    Text Types Tokens Sentences
##   text1    22     23         2
##   text2    14     16         1
##   text3     2      7         1
##   text4    20     34         1
##   text5     9      9         1
##   text6    25     27         2
##   text7     8      8         1
##   text8     3      3         1
##   text9    18     18         1
##  text10     6      6         1
##
## Source: /Users/rhymenoceros/Dropbox (UNC Charlotte)/dsba5122-spring2019/static/slides/* on x86_64 by rhymenoceros
## Created: Sun Mar 17 21:11:08 2019
## Notes:
```

Document-Feature Matrix

```
# additional stop words to remove, unique to Twitter
stopWords <- c("t.co","https","rt","amp","http","gt","f","u","w")
# add profile ID
docvars(twcorpus, "actor.id") <- as.character(tweets$actor.id)

twdfm <- dfm(twcorpus,
             remove = c(stopwords("english"), stopWords),
             remove_punct = TRUE,
             remove_numbers = TRUE,
             remove_symbols = TRUE,
             remove_url = TRUE,
             ngrams= 1L)
# remove sparse terms
twdfm <- dfm_trim(twdfm, min_docfreq = 3)

head(twdfm)
```

```
## Document-feature matrix of: 6 documents, 11,767 features (100.0% sparse).
```

Word Clouds

Raw Weighting

```
library(RColorBrewer)

textplot_wordcloud(twdfm,
                   min_size = .75,
                   max_size = 3.5,
                   color = brewer.pal(8, "Dark2"),
                   random_order = F,
                   rotation = 0.1,
                   max_words = 250)
```

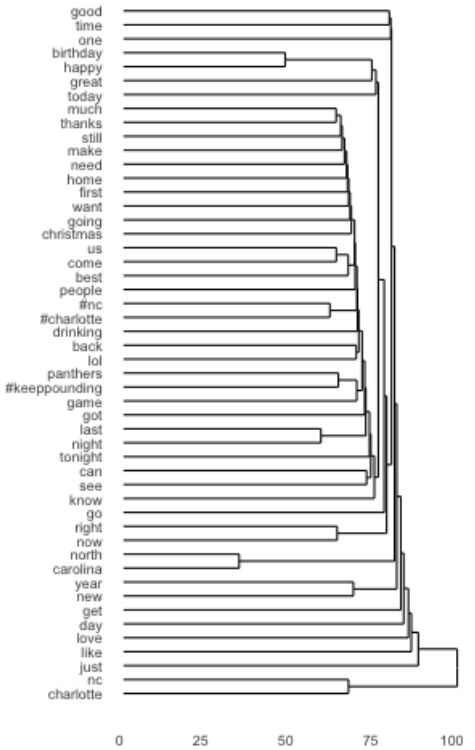
TF-IDF Weighting

```
textplot_wordcloud(dfm_tfidf(twdfm),
                   min_size = .75,
                   max_size = 3.5,
                   color = brewer.pal(8, "Dark2"),
                   random_order = F,
                   rotation = 0.1,
                   max_words = 250)
```

https://quanteda.io/articles/pkgdown/examples/plotting.html

Clustering

```
numWords <- 50

wordDfm <- twdfm %>%
  dfm_tfidf() %>%
  dfm_sort()

wordDfm <- t(wordDfm)[1:numWords,]  # keep the top numWords words
wordDistMat <- dist(wordDfm)
wordCluster <- hclust(wordDistMat)
# create dendrogram
ggdendro::ggdendrogram(wordCluster, rotate = TRUE)
```



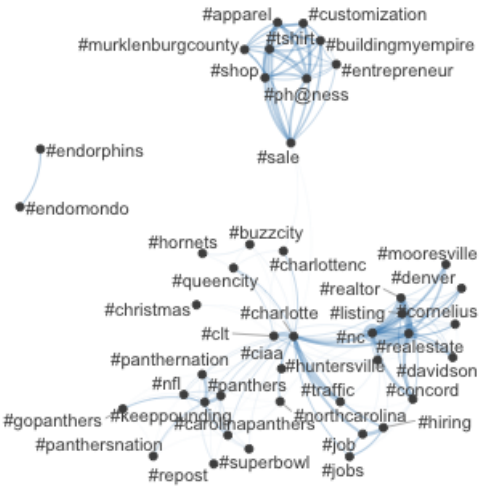
```
tag_dfm <- dfm_select(twdfm, pattern = ("#*"))
toptag <- names(topfeatures(tag_dfm, 50))
head(toptag)
```

```
## [1] "#keeppounding" "#charlotte"    "#nc"           "#realestate"
## [5] "#clt"          "#traffic"
```

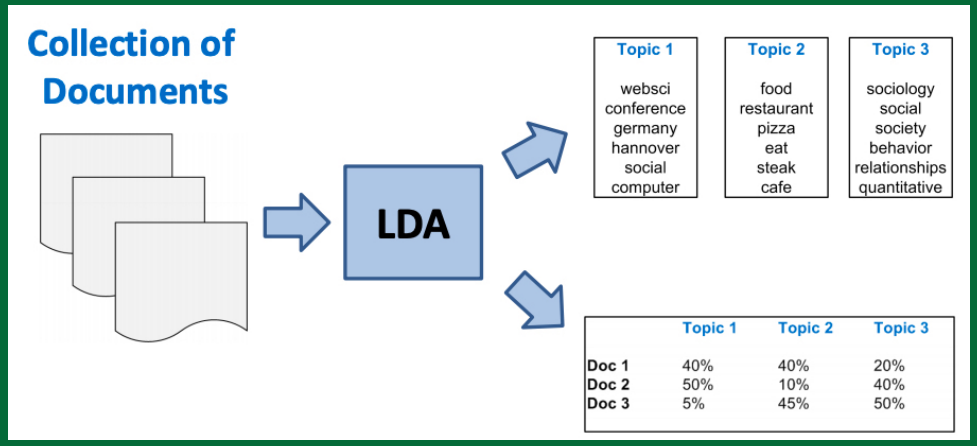
```
tag_fcm <- fcm(tag_dfm)
head(tag_fcm)
```

```
## Feature co-occurrence matrix of: 6 by 6 features.
## 6 x 6 sparse Matrix of class "fcm"
##             features
## features     #vsco #vscocam #primus #charlotte #livemusic #lunch
##   #vsco          0        3       1          1          1      0
##   #vscocam       0        0       1          1          1      0
##   #primus        0        0       0          1          1      0
##   #charlotte     0        0       0          0          5      0
##   #livemusic     0        0       0          0          0      0
##   #lunch         0        0       0          0          0      0
```

```
topgat_fcm <- fcm_select(tag_fcm,
                         pattern = toptag)

textplot_network(topgat_fcm,
                 edge_alpha = 0.3,
                 edge_size = 2)
```

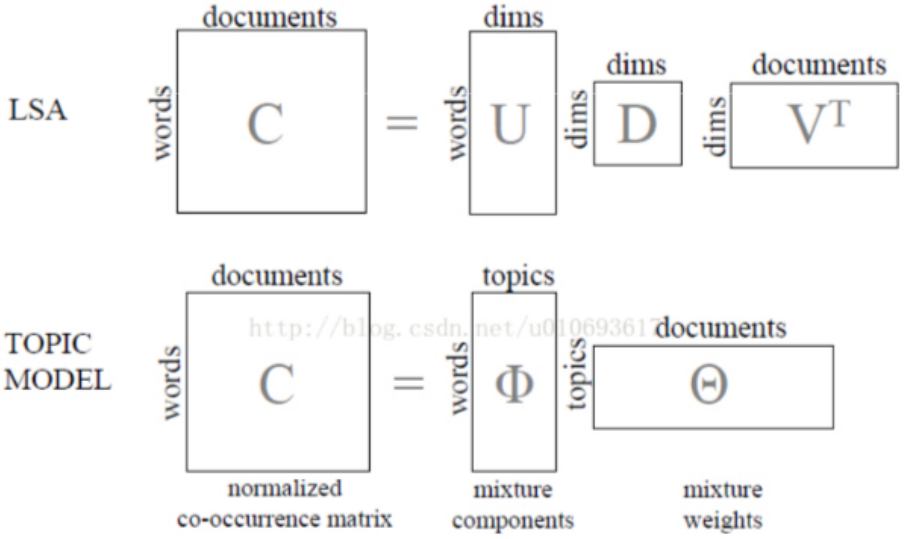


Topic Modeling



Latent Dirichlet Allocation

Dimensionality Reduction on DTM



Interpreting Topics

```
# install.packages("topicmodels")
library(topicmodels)

# we now export to a format that we can run the topic model with
dtm <- convert(twdfm, to="topicmodels")

# estimate LDA with K topics
K <- 20
lda <- LDA(dtm, k = K, method = "Gibbs",
                control = list(verbose=25L, seed = 123, burnin = 100, iter = 500))
```

```
## K = 20; V = 11767; M = 44955
## Sampling 600 iterations!
## Iteration 25 ...
## Iteration 50 ...
## Iteration 75 ...
## Iteration 100 ...
## Iteration 125 ...
## Iteration 150 ...
## Iteration 175 ...
## Iteration 200 ...
## Iteration 225 ...
## Iteration 250 ...
## Iteration 275 ...
## Iteration 300 ...
## Iteration 325 ...
## Iteration 350 ...
## Iteration 375 ...
## Iteration 400 ...
## Iteration 425 ...
## Iteration 450 ...
## Iteration 475 ...
## Iteration 500 ...
## Iteration 525 ...
## Iteration 550 ...
## Iteration 575 ...
## Iteration 600 ...
## Gibbs sampling completed!
```

Interpreting Topics

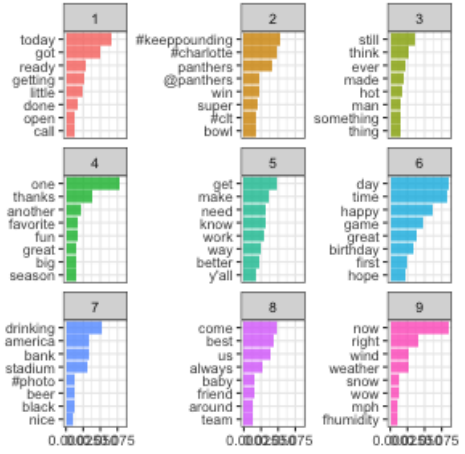
```
# see Ch 6 of tidytext mining
library(tidytext)
beta <- tidy(lda, matrix = "beta") %>%
  arrange(desc(topic), desc(beta))

head(beta, n = 10)
```

```
## # A tibble: 10 x 3
##    topic term         beta
##    <int> <chr>       <dbl>
##  1    20 carolina  0.0898
##  2    20 north     0.0801
##  3    20 good      0.0787
##  4    20 charlotte 0.0673
##  5    20 morning   0.0272
##  6    20 pretty    0.0114
##  7    20 news      0.00869
##  8    20 top       0.00817
##  9    20 boys      0.00683
## 10    20 today     0.00654
```

```
top_terms <- beta %>%
  group_by(topic) %>%
  top_n(8, beta) %>%
  ungroup() %>%
  arrange(topic, -beta)

top_terms
```

```
## # A tibble: 161 x 3
##    topic term            beta
##    <int> <chr>          <dbl>
##  1     1 today         0.0668
##  2     1 got           0.0500
##  3     1 ready         0.0290
##  4     1 getting       0.0267
##  5     1 little        0.0239
##  6     1 done          0.0170
##  7     1 open          0.0134
##  8     1 call          0.0119
##  9     2 #keeppounding 0.0527
## 10     2 #charlotte    0.0472
## # … with 151 more rows
```

```
library(ggthemes)

scale_x_reordered <- function(..., sep = "___") {
  reg <- paste0(sep, ".+$")
  ggplot2::scale_x_discrete(labels = function(x) gsub(reg, "", x), ...)
}

reorder_within <- function(x, by, within, fun = mean, sep = "___", ...) {
  new_x <- paste(x, within, sep = sep)
  stats::reorder(new_x, by, FUN = fun)
}

top_terms %>%
  filter(topic %in% 1:9) %>%
  mutate(term = reorder_within(term, beta, topic),
         topic = factor(topic)) %>%
  ggplot(aes(term, beta, fill = topic)) +
  geom_col(alpha = 0.8, show.legend = FALSE) +
  facet_wrap(~ topic, ncol = 3, scales = "free_y") +
  theme_tufte(base_family = "IBMPlexSans", ticks = FALSE) +
  scale_x_reordered() +
  theme_bw() +
  coord_flip() +
  labs(x = "", y = "")
```



Retrieving Documents by Topic

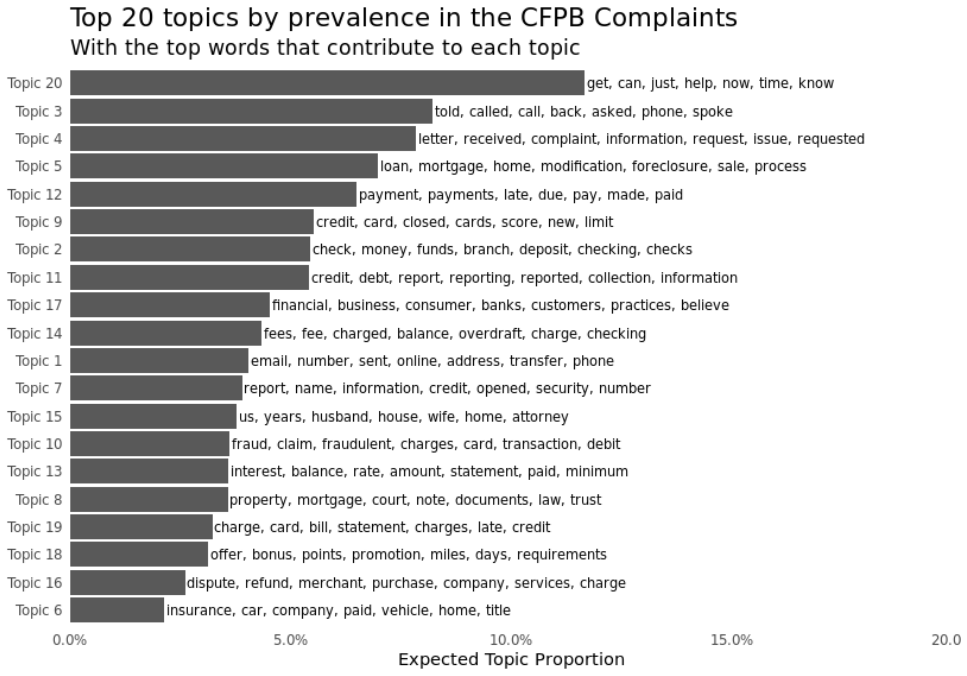
```
td_gamma <- tidy(lda, matrix = "gamma")

head(td_gamma)
```

```
## # A tibble: 6 x 3
##   document topic  gamma
##   <chr>    <int>  <dbl>
## 1 text1        1 0.0417
## 2 text2        1 0.0455
## 3 text3        1 0.0490
## 4 text4        1 0.0439
## 5 text5        1 0.0472
## 6 text6        1 0.0424
```

```
td_gamma %>%
  filter(topic == 2) %>%
  arrange(desc(gamma)) %>%
  head(n=6)
```

```
## # A tibble: 6 x 3
##   document  topic gamma
##   <chr>     <int> <dbl>
## 1 text5172      2 0.25
## 2 text24680     2 0.246
## 3 text1337      2 0.242
## 4 text10525     2 0.227
## 5 text23298     2 0.223
## 6 text31622     2 0.214
```

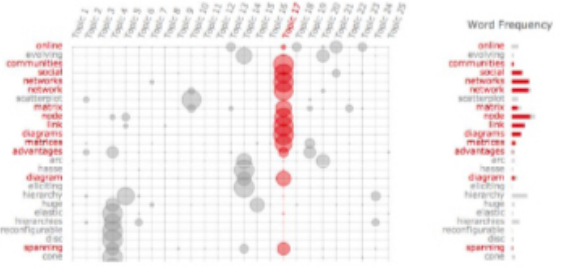
Summarizing Topic Models



For code, see https://github.com/wesslen/nlp-ryan/blob/master/complaints.R

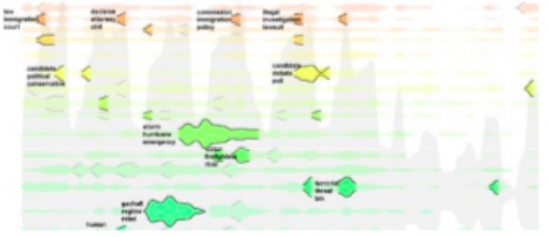
Visualizing Topic Models

Topic-Oriented



Termite (Chuang et al 2012)

Time-Oriented

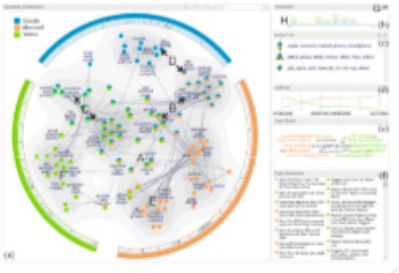


LeadLine (Dou et al 2012)

Hierarchical

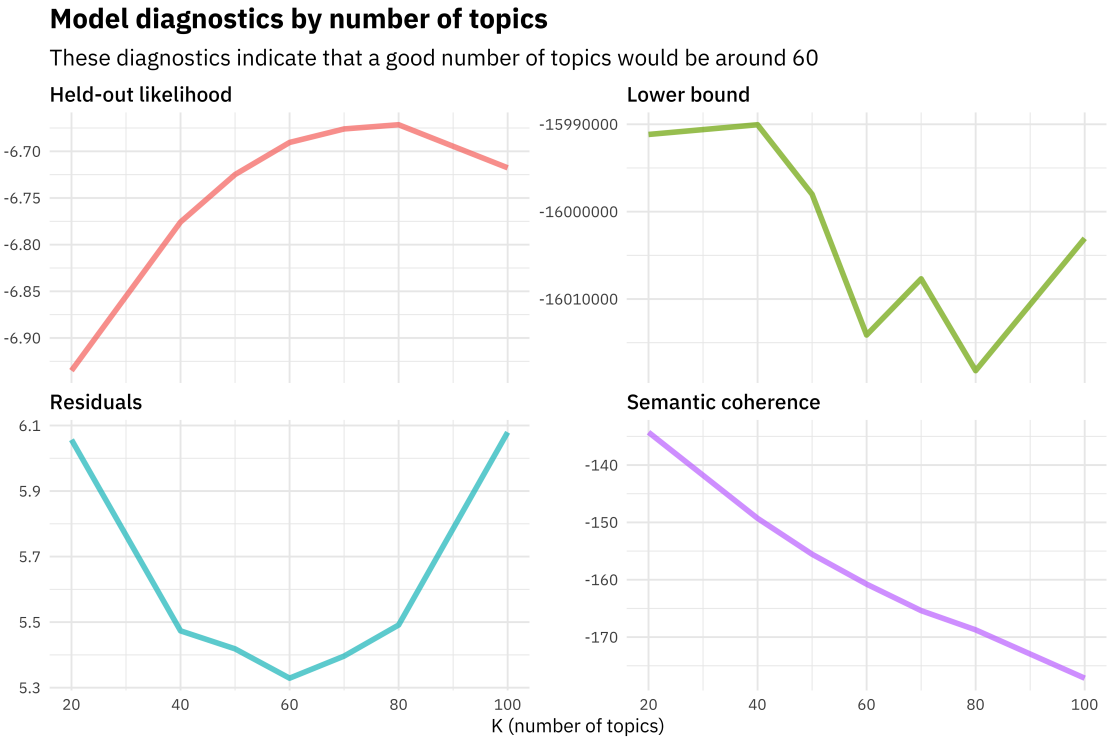
HierarchicalTopics (Dou et al 2013)

Graph (Relational) Based



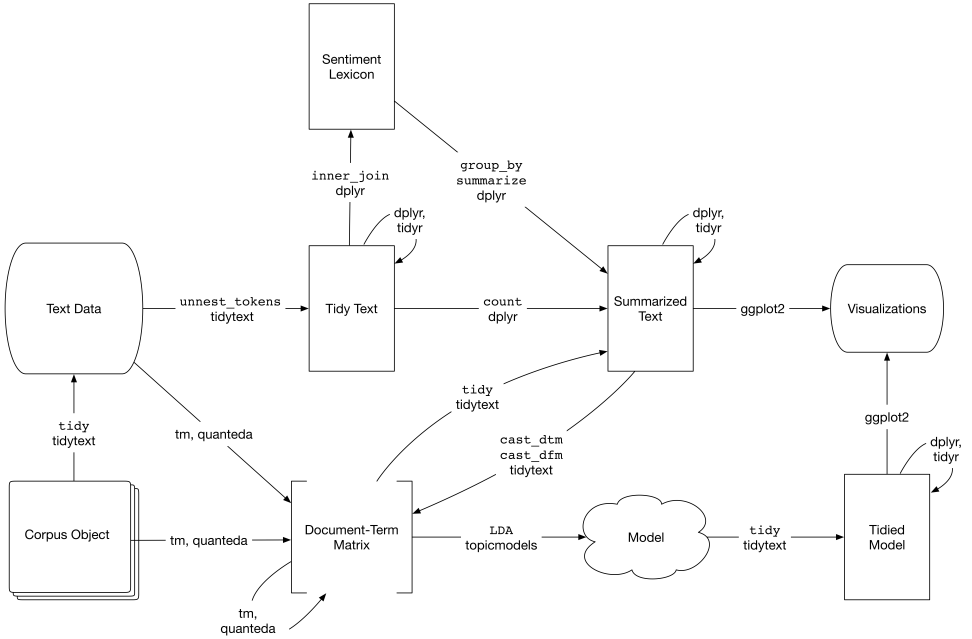
TopicPanorama (Wang et al 2016)

Evaluating Topic Models

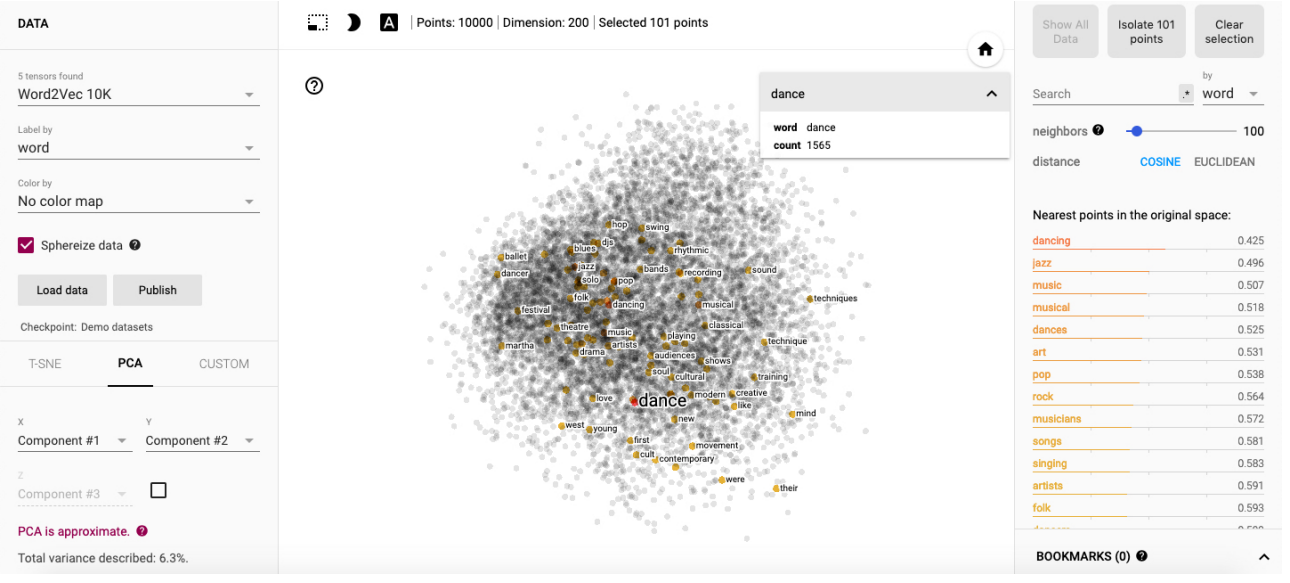


https://juliasilge.com/blog/evaluating-stm/

Text Workflows



Word Embedding Models



https://projector.tensorflow.org/