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)

Notation and Terminology (I)

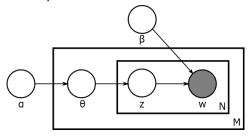
- Words w: instances of a vocabulary of V unique terms.
- Documents $d \in \{1, ..., D\}$: sequences of words of length N_d ; $w_{d,n}$ denoting n-th word of document d
- Corpus: collection (or set) of D documents
- Topics $k \in \{1, ..., K\}$: latent thematic clusters within a text corpus; (implicit)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

Notation and Terminology (II)

- Topic assignments $\mathbf{z}_{d,n}$: 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 θ_d : proportions of document d's terms assigned to each of the topics; $\sum_{k=1}^K \theta_{d,k} = 1$, for all $d \in \{1, \dots, D\}$
- Bag-of-word assumption: only words themselves meaningful, unlike word order or grammar; equivalent to assuming exchangeability aldous1985exchangeability.

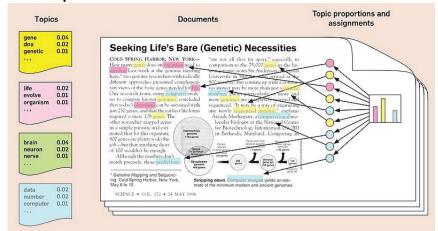
Latent Dirichlet Allocation (LDA) (I)

- First topic model with entirely probabilistic generating process: LDA
 blei2003latent
- Generative process for each document $d \in \{1, ..., D\}$:
 - ① Draw topic proportions $\theta_d \sim \mathsf{Dir}_K(\alpha)$.
 - ② For each word $n \in \{1, ..., N_d\}$:
 - ① Draw a topic assignment $z_{d,n} \sim \mathsf{Multinomial}_{\mathcal{K}}(\theta_d)$.
 - ① Draw a word $w_{d,n} \sim \text{Multinomial}_V(\beta_{d,n})$.
- Graphical model representation of LDA: blei2003latent



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

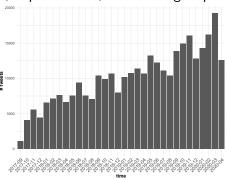


 Socioeconomic data and 2017 German federal election results: from www.bundeswahlleiter.de

Data

Data Collection (II)

- Tweets (and further Twitter features): via the official Twitter API using Python's tweepy libraryroesslein2020tweepy
- 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

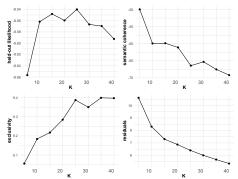
Data

Data Preprocessing

- Preprocessing: in R R, using the quanteda package quanteda
- Transcription of German umlauts $(\ddot{a}/\ddot{A}, \ddot{o}/\ddot{O}, \ddot{u}/\ddot{U})$ and ligature (\dot{B})
- 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., $politisch \rightarrow polit$) lucas2015computer

Model Selection

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



• Best trade-off: K = 15

Labeling (I)

- Three-step procedure for labeling
- First step: top words for different weighting methodologies

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:

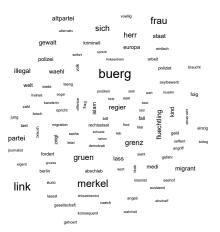
Highest Prob: gruen, klimaschutz, brauch, klar, euro

FREX: fossil, erneuerbar, kohleausstieg, verkehrsminist, verkehrsw Lift: abgasbetrug, abgebaggert, abschalteinricht, abschaltet, ammoniak

Score: erneuerbar, fossil, zdebel, verkehrsminist, klimaschutz

Model Selection and Global Characteristics Labeling (II)

Another illustration of **Highest Prob** top words (for topic 1):



Word size corresponding to word frequency in topic 1

Model Selection and Global Characteristics Labeling (III)

 Second step: look at documents (i.e., original tweets) with highest proportion of topic 1



Ehem. Verfassungsrichter bestätigt AfD-Forderung: Zurückweisung illegaler Migranten dringend geboten. Gegenwärtige Politik widerspricht dem Verstand und auch der Verfassung. Wir müssen zurück zu Recht & Ordnung, wie die #AfD seit fast 3 Jahren fordert!



Hans-Jürgen Papier hält Zurückweisung von Migranten an deutscher Grenze für ... Im Asylstreit meldet sich nun Ex-Verfassungsrichter Papier zu Wort. Die Zurückweisung von Migranten an den Grenzen sei zwingend nötig, schreibt er in... \mathscr{G} welt.de

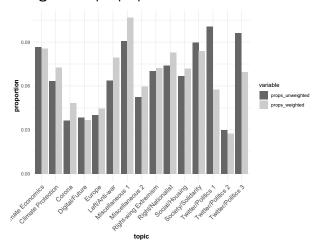
Labeling (IV)

Third step: assigning labels

Topic1	Right/Nationalist
	9 /
Topic2	Miscellaneous 1
Topic3	Climate Economics
Topic4	Social/Housing
Topic5	Digital/Future
Topic6	Climate Protection
Topic7	Europe
Topic8	Corona
Topic9	Left/Anti-war
Topic10	Twitter/Politics 1
Topic11	Twitter/Politics 2
Topic12	Miscellaneous 2
Topic13	Twitter/Politics 3
Topic14	Right-wing Extremism
Topic15	Society/Solidarity

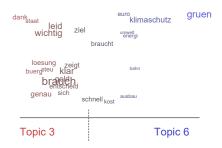
Global Topic Proportions

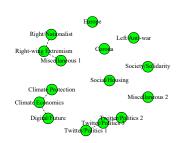
• Illustration of global topic proportions:



Global Topic Correlations

• Vocabulary overlap (left) and topic correlations (right):





Bibliography