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# TWITTER AND THE POLITICAL LANDSCAPE – A GRAPH ANALYSIS OF GERMAN POLITICIANS

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# TWITTER AND THE POLITICAL LANDSCAPE – A GRAPH ANALYSIS OF GERMAN POLITICIANS

*Research*

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## Abstract

*This paper examines the Twitter social graph of German politicians and political parties during a time period not potentially biased by nearby elections. Based on a data set of 1,719 politicians across the entire political spectrum of this important country in the EU, two graphs are constructed, which also reflect relationships within and between parties: the follower graph, consisting of all follower-followee relationships between German politicians, and the "mention graph", which models direct references of politicians to their colleagues.*

*Our main contributions are as follows: First, we analyse these graphs according to several statistics and graph metrics, characterizing political parties according to their collective participation in Twitter. We also investigate the openness for following ideas across political camps, resulting in the discovery of three distinct groups of political parties. We also find that membership in political parties itself explains only little of the variation in the formation of ties. There is also evidence that politicians with less activity exhibit a higher degree of openness than users with active engagement in tweets and discussions. This case study on social media adoption in politics leads to interesting insights into political debate in the information society.*

*Keywords: Twitter, Graph Analysis, Politics, Germany.*

## 1 Introduction

Since its foundation in 2006, Twitter has become the most famous microblogging services worldwide with more than 300 million monthly active accounts in 2015 (Statista, 2015). The use and impact of social media among the political sphere is growing as well. Politicians use microblogging for direct interaction with colleagues and the electorate, comments on current political discussions and affairs as well as a medium for self-portrayal and marketing. There is a growing use of social media to foster the formation of public opinion and engaging in substantial political discussion (Tumasjan et al., 2010).

German political parties started to adopt online media on a larger scale just prior to the general elections in 2002 (Gibson et al., 2003). Nowadays, even though some German politicians have adopted microblogging via Twitter, others are still rather reluctant to use this new medium at a larger scope (Jungherr, 2013). This also causes a lack of research on the use of microblogging platforms among

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German politicians and their corresponding parties, since the focus of earlier studies was mostly on US and UK related campaigning activities on Twitter (Jungherr, 2014) despite Germany being one of the most influential countries in the EU in terms of politics and economics (WEF, 2015). Understanding the exchange of opinions among German politicians can therefore foster the study of global political developments.

Social media and especially microblogging platforms can be used to reach millions of potential voters and to directly interact with other politicians by creating an additional political platform for campaigns. In case of the US election in 2016 some of the presidential candidates had millions of followers in March 2016 (Statista, 2016), e.g., Donald Trump with 6.92 million followers and Hillary Clinton with 5.69 million followers. Since election candidates and political parties are in direct competition with each other, their interaction on microblogging platforms such as Twitter can attract immense attention. Thus, it is not only important to understand how politicians interact with externals via Twitter but also how they communicate and engage with each other on such an online platform.

Authors such as Gibson et al. (2003), Glassman et al. (2009) as well as Larsson and Moe (2012) ascertained that Internet activities facilitate the propagation of various political views when used for typical campaigning activities such as information dissemination and opinion formation. Furthermore, Utz (2009) finds that the usage was able to not only draw attention to their political program but also to increase the involvement of voters and the reputation of politicians. Therefore, reconstructing and analysing networks of politicians in online social media can lead to a deeper, empirical, and data-driven understanding of political exchange within and across political parties. Moreover, it could lead to a structural characterization of the internal and external exchange of particular camps. Not least, such analyses help to identify influential politicians and common themes that can form bridges between opposing parties, in particular if no elections are nearby that heat up the debate.

Furthermore, since the use of social media platforms by politicians was often in the focus of research during time frames of political booms such as election campaigns, we collected a unique dataset of a time span well-known for rather low frequent activities of political parties in Germany. This enables us to gain a deeper knowledge on how actively politicians behave on Twitter without the pressure of being overly present, i.e., their behaviour when there is no federal election nearby. This will be helpful to gain a deeper understanding on the pairwise relationships and interaction with their colleagues in times of political recessions. Therefore, our research contributes to understanding how politicians in Germany act in times when there is no event related to their activities on Twitter. A similar research has been conducted for the case of Australian politicians (Macnamara, 2011).

In order to gain a deeper and quantitative understanding on the interaction among politicians on Twitter and based on the suggestions of Yoon and Park (2014) as well as Hegelich and Shahrezaye (2014), we adopt recent methodological advances and conduct graph analyses by investigating two different graph structures – the *follower* graph, containing all connections to followers and followees, and the *mention* graph, consisting of all mentions of politicians by other German politicians. Mentions are part of tweets that contain the textual structure *@username*, which is explicitly referring to another user. These graphs are analysed with respect to reciprocity, clustering, density, homophily as well as further important statistical and structural measures. A particular focus will be placed on differences between German parties in their online activity and the willingness to engage in cross-party discussion.

The remainder of this paper is organized as follows: First, we will summarize related literature and give a brief introduction to the German political landscape. Afterwards, we will explain how we gathered the dataset that we used to generate the Twitter graphs. This is followed by the results of our graph analyses. We will conclude with a summary, limitations and an outlook on future work.

## 2 Related Work

Although the microblogging platform Twitter was founded not earlier than 2006, the use of Internet-based activities for political contexts has been known before. Following the US presidential elections in 2000 where the electoral campaign was supported by the use of different digital media channels, the first notable usage of Internet campaigning in Germany took place prior to the federal elections in 2002 (Gibson et al., 2003).

Mainly those related studies were relevant for our work that focused on politicians as entities of interest and used the microblogging platform Twitter as the main data source. Therefore, research on citizen engagement on Twitter in the political context was considered out of scope. As Table 1 shows, there is a lot of research on how politicians use Twitter focusing on either the US or the UK (Jungherr, 2014) – but looking at selected other countries on which the most research is available, evidence is clear that several studies analysed data prior to election campaigns. This is especially true for the case of Germany. In contrast, our research focuses on the analysis of German politicians' behaviour on Twitter in a non-event related time frame.

| **Country** | **Data Focus –Politicians, (Partial) Use of Twitter data** | |
|---|---|---|
| | **Campaign-related** | **Not Campaign-related** |
| Australia | Bruns and Highfield, 2013*<br>Macnamara, 2011 | Grant et al., 2010*<br>Macnamara, 2011 |
| Asia | | Hsu and Park, 2012<br>Kim and Park, 2011*<br>Lee, 2013<br>Lee and Oh, 2012<br>Lee and Shin, 2012<br>Otterbacher et al., 2013<br>Yoon and Park, 2014* |
| Germany | Elter, 2013<br>Hegelich and Shahrezaye, 2014<br>Jungherr, 2010, 2012<br>Plotkowiak and Stanoevska-Slabeva, 2013*<br>Plotkowiak et al., 2010<br>Thimm et al., 2012 | Otterbacher et al., 2013<br>Thamm and Bleier, 2013 |
| Netherlands | Broersma and Graham, 2012<br>Vergeer and Hermans, 2013<br>Vergeer et al., 2011, 2013 | Verweij, 2012 |
| Nordic Countries (DK, FI, NO, SE) | Grussel and Nord, 2012 | Sæbø, 2011 |
| United Kingdom | Broersma and Graham, 2012<br>Baxter and Marcella, 2013<br>Graham et al., 2013a, 2013b<br>Jackson and Lilleker, 2011 | Aharony, 2012<br>Otterbacher et al., 2013 |
| United States of America | Ammann, 2011<br>Bode et al., 2011a, 2011b<br>Christensen, 2013<br>Conway et al., 2013<br>Hanna et al., 2011<br>Mirer and Bode, 2013 | Aharony, 2012<br>Chi and Yang, 2011<br>Glassmann et al., 2009<br>Golbeck et al., 2010<br>Hemphill et al., 2013<br>Hong, 2013<br>Lassen and Brown, 2011<br>Otterbacher et al., 2013<br>Peterson, 2012<br>Williams and Gulati, 2010 |

*Table 1. Overview of related work focusing on country of origin of the data (references marked with * used graph analysis methods in their work).*

Furthermore, graph analysis is a method which so far has not been conducted that often (references marked with * in Table 1). In general, most of the studies using this method concentrate on the understanding of who interacts with whom (Jungherr, 2014). Other methods that have been applied are content analysis (e.g., Jackson and Lilleker, 2011) or descriptive analysis of tweets and hashtags, sentiment analysis (e.g., Plotkowiak and Stanoevska-Slabeva, 2013), experiments (e.g., Lee, 2013; Lee and Oh, 2013; Lee and Shin, 2012) or interview (e.g., Grussel and Nord, 2012). We will apply graph analysis methods to close this research gap and gain a better understanding of politicians on Twitter from a graph perspective.

In summary, most related research has studied countries such as the US and the UK without the methodological approach of graph analysis. Thus, we focus on these aspects and analyze follower-followee relationships as well as mentions among German politicians using graph analysis to close this research gap. Moreover, most of earlier research used time intervals prior to elections – especially in case of Germany, which could potentially bias the results. In contrast, our research aims to analyze political interaction on Twitter if there is no federal election nearby.

# 3 Political Parties in Germany

The number of parties in the political system of Germany varies. The last federal election took place in 2013 with 30 different parties. Only a few of them reached the critical threshold of five percent to be represented in the German Bundestag. At the time of writing, the Bundestag consists of four different parties: The *Social Democratic Party*, the *Christian Democratic Union* in combination with the *Christian Social Union*, the *Left Party* and the *Green Party* (BPD, 2013). In order to depict a clearer picture of the political landscape, we will not only focus on those four parties but will also include the *Free Democratic Party*, the *Alternative for Germany* and the *Pirate Party*. All others will be aggregated into the pool *Other*.

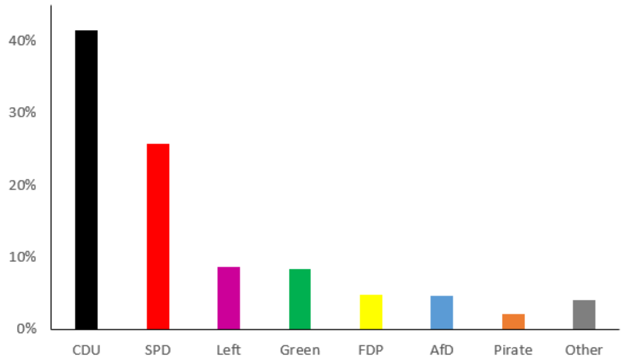


*Figure 1. Election result of the last federal election in 2013.*

The *Christian Democratic Union* (CDU) and the *Christian Social Union* (CSU) together constitute the conservative camp in the Germany. We will refer to these two parties by the abbreviation *CDU*. The core principles of the *CDU* are centered on traditional and Christian values of family, social cohesion, and harmony among different social classes (CDU, 2007). Some of their most important coalition partners are either the *Free Democratic Party* (FDP) or the *Social Democratic Party* (SPD).

The *Social Democratic Party* (SPD) is a traditional labour party addressing a large share of the German population. After the conservative group of *CDU* and *CSU*, it is the second largest party in Germany in terms of membership and political impact (Niedermayer, 2015). Its core values comprise justice and solidarity, aiming to establish equality in participation and opportunities (SPD, 2007). Their main coalition partners are the *CDU*, the *Left Party* and the *Green Party*.

The *Green Party* developed and established itself in the late 70s. Its main principles revolve traditionally around ecological and sustainable solutions in all aspects of life (Die Grünen, 2015).

The *Left Party* is rather socialistic and its core values revolve around solidarity. The party claims that participation and freedom can only be truly achieved when the economy is subordinated to solidarity and self-determination (Hildebrandt 2015). Their main coalition partners in the past have been either the *SPD* or the *Green Party*.

The *Free Democratic Party* (FDP) was not able to surpass the five percent clause in the federal election in 2013. Nonetheless, the *FDP* is represented in certain parliaments on the state level. The party's core values are mainly centered around personal freedom and personal responsibility (Patton, 2015). The party's former coalition partner was the *CDU*.

The *Pirate Party* was founded in 2006 and had initially a narrowed focus on Internet policy, focusing on freedom and data privacy. Their core principles are open access to education and public welfare systems as well as rejecting digital monitoring or data retention (Hebenstreit, 2015). Naturally, due to their digital focus, the *Pirate Party* members are often very active on Twitter.

The most recent party is *the Alternative for Germany* (AfD). Its core topics are constantly evolving from euro criticism to mainly national-conservative goals in recent times. The *AfD* is often criticized for being a right-wing populist party which enables it to attract mostly protest voters and conservatives but also strands of the political right (Lewandowsky, 2014).

# 4 Methodology

We decided to use a graph analysis approach to conduct our study of interactions of politicians on Twitter. A graph is a mathematical construct which consist of nodes and edges that connect two nodes. Nodes represent certain objects of interest and edges their interaction with each other. In our case, a node represents a specific politician. Depending on the selected graph, an edge reflects a different type of interaction. Based on the approach of Yoon and Park (2014) and suggested by Hegelich and Shahrezaye (2014), we decided to build two different graphs – the *follower* graph, containing all connections of followers and followees as well as the *mention* graph, which consists of all mentions of politicians by other German politicians. Both graphs are so-called directed graphs, which means that a specific interaction between two nodes is one-sided, e.g. two politicians do not have to necessarily follow each other since it is sufficient if only one follows the other.

We gathered data within a two-week period in August 2015, using the Twitter REST API. We decided to collect data originating from this time period since we wanted to understand how politicians use the communication platform Twitter during times where political actions are rather at a low frequency since the summer holiday takes place in Germany at this time span. The selection of this time frame helps us to understand if politicians are still actively using open communication tools to show presence to others such as potential voters as well as how they interact with each other.

The selection of relevant politicians and their respective Twitter accounts was based on information taken from pluragraph.de (Pluragraph, 2015). This non-for-profit website depicts all non-commercial social media accounts of politicians, organizations as well as cultural and administrative entities. In August 2015, it listed 3,511 German politicians, of which 1,719 had an active Twitter account. Deleting all protected accounts, where access to tweets is only granted to Twitter users with permission, this resulted in 1,683 valid accounts in the final data set. The retrieved data contains information such as the number, content, and hashtags of tweets, the number of followers and friends as well as personal details, including name and Twitter membership data. To obtain a recent snapshot of the Twitter social graph, we downloaded the 200 most recent tweets of every considered politician, with hashtags and mentions of other politicians. Descriptive statistics of the dataset are shown in Table 2.

Based on the approach of Yoon and Park (2014), the analysis of the graphs considers only relations of nodes inside the data set to focus on the connections between German politicians. This means that only those nodes and edges are represented in the final graph which belong to the political sphere, i.e. nodes representing a German politician and edges containing a follower-relationship respectively mention between two politicians. Therefore all follower-relationships and mentions of a politician to another entity that is not a German politician, e.g., a news agency, a public person or a company, were deleted from the graph.

Furthermore, in the subsequent analysis, the mention graph will be compared to the follower graph. In order to facilitate this comparison, the follower graph should contain only the same source nodes as the mention graph, i.e., an interaction of both our defined graphs. Of the 1,719 politicians in the data set, 1,284 are found to be actively engaging in direct discussions with mentions, i.e., referring to other German politicians in their tweets.

In summary, three different graphs are analysed:

- first, the full follower graph containing all follower-followee relationships between German politicians;
- second, the mention graph with all mentions of politicians regarding other colleagues;
- and third, the intersection graph, containing only the nodes that both exist in the follower as well as the mention graph.

| Party | # Accounts | Average # / Median # | | |
|---|---|---|---|---|
| | | Tweets | Follower | Followees |
| **AfD** | 26 | 465 / 50 | 186 / 63 | 1,007 / 106 |
| **CDU** | 421 | 1,441 / 285 | 274 / 106 | 1,428 / 218 |
| **Green** | 313 | 2,316 / 695 | 531 / 348 | 3,158 / 1,074 |
| **Left** | 171 | 2,093 / 391 | 418 / 200 | 2,728 / 543 |
| **FDP** | 165 | 1,580 / 482 | 522 / 213 | 1,294 / 443 |
| **Pirate** | 110 | 2,876 / 1,374 | 880 / 506 | 15,906 / 10,770 |
| **SPD** | 447 | 2,023 / 325 | 331 / 151 | 1,391 / 299 |
| **Other** | 66 | 814 / 197 | 239 / 105 | 2,482 / 449 |
| Total | 1,719 | 1,883 / 407 | 410 / 190 | 2,810 / 469 |

*Table 2. Descriptive statistics of the retrieved dataset.*

| | AfD | CDU | Green | Left | FDP | Pirate | SPD | Other |
|---|---|---|---|---|---|---|---|---|
| **AfD** | 47 | 9 | 7 | 4 | 4 | 4 | 5 | 2 |
| **CDU** | 6 | 2,416 | 425 | 127 | 79 | 64 | 410 | 8 |
| **Green** | 9 | 384 | 4,522 | 206 | 50 | 118 | 566 | 7 |
| **Left** | 5 | 105 | 220 | 1,232 | 13 | 47 | 156 | 2 |
| **FDP** | 10 | 154 | 159 | 30 | 729 | 23 | 190 | 5 |
| **Pirate** | 1 | 72 | 105 | 40 | 31 | 1,023 | 122 | 23 |
| **SPD** | 6 | 338 | 442 | 138 | 61 | 82 | 2,891 | 7 |
| **Other** | 1 | 17 | 16 | 4 | 14 | 12 | 26 | 82 |

*Table 3. Overview of inter-party follower relationships.*

The final follower graph consists of 1,683 nodes and 99,792 edges. Furthermore, in total, 240,925 tweets have been retrieved. Of those, 51,375 tweets mention another German politician and 74% of politicians used the mentioning feature in their last 200 tweets. Finally, all self-references (789) as well as retweets (32,692) were deleted from the final data set, resulting in a mention graph consisting of 1,284 nodes and 17,501 edges.

The graphical representation in Figure 2 of both graphs was depicted using the ForceAtlas2 algorithm with the help of the graph visualization software Gephi (Bastian et al., 2009).

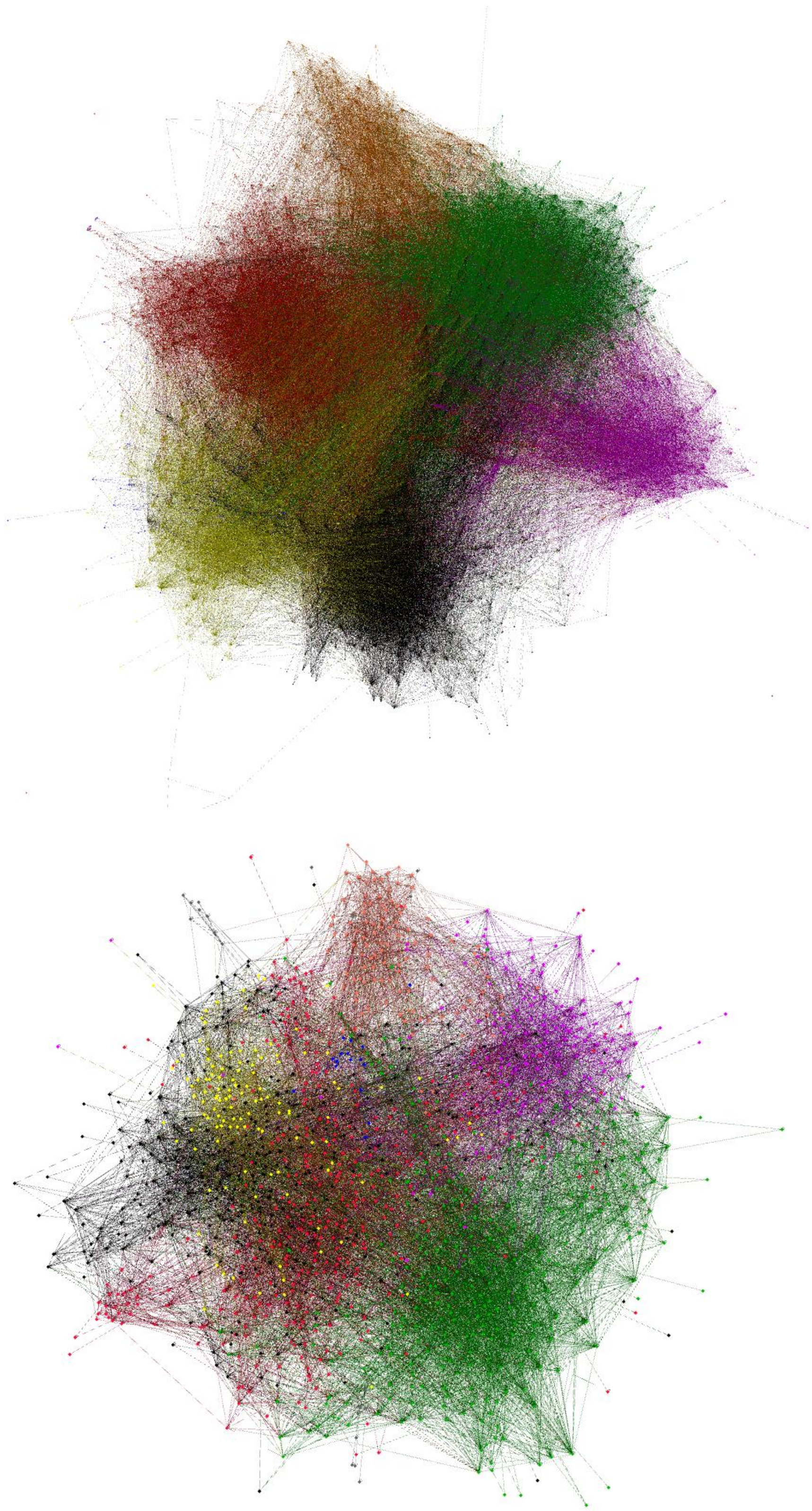

*Figure 2. Visualization of the follower (top) and the mention graph (bottom) [SPD: red, CDU: black, Green: green, Left: purple, FDP: yellow, Pirate: orange, AfD: blue]*

# 5 Results

In the following, we provide analyses of the follower graph (FG), the mention graph (MG) and the intersection graph (FG-MG), which consists of FG reduced by the nodes not present in the MG. Visualizations of the FG and MG are shown in Figure 2. Nodes are allocated a specific colour depending on the party they belong to. The colour of an edge indicates an outgoing tie from a node of this particular party. Since the number of edges differs significantly (99,792 for FG, 17,501 for MG), the FG is a lot denser than the MG. It is visually apparent that parties are interwoven and interact with each other on Twitter. In case of MG, it seems that heterogeneity is more common.

Focusing on specific parties, the *CDU* has mostly internal connections and only a few ties with the *SPD* and *Green Party* (see also Table 3). The *Left Party*, in contrast, has a stronger tendency to also form connections with the *SPD* as well as the *Green Party*. The members of the latter two appear to be most active in both graphs in terms of internal and external ties. The *Green Party* rather dominates the FG, indicating that users of this group are most actively following users across all parties.

The MG depicts the *SPD* in the center, indicating that it receives and sends most mentions in tweets, both inside and outside of the party. Again, the *Green Party* appears to be most active but also with a focus on its own organization. The *FDP* has most of its ties with the *CDU* as well as the *SPD*. Furthermore, the *Pirate Party* is closely positioned to the *Green Party*. An intensive exchange of tweets and reciprocal relationships can be observed in this case.

## 5.1 Reciprocity and Clustering

Since the considered graphs are directed, we analysed whether ties between nodes are bi-directional or not, i.e., if users mutually follow one another. Reciprocity shows that in the majority of the cases the follower-relationship is only one-sided (see Table 4): For both, the FG and FG-MG, reciprocity is around 0.4, indicating that forty percent of the users in the graph are mutual followers. In case of the MG, only around 13 percent of all mentions are returned. This provides evidence that mentions are not used as bi-directional communication devices but to rhetorically accentuate messages.

The clustering coefficient is defined as the ratio of the number of edges existing between the neighbours of a node to the maximum possible number. The rather high number of 0.36 for the MG and 0.43 for the FG shows that several of the possible edges are realized and German politicians on Twitter are well connected with each other (see Table 4). To also take the size of existing cliques into account, i.e., sub-graphs with high density, we also computed the weighted clustering coefficient. This metric assigns higher weights to those sub-graphs that contain more nodes and edges. In case of this weighted clustering coefficient, the respective values are generally lower but the same trend remains. This gives evidence that indeed the political social graph on Twitter consist of several sub-graphs consisting of the specific political parties. In case of MG even if mentions are rather uni-directional as seen in the case of reciprocity, there are still several politicians who seem to be encouraged to mention others, maybe due to being triggered because another politician used this feature on themselves.

| | **Reciprocity** | **Clustering Coefficient** | |
|---|---|---|---|
| | | **Overall** | **Weighted** |
| **FG** | 0.39 | 0.43 | 0.25 |
| **MG** | 0.13 | 0.36 | 0.18 |
| **FG-MG** | 0.40 | 0.41 | 0.27 |

*Table 4. Reciprocity and clustering coefficient for each graph.*

## 5.2 Centrality

An important measure to describe the structure of a graph is the degree, i.e., the number of nodes a node is connecting to. In our case this gives an indication of how often members of a specific party are being followed and how many other politicians they follow or respectively mentioned. Since all considered graphs are directed, they can be characterized by the in- and out-degree, referring to the number of followers and the number of followees or the number of ingoing and outgoing mentions, respectively. As shown in Table 5, except for the *AfD*, these values are similar for each party. However, the *Green Party* is better connected than all others. *Green Party* members are followed on average by 105.62 politicians and follow on average 105.53 other colleagues. Compared to the second largest political groups in the data set consisting of the *CDU* and the *SPD*, this results in 70 percent more ties on average for each *Green Party* member. Furthermore members belonging to the *Green Party* receive and give on average three more mentions compared to the next largest party.

| | Out-Degree FG-MG | In-Degree FG-MG | Out-Degree MG | In-Degree MG |
|---|---|---|---|---|
| **AfD** | 14.32 | 8.44 | 4.27 | 3.74 |
| **CDU** | 60.98 | 62.11 | 6.50 | 6.35 |
| **Green** | 105.53 | 105.62 | 9.62 | 9.72 |
| **Left** | 60.97 | 61.92 | 5.35 | 5.54 |
| **FDP** | 68.45 | 66.33 | 5.85 | 4.02 |
| **Pirate** | 62.87 | 58.33 | 7.62 | 7.96 |
| **SPD** | 66.35 | 68.03 | 5.82 | 6.60 |
| **Other** | 24.36 | 16.67 | 2.68 | 1.90 |

*Table 5. Average degree centrality measures per party.*

Since the degree only covers the direct neighbourhood of a node, we also considered the closeness centrality. This metric measures the average distance from a node to all other nodes, taking therefore the whole graph into account. The higher value, i.e., the closer it gets to one, the less separated a node is from others. As Table 6 shows, except for the *AfD*, the values are similar for in- and outward closeness across all parties. Nevertheless, the average member of the *Green Party* appears to be slightly more centralized in the political Twitter sphere.

| | Out-Close FG-MG | In-Close FG-MG | Out-Close MG | In-Close MG |
|---|---|---|---|---|
| **AfD** | 0.38 | 0.35 | 0.16 | 0.12 |
| **CDU** | 0.42 | 0.42 | 0.15 | 0.16 |
| **Green** | 0.46 | 0.45 | 0.17 | 0.18 |
| **Left** | 0.42 | 0.41 | 0.15 | 0.16 |
| **FDP** | 0.43 | 0.42 | 0.15 | 0.15 |
| **Pirate** | 0.42 | 0.40 | 0.16 | 0.17 |
| **SPD** | 0.43 | 0.42 | 0.15 | 0.16 |
| **Other** | 0.36 | 0.36 | 0.14 | 0.10 |

*Table 6. Average closeness centrality measures per party.*

In general, there seem to be three different clusters apparent based on centrality measures. The first one consists of the Green Party which seems to be best connected. The second cluster consists of the

*AfD* and the party containing *Other* since compared to others they are not so well connected. All other parties not mentioned so far, i.e., *CDU, Left Party, FDP, Pirate Party* and *SPD,* are quite homogenous in terms of degree and closeness, having quite similar values and therefore a comparable behaviour on Twitter.

## 5.3 Density and Homophily

With respect to density, which gives the proportion of all theoretical connections to those that are actually present, we observe that for all graphs the overall density is rather low. The FG-MG has the largest value of 0.06. The density of the mention graph is lowest with 0.01, which is reasonable as it reflects politicians talking explicitly about other colleagues during the observation period.

Regarding the densities *within* parties focusing on follower-followee relationships, we find that the internal density in the *AfD* is by far the largest (0.17), followed by the *Green Party* with 0.11. All other parties range between 0.04 and 0.01. This gives evidence that both, *AfD* and the *Green Party,* have the strongest focus to connect with their own political sphere compared to all others to connect. Considering mentions, we observe a similar picture. Again the *AfD* ranks highest with a density value of 0.45. The second highest value is reached by the *Pirate Party* with 0.14. Again, all other parties have rather similar density values for mentions ranging between 0.08 and 0.02.

When calculating densities within and between groups for FG-MG, this observation becomes even more prevalent (see Table 7). Here we only consider those politicians who follow each other and mention others and the density is comparably larger than in FG. Again, the *AfD* has by far the largest density value of 0.45. Across the main diagonal the densities are consistently higher than elsewhere. This gives evidence that political parties are more likely to support their own party not only though following but also through mentions. Especially the AfD seems to have the habit to extensively support their inner circle since they are more prone to mention their colleagues.

| | **AfD** | **CDU** | **Green** | **Left** | **FDP** | **Pirate** | **SPD** | **Other** |
|---|---|---|---|---|---|---|---|---|
| **AfD** | 0.45 | 0.00 | 0.01 | 0.01 | 0.01 | 0.00 | 0.01 | 0.01 |
| **CDU** | 0.00 | 0.15 | 0.02 | 0.01 | 0.03 | 0.01 | 0.02 | 0.00 |
| **Green** | 0.00 | 0.02 | 0.28 | 0.03 | 0.02 | 0.03 | 0.03 | 0.01 |
| **Left** | 0.00 | 0.03 | 0.01 | 0.31 | 0.01 | 0.02 | 0.02 | 0.01 |
| **FDP** | 0.00 | 0.03 | 0.04 | 0.01 | 0.35 | 0.02 | 0.02 | 0.03 |
| **Pirate** | 0.00 | 0.03 | 0.01 | 0.03 | 0.03 | 0.36 | 0.02 | 0.03 |
| **SPD** | 0.00 | 0.03 | 0.02 | 0.02 | 0.02 | 0.01 | 0.14 | 0.01 |
| **Other** | 0.00 | 0.02 | 0.01 | 0.01 | 0.04 | 0.03 | 0.02 | 0.09 |

*Table 7. Between and in-group densities of parties in FG-MG.*

Using a bootstrap paired sample T-test with 5,000 samples, we tested for differences in the probabilities of a tie in FG-MG and MG. We have chosen to only test these two graphs since the nodes are the same and they are therefore easily comparable. The difference between densities of 0.05 (0.06 for FG-MG, 0.01 for MG) is found significant ($p < 0.01$, std $< 0.01$). We may therefore conclude that the densities of the FG-MG are significantly larger.

Since we found evidence that the densities within parties are relatively higher than between groups, we applied an Anova Density Test using a structural blockmodel to test for homophily (Hanneman and Riddle, 2015). This method verifies the differences between groups across a range of pre-defined clusters. In our case, these clusters are representing political parties. Importantly, the test does not impose explicit requirements on differences between clusters in order to verify them. We assume that this relaxed assumption better fits our dataset than other homophily blockmodels as there is no theoretical intuition to expect a recurring pattern across all groups.

We applied the test to FG as well as to MG with 5,000 permutations to gain robust results. Significant differences between parties for FG are enlisted in Table 8. However, although some deviations are most likely occurring not randomly the actual differences can be rather small. The calculated R-Square, indicating how homophily accounts for the variances in pair-wise ties, values to 0.01. Thus, despite some significant results, the overall degree of homophily in FG does not to account for the variance in pair-wise ties. Most notably, the differences in densities are most of the times significant for the *AfD* as well as the *Green Party*. Thus, political parties represent a certain form of clustering in the Twitter social graph, but they account only for a minor part of the observed variation in follower behaviour.

The homophily test of the mention graph finds significant results for all cases, proposing significant differences in mentioning behaviour across parties. However, the calculated R-Square of 0.01 indicates that the impact is rather minimal and other factors account for the observed variation.

The observation that FG-MG has a slightly larger density compared to FG in case of the whole graph as well as within party gives evidence that politicians who are being active in communication on Twitter are more connected overall, especially within their respective parties. Overall, the density of ties within the studied graphs is generally low but higher within individual parties.

| | **AfD** | **Green** | **CDU** | **Left** | **FDP** | **Pirate** | **SPD** | **Other** |
|---|---|---|---|---|---|---|---|---|
| **AfD** | - | * | * | - | * | * | - | - |
| **CDU** | * | - | - | - | * | - | - | - |
| **Green** | * | * | * | * | * | * | * | - |
| **Left** | * | * | - | - | - | - | - | - |
| **FDP** | * | * | * | - | - | * | - | - |
| **Pirate** | * | * | * | - | * | - | - | - |
| **SPD** | - | * | - | - | - | - | - | - |
| **Other** | - | * | - | - | - | - | - | - |

*Table 8. Significant differences between party densities in FG (* significant at .05%).*

## 5.4 Group-external and Group-internal Ties

To better understand if certain political parties have ties rather within their own boundaries or not, we calculated the *E-I index*, developed by Krackhardt and Stern (1988). This metric ranges from -1 to +1 mapping respectively to total closure or total openness. This can then be compared to a hypothesized value of a graph with a random distribution of ties having no propensity in either direction. The following calculations were based on a reasonably high number of 5,000 permutations.

Table 9 (left) gives an overview of the results on the level of the whole graph. FG-MG has a significantly different value than FG on which it is based, but is close to the value of MG. In case of FG, 77% of ties go outside the peer groups which is in line with the idea of users wanting to be informed by the whole political spectrum. At the same time, users actively mentioning others exhibit a propensity of keeping their ties closer in their group. This might also give evidence that mentions are rather used to support than to oppose other politicians.

Table 9 (right) considers the graph on party level. Notably, only the blocks of *Other* and the *AfD* show a positive sign for FG-MG and MG. Given the relatively small sample size of both groups, the results have to be interpreted carefully. For smaller parties, it is likely that the share of internal connections is relatively smaller having a less deteriorating effect on the E-I index.

| | Intern | Extern | E-I | StD | E(E-I) |
|---|---|---|---|---|---|
| **FG** | 0.23 | 0.77 | 0.54 | 0.01 | 0.62 |
| **MG** | 0.65 | 0.35 | -0.29 | 0.01 | 0.63 |
| **FG-MG** | 0.64 | 0.36 | -0.28 | 0.01 | 0.63 |

| | FG | MG | FG-MG |
|---|---|---|---|
| **AfD** | 0.91 | 0.30 | 0.10 |
| **CDU** | 0.49 | -0.29 | -0.22 |
| **Green** | 0.33 | -0.41 | -0.40 |
| **Left** | 0.83 | -0.26 | -0.21 |
| **FDP** | 0.79 | -0.08 | 0.01 |
| **Pirate** | 0.86 | -0.16 | -0.43 |
| **SPD** | 0.53 | -0.30 | -0.24 |
| **Other** | 0.97 | 0.75 | 0.33 |

*Table 9. E-I index for whole graphs and for each political party.*

### 5.5 Krackhardt's Graph Theoretical Dimensions of Hierarchy

The previous analyses were based on the underlying idea of horizontal differentiation. However, it is also possible to study vertical differences in the form of hierarchies. Krackhardt et al. (1994) proposed the Graph Theoretical Dimensions of Hierarchy (GDT), providing four dimensions of hierarchy in directed graphs, which are interpretable as indices from 0 to 1 where a higher value points out a stronger presence of hierarchy. The baseline scenario assumes a purely hierarchical structure of one superior node having outward ties to all other nodes in the graph with an in-degree of zero. Krackhardt's indicators measure the deviation from this idealistic case.

The first variable, connectedness, indicates that at least one node is able to reach and connect to all other nodes, though not necessarily directly. The second item, hierarchy, shows whether hierarchies are revoked through reciprocal ties demonstrating equal status. Third, the efficiency variable denotes to which extent a graph exhibits no redundant or multiple paths but only has the least amount of ties to remain connected. The last item, least upper bound (LUB), indicates whether there are only few nodes dominating the majority of others. The resultant values are shown in Table 10.

| | Connectedness | Hierarchy | Efficiency | LUB |
|---|---|---|---|---|
| FG | 1 | 0.18 | 0.95 | 1 |
| MG | 1 | 0.5 | 0.99 | 0.95 |
| FG-MG | 1 | 0.05 | 0.92 | 1 |

*Table 10. Krackhardt GDT for each considered graph.*

The level of hierarchy is with 0.5 highest for the mention graph but ten times smaller for FG-MG. The first observation possibly reflects that tweets containing mentions are not returned automatically, resulting in nonreciprocal ties. A low hierarchy in the reduced follower network, on the other hand, is related to the idea that active users are relatively more likely to make followers to friends and vice versa, i.e., having bi-directional ties. The level of efficiency is relatively high for all studied graphs. LUB is close to 1 and notably high for all three graphs. This item combines the previous observations and states that most of the nodes are eventually linked to a single group of superiors. Krackhardt's GDT indicates therefore a decent level of hierarchy in the Twitter graph which is only partly counteracted by reciprocity.

## 6 Summary, Limitations, and Future Outlook

Based on the results of the various applied graph metrics applied to a not-campaign biased dataset we observe three different groups of parties. First, the *Green Party* appears to be most connected and active inside the political group of users. Although the *Pirate Party* surpasses the *Green Parties'* average number of tweets and followers, the case is different when restricting the group to political users, exclusively. Second, the *CDU*, *SPD*, the *Left Party* and *FDP* appear to be quite homogenous in terms of graph statistics. Given the relatively minor differences, it appears that these parties behave similarly in terms of networking and posting. The third group is consisting of the *AfD* and further parties, and indicates the lowest level of overall involvement in the Twitter network. On Twitter, the usage behaviour of the established parties is found to be rather homogenous. Thus, with the exceptions of the *AfD* and the *Green Party*, political users have a common approach on how to use Twitter in contact with peer politicians.

Furthermore, we find a notable difference between the regular FG and the FG-MG, which excludes nodes not present in MG. Graph densities are higher in FG-MG, while at the same time the closeness of individual clusters increases. Hence, even though active Twitter users have a broader network in terms of mentioning other users in messages, their actual follower graph is closer, consisting of users with similar political beliefs. In contrast, inactive users appear to have a broader scope of followees and are not limited by their individual party, exhibiting a higher openness.

Interestingly, according to our various graph metrics applied, we find that party membership itself explains only little variation of the relationships in both graphs. Previous research from Plotkowiak et al. (2010) and Yoon and Park (2014) could only be partially confirmed. Although politicians tend to follow their own party, we only find three distinct groups for the eight studied parties. Given the diversity of political beliefs and organisation, this result is rather surprising. MG exhibits an increased amount of clustering. In line with Yoon and Park (2014), this might imply that politicians tend to support each other in active conversations.

Our research is subject to some limitations. In general, the restrictiveness of the public Twitter API only allows the retrieval of a limited amount of Tweets. The data set was retrieved in a time span of only two weeks in August 2015. The dynamic evolution of the graph should therefore be investigated in future work. The list of Twitter accounts was based on data retrieved from a website, relying on the completeness of this information. There is also no guarantee that the actual person is really being in charge of a user account. Despite the fact that one third of accounts are verified on Twitter, there is always the possibility of misused accounts (Glassman et al., 2009).

In future work, an analysis could take all available factors into account, such as length of membership, gender or location. In addition, the studied user base contained also politicians who are currently not active in policy-making or in a parliament. A distinction of active and passive politicians could therefore be of interest. Moreover, so far we only considered tweets in the MG containing mentions of another German politician. This could be extended to international politicians. Furthermore, hashtags and contents of tweets have been out of the focus so far. In the next step, we would like to include this additional information. We also plan to additionally derive the sentiment of each Twitter post to observe the underlying motivation of each politician to maintain a Twitter account and mention others.

We also aim to study the *n-hop neighbourhood* of each politician, including the non-political sphere. Inspired by the study of Verweij (2012) who studied the Twitter relationships between politicians and journalists in the Netherlands, we would like to apply similar research for the case of German politicians. Importantly, the question whether lobbyism could be discernible on Twitter is of high political interest. A first look at the top 30 most followed non-political users in our underlying dataset reveals that this lists contains mostly newspapers and magazines, indicating a rather objective follower network. However, a future in-depth investigation could reveal different patterns.

In summary, our case study on microblogging adoption in German politics leads to several insights into the political debate in the information society and prepares the ground for analysing influencers and lobbyism in politics.

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