
Sentiment Political Compass: A Data-driven Analysis of Online Newspapers regarding Political Orientation

Fabian Falck¹ Julian Marstaller² Niklas Stoehr³ Sören Maucher² Jeana Ren²
Andreas Thalhammer⁴ Achim Rettinger⁴ Rudi Studer⁴

Abstract

In most cases, voters only have a vague and subjective perception of a newspaper's proximity to political parties. If voters are uninformed about the political attitude of media reporting, they may be manipulated in their democratic opinion-forming. One answer to biased news and false information is transparency and quantifiability. For this reason, we introduce the *Sentiment Political Compass*, a data-driven framework to analyze newspapers with respect to their political conviction. Newspapers are embedded in a two-dimensional space (left vs. right, libertarian vs. autocratic) resembling a compass, which serves as a tool for analysing relative political proximity. We provide technical details of the system, including the framework to crawl newspaper articles, locate and extract entities and perform entity sentiment analysis. We demonstrate the analytical power and informative value of our approach by analyzing over 180,000 newspaper articles with over 740,000 sentiments surrounding the federal elections 2017 in Germany. Since our model can be reproduced entirely open-source, it may be applied to classify the political landscape in any country in the world.

1. Introduction

1.1. Political Bias of Online Newspapers

News media is known as the fourth power in the democratic process taking the position of a mediator between politics and society (Beck, 2012). Assuming this powerful

¹Department of Computing, Imperial College London, London, United Kingdom ²Karlsruhe Institute of Technology, Karlsruhe, Germany ³Department of Computer Science, University of Oxford, Oxford, United Kingdom ⁴Institute of Applied Informatics and Formal Description Methods, Karlsruhe Institute of Technology, Karlsruhe, Germany. Correspondence to: Fabian Falck <fabian.falck17@imperial.ac.uk>.

role, it may strongly influence public beliefs and act as an opinion maker, as evidenced through many historic election campaigns. In most cases, voters only have a vague and subjective perception of a newspaper's proximity to the political parties. If voters are uninformed about the political purpose of media reporting, they may be manipulated in their democratic opinion-forming (Mutz, 1989). In particular, in the context of the reinvigoration of right wing movements in recent years, the position of online newspapers towards false information has acquired a new significance (Bessi et al., 2015). In many countries, the political landscape has undergone a fundamental change. The traditional terminology of left- or right-wing which is an integral part of common parlance is becoming more difficult to assess (Dalton and McAllister, 2015). Therefore, qualitative efforts for classifying political conviction need to be replaced by more quantitative models. How can we measure the political convictions of newspapers and their proximity to political parties using big data?

1.2. The Sentiment Political Compass

One answer to biased media reporting and false information is transparency and quantifiability. This paper analyses newspapers with respect to political opinion forming by making the following three contributions:

(a) We present the *Sentiment Political Compass (SPC)*, a data-driven framework that classifies the attitude of newspapers towards political parties. The approach is completely transparent since it is based on entity sentiment analysis of thousands of newspaper articles. The Sentiment Political Compass discloses the temporal dimension of connections between political events and societal shifts. These connections are visualized in a two-dimensional space resembling a compass, which serves as a tool for media monitoring.

(b) We present all technical details of the system including the framework to crawl newspaper articles, locating and extracting entities and performing entity sentiment analysis. We provide two full-fledge implementations of the entire working pipeline, one version using commercial services and another being entirely open-source. For this reason, the Sentiment Political Compass may be reproduced and applied to analyze the relation between the media landscape

and politics in any country in the world.

(c) In this paper, we demonstrate the analytical power and informative value of our approach, by analyzing the political media sentiment in Germany during the election year of the German federal parliament and the subsequent coalition negotiations in 2017/2018. Our final dataset contains over 180,000 newspaper articles with around 740,000 matched entity sentiments. Our analysis yields new insights about the effects of right-wing media coverage on the overall media landscape and the political parties.

The general working pipeline of the Sentiment Political Compass, as illustrated in figure 1, involves three high-level steps: (1) Article crawling: extraction of newspaper articles (2) Entity extraction and sentiment analysis: identification of political entities in newspaper articles and analysis of their contextual sentiment (3) Sentiment Political Compass: computation of the political position of the newspapers and subsequent analysis. Even though we present a generic

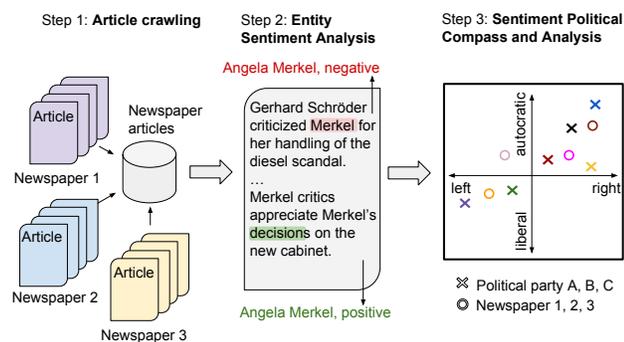


Figure 1. Schematic illustration of the high-level steps to perform the entity sentiment analysis and its subsequent analysis, concluding in the Sentiment Political Compass.

framework that is applicable to any possible country and time frame, we make use of a particular dataset throughout the paper. For ease of explanation and consistency, we build the technical framework upon a dataset of newspaper articles published during the election year of 2017 and 2018 in Germany.

First, we introduce related work and shed light on the technical details of the framework. This involves a description of how to crawl the newspaper articles, retrieve entities and perform entity sentiment analysis. These steps form the basis of our data pipeline. We showcase the analytical power of our approach and present encompassing analytical results, concluding in the the composition of the Sentiment Political Compass.

2. Related Work

2.1. Classification of Political Conviction

In this section, we present models and fundamental research in political science that form the basis of the Sentiment Political Compass. In the French revolutionary era, the terms left-wing politics and right-wing politics first originated (Lester, 1994). Early attempts to quantify political conviction date back to 1950 and 1956 respectively, when Leonard W. Ferguson and Hans Eysenck both designed models for a factor analysis of political values. In 1969, David Nolan created a chart diagram contrasting four major political convictions, conservative and liberal, authoritarian and libertarian in a 2-dimensional space (Nolan, 1971). According to the Nolan Chart, a differentiating criterion is a partys view towards economic and personal freedom. Numerous alterations of the Nolan Chart exist, introduced by Pournelle, Meltzer and Christie, Bryson and McDill, and also more dimensional variants like the Vosem Chart. Fritz first developed a model that introduces political parties into the Nolan Chart: The worlds smallest political quiz (Fritz, 1987) assigns a position in the plot according to a test takers answers to 10 questions which are divided into two kinds: economic and personal. In 2003, Greenberg and Jonas (Greenberg J, 2003) constructively discussed “psychological motives and political orientation” and laid the foundation of the “political compass”, a two-axis model introduced by the anonymous organisation politicalcompass.org (politicalcompass.org, 2001). The “political compass” constitutes a restructured version of the Nolan Chart by shifting back its interpretation to the standard left-right axis and a vertical axis representing ideological rigidity. Even though the “political compass” still tries to capture the political landscape in a two-dimensional space only, it combines long-established terminology with a more stretched classification and allows for quantitative analysis. In order to translate political views into the space, the model builds upon Fritz’s rule-based quiz by scoring the answers to 61 questions on the scale “strongly agree”, “agree”, “disagree”, “strongly disagree”. In a similar fashion, the German Federal Agency for Civic Education offers a question-answer-website to let voters compare their political conviction to specific topics with those of political parties (BPB, 2002). The so-called “Wahl-o-Mat” uses a scoring framework that resembles “The world’s smallest political quiz”. Politicalcompass.org provides a finalized model of the German party landscape in the election year 2017. We would like to highlight that we build on top of this existing model, enriching it with the political orientation of newspaper articles towards political parties based on sentiment information.

2.2. Sentiment Analysis on Newspaper Articles

Having introduced scientific approaches to measuring political conviction, we have a more detailed view on sentiment analysis in news media. Sentiment Analysis is an established term in natural language processing and is sometimes referred to as “opinion mining” in the context of newspaper analysis (Pang et al., 2008). Pang et al. (Pang et al., 2002) study the suitability of different machine learning approaches for sentiment analysis. The Sentiment Political Compass takes their findings into account by making use of entity sentiment analysis, which exploits rich semantics. The “subjectivity” in speech towards different political opinions has been studied extensively in various contexts (Carbonell, 1979) (Wilks and Bien, 1983). With the uprise of online newspapers and social media, sentiment analysis has gained fresh impetus. An extremely popular platform for sentiment analysis is Twitter. There exist numerous frameworks that analyze the political alignment of twitter users (Ceron et al., 2014) (Gautam and Yadav, 2014) (Gao and Sebastiani, 2015). Some researchers even debate the potential of Twitter analysis to replace traditional polls (Gayo-Avello, 2013). Other work is concerned with facebook posts regarding the user sentiment. In contrast to the Sentiment Political Compass, Neri et al. analyze the attitude towards media rather than politics. However, the size of their dataset is comparably small (Neri et al., 2012). Indicating the variety of media sources, Holtzman et al. explore media bias in television transcripts using semantic analysis tools (Holtzman et al., 2011). Other work is more social science-oriented and focuses on the identification and prediction of disruptive events in digital media. Specific Events with a large political scope are well suited for an online analysis, like the the Arab Spring (Boecking et al., 2014) or the Brexit votum (Hurlimann et al., 2016). Taking a very qualitative approach, Anstead et al. study political opinion during the UK election in 2010 (Anstead and O’Loughlin, 2014). To the best of our knowledge, there exists no prior work assessing the relationship between newspaper media and political parties using entity sentiment analysis of a huge amount of crawled newspaper articles.

3. Technical Framework

This section describes the data pipeline to generate a corpus of semantically labeled entities which all subsequent analysis will be based on. The high-level steps of this technical framework are as follows: First, we construct a database of political entities from different categories (such as party names or political representatives) and a second database of mass-media newspapers with diverse political orientations. Then, we search for a subset of these entities on the selected newspaper domains in dynamically adjusted time periods and gain article URLs stored in a database. The entity cate-

gories and whether they are used as search terms are listed in table 1. We also extract various meta-information from the articles (such as the article date). Subsequently, we extract the raw entities from the text and match them with our previously defined entity corpus. Finally, the sentiments of these entities based on their textual context are computed. This last step relies on state-of-the-art machine learning libraries and approaches. An overview of the data pipeline which will now be discussed in detail is given in figure 2. Note that the six steps in the figure correspond to the following six subsections.

Online newspaper selection. We analyzed both qualitative and quantitative criteria to decide which online newspapers, political magazines and party-related information websites are chosen for data crawling. For a *qualitative* selection, we put particular emphasis on independent, nationwide newspapers. Although local newspapers play an important role in the German media landscape, they often discuss content only relevant to a locally restricted group of people. Moreover, local newspapers often duplicate content relevant to a wider audience, such as foreign affairs or economic issues, from a sister newspaper within the same publisher (Maute, 2011) (Butenschön et al., 2017). In spite of their high net reach, we exclude news streaming services, such as upday (Samsung) or Google news, since they often republish and link articles from other sources and often do not publish own content. As a sanity check, we took presumably highly biased party newspapers and magazines of each major political party as well as few extremist newspapers into account, in spite of their smaller audience. We also considered the public opinion of the newspaper’s political orientation to ensure a both homogeneous and complete spectrum. Note that the consistency between the newspaper’s data-inferred political orientation and public opinion on its orientation is one major research question to be analyzed by this study, which is why we consider the public opinion of political orientation only for selection purposes, not as the “ground truth”.

Furthermore, two *quantitative* criteria both assessing the popularity of newspapers were evaluated. First, we considered the average number of monthly *PageImpressions* within the observation period from the category online offerings restricted to image and text content in German (ivw, 2018b), as measured by the German Audit Bureau of Circulation (IVW), an “independent, non-commercial and neutral auditing agency” (ivw, 2018a). *PageImpressions* are defined as clicks on a website unequivocally assigned to the newspaper by its fully qualified domain (FQDN) or an alias/redirect and explicitly caused by user input (IVW, 2018). As a second criterion, we analyzed the net reach of online newspapers in terms of unique users (statista.com, 2018).

Entity selection. Endeavoring to analyze a newspapers

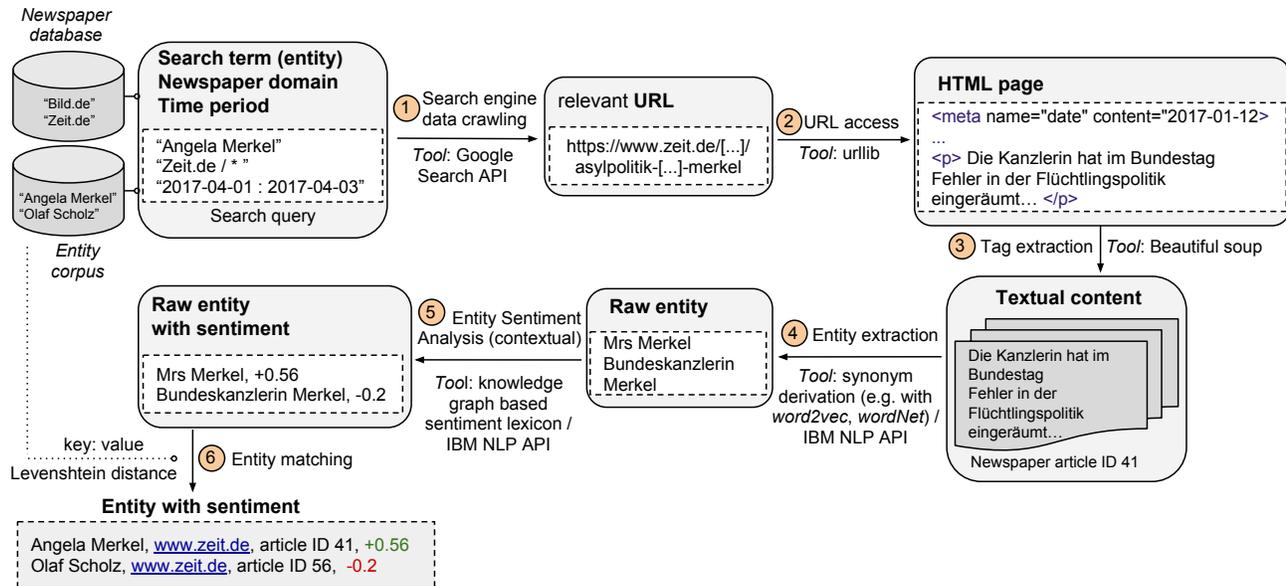


Figure 2. Schematic illustration of the pipeline to obtain the data underlying our analysis.

Entity category	# of unique entities	Search term
party name	10	✓
youth organization name of party	7	✓
chairperson	9	✓
deputy chairperson	31	✓
chancellor	1	✓
minister of the federal government	21	✓
secretary general	6	✓
state premier	16	✓
member of federal parliament	918	
honorary chairperson	12	

Table 1. Entity corpus categories. Note that if an entity belongs to two groups (e.g. is member of the federal parliament and member of the government), the categorization with the least entities (here member of government) is listed. If an entity is present in two different legislative periods, it is only listed once. Any entity occurring in an article that is also in the entity corpus is enriched with a sentiment. A subset of the entity corpus is used as search terms.

sentiment towards a political party, we need to establish a corpus of associated entities. Since the composition and size of the corpus strongly influences the latter sentiment analysis, we suggest a party-independent corpus selection schema. In particular, we decide to include the name of the political party and their youth organization, chairpersons, deputy chairpersons, secretary generals and honorary chairpersons of the parties, the names of chancellor and ministers of the old and new government, state premiers (Ministerpräsidenten) as well as the members of the federal parliament (Bundestag) during both legislative periods. We exclude members of state and communal parliaments or governments and ministerial staff (in particular secretaries of

state) due to their low coverage in the chosen target media. This comprises our entity corpus.

3.1. Search engine based URL crawling

The first step of our data pipeline is to crawl URLs of articles from domains in our newspaper database. The goal is to find such articles that are *relevant* to the public opinion forming process and that have been read by a large number of people. Typical approaches employ graph based spider-algorithms that recursively search for links on a certain domain (various open-source tools exist such as (scrapy.org, 2018)). However, this type of approach typically yields highly undirected and irrelevant results, in particular when one is interested in links from only one domain in contrast to articles discussing a common topic. Therefore, we employ a search engine based approach using the *Google Cloud Custom Search JSON API* (cloud.google.com, 2018). Using a search engine, relevance is determined by the search engine’s internal page rank algorithm and intuitively matches the attention it causes to a human reader.

Each search query consists of a search term, a target domain, the target language and a time period of interest. The search term is an entity from a subset of the entity corpus (we limited the search corpus to eliminate a large number of searches with no results). The target domain specifies the newspaper website to crawl articles from. The target language is German in our use case. Furthermore, in order to have an article distribution homogeneous in publication

date¹, we limit query results to such publications that lie in consecutive time periods, shifted over the full observation period. To determine the publication date at query time, we used *Page Dates* which is meta data provided by the search engine estimating the date of an HTML page based on features of the html page such as dates in the title and URL. The number of URLs extracted in a specific time period highly varies and is due to API constraints upper bounded to 10 URL queries. Therefore, we dynamically adjust this time period based on a protocol applied to the number of URLs extracted during the last query. If this number of URLs is high, the time period is shrunk so to limit the risk of exceeding the API upper bound with possibly relevant URLs to extract, if it is low, the time period is increased to avoid wasting quota.

3.2. URL augmentation and access

The URLs extracted by the search engine point to a particular page (for example, but not always the first page) of an article. However, we are interested in the full text of a crawled article, in particular to provide the full semantic context for all entities given. Therefore, we build a domain-specific augmentation mechanism that appends a page suffix or infix in the URL crawled by the search engine and accesses it using the HTTP/HTTPS protocol. If the domain responds with an HTTP 404 error, the page is non-existent. Otherwise, the accessed URL is added to the URL database. At the same time, we store the complete HTML pages of the accessed URLs in an intermediary storage.

3.3. Text and meta data extraction

Having extracted the URLs' HTML files, we now want to extract selected contents from the articles' HTML pages. This is required, since the largest amount of information on a typical HTML page on the web contains cluttered strings, for example for the layout or advertisement, which shall be excluded from the analysis. To do so, we access the URL and extract its title, the paragraph content and meta data information (such as the publication date) from the HTML file using the open-source tool *beautiful soup* (crummy.com, 2018). This required us to manually find the domain-specific HTML tags for each content type. One problem we were confronted with was that advertisement was on some domains embedded with the same HTML tags as article content and could therefore not be distinguished without further action. We solved this problem by finding characteristic, domain-specific text contents that were – if contained in the extracted paragraph strings – used to

¹If queries were made for each search term and target domain during the whole observation period, the article distribution would be biased towards more recent articles, since a more recent publication date tends to increase the relevance of an article.

exclude that part of the text.

3.4. Entity extraction

In this fourth step of our data pipeline, we want to extract entities from the crawled article contents that correspond to the entities in our original entity corpus. Often, articles use variations of the original entities in our corpus that refer to them. For example, the extracted entities “Sozialdemokratische Partei”, “Sozialdemokratische Partei Deutschlands” and “Sozis” all map to the original entity “SPD” in our entity corpus. Therefore, we manually include common synonyms, colloquial terms and abbreviations of entities in the corpus that can be directly mapped to these entities as illustrated in the example. Aiming at a quantifiable approach, one may fall back to machine learning approaches such as *word2vec* that classifies semantically similar words based on high-dimensional vector representations ([Mikolov et al., 2013](#)) or *wordNet* that compares semantic similarities hierarchically ([Miller, 1995](#)). One may also parse the newspaper articles in search of party-associated keywords by exploiting a multilingual entity database, e.g. established by Al-Rfou ([Al-Rfou et al., 2015](#)).

3.5. Entity Sentiment Analysis

Given these entities, we now aim at yielding sentiments for the extracted entities. The term *sentiment* can be defined as “settled opinion reflective of one’s feelings” ([Pang et al., 2008](#)). While literature differentiates multiple types of sentiments and related emotions, in this study, we focus on the simple classification of positive and negative sentiment on a continuous, upper and lower bounded scale. It is important to distinguish sentiment analysis from entity sentiment analysis. Sentiment analysis, extensively studied by academia and free enterprise, targets at figuring out whether a sentence or entire paragraph expresses a positive or negative sentiment. The sentiment, however, does not differentiate any individual entities within the text content and is specified as a decimal number ranging between 1 and -1 for a whole complete article. As displayed in figure 3, an entity may be associated with a negative sentiment even though it is actually contrasted positively. Moreover, the atomar decision to classify a certain entity with a certain sentiment is much easier to verify in comparison to judging the sentiment of a whole article with large variance in atomar sentiment which is another desirable property. Therefore, the more fine-grained technique of entity sentiment analysis is preferred. The IBM natural language processing API and similar platforms offer fee-based entity sentiment analysis services. Additionally, Chen et al. provide a multilingual, open-source implementation based on knowledge graph propagation algorithms and embeddings trained on the wikipedia corpus ([Chen and Skiena, 2014](#)). By utilizing their pre-trained implementation, we not only manage

Sentiment Political Compass: Data-driven analysis of political orientation

Newspaper domain	Category	Articles	Observations
bild.de	newspaper	10,182	37,931
der-postillon.com	satire newspaper	247	701
faz.net	newspaper	13,585	50,683
fr.de	political newspaper	9,645	36,348
focus.de	political magazine	21,590	94,886
handelsblatt.de	newspaper	5,569	17,417
huffingtonpost.de	newspaper	7,520	33,871
jungefreiheit.de	political newspaper	1,548	6,504
jungewelt.de	political newspaper	2,802	6,764
n-tv.de	news medium	8,217	36,065
spiegel.de	newspaper	11,084	56,815
stern.de	political magazine	3,572	12,916
sueddeutsche.de	newspaper	15,116	51,945
taz.de	newspaper	10,712	39,443
tagesschau.de	newspaper	3,024	14,245
tagesspiegel.de	newspaper	8,360	34,942
welt.de	newspaper	20,460	92,384
zeit.de	newspaper	12,059	51,925
<hr/>			
afdkompakt.de	party newspaper (AfD)	2,758	15,861
bayernkurier.de	party newspaper (CSU)	1609	6540
gruene.de	party newspaper (Die Grünen)	217	750
national-zeitung.de	party newspaper (DVU)	45	208
neues-deutschland.de	party newspaper (Die Linke)	10,478	33,918
unsere-zeit.de	party newspaper (DKP)	705	2,086
vorwaerts.de	party newspaper (SPD)	1,934	6,970
<hr/>			
Total	25 newspapers	183,038	742,118

Table 2. The newspaper domains in the final dataset and their categorization, together with the numbers of articles, mentioned politicians and entities.

in September 2017. Note that in this observation period, an exceptionally high amount of 5 state elections and one federal convention (election of the federal president) took place. The observation period comprises two legislative periods of the federal parliament. We chose this observation period, since it 1) corresponds to the most recent major political event in Germany and 2) is of high interest due to a 6-month long negotiation and foundation period of the government until March 2018. All analytical results are based on sentiments extracted using the IBM NLP API in steps 4 and 5 of the data pipeline. We published the final dataset together with all data analysis provided in a user-friendly Python Jupyter Notebook on the website www.politicalcompass.de.

4.1. Descriptive Analysis

To get a first overview of the dataset, we analyze the absolute and relative number of entities per newspaper and party affiliation in figure 5. Two observations can be made: First, the total number of entities highly varies depending on the newspaper, as every newspaper publishes differing numbers of articles. In particular, party newspapers yield less coverage than commercial newspapers. Second, party newspapers such as Afdkompakt.de (AfD), Vorwaerts.de (SPD), Bayernkurier.de (CSU) or Gruene.de (Die Grünen) have significantly higher coverage of representatives from their own party in comparison to others. This result is expected: The deviation from the normal relative coverage indicates the political bias of such newspapers.

Party-level analysis. We begin analyzing the sentiments on a party level: Figure 6 analyzes the average sentiment

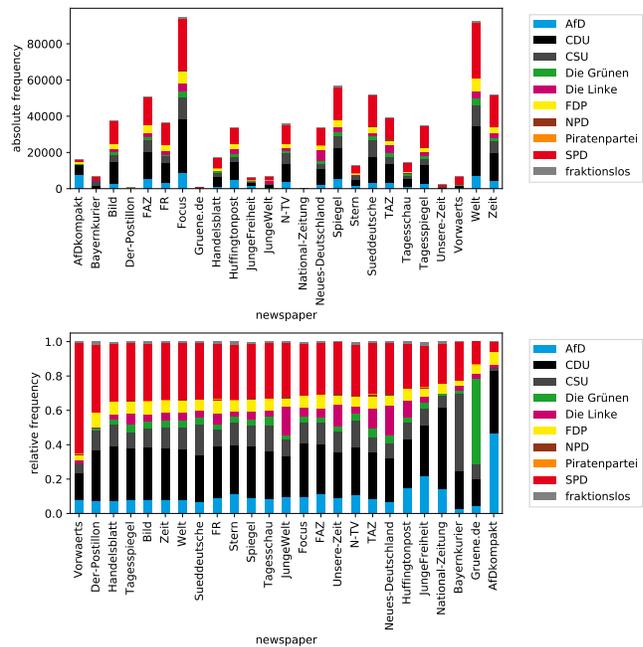


Figure 5. Top: Absolute entity mentions per newspaper and party Bottom: Relative entity mentions per newspaper and party

over all entities of a political party, separately for each newspaper. Several interesting conclusions can be made: First, the governing parties (CDU, CSU and SPD) are rather positively evaluated over almost all newspapers. Second, right and left parties like AfD and Die Linke are rather negatively evaluated by all newspapers. In particular, the party AfD, which in 2017 entered the federal parliament for the first time, is very negatively covered in accordance with the general opinion that media would negatively cover this party. As expected, the sentiments of the party newspapers of Die Grünen, SPD and CSU show a particularly positive average sentiment of their own party, strengthening the argument that sentiment analysis is a valid method for exposing political bias. Surprisingly, the Afdkompakt sentiment towards AfD representatives is rather low compared to FDP. A negative bias towards its own party is rather unlikely. A vague explanation could be inner-party disunity. The fact that Afdkompakt generally has more negative sentiments throughout all parties supports their characterization as a protest party (Arab, 2017). Given a general negativity of articles, misleading sentiments could result for AfD politicians, because they are mentioned in an overall negative article and the sentiment extracting algorithm is directing this global judgement to all entities in the article.

Entity-level analysis. After analyzing the newspapers' coverage on a party level, we now dive a level deeper and analyze sentiments towards politicians. Figure 7 shows a hi-

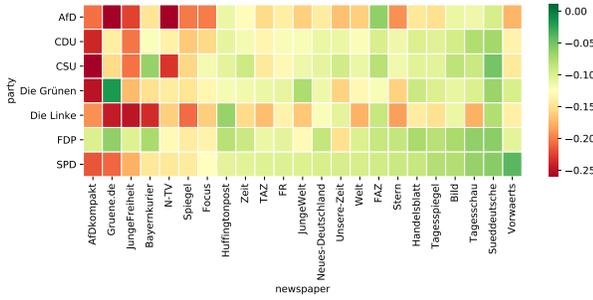


Figure 6. Sentiments averaged over all entities of a particular party, split by newspaper.

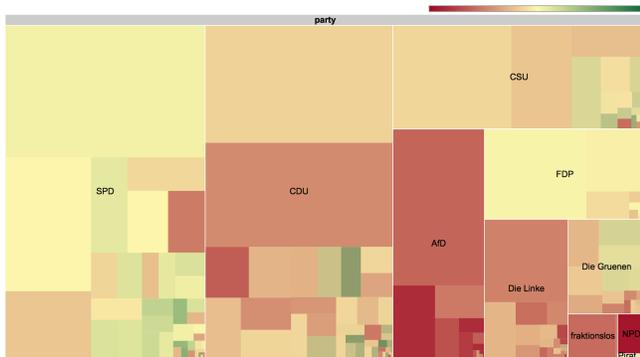


Figure 7. Heat map split by political party (areas) and entities (sub-areas). The size of the areas corresponds to the number of sentiments found in articles. The color reflects negative (red) or comparatively positive (green) sentiments.

erarchical tree map representing the sentiments by political party. The bigger the party’s sub-area in the map, the more articles mention the party and its affiliated politicians. Every political party is subdivided in smaller tiles that reflect mentions of individual politicians of the respective party. Again, we find varying sizes of the tiles according to the number of mentions. A red colored tile indicates a negative, green color a more positive sentiment. Since red tiles are predominant, we may conclude that the media sentiment is generally more negative than positive which coincides with the often spawned allegation against newspapers. Moreover, we find that some parties are more heterogeneous than others in the sense that the sentiments towards their affiliated politicians exhibit a wider range. While all politicians of the party AfD are reported negatively, the politicians of the party CDU range from strongly negative (dark red) to strongly positive (dark green).

In order to understand the sentiment values, figure 8 shows the distribution of negative and positive sentiments ranging

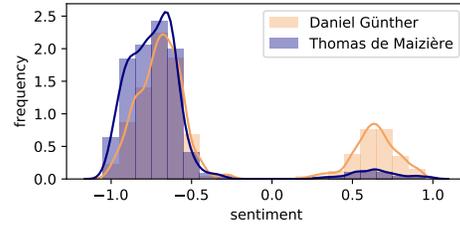


Figure 8. Histogram of positive versus negative mentions of Thomas de Maizière and Daniel Günther.

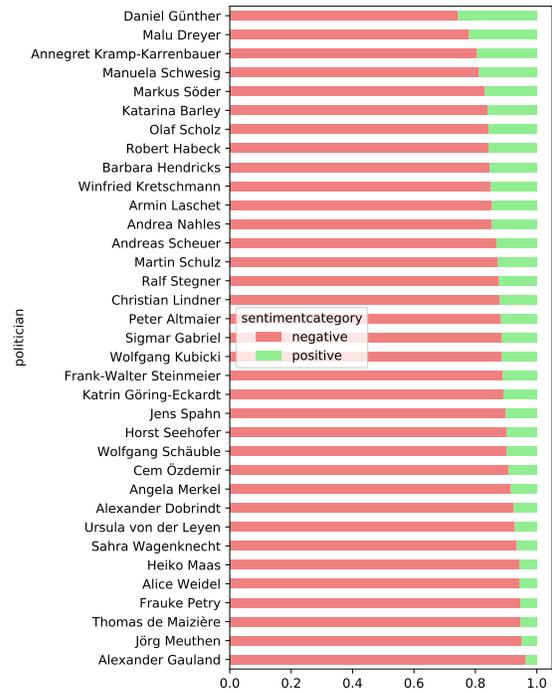


Figure 9. Comparison of positive versus negative mentions of several important politicians

from -1 to 1 of the CDU politicians Thomas de Maizière and Daniel Günther. The imbalance of negative compared to positive sentiments underline the general critical reporting towards politicians. Moreover, Günther is mentioned more frequently in positive context. He was elected state premiers (Ministerpräsident) of Schleswig-Holstein in June 2017.

Transforming the real-valued sentiments into the discrete, binary categories positive and negative, a comparison of relative frequencies in figure 9 yields a ranking reflecting popularity and media acceptance of the politicians. Four of the five best ranked politicians (Daniel Günther, Annegret Kramp-Karrenbauer, Manuela Schwesig and Markus Söder) were elected or promoted state premier (Ministerpräsident)

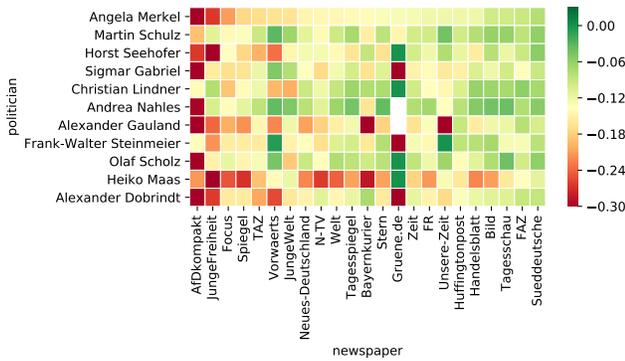


Figure 10. Sentiments averaged over selected entities, split by newspaper.

of a federal state of Germany during the analyzed time frame. This is another strong indication of the influence of newspaper bias on public opinion.

A heatmap of the average sentiments of politicians in different newspapers in figure 10 further examines the bias discovered on politician-level. Naturally, the SPD party newspaper Vorwärts positively mentions Martin Schulz, Sigmar Gabriel, Andrea Nahles, Frank-Walter Steinmeier and Olaf Scholz while they are criticized in AfDkompakt. Looking at Junge Freiheit, a pattern of positive attitude towards FDP politician Christian Lindner and several SPD politicians is visible suggesting a socio-liberal tendency of the newspaper.

Next, we bring together three perspectives: the party-level, the politician-level and the newspaper-level view. The Sankey diagram in figure 11 visualizes the number of mentions grouped according to these three aggregates. We observe the number of sentiment occurrences in newspapers and political parties (left → middle) and the number of sentiments affiliated with parties split by their corresponding politicians (middle → right). Two observations are particularly striking: First, the number of sentiments, split by the different parties in the middle section, is roughly proportional to the share of politicians of that party in the federal parliament. A second interpretation results from considering the right half of the Sankey diagram. Few entities make up most of the sentiments of a political party. For example, the entities CDU and Angela Merkel make up roughly half of the sentiments associated with the CDU party. This result is very surprising, since roughly 100 entities were used as search terms in the data crawling stage. Only few politicians consequently influence the political opinion, since they are over-proportionally covered by news media.

Time-varying analysis. As a last step of the descriptive

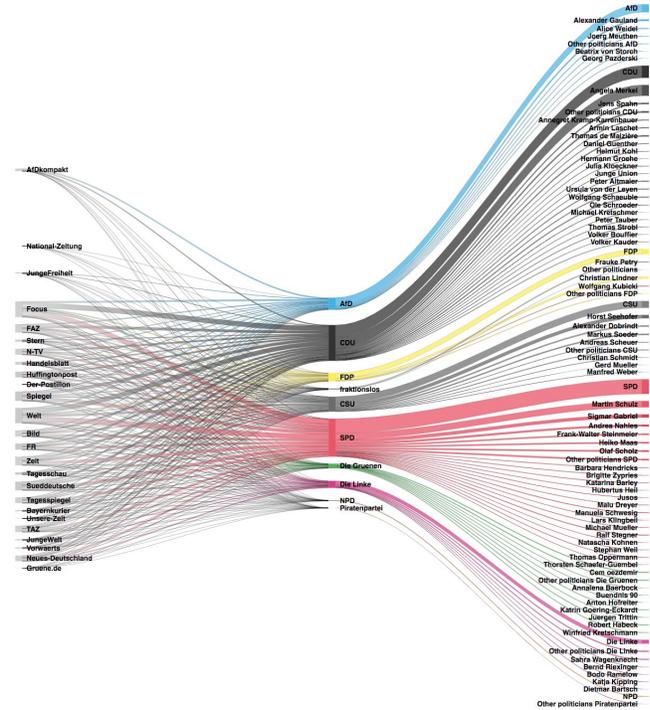


Figure 11. Sankey diagram visualizing the number of sentiments occurring in newspapers which are affiliated with political parties (left → middle) and the party’s split by entity (middle → right).

analysis, we turn towards the temporal dimension. Figure 12 visualizes the total number of sentiments per week, as extracted from articles with publication date in a certain week. We can observe that the number of sentiments is not distributed uniformly over the course of time. There exist several peaks next to important events such as elections or negotiations and rather small numbers of sentiments extracted during the summer slump (June to August) or the winter holiday (December, January). This effect was expected, since important political events produce more relevant political news which is subsequently reflected in the articles crawled by the search engine.

The sentiment of a politician or party over time is a noisy signal with high variance as seen before in the distribution in figure 8 resulting from multiple negative and positive observations in a single time frame. This is an undesirable property of the time series sentiments, since it prevents the analysis of smooth trends in the data. One way to treat this would be by choosing a different temporal aggregation (e.g. daily, weekly or monthly). However, this would increase the influence of periods with less mentions and would lead to heteroscedastic aggregations that oscillate in periods with less mentions. Instead, we treat the time series as a sequence and use convolution with window functions to smooth the

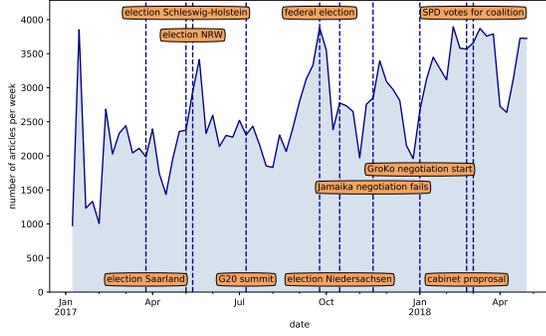


Figure 12. Absolute number of sentiments per week. Markers indicate important political events in time that might have an impact on the sentiment trajectory.

signal. In particular, the Boxcar (moving average), Tukey and Bohman window methods were tested. In a similar setting on empirical time series classification, the Bohman window performed well and likewise yields interpretable results in our case (Kim and Park, 2010). Given an input x , the general Bohman window with size M is defined as

$$W_M(x) = \begin{cases} \left(1 - \frac{|x|}{M}\right) \cos\left(\pi \frac{|x|}{M}\right) + \frac{1}{\pi} \sin\left(\pi \frac{|x|}{M}\right) & \text{if } |x| \leq M, \\ 0 & \text{if } |x| > M \end{cases}$$

Formally, a sentiment series S^P of a politician in the observed time $t \in 1, \dots, T$ with $t = 1$ referring to the first day and T referring to the last observed day can be formulated as follows:

$$S = \{S_1, S_2, \dots, S_T\}$$

$$S_t = \{s_{t,1}, s_{t,2}, \dots, s_{t,n_t}\}$$

The i^{th} sentiment on day t of a politician is described by $s_{t,i}$. Note that the number of observation n_t of a politician varies from day to day. To smooth the sentiment, we define the size M of the window depending on the average number of observations in a given time interval Δt and $J = \frac{T}{\Delta t}$ as

$$M = \max\left\{\frac{1}{J} \sum_{j=0}^J C(j, \Delta t), 3\right\}$$

With the max-operator limiting the minimum size of the window to 3 in case of very few sentiments and $C(j, \Delta t)$ denoting a counter function of observations in a given time interval defined as

$$C(j, \Delta t) = |\{s_{t,i} \mid \forall i \in \{1, \dots, n_t\}, \forall t \in \{j \cdot \Delta t, \dots, (j+1) \cdot \Delta t\}\}|$$

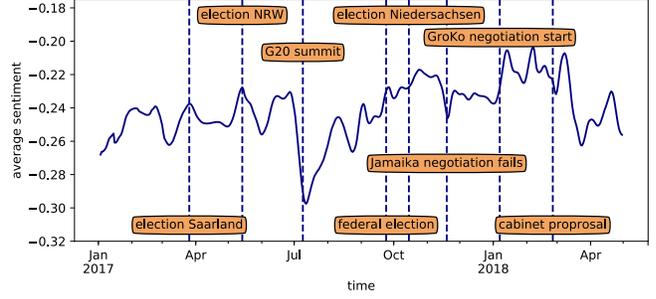


Figure 13. Average denoised sentiment over time

Finally, the denoised sentiment signal is extracted by convolving the window through the whole series

$S = \{s_{1,1}, \dots, s_{1,n_1}, s_{2,1}, \dots, s_{2,n_2}, s_{3,1}, \dots, s_{T,n_T}\}$ with index x for all observations as

$$\tilde{S} = (S * W)(x) = \sum_{k=1}^M S(x-k)W(k)$$

Defining the window dependent on the number of observations in a time window is intuitive, since it will yield time-consistent, smoothed sentiments for politicians independent of their mention frequency. This makes smoothed sentiments of different entities time-comparable. In our case, we set the time interval Δt to four weeks, providing a good trade-off between a denoised, smoothed time series and a conservation of the sentiment changes.

Figure 13 outlines the temporal change of average, denoised sentiments over the course of time. Again, we find a correlation between major political events and the average news sentiment. An eye-catching anomaly can be observed in July 2017, around the G20 summit that took place in Hamburg, Germany. The sentiment throughout all newspapers is more negative in this period. This could be due to the civil violence and the demonstrations against the summit that were strictly condemned by public opinion.

Figure 14 sheds another light on this finding as it separates the aggregated sentiment into the sentiments per political party. Here, we can find further explanations for the observations around the G20 summit. The media sentiment towards the left-wing party Die Linke is particularly negative in this time period. This may be traced back to the allegations that most of the violent protestants were left-wing extremists and the party was accused of not clearly enough differentiating itself from the violent acts. To give another example, in the context of the so-called ‘‘Jamaika coalition negotiations’’, the four involved parties FDP, Die Grunen, CDU and CSU experience a drop in media sentiment. After a 4-week long process, the liberal party FDP unexpectedly terminated the negotiations and beard criticisms for this act.

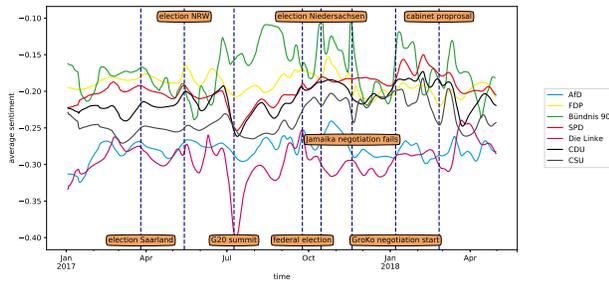


Figure 14. Average sentiment by parties over time

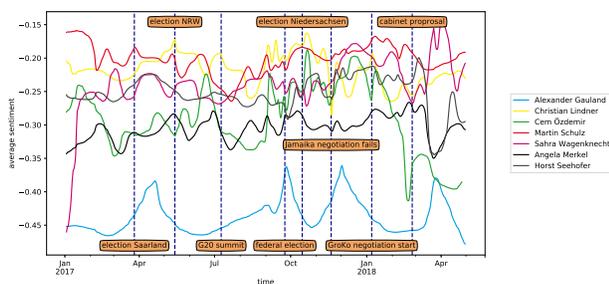


Figure 15. Average sentiment by politicians over time

Figure 15 reveals sentiment changes over time for the main representatives of the seven largest parties. For example, in January 2017, Sahra Wagenknecht (Die Linke, left-wing party) was confronted with major criticism from within her party after having criticized the refugee policy of Angela Merkel by utilizing an argument that was previously voiced by right-wing parties. Another clear change in sentiment can be observed for Cem Özdemir in the beginning of 2018 before his resignation as federal chairman of the party Die Grünen. Lastly, the average sentiment of Horst Seehofer (CSU party chairman) decreased in March 2018 after stating his famous sentence “*Der Islam gehört nicht zu Deutschland.*” (*Islam does not belong to Germany.*). This started a debate between Angela Merkel and Horst Seehofer leading to a more negative coverage for both entities. Since there are many more changes visible, we like to conclude this part of the analysis by calling for and encouraging further research on this dataset.

4.2. Sentiment Political Compass

Recalling our results in the previous section, we already gained detailed insights into the newspapers’ conviction towards political parties and their affiliated politicians. The previous analysis focused on a fine-grained view of the

sentiments of each newspaper towards parties and politicians separately. With the *Sentiment Political Compass (SPC)*, we aim at combining these proximities of newspapers towards all parties in a well-established framework.

As its predecessors, the SPC is a two-dimensional visualization that aims at classifying political attitudes on two scales: left vs. right and libertarian vs. autocratic. In our specific case, we take the political classification of political parties in this metric by *politicalcompass.org* as given and extend it with the positions of *newspapers* towards these parties (*politicalcompass.org, 2001*). Our goal is to find a two-dimensional embedding of the newspapers’ conviction relative to fixed party locations that as closely as possible represents the underlying biases and positions in the data. Contrary to prior approaches with a political compass, our model is data-driven based on the extensively discussed sentiments, making it reproducible with machine-based methods.

We model the political compass within a two dimensional space \mathbb{R}^2 . Each party is given at a fixed location (δ_1, δ_2) . For each party, our data yields distributions of sentiments towards entities in this party which vary by newspaper. Formally speaking, let S be a continuous random variable in the interval $(-1, 1)$, N be a newspaper and Y be a political party. Then, we are given distributions of the sentiments conditional on newspaper and party $P(S|N, Y)$. Each conditional distribution is well-defined and constituted by a statistically sufficient, yet potentially small amount of observations in our dataset. To increase the number of samples per conditional distribution, we use a technique inspired by statistical *bootstrapping* that samples from the distribution with replacement. In the Sentiment Political Compass, these conditional distributions represent the sentiment of the newspaper at the exact point of a particular party location assuming that they are given as “ground truth”.

However, the fixed party locations must be assumed uncertain: The positions of political parties within the applied scales is to some degree subjective and imprecise, since its measurement relies on a questionnaire based evaluation. Furthermore, the positions of political parties is time-dependent. Therefore, since we are only given the positions of the political parties once for the whole observation period, it is likely that they slightly change through time and adapt due to new political circumstances and events. Therefore, instead of considering samples from the conditional distribution at the exact party location, we utilize *jittering* that introduces an artificial variance circular around the party location that expresses this uncertainty.

Specifically, for each bootstrapped sample, we draw jitter samples γ_1, γ_2 for the two coordinates from a standard nor-

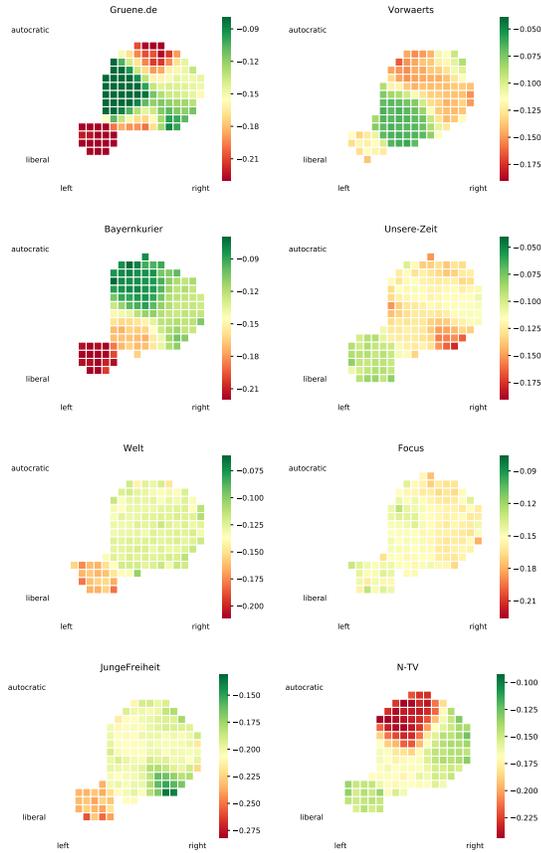


Figure 16. Sentiment distribution of several newspapers using jittered, bootstrapped samples from their distributions conditional on party and newspaper. The figures illustrate the bias of newspapers in the political dimensions left vs. right and libertarian vs. autocratic.

mal distribution

$$\gamma_1, \gamma_2 \sim \mathcal{N}(0, 1)$$

and weigh them by multiplication with a positive hyperparameter α . Note that $\gamma_i \alpha, i \in \{1, 2\}$ can be negative. α is user-defined depending on the level of uncertainty towards the party locations that shall be expressed. Also, α is equal for all newspapers and parties. Finally, we apply the jittering through shifting every bootstrapped sample of the sentiment distribution away from the party location by adding the weighted jittering sample to both coordinates of the sample as

$$\delta_1^* = \delta_1 + \gamma_1 \alpha$$

$$\delta_2^* = \delta_2 + \gamma_2 \alpha$$

δ_1^* and δ_2^* refer to the new coordinates of the bootstrapped sentiment sample after jittering. With this technique highly resembling *Monte Carlo sampling*, we now draw a total of

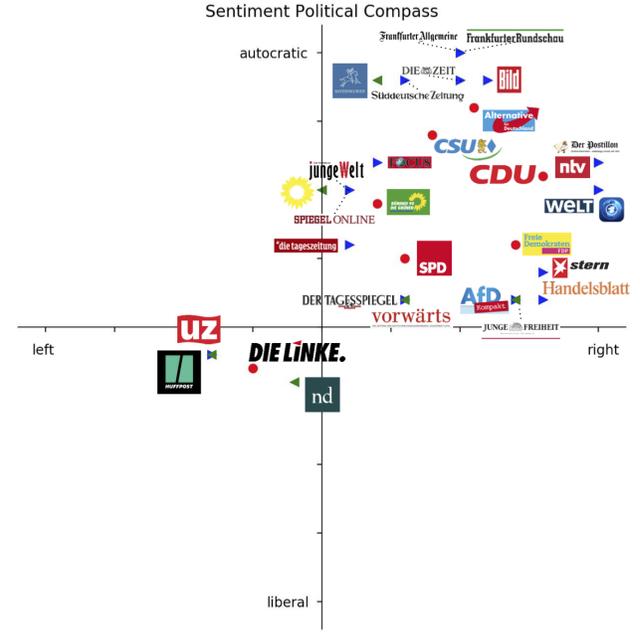


Figure 17. The Sentiment Political Compass. The party locations (red points) are fixed, the party-affiliated newspapers' (green triangles) and all other newspapers' (blue triangles) locations are estimated as drawn from their political bias.

one million jittered sentiment samples from our conditional distributions at all party location. By forming discrete bins for every region in the political compass, we can extract the mean bias of the newspaper at each location.

As a last step, we aim at reducing the fine-grained distribution analysis by newspaper to a point estimate of the newspaper, just as the given point locations of the political parties. To do so, we follow the intuition that the location of a newspaper should be defined as *the center of a region with the most positive bias*. Formally, this position is extracted with the argument of the maximum over all means of every 3×3 block of bins containing information on political bias illustrated before in figure 16. With these point estimates, we get our final product, the Sentiment Political Compass, in figure 17.

The results for a few example newspapers are illustrated in figure 16. Note that far autocratic-left as well as far liberal-right are not shown since there are currently no German party positioned and thus no information on political bias exists in these regions. The upper four maps show the political bias of party newspapers. As expected each display a stronger political bias when political attitudes are close to the associated party. Bayernkurier for example tends towards autocratic bias while strongly rejecting the left-liberal quadrant. Vorwärts positions itself closer to left-liberal than autocratic-right and Unsere-Zeit agrees to left-liberal be-

lieves. Considering the newspapers Welt and Focus, there is no extreme gradient, only a bit of negative bias towards the left-liberal from Welt. However, the newspaper Junge Freiheit shows a stronger positive political bias in the liberal-right quadrant claimed by the FDP. One very strong negative bias is observed with N-TV towards autocratic parties such as AfD or CSU. Since CNN was the major shareholder of the media channel right from its beginnings in 1992 till 2002 (Online, 1992), further research could compare political tendencies across international networks. Additionally empirical studies on article headlines could be conducted to harden the proof of this bias. Similar studies on FOX News and CNN verified perceptual bias before (Weatherly et al., 2007). In conclusion, the transformation of sentiments into political dimensions leads to further insights of media reporting.

Several insights can be deduced from the compass. First, the party newspaper Vorwärts is in proximity to SPD, Neues-Deutschland is in proximity to Die Linke, Bayernkurier is close to CSU and Gruene.de also shows proximity to the location of Die Grünen. With these findings, the sanity check of the political compass that party newspapers tend to be close to their corresponding parties is passed. Only AfDkompakt misses its spot next to AfD which results from the misleading negative sentiments towards its own party explained earlier. Unsere-Zeit as well as Huffington Post are located in the left-liberal quadrant in close proximity to Die Linke. Unsere-Zeit is the party newspaper of the German Communist Party, again validating the approach. A survey conducted in 2014 also showed left-tendencies of readers of the American Huffington Post (Pew Research Center, 2014). One cluster of newspapers in close proximity to FDP consists of Junge Freiheit, Stern and Handelsblatt. One cluster close to Die Grünen consists of Focus, Spiegel, Junge Welt, TAZ. A cluster of newspapers that seems to write less negative about autocratic parties like AfD and CSU compared to other newspapers are FAZ, FR, Süddeutsche, Bild and Zeit. Lastly a cluster close to CDU consists of Tagesschau, N-TV and Welt.

5. Conclusion

We presented the Sentiment Political Compass, a data-driven framework to analyze the media landscape regarding political conviction. Our contributions comprise a generic technical description of a data pipeline that results in a comprehensive analysis. We showcase our approach analyzing online news from 25 publishing houses in Germany during the election year of 2017. A main motivation behind our work is to tackle misinformation and deficiencies in media reporting with transparency and quantifiability. Media bias may affect uninformed voters in democratic opinion-forming. Holding quantifiable evidence, however, problems

may be soundly discussed on a scientific basis. By utilizing the proposed analytical framework, informative measures and standards can be formed or even regulatory measures for search engines or tagging could be considered. Also empowering editorial staff with these insights could potentially lead to more balanced reporting out of self-interest for newspapers. We make the source code of our framework publicly available, voicing the hope our approach will be applied to different countries leading to insight on a global scale. In future alterations, we could consider entities other than politicians and political parties, such as labor unions, non-governmental organizations, supranational or religious associations and companies. Further extension could include real-time updates to monitor the latest news and trends. The media sources may also be extended to social networks and print media. The Sentiment Political Compass aims at exploiting the possibilities of data science to contribute to a more fact-base political discourse.

References

- (2018a). German audit bureau of circulation - goals & tasks. <http://www.ivw.de/ivw/ziele-und-aufgaben-ivw>.
- (2018b). Iwf - online offerings - pageimpressions. <http://ausweisung.ivw-online.de/index.php>.
- Al-Rfou, R., Kulkarni, V., Perozzi, B., and Skiena, S. (2015). Polyglot-NER: Massive multilingual named entity recognition. *Proceedings of the 2015 SIAM International Conference on Data Mining, Vancouver, British Columbia, Canada, April 30 - May 2, 2015*.
- Anstead, N. and O'Loughlin, B. (2014). Social media analysis and public opinion: The 2010 uk general election. *Journal of Computer-Mediated Communication*, 20(2).
- Arab, A. (2017). Welche Parteien die meisten Stimmen an die AfD verloren. <https://www.welt.de/politik/deutschland/article168989573/Welche-Parteien-die-meisten-Stimmen-an-die-AfD-verloren.html>.
- Beck, K. (2012). *Grundlagen und Infrastrukturen des deutschen Mediensystems*, pages 33–72. VS Verlag für Sozialwissenschaften, Wiesbaden.
- Bessi, A., Coletto, M., Davidescu, G. A., Scala, A., Caldarelli, G., and Quattrociocchi, W. (2015). Science vs conspiracy: Collective narratives in the age of misinformation. *PLOS ONE*, 10(2):1–17.
- Boecking, B., Hall, M., and Schneider, J. (2014). Predicting events surrounding the egyptian revolution of 2011 using learning algorithms on micro blog data.
- BPB (2002). Wahl-o-mat - Question-answer-tool to evaluate the proximity of personal political conviction with political parties. <https://www.bpb.de/politik/wahlen/wahl-o-mat/>.

- Butenschön, R., Ganser, D., Wernicke, J., Hautsch, G., Goeßmann, D., Krüger, U., Dahn, D., Gritsch, K., Bruder, K.-J., Becker, J., et al. (2017). *Lügen die Medien?: Propaganda, Rudeljournalismus und der Kampf um die öffentliche Meinung*. Westend Verlag.
- Carbonell, J. G. (1979). Subjective understanding: Computer models of belief systems. Technical report, Yale University, Department of Computer Science.
- Ceron, A., Curini, L., Iacus, S. M., and Porro, G. (2014). Every tweet counts? How sentiment analysis of social media can improve our knowledge of citizens political preferences with an application to Italy and France. *New Media & Society*, 16(2).
- Chen, Y. and Skiena, S. (2014). Building sentiment lexicons for all major languages. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Short Papers)*.
- cloud.google.com (2018). Google Cloud - Custom Search JSON API. <https://developers.google.com/custom-search/json-api/v1/overview>.
- crummy.com (2018). Beautiful soup. <https://www.crummy.com/software/BeautifulSoup/bs4/doc/>.
- Dalton, R. J. and McAllister, I. (2015). Random walk or planned excursion? continuity and change in the leftright positions of political parties. *Comparative Political Studies*, 48(6):759–787.
- Fritz, M. (1987). World’s smallest political quiz. <https://www.theadvocates.org/quiz/>.
- Gao, W. and Sebastiani, F. (2015). Tweet sentiment: From classification to quantification. In *Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015*.
- Gautam, G. and Yadav, D. (2014). Sentiment analysis of twitter data using machine learning approaches and semantic analysis. In *2014 Seventh International Conference on Contemporary Computing (IC3)*.
- Gayo-Avello, D. (2013). A meta-analysis of state-of-the-art electoral prediction from twitter data. *Social Science Computer Review*, 31(6).
- Greenberg J, J. E. (2003). Psychological motives and political orientation - the left, the right, and the rigid: Comment on jost et al.
- Holtzman, N. S., Schott, J. P., Jones, M. N., Balota, D. A., and Yarkoni, T. (2011). Exploring media bias with semantic analysis tools: Validation of the contrast analysis of semantic similarity (cass). *Behavior Research Methods*, 43(1).
- Hurlimann, M., Davis, B., Cortis, K., Freitas, A., Handschuh, S., and Fernandez, S. (2016). A twitter sentiment gold standard for the brexit referendum. In *Proceedings of the 12th International Conference on Semantic Systems*.
- ibm.com (2018). IBM Watson - Natural Language Understanding API. <https://www.ibm.com/watson/services/natural-language-understanding>.
- IVW, G. A. B. o. C. (2017-2018). Ivw - definitions and technical explanations. http://daten.ivw.eu/download/pdf/Online_RichtlinienV2_1_Anlage1.pdf.
- Kim, H.-Y. and Park, M. (2010). Classification of time-series data based on several lag windows. 17.
- Lester, J. (1994). The evolution of the political compass (and why libertarianism is not right-wing). *Journal of Social and Evolutionary Systems*, 17(3).
- Maute, K. (2011). Das Mediensystem der USA und Deutschlands im Vergleich.
- Mikolov, T., Chen, K., Corrado, G., and Dean, J. (2013). Efficient estimation of word representations in vector space. *CoRR*, abs/1301.3781.
- Miller, F. P., Vandome, A. F., and McBrewster, J. (2009). *Levenshtein Distance: Information Theory, Computer Science, String (Computer Science), String Metric, Levenshtein Distance, Spell Checker, Hamming Distance*. Alpha Press.
- Miller, G. A. (1995). WordNet: a lexical database for English. *Communications of the ACM*, 38(11).
- Mutz, D. C. (1989). The influence of perceptions of media influence: Third person effects and the public expression of opinions. *International Journal of Public Opinion Research*, 1(1):3–23.
- Neri, F., Aliprandi, C., Capeci, F., Cuadros, M., and By, T. (2012). Sentiment analysis on social media. In *Advances in Social Networks Analysis and Mining, 2012 IEEE/ACM International Conference on*.
- Nolan, D. (1971). Classifying and analyzing politico-economic systems.
- Online, S. (1992). Reich und berühmt. <http://www.spiegel.de/spiegel/print/d-13682966.html>.
- Pang, B., Lee, L., et al. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, 2(1–2).
- Pang, B., Lee, L., and Vaithyanathan, S. (2002). Thumbs up?: sentiment classification using machine learning techniques. In *Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10*. Association for Computational Linguistics.
- Pew Research Center (2014). Ideological placement of each source’s audience. http://www.pewresearch.org/pj_14-10-21_mediapolarization-08-2/.
- politicalcompass.org (2001). The political compass. <https://politicalcompass.org>.
- scrapy.org (2018). Scrapy - open source and collaborative framework for crawling websites. <https://scrapy.org/>.
- statista.com (2018). Net reach of top 15 online newspapers in unique users in may 2018. <https://de.statista.com/statistik/studie/id/6551/dokument/zeitungen-statista-dossier/>.
- Weatherly, J. N., Petros, T. V., Christopherson, K. M., and Haugen, E. N. (2007). Perceptions of political bias in the headlines of two major news organizations. *Harvard International Journal of Press/Politics*, 12(2).
- Wilks, Y. and Bien, J. (1983). Beliefs, points of view, and multiple environments. *Cognitive Science*, 7(2).