Twitter in the Parliament - A Text-based Analysis of German Political Entities

Patrick Schulze, Simon Wiegrebe

Supervisors:
Prof. Dr. Christian Heumann, Prof. Dr. Paul W. Thurner

7. Juli 2020

Outline

- Introduction
- Topic Modeling: Motivation and Theory
- Data: Collection and Preprocessing
- Model Selection and Global Characteristics
- Metadata Analysis
- Causal Inference
- Discussion

Introduction

- Rise in popularity of social media is producing huge amounts of data, especially text.
- *Politics* is a field of particular interest in the context of social media and big data (Brexit, 2016 presidential election in the US, Facebook data scandal).
- Simultaneously, advances in *Natural Language Processing* (NLP) are providing tools of analysis for such data.
- One instance of such analysis is the discovery and exploration of latent thematic clusters within text - *topic analysis*.
- In this project, we apply the *Structural Topic Model* (STM) to a self-created dataset containing Twitter posts by members of the German Bundestag (and a variety of metadata)

Topic Modeling: Motivation and Theory

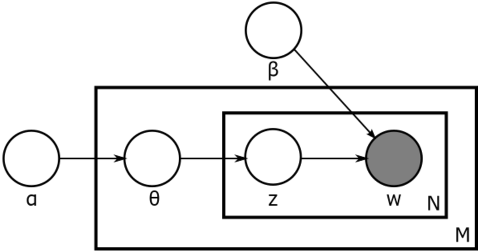
Notation and Terminology

- A *word* is an instance of a vocabulary of V unique *terms*.
- A *document* $d \in \{1, \ldots, D\}$ is a sequence of words of length N_d. The n-th word of document d is denoted by $w_{d,n}$.
- A *corpus* is a collection (or set) of D documents. Therefore, $d \in \{1, \ldots, D\}$ means that our corpus contains D documents.
- A *topic* $k \in \{1, \ldots, K\}$ is a latent thematic cluster within a text corpus. That is, we imply a corpus can be represented by K topics.
- A *topic-word distribution* $\boldsymbol{\beta}$ is a probability distribution over words. We denote the word distribution corresponding to the k-th topic by $\boldsymbol{\beta}_k$.
- A *topic assignment* $\boldsymbol{z}_{d,n}$ assign $w_{d,n}$ to a specific topic $k \in \{1, \ldots, K\}$. We represent the word distribution for $w_{d,n}$ as $\boldsymbol{\beta}_{d,n}$.
- *Topic proportions* $\boldsymbol{\theta}_d$ are the proportions of the document d's terms assigned to each of the topics. $\sum_{k=1}^{K} \theta_{d,k} = 1$, for all $d \in \{1, \ldots, D\}$.

Topic Modeling: Motivation and Theory

Latent Dirichlet Allocation (LDA)

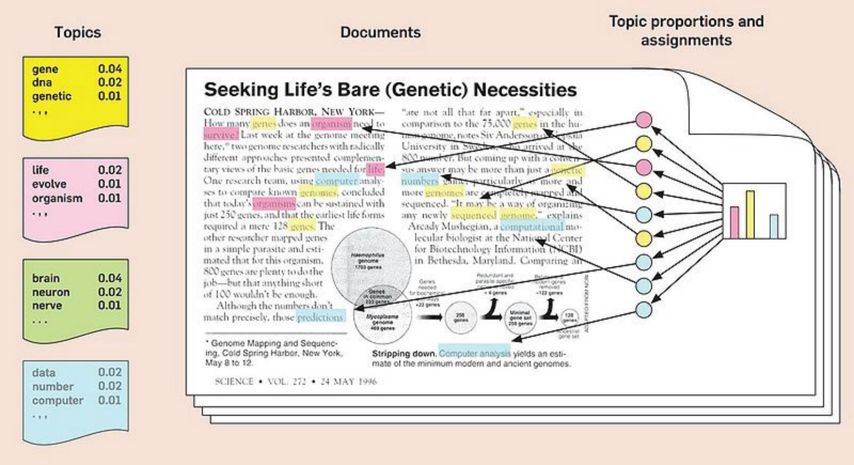
- LDA by **blei2003latent** is the first probabilistic topic model.
- Its generative process for each document $d \in \{1, \ldots, D\}$ is:
  1) Draw topic proportions $\boldsymbol{\theta}_d \sim \text{Dir}_K(\boldsymbol{\alpha})$.
  2) For each word $n \in \{1, \ldots, N_d\}$:
     a) Draw a topic assignment $\boldsymbol{z_{d,n}} \sim \text{Multinomial}_K(\boldsymbol{\theta}_d)$.
     b) Draw a word $w_{d,n} \sim \text{Multinomial}_V(\boldsymbol{\beta}_{d,n})$.
- Graphical model representation (**roberts2016model**, p. 990):



Topic Modeling: Motivation and Theory

Latent Dirichlet Allocation (LDA)

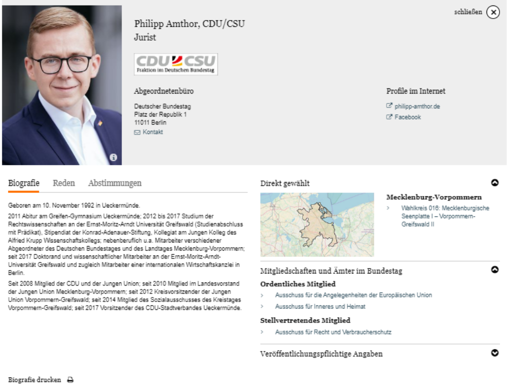
- The topic assignment of a document's words can be illustrated as follows:



Data

Data Collection

- MP-level data was scraped from `www.bundestag.de/abgeordnete` using Python's *BeautifulSoup* and a *selenium web driver*

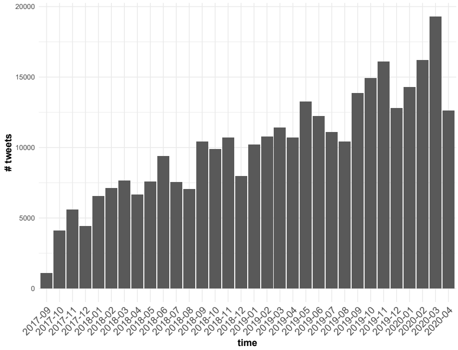


- Socioeconomic data and 2017 German federal election results were extracted from `www.bundeswahlleiter.de`.

Data

Data Collection

- Tweets (and further Twitter features) were downloaded via the official Twitter API using Python's *tweepy* library.
- Monthly tweets (after dropping MPs without electoral district) for our period of analysis, September 24, 2017 through April 24, 2020:



- Henceforth, we grouped each MP's tweets on a monthly basis.

Data

Data Preprocessing

- For preprocessing, we used the *quanteda* package in R.
- We immediately transcribed German umlauts (ä, ö, ü) and ligature (ß) and removed hyphens due to the presence of compound words in the German language (*Corona-Krise* vs *Coronakrise*).
- Next, we transformed the text data into a document-feature matrix (DFM), converted all characters to lowercase, and removed stopwords, units, interjections, etc.
- Finally, we performed word stemming, which cuts off word endings to remove discrepancies arising purely from declensions or conjugations (e.g., *politisch* $\rightarrow$ *polit*).

Results

- Hyperparameter search yields 15 distinct topics
- Topic labeling conducted manually (human judgment)
- Descriptive discussion of relationship between metadata and topics
- Causal inference: estimation of cause-effect relationships between document-sepcific features (e.g. political party) and topics

Bibliography