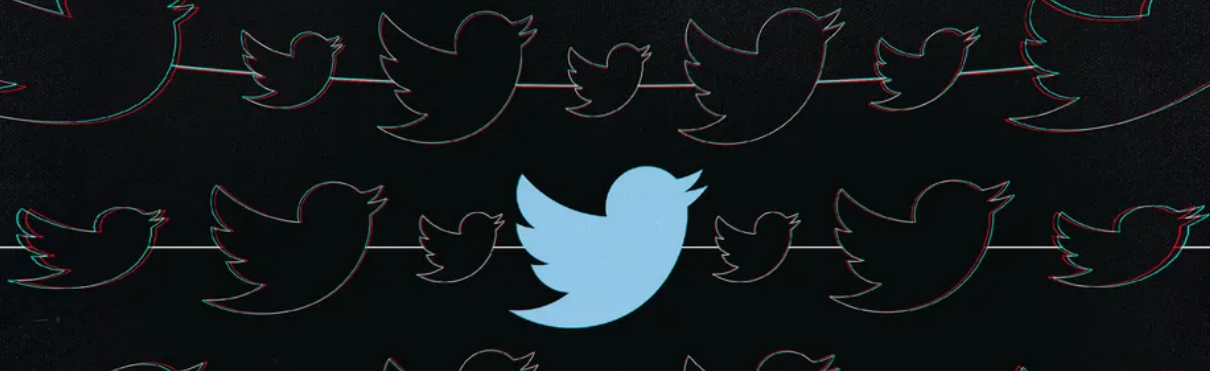

Topic-specific sentiment analysis for tweets by German MPs

Statistical consulting

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OUTLINE

1 INTRODUCTION & PROJECT OUTLINE

1 INTRODUCTION

- Social media: constant stream of publicly available **text data**
- **Twitter** established as a medium for political discourse and constant source of information
- Frequently resurfacing **research questions:**
  - Which **topics** are being addressed?
  - What kind of **sentiment** is expressed about these topics?

1 PROJECT OUTLINE

- **Primary goal:** analysis of public sentiment in a topic-aware manner for posts scraped from Twitter by German Members of Parliament (MPs)

  → Explore how **topic-specific sentiment analysis** can be implemented with (1) standard ML techniques and (2) more complex DL models.

- **Secondary goal:** make analysis of social media texts in a political context more easily accessible to researchers

  → Provide teaching material on both approaches, composed as a coherent online course

2 GENERAL THEORETICAL CONTEXT

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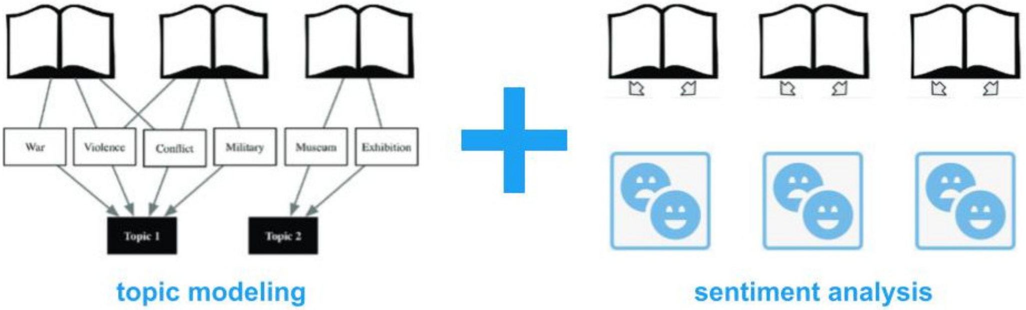

Figure 1: adopted and modified from Min and Park (2016)

→ Topic-specific sentiment analysis

2 TOPIC MODELING: IDEA

- **Goal**: discover latent semantic structures in a corpus & group documents into topical clusters with characteristic topic-word distributions
  - Exploratory tool → unsupervised learning task
  - Means of dimensionality reduction
- For each document $d \in \{1, 2, \dots, D\}$, assign a topic label $k \in \{1, 2, \dots, K\}$
  - K: key **hyperparameter**
  - Interpretability up to human practitioner

2 TOPIC MODELING: TAXONOMY

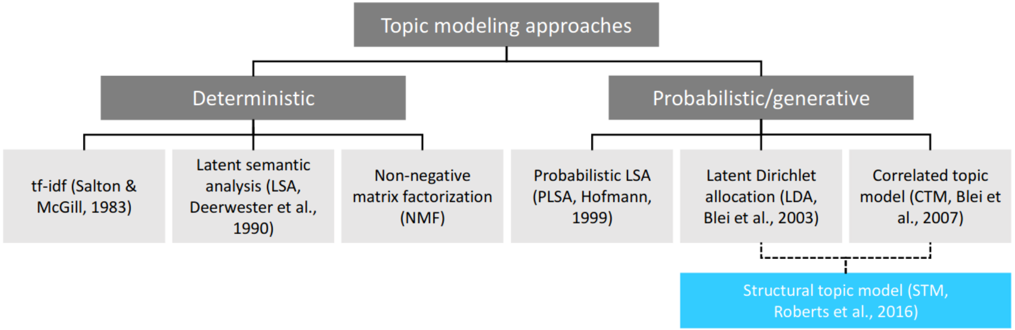

Figure 2: own representation, published on https://lisa-wm.github.io/nlp-twitter-r-bert/

2 TOPIC MODELING: GENERATIVE APPROACHES

Idea: reverse-engineer the imaginative process of document generation with hierarchical Bayesian mixture models

1. For each document $d \in \{1, 2, \dots, D\}$, draw a vector of topic proportions from some assumed distribution
2. For each word position $n \in \{1, 2, \dots, N_d\}$, $N_d \in \mathbb{N}$,
    1. draw a topic assignment from the distribution associated with the document-specific topic proportions
    2. draw a word from the distribution associated with the topic

2 TOPIC MODELING: GENERATIVE APPROACHES

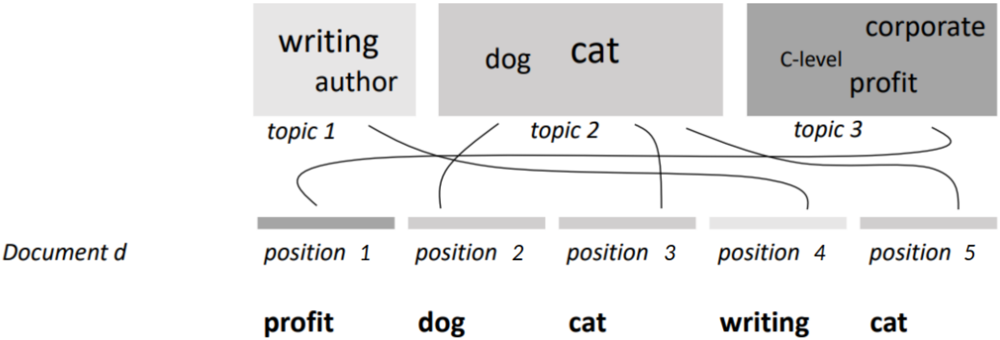

Figure 3: own representation, published on https://lisa-wm.github.io/nlp-twitter-r-bert/

2 SENTIMENT ANALYSIS

- **Goal**: assign sentiment labels to documents - in our case, out of $\{$positive, negative$\}$, formalized as $y \in \mathcal{Y} = \{0, 1\}$

- Standard **classification** task

- Find $f : \mathcal{X} \rightarrow \mathbb{R}^g$, $\mathcal{X} \subseteq \mathbb{R}^p$ for $p \in \mathbb{N}$

- Methods considered:

    - Standard ML: random forests & regularized logistic regression

    - BERT: fine-tuning to sentiment analysis

2 TOPIC-SPECIFIC SENTIMENT ANALYSIS

- **Idea:** combine **topic modeling & sentiment analysis**

- Subsequent modeling mostly due to the complexity of joint models

- Standard ML:
    - Build clusters of tweets based on topic modeling
    - Use clusters to generate topic-specific word embeddings

- BERT:
    - Aspect-based sentiment analysis (ABSA)
    - Aspect extraction & aspect sentiment classification

3 ANALYSIS

3.1 DATA

3 DATA COLLECTION: WEB SCRAPING

Idea: collect tweets by members of the German parliament (*Bundestag*) issued after the last federal election in September 2017

1. Gather MPs' names and basic information from the official Bundestag website
2. Find Twitter account names
3. Acquire socioeconomic information for the time of the last federal election on a per-district level
4. Scrape actual tweets along with some additional variables

→ **Manual labeling process**

3 DATA COLLECTION: WEB SCRAPING

Figure 4: urlhttps://www.bundestag.de/abgeordnete/

Figure 5: https://www.twitter.com/

3 DATA LABELING

- For each tweet: assign polarities **positive** or **negative**, and also **topic** descriptions required for BERT's ABSA task

- Note: large number of tweets with no apparent sentiment, aspect detection often difficult

- Class label distribution: **72%** negative labels

username	party	created_at	text	followers	unemployment_rate	label
karl_lauterbach	spd	2019-12-01 09:44:00	"Die Wahl ..."	337001	8.5	negative
Martin_Hess_AfD	afd	2018-08-17 07:15:00	"Vor den ..."	6574	3.5	negative
BriHasselmann	gruene	2019-09-25 15:35:00	"Ich finde ..."	20299	8.6	positive
danielakolbe	spd	2020-05-12 06:05:00	"Aber verpflichtend ..."	8158	8.3	negative
JuergenBraunAfD	afd	2020-08-13 22:05:00	"Panik-Latif + ..."	3188	3.4	negative

3 DATA: DISTRIBUTION OVER TIME

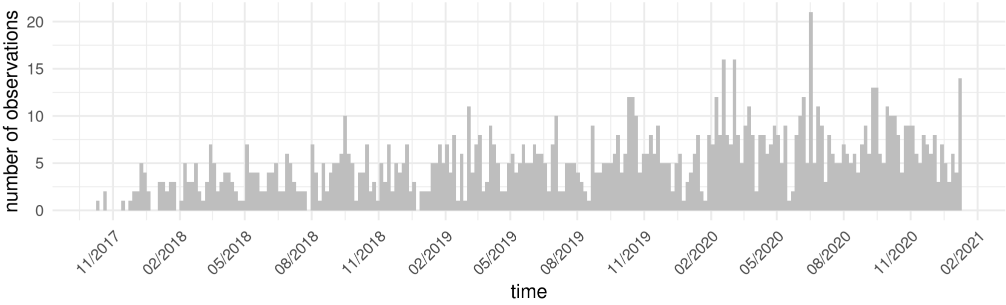

Figure 6: tweet issuance over time

Periodical fluctuations in the number of tweets over time and a general upward-sloping trend

3 DATA: DISTRIBUTION ACROSS PARTIES

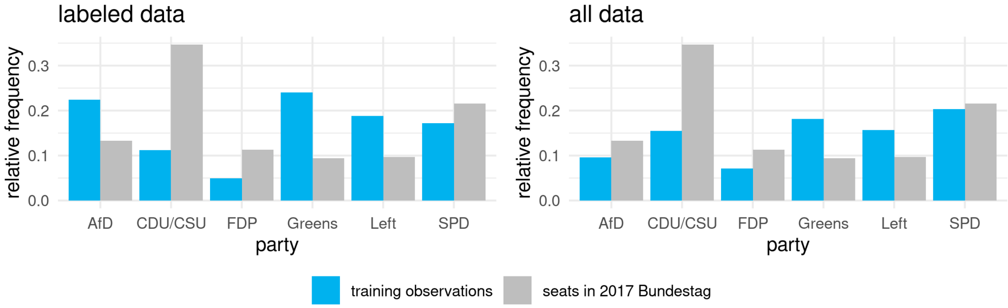

Figure 7: tweet issuance across parties

Observations per party in labeled training data (left) and entire scraped data example (right), both depicted against seat distribution in current parliament

3 DATA PRE-PROCESSING

- **Basic text cleaning:** transcription of German umlauts and ligature s into standard-Latin characters and removal of non-informative symbols

- **Twitter-specific preparation:** identification, separate storage and subsequent removal of special characters (i.e., hashtags, emojis and user tags)

Wir gedenken Willy Brandt, der heute vor 28 Jahren, am 8. Oktober 1992, verstarb. Mit seinen Reformen in der Sozial-, Bildungs- und Rechtspolitik hat er innenpolitisch neue **Massstaebe** gesetzt. **Kniefall Friedensnobelpreis mehrdemokratiewagen spd willybrandt**

3 DATA CHALLENGES

- **Language-specific:** many approaches predominantly tailored to English

  $\rightarrow$ possible complications with regards to German grammar and syntax

- **Twitter-specific:** limit of 280 characters; no explicit mentioning of the event or topical entity the author is referring to; informal language style

- **Context-specific:** requirement of domain knowledge within political context (specific vocabulary); sarcasm and irony

3.2 STANDARD MACHINE LEARNING SOLUTION

3 ANALYTICAL CONCEPT

Conceptualization as analytical **pipeline**

→ Exchangeability of components

→ Usability as integrated object

→ Preserving train-test dichotomy

→ Seamlessly integrated in `mlr3`

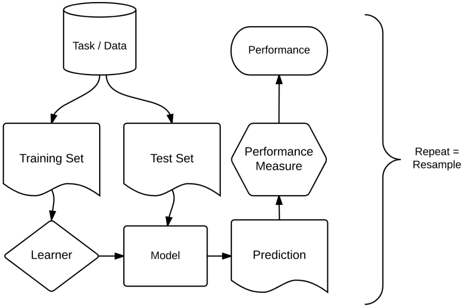

Figure 8: Becker et al. (2021)

3 STRUCTURAL TOPIC MODEL

wip

3.3 DEEP LEARNING SOLUTION

4 KNOWLEDGE TRANSFER

5 CONCLUSION

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