

Text as Data

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19 November 2015
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Word clouds are the pie charts of text analysis!

Today

A satellite look:

some basic principles (1), different goals & methods (2), and example (3)

Resources

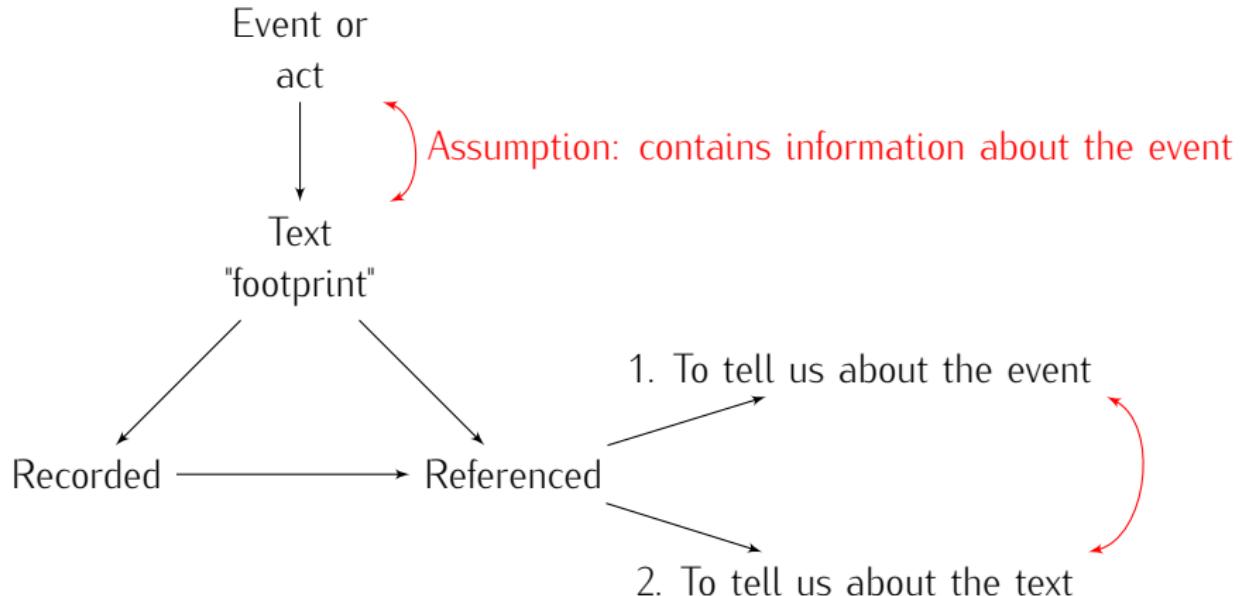
- ▶ Names (selective)
 - ▶ Will Lowe, Justin Grimmer, Kenneth Benoit, Margaret E. Roberts, Sven-Oliver Proksch
- ▶ R packages
 - ▶ `tm`, `austin`, `quanteda`, `stm`, `RTextTools`, `stringr`
- ▶ No matter how frustrating: regular expressions

Some goals

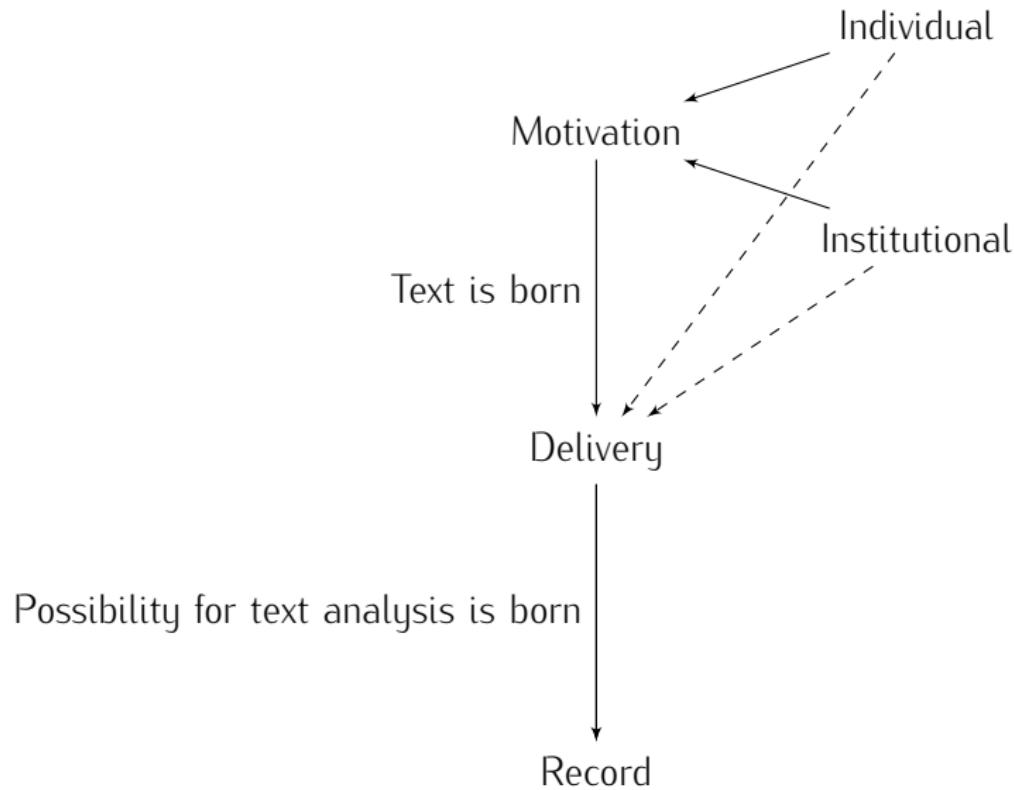
1. **Reveal** mechanisms according to which words influence and are influenced by human behavior (Roberts, 2000)
2. **Systematic** analysis of large scale text collections (Grimmer & Stewart, 2013)

We want to understand society (or the social) as expressed through words, but should this understanding be based on our conception (theory) of society or simply identify the intended meaning?

General framework



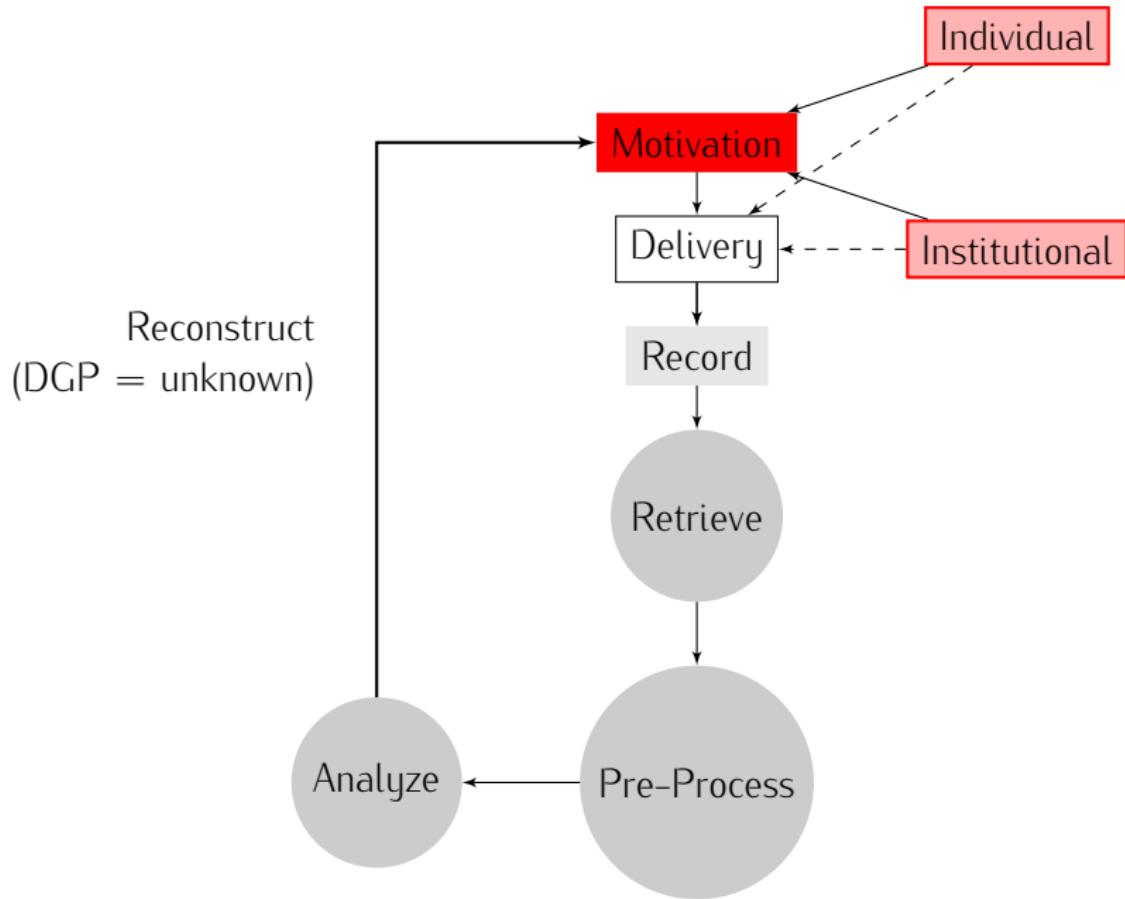
General framework



From text to data

- ▶ Requirements
 - ▶ Transform to *something* that can serve as input for analysis
 - ▶ What makes texts similar or different?
- ▶ Word (token) frequency, shared and unshared tokens – term-document matrix/document-term matrix
- ▶ (common) Assumption: bag of words
- ▶ Uni-grams, bi-grams, *n-grams*
- ▶ All tokens supposedly informative?
 1. Pre-processing – which steps and why?
 2. Substantive decisions

The grand scheme



The wide variety

2

Justin Grimmer and Brandon M. Stewart

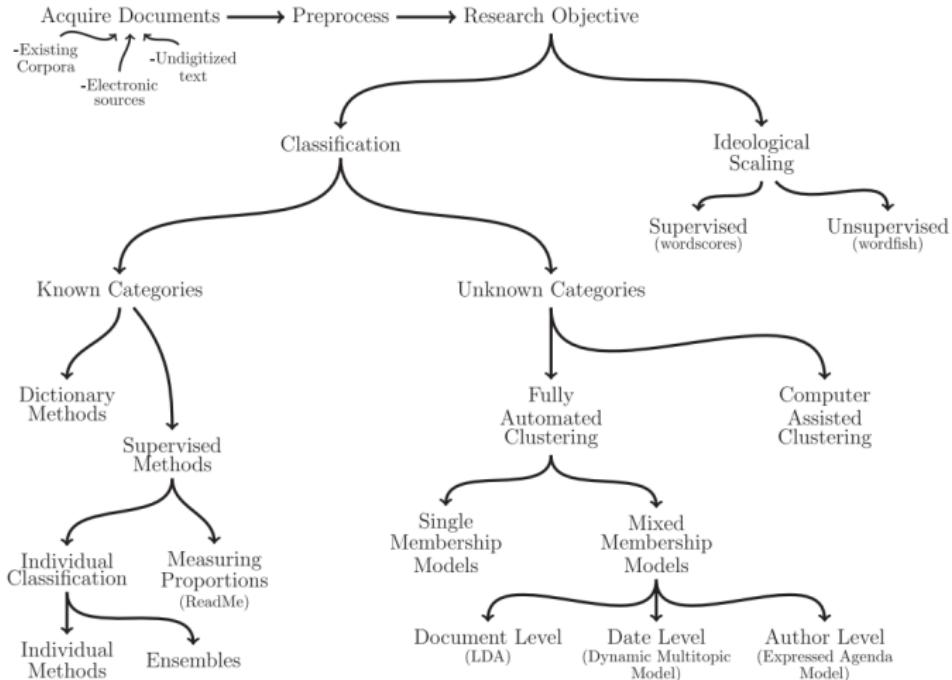


Fig. 1 An overview of text as data methods.

For some branches

The 'one' way

Lowe, W. (2013). There's (basically) only one way to do: Some unifying theory for text scaling models.

No matter what: VALIDATE!

Application

Example: which texts?

- ▶ Prime minister's opening addresses, Denmark, 1953-2013
- ▶ (substantive) Properties you might want to consider:
 - ▶ When?
 - ▶ Where?
 - ▶ Why?

Example: content

- ▶ An account of the current state of Danish affairs (established in the § 38 (1) of the Danish Constitutional Act): (1) overarching, (2) mixture of 'what has been done' and 'what will be done'
- ▶ Touches upon multiple domains, or 'topics'
- ▶ Given the current state of Danish affairs and government priorities:
 - ▶ Some topics are selected to be included (limited space)
 - ▶ Some topics are addressed more in detail
- ▶ Non-technical political speech (with extended general interest in recent years, i.e. broadcast)

Example: metadata and tasks

- ▶ Year, prime minister (who gave the talk), prime minister's party, coalition government – single party government
- ▶ Goals
 - 1. Load, inspect, and pre-process texts
 - 2. Classification/prediction application: elections next year?

Before we start

THE NEW YORKER



• • • • • • • • • • • • • • •
"I think whatever's going to happen next has already happened."

Example: follow along

- ▶ Code: https://zfazekas.github.io/resources/text_class/text_classification.R

```
data_path <- "https://zfazekas.github.io/resources/text_class/data.zip"
download(data_path, dest = "data.zip", mode = "wb")
unzip("data.zip", exdir = "./")
```

Example: some metadata

```
library("dplyr")
pm <- read.table("./data/pm-data.txt", sep = "\t",
                  header = TRUE,
                  stringsAsFactors = FALSE, encoding = "UTF-8")
elections <- read.csv("./data/elections.csv", header = TRUE,
                      stringsAsFactors = FALSE)
head(elections)

##      year next_elect
## 1 1953  5/14/1957
## 2 1954  5/14/1957
## 3 1955  5/14/1957
## 4 1956  5/14/1957
## 5 1957 11/15/1960
## 6 1958 11/15/1960
```

Example: some metadata

```
elections$next_date <- as.Date(elections$next_elect,
                                format = "%m/%d/%Y")
elections$speech <- as.Date(paste0("10/3/", elections$year),
                            format = "%m/%d/%Y")
elections$dist_weeks <- difftime(elections$next_date,
                                   elections$speech,
                                   unit = "weeks") %>%
  round(., 0) %>%
  as.numeric()
elections$dist_category <- "0"
elections$dist_category[elections$dist_weeks < 51] <- "1"
pm <- merge(pm, elections[, c("year", "dist_category")],
            by = "year")
```

Texts

```
library("tm")
tm_corp <- Corpus(DirSource("./data/pm_speeches"),
                     readerControl = list(language = "da"))
pm$texts <- sapply(tm_corp, function (x) paste(x, collapse = " "))

library("quanteda")
pm_corp <- corpus(pm$texts, docvars = pm[, 1:5])
```

Collecting specifics: PM names

```
library("stringr")
library("dplyr")

pm_name <- docvars(pm_corp)$pm %>%
  unique(.) %>% tolower() %>%
  paste(., collapse = " ") %>%
  str_split(., " ") %>%
  unlist() %>%
  unique(.)
```

pm_name

## [1] "hans"	"hedtoft"	"christian"
## [4] "hansen"	"viggo"	"kampmann"
## [7] "jens"	"otto"	"krag"
## [10] "hilmar"	"baunsgaard"	"anker"
## [13] "jørgensen"	"poul"	"hartling"
## [16] "schlüter"	"nyrup"	"rasmussen"
## [19] "anders"	"fogh"	"lars"
## [22] "løkke"	"helle"	"thorning-schmidt"

Corpus

```
tail(summary(pm_corp, verbose = FALSE))[, 1:7]
```

```
## Corpus consisting of 61 documents.
```

	Text	Types	Tokens	Sentences	year	party	coalition	
##	text56	text56	1401	4799	449	2008	V	1
##	text57	text57	1498	5114	391	2009	V	1
##	text58	text58	1342	4649	412	2010	V	1
##	text59	text59	1338	4946	497	2011	S	1
##	text60	text60	1246	4442	424	2012	S	1
##	text61	text61	1373	4871	424	2013	S	1

Document-feature matrix

```
pm_dfm <- dfm(pm_corp, language = "danish",
                 toLower = TRUE,
                 removePunc = TRUE,
                 removeSeparators = TRUE,
                 stem = TRUE
               )

## Creating a dfm from a corpus ...
##     ... lowercasing
##     ... tokenizing
##     ... indexing documents: 61 documents
##     ... indexing features: 20,688 feature types
##     ... stemming features (Danish), trimmed 7214 feature variants
##     ... created a 61 x 13474 sparse dfm
##     ... complete.
## Elapsed time: 1.238 seconds.
```

Document-feature matrix

```
head(pm_dfm)
```

```
## Document-feature matrix of: 61 documents, 13,474 features.
## (showing first 6 documents and first 6 features)
##          features
## docs      der majestæt æred medlem af folketing
##   text1    59        3     1     2    93      5
##   text2    61        0     0     1    98      7
##   text3    74        0     0     0   113      4
##   text4    65        0     0     1   115      6
##   text5    69        0     0     1   123      2
##   text6    63        0     0     0   122      3
```

Additional terms

```
folk_terms <- grep("folket", colnames(pm_dfm), value = TRUE)
dk_terms   <- grep("dansk", colnames(pm_dfm), value = TRUE)
rem_terms  <- c("ing", "ning", "vor", "fordi", "danmark",
               "vores", "derfor", "mellem", "mere", "tak",
               "ingen", "majestæt", "kong", "dronning",
               dk_terms, folk_terms, pm_name)
length(rem_terms)

## [1] 74
```

Stopwords and collected features

```
pm_dfm <- dfm(pm_corp, language = "danish",
                toLower = TRUE,
                removePunc = TRUE,
                removeSeparators = TRUE,
                stem = TRUE,
                ignoredFeatures = c(stopwords("danish"),
                                    rem_terms),
                verbose = FALSE
              )
```

```
head(pm_dfm)
```

```
## Document-feature matrix of: 61 documents, 13,351 features.
## (showing first 6 documents and first 6 features)
##          features
## docs      æred medlem bring ærbød overvær først
## text1      1     2     3     1     1     4
## text2      0     1     0     0     0     4
## text3      0     0     1     0     0     8
## text4      0     1     1     0     0     6
## text5      0     1     1     0     0     3
```

Trimming

```
pm_dfm <- trim(pm_dfm, minDoc = 9) ## 15% of documents

## Features occurring in fewer than 9 documents: 11526

dim(pm_dfm)

## [1] 61 1825

head(pm_dfm)

## Document-feature matrix of: 61 documents, 1,825 features.
## (showing first 6 documents and first 6 features)
##          features
## docs      regering ikk kan bliv vær år
##   text1      38   8   9   18   7   4
##   text2      43  16  12   26  16  16
##   text3      34  14   6   33  15  23
##   text4      33   3  10   31  17  20
##   text5      46   6   9   45  14  22
##   text6      39   8  13   50  16  18
```

Classification

```
total <- 1:61 ## total # documents
set.seed(162648)
train_docs <- sample(1:61, 40, replace = FALSE) ## training set
test_docs <- total[total %in% train_docs == FALSE] ## test set
library("RTextTools")
pm_cont <- create_container(pm_dfm,
                             docvars(pm_corp)$dist_category,
                             trainSize = train_docs,
                             testSize = test_docs,
                             virgin = FALSE)

## Train
support_train <- train_model(pm_cont, "SVM")
glm_train <- train_model(pm_cont, "GLMNET")

## Classify
support_class <- classify_model(pm_cont, support_train)
glm_class <- classify_model(pm_cont, glm_train)
```

How did we do?

```
analytics <- create_analytics(pm_cont,
                               cbind(support_class, glm_class))
summary(analytics)

## ENSEMBLE SUMMARY
##
##          n-ENSEMBLE COVERAGE n-ENSEMBLE RECALL
## n >= 1           1.00           0.57
## n >= 2           0.76           0.69
##
##          n-ENSEMBLE COVERAGE n-ENSEMBLE RECALL
## n >= 1           1.00           0.57
## n >= 2           0.76           0.69
##
## ALGORITHM PERFORMANCE
##
##          SVM_PRECISION      SVM_RECALL      SVM_FSCORE GLMNET_PRECISION
##          0.590           0.535           0.505           0.500
##          GLMNET_RECALL      GLMNET_FSCORE
##          0.500           0.475

doc_summary <- analytics@document_summary
```

Housekeeping

```
svm_results <- paste0(doc_summary[, 1],  
                      " (",  
                      round(doc_summary[, 2], 3),  
                      ")")  
glm_results <- paste0(doc_summary[, 3],  
                      " (",  
                      round(doc_summary[, 4], 3),  
                      ")")  
all <- data.frame(docvars(pm_corp)[test_docs, c(1, 3, 5)],  
                   svm_results, glm_results)
```

Where did we do well?

```
all[1:10, ]
```

	year	coalition	dist_category	svm_results	glm_results
## text1	1953	0		0 0 (0.724)	0 (0.787)
## text5	1957	1		0 1 (0.614)	0 (0.882)
## text8	1960	1		1 1 (0.514)	0 (0.937)
## text14	1966	0		1 0 (0.897)	1 (0.746)
## text17	1969	1		0 0 (0.766)	0 (0.981)
## text18	1970	1		1 0 (0.816)	0 (0.852)
## text19	1971	1		0 0 (0.666)	0 (0.967)
## text23	1975	0		0 0 (0.887)	0 (0.982)
## text31	1983	1		1 0 (0.687)	0 (0.945)
## text34	1986	1		1 0 (0.739)	0 (0.967)

Where did we do well?

```
all[11:21, ]
```

	year	coalition	dist_category	svm_results	glm_results
## text35	1987	1		0 0 (0.847)	0 (0.668)
## text36	1988	1		0 0 (0.637)	1 (0.944)
## text37	1989	1		0 0 (0.884)	0 (0.968)
## text38	1990	1		1 0 (0.814)	0 (0.601)
## text40	1992	1		0 0 (0.697)	0 (0.982)
## text42	1994	1		0 0 (0.778)	0 (0.876)
## text44	1996	1		0 0 (0.805)	0 (0.983)
## text46	1998	1		0 0 (0.685)	0 (0.854)
## text49	2001	1		1 0 (0.63)	0 (0.993)
## text54	2006	1		0 0 (0.738)	1 (0.97)
## text59	2011	1		0 0 (0.715)	0 (0.959)

Cross-validation (SVM)

```
cross_validate(pm_cont, 3, "SVM")  
  
## Fold 1 Out of Sample Accuracy = 0.75  
## Fold 2 Out of Sample Accuracy = 0.6190476  
## Fold 3 Out of Sample Accuracy = 0.7  
  
## [[1]]  
## [1] 0.7500000 0.6190476 0.7000000  
##  
## $meanAccuracy  
## [1] 0.6896825
```

Cross-validation (GLMNET)

```
cross_validate(pm_cont, 3, "GLMNET")

## Fold 1 Out of Sample Accuracy = 0.9444444
## Fold 2 Out of Sample Accuracy = 0.7826087
## Fold 3 Out of Sample Accuracy = 1.25

## [[1]]
## [1] 0.9444444 0.7826087 1.2500000
##
## $meanAccuracy
## [1] 0.992351
```

Limitations

- ▶ How about the baseline?

```
prop.table(table(all$dist_category))
```

```
##  
##          0           1  
## 0.6666667 0.3333333
```

- ▶ How about substantive issues?
- ▶ And granularity?

Transparency!