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

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Introduction

- Huge amounts of data, especially text, produced by social media
- Field of particular interest in the context of social media and big data: *Politics* (e.g., Brexit, 2016 presidential election in the US, Facebook data scandal).
- Tools of analysis for such data simultaneously provided by advances in *Natural Language Processing* (NLP)
- *topic analysis*: analytical tool for discovery and exploration of latent thematic clusters within text
- In this project: application of the *Structural Topic Model* (STM) **roberts2016model** 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 (I)

- *Words* w: instances of a vocabulary of V unique *terms*.
- *Documents* $d \in \{1, \ldots, D\}$: sequences of words of length N_d; $w_{d,n}$ denoting n-th word of document d
- *Corpus*: collection (or set) of D documents
- *Topics* $k \in \{1, \ldots, K\}$: latent thematic clusters within a text corpus; (implicit) representation of a corpus
- *Topic-word distributions* $\boldsymbol{\beta}$: probability distributions over words; $\boldsymbol{\beta}_k$ denoting the word distribution corresponding to the k-th topic

Topic Modeling: Motivation and Theory

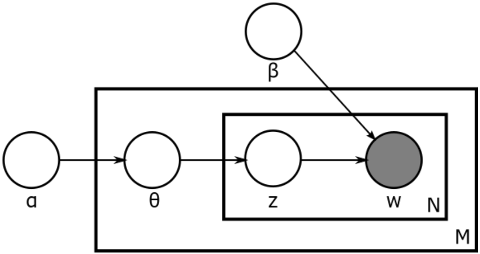
Notation and Terminology (II)

- *Topic assignments* $\boldsymbol{z}_{d,n}$: assignment of $w_{d,n}$ to a specific topic $k \in \{1, \ldots, K\}$; $\boldsymbol{\beta}_{d,n}$ representing the (assigned) word distribution for $w_{d,n}$
- *Topic proportions* $\boldsymbol{\theta}_d$: proportions of document d's terms assigned to each of the topics; $\sum_{k=1}^{K} \theta_{d,k} = 1$, for all $d \in \{1, \ldots, D\}$
- *Bag-of-word* assumption: only words themselves meaningful, unlike word order or grammar; equivalent to assuming *exchangeability* **aldous1985exchangeability**.

Topic Modeling: Motivation and Theory

Latent Dirichlet Allocation (LDA) (I)

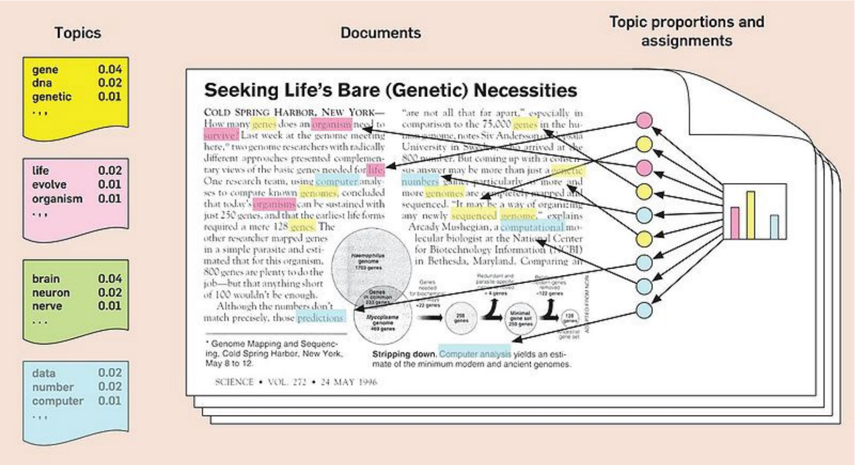
- First topic model with entirely probabilistic generating process: LDA **blei2003latent**
- Generative process for each document $d \in \{1, \ldots, D\}$:
  1. Draw topic proportions $\boldsymbol{\theta}_d \sim \mathrm{Dir}_K(\boldsymbol{\alpha})$.
  2. For each word $n \in \{1, \ldots, N_d\}$:
     a) Draw a topic assignment $\boldsymbol{z_{d,n}} \sim \mathrm{Multinomial}_K(\boldsymbol{\theta}_d)$.
     b) Draw a word $w_{d,n} \sim \mathrm{Multinomial}_V(\boldsymbol{\beta}_{d,n})$.
- Graphical model representation of LDA: **blei2003latent**



Topic Modeling: Motivation and Theory

Latent Dirichlet Allocation (LDA) (II)

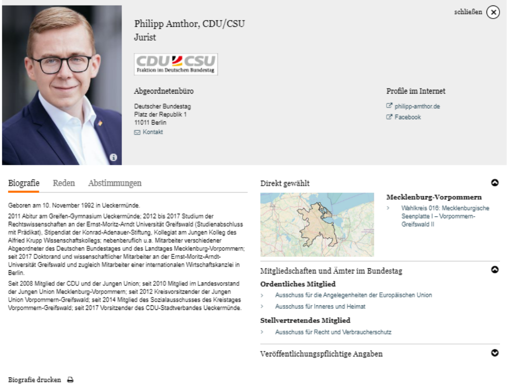
- Illustration of topic assignment for the words of a document: **blei2012probabilistic**



Data

Data Collection (I)

- MP-level data: from `www.bundestag.de/abgeordnete` using Python's *BeautifulSoup* and a *selenium web driver* **van1995python richardson2007beautiful**

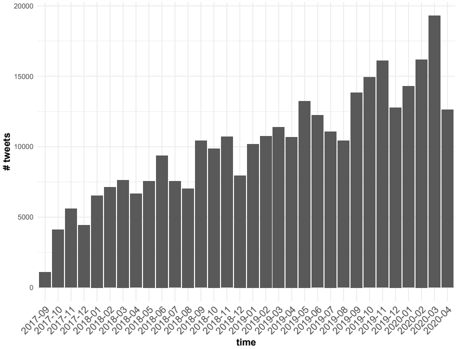


- Socioeconomic data and 2017 German federal election results: from `www.bundeswahlleiter.de`.

Data

Data Collection (II)

- Tweets (and further Twitter features): via the official Twitter API using Python's *tweepy* library**roesslein2020tweepy**
- Monthly tweets (after dropping MPs without electoral district) for our period of analysis, September 24, 2017 through April 24, 2020:



- In the following: grouping each MP's tweets on a monthly basis

Data

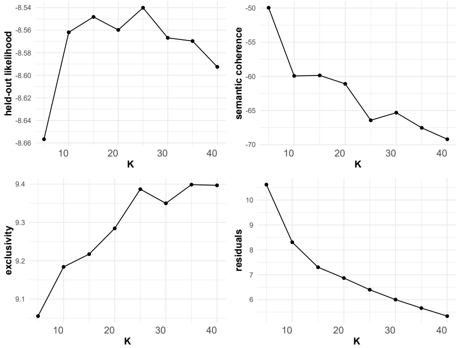
Data Preprocessing

- Preprocessing: in R **R**, using the *quanteda* package **quanteda**
- Transcription of German umlauts (ä/Ä, ö/Ö, ü/Ü) and ligature (ß)
- Removal of hyphens: relevant for compound words (e.g., *Corona-Krise* vs *Coronakrise*)
- Transformation of text data into document-feature matrix (DFM); conversion to lowercase; removal of stopword, units (*kg*, *uhr*), interjections (*aaahhh*, *ufff*), etc.
- Word stemming, i.e., cutting off word endings (e.g., *politisch* → *polit*) **lucas2015computer**

Model Selection and Global Characteristics

Model Selection

- Model evaluation metrics for hyperparameter K (number of topics):



- Best trade-off: $K = 15$

Model Selection and Global Characteristics

Labeling (I)

- First step: inspection of top words

Topic 1 Top Words:
Highest Prob: buerg, link, merkel, frau, sich
FREX: altpartei, islam, linksextremist, asylbewerb, linksextrem
Lift: eitan, 22jaehrig, abdelsamad, abgehalftert, afdforder
Score: altpartei, linksextremist, frauenkongress, islamist, boehring
Topic 3 Top Words:
Highest Prob: brauch, wichtig, leid, dank, klar
FREX: emissionshandel, soli, marktwirtschaft, feedback, co2steu
Lift: aequivalenz, altersvorsorgeprodukt, bildungsqualitaet, co2limit, co2meng
Score: emissionshandel, co2limit, basisrent, euet, technologieoff
Topic 4 Top Words:
Highest Prob: sozial, miet, kind, arbeit, brauch
FREX: mindestlohn, miet, wohnungsbau, mieterinn, loehn
Lift: auseinanderfaellt, baugipfel, bestandsmiet, billigflieg, binnennachfrag
Score: miet, mieterinn, mietendeckel, grundsicher, bezahlbar
Topic 6 Top Words:
Highest Prob: gruen, klimaschutz, brauch, klar, euro
FREX: fossil, erneuerbar, kohleausstieg, verkehrsminist, verkehrsw
Lift: abgasbetrug, abgebaggert, abschalteinricht, abschaltet, ammoniak
Score: erneuerbar, fossil, zdebel, verkehrsminist, klimaschutz

- XXX

Model Selection and Global Characteristics

Labeling (II)

- word cloud
- Twitter excerpt!!

Model Selection and Global Characteristics

Labeling (III)

- Final labels
- XXX

Model Selection and Global Characteristics

Global Topic Proportions

- graph: weighted and unweighted props
- XXX

Model Selection and Global Characteristics

Global Topic Correlations

- topic 3 and 6 overlap
- topic correlation graph

Bibliography