Identifying Media Bias by Analyzing Reported Speech

Konstantina Lazaridou, Ralf Krestel and Felix Naumann
Hasso-Plattner-Institut, Potsdam
Email: firstname.lastname@hpi.de

***Abstract*—Media analysis can reveal interesting patterns in the way newspapers report the news and how these patterns evolve over time. One example pattern is the quoting choices that media make, which could be used as bias indicators. Media slant can be expressed both with the choice of reporting an event, e.g. a person's statement, but also with the words used to describe the event. Thus, automatic discovery of systematic quoting patterns in the news could illustrate to the readers the media' beliefs, such as political preferences. In this paper, we aim to discover political media bias by demonstrating systematic patterns of reporting speech in two major British newspapers. To this end, we analyze news articles from 2000 to 2015. By taking into account different kinds of bias, such as selection, coverage and framing bias, we show that the quoting patterns of newspapers are predictable.**

I. Media Bias

Media analysis is the task of identifying patterns in the way media, such as newspapers and blogs, report the news. These patterns can be found in the word choices or topic preferences of a source. They can also be observed in whether a news source is up-to-date or how much space it occupies for different events. In addition, considering how popular online media are, it is undeniable that they can influence the general public's opinion. Thus, media analysis can also assist us in understanding the extent of this influence. Automatically recognizing and quantifying media bias will not only benefit the readers, but it can also support journalists to reflect on their work.

Media slant can be expressed in different ways [1]. The first decision that a reporter faces with the emergence of an event is whether it should be reported or not. This type of media bias is called *selection bias*. It is based on the interestingness of a topic and the involved individuals [2], as well as the physical location of the news source. Another kind of bias is called *coverage bias* and refers to the completeness of a news piece in terms of the space (e.g., article length) and the reported aspects or opinions. For instance, it has been shown that media often criticize disproportionately different political parties [3]. Finally, the language a fact is described with, either positive, neural or negative, is called *framing bias*. In addition, the author's explicit remarks on a news topic are referred to as *statement bias*. All above-mentioned kinds of bias are very challenging to identify in political news and even harder to quantify. That is, when bias is observed in the text, it is more likely to be subtle and underlying, than explicitly given as an opinion or a comment.

Reported speech is an integral part of the news storytelling. It is used by the media as an element of argumentative discourse to inform and persuade readers [4]. Our hypothesis is that one representative indicator of media slant is how reported speech is used, where journalists are responsible of deciding whether and how they will present, e.g., a person's statement. These quoting choices could potentially reveal the source's beliefs. Our work aims at discovering systematic quoting patterns in news over time, which could stem from the political preferences of a source and thus introduce political bias in the news articles.

We leverage the word choices of the reporters to classify extracted quotations from news articles to the sources they were originally published in. Our motivation derives from the different way that each source describes the news, which we will show to be discriminative for news outlets. We use various features, such as the introductory verb and the speaker of a quote, and present our results for two major UK news outlets in 2000–2015. Hence, our contributions include:

- using direct and indirect speech extracted from news articles as an innovative media bias indicator
- enriching the quotations by detecting their speaker with a context-aware approach specifically for the news domain
- successfully modeling the media bias detection problem as a classification task of predicting a quotation's news source
- proving the existence of different bias kinds in reported speech, i.e. *selection*, *coverage* and *framing* bias

II. Related Work

Identifying disputed topics that reporters have diverse opinions about is closely related to media bias detection, since a writer's view could be classified as conservative, liberal etc. Related research in this field includes a new version of the HITS algorithm [5] that identifies the main disputants of a topic in Korean media and classifies the news articles into different viewpoints of a story [6]. Topic-based bias analysis is also conducted by De Clercq et al. [7], where the discussed topics in UK and US newspapers are extracted by making use of DBpedia links.

2374-8486/17 $31.00 © 2017 IEEE
DOI 10.1109/ICDM.2017.119

Sentiment and subjectivity are measured for each topic, in order to discover conflicting ones. The presented results are promising and motivated us to investigate whether English-speaking media differ not only in the way they discuss topics, but also in the way they report quotations.

Saez et al. [1] analyzed the characteristics of 100 English-speaking social and news media sites in terms of different bias measures in a two-week period. The authors show that bias is more frequently observed in social than news media. They also illustrate that selection bias metrics are not as indicative as coverage metrics, which provide more interesting evidence for bias, especially in the political context. This finding is incorporated in our analysis, by using coverage bias as a feature of our bias-aware classifier.

An alternative way of detecting media bias is by taking into account the readers' political affiliation. Among others, user comments [8] and user reactions [9] have been exploited in order to predict the political position of the media. The authors assume that a liberal reader will express a negative sentiment on a conservative article and a positive one to an article that favors the liberals. Additionally, according to a study in economics [10], one is more likely to perceive bias the further the slant of the news is from one's own political position.

Unlike prior research, we focus on a specific bias kind, which is the political media bias expressed through reported speech choices. We perform a large-scale analysis on a 16-year news dataset and our task does not require any external knowledge that classifies media into liberal, conservative, etc. [11]. It does also not depend on manual labeling of existing media slant in news articles [3], [4], which is cumbersome to obtain and sensitive to *annotator bias*. We solely leverage the utterances that media cite and their context to illustrate systematic quoting patterns over time.

To the best of our knowledge, the only work that is closely related to our analysis is the selection bias framework *QUOTUS* [11], which observes how often political blogs and newspapers quote Barack Obama's White House speeches. The results show that after projecting these quotations into a latent space, some of the outlets cluster together by their political affiliation in the first two latent dimensions — for instance Fox News is close to New York Times. The authors manually classify the media into four categories, that is declared liberal (DL), declared conservative (DC), suspected liberal (SL) and suspected conservative (SC). Initially, *QUOTUS* matches segments of the presidential speech transcripts to the news. Furthermore, it estimates the likelihood that a quote q will be cited by an outlet A of a certain category, given that q is already mentioned by another outlet B of a different category. An interesting result is that DC outlets are less likely to quote a statement that DL media reported compared to a random quote. This outcome motivates our work, since it brings evidence that quote selection choices among outlets can differ.

An additional task of *QUOTUS* that is more relevant to our work is to predict for a given outlet and quote q whether the outlet will report q or not. Given a bipartite quote-to-outlet graph G, this problem is tackled by performing a matrix-completion approach on the adjacency matrix of G and it yields a precision of 0.25, while recall is 0.33. Although our classification task is similar, we aim at predicting the news outlet in which a politician's quotation will be published and by extension show that the text and context of reported speech is presented differently among newspapers. On the contrary, *QUOTUS* focuses only on Barack Obama's speech segments and disregards indirect quotations both from Barack Obama and other politicians. In our work, we use a state-of-the-art semi-Markov model [12] that detects direct and indirect quotes in the text and additionally provides us with the introductory verb of the quote, denoted as *cue verb*. We further enrich our dataset (as described in Section III) by determining the author of a quotation based on the context around the quote and the preceding text of the news article.

III. Datasets

This section includes the datasets' description as well as the preprocessing steps prior to our analysis. We also elaborate on the implementation of the quotation extraction algorithm we deploy.

A. Newspapers

Our analysis focuses on two major British newspapers, namely the *Guardian*[1] and the *Telegraph*[2]. We extracted news articles from both outlets from 2000 until 2015. We are interested in news from sections related to the UK and politics, thus irrelevant topics were excluded, such as sports and lifestyle articles. As illustrated in Table I, the news sources show very similar characteristics regarding the number of articles and quotes they published. Given that the examined period is long, i.e. 16 years, we are confident to argue that these two newspapers indeed exhibit similar profile and publishing behavior. This observation motivates us to delve into the text and discover potential bias manifestations in each news outlet. Note that in the presented statistics all quotations are taken into account. Namely, utterances from various people, e.g. politicians, researchers, celebrities etc. The political context is introduced in the next subsections.

TABLE I
Article and quote statistics for both news corpora

Newspaper	#Articles	#Quotes	Avg.Articles/Day	Avg.Quotes/Article
Guardian	200,185	1,994,272	34.27	9.96
Telegraph	189,177	1,954,737	32.39	10.95

[1]https://www.theguardian.com/international
[2]http://www.telegraph.co.uk

B. Politicians

In order to detect reported speech that originates from parties in the United Kingdom, we extracted the politicians' names and affiliations from a publicly available parliament dataset[3] provided by *mySociety*. This corpus contains information about all officially recorded general elections in the United Kingdom, all political parties and their members. During the time period that our analysis covers, the number of party members was 1154 and the number of parties was 11. For the purpose of merging parties that share the same ideology, we have combined all independent parties (e.g. Independent, Independent Conservative, Independent Labour) into a unified party label called *independent*. Similarly, we consider the Labour and Labour co-operative to be one political party, called *labour* and all unionist parties (e.g. UK Unionist Party and Ulster Unionist Party) to constitute a global *unionist* party.

C. Quotations

We discover direct and indirect quotations[4] from the news articles using a state-of-the-art semi-Markov quotation detection model [12]. Scheible et al. introduce a relaxed Markov model (SEMIMARKOV) and improve the previously proposed linear-chain conditional random field [13] for quotation extraction. The benefit of this approach is that it takes into account the full quote span and makes a joint decision about the start and end points of a quotation. Hence, SEMIMARKOV successfully competes the CRF [13] and exhibits 3% higher F1 score, by analyzing the context of the quotes and considering global information in the text.

In order to reduce the false positives of SEMIMARKOV, we prune the resulting quote collection by excluding both quotations with length smaller than 3 and the ones without a cue verb. The application of both filters does not change our collection drastically, resulting in less that 10% of the quotes being discarded.

D. Speaker detection

We introduce a dictionary- and context-based approach to discover the speaker of the reported speech in news articles. Namely, our technique matches the list of politician names found in the above-mentioned parliament dataset to the news text. The nearest politician's name to the cue verb is identified. For instance, in "The shadow chancellor, **Michael Howard**, said the "vast majority" of his own party could not see how joining would benefit Britain (Guardian)", *Michael Howard* is detected. In the cases where only the last name of a politician is mentioned, we disambiguate this speaker via using the article text prior to the quotation. Namely, in "**Burley** told the BBC on Thursday: They are launching a preliminary investigation and I understand I am not the focus of it (Guardian)", we extract the name *Burley* and find that it corresponds to *Aidan Burley* by searching in the preceding paragraphs. We assume that the full name of each discussed politician is included at least once before an abbreviation is used[5], considering that every journalist is responsible of defining the persons that an article is about. In addition, given that we are interested specifically in the political domain, a reliable dictionary approach seems more appropriate than a universal named entity recognition tool.

Since there is a wide range of sources that newspapers quote in the political domain, such as parties worldwide, think tanks, companies, analysts etc. the quotations from UK parties form only a small part of the initial data set. That is, we analyze 11% of the overall extracted data, in particular 438,541 quotations. These utterances split into 246,664 quotes in the *Guardian* and 191,877 in the *Telegraph*.

IV. Distribution of politicians' quotations

As discovered in two recent news bias analyses for German [14] and British [15] media respectively, an initial indicator of media bias is the frequency that an outlet refers to a certain political party and its members. The results show that there are indeed relative differences in the mentioning patterns of the newspapers, although they are not always statistically significant and conclusive for the newspaper's ideology. For instance, both *Guardian* and *Telegraph* tend to cover stories that concern the governing party and disproportionately report news about other parties [15].

We are motivated by the above studies and aim to discover how party quotations are covered by the media as well. Figure 1 shows the distribution of the UK politicians' quotations in the *Guardian* and Figure 2 respectively in the *Telegraph*. For visualization purposes, we group parties whose quotations are extremely few together in a single label called "others". As illustrated in both figures, we can confirm that both newspapers quote more often the current governing party and that is why a simple enumeration of the quotes is not able to distinguish the two news sources from each other. This is shown in 2010, when the government changed from the *labour* party to the *conservative* party and the quotations by the latter started to outreach the quotations by the former in both outlets. As expected, in the general election dates, i.e. during 2001, 2005, 2010, and 2015, the citation curves of the *conservative* and the *labour* converge in both newspapers.

V. Classifying Quotations to their News Source

We model the bias detection problem in media as a classification task. Given the reported speech extracted from news articles, we argue that we can find differences in the reporting text and context by applying a classification algorithm. These systematic differences are indicative

[3] https://github.com/mysociety/parlparse

[4] https://github.com/christianscheible/qsample

[5] https://www.theguardian.com/guardian-observer-style-guide-a

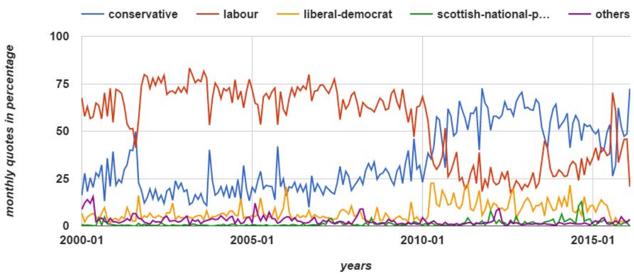

Fig. 1. Relative number of quotations for different parties in the *Guardian* over a 16-year period.

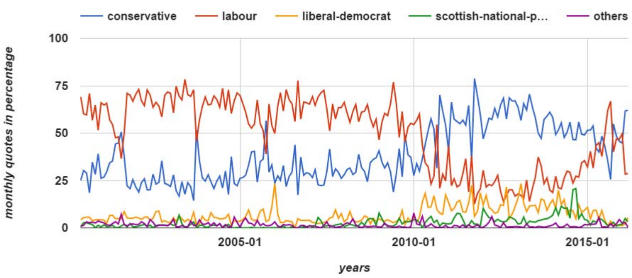

Fig. 2. Relative number of quotations for different parties in the *Telegraph* over a 16-year period.

enough to reveal in which newspaper a particular quote was published in. Hence, we propose a bias-aware model to classify the reported speech to its original outlet and compare our approach against a naive baseline that only leverages the content of reported speech. We use a Random Forest classifier [16] for both approaches.

A. Baseline model

Our baseline model takes into account the text inside UK politicians' quotes and classifies it to its original news source. To detect bias in the news we want to uncover representative characteristics in the way media describe people's utterances. For instance, whether a given utterance is altered according to the editor's writing style and thus it is written differently in different outlets. Apart from the word usage, another aspect captured by the naive model is the choice itself of whether an outlet reports about a news event or not. A quote constitutes such an event and can therefore be used as a *selection bias* metric [1].

B. Bias-aware model

Our proposed approach to address the media bias detection problem in reported speech combines multiple bias types inferred from the article text, i.e *selection*, *framing* and *coverage* bias. Similarly to the naive model, the *selection* bias dimension of the problem is taken into account by including the quote text as the first feature set of the classifier. Moreover, in order to capture the extend of framing bias, we incorporate the contextual information of the quote by considering the *cue verb* that introduces the reported speech and the speaker's name. We also include the speaker's political party as an additional categorical attribute. Finally, the last two features of the classifier are *coverage bias* metrics, namely the quote and article lengths, which are indicators of the scope that newspapers cover politicians' statements. Table II demonstrates differences of quotations that our strategy aims to detect. In the first example, the same utterance is reported partially by the two newspapers and in the second one, the quote text is slightly altered. The last quote is framed with a unique context, that is a different *cue verb* in each case.

TABLE II
EXAMPLE QUOTES WITH DIFFERENT REPRESENTATIONS IN THE GUARDIAN (LEFT) AND THE TELEGRAPH (RIGHT)

	Guardian	Telegraph
1	Tory MP Michael Fabricant, shadow minister for industry and technology, told PA: "**It is quite clear that they are planning to mount a desperate dirty tricks campaign.**"	"Michael Fabricant, the Tory MP who discovered the sites, said: **It is quite clear that the Labour Party is planning to mount a desperate dirty tricks campaign. How desperate they have now become.**"
2	he was **deeply saddened** by the deaths	he was **shocked and saddened** by the deaths
3	he **told Tony Blair** to sack Gordon Brown	that he **urged Tony Blair** to sack Gordon Brown

VI. Experiments

We divide the evaluation of our approach into two tasks: (1) a global analysis concerning all politicians' quotations, where we compare the performance of the baseline and the bias-aware model, and (2) a comparative analysis that shows how the proposed model behaves for each news outlet. The quote content is represented as a bag of words and each term corresponds to its frequency in the text. We also exclude stopwords and rescale all features so that they have a mean value of 0 and a standard deviation of 1.

A. Model evaluation

1) Cross validation: We apply 10-fold cross validation and train our model and the baseline in a randomly selected 90% of the quotes and test both approaches in the remaining 10%. The bias-aware technique outperforms the naive one by almost 4% higher accuracy (71% vs. 67.3%). This outcome indicates that *selection bias* in reported speech is existing and it is pointing us to the right direction to uncover the newspaper of a given quote. Hence, the finding of this experiment is two-fold: the relative differences of the reported speech choices are sufficiently indicative for the newspapers and the content of the quotes is systematically different as well. Therefore, our bias-aware approach is able to achieve better results than a competitive baseline model.

2) Temporal patterns: In order to exploit the temporal nature of our data set and confirm the above-mentioned findings for different time periods, we evaluate our model separately for each of the 16 examined years. We compare the accomplished accuracy of the proposed model and the naive one in Figure 3. As in the previous experiments, their performance remains similar over time. However the bias-aware approach constantly outperforms the naive method. One can also observe that both solutions' accuracies exhibit peaks during the years that general elections were held in the UK (2001, 2005, 2010 and 2015). This effect could be explained if we consider the elections as an opportunity of the media to deviate from each other. That is, prior to crucial political events, media potentially make their endorsements more obvious and thus differentiate from each other in terms of the news they report.

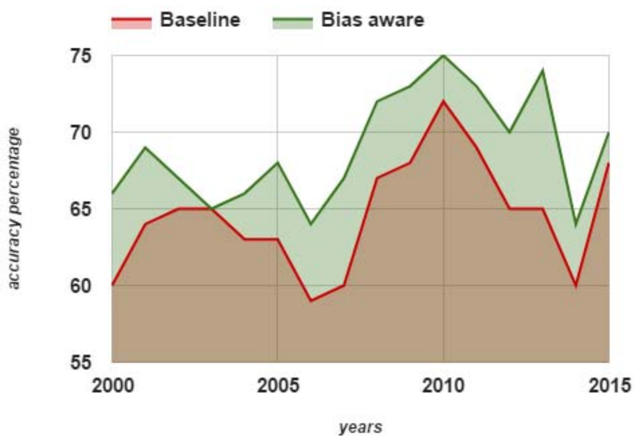

Fig. 3. Comparison of the baseline and the bias-aware model in terms of achieved accuracy per year

B. Comparative Evaluation

We investigate our results separately for each newspaper in Figure 4. We show the rate of correctly classified quotations for both outlets in each examined year from 2000 until 2015. As illustrated, we are able to identify quotes that originate from the *Guardian* on average 82% of the times. Particularly in 2010, 95% of *Guardian*'s quotes are correctly classified. On the contrary, *Telegraph* is a much less predictable news source, as its accuracy ranges from 35 to 70%, with an average value of 52% for the entire time span. Thus, the *Telegraph* does not exhibit as apparent and systematic preferences and writing styles as the *Guardian* does in reporting quotations.

Therefore, newspapers can be predictable to different extents. This means that the combination of all three bias kinds, namely *selection*, *coverage* and *framing* bias, may deliver different performance for each outlet. Towards further interpreting the above results, we execute an additional experiment based on an interesting use case of reported speech. Namely we analyze quotations

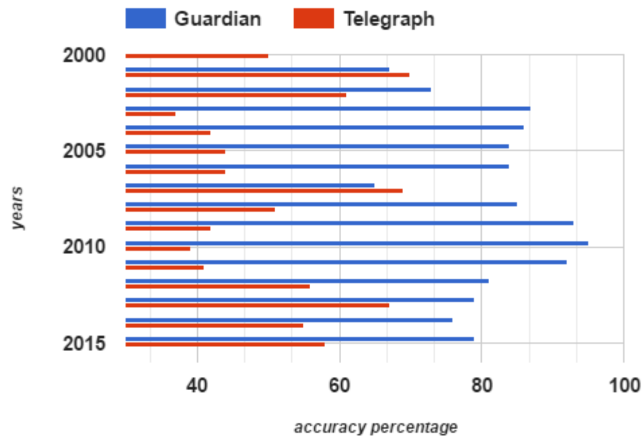

Fig. 4. Comparison of the accuracy results for both newspapers using the Bias-aware approach

by the same politicians that are published differently in the newspapers. We perform a speaker-based comparison between the two outlets and show the usefulness of *framing* and *coverage* bias metrics for this application.

Speaker-focused analysis. In real-word scenarios, it is possible that different media outlets will report the same utterance of the same person in dissimilar ways, as depicted in Table II. For instance, given a quote q from a party leader in the UK, will the *Guardian* cite the complete statement or only a part of it? Alternatively, will the *Telegraph* and the *Guardian* present q in a different way? In order to answer the above questions we perform a focused analysis on a speaker level for similar quotations between the outlets.

As demonstrated in the previous results, *selection* bias in reported speech is predictable even by a baseline approach. Armed with this finding, we perform our classification task in a different setting that doesn't leverage *selection* bias anymore. We classify quotations only by using their context and scope. The context corresponds to all tokens that surround the quote in the sentence (including the *cue verb*) and the extent refers to the quote and article lengths. Hence, we completely exclude the quote text as a feature of the classifier and only exploit *framing* and *coverage* bias metrics of reported speech to identify the news source of a quotation.

Experimental setting. Since we are interested in discovering different representations of the same utterance by a given person, we computed the Jaccard similarity between the quotations from the *Guardian* and the *Telegraph* that originate from the same speakers. We consider text similarity on a word level. Given the set of tokens of a *Guardian* quote and *Telegraph* one, denoted as T_1 and T_2 respectively, we calculate their similarity as follows:

$$Sim = T_1 \cap T_2 \div T_1 \cup T_2$$

We analyze only quotations that are sufficiently related, thus exhibit a similarity score higher than 0.6, which results in a data set of 5,618 quotes. We use these utterances as test set and train our model on the remaining quotations. Similarly to the previous subsection, we use a Random Forest classifier.

Results. Table III demonstrates the accuracy we accomplish with the speaker-based analysis. Apparently, an approach based solely on *framing* and *coverage* bias achieves higher accuracy in the current test set than the global bias-aware model achieved in the previous experiments. The average accuracy is 79% with approximately 86% for the quotations of the *Guardian*, whereas 72% for the *Telegraph*. Therefore, our intuition that each media outlet is presenting the same utterances by the same speakers in a unique linguistic way is confirmed. Note that this conclusion is not leading us directly to characterize media outlets neither as biased or not, nor as left or right wing. However, it is proving their systematic differences on writing styles, coverage choices and news presentation in general. These patterns can introduce deliberate or accidental bias in the news articles and by extension in the readers' everyday news consumption. Hence, one can take into account the predictability of an outlet among other parameters and decide which source to read in order to capture a particular view.

TABLE III
Accuracy of the speaker-focused model for each newspaper

Guardian	Telegraph	Average
86.76	72.79	79.77

VII. Conclusions and Future Work

In this paper, we investigated bias in media by showing systematic quoting differences among news outlets. To this end, we analyzed both direct and indirect reported speech by all political parties in the United Kingdom in news articles from the *Guardian* and the *Telegraph* from 2000 until 2015. We classified the quotations to their original sources and showed that the proposed feature sets are suitable for uncovering the newspaper that cited a certain quote. We proved that media bias exhibits various manifestations in reported speech and we can model it successfully, though with varying performance for different newspapers. Our bias-aware model that combines *selection*, *coverage* and *framing* bias metrics is a powerful approach that yields promising results and shows that quotations are indeed represented in different ways in media. Hence, we proved our hypothesis that news outlets can be predictable in the quotes they report and consequently, readers are aware of this finding.

For future work, we plan to extend our technique and include more English-speaking news sources and politicians. The more evidence our model creates, the more readers are aware of the media's writing styles and potential political preferences. Additionally, given a news article, the quote sentiment and the overall discussed topic could also be supplementary parts of our classifier. This could improve the source prediction, considering that some topics are discussed extensively (or briefly) and negatively (or positively) in different outlets. Hence, the readers wouldn't limit themselves only to certain aspects of an event.

References

[1] D. Saez-Trumper, C. Castillo, and M. Lalmas, "Social media news communities: gatekeeping, coverage, and statement bias," in *Proceedings of the 22nd ACM International Conference on Information & Knowledge management*. ACM, 2013, pp. 1679–1684.

[2] E. M. Kearns, A. Betus, and A. Lemieux. (2017, March) Why do some terrorist attacks receive more media attention than others? [Online; accessed 10-May-2017].

[3] C. Budak, S. Goel, and J. M. Rao, "Fair and balanced? quantifying media bias through crowdsourced content analysis," *Public Opinion Quarterly*, vol. 80, no. S1, pp. 250–271, 2016.

[4] A. V. Smirnova, "Reported speech as an element of argumentative newspaper discourse," *Discourse & Communication*, vol. 3, no. 1, pp. 79–103, 2009.

[5] J. M. Kleinberg, "Authoritative sources in a hyperlinked environment," *Journal of the ACM*, vol. 46, no. 5, pp. 604–632, 1999.

[6] S. Park, K. Lee, and J. Song, "Contrasting opposing views of news articles on contentious issues," in *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1*. Association for Computational Linguistics, 2011, pp. 340–349.

[7] O. De Clercq, S. Hertling, V. Hoste, S. P. Ponzetto, H. Paulheim *et al.*, "Identifying disputed topics in the news," *Proceedings of the 1st International Conference on Linked Data for Knowledge Discovery*, pp. 32–43, 2014.

[8] S. Park, M. Ko, J. Kim, Y. Liu, and J. Song, "The politics of comments: predicting political orientation of news stories with commenters' sentiment patterns," in *Proceedings of the ACM 2011 conference on Computer supported cooperative work*. ACM, 2011, pp. 113–122.

[9] D. X. Zhou, P. Resnick, and Q. Mei, "Classifying the political leaning of news articles and users from user votes." in *Proceedings of International Conference on Web and Social Media*, 2011.

[10] T. Groseclose and J. Milyo, "A measure of media bias," *The Quarterly Journal of Economics*, vol. 120, no. 4, pp. 1191–1237, 2005.

[11] V. Niculae, C. Suen, J. Zhang, C. Danescu-Niculescu-Mizil, and J. Leskovec, "Quotus: The structure of political media coverage as revealed by quoting patterns," in *Proceedings of the 24th International Conference on World Wide Web*. ACM, 2015, pp. 798–808.

[12] C. Scheible, R. Klinger, and S. Padó, "Model architectures for quotation detection," in *Proceedings of Association for Computational Linguistics*, 2016.

[13] S. Pareti, I. Konstas, J. R. Curran, and I. Koprinska, "Automatically detecting and attributing indirect quotations." in *Proceedings of the EMNLP*, 2013, pp. 989–999.

[14] A. Dallmann, F. Lemmerich, D. Zoller, and A. Hotho, "Media bias in german online newspapers," in *Proceedings of the 26th ACM Conference on Hypertext & Social Media*. ACM, 2015, pp. 133–137.

[15] K. Lazaridou and R. Krestel, "Identifying political bias in news articles," *Bulletin of the IEEE TCDL*, vol. 12, 2016.

[16] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The weka data mining software: An update," *SIGKDD Explor. Newsl.*, vol. 11, no. 1, pp. 10–18, Nov. 2009.