A Quantitative Social Network Analysis of Politicians' Tweets to Explore Political Communication

Heidi Schuhbauer, Sebastian Schötteler, Johannes Niu, Bernhard Schiffer, David Wolfarth
Computer Science Department
Nuremberg Institute of Technology
Nuremberg, Germany
heidi.schuhbauer@th-nuernberg.de; sebastian.schoetteler@th-nuernberg.de

***Abstract*— This paper illustrates the practical application of cluster analysis, social network analysis and sentiment analysis in a case study. These techniques provide insights into the public communication patterns between German Members of Parliament (MPs) on Twitter around the time of the 2021 federal election. The question of this work was to determine whether a potential shift in communication towards the inaugurated "Ampel" coalition, made up of the parties SPD, Greens and FDP, can be derived from Twitter interactions. In distinct scenarios, mention, retweet, and reply interactions are first considered together and then separately. In these scenarios, the Girvan-Newman Algorithm detects clusters of MPs dependent on the interactions observed. Then, the average inbreeding homophily and other network metrics of the pre- and post-election area are compared. An additional scenario focuses on intra- and inter-party sentiments conveyed within tweet texts. In a fourth scenario, MPs are grouped according to their party affiliation, the average inbreeding homophily values of parties and potential coalitions. The communication clusters of those MPs differ mostly before and after the election. The average sentiment of the parties towards each other changed positively, although no significant tendency could be derived regarding later coalition formations.**

Keywords-Cluster Analysis; Microblog; Network Metrics; Sentiment Analysis; Social Network Analysis.

I. INTRODUCTION

For the political communication between parties, politicians and their constituents, social media platforms play an important role. By communicating through platforms, such as Facebook, Twitter, and Instagram, political actors reach wide audiences within a short period. On these platforms, politicians publicly communicate with each other.

Among those services, Twitter promotes the dialogue between politicians and between politicians and their constituents via mention and reply interactions, which allow users to engage in direct communication. Consequently, social media have become a central component of political communication.

Relations between individual MPs can be examined in more detail using social network analysis. Interactions can be derived from public tweets referring to other people, i.e., retweets of or replies to another user's tweet, or mentions of a user. Analysis of interaction networks explore these relations, as well as their textual contents, which can be examined through sentiment analysis. This article applies such methods to explore changes to the communication of German MPs from selected political parties around the 2021 federal election.

Section 2 of this paper presents related works, formulates the research gap and specifies the hypotheses. Section 3 introduces the methodology used to aggregate and analyze the data. Section 4 presents the results of each perspective and discusses them. Section 5 illustrates the limitations of this research, as well as starting points for possible future work.

II. RESEARCH GAP

Virk [1] compares different Social Network Services (SNS) as a type of social media and explores the special role of Twitter in public communication. The author examines the communication patterns between Twitter users and applies the tie strength theory postulated by Granovetter [3] to conclude that interactions on Twitter – unlike other SNS – focus on content rather than user relationships, and thus can reach wider audiences.

Lassen and Brown [2] examine the Twitter use of members of congress in the United States of America. They state that SNS enable politicians to communicate more directly and personally with peers and supporters by eliminating limits on message visibility, allowing content to be redistributed beyond one's own followers. The application of social network analysis to political networks shows the fragmentation and clustering of politicians, parties, or political systems.

Boireau [4] identifies communities among Belgian MPs along party and linguistic lines. For this purpose, the Girvan-Newman Algorithm (GNA) was applied on a network generated from the MPs' connections to followers, and retweet interactions to find hidden communities and homogeneous clusters by calculating their homophily indices, which express the degree of similarity of members within a cluster.

Caetano et al. [5] analyze social networks between Twitter users during the 2016 American presidential election by analyzing tweets about the candidates. Users were clustered based on their sentiment towards a candidate with their mentioning behavior and hashtag use. By obtaining homophily indices of these clusters, the authors could identify users with high degrees of relative similarity.

Sentiment analysis attempts to quantify attitudes conveyed in a text. Giachanou and Crestani [6] discuss common procedures for sentiment analysis, as well as their respective limitations, e.g., the detection of irony or emotions. The work

Copyright (c) IARIA, 2022. ISBN: 978-1-68558-002-5

explicitly focuses on methods suitable to retrieve sentiments from tweets.

Until now, literature does not describe possible changes in Twitter communication behavior between MPs before and after an election. An exploration of the change in tone by analyzing the sentiment of tweets before and after an event has also not yet been described. Interesting aspects of political communication behavior on social media are expected results of this analysis.

Consequently, this article examines how Twitter interactions (mentions, retweets, replies) between MPs of possible coalition partners (CDU, CSU, SPD, Greens, FDP) changed before and after the 2021 German federal election. It furthermore explores potential differences in intra- and inter-party communication and attempts to show whether the political shift towards the inaugurated "Ampel" coalition could be derived from the observed changes.

The following hypotheses form the basis for the communication behavior analysis: The article hypothesizes that different interactions between MPs can be observed during the pre- and post-election period (H1) and that the resulting interaction networks for each period show a difference in intra- and inter-party communication (H2). The article further assumes that "Ampel" MPs' mutual sentiment changed positively (H3). By analyzing the sentiment between parties, as well as the average homogeneity within parties and party groups, political tendencies towards an "Ampel" coalition can be observed (H4).

Thus, this article attempts to describe the change in communication between MPs by analyzing their Twitter interactions before and after the federal election 2021. It aims to understand whether changing interaction intensities between MPs of potential coalition partners yield conclusions about the emerging "Ampel" coalition. This would be of relevance for future research into the interdependencies of political communication on Social Network Services, such as Twitter.

III. METHODS

Mention, retweet and reply interactions between MPs from the SPD, Greens, FDP, CDU, and CSU were collected to explore changes in communication on Twitter. One MP using another MP's handle denotes a mention interaction. Retweets refer to the redistribution of another user's tweet and can contain commentary by the retweeter. A reply is defined as a comment posted under another MP's tweet. The resulting social networks of MPs connected by their interactions is analyzed in four separate scenarios.

A. Network Scenarios

Scenario 1 considers all interaction types, while in scenario 2, a) mention, b) retweet, and c) reply interactions were examined separately. For each scenario, MPs were grouped using automated cluster detection and examined for modularity and homophily.

In scenarios 3 and 4, MPs were grouped based on their party affiliation. In scenario 3, interactions were examined for the tweet author's sentiment towards the addressed MP using sentiment analysis. The sentiment for every interaction was evaluated based on the tweet's text. To determine changes to the inter-party relations, each party's average sentiment toward all other parties was then calculated and compared between the pre- and post-election networks. Scenario 4 examined the average homophily within each party and party group. Party groups were based on politically and numerically possible coalition compositions ("Ampel", "Jamaica") and for the Union parties.

B. Data Aggregation

Publicly available Twitter data can be divided into three categories: (1) User information, such as the username, the Twitter handle (identified by @), or account description; (2) following and liking behavior of a user, and the user's followers; (3) the user's tweet timeline, in which all self-published or retweeted tweets appear, as well as the user's replies to others' tweets.

As a basis for this study, publicly available tweets from MPs of the 19th (2017-2021) and 20th (2021-2025) legislative sessions were collected for the period from July 26, 2021, 0:00 a.m. to November 26, 2021, 12:00 p.m. The end date was chosen to serve as cut-off due to the official presentation of the coalition agreement between the SPD, Greens, and FDP on November 24, 2021. To collect reactions to this announcement, two more days were added. The period between the closing of polls on September 26, 2021, 6 p.m. and the end date covers 60 days and is considered as the post-election period. An equally long time before the closing of polls was considered for the pre-election period.

Twitter accounts were selected from all MPs with a public Twitter timeline who are members of the parties SPD, CDU, CSU, Greens, and FDP. Members of the parties "The Left" and AfD were not included in this analysis, as neither party was relevant for coalition negotiations after the election. The timelines of all selected accounts were then scraped from Twitter's website.

Data Collection. Scraping of timelines was done using the Python package Scweet [7]. Scweet uses the Chrome plugin Selenium [8] to access the desired Twitter page, to extract the information of the tweet from the page and save it to a CSV-file.

Data Processing. A custom Java application was developed to generate uniformly formatted and sanitized datasets. The data originally scraped from Twitter included the timelines of all MPs, i.e., all their tweets, retweets of and replies to other tweets within the time frame. The information generated for each of these messages included the time of publication, the author's username and handle, the textual contents of the tweet, as well as information on whether it was posted as a retweet of, or reply to another tweet. If other users were mentioned within the tweet, they could be identified through their handle.

Additionally, the application enriches the data with information on party affiliation and membership of the 19th or 20th legislative period. It produced output data in the GEXF-format [9], which is limited by specified procedures. First, all tweets that did not represent a connection between two MPs were removed. The dataset was then divided into a pre- and a post-election partition. For this purpose, all tweets that were created before the time of the closing of polls on September 26, 2021, 6:00 p.m. were assigned to a first partition. The elements from the timeline after this date were assigned to a second partition. Additionally, the output is restricted to specific interaction types. This allowed the creation of one pre-election and one post-election dataset for each of the scenarios defined.

Data Description. The data set collected from Twitter consisted of 26,888 German language tweets from 736 Twitter accounts. 15,770 of these tweets were posted before and 11,118 after election day. 1,030 MPs were elected for the 19th and 20th legislative periods. 71.5% of them maintained a Twitter account. Once filtered, the dataset consisted of 622 accounts and 9,582 tweets. After removing all tweets that did not connect two MPs, 5,766 tweets from 466 MPs remained in the pre-election dataset and 3,816 from 476 MPs in the post-election dataset. Figure 1 shows the percentage distribution of all tweets among the parties before and after the election.

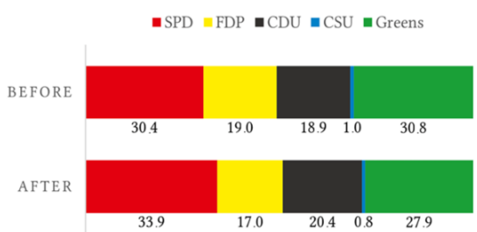

Figure 1. Percentage distribution of MPs' tweets by party

The pre- and post-election data contain nodes and edges depending on the interaction types selected during the data processing step. Scenarios 1 and 4 thus contained all MPs, while scenario 2 contained three separate data sets, differentiated by interaction types. Scenario 3 handled only those interaction types whose tweet text field were not empty. The aggregated data and source code can be accessed at [13].

C. Cluster Detection

Cluster detection extracts groups of individuals from a network based on similarity of one or more attributes. This work used connectivity-based clustering, which identifies clusters based on the connections between nodes in the network, as well as the weights of connections. For this purpose, the Girvan-Newman Algorithm [10] was used. This algorithm assumes that members of a cluster have more connections to other members of the same cluster, and fewer connections to other nodes in the remaining network. By iteratively removing connections whose Edge Betweenness Centrality (EBC) is the highest, clusters are separated from each other. The EBC is defined as "the number of [the] shortest paths between pairs of vertices that run along it" [10]. In each step, the edge with the highest EBC is removed from the network and its modularity is calculated. The modularity of a network denotes how well clusters are separated from each other. The iteration continues until every connection between nodes has been eliminated. The intermediate step with the highest modularity is the result of the algorithm.

To guarantee that an MP's allocation to a cluster is based on their interactions and not their party affiliation, a χ^2 test is performed on the network. The test's p-value denotes the probability p of MPs' party affiliation determining the results of the cluster detection.

D. Sentiment Analysis

The textual contexts of MPs' tweets were examined to analyze the sentiment for which the Python package TextBlob [11] was used. The package uses a lexicon-based approach to compute the sentiment. For the analysis of German language texts, the plugin TextBlobDE [12] was used. A predefined dictionary of words associated with positive or negative emotions is used to weigh a text's sentiment. An individual score is assigned to each word in the examined text. The overall sentiment is defined by the average sentiment across all words in the text. The algorithm generates a polarity score from –1.0 to +1.0 for each tweet, which classified the tweet as either positive, neutral, or negative. Each tweet in the data set is then enriched with the polarity value, as well as the polarity class as additional attributes.

E. Homophily

The homophily index H measures a cluster's relative homogeneity. To determine H for a cluster i, the connections of all nodes of the cluster are examined. Caetano et al. [5] calculate $H_i = \frac{s_i}{si+d_i}$ where s_i denotes homogeneous links, i.e., those that connect a node of class i to other nodes of the same class, while d_i denotes heterogeneous connections, i.e., those that connect a node of class i to nodes of another class. By normalizing H_i over the whole network, H can be compared across different clusters. This inbreeding homophily index IH is determined by $IH_i = \frac{H_i - w_i}{1-w_i}$, where w_i denotes the relation of nodes between cluster i and the total number of nodes in the network. Clusters whose IH_i is greater than 0 are considered homogeneous. The average of IH across all clusters in a network is used to compare the clusters detected in the pre- and post-election networks.

F. Evaluation

The procedure resulted in a set of network pairs, each consisting of a pre- and a post-election network. The two networks created for scenario 1 contained all MPs that have interacted via mentions, retweets, or replies within the respective timeframe. The number of connections between two nodes weighted the edges.

Scenario 2 generated one network pair for each of the three interaction types. Thus, one pre- and one post-election network each were generated which included all those MPs that a) mentioned each other, b) replied to one another, and c) retweeted each other. Edges represent the connections. They are weighted by the interaction count. These scenarios were examined separately. For each network automated cluster detection was applied. The H and IH indices were calculated to determine the homogeneity of each cluster. Additionally, the number of nodes and edges in the network, the number of clusters identified by the GNA, as well as their networks' average homophily and inbreeding homophily indices and the maximum modularity were determined. Statistical significance was ensured using the χ^2 test. The results of these

Copyright (c) IARIA, 2022. ISBN: 978-1-68558-002-5

analyses were then compared for the pre- and post-election network pair. To illustrate the results of the automated cluster detection, each pre- and post-network pair is visualized as a cluster graph.

In scenario 3, each party's average sentiment towards all other parties was examined. For this purpose, MPs were clustered according to their party affiliations.

Scenario 4 looked at the inbreeding homophily of each party, as well as the coalition options before and after the election. The *IH*-values for the coalitions where also checked for statistical significance using the χ^2 test and its p-value.

IV. Results

A. *Scenario 1: Multiple Interactions*

In scenario 1, automated cluster detection included all interaction types. An overview of the collected metrics can be found in Table I.

TABLE I. NETWORK AND CLUSTER METRICS CONSIDERING ALL INTERACTIONS

Metric	Value (pre)	Value (post)	Difference
Number of nodes	466	476	10
Number of edges	5766	3816	-1950
Number of clusters	256	188	-68
Maximum modularity	0.026	0.356	0.330
Average *IH*	0.0212	0.0571	0.0359
p-value from χ^2-Test	< 0.001	< 0.001	

The number of MPs (nodes) tweeting after the election did not vary much from that before the election. However, the number of connections (edges) was reduced by 33%, which suggests that tweeting activity was distributed more equally among MPs after the election. The GNA identified 256 clusters of the pre-election network with 466 MPs, and very low modularity, homophily and inbreeding homophily indices. After the election, 476 MPs could be assigned to 188 clusters. The maximum cluster size was reduced by 54.5% to 97. The modularity increased by 1369%, from 0.026 to 0.356, and homophily and inbreeding homophily also increased significantly. Figure 2 shows a visualization of these clusters. Node colors represent each MP's party affiliation. The size of a node depicts the sum of all incoming and outgoing edges, i.e., the node's degree. Edges were omitted from these figures for improved visibility.

Pre-election, the visualization shows a distinctive, large cluster which unites MPs across all parties. Outside of this cluster many MPs are scattered into tiny groups or unassigned to any notable cluster. Post-election, four large clusters separated along party affiliation can be identified. A heterogeneous group of MPs was not assigned to any notable cluster.

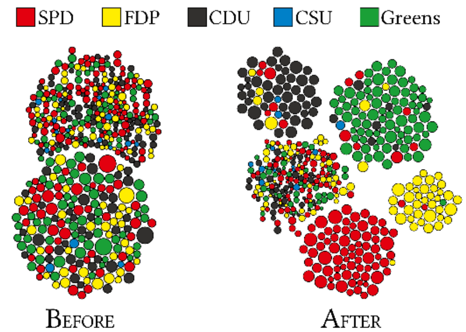

Figure 2. Clusters found by GNA before and after election considering all interactions

The pre-election results of scenario 1 show that MPs were likely allocated to the dominant cluster based on their general activity on Twitter. Nodes with higher degrees were allocated to the dominant cluster. Post-election, distinct clusters are clearly separable, which consist mainly of MPs of either the SPD, CDU, Greens or FDP. The number of nodes that could not be allocated to any major cluster decreased. This indicates that post-election, MPs predominantly communicated within their own parties, while they communicated much more openly before the election. The overall count of interactions decreased significantly.

B. *Scenario 2: Single Interactions*

When interaction types are considered separately, these findings can be analyzed in more detail.

Mentions. In this particular scenario, clusters were determined based on mentions only. Table II shows the collected metrics.

TABLE II. METRICS OF NETWORK AND CLUSTERS DERIVED FROM MENTIONS

Metric	Value (pre)	Value (post)	Difference
Number of nodes	433	428	-5
Number of edges	3247	1758	-1489
Number of clusters	95	38	-57
Maximum modularity	0.237	0.441	0.204
Average *IH*	0.1158	0.4550	0.3292
p-value from χ^2-Test	< 0.001	< 0.001	

Almost as many (433 vs 428) MPs mentioned one another in the pre- and post-election period. Interactions decreased by 54%, and the number of detected clusters decreased by 40%. After the election, 38 clusters with a modularity of 0.441 could be identified, compared to 95 clusters with a modularity of 0.237 before the election. Average IH across all clusters in both networks increased by more than 300%. Figure 3 visualizes the detected clusters.

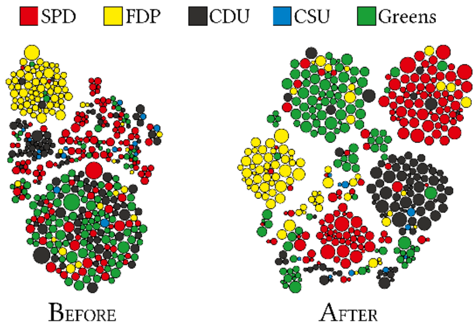

Figure 3. Clusters found by GNA before and after election considering only mentions

Pre-election, three distinct clusters can be identified, one portraying a large cluster mainly dominated by Greens but including MPs across all parties, one dominated by FDP MPs, and a smaller one dominated by CDU MPs. The large, heterogeneous cluster dominated by Green MPs could be caused by many mentions of the Greens' chancellor candidate, Annalena Baerbock.

Distinct clusters are detected in the post-election network separated along party lines. Two SPD clusters are found, as well as several smaller but still homogeneous clusters. The number of mentions increased. A subsequent analysis revealed that the distinct party clusters might be caused by MPs congratulating their party peers.

Retweets Cluster analysis detected several well-separated clusters with relatively high homogeneity before and after the election. A possible explanation is that MPs attempted to promote tweets of party peers. The clusters in the post-election network were smaller. Retweets play a smaller role in the communication among MPs.

Replies. Solely considering reply interactions, one large and many small clusters were found in the pre-election network. The main cluster contains many nodes with a high in– and out-degree. In the post-election network, more nodes are identified but fewer connections between them are found. Two main clusters were identified, notably consisting mainly of SPD and Green party members. One cluster of CDU and FDP MPs indicates active conversations between these two parties, potentially on the FDP's willingness to enter coalition negotiations with the SPD and Greens shortly after the election which supports hypothesis H1.

C. Scenario 3: Sentiment Analysis

Each interaction's textual content was analyzed to retrieve the parties' mutual sentiment. The average sentiment of interactions from MPs of one party towards MPs of the other parties was calculated. The results are shown in Table III. Notably, polarity does not score very highly overall, except for the sentiment from MPs of the CSU towards MPs from the CDU. FDP MPs communicated neutrally in general. The SPD scores positively towards the "Ampel" parties. On average, Green party MPs showed positive polarities only towards other MPs of their own party.

TABLE III. AVERAGE SENTIMENT BETWEEN PARTIES BEFORE THE ELECTION

Source \ Target	SPD	FDP	CDU	CSU	Greens
SPD	0.25001	0.21293	0.00002	-0.11499	0.35683
FDP	0.05095	-0.01008	0.06981	0.09734	0.01032
CDU	0.00070	0.02997	0.13179	-0.12469	0.00483
CSU	0.04297	-0.01875	0.70728	0.10625	0.11405
Greens	-0.16582	0.03257	-0.16458	0.00053	0.35588

Table IV shows the average sentiment between parties after the election. The post-election sentiments between parties notably tend towards an overall positive sentiment. The SPD received overall positive interactions, especially from the CDU. The SPD communicated relatively neutrally, both internally, as well as towards their subsequent coalition partners. The polarity of the interactions among MPs of the Greens and interactions from MPs of the CSU towards CDU MPs did not change significantly from their pre-election scores. The overall sentiment across all parties after the election was on average more positive than before the election. The FDP especially shows notable increases in positive sentiments towards the SPD and the Greens, considering that the FDP moved towards the "Ampel". This strongly hints at successful coalition negotiations which ended with the signing of the coalition contract.

TABLE IV. AVERAGE SENTIMENT BETWEEN PARTIES AFTER THE ELECTION

Source \ Target	SPD	FDP	CDU	CSU	Greens
SPD	0.00166	0.25408	0.31106	0.84063	0.06433
FDP	0.33102	0.54495	-0.11953	0.00391	0.27281
CDU	0.79865	-0.00598	0.09291	-0.08487	0.67012
CSU	-0.16250	0.24688	0.59688	0.12500	0.39146
Greens	0.43225	0.09978	0.62791	-0.06024	0.38109

D. Scenario 4: Party and group dependent clustering

In this scenario, MPs were clustered along party affiliation. Additionally, the two potential government coalitions, "Ampel" (SPD, Greens, FDP) and Jamaica (CDU, CSU, Greens, FDP), as well as the Union (CDU, CSU), were clustered. To compare the homogeneity within each cluster, the average *IH* before and after the election was calculated and compared. Table V displays the average *IH* values of each party, as well as the coalition and union clusters for the pre- and post-election networks.

The biggest differences are within the SPD and CDU. Their relative homophily increased. CSU and FDP decreased in *IH*. SPD received the biggest increase in homogeneity. This could be explained by their win of the election, and the positive feedback MPs received from their peers, as well as the election of SPD MPs Olaf Scholz as chancellor and Bärbel Bas as president of the parliament. The biggest positive change among grouped MPs took place in the "Ampel" coalition, but *IH* increased for the Jamaica and Union clusters as well. However, a significant statistical independence of these findings is not reliably provable, as the χ^2-test results in relative high p-values for the pre- and post-election homophily.

TABLE V. RELATIVE IH IN PARTIES AND PARTY GROUPS

	Before	After	Difference
CDU	0.4749	0.5596	0.0848
CSU	0.0721	0.0516	-0.0205
SPD	0.5272	0.6392	0.1120
Greens	0.5682	0.5729	0.0047
FDP	0.5397	0.4618	-0.0779
"Ampel" Coalition	0.4519	0.6272	0.1754
Jamaica Coalition	0.5209	0.5307	0.0098
Union Group	0.4632	0.5422	0.0791
p-value from χ^2-Test	0.057764	0.106983	

V. CONCLUSION

This paper illustrates the application of techniques from social network analysis, sentiment analysis and cluster analysis in combination to analyze communication on social media especially on micro blogs.

H1 is proven, as differences are found for mention and reply interactions. The networks for each interaction type yield differences in both intra- and inter-party interactions, which is shown by the results of the GNA. These findings are statistically significant due to the low p-values. H2 can therefore be considered as true. The p-value of the χ^2 test indicates a low likelihood that party affiliation influences the assigned cluster.

H3 cannot be answered clearly. MPs' mutual sentiment changed positively. The FDP's positive change towards the coalition partners SPD and Greens can be considered as a sign of a generally improved attitude towards these parties. However, the notable overall increase in positivity across most parties could indicate that the findings of the FDP are not unique. The generally positive attitude between parties after the election can be caused by MPs congratulating one another. A lack of German language sentiment analysis models for short text fragments limits this research. Improved models utilize machine learning techniques and so can comprehend sentiments on a broader level and can also recognize nuances.

Statements about H4 are not reliable. However, while positive tendencies towards an "Ampel" coalition can be shown from both the sentiment analysis and the inter-party and intra-coalition homogeneity, neither can be proven as statistically significant.

Definitely results are: Different interactions between MPs can be observed during the pre- and post-election periods and the resulting interaction networks for each period show a difference in intra- and inter-party communication. However, this paper handles the political communication only via Twitter. Results are partially transferable to other countries.

Future work may include "The Left" and AfD in these considerations to produce more information. Expanding the evaluated timeframes or continuous monitoring would produce more data. Analyzing follower and friend networks and MPs' liking behavior in combination with the findings of this article would yield insights into differences in parties' mutual relationships around elections.

REFERENCES

[1] A. Virk, "Twitter: The Strength of Weak Ties", University of Auckland Business Review, Vol. 13, No. 1. University of Auckland, Auckland, AUK, NZL, pp. 19-21, Jan 2011.

[2] D. S. Lassen and A. R. Brown, "Twitter: The Electoral Connection?", Social Science Computer Review, Vol. 29, No. 4. SAGE Publications, Thousand Oaks, CA, USA, pp. 419-436, Nov 2011.
DOI: https://doi.org/10.1177%2F0894439310382749

[3] M. S. Granovetter, "The Strength of Weak Ties", American Journal of Sociology, Vol. 78, No. 6. The University of Chicago Press, Chicago, IL, USA, pp. 1360-1380, May 1973.

[4] M. Boireau, "Uncovering Online Political Communities of Belgian MPs through Social Network Clustering Analysis", Proceedings of the 2015 2nd International Conference on Electronic Governance and Open Society: Challenges in Eurasia (EGOSE '15). Association for Computing Machinery, New York, NY, USA, pp. 150-163, Nov 2015. DOI: https://doi.org/10.1145/2846012.2846049.

[5] J. A. Caetano, H. S. Lima, M. F. Santos, and H. T. Marques-Neto, "Using sentiment analysis to define Twitter political users' classes and their homophily during the 2016 American presidential election", Journal of Internet Services and Applications, Vol. 9, Article 18, Sep 2018. Springer Open, DOI: https://doi.org/10.1186/s13174-018-0089-0.

[6] A. Giachanou and F. Crestani, "Like It or Not: A Survey of Twitter Sentiment Analysis Methods" ACM Computing Surveys, Vol 49, No. 28. Association for Computing Machinery, New York, NY, USA, pp. 1-41, Jun 2017. DOI: https://doi.org/10.1145/2938640.

[7] Y. A. Jeddi, Scweet (Version 1.6), [Online]. Available from: from https://github.com/Altimis/Scweet, Dec 2021.

[8] The Selenium Project, Selenium (Version 4.1.0), [Online]. Available from: https://github.com/seleniumhq/selenium, Dec 2021.

[9] GEXF Working Group, GEXF File Format (Version 1.2), The Gephi Community Project, 2009. [Online]. Available from: http://gexf.net, Dec 2021.

[10] M. Girvan and M. E. J. Newman, "Community structure in social and biological networks", Proceedings of the National Academy, Vol. 99, No. 12. National Academy of Sciences of the United States of America, Washington DC, USA, pp. 7821-7826, Jun 2002.
DOI: https://doi.org/10.1073/pnas.122653799.

[11] S. Loria, TextBlob (Release v0.16.0) Documentation. TextBlob: Simplified Text Processing. [Online]. Available from: https://textblob.readthedocs.io/en/dev/index.html#, Dec 2021.

[12] M. Killer, textblob-de. (Version 0.4.3), German language support for TextBlob by Steven Loria. [Online]. Available from: https://github.com/markuskiller/textblob-de, Dec 2019.

[13] Datawork, [Online]. Available from: https://git.informatik.fh-nuernberg.de/wolfarthda82341/sna-germanys-members-of-parliament-on-twitter, Oct 2022.