Introduction to Computational Social Science

Session 3: Text analysis for political texts

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Room B U103, Tue 14:00–18:00 (bi-weekly)

Today's session

Lecture

1. Text data
2. Dictionary
3. Scaling models
4. Topic models

Lab

1. How often do MPs in the Bundestag talk about environment?
2. How do parties position themselves in speeches?
3. What are the main topics of debate?

Why text?

Sources

Often times political action has a text trail:

- Political speeches and debates are transcribed
- Laws are written down
- Opinions are expressed in written form (Twitter, press releases)

Opportunity

Using computational social sciences methods allows us to:

- Collect and analyse vast amounts of preexisting text data
- Without the huge costs associated with manual coding

Principles

From Grimmer & Stewart (2013):

1. All quantitative models of language are wrong—but some are useful.
2. Quantitative methods for text amplify resources and augment humans.
3. There is no globally best method for automated text analysis.
4. Validate, Validate, Validate.

From text to data

Text

- Text is immensely complex
- First step in most text analysis process is finding a way to represent text as data

Some lingo:

- **Document**: Often times the unit of analysis, therefore one unique text
- **Corpus**: A collection of documents
- **Meta data**: Additional data that describes each document, e.g. its release date

Text as data

We can differentiate roughly two text representation forms:

- **sparse** (many zeros, or less abstract)
- **dense** (few zeros, or more abstract)

Bag-of-words

The most common form of representation is **bag-of-words**:

Given a collection of documents, thus a corpus,

1. List each *unique* word occurring across all documents in the corpus (-> **vocabulary**)
2. Count how often each word appears for a given document
3. Create a vector from the counts

Bag-of-words: Example

Text:

- We prefer policy option one over policy option two.

Becomes:

We	prefer	policy	option	one	over	two	.
1	1	2	2	1	1	1	1

Bag-of-words: Limitation

Text:

- We prefer policy option one over policy option two.
- We prefer policy option two over policy option one.

Becomes:

We	prefer	policy	option	one	over	two	.
1	1	2	2	1	1	1	1
1	1	2	2	1	1	1	1

Bag-of-words: Limitation

- Problem: Bag-of-words is often unable to depict the **meaning** of a text.
- Reminder: “All quantitative models of language are wrong—but some are useful.”
- Possible solution: Abstract (dense) representation of texts based on more complex models (e.g. Transformers)

Preprocessing text

A short word on pre-processing:

Problem:

- Textual data is often messy!
- Messy data is very problematic when it comes to drawing conclusions from your analysis

Common issues:

- Formatting issues
- Unwanted inclusions
- Punctuation
- Different inflections (playing, play, player)
- Words without much information (stopwords)

Preprocessing text

Possible solution(s):

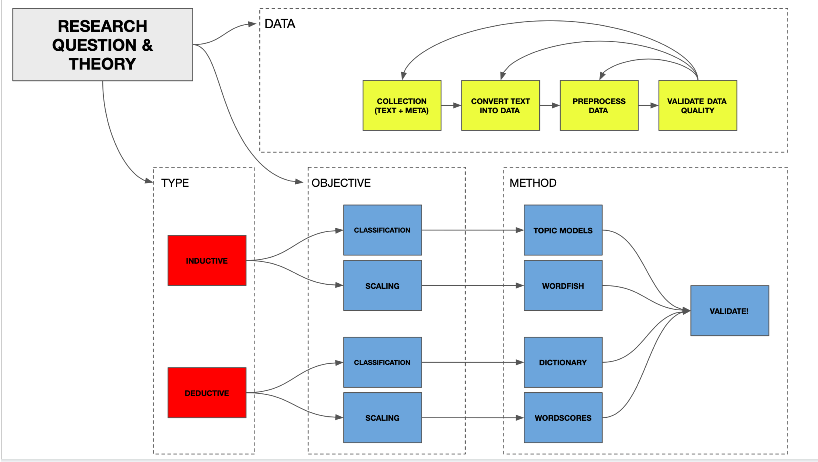
- Stemming and lemmatization (removing/reducing inflections)
- Reduction of vocabulary (e.g. removing very common and very rare words)
- Removing special characters (punctuation, numbers, etc.)
- ...

Important

- Always control which impact your pre-processing has on the final results!
- Always inspect your text manually!

Analysing text data

Overview


RESEARCH QUESTION & THEORY
DATA
COLLECTION (TEXT + META)
CONVERT TEXT INTO DATA
PREPROCESS DATA
VALIDATE DATA QUALITY
TYPE
INDUCTIVE
DEDUCTIVE
OBJECTIVE
CLASSIFICATION
SCALING
CLASSIFICATION
SCALING
METHOD
TOPIC MODELS
WORDFISH
DICTIONARY
WORDSCORES
VALIDATE!

Type

Inductive

- No prior deeper understanding of the subject matter

Deductive

- Profound understanding of the subject matter

Objective

Classification

- Assign values or labels to unlabeled data

Scaling

- Place observations within a space (e.g. on a left-right scale)

Dictionary

Dictionary

Goal:

- Classifing documents into *known* categories

Basic idea:

1. Define a list of words that is connected to a concept that you want to measure
2. Count how often the predefined words appear in each document
3. Construct measure based on matches

Dictionary: Example Sentiment analysis

```
library(tidytext)

get_sentiments("bing")
```

```
## # A tibble: 6,786 x 2
##    word        sentiment
##    <chr>       <chr>
##  1 2-faces     negative
##  2 abnormal    negative
##  3 abolish     negative
##  4 abominable  negative
##  5 abominably  negative
##  6 abominate   negative
##  7 abomination negative
##  8 abort       negative
##  9 aborted     negative
## 10 aborts      negative
```

Dictionary: Example Sentiment analysis

```r
library(tidytext)
library(tidyverse)

reviews <-
  data.frame(
    text = c(
      "I think this class was amazing.
      The lecuteres were absolutely fantastic!",
      "What a waste of time.
      Never before have I been this disappointed"
    ),
    student = c(1, 2)
  )
```

Dictionary: Example Sentiment analysis

```r
reviews %>%
  unnest_tokens(word, text) %>%
  inner_join(get_sentiments("bing"))
```

```
##   student         word sentiment
## 1       1      amazing  positive
## 2       1    fantastic  positive
## 3       2        waste  negative
## 4       2 disappointed  negative
```

Dictionary: Example Sentiment analysis

```r
reviews %>%
  unnest_tokens(word, text) %>%
  inner_join(get_sentiments("afinn"))
```

```
##   student         word value
## 1       1      amazing     4
## 2       1    fantastic     4
## 3       2        waste    -1
## 4       2 disappointed    -2
```

Dictionary: Example Sentiment analysis

```r
reviews %>%
  unnest_tokens(word, text) %>%
  inner_join(get_sentiments("nrc"))
```

```
##   student         word    sentiment
## 1       2        waste      disgust
## 2       2        waste     negative
## 3       2         time anticipation
## 4       2 disappointed        anger
## 5       2 disappointed      disgust
## 6       2 disappointed     negative
## 7       2 disappointed      sadness
```

Dictionary: Example Sentiment analysis

Word Count:

$$Sentiment_i = \sum P_i - \sum N_i$$

The sum/number of postive words P from a document i minus the sum/number of negative words N for a document i.

Dictionary: Example Sentiment analysis

Relative Word Count:

$$Sentiment_i = \frac{\sum P_i - \sum N_i}{\sum W_i}$$

The sum/number of postive words P from a document i minus the sum/number of negative words N for a document i divided by the total number of words W.

Dictionary: Example Sentiment analysis

Including confidence:

$$Sentiment_i = \frac{\sum P_{i,m} * C_{i,m} - \sum N_{i,m} * C_{i,m}}{\sum W_i}$$

For the sum of postive words P from a document i multiplicated by the confidence for each word m that it represents a postive word…

Dictionary: Postives and negatives

Positive

- Very simple
- Often easy to connect to theoretical framework (deductive!)
- High precision

Negative

- Often low recall
- Difficult to construct dictionaries that capture every variation of the concept

Topic models

Topic models

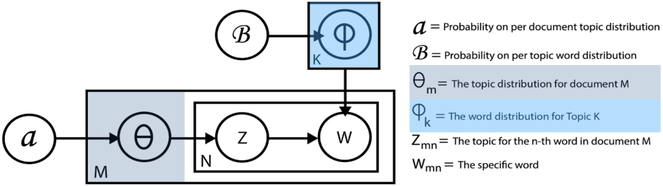
Goal:

- Classify documents without knowing the categories beforehand

Basic idea (in this case simplyfied):

1. Documents are created by repeatedly drawing words that belong to a limited amount of topics
2. Each topic represents a distribution of words
3. Each document represents a distribution of topics
4. We can infer from which topic words “originated” based on their concurrence
5. We can infer the distribution of topics across a document

Topic models: Closer look

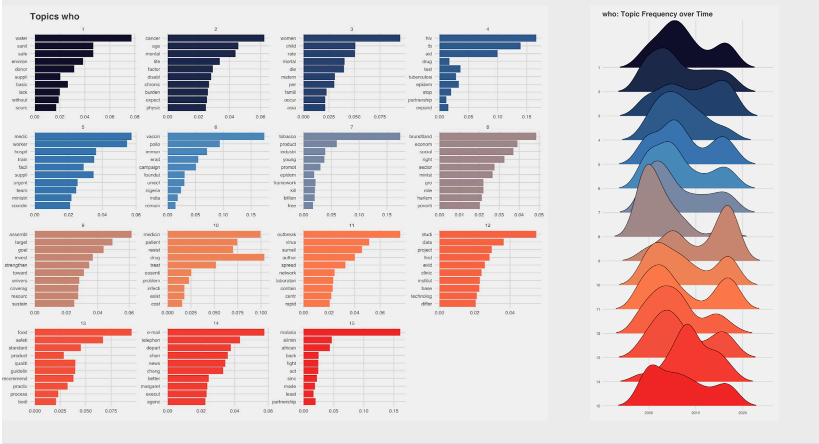


Topic models: Basic idea simplified...

dogs,
cute, best friend
cuddle, love

cats,
devil, scratch
evil, jerk

Topic models: Example



Topic models: Postives and negatives

Positive

- Can give a quick **explorative** overlook over the contents of your text data
- Possibility to include further parameters into the estimation (structural topic models)
- Can be used for other means -> matching

Negative

- Difficult to connect to theory
- Uncertainty what exactly is measured
- Rely on many hyper parameters
- Very senstitive to input

Scaling models: Wordfish

Wordfish

Goal:

- Placing actors on/along a predefined dimension, without knowing their position beforehand

Basic idea:

1. Language is marked by ideology
2. Political actors differ how they talk about issues and which issues they talk about
3. By finding *discriminating* words we can place actors along a scale based on the words they use

Wordfish: Model

Frequency of word j in in document i

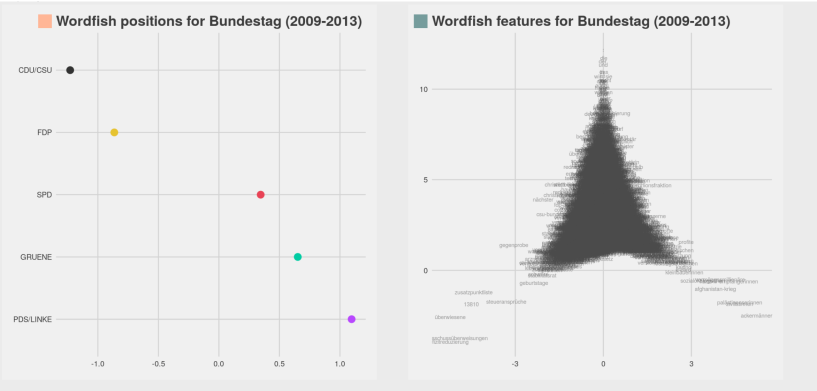
$$y_{ijt} \sim Poisson\ (\lambda_{ijt})$$
$$\lambda_{ijt} = \exp\left(\alpha_{it} + \psi_j + \beta_j * \omega_{it}\right)$$

Mean / variance of Poisson-Distribution ij

How strong does j differentiate between positions

Position of document i

Wordfish: Results example



Wordfish: Positive and negatives

Positives:

- Intuitively results make sense
- Results in a continues measure of ideology

Negatives:

- Strong assumptions (unidimensional issue space, ideological language, naive bayes)
- Weak performance when used outside of party manifestos and speeches
- Very specific use case