RESEARCH ARTICLE

Measuring Variety, Balance, and Disparity: An Analysis of Media Coverage of the 2021 German Federal Election

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ABSTRACT

Determining and measuring diversity in news articles is important for a number of reasons, including preventing filter bubbles and fueling public discourse, especially before elections. So far, the identification and analysis of diversity have been illuminated in a variety of ways, such as measuring the overlap of words or topics between news articles related to US elections. However, the question of how diversity in news articles can be measured holistically, i.e., with respect to (1) variety, (2) balance, and (3) disparity, considering individuals, parties, and topics, has not been addressed. In this paper, we present a framework for determining diversity in news articles according to these dimensions. Furthermore, we create and provide a dataset of Google Top Stories, encompassing more than 26,000 unique headlines from more than 900 news outlets collected within two weeks before and after the 2021 German federal election. While we observe high diversity for more general search terms (e.g., "election"), a range of search terms ("education, "Europe," "climate protection," "government") resulted in news articles with high diversity in two out of three dimensions. This reflects a more subjective, dedicated discussion on rather future-oriented topics.

KEYWORDS

news media; variety; balance; disparity; election

1. Introduction

Researchers have emphasized the importance of exposing people to different viewpoints in order to broaden their understanding of political debates (Loecherbach et al., 2020) and empower them to become responsible citizens in democracies. Especially before elections, the choice can be crucial as to which parties, people, and topics are reported on. Nowadays, a large part of news media is consumed online (Newman et al., 2021). In particular, people are exposed to news articles when they search for politics-related keywords using search engines, like Google. With the integration of Google Top Stories in the Google search results, users receive an excerpt of current news directly with their search results. Remarkably, the Google search engine is currently used by over 80% of desktop users and over 95% of mobile users.[1] Thus, Google's role in the context of the 2021 German federal election was likely the same in terms of importance as it was in the German federal election 2017 (Unkel and Haim, 2019) and the United Kingdom general election 2015 (Ørmen, 2018). Research has found a significant effect on short term voting intentions though media coverage of parties and candidates (Dewenter

[1]See https://de.statista.com/statistik/daten/studie/301012/umfrage/marktanteile-der-suchmaschinen-und-marktanteile-mobile-suche/

et al., 2019). Since news publishing and especially Google Top Stories occupy such a prominent position (Kawakami et al., 2020a), the question arises: *How diverse are top news stories concerning political issues, individuals, and parties related to the German federal election 2021?*

In previous works, authors have already performed research in the area of media diversity (Amsalem et al., 2020; Beckers et al., 2019; Hendrickx and Van Remoortere, 2021; Masini and Van Aelst, 2017; Sjøvaag et al., 2016; Vogler et al., 2020). Determining diversity involves several steps from collecting data, labeling the data, defining what diversity is, and applying appropriate measurements. Our observation is that previous papers often lack these concrete definitions of diversity. Additionally, most researchers have focused on structural diversity of the news headlines and articles. This in itself is not an issue, but the general research landscape lacks of diversity measurements for news landscape besides these. This is especially important as only considering multiple diversity dimensions can provide a full picture of diversity. To the best of our knowledge, there are no works that have examined content diversity using suitable and exhaustive measures and using automated methods for media analysis.

In this paper, we propose a *novel framework for measuring the diversity of news headlines* based on news aggregator's results. Our framework integrates three diversity measures: *variety*, *balance*, and *disparity*. We look at the diversity of topics, as this is information that is directly perceived by the user and plays an important part in whether a user is interested in reading the article. In addition, we construct a new and timely data set about the news coverage of the latest German Federal election. We gather a data set on the news reporting of the German federal election 2021, ranging from two weeks prior to two weeks after the election and using Google Top Stories,[2] Google,[3] and Bing News.[4] We measured the *variety* of the news articles based on the number of topics in a result set. *Balance* is measured by using Shannon's Evenness Index (SEI) (Loecherbach et al., 2020). As no established metric for measuring *disparity* was introduced, we propose a novel metric based on topic modeling. Specifically, we extract topics, assign the headlines to a topic, and then investigate the disparity by calculating the similarities between all occurring topics within a result set.

In total, we make the following contributions in this paper:

- We create a conceptual framework for comprehensively measuring the diversity of news headlines using the dimensions *variety*, *balance*, and *disparity*.
- We propose a novel way to measure *disparity* based on topic modeling.
- We create and publish a data set on the news reporting of the German federal election 2021.[5]
- We show the results of applying our diversity framework to our data set.

The structure of the paper is as follows: First, we discuss related work in Section 2. In Section 3, we present the collection procedure and core information about the created data set. Section 4 goes deeper into the research questions and our solutions. In Section 5, we apply a comprehensive analysis to the data set and demonstrate the results. Finally, in Section 6, we conclude and outline future work.

[2] `https://news.google.com/topstories`
[3] `https://google.com/`
[4] `https://www.bing.com/news`
[5] All data and code is available at `https://figshare.com/s/c62f030e8693234e4634`.

2. Related Work

2.1. Measuring Media Diversity

Various approaches have been used for measuring diversity in the news. Besides the methods of quantifying political tendencies, there exist approaches such as ones based on measuring the overlap of topics in articles from several news outlets (Beckers et al., 2019), computing the word overlap of articles (Hendrickx and Van Remoortere, 2021) or a simple counting of occurring categories (Masini and Van Aelst, 2017). Vogler et al. (2020) analyzed the percentage of shared articles based on a sample of 13,993 news articles published in seven Swiss newspapers by comparing n-grams and using the Jaccard coefficient. They have demonstrated an increase in the concentration of media material, particularly in the coverage of common international events. Sjøvaag et al. Sjøvaag et al. (2016) used a semi-automatic approach of combining manual and computer-assisted coding of news articles published in Norway over time and visualized the temporal stability of coded categories like culture, crime, politics, etc. A more advanced approach was proposed by Amsalem et al. (2020) who first manually coded news articles and then used a classifier to continue with automatic label assignment. Based on that, the diversity was computed based on entropy.

To the best of our knowledge, no prior work has yet targeted to determine news diversity using all the three of Stirling's categories variety, balance, and disparity (Stirling, 2007), although they have been adapted in various disciplines. We will define how to measure topic diversity using these dimensions in our work. While most researchers used manual coding techniques to label the data and hence process relatively small data samples, we apply an automated approach through the use of topic modeling. We provide a novel, holistic framework for the automatic media diversity estimation, which is relatively easy to be applied and based on theoretical foundations. Although we focus on the case of German elections, our approach can be easily applied to other events and to other data sources.

2.2. Measuring Media Bias

Our research is related to media bias detection (Hamborg et al., 2019), because determining and measuring diversity, as well as identifying media bias deal with finding a balance. Media bias has recently attracted attention of various researchers, in addition to several other close tasks such as fake news and rumor detection. Detecting media bias in news items is crucial since news stories remain the key source for acquiring knowledge and forming views on current events. Botnevik et al. (2020) demonstrate how news bias detection algorithms may be integrated with browser plug-ins to aid online news readers in recognizing biased content. Furthermore, a system that is incorporated into journalistic processes can help journalists obtain instant feedback on bias when writing news content (Patterson and Donsbagh, 1996). Computational approaches to media bias detection mainly rely on text mining methods. For instance, word groups indicative of bias can be found and extracted from news (Potthast et al., 2018; Recasens et al., 2013).

Recasens et al. (2013) investigate linguistic characteristics of bias by analyzing "neutral point of view" policy of Wikipedia. Hutto et al. (2015) compared 26 structural and linguistic features in order to provide novel classification of the degrees of bias found in fictional news texts. The authors used also word indicative of bias that were part of bias dictionary constructed by Recasens et al. (2013). Lim et al. Lim et al. (2018)

used crowdsourcing to analyze news bias on a sentence level in a sample of 88 news articles that report the same news events. Finally, Baumer et al. (2015) investigated how average readers perceive linguistic characteristics related to framing.

2.3. Role of News Articles in Elections

Many researchers have named the citizens' need for a diverse mix of news. One of the most cited term in this discussion is the "marketplace of ideas" (Napoli, 1999) whose basic idea is that media and news should have a large offer of different viewpoint.

Related to Google, there are 3 different ways to obtain news as a user: via Google search results, Google Top Stories (as a part of the Google Search results page) and Google News. Existing research on German elections includes the work of Haim et al. (2018), which investigated the personalization of search results on Google News using agent-based testing (Haim et al., 2018). However, this was not done in the context of an election, but independently over the year in the areas of politics, sports, and entertainment. In comparison, Krafft et al. (2017) examined Google search results of the 2017 federal election. They also looked at the personalization of search results, but without limiting it to news, looking at all Google search results for parties and candidates. Unkel and Haim (2019) also examined Google search results for structural features (e.g., which sources appear) and for party positions on topics in the 2017 federal election (Unkel and Haim, 2019). A study on Google Top Stories for a federal election is missing and will be conducted with this work.

2.4. Role of News Articles on Politics

Compared to Europe, in the United states there exists more research on Google Top Stories, also in the context of elections. Mustafaraj (2020) collected Google Top Stories on the 2020 presidential election and then examined the political orientation of the sources displayed – i.e., whether Google Top Stories tend to be "left" or "right" and, in the broadest sense, how "diverse" (or balanced) the results are. Kawakami et al. (2020a) also took a similar approach, examining this political bias in search results for 30 candidates also for the 2020 presidential election (Kawakami et al., 2020a). Lurie and Mustafaraj (2019) have already examined the sources displayed on Google Top Stories independently of an election coverage in the previous year and illustrated which sources report on the same topics and thus focus on vertical diversity in a media outlet (Lurie and Mustafaraj, 2019). However, since the media and political landscape in Germany is significantly different from that in the U.S., we consider an investigation for the German market as useful. Additionally, we see the need for an examination of more of the shown content itself, instead of its sources.

Further important is the choice of the used search terms. While the work of Lurie and Mustafaraj (2019); Mustafaraj (2020); Mustafaraj et al. (2020), and Kawakami et al. (2020a,b) primarily used names of candidates and parties, Unkel and Haim (2019) have expanded this to include additional categories. These categories are *Issues*, *Election Facts*, and *Election Guidance.*

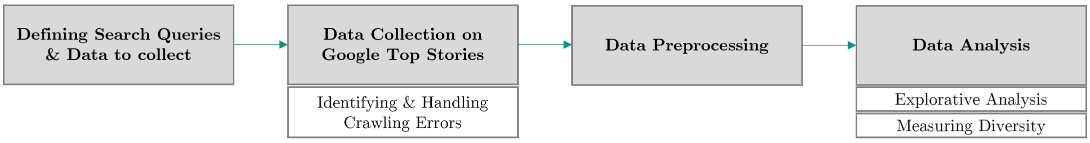


Figure 1.: Illustration of workflow for main data set

Table 1.: Used search query categories

Category Name	# Queries	Example in German	Example translated
Candidates	9	*Olaf Scholz*	*Olaf Scholz*
Established Parties	12	*CDU*	*CDU*
Politics Fields	31	*Klimapolitik*	*Climate politics*
Election Facts	27	*Bundestagswahl Ergebnis*	*Federal election result*
Government Formation	27	*Koalition*	*Coalition*
Election Guidance	11	*Wen soll ich wählen?*	*Who should I choose?*
Topics	62	*CO2 Preis*	*CO2 Price*
$\sum$	179		

3. Data Set

We were interested in news articles before and after the German Federal Election 2021, as search interest and news coverage might change after first election results are published. Therefore, the data collection spanned the time frame between September 13, 2021 (2 weeks prior to the election) and October 10, 2021 (two weeks after the election). Our data set includes the metadata of search results, including news headlines, for a selected query list concerning the German federal election. Our data set is the result of 179 queries running on three news aggregators, namely Google Top Stories, Google News, and Bing News. We use Google Top Stories as our main data set for the media diversity analysis (see Section 4), while the remaining data sources are used as a control data set.

3.1. Data Collection

In the following, we present the process of our data collection. Figure 1 shows the overall workflow for obtaining our main data set.

Search Queries. For gathering the results, we used a set of search queries that can be categorized into several categories around the federal election (see an overview in Table 1). These categories are based on the used keywords from Unkel and Haim (2019) but were extended with the categories *Politics Fields* and *Government Formation*. *Politics Fields* was added to see whether searches for a specific relevant topic (i) show Top Stories at all and (ii) how Top Stories enables users to also see related topics. *Government Formation* is especially interesting to track, because it is likely to have some bigger changes in power, and the distribution of seats in the parliament.

The keywords (i.e., search queries) were derived as follows: (1) The keywords of *Government Formation* were derived from a few example articles. (2) The *Politics Fields* keywords were obtained from the German 2019 “Wortschatz Leipzig” project

Table 2.: Structure of collected dataset

Field	Description	Example (in German)
Location	Abbreviation of server location	*MU*
Search query	Used search term	*Annalena Baerbock*
Timestamp	Date and time of the request	*21-09-12_ 00:00:44*
Rank	Position of a result in a set	*2*
Published	Publishing date of article	*vor 1 Tag*
Title	Headline of the linked article	*Hungerstreikende in Berlin: Sie wollen nichts mehr essen. Bis Laschet, Scholz und Baerbock mit ihnen reden*
Source	Name of the news outlet	*Spiegel*
Query Category	Category of search query	*Candidates*
(Estimated) Publishing Date	Subtraction of the "published" field from the timestamp	*21-09-11_ 00:00:44*
Title Length	Length of title in words	*16*

Goldhahn et al. (2012). This dataset contains word counting of news articles, mainly from 2019 and earlier. (3) The *Politics Fields* used by us were identified by selecting the top most occurring words ending with the suffix "-politik" (engl. politics). (4) The keywords of *Topics* were derived from two larger voting advice applications in Germany: the most popular *Wahl-O-Mat* operated by the BPB (engl. Federal Agency for Civic Education) and a smaller *Wahlswiper* operated by the WahlSwiper e.V. in cooperation with the University of Freiburg.[6] Voting advice applications like Wahl-O-Mat ask users for their positions on different political questions and match these with answers from political parties or candidates. The application then presents the extent to which the own opinion match with these of the parties (Louwerse and Rosema, 2014).[7] The extensive list of all search queries can be found online in our repository.

Schema. Our data set includes information about the server location, the used search query, a timestamp, the rank of the result, the publishing date, the news title and source (see examples in Table 2). We enriched the data with the query category, an estimated publishing date, and the title length to enable additional data analysis.

Data Collection Procedure. The data was scraped by automatic requests to the

[6] `https://www.voteswiper.org/de/page/press/releases/inklusiv-innovativ-informativ-wahlswiper-startet-zum-superwahljahr-in-sieben-sprachen`

[7] The Wahl-O-Mat editorial is based on an editorial team consisting of young voters, multiple politics researchers, statisticians, and educators, and experts on the topics and representatives from the BPB, see `https://www.bpb.de/themen/wahl-o-mat/45292/die-entstehung-eines-wahl-o-mat/`

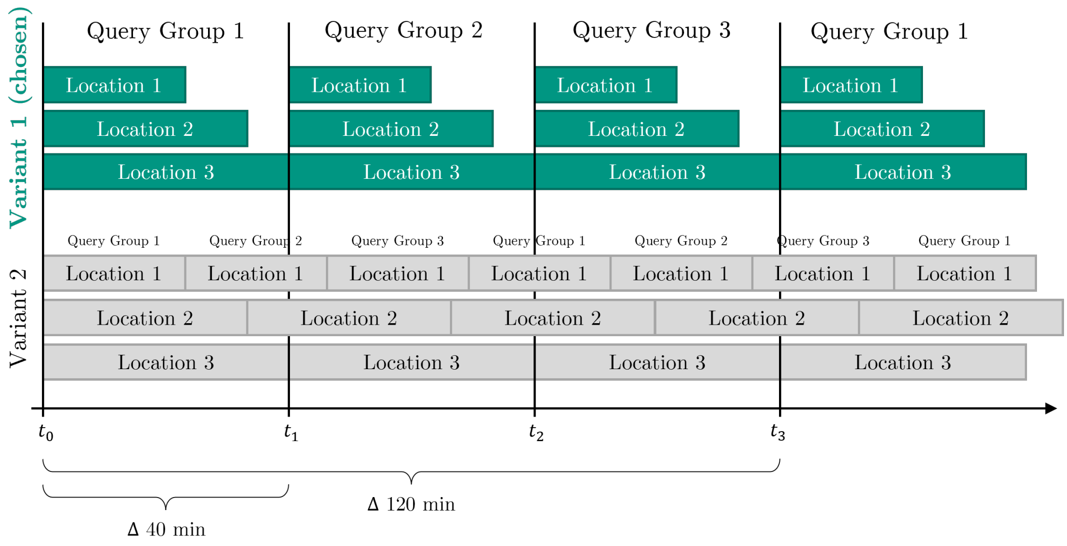


Figure 2.: Illustration of crawling timing

search engines (including the keywords as search terms) and extracting the relevant data from the web page. For enabling automatization, we used Selenium[8] with Python. This allowed us to have an agent-based testing with a new agent and a fresh instance for every search, minimizing possible personalization based on the browser (Haim, 2020).

All search terms used were divided into three roughly equal groups and queried cyclically on the search engines. In addition to Google Search (Top Stories feature), Google News and Bing News were also queried to later compare the results and make topic modeling more accurate as more data is available. We identified 40 minutes as an appropriate timespan, in which a new cycle can start with the next category. With using 40 minutes' long time period, each category is queried every two hours, which distributes the crawls exactly over 24 hours. Therefore, each category starts at the same time on all servers, each day. The split in three groups with fixed starting points avoids servers from "running away", as some servers may process the queries faster, as exemplified in Figure 2.

As seen in Table 1, we used a set of 179 search queries for search. Each search query resulted in a set of Top Stories search results with zero to a maximum of 10 headlines. We gathered data from the server locations in Duesseldorf (DU), Falkenstein (FA), Frankfurt (FR1, FR2, FR3), Karlsruhe (KA), Munich (MU), and Nuernberg (NU). Through spreading our locations all over Germany, we can assume that there was only little localization of search results, as discussed later in Section 5.4.

3.2. Data Preprocessing

In the first step, we clean the data by removing all information that is not used for evaluation and by translating HTML encodings back to characters. After that, the data is divided in two data sets as seen in Figure 3, consisting of D_A with all results excluding the searches without any results (meaning a Google Search did not show Google Top Stories) and D_U with only unique headlines.

[8] `https://www.selenium.dev/`

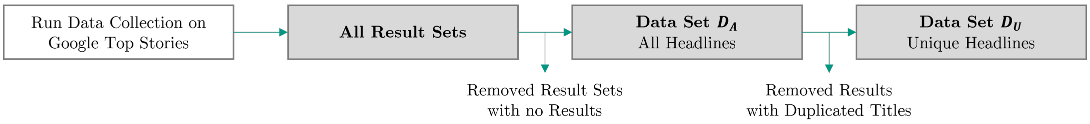


Figure 3.: Data set splitting of Top Stories data set

Table 3.: Overlap of the data sets, read as x% of articles in B are also included in A

A \ B	Google Top Stories	Google News	Bing News
Google Top Stories	-	42.2%	12.8%
Google News	50.8%	-	14.7%
Bing News	30.8%	29.6%	-

3.3. Collection Analysis

Data Analysis Settings. The data analysis was performed using Python 3.9. To handle, transform, and visualize the data, we used the libraries Pandas[9], matplotlib[10], and seaborn[11].

Explorative Data Analysis. Looking at the different vendors (see Table 3), we observe that Google Top Stories and Google News have a larger overlap of the shown articles (50.8% and 42.2%) compared to Google Top Stories and Bing News or Google News and Bing News.

If not noted differently, the following numbers now only refer to the Google Top Stories data set. This collection described in Section 3.1 resulted in 1,837,214 saved result entries containing 26,582 unique headlines from 916 news outlets.

As a news aggregator should reflect current news and happenings, it is interesting to see how old articles are (i.e., time since publication), when they appear in a search result. As Table 4 shows, more than 75% of the articles are at a maximum one day old. Over half of all articles were published in the 24 hours prior to the search.

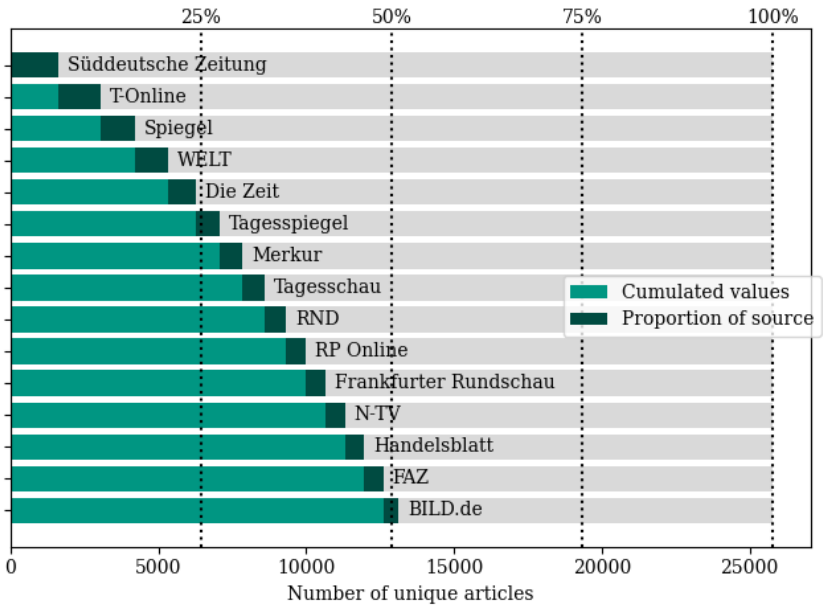
News Outlets. As Figure 4 shows, out of these 916 news outlets, 50% of the

[9] https://pandas.pydata.org
[10] https://matplotlib.org
[11] https://seaborn.pydata.org

Table 4.: Age of articles

Article Age	# Articles	%	Cumulative
0 days (<24h)	13,577	52.6%	52.6%
1 day (<48h)	6,250	24.2%	76.8%
2 days (<72h)	2,451	9.5%	86.3%
3 days (<96h)	2,547	9.9%	96.2%
≥4 days (≥96h)	977	3.8%	100%
$\sum$	25,802		

Figure 4.: Accumulated proportions of top sources



news articles came from just 15 outlets, and 5 of those published just under 25% of all news articles in this dataset. These top publishers are *Süddeutsche Zeitung*, *T-Online*, *Spiegel*, *WELT* and *Die Zeit*. The over 900 sources included different kind of news outlets, including online-only media, newspapers with online and offline media, websites of radio stations, blogs and more.

4. Diversity Framework

To investigate the mixture and diversity of topics of news articles, we first extract the topics from the headlines. This is a text mining and natural language processing task, usually based on topic modeling in existing works. Having the allocation between headlines and topics, we can investigate the diversity of the result sets.

4.1. Topic Modeling

Topic modeling is based on the assumption that documents are composed of one or more topics. We used two topic modeling methods to see which performs superior on our data set. The first one is the widely used Latent Dirichlet Allocation (LDA). Existing literature pointed out that LDA perform weak on shorter texts (even when optimized) as there is little word co-occurrence information (Li et al., 2017; Lin et al., 2014; Qiang et al., 2020). Furthermore, LDA assumes that there are multiple topics in a document, which might not be true for headlines. Considering only headlines, our documents are very short, namely in the case of the Top Stories data set on average 9.023 words with a standard deviation of 2.872. The authors of the survey Qiang et al. (2020) identified GPU-PDMM as best algorithm for their Google News data set with the highest classification accuracy (Qiang et al., 2020). We therefore use this method as second one for our work.

Table 5.: Topic modelling parameters

	LDA	GPU-PDMM
Number of topics	3-50	3-50
Number of iterations	1000	48
α hyperparameter	0.1	0.1
β hyperparameter	0.01	0.01

GPU-PDMM is a Poisson-based Dirichlet Multinomial Mixture model (PDMM) with a generalized Pólya urn (GPU) model. Despite its reliance on a Poisson-based model, each document consists of only a few topics (Qiang et al., 2020). Using the GPU-model, additional external knowledge about word semantics can be used to improve topic modelling, especially with short texts (Li et al., 2017). This paper will build on Qiang et al. (2020)'s result and use an implementation[12] of GPU-PDMM and LDA provided by Qiang et al. (2020).

Preparing Data Set for Topic Modeling. To identify the topics in the overall news as accurately as possible, we consider not only the data gathered from Google Top Stories, but also from Google News and Bing News.

To run topic modeling, the headlines are preprocessed, including (i) the removal of special characters, (ii) lower casing text, (iii) lower casing text, (iv) tokenization of text, (v) lemmatizing, (vi) the removal of rare words (with fewer than 3 occurrences), and (vii) the removal of words with little context.

Running Topic Modeling on our Data Set. The α and β hyperparameters of our approaches are based on defaults used in the literature[13]. All used parameters are noted in Table *5*.

To select the optimal amount of topics, we run topic modeling multiple times with each iteration having a different setting for the number of topics, ranging from 3 to 50 topics. The final amount of topics is then determined by comparing the coherence scores per setting and selecting the maximum. For this task, we used the built-in function of the STTM framework (Qiang et al., 2020).

Figure *5* shows the identified coherence scores for both LDA and GPU-PDMM on our data set. The maximum coherence score in our example was 0.3566 using GPU-PDMM and 15 topics, and was therefore used. We see, in general, that GPU-PDMM performs better on our data set, looking at the coherence scores. With a high number of topics, the topics get so fine-grained that the differences are not that large any more. Running the topic modeling on this corpus and optimizing topic coherence scores, we find 15 topics as the best in our case. For the full list of all identified topics and its related top 20 words, we can refer to our repository.

Document-Topic Assignment. To analyze the topic diversity of headlines, we need an assignment of a topic for a headline. We introduce a notation for this headline-topic assignment: $t(h) : Headline \rightarrow Topic$. For instance, the topic of headline h_1 would be: $t(h_1) = t_5$.

After preprocessing our headlines, we use the transformed headlines from Section 3.2 as an input for our topic modeling.

[12]https://github.com/qiang2100/STTM (Last accessed 01/03/2022)
[13]`https://github.com/qiang2100/STTM`

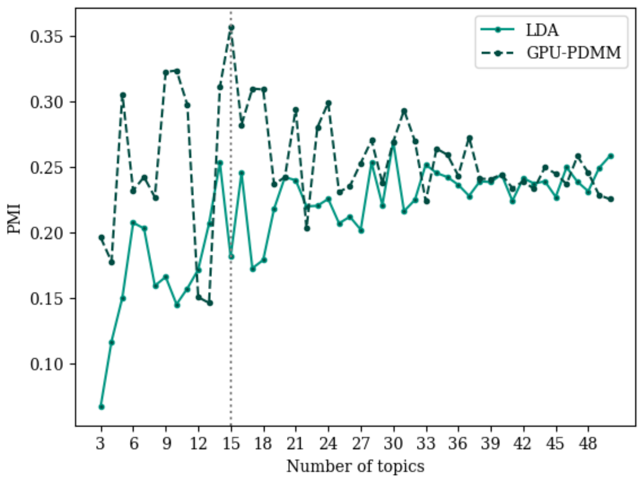


Figure 5.: Coherence scores

The used STTM framework then provides different outputs in the form of

- **document-to-topic distributions**: Each headline has a probability distribution over all topics. $t(h)$ is then the topic with the highest probability. If two topics have the same probability, $t(h)$ is the topic with the lower index.
- **topic assignment**: Each word in the headline is connected to one topic. $t(h)$ is the topic appearing the most. If two topics occur the same number of times, we define $t(h)$ as the topic with the lower index.

4.2. Measuring Topic Diversity

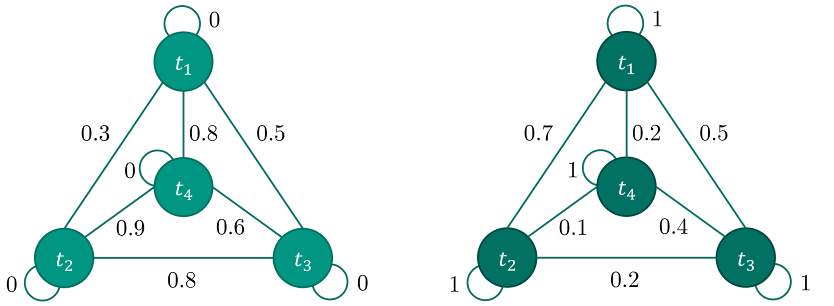
In this section we discuss how the dimensions variety, balance and disparity apply on the level of the whole data set. Section 4.3 then discusses how these dimensions apply to the result sets of the searches. Whilst Section 4.2 and 4.3 discuss these applications in theory, Section 5 applies this to the Google Top Stories federal election data set.

4.2.1. Variety

Variety gives information about how many categories occur (Macarthur, 1965), in our case counting all unique topics. As the topic model takes the number of topics as an input and then outputs exactly this amount of topics, the variety is exactly the number of topics in topic modeling. As one can create the value of variety “manually”, looking at variety would only make sense comparing subsets of the data set. One could, for instance, investigate in the number of topics per search query. Another example will be discussed in Section 4.3, looking into the structure and diversity of result sets (which then of course could also be aggregated again into result set diversity per query or query category).

4.2.2. Balance

The balance of the overall topics of the data set can be measured in our case as how many headlines are assigned to each topic. How a distribution should look in order to be considered diverse differs according to the underlying normative frameworks. We argue



(a) Example disparity graph (b) Corresponding similarity graph

Figure 6.: Relationship between disparity and similarity graph

that in the deliberative normative framework, this would be a uniform distribution or a distribution similar to it (Loecherbach et al., 2020). Thus, every topic has the same or at least a similar amount of assigned headlines. Consequently, all viewpoints, entities and in this case topics, should be represented equally in the news debate.

To bring the theoretical concept of balance into a measurable variable, we use Shannon's evenness index (SEI) (Loecherbach et al., 2020). Originating from diversity of biotopes in biology, SEI has found broad adaption in different research disciplines (van Dam, 2019). The SEI of a result set X is calculated by dividing the Shannon Diversity Index (SDI) of X by its maximum:

$$SEI(X) = \frac{SDI}{max(SDI)} = \frac{SDI}{ln(|X|)} = \frac{-\sum_i^{|X|}(p_i * ln(p_i))}{ln(|X|)} \in [0,1]$$

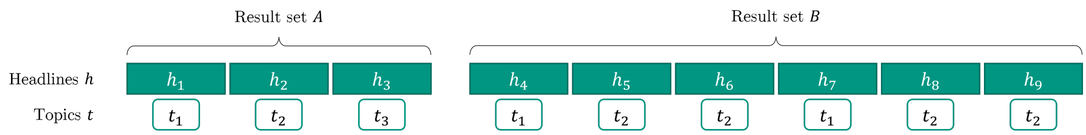
with p_i being the proportion of articles that belongs to the topic currently iterated over. The higher the SEI value, the more uniform a distribution is.

4.2.3. Disparity

In contrast to variety and balance where it is only important that different topics are distinct, disparity measures how similar and therefore also different the topics are semantically.

Our approach is as follows: We use the generated top words from topic modeling to calculate a numerical representation of each topic. For each top word, we obtain the word embedding of a representation. The average of all top word embeddings then represents the embedding for the overall topic. To get the similarity between different topics, we use the cosine-similarities between every topic. The correlation between these two sizes is $Disparity = 1 - Similarity$. A similarity value of 1 means that the two topics are identical, and lower weights meaning less similarity. The other way around, a disparity value of 0 means that the two topics are identical and higher values meaning higher disparity. These values could be represented by "disparity weights" on weighted edges of a complete graph $G = (V, E)$ with $V = t_0, ..., t_n$ and $E = \{\{t_i, t_j\} : 0 \leq i \leq j \leq n\}$ the respective weights $w : E \to \mathbb{R}$. Figure *6a* illustrates this in an example.

Disparity for the full data set would mean looking into how distinct and different from each other the identified topics are. Motivated on a simple example, this would, for instance, mean that the two topics "football" and "finance" have a higher disparity



	Result set A	**Result set** B	**Diversity**
Absolute topics	$\lvert\{t_1, t_2, t_3\}\rvert = 3$	$\lvert\{t_1, t_2\}\rvert = 2$	$V(A) = 3 > V(B) = 2$

Figure 7.: Simple example for variety with one topic

(=lower similarity) than "football" and "athletes". By quantifying these "distances", one can better understand how similar or different two search results are by comparing all the topics against each other.

4.3. Determining Topic Diversity of Result Sets

The following section discusses the same dimensions as in Section 4.2, but now on the level of result sets. For the Section 5, the respective values are calculated for each result set and then aggregated into one overview.

4.3.1. Variety of Result Sets

In the following, let $V(X)$ denote the variety of a result set X. The basic intuition behind variety is "the more, the better". In the case of topic diversity, that would be: The more topics covered by a result set, the better.

Limited only through the overall data set variety (i.e., not considering the number of results), the following applies to the variety V of a result set S:

$$0 \leq V(S) \leq \text{number of topics}, \quad V(S) \in \mathbb{N}_0.$$

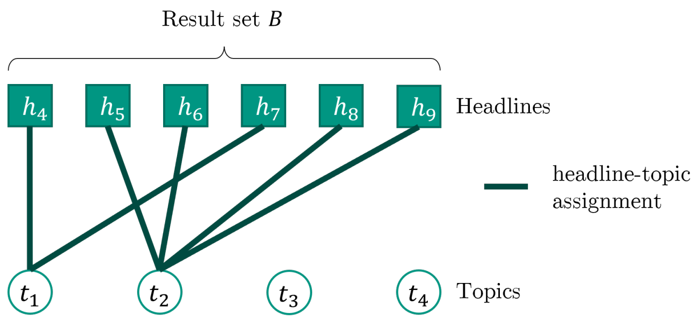
To determine the variety of a result set, one has to count all unique topics. As each result set has a maximum of 10 results in our case and each result has exactly one topic, the variety of this result set is exactly the number of unique topics. Considering only one topic per headline and the maximum amount of 10 results per result set, we can restrict above condition further to

$$0 \leq V(S) \leq 10 \text{ with } V(S) \in \mathbb{N}_0.$$

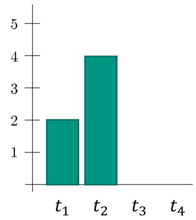
A variety of 10 would mean that every result in the result set has a different topic.

In the example in Figure 7, result set A is – only related to variety – more diverse than B, as it has 3 instead of only 2 unique topics. That might be unintuitive at first glance, as result set B has more results than A.

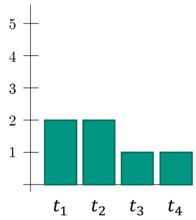
Variety in itself is not sufficient to determine diversity, although it is often used as such. The approach of using variety as a measure for diversity is often used on source diversity, where researchers argue that higher source variety (so the more news sources) the better the diversity. This has been critiqued by multiple researchers (Carpenter, 2010; Napoli, 1999).



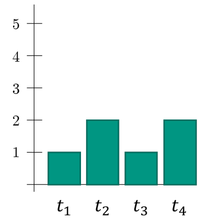
(a) Alternative visualization of result set B in Figure 7



(b) Actual balance



(c) Optimal balance



(d) Alt. optimal balance

Figure 8.: Example for balance

4.3.2. Balance of Result Sets

Building on variety, which only take into account the absolute number of topics, balance now looks at how the topics are distributed across the headlines. In most cases, a result set would be considered diverse if the distribution of the topics are somehow equal or even (discrete uniform distribution). An extreme example with a low diversity would be a result set with 10 results, of which 8 are about the same topic and the other both another one. This could be considered having a low balance.

Coming back to the example in Figure 7, an optimal balance is give in Figure 8b and 8c. The goal is to have a complete even distribution, where every topic occurs equally, so exactly the same number of times. To translate these distributions in a explicit measurement, we use Shannon's Evenness index (SEI) (Loecherbach et al., 2020). SEI $\in [0, 1]$, where a value of 1 corresponds to an optimal balance.

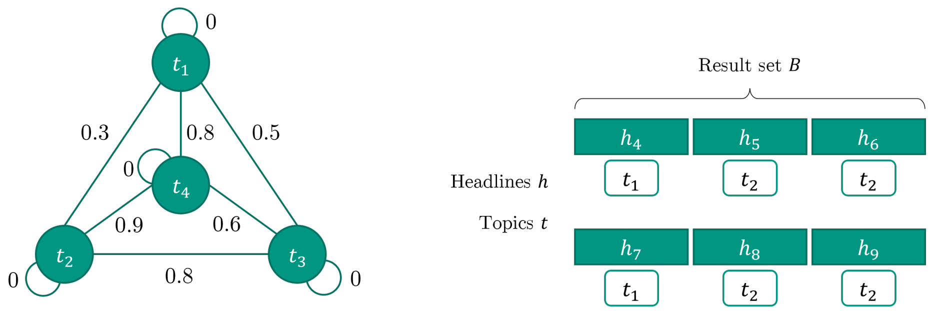
4.3.3. Disparity of Result Sets

Let $D(X)$ denote the disparity of a result set X and $t(h)$ the topic of headline h. Then $D(h_i, h_j) = w((t(h_i), t(h_j))) = w((t(h_j), t(h_i)))$ denotes the disparity between the headlines h_i and h_j. When summing up all pairwise disparities between all topics of headlines in a result set and dividing it by the amount of pairs, we receive the disparity for a result set. Therefore, we aim for a minimum normalized pairwise sum.

We propose the following way to calculate disparity of a result set X:

$$D(X) = \frac{\sum_i \sum_j D(h_i, h_j)}{\binom{n}{2}}; \quad \forall i < j \leq n$$

Following this calculation, the disparity of result set B from the example in Figure 9 would be 0.18.



(a) Disparity values as weighted graph (b) Example result set

Figure 9.: Example for disparity

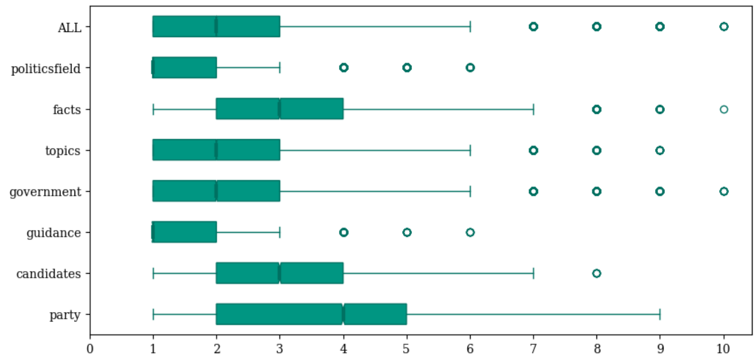


Figure 10.: Topic variety of result sets per query category

5. Results

In this section, we present our findings obtained by applying our framework (Section 4) to our dataset (Section 3). For better illustration, we focus on the categories *candidates* and some queries from *topics* and *facts* due to the importance of these categories for the federal election.

5.1. Results for Variety

Overall Data Set. The variety for the overall dataset is the number of topics identified from the topic modeling (see Section 4.2.1). For this data set, we considered 15topics (see Table 6). Additionally, as each topic is covered by a minimum of one headline, the variety of the data set is 15.

Result Sets. Looking at all result sets over all categories in our dataset (as seen in Figure *10*), the mean variety of topics over all results sets was 2.534 topics. This is lower than expected, but reasonable as many search results from guidance and politics field have low variety, as they are very specific search terms that often only allow for low variety (see the figures in our repository). Broken down into each category, the variety of topics was in general higher in the categories *facts*, *candidates* and *parties* compared to other categories.

Please note that this is an aggregation of all search queries of a category (for the used search queries per category see our repository online). In some cases there exist notable

Table 6.: Identified topics

#	Topic	Interpretation
0	regierung fordern bundesregierung euro bundeswehr deutsch neu stellen deutschland wirtschaft afghanistan million nächster mindestlohn milliarde brauchen rente einsatz erwartet warnen	Politics
1	scholz laschet triell baerbock tv olaf live kanzler armin letzter stream 2021 ard kanzlerkandidat annalena wahlkampf zdf nord frage sehen	TV Duel
2	fdp grüne spd koalition grün ampel union jamaika sondierung lindner gespräch regierungsbildung chef habeck partei christian sprechen ticker regierung sehen	Government Formation
3	corona impfung covid pandemie 19 kind vorpommern mecklenburg coronavirus impfstoff impfen rheinland studie pfalz jung trotz grippe lassen booster empfehlen	Corona Vaccination
4	minister to for of the new prime on future fridays says japan day with as and at is freedom health	News in English
5	duell europa league union fußball fc 1 vs frankfurt sieg bayern hängen berlin team plakat bundesliga gewinnen bvb cup eintracht	Football
6	corona regel schule bayern bildung baden test württemberg land landkreis 3 kabinett zahlen hoch oktober maskenpflicht ungeimpfte kind aktuell fordern	Corona Regulations
7	corona pandemie inzidenz new coronavirus impfpflicht ticker lockdown steigen rki deutschland neuinfektion sinken aktuell fall zahlen melden gesundheit liveticker spahn	Corona Incidence
8	steuer klimaschutz sachsen co2 umwelt polizei anhalt preis tempolimit schleswig klima holstein hamburg auto deutsch bringen steuerreform unfall leben stadt	German Politics
9	cdu laschet csu afd union söder armin nrw linke chef fordern politiker partei nachfolge wahlkampf merz markus laschets kritik sehen	CDU/CSU
10	merkel kanzler wähler deutsch frei angela deutschland bundestag österreich politik jung frau wählen bleiben ziehen 16 abgeordnet ära wahlkampf kommentar	Old Government
11	2021 ergebnis wahlkreis partei kandidat wählen afd wahlergebnis kreis live umfrage bundestag wahlbeteiligung kommunalwahl prozent ticker linke niedersachsen briefwahl gewinnen	Elections
12	eu us cannabis usa russland regierung migration polen streit migrant europa biden europäisch abschiebung china drohen parlament kommission frankreich grenze	Foreign Policy
13	klimaschutz klimawandel europa energie pflege erneuerbar elektromobilität setzen neu umwelt aktie thema bildung zukunft deutschland stark umweltschutz region klima politisch	Future Politics
14	spd berlin rot grün prognose union umfrage 2021 grüne cdu berliner linke stark sehen prozent deutlich hochrechnung liegen gewinnen klar	Election Forecast

differences between different queries in a category. This can for example be seen with the detailed view of *government* in Figure 11, where the search terms *Bundesregierung*, *Kanzler* and *Minister* have way higher topic variety than other search terms. All other results per search query, that are not included in this section here, can be found online.

Although variety is solely about the absolute number of different topics, information about how many results were included in the result set can be helpful. An example of this can be seen in the category *candidates*. In that case, the topic variety of *Christian Lindner* and *Dietmar Bartsch* is similar (see Figure 12). However, we see a large difference in how many articles are shown with every search. Whilst *Christian Lindner* has almost every time 10 results, the number of results of *Dietmar Bartsch* range the whole spectrum from 0 to 10 results with mainly less than 6 results (see Figure *13*). An aggregated view of how many results were viewed per query can be found in our repository.

As we look at absolute numbers with variety, one effect occurs: The number of topics is limited by the number of results. Thus, also the variety is likely to be lower. This is

Table 7.: Variety of result sets per category (absolute numbers)

		Absolute					Relative	
Category	# Result Sets	Mean	Median	Std.Dev.	Min	Max	Mean	Std.Dev.
Guidance	11,062	1.449	1.000	0.653	1	6	0.481	0.272
Topics	102,573	2.451	2.000	1.402	1	9	0.534	0.280
Politics Field	38,328	1.633	1.000	0.788	1	6	0.890	0.203
Candidates	21,910	2.837	3.000	1.174	1	8	0.396	0.224
Party	31,169	3.631	4.000	1.610	1	9	0.449	0.199
Government	54,011	2.457	2.000	1.565	1	10	0.547	0.257
Facts	51,046	2.893	3.000	1.626	1	10	0.570	0.268

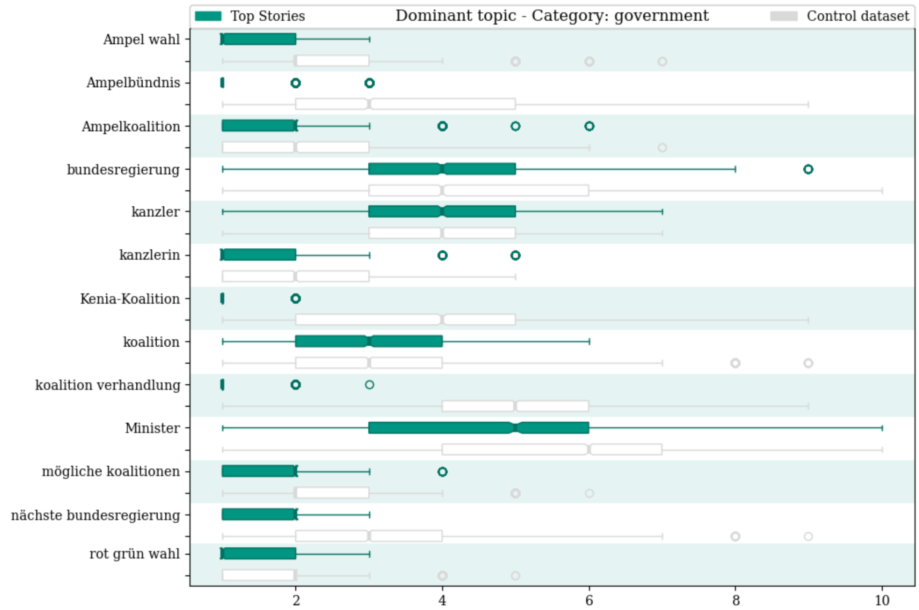


Figure 11.: Excerpt of topic variety of government search terms

not visible in this overview. We can get around this by displaying the variety in relative values. It is important to say that this can help with getting another view onto the topic but is not a value for variety, as variety is per definition the absolute amount of topics. The "relative variety" then is the number of unique topics in a result set divided by the number of results of that result set. Figure 14 shows these relative values per category.

Although *candidates* and *party* have the best absolute number of topics, when taking into account the relation of number of topics to the number of shown results, both categories find themselves at the bottom of relative values.

Additionally, we see that in general the control dataset has higher values in topic variety (particularly the category *politicsfield*). That is the case as usually Google News and Bing News always try to show results, whereas Google Top Stories are only shown if relevant news matching to the search query are available and the search interest is high enough.

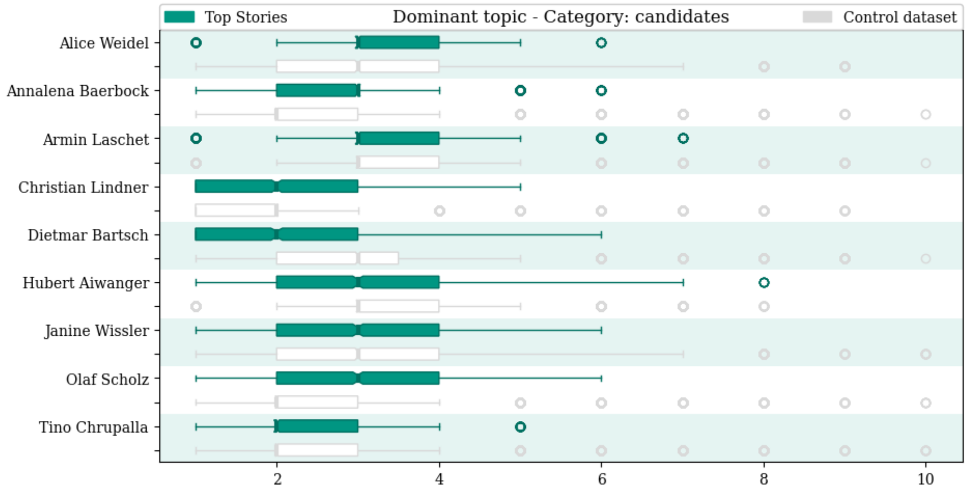


Figure 12.: Topic variety of result sets for category *candidates*

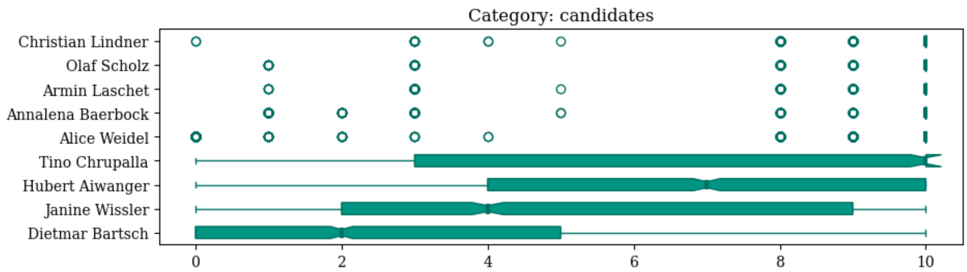


Figure 13.: Number of results in result sets for *candidates*

5.2. Results for Balance

Data Set. Figure 15 shows the distribution of all headlines over their topics. The overall SEI balance of all these topics is 0.928, while it is even a bit higher with 0.98 for all unique results.

The distribution of topics of all results and unique results mostly have a smaller delta. This is a sign that headlines of topic are not heavily under- or overrepresented. If a positive delta (see the + in Figure *15*) is large, this indicates that the proportion of unique articles were higher than all articles reflected, which results in an under-representation of this category in the result sets. The same is with a negative delta (−), with a over-representation respectively. The only topics that differ a bit are topic 1 (*TV Duel*), topic 3 (*Corona Vaccination*), topic 7 (*Corona Incidence*), and topic 9 (*CDU/CSU*).

Figure 16 shows the distribution of topics per search query category. It is visible that in general the topics 2 (*Government Formation*) and 11 (*Elections*) occur the most in the search results. These topics mainly occur in the categories *party* and *candidates*. This comes as no surprise, as candidates are strongly interconnected with parties and in the debate around the federal election. This is the same for how a future government could look like and how to vote to receive a desired outcome.

We found a difference in-between the SEIs of categories, with the unbalanced category *guidance*. Spreaded the most, with the highest SEIs are *politicsfield* and *topics*,

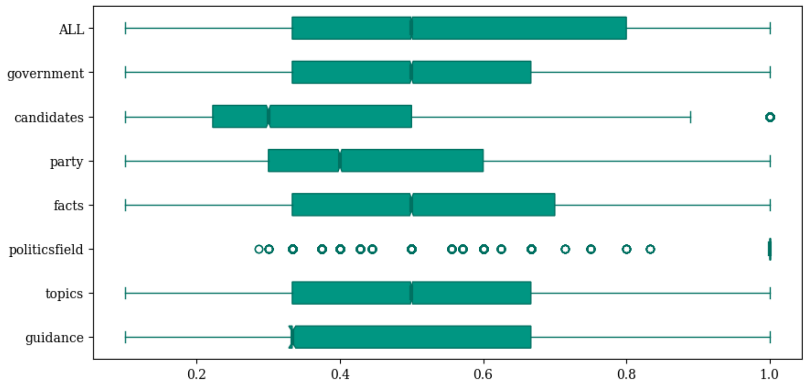


Figure 14.: Different topics in result sets over categories with relative values

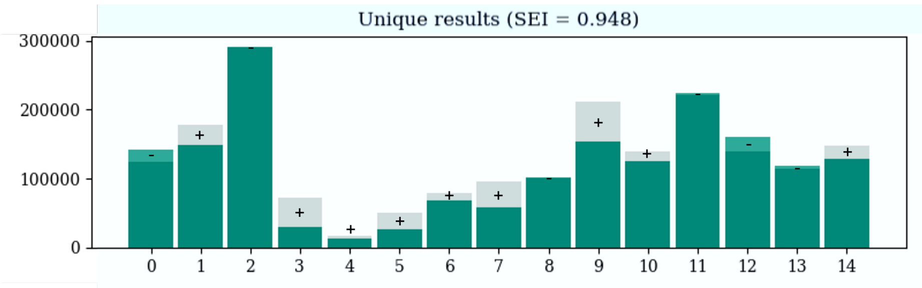


Figure 15.: Distribution (balance) of occurring topics (gray: all results; overlay: unique results; see Table 6 for the list of topics)

the categories that by definition span different "semantical" topics. As with variety, the whole picture is only seen with a break-down to search query level. As for the election, the categories *candidates*, *party* and *topics* are remarkable (see Figure *17*).

As all candidates have many occurrences in the topics 1 (*TV Duel*), 2 (*Government Formation*), 9 (*CDU/CSU*) and 11 (*Elections*) (in case of the AfD with *Alice Weidel* and *Tino Chrupalla* and The Left with *Janine Wissler* and *Dietmar Bartsch*), we do not take those topics into consideration and removed them from the graph, in order to get a better overview over the distribution of the other topics, as seen in Figure *18*. We then see distinctive, what search results are shown for different candidates, especially in the topics 0 (*Politics*), 10 (*Old Government*), 12 (*Foreign Policy*), and 14 (*Election Forecast*). It is noteworthy that besides these topics, especially *Annalena Baerbock* and *Janine Wissler* have relatively high values of topic 13 (*Future Politics*). Also surprising is the low values of results for topics 6 (*Corona Regulations*) and 7 (*Corona Incidence*), as Corona/Covid-19 was still a topic to deal with during and after the election.

Coming back to the balance of the search queries, we see a drastic improvement in SEI values with all candidates, but especially high for *Christian Lindner* (from least balanced to second highest balanced), as the main topic from his headlines are from topic 2 (*Government Formation*).

Regarding the other search categories, most queries (e.g. in *facts*) have a similar manifestation in just one topic. Surprisingly, the search results from the search terms *wahl* (engl. election) and *wahl 2021* differ relative strongly (SEI from 0.869 and 0.706). This effect is not as strong with *Bundestagswahl* (engl. federal election) and *Bundestagswahl 2021* (SEI of 0.782 and 0.724) (see Figure *19*). Thus, querying these terms

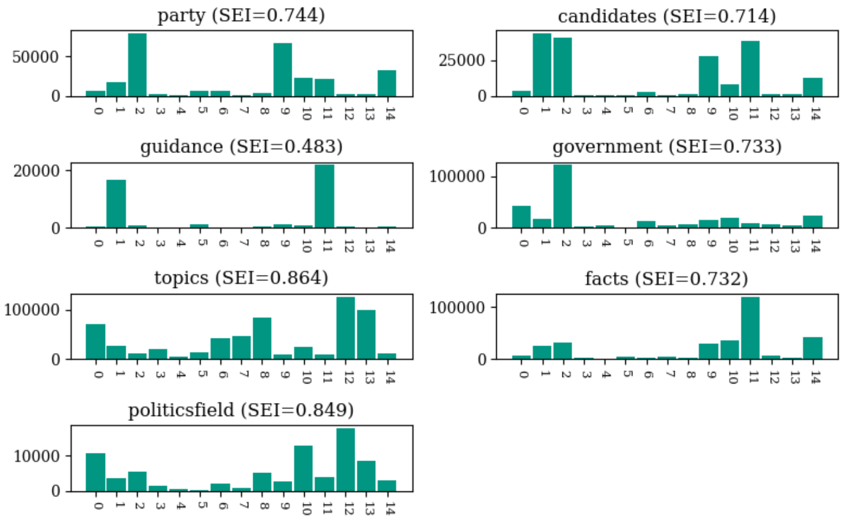


Figure 16.: Distribution of occurring topics over categories

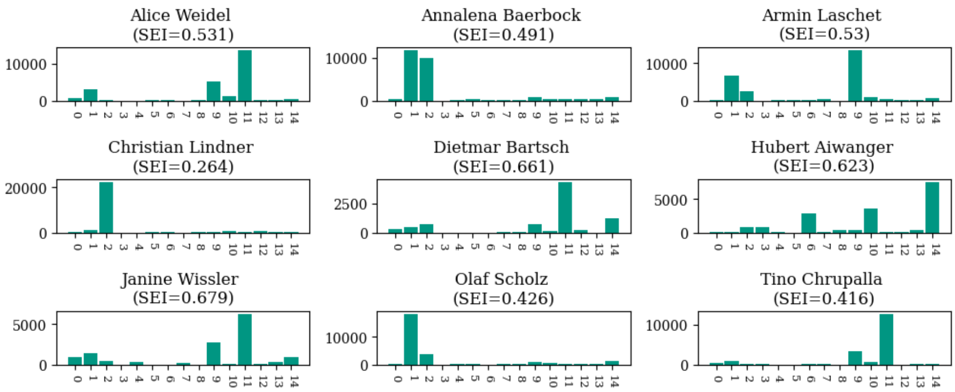


Figure 17.: Balance values candidates

wahl/bundestagswahl instead of *wahl/bundestagswahl 2021* leads to an increased balance of results.

Result Sets. Looking into the balance of topics in each result set, the SEI for each result set is calculated and then cumulated in an overview in Figure 20. The shorter and the more towards 1.0 the bar of the box plot is, the better. We see for *politicsfield* the biggest span of all categories, showing that the balance of result sets can be considered unstable. Most of the result sets are (well-)balanced with SEIs larger than 0.8 or even 0.9 but with a few outliers also far below 0.6, which is a rather poor balance.

5.3. Results for Disparity

Data Set. Disparity on the level of the data set is determining the disparity/similarity measures in-between all topics. This is in our case based on word2vec embeddings trained on the German 2022 Wikipedia dump[14] using Wikipedia2Vec (Yamada et al.,

[14]dewiki dump 02.01.2022 from https://wikimedia.bringyour.com/dewiki/

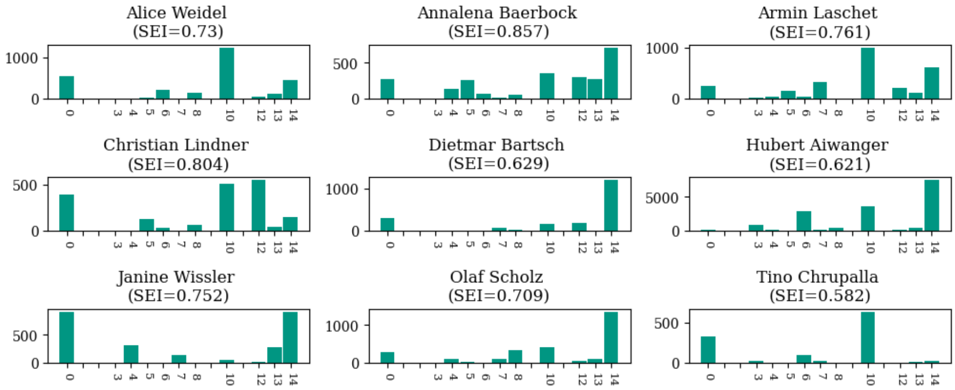


Figure 18.: Cleaned balance values candidates

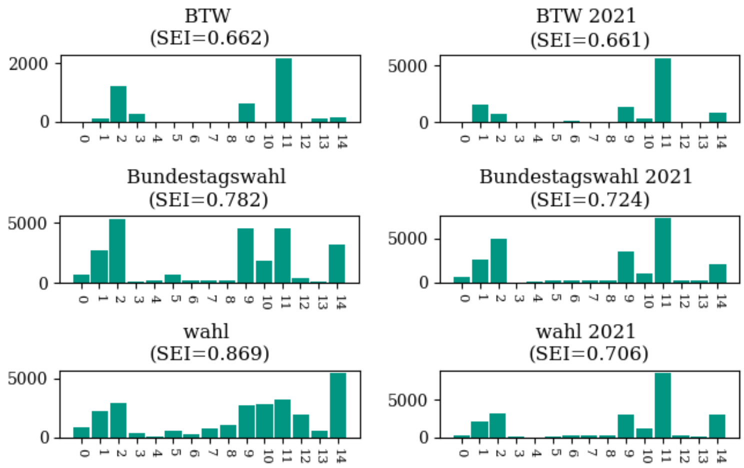


Figure 19.: Comparison of balance graphs of search queries with and without "2021"

2020). The list of all used words for calculating the word embedding are listed in our repository. The calculated disparity between each topic is displayed in Figure 21. As discussed in Section 4.2.3, a higher number means higher disparity.

We see that topic 4 (*News in English*) has the highest disparity to all other topics than any other topic. This comes as little surprise, as word embeddings in English compared to the German Wikipedia dump used to generate the embeddings lead to low similarities and therefore high disparity. On the other hand, the lowest disparity (the highest similarity) is in-between topics 9 (*CDU/CSU*) and topic 2 (*Government Formation*) with a value of 0.12, as well as topic 7 (*Corona Incidence*) and topic 3 (*Corona Vaccination*) with 0.13. As the *CDU/CSU* have been the largest government party for years, the high similarity between *CDU/CSU* and *Government Formation* comes as low surprise as the big question of this election was, whether the CDU/CSU continue as the main party running the parliament and the government, which they in the end did not. Also, everything related to *Corona* having low disparities, as the nuanced differences between the identified topics and information around Corona/Covid-19 are very interrelated and similar.

Result Sets. Looking at the disparity of result sets in Figure 22, we observe relatively low values (mostly lower than 0.15). That indicates that results either having

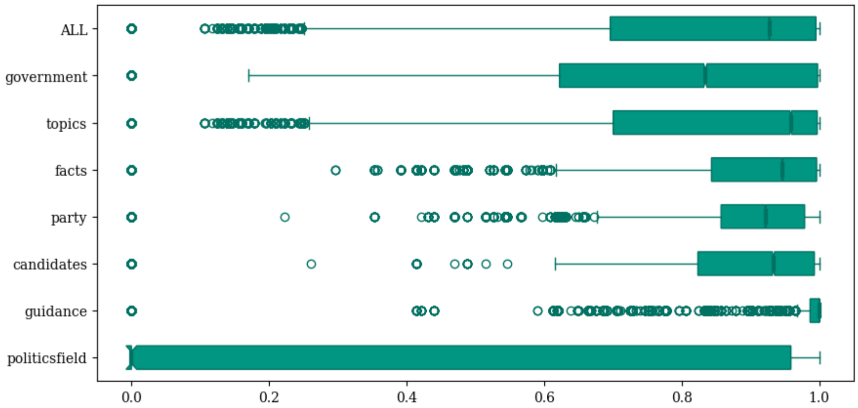


Figure 20.: SEI of result sets per category

Table 8.: Balance of result sets per category (absolute numbers)

Category	# Result Sets	Mean	Median	Std.Dev.
Guidance	11,062	0.902	1.000	0.252
Topics	102,573	0.762	0.959	0.365
Politics Field	38,328	0.411	0.000	0.446
Candidates	21,910	0.865	0.933	0.211
Party	31,169	0.903	0.922	0.107
Government	54,011	0.720	0.834	0.327
Facts	51,046	0.840	0.946	0.274

low disparities in themselves, or multiple occurrences of one topic in the result set. Under optimal conditions (meaning a uniform distribution in balance) we would expect a score between 0.2 and 0.3 at maximum (as most disparity values lie in this region; see Figure 21). Therefore, we find result sets with topics with multiple occurrences (e.g., Figure 25).

Result sets in the categories *facts*, *topics* and *party* are those with the highest disparity. Interestingly, Figure 25 shows that both extreme parties in Germany – the *AfD* and *The Left* – are the two parties with the highest disparity in our data set. This is congruent to the finding in balance, where both parties are having also the highest balance overall (see Figure online). With both parties not in the run for the chancellorship, we could interpret that they are more involved in other topics, besides the run

Table 9.: Disparity of result sets per category (absolute numbers)

Category	# Result Sets	Mean	Median	Std.Dev.
Guidance	11,062	0.036	0.000	0.052
Topics	102,573	0.085	0.091	0.070
Politics Field	38,328	0.061	0.000	0.067
Candidates	21,910	0.087	0.090	0.052
Party	31,169	0.104	0.108	0.055
Government	54,011	0.074	0.066	0.069
Facts	51,046	0.092	0.100	0.061

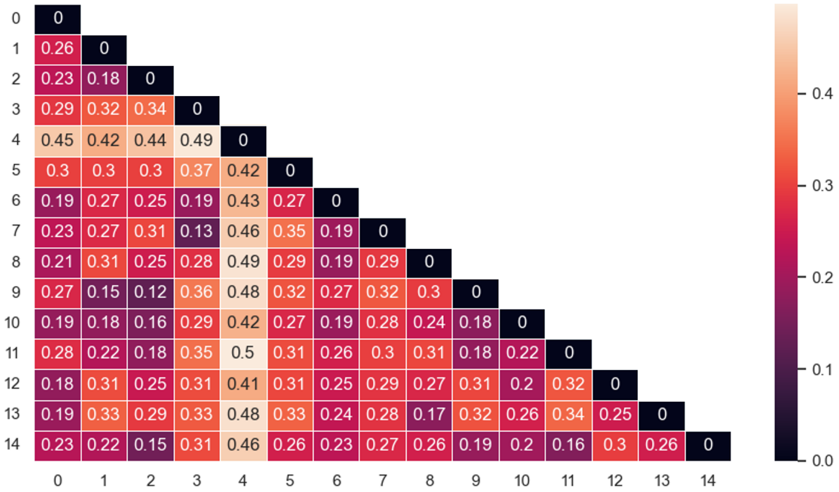


Figure 21.: Disparity values between every topic (see Table 6)

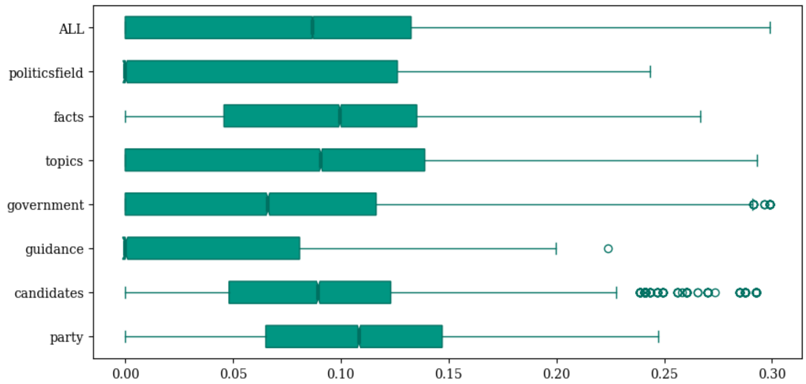


Figure 22.: Topic disparity of result sets per query category

for government. Figure 23 and 24 show the disparity values for the category *topics*. Further results can be found in our repository.

Looking again at *candidates* in Figure 26, search results occurring when searching for *Christian Lindner* had the lowest disparity, which comes from the high concentration of articles regarding topic 2 (*Government Formation*) as seen in our repository. We also once again find the highest disparity at candidates from the *AfD* and *The Left*.

5.4. Regional Differences

To prevent personalization and localization effects of search results, we used different server locations for obtaining the news headlines. We collected the data from the following locations: Munich (MU), Falkenstein (FA), Duesseldorf (DU), Frankfurt (FR1, FR2, FR3), Nurnberg (NU) and Karlsruhe (KA), with FR2 and FR3 being servers at the same vendor in the same data centre to inspect into possible location differences as we would expect the same results.

Overall, we noticed a few differences between the locations. The majority (over 70%) of headlines are listed in results of all 8 locations. The relative high amount of 2,695

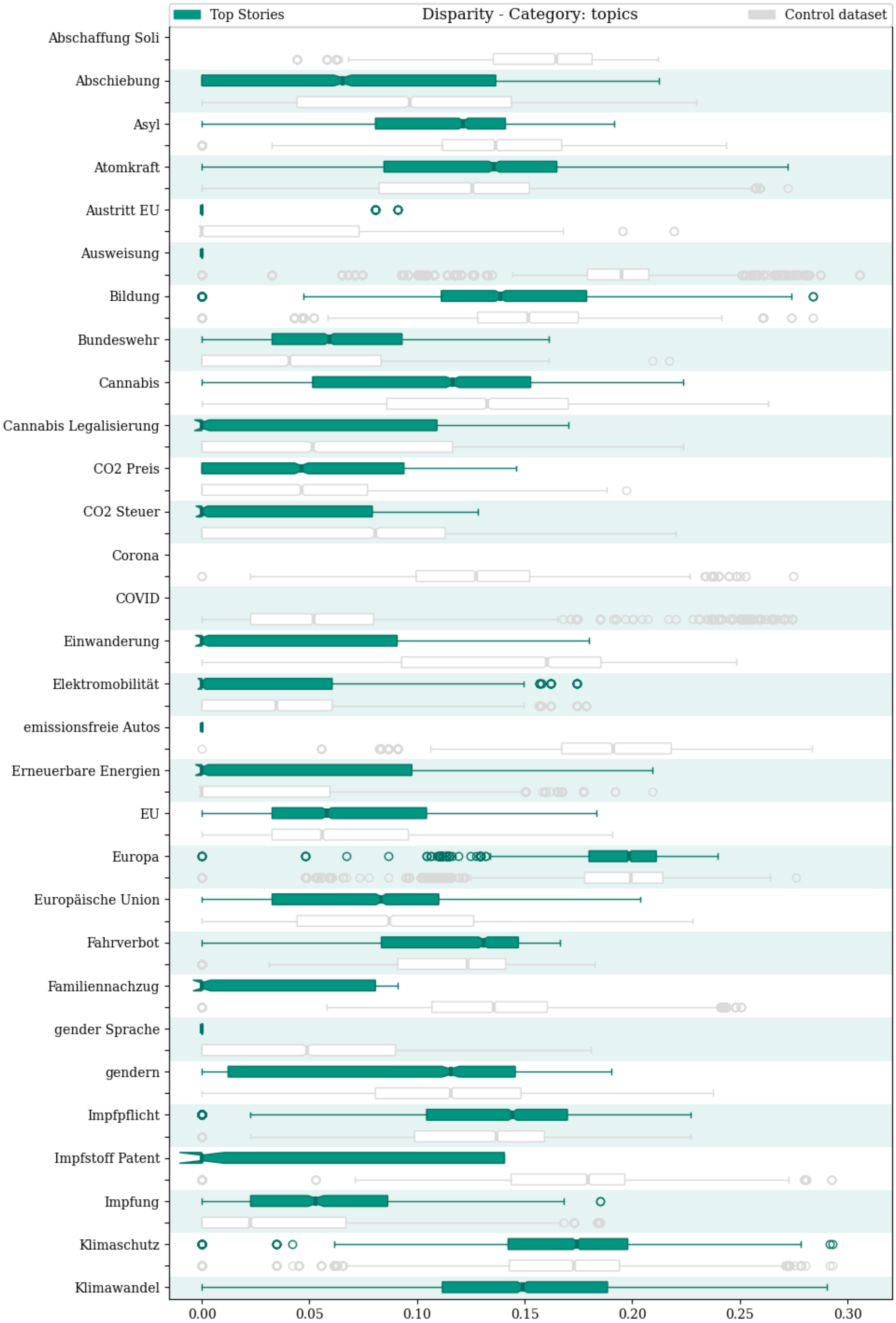


Figure 23.: Disparity values for category *topics* (part 1)

Figure 24.: Disparity values for category *topics* (part 2)

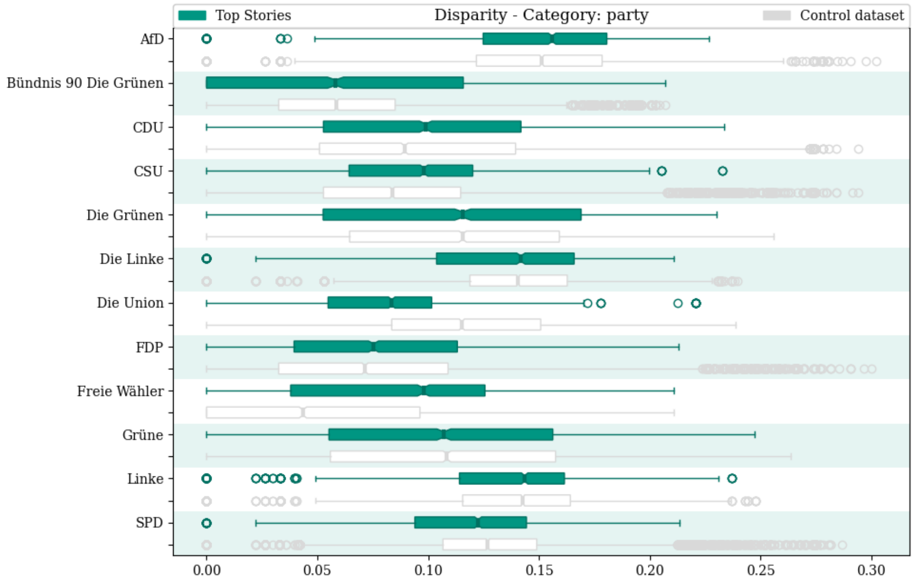


Figure 25.: Disparity of results sets of category *party*

results on 7 instead of 8 locations can be explained by crawling errors over time, when some locations are temporarily not crawling any more.

Regarding the shown sources, we identified the following effects:

(1) Some outlets occur primarily at specific locations. For instance, “Antenne Düsseldorf”, “Hessenschau” and “Frankfurter Rundschau” appear mainly in Duesseldorf and Frankfurt, while articles from “Ruhrnachrichten” (from Dortmund), “Landeshauptstadt Düsseldorf” (from Duesseldorf), Der Westen (from Funke Mediengruppe North Rhine-Westphalia), and Express (from Cologne) were retrieved mainly in Duesseldorf.

(2) Nevertheless, all other local media outlets like “Badische Zeitung”, “BR”, “Berliner Morgenpost” or “Braunschweiger Zeitung” and more were shown equally on all locations.

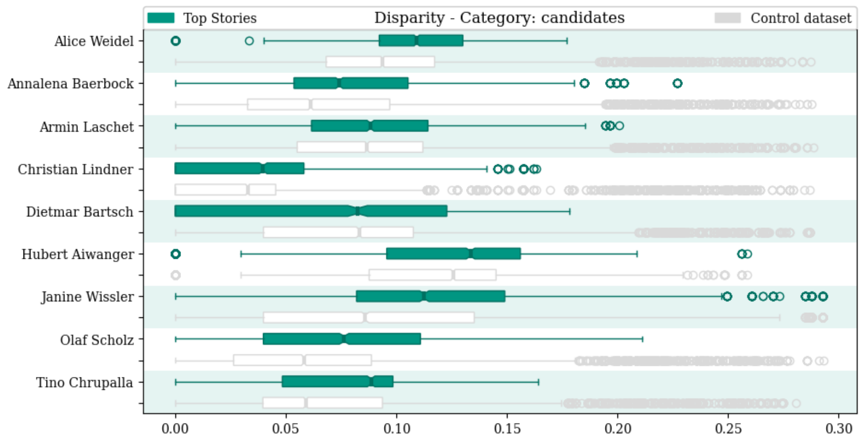


Figure 26.: Disparity of results sets of category *candidates*

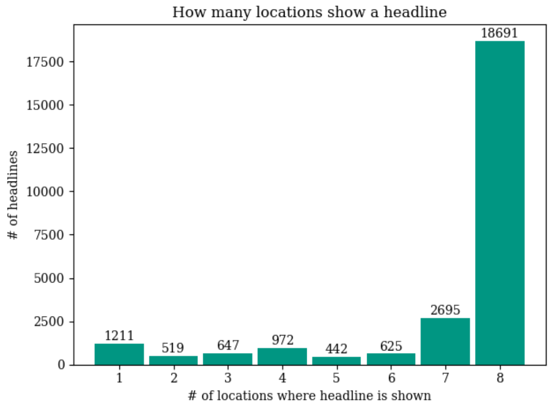


Figure 27.: Location differences measured by overlapping headlines

(3) We find a surprising under-representation of the two big news outlets in FR1, FR2 and FR3 with "BILD.de" with only around 150 headlines per location compared to around 500 headlines on all other locations and similar with "FOCUS Online" and around 120 in Frankfurt and around 680 elsewhere (also per location).

Although we observe some localization in our results, there exits little impact on the overall search results as their proportions on the overall data set are relatively low.

6. Conclusion and Outlook

Previous works on media diversity has relied mostly on manual work, such as conducting surveys, coding, and labeling data by experts. In this paper, we automated this process. Firstly, we presented a framework for measuring the media diversity dimensions *variety*, *balance*, and *disparity*. *Variety* was determined by counting the absolute amount of topics in a result set. For *balance* we used Shannon's Evenness Index (SEI). To measure *disparity*, we used a topic modeling approach to assign the headlines to a topic and then compute the similarities between all occurring topics in a result set. Secondly, we created and provided a data set of Google Top Stories related to the 2021 German federal election. Thirdly, we applied our framework to this data set and looked at each dimension individually, once at the level of the entire dataset, and once aggregated at the level of the result sets. We found that some search terms (namely, *bundestagswahl* and *wahl*) generally lead to a higher diversity, resulting in one of the most diverse result sets in all three dimensions. Other search terms that lead to a high diversity in at least two of our diversity dimensions. These are *Bildung* (engl. education), *Europa* (engl. Europe), *Klimaschutz* (engl. climate protection/politics) and *Regierung* (engl. government). These are generally more future-oriented topics, and could be a sign that a broad discussion around these topics happened in the public. The shown results for *candidates*, *parties*, and *facts* are among the most diverse results we see in our data set. Searching on Google about the election with these search terms will lead to sufficient diverse results according to our findings.

Although Google Search is likely to be a main source of information gathering for many users, it is not a sole source. The final information gathering process consists of a much broader media mix, including elements like social media platforms, newspapers and magazines, the personal environment, radio and much more. The thin line between what is news and what not, smashes more and more into one. Is a tweet of the German chancellor news? If not, does it become news if, for instance, SpiegelOnline retweets it Hendrickx et al. (2020)?

Besides the limitations on Google Top Stories, one larger restriction of this work is that it focuses on topic diversity. Other forms of diversity (e.g., considering the reader) are left for future work. Furthermore, one new way to measure disparity could be to use of knowledge graphs to represent better how topics are connected with each other.

Disclosure statement

The authors have no competing interests to declare that are relevant to the content of this article.

Funding

The authors did not receive support from any organization for the submitted work.

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