CENTER FOR
CIVIL SOCIETY
RESEARCH

Automated protest event analysis

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Exciting times

- previously: data are **rare, hard to collect, expensive**
- humans produce **a lot of text**
- available **computational power**

What do we mean by “text-as-data”?

- Texts are used to communicate → contain information
- understanding texts as data, not main intention of the communication
- necessary: simplification
- imposing abstraction

On the shoulders of giants

- *"if I have seen further [than others], it is by standing on the shoulders of giants."*
- *need* to build on decades long research traditions and theories
- *provide* a toolkit to further develop established methods
- CSS in itself as *cumulative process*
- for instance: **Protest Event Analysis**

Protest Event Analysis

- modern societies as protest societies
- protest as non-institutional arena for attitudinal polarization and political conflict

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Protest Event Analysis

- standard methodology for the **systematic collection of protest events** among political scienstist sociologists
- often based on **media reporting**, i.e. newspaper articles, and - more recently - on social media
- human coding → **labour- and resource-intensive**

A more computational take on PEA: Automatisation

- protest event analysis based on **automated event extraction**
- **classifiers** to pre-select relevant texts from newspaper articles
- standard approaches and cutting-edge methods, such as transformer models
- **geo-referencing** based on Named-Entity-Recognition and GoogleMaps API
- combined with reduced human coding

The German Political Protest and Radicalization Monitoring - MOTRA

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Goals

- Systematic gathering of protest events across in length and depth across political phenomena, space, and time in Germany → demonstration, confrontational, violence
- Embedding of political protest and radicalization in public debates
- Understand radicalization of individuals and bridge to organized actors

Three data collection instruments

- Protest Event Analysis (PEA)
- Public debates in mass and social media
- Biographic profiles of radicalized protest actors

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- **Protest Event Analysis (PEA) → AUTOMATIZATION**
- Public debates in mass and social media
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Nationwide Protest Monitoring in Depth and Length - PEA

Research items of interest

- When, where, who, with which claims does protest occur?
- To what degree do we see politically motivated violence in the protest arena?
- Which spatial foci can we link with radicalized protest?

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Main challenge

- collection of protest event data from newspapers (Süddeutsche Zeitung)
- combine with ProDat data (1950-2000)
- many articles
- planned expansion with regional newspapers

Nationwide Protest Monitoring in Depth and Length - PEA

Data gathering

- Identification of protest events in print news media
  - Start and basis of the process: full corpus of **Süddeutsche Zeitung**
  - Extensions: taz, Die WELT, regional press, Junge Freiheit + police press releases

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- Post-classification: **human coding** of protest form, actors' constellation, addressees and political claims

Protest Monitoring - PEA

Structure of pipeline

- collecting articles
- pre-filtering
- coding training data (needs to be balanced)
- training classifier
- apply classifier
- human coding
- de-depulication and cleaning

Automatization of PEA

The “Haystack”

- many documents → electronic news databases and computational tools
- first (important!) step: **Which documents contain protest?**

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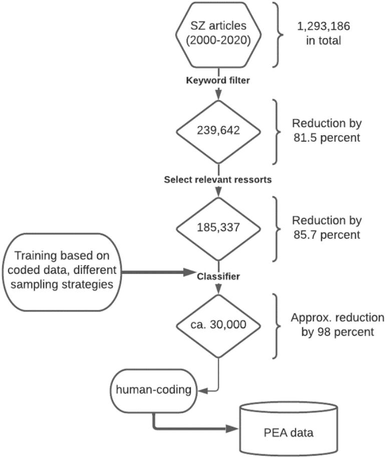
- supervised and unsupervised classifiers: need for training data
- example: Spam, Netflix suggestions

Protest Event Data generating process

Figure 1: PEA pipeline


SZ articles (2000-2020)
1,293,186 in total
Keyword filter
239,642
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Training based on coded data, different sampling strategies
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Variables of interest

Included Variables:

- Location of protest
  - Categorical: in Germany or abroad
  - If in Germany: state and city
- Protest offline or online
- Protest event: selection of all relevant sentences (strings)
- Action form: categorical and exact wording as string
- Claim, Actors, Addressee
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Carried out by a team of ca. 4 RAs in the PolDem Coding-Tool

Pre-filtering

Protest keywords

- e.g. *protest*, politically motivated*, (extreme left*, extreme right*, racist*, islamist*, antisemiti*) AND (motivated*, background, criminal*), confessor*, Staatsschutz*, demonstr*, *demo, *demos, *manifestation*, torch parade*, *march*, human chain*, *bomb*, Molotow*, graffiti*, arson*, *attack*, *attacks*, *graffiti*, graffiti*, hostage, *attack*, *terror*, *assault*, *attack*, death threat*, hate message*, hate mail*, threatening mail*, threatening letter*, etc.

Pre-Filtering

Excluded sections

- Forum & Leserbriefe, Geld & Technik, Hobby, Immobilien, JETZT.DE, jetzt.muenchen, Jugend, Schule, Berg- und Ski-Journal, Kinder- und Jugendliteratur, Kinder- und Jugendmedien, Kinderseiten, Kunstmarkt, Literatur, Literaturbeilage, Meinungsseite, Mietmarkt, Mobiles Leben, Mode, Reise, Zeitung in der Schule, Zeitvertreib, Sport

Balancing pipeline

▷ With a list of German *places* from Wikipedia we balance the training towards domestic events: mentioning one German location and being reported from Germany

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Location Entity Recognition & GoogleMaps API

- Identify locations with Name Entity Recognition-NER in spacyr:: to benefit from a Python-based pre-trained model (de_core_news_sm)
- Send request through GoogleMaps API to obtain latitude and longitude
- Is the "place" in Germany?

Protest Event Data training samples

Table 1: Sampling and Balancing Strategy over Rounds

Sample	Sampling selection strategy	N	
1	Ressorts + Protest Keywords	2712	
2	Negative Cases	2107	
3	1 + List of German Locations	2045	
4	1 + Location Entity Recognition & GoogleMaps & narrative differentiation	1979	
		Total=	8661

▷ Goal: looking for the needle in the haystack

Sample balancing - validation

Figure 2: Observations by sample

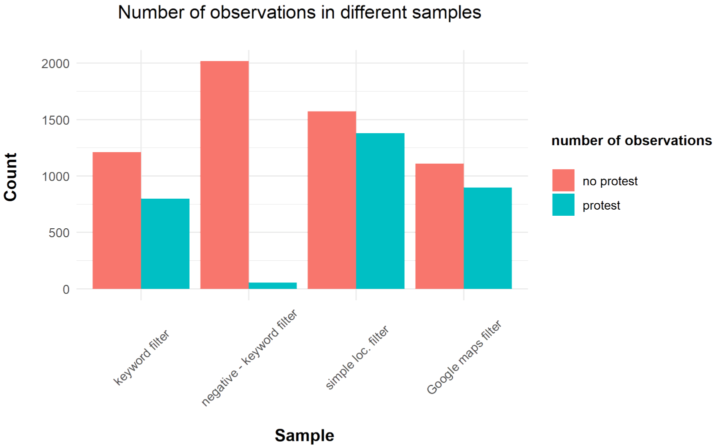

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Figure 3: Protest location by sample

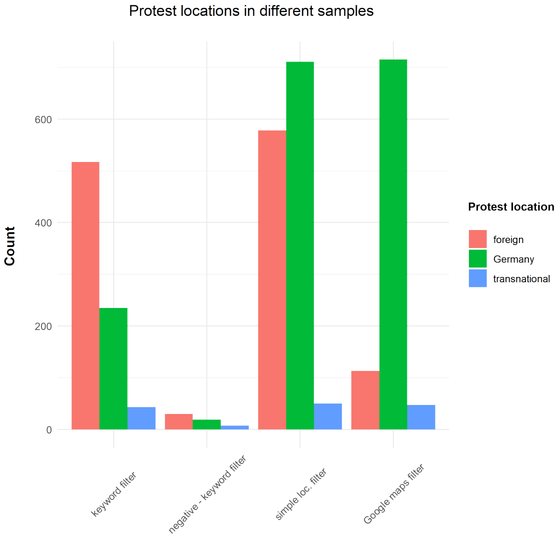

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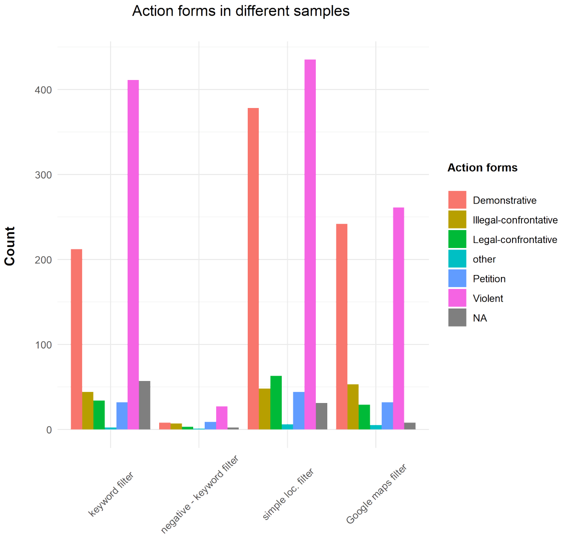
Figure 4: Action form by sample



Special additional variable

Protest narratives

- Beyond differentiating from *concrete* protest events and just articles containing protest keywords (e.g. "MP Weidel protested in the parliamentary session..."), we introduce "narratives"
- **Narratives**: actual content on protest dynamics, however, only mentioning references without talking about concrete events, e.g. "The 1970s protests changed politics" or "Terrorist threats remain latent in France..."
- Expectation: generate a fine-grained differentiation in semantics by discriminating between concrete "acts" and references; the latter being able to contaminate negative articles including *other* protest wording

Machine learning classifiers

Figure 5: Binary classification problem

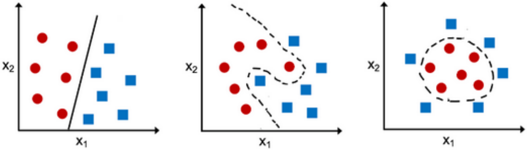


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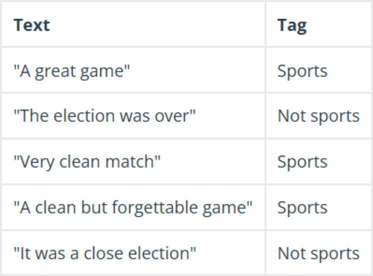
Figure 6: Naive Bayes



Text	Tag
"A great game"	Sports
"The election was over"	Not sports
"Very clean match"	Sports
"A clean but forgettable game"	Sports
"It was a close election"	Not sports

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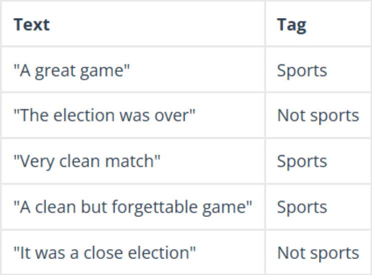

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Figure 7: What about this?

$$P(a\,very\,close\,game) = P(a) \times P(very) \times P(close) \times P(game)$$

Automatized classification of German events in news: machine learning predictions

Machine learning models

- Different performance across classic quanteda.textmodels and tidymodels in R, and Python models with nltk and skitlearn
- Overall tested: Random Forest, SVM, Logistic Regressions, Naive Bayes, Lasso regressions

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- Removal of numbers, symbols, punctuation
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Best performance: lemmatized Naive Bayes classifier with quanteda (multinomial distribution specification) reaching specificity of 0.74 and precision of 0.36

Post-classification coding

Human coding including

- Actors
- Number of participants
- Demands/claims
  - based on updated Prodat issue list
  - directional
- Addressees

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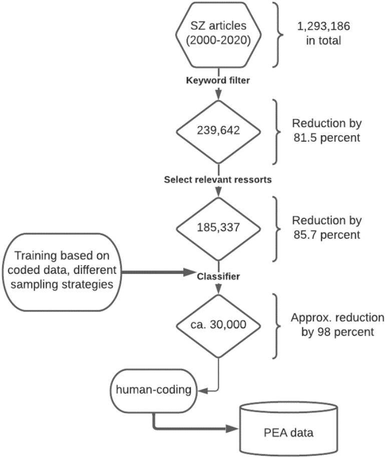
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What to do with this?

The bridging power of text-as-data

- highlights the value of description
- leaves room for discovery
- text-based automated analyses can connect quantitative and qualitative scholars

Protest Event Analysis

Research interests 2020/2021

- What was the influence of the pandemic on protests in Germany?
- Covid protests: Formation of a new movement? Radicalization?
- Was the new "Querdenken" movement able to dominate German street protests?
- Other movements: Continuous constraints or adaptation to a "new normal"?

Main findings

Development and radicalization of the German protest landscape

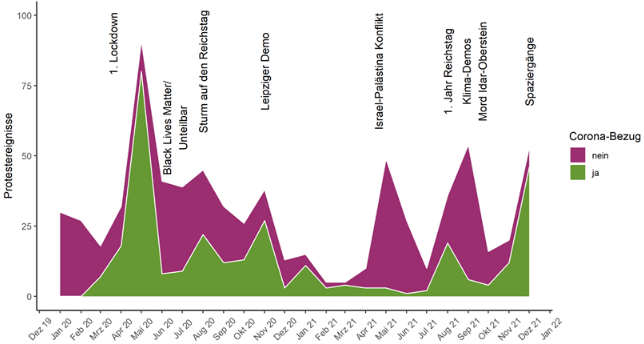
- **Re-mobilization** of the protest arena in the second year of the pandemic - still marked by anti-containment protests
- parallel **radicalization of the action repertoire** - "Querdenker" and radical right as main drivers of street radicalization

Core findings

- **Street protest:** still the **central means** of collective expression of opinion during the pandemic
- **Radicalization** of protest dynamics during the second year of the pandemic
- Dominance of Covid protests mainly in 2020
    - Institutionalization of ”Querdenken”
    - but no complete displacement of other movements
- Relative **re-mobilization** of the protest landscape in 2021
    - fewer restrictions and politicization in the context of the German federal elections

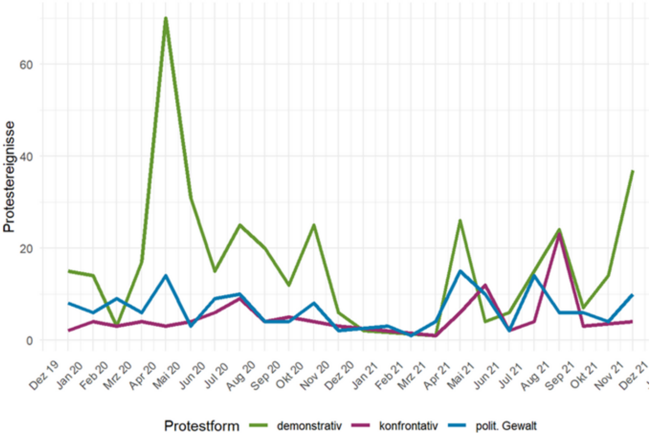
2020 and 2021: Covid and other protests in comparison

Figure 9: PEs in Germany



Forms of protest in comparison

Figure 10: Protest forms



Forms of protest in comparison

- still (mainly in 2020) dominance of demonstrations
- 2021: relative radicalization of the action repertoire
- driven by which issues?

Main issues

Dominance of Covid/"Querdenken" protest (43 percent)

- Mobilization in waves
- Mass events but also increasingly confrontational and violent

Environment and mobility

- Less confrontational

Integration, migration and racism

- Mobilization on both sides
- Often violent: Right-wing extremism and Islamism

Combination with ProDat

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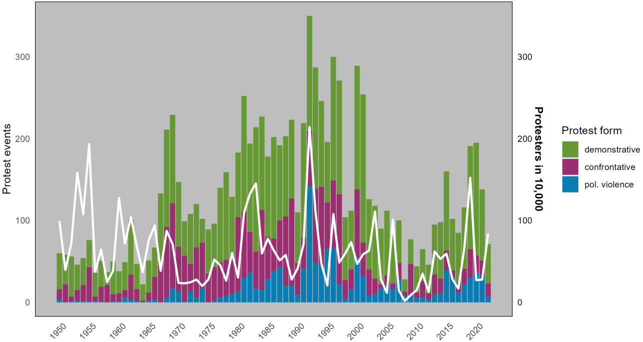

Figure 11: Protest 1950 - 2022

Many thanks for your attention!

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