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<td>MSc Sociology and Global Change (2017-2018)</td>
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Abstract

Background
While earlier studies on the German right-wing populist party AfD on Twitter have noted a very high frequency of the party’s hashtag use, there is a lack of understanding if this expresses support or opposition to the party. Thus, the aim of this research is to discover strategic expressions of retweeting and political hashtag use of German parties and shed light on the use of the AfD hashtag and the success of populist parties on social media in general.

Methods
To investigate strategic retweeting behaviour and hashtag use among a large sample (n=173,216) of collected Tweets that used political party hashtags, the study uses a network approach to visualise and analyse the retweet networks pertaining to these hashtags.

Findings
The analysis of the AfD retweet network finds two highly polarized clusters of users that barely retweet each other. One strongly politically aligned cluster is dominated by AfD politicians and thus identified as a support cluster, whereas the other cluster is opposed to the AfD. Furthermore, the AfD support cluster occurs also in the other party networks, which indicates strategic hashtag use by AfD politicians and supporters.

Conclusion
The study finds convincing evidence to support the thesis that AfD supporters and officials use their own party hashtag, but also the hashtags of other parties strategically. Moreover, the findings strongly suggest strategic retweeting behaviour and hashtag use and suggest that this represents a social media strategy of the AfD. This could encourage further research to also merge the study of populism on social media with existing research on political polarization and political campaigning on Twitter that have not been applied to populist parties.
Acknowledgements

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API – Application programming interface

Indegree – Measure of edges that terminate in a node (here equivalent to the number of times an account was retweeted)

Outdegree - Measure of edges originate from anode (here equivalent to the number of times an account retweeted others)

Cluster Abbreviations:

AfDClusters – AfD support and opposition cluster
AfDNetwork - AfD Retweet network
AfDOpposition - AfD-opposition Cluster in AfD network
AfDSupport – AfD-support cluster in AfD network

X – all other parties than AfD or ∀ ∈ {LINKE, GRUENE, SPD, CDU, CSU, FDP}

XClusters – AfD-support and AfD-opposition cluster of network X
XNetwork – Retweet networks of all other parties
XSupport – AfD-support cluster in network X
XOpposition – AfD-opposition cluster in network X

Party Abbreviations:

AfD – Alternative for Germany
CDU – Christian Democratic Union of Germany
CSU – Christian Social Union in Bavaria
FDP – Free Democratic Party
GRUENE – Alliance 90/The Greens
NPD – National Democratic Party of Germany
SPD – Social Democratic Party of Germany
1. Introduction

The past years have shown significant successes of populist parties and candidates in democratic elections and inclined some authors to call out the ‘rise of populism’ (Inglehart and Norris, 2016; Moffitt, 2016). Also in Germany, which did not have a right wing populist party in the federal parliament, the ‘Alternative für Deutschland’ (AfD) was able to establish itself by entering the parliament in the federal elections of 2017 (Stier et al., 2018; Arzheimer 2015).

These political changes are taking place in an era where traditional media is increasingly competing with social medial as a source of information for citizens, creating a high-choice media environment. Thus, this process of a wider media transformation raises important concerns for democracies (Vowe, 2017). Moreover, social media have been analysed benefitting populist parties, since it allows them to address potential voters directly and circumvent traditional gatekeepers, like television channels or print media (Van Aelst et al., 2017; Engesser et al., 2017; Krämer, 2017). Social media instead, allow forming online communities, which entail selective exposure of participants with the possibility to direct and manipulate political content (Krämer, 2017).

The online platform Twitter provides an ideal example to illustrate the trend described above and is used by politicians and citizens. Furthermore, Twitter plays and increasingly important role in national and international politics. Additionally, Donald Trump’s intensive Twitter use has made the platform and the characteristic hashtag a well-known feature among the wider population, since no day passes without another headline provoking Tweet of the American president. On Twitter, hashtags present the function of organizing online discourses and provide a possibility for individuals to link their messages (Tweets) to wider debates. Thus, political hashtags have become a crucial aspect and maximizing the hashtag use frequencies an important goal of political campaigning (Bode and Dalrymple, 2016). In political contexts, politicians and citizens use retweets and hashtags strategically, and often even use the hashtags of political opponents to confront them with adverse opinions or to take over their hashtags, a strategy which Bode et al. (2015) call ‘hashjacking’.
In case of Germany, the AfD is particularly successful in generating attention around their hashtag, which was by far the most used political hashtag prior to the 2017 federal election. This indicates that the party takes advantage of the functions of social media effectively, which may have been an important factor for their high electoral turnout in 2017 (Stier et al., 2018). For this reason, the present study investigates strategies in the use of German political party hashtags, with a focus on the use of the AfD hashtag (#AfD) on Twitter. As such, the research questions are as follows:

1. Why are populists so successful on social media?
2. To what extent does the high frequency of the #AfD on Twitter express support of or opposition to the right-wing populist party?
3. Is there indication that the AfD uses hashtags strategically?

To address these questions the study collects a large data set of all Tweets (n=173,612) that used one or several of the hashtags of German political parties during an eight-day observation period. From this data retweet networks are created and quantitatively explored with network visualisation and analysis methods. In order to execute the analysis, the study furthermore employs computer-assisted digital methods for data collection.

One major finding shows that the extremely high frequency of the AfD hashtag is to a large part generated by party supporters, although the majority of the hashtag users is opposed to the party. Furthermore, the results indicate strategic hashtag use by official AfD accounts, which are retweeted by a very active support community and use other party hashtags for strategic reasons. Moreover, the findings indicate that this ‘hashjacking’ strategy is successful, since on average AfD supporters represent more than half of the users of the other political party hashtags. These findings illuminate the perceived overrepresentation of populist actors on social media and suggest interpreting their high popularity also as a consequence of effective political communication and networking strategies.

Firstly, the literature review (2.Literature Review) will situate this study at crossroads between political communication research on populism and social media and a strand of advanced empirical studies on strategic expression and political polarization on Twitter in computational sociology. The following chapter (3. Methods and Ethics)
introduces the innovative digital approach applied for data collection and the network analysis. The chapter also considers ethical considerations and limitations of the approach involved. Thereafter, the findings and steps of analysis are presented in detail (4. Analysis and Findings) and discussed in the following chapter (5. Discussion). Moreover, the discussion emphasises the need for further empirically driven social research on populism and social media and underlines the successful communication strategies of populist parties. Finally, the conclusion (6. Conclusions) briefly summarises the main findings.
2. Literature Review

This chapter introduces the reader to current debates about social media and politics and in particular populism on social media. While for many years the influence of Internet and social networks were discussed in a dichotomous understanding between participation/deliberation or polarization, the recent rise of populist politicians and supporters and their success in social media campaigning requires a more focussed analysis of the mechanisms and structures of social media platforms. Thus, this chapter also reviews two studies that inform the methodological approach and provide the concepts of partisanship (Conover et al., 2011) and ‘hashjacking’ (Bode et al., 2015) to empirically investigate the networked structure of communication on Twitter.

2.1 The Internet and politics

In the past decades a number of articles in the academic literature have observed and evaluated the changes that the Internet and Internet-based Communication Technologies (ICTs) like social media are bringing to the social life and politics. The effects are often discussed in the understanding of two dichotomous frameworks that relate to the understanding of the changes that digital media initiate. While the first one interprets digital media to enhance the formation of a public sphere, in which people can interact and politics become more democratic, the contrary, it is understood as an echo chamber where only established parties and interests are reinforced (Colleoni et al., 2014).

The first interpretation draws from Habermas (1989) who developed the concept of the ‘public sphere’. Later academic work has re-applied the concept to the emergence of the Internet and ICTs to evaluate if these may reinvigorate the public sphere or multiple public spheres (Holt, 2004; Dahlgren, 2005). Dahlgren (2005) defines a public sphere as “a constellation of communicative spaces in society that permit the circulation of information, ideas, debates— ideally in an unfettered manner—and also the formation of political will (i.e., public opinion)” (Dahlgren, 2005:148). Consequently, the Internet and social media are understood to increase democratic participation of citizens and facilitate deliberation (Van Aelst et al., 2017; Blumler, 2016). This interpretation however, is criticised for carrying a positive bias, and omitting the risks of
a destabilization of societies, while overemphasising the reconstitution of the public sphere and re-democratization of politics (Lutz and Hoffmann, 2017).

Conversely to the public sphere interpretation, the second strand of academic research on social media and politics understands digital spaces as an ‘echo-chamber’ of the society in which debates and groups mirror the offline world. Political orientation is consolidated due to a selective exposure to political content. (Sunstein, 2001; Colleoni, 2014). Because citizens are only confronted with similar political opinions, social media widens the gap between citizens of different political allegiances and further fragment society.

A recent study by Van Aelst et al. (2017) for instance, analyses six main concerns that the digital media transformation towards high-choice media raises in democracies. One of the main concerns raised is the “increasing fragmentation and polarization of media content and media use in the wake of the transformation into high-choice media environments” (Van Aelst et al., 2017:12). This notion of high-choice media refers to social media, in which users have more control over the political content they wish to see than in traditional media newspapers or television. Additionally, Van Aelst et al. (2017) state an increasing relativism and a decreasing quality of news as dangers for democracies. These dangers, relativism and decreasing quality of news, might be best illustrated by Donald Trump’s light use of the term ‘fake news’ to discredit traditional media and spread alternative facts, while not providing any proof of his assertion. With respect to these fragmenting effects, the transformation from traditional media to social media is described as carrying destabilizing effects on democracies and benefiting populist actors (Van Aelst, 2017; Krämer, 2017). Consequently, the next section further explores some of the academic work on populism and social media as a central factor for the recent success of populists in democratic elections.

2.2 Understanding populism on social media
One of the central understandings regarding the latest political success of populists in political communication literature is the “pivotal role of social media in these processes, enabling populist parties and politicians to bypass media gatekeepers and transmit direct messages to target audiences” (Stier et al., 2017:1365). While populist parties follow a hybrid communication strategy in which they also use traditional media to reach wider audiences they face difficulties because “journalists of the upmarket press
are presumed to act as ‘paladins’ of the elites and to attenuate or to criticize populist statements in their articles” (Engesser et al., 2017:1113). In contrast, social media offer a channel of communication with citizens and party supporters, in which populists do not need to follow the norms and values of traditional media and are able spread their fragmented ideology (Engesser et al., 2017).

Additionally, Krämer (2017) discusses the role of the Internet and online platforms for populism. With respect to this, the author raises the effect of self-socialisation of users into right wing populist worldviews. Besides, social media may support this self-socialization in a populist worldview by providing a framework for users use to make sense of events and ideas without traditional media influences. Thus, social media also provide an opportunity for top-down claims of leadership for populist parties and politicians (Krämer, 2017). For these reasons, populist actors arguably benefit hugely from the media transformation towards a high-choice environment of information and communication (Vowe, 2017).

In addition to the theoretical literature discussed in this section, that highlighted the importance of social media for populist communication, the following section explores empirical studies that have investigated the strategies of populist politicians and parties on social media.

2.3 Researching populism on social media empirically
For empirical research social media provide the opportunity to examine communication practices of institutional populist actors and their audience or supporter (Krämer, 2017). Thus a number of studies have investigated populism empirically, of which this section introduces a selection that researched the AfD and other populist and non-populist parties.

Ernst et al. (2017) for instance, found in a study across six Western democracies that populist communication as a rhetorical style on Facebook and Twitter is mainly used by extreme and opposition parties and is more common to be used by right wing politicians. In the case of Germany a study by Stier et al. (2017) identified the AfD and the anti-migration movement PEGIDA (‘Patriotic Europeans against the Islamisation of the West’) in Germany as the main promoters of populist topics on Facebook. Moreover, the study found that smaller parties copy these topics to varying degrees from populists,
while the governing parties CDU and SPD “clearly deemphasize” (Stier et al., 2017:1367) these events and topics. The authors underline that “the AfD has firmly established itself as the melting pot of populism in the German party system” (Stier et al., 2017:1382) and that social media are used as a crucial communication channel.

Furthermore, the German GESIS Institute (Cologne) conducted the widest study monitoring the social media attention for German parties and politicians before federal elections (Stier et al., 2018). The more recent study about the 2017 election campaigns found that the AfD was particularly successful in “exploiting the potential of social media” (Stier et al., 2018:20). The authors understand ‘success’ as the frequency with which the party hashtag was used and found that the #AfD generated the highest number of positive and negative attention on Twitter. Although, the researchers note the uncertainty about the “tone of these debates” (Stier et al., 2018:16) they leave a more detailed analysis of the underlying structures to future research by stating that “as the political role of social media continues to grow, researchers will have to continue focusing on these partisan” (Stier et al., 2018:20). Correspondingly, the study provides important methodological guidelines for future research and the reproducibility of social media studies, but lacks a more detailed analysis of the investigated political party hashtag use and partisanship on Twitter.

The existing studies reviewed above provide empirical evidence to confirm the theoretical claims that social media have a particular importance for populist parties compared to regular parties. However, they fail to relate their research to existing Anglo-Saxon studies on politics on Twitter that provide findings and innovative methodological approaches to analyse the underlying structures and practices on Twitter. This underlines the necessity to merge these separated fields of literature and illuminate the success of the AfD and other populist parties on Twitter. Consequently, the next section reviews theoretical and empirical literature about Twitter and it’s increasing relevance in politics.

2.4 Twitter hashtags and politics

The social media platform Twitter has grown substantially in user numbers in the past decade and becomes increasingly important for election campaigns (Gruzd and Roy,
In addition, Twitter also supports the everyday self-promotion of politicians in front of an audience of politically interested citizens and journalists (Enli and Simonsen, 2018). Thus, Twitter use and the promotion of party hashtags become more urgent for politicians and parties.

Hashtags became available on Twitter in 2007 and diffused into other social media. Its primary function is to coordinate communication between larger groups of users (Bruns and Burgess, 2011). While the hashtag itself is democratic, meaning that everyone may introduce a new hashtag or initiate a viral Tweet, Twitter largely remains a hierarchical platform, where elite actors such as politicians, journalists and celebrities are retweeted much more often than normal citizens and have a higher chance to successfully initiate new hashtags (Enli and Simonsen, 2018; Lee et al., 2010).

Moreover, popular topics and actors on Twitter also have a higher chance of getting recognized and being broadcasted on traditional media. Thus, generating a high frequency of political party or candidate hashtags has become a crucial aspect of political campaigning in electoral periods (Bode and Dalrymple, 2016). However, also in non-campaigning times hashtags are used functionally to “identify political allegiances, form discursive clusters, label particular races, name media sources, and otherwise focus and direct exchanges on topics of interest” (Bode et al, 2015:153).

In terms of this research, two main studies inform the analytical approach to investigate the use of political party hashtags and in particular the popularity of the #AfD on Twitter. The first one by Conover et al. (2011) uses an approach based on network analysis and exercises a detailed investigation of political partisanship among American Twitter users. The methods to visualise and analyse the networks helped them find a “highly segregated partisan structure” (Conover et al., 2011:89) among political hashtag users in the 2010 US congressional midterm elections. They also find that a “retweet network contains two clusters of users who preferentially propagate content within their own communities” (Conover, 2011:91), which suggests that “content of political discourse on Twitter remains highly partisan” (Conover, 2011:95). A similar analysis has not been conducted with a focus on the German Twitter sphere or populism. Thus, the article by Conover et al. (2011) will inform the following methods section and the analytical approach to go beyond a merely descriptive analysis of the data and illuminate the high frequently use of the #AfD hashtag on Twitter.
Another approach that allows for a more in-depth analysis of political hashtag use on Twitter can be found in Bode et al. (2015), who investigate strategic hashtag use in the 2010 midterm election campaign in the US. The study finds contradicting evidence and argues for a more differentiated understanding of hashtag use than partisanship with two groups. Moreover, the authors “pay particular attention to the presence of strategic expression such as “retweeting” (sharing someone else's tweet with one’s followers) and “hash-jacking” (co-opting hashtags preferred by political adversaries)” (Bode et al., 2015:150) and conclude that simple Left-Right distinctions are inadequate to account for the plurality of hashtags use. Thus, the authors interpret their findings as a representation of multiple public spheres. Consequently, our study will adapt the focal point on strategic hashtag use and re-appropriate the concept of ‘hashjacking’ for the investigation of German political party hashtag use and the success of populists on social media.

Concluding, the literature review has introduced crucial debates about the Internet and politics, populism on social media and Twitter and politics pertaining to the scope of this study. Besides, the review identified two studies by Conover et al. (2011) and Bode et al. (2015) that will provide a guideline for the methodological approach and that are helpful to improve the analysis and understanding of the success of the AfD and other populist parties on social media.
3. Methods and Ethics

In light of the literature on strategic expression and partisanship on Twitter this chapter presents the methodological approach to collect and analyse Twitter network data in order to shed light on political hashtag use of the AfD hashtag and the political hashtags of other German parties. The first section gives an overview of the large sample of Tweets collected and introduces the audience centred collection approach. This approach was used to collect the Twitter data pertaining to the selected party hashtags, while allowing the inclusion of all Tweets that used these hashtags during the observation period. In particular, the analysis focuses on retweet networks that evolve around these political party hashtags, which Bode et al. (2015) identified as strategic expression on Twitter. The second section outlines the collection procedures and technicalities of the computer-assisted collection method. The data was gathered on Twitter in an automated way called “Scraping” that requires programming skills from the investigator.

The measures section and the analysis section follow the explanation of the collection procedures. Due to the networked nature of the data the research uses an explorative social network approach to investigate the structure of retweet networks that evolve around the use of the political party hashtags selected. These, retweet networks stand at the focal point of the analysis since retweeting a Tweet with political hashtags is seen as a strategic action. Furthermore, the network structures reveal insights into the practices and communities of political party hashtag use. Thus, the distinct communities of #AfD users indicate if the hashtag was used in support or opposition to the party. In addition, the co-occurrence of the same Twitter user (represented by network nodes) in several party networks denotes the use of multiple party hashtags during the observation period. This is used as a measure for strategic hashtag use (Bode et al., 2015). Consequently, the analysis section explains how these measures are derived in the practical computer-assisted analysis by using network visualisation and analysis, a community detection algorithm and statistical methods. Thereafter, the last two sections of this chapter, discuss important ethical considerations of collecting and investigating digital data and the limitations of the collection and analysis approach.
3.1 Sample description

In total this study builds on a large sample (n=173,612) of all public Tweets using one or multiple political party hashtags used between May 28th 00:00:00 and June 4th 2018 23:59:59 on Twitter. The data was purposefully collected in a random period of time outside of election periods and therefore not influenced by campaigns. Previous studies have shown the specifically high frequency of the #AfD before the German federal election in 2017 and this study investigates the use of political hashtags without a federal election in the next year and the next state election in more than 3 months ahead. Furthermore, the collection focused on the political party hashtags of parties represented in the federal parliament ‘Bundestag’, because they are the most relevant in everyday political discussion and will provide a comparison to the use of the AfD hashtag.

Twitter is an event sensitive medium and it is important to determine if there have been any party specific events that might have affected the frequency of only one party. Thus, figure A2 in the Appendix shows the daily frequencies of party hashtag use, which vary in more or less the same way. This helped ensure the absence of major party specific events during the observation period.

The selected political party hashtags occurred in the following order: #AfD, #SPD, #CDU, #GRUENE, #CSU, #LINKE, #FDP and the number of collected Tweets for each hashtag are depicted in Table 2.1. These party hashtags were chosen as a collection selector, because previous studies have observed a high frequency of the party hashtags on Twitter as a success for the parties. Stier et al. (2018) for instance, interpreted the high frequency of the #AfD as a success of the party and an important factor for the high electoral turnout in the 2017 federal election. Moreover, Table 2.1 shows the total number of collected Tweets divided into the three different types of Tweeting (retweets, mentions, free text). On twitter users have the possibility to retweet the messages of other users, mention other users by directly addressing them or naming them in third person and free text Tweets that are not linked to other users within the network (except for the hashtag).
Table 2.1: Investigated sample of different types of Tweets for each party hashtag during the selected index period from May 28th 00:00:00 to June 4th 2018 23:59:59

<table>
<thead>
<tr>
<th>Sample</th>
<th>#AfD</th>
<th>#SPD</th>
<th>#CDU</th>
<th>#CSU</th>
<th>#FDP</th>
<th>#Gruene</th>
<th>#Linke</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retweets</td>
<td>100726</td>
<td>13702</td>
<td>11710</td>
<td>5243</td>
<td>2547</td>
<td>6040</td>
<td>2905</td>
</tr>
<tr>
<td>in %</td>
<td>86</td>
<td>73</td>
<td>79</td>
<td>71</td>
<td>64</td>
<td>78</td>
<td>73</td>
</tr>
<tr>
<td>Mentions</td>
<td>4827</td>
<td>2188</td>
<td>1341</td>
<td>814</td>
<td>629</td>
<td>729</td>
<td>440</td>
</tr>
<tr>
<td>in %</td>
<td>4</td>
<td>12</td>
<td>9</td>
<td>11</td>
<td>16</td>
<td>9</td>
<td>11</td>
</tr>
<tr>
<td>Free text</td>
<td>11432</td>
<td>2828</td>
<td>1792</td>
<td>1336</td>
<td>803</td>
<td>936</td>
<td>644</td>
</tr>
<tr>
<td>in %</td>
<td>10</td>
<td>15</td>
<td>12</td>
<td>18</td>
<td>20</td>
<td>12</td>
<td>16 %</td>
</tr>
<tr>
<td>All Tweets</td>
<td>116985</td>
<td>18718</td>
<td>14843</td>
<td>7393</td>
<td>3979</td>
<td>7705</td>
<td>3989</td>
</tr>
</tbody>
</table>

The collection pertaining to hashtags results in a sample that contains all three of these types and for all seven party hashtags the majority of Tweets were retweets on which the succeeding network analysis will focus (Table 2.1). In addition, further considerations related to the collection approach are discussed in the following section.

3.2 Sampling design

Twitter hashtags are generally used to link a Tweet to a certain topic and function as a means of coordination for debates of large number of users that do not need to be connected by their follower networks, but publicly participate in a debate under the respective hashtag (Bruns and Burgess, 2015). While a number of studies examine e.g. follower networks as an indicator of information diffusion and or fragmentation, the research question of this study explores if there is a detectable political strategy when using political party hashtags. Thus, a collection directly via the political party hashtags only takes those users into consideration that have purposefully linked their messages to this discourse. In other words, hashtag use is “effectively a ‘bot-tom-up’ curation of Tweets around a particular topic into a single stream of data” (Tinati et al., 2014:668), which is then collected by the researcher. However, the precondition is a user being informed and aware about the use and effects of a hashtag in a structured debate on Twitter.

Thus, this study uses an audience-centred design and collects all Tweets that use the selected political party hashtags during the observation period, to better understand
the overall use of the selected political hashtag (Stier et al., 2018). Furthermore, the chosen approach does not require a sampling on the data, but collects the data as it emerges on the platform and therefore allows exploring, which users are important due to the number of times being retweeted or retweeting (Tinati et al., 2014). Consequently, the political hashtags were chosen as a selector criterion since the aim of this study is to investigate the structural features networked Twitter discourse about political parties in Germany. Self understandably, the collection of such large amounts of data and their quantitative analysis had to be computer assisted and the following section will describe the procedures of the collection process in more detail.

3.3 Collection Procedures using Twitter’s API
Since its creation over a decade ago Twitter has drawn substantial attention by social scientists and voluntarily supplied data for qualitative and quantitative analysis, by allowing researchers to access the data through its application-programming interface (API). Furthermore, Rogers (2013) formulated in a proposal for digital research to “consider first and foremost the availability of computing techniques” (Rogers, 2013:21). For this reason and the possibility of collecting very large datasets this study is based on an automated collection approach.

The method to collect data from websites via the API is called ‘scraping’ and currently there exist a variety of scraping tools that do not necessitate any programming skills, and for instance collect timeline data as we see it on the computer screen by accessing Twitter’s Streaming API (Marres and Maltevrede, 2013). However, the data collected with these tools is biased, because Twitter relevance algorithms filter the content shown by the popularity of users. Thus, this study collected Twitter data by accessing Twitter’s Rest API and used the statistical programming software R for data collection, which results in less biased data.

With the R package ‘TwitteR’ developed by Gentry (2015) it was possible to collect a maximum of 18,000 tweets at a time, but still underlying Twitter’s regulation of the Rest API access to a maximum of two weeks retrospective. The collection focuses on Tweets in German language, since the party abbreviation hashtags are internationally often used for other purposes or institutions. Furthermore, the software package enables a collection of Tweets by using keywords, hashtags or usernames and a
collection of followers of accounts as selectors. Consequently, these multiple sampling or collection opportunities enable a number of different approaches. All of the approaches are based on the network structure of Twitter since following and being followed, as well as Retweeting or mentioning, creates a directed link between two users that is represented by an edge in a network graph.

The collection approach based on political hashtags was chosen to allow a self-structuring of the users of certain hashtags. Consequently, their position in the networks is determined by retweeting behaviour or by whom they retweeted and by whom they were retweeted. For this reason no sampling is forced on the data and in the analysis of the networks distances between nodes can be interpreted in terms of retweeting behaviour and which users were important in the debate (Tinati et al., 2014). Consequently, the collection approach is chosen in consideration of the platforms characteristics to ensure a meaningful interpretation of the results. Therefore, knowledge of the platform and different collection techniques are crucial to this approach. The following section will introduce the measures for strategic retweeting behaviour and hashtag use.

3.4 Measures for strategic retweeting and hashtag use

After the previous sections described the sample and the collection design and procedures, this section describes the main network approach and measures that are applied to make sense of the collected data. The methodological approach of this study is closely related to the origin of the data from a social networking site (SNS) or social media platform. While the collection retrieved large data sets that replicate the network structure of Twitter and allowed the creation of network datasets, the analysis will make use of social network analysis to graph and subsequently analyse the data. Analysing the structure of the network reveals information about the political identity and strategies of the hashtag users. Consequently, the exploration of the research question starts with a visualisation of the party network (2.3.1), in which the location or cluster membership of nodes implies political alignment with the other cluster members. Thus, the cluster membership in the polarised AfD retweet network indicates support or opposition to the party (2.3.2). As a measure for strategic hashtag by AfD politicians or supporters this study measures the co-occurrence of nodes from AfDSupport in the other party networks called XNetwork in the analysis (2.3.3).
3.4.1 Visualisation of the retweet networks

“Social network visualization reduces complexity and enables researchers to more easily pinpoint key participants and clusters within the network, by using a variety of metrics from social network analysis (from simple measures such as in- and outdegree to more complex metrics such as centrality or eccentricity) as the foundations for their visualizations” (Bruns, 2012:1331)

In the collected sample the Tweet texts contain information about the user that was retweeted and the collected data also contains the name of the retweeted user. Consequently, the retweet networks for each party hashtag are created by linking the retweeted account with the other user who retweeted. This link is called a directed edge and the direction was defined as going from the account retweeting to the one who is retweeted.

Thus, the analysis and visualisation of these retweet networks enables the researcher to interpret and analyse the connections between the users, represented by network nodes, and identify important users and cluster in the network graphs (Bruns, 2012). Consequently, the analysis of the different party networks acknowledges the mechanisms of Twitter and will contribute to shed some light on the strategic retweeting and hashtag use as a factor of the success of populist parties or movements on social media.

The retweet networks are chosen for three reasons. First, they are the most commonly used type of Tweets in the collected sample (Table 2.1). Second, it “offers a way to observe which information and which actors become important as the network evolves: what the network produces, rather than using the network as a data source to observe actors or tweets selected in advance” (Tinati et al., 2014:668). Third, this approach is based on the observation that most Twitter users only retweet messages that they politically agree with. Generally being retweeted in Twitter networks is seen to represent influence or publicity beyond the personal network and “retweeting in a social network can serve as a powerful tool to reinforce a message” (Cha et al., 2010:13). While this section has explained the understanding of the retweet networks the following section will explain how cluster membership in the politically aligned network functions as a measure for support or opposition to the AfD.
3.4.2 Cluster membership as a measure of support or opposition

The cluster in which a user or node is located in political retweet networks allows to draw inferences about political identity. Thus, the cluster membership in the collected retweet networks is a crucial measure for the identification of support or opposition to the AfD.

The social network approach follows the understanding of Conover et al. (2011), who analysed the clustered structure of Twitter networks that emerge around the use of political hashtags. As mentioned in the preceding section retweeting in political contexts is seen as a way of reinforcing the meaning or the issuer of a tweet (Cha et al., 2010; Conover, 2011). In this case retweeting an official party account for instance, is evaluated as support for the party line. This retweeting behaviour results in clustered retweet networks, in which cluster membership resembles political alignment (Conover, 2011). Thus, the position and cluster membership of actors or in network terms nodes, holds information about their political identity and in strongly politically aligned clusters about partisanship.

Consequently, the network visualisation and cluster membership is used as an indicator of the overall use of the #AfD. If a cluster is identified to be politically aligned with the AfD the number of nodes positioned in this cluster is evaluated as the number of supporters and amount of Tweets issued by these is the share of supportive Tweets of the overall hashtag frequency (Conover, 2011).

Moreover, the network data allows the application of Indegree and Outdegree as node centrality measures (Wasserman and Faust, 1994:IV). Consequently, the network measure Indegree that counts how many edges terminate in a network node, represent how often a user was retweeted by others. The measure of Outdegree correspondingly, as the opposite of Indegree, determines how often a Twitter user retweeted others. If an actor retweeted others or was retweeted by another multiple times, these parallel edges are also considered in the measures of Indegree and Outdegree when calculated in Gephi (Bastian et al., 2009). These measures are used in the analysis to estimate the overall amount of Tweets issued by the different clusters and allow a cluster comparison based on the structural characteristics of the network. Furthermore, the Indegree as a
measure of the number of times a user was retweeted is applied as a measure of influence to identify the accounts that contributed most to the content within a cluster (Cha et al., 2010).

While this section outlined the network measures and cluster membership as an indicator of political alignment, the next section will present coherent co-occurrence of nodes in multiple networks as a measure for strategic hashtag use.

### 3.4.3 Coherent co-occurrence as a measure for strategic hashtag use

“Analysis of the co-occurrence of particular hashtags and their frequency of use within clusters provides a glimpse into the self-structuring of online clusters around shared ideas and strategies.” (Bode et al., 2015:153)

The quote expresses the central idea behind the second pivotal measure in this study that refers to the third research question and the strategic use of political hashtags. Former research has underlined the widely used strategy of using the hashtags of political opponents to confront these with the personal political opinion (Conover et al. 2011). Bode et al. (2015) call this strategy ‘hashjacking’ with the aim of “co-opting the hashtags preferred by political adversaries” (Bode et al., 2015:152), while Conover et al. (2011) named the strategy ‘content injection’ referring to the injection of content into politically opposed hashtag networks. The next paragraph explains how the hashjacking measure of co-occurrence by Bode et al. (2015) is modified for this study.

In the case of political party hashtag use in Germany the researcher would expect the supporters of the AfD to apply this strategy in order to confront the established parties with critic or insults. Since the retweet networks are coded as actor-networks Twitter users that applied multiple political hashtags in one or several Tweets will occur in each of the respective hashtag networks. Thus, the fraction of co-occurring nodes between different networks and clusters will be interpreted as an indicator for strategic hashtag use.

Correspondingly, high proportions of co-occurring nodes in a network or cluster indicate that a lot of the users represented by the nodes retweeted messages with multiple party hashtags or used other party hashtags strategically during the
observation period. This interpretation of co-occurrence as a measure of strategic hashtag use is taken from Bode et al. (2015) and modified to the network approach of this study. As a final measure, only those nodes that occur in the AfD support cluster (AfDSupport) and the respective AfD support cluster in the other party networks (XSupport), will be taken into consideration as coherently co-occurring and thus interpreted as a measure of strategic hashtag use in a politically aligned way.

Measurement of node co-occurrence will thus provide a confirmation of the cluster identification, if AfD supporters are more likely to co-occur in the expected AfD support clusters of the other party networks. However, before the final measure of coherent node co-occurrence in politically aligned clusters is derived, the node co-occurrence on the network level must be calculated.

Thus a sequential analysis investigates the co-occurrence on the network and cluster level and these steps of the analysis are presented in the next section.

3.5 Data Analysis

The analysis of the large network datasets in order to explore the research questions and calculate the measures demands computer-assisted analysis. To handle the large data set and create the network graphs, the research uses the statistical programming software R Studio (Version 1.1.423 – © 2009-2018 RStudio, Inc.) in combination with the network visualisation software Gephi (Gephi 0.9.2 - © 2008-2017 Gephi contributors), which was developed by Bastian et al. (2009).

The first part of the analysis explores the second research question and investigates the network structure of the AfDNetwork. Moreover, a community detection algorithm supported by a qualitative content analysis is used to identify clusters in the network and reaffirm their interpretability as politically aligned users. Furthermore, an inspection of the top accounts and their co-occurrence as most retweeted users in the other networks indicates larger effects of co-occurrence between the different party networks that are analysed in detail in the second part of the analysis.

Consequently, the second part focusses on the co-occurrence between the AfD network and the other networks in detail. The analysis begins first to investigate the co-
occurrence on the network level and continues in the second step with the co-
occurrence between the AfDClusters and XNetwork (with X standing for any of the other
political parties). Thereafter, the calculation of the co-occurrence of nodes between
AfDSupport and XSupport provides a final measure for strategic hashtag use by politically
aligned AfD officials and their supporters.

3.5.1 The AfDNetwork
For the visualisation of the retweet networks in Gephi the built-in ForceAtlas2 layout
algorithm was used in order to graph the individual networks based on their structural
features. These are the connections that one node has with the other nodes and the
direction of the link. The developers of the algorithm simplify the functioning of the
Force2 layout algorithm in the way that “nodes repulse each other like charged particles,
while edges attract their nodes, like springs” (Jacomy et al., 2014:2). Consequently the
network spreads out and takes on a form that allows a visual comparison of the
distances between nodes as results of structural features, in this case the distance
between two nodes and their neighbours, which is based on the similarity retweeting
behaviour. However, the visual clustering needs to be confirmed by a community
detection algorithm and the interpretability will be controlled by a qualitative content
analysis, which are outlined in the following paragraphs.

The primary hypothesis that the use of the #AfD is divided into supportive and
opposed usage is investigated based on the visualisation of the AfDNetwork using the
ForceAtlas2 layout algorithm. The further analysis builds on a hierarchical clustering of
the networks that is executed using the community detection algorithm developed by
Blondel et al. (2008) for Gephi. Thereafter, a qualitative content analysis based on
Neuendorf (2017) is applied to test if the cluster assignments of the community
detection algorithm can be meaningfully interpreted as different political alignments.

Correspondingly, the qualitative content analysis examines the profile
information of the 50 most retweeted accounts in the AfDNetwork to evaluate the political
orientation in terms of being supportive or opposed to the AfD. The 50 most retweeted
accounts are chosen, since these are representative for a high proportion of the
retweeted content in the network. The content analysis serves as a control of the visual
and modularity based clustering and accomplishes a triangulation of the approach.

Thereafter, the clusters are compared and will contain the measures of node membership in the support and opposition cluster and the activity in each cluster will be estimated as the product of the sum of cluster members and the average Outdegree of all nodes in a cluster. This derives the final measure of the fraction of users and retweeting activity that are supportive of or opposed to the AfD.

The following step of analysis will investigate the clustering of the other party networks $X_{Network}$ and investigate and graphically display the co-occurrence of the most retweeted accounts in the $AfD_{Network}$. Because this co-occurrence of official party or AfD support accounts indicates the co-occurrence of wider audiences, this will be the focus of the second part of the analysis.

### 3.5.2 Calculating co-occurrence between networks and clusters

The second part of the analysis uses descriptive statistics for the cluster analysis to derive the final measure of coherent node co-occurrence as an indicator of strategic hashtag use by AfD officials and supporters. The aim of the analysis is the calculation of the number (or percentage) of nodes that co-occur in $AfD_{Support}$ and the respective $X_{Support}$. This is seen as an indicator that the account is coherently politically aligned and retweeted or was retweeted using one or multiple hashtags of other parties. Thus, co-occurrence in $AfD_{Support}$ and $X_{Support}$ is evaluated as a useful measure for strategic hashtag use and coherent behaviour that indicates political alignment with the AfD. This however, is the final result of the second part of the analysis and derives findings relating to the second research question. The steps that lead to this final measure of coherent node co-occurrence are outlined in the following paragraphs.

The analysis progresses in three sequential steps to derive the final measure for strategic hashtag use by AfD officials and supporters, which is the network share of the co-occurring nodes between $AfD_{Support}$ and $X_{Support}$. This is the number of co-occurring AfD supporters that were also in the other party network ($X_{Network}$) coherently assigned to the AfD support cluster ($X_{Support}$).

The first step calculates the co-occurrence between the $AfD_{Network}$ and each $X_{Network}$. Since the AfD network is significantly larger than the others, the co-occurrence shares will be defined in relation to the other party network sizes.
After this, the second step examines how many of the co-occurring nodes in $X_{\text{Network}}$ are co-occurring in $AfD_{\text{Support}}$ or $AfD_{\text{Opposition}}$. To express the findings more comprehensively, the co-occurrence likelihood of AfD supporters and opponents will be contrasted to each other and between the different party networks. The calculation is based on the expected probability pertaining to the cluster weight in $AfD_{\text{Network}}$ and the observed probability of co-occurrence, which is similar to the probability measure Conover et al. (2011) applied for edge probabilities, but configured to the node based approach of this study.

The final step builds on the results of the preceding analysis, to calculate how many nodes of the $AfD_{\text{Support}}$ co-occur in each $X_{\text{Support}}$. The other parties, although less clearly, are also divided into two clusters with one remarkable blue cluster, that is representative of AfD supporters. In this cluster the most retweeted AfD accounts co-occurred and all $X_{\text{Support}}$ are therefore expected to be projections of members from $AfD_{\text{Support}}$ that use the other party hashtags in popular Tweets. The result of the analysis is the number of co-occurring nodes between the four possible cluster combinations of the $AfD_{\text{Clusters}}$ and of each $X_{\text{Cluster}}$. Besides, these results are put in relation to the overall network size of the respective $X_{\text{Network}}$. This distils the final result, which is the share of AfD supporters that used the other party hashtags strategically and thus co-occur in both $AfD_{\text{Support}}$ and $X_{\text{Support}}$. Moreover, to underline the significance of the findings for the support co-occurrence, the results for the other cluster combinations of co-occurrence will be presented in the analysis.

Concluding this section has explained the steps of co-occurrence analysis that lead to the final measure of coherent co-occurrence that for the co-occurrence between $AfD_{\text{Support}}$ and $X_{\text{Support}}$ indicates strategic hashtag use. The following section will discuss important ethical considerations pertaining to the collection of social media data.

3.6 Ethical Considerations

This study following Rogers (2013) proposal for digital methods in the social sciences takes ethical considerations into account during all research steps. Due to the digital origin of the data it is important to recognize “the privacy concerns inherent with the collection and release of social networking data” (Zimmer, 2010:313). These privacy concerns, relate directly to digital social science debates about the difficulties of platform users to protect their privacy (Barnes, 2006; Crabtree et al., 2017). Although,
users of Twitter might be more aware about the public nature of their actions, the research “challenges us to find ways to govern our practice in ethical ways” (Tinati et al., 2014:678). Consequently, this study was completely anonymized and does not show or name usernames or ID codes of individual accounts in network graphs or tables. In the conclusion, this study reaffirms the ethical concerns raised throughout the process and that the collected data will be deleted after the completion of this study.

3.7 Limitations

The main limitations of this study lie in the representativity of the data, reproducibility of the results and resources for the project (that resulted in computational limitations).

The first main limitation is the representativity of Twitter for other social media and the possibility to compare the German Twitter community to other countries. Indeed, Twitter use in Germany is increasing, but still remains primarily used by politically interested citizens, media professionals and political professionals (Frees and Koch, 2015). Citizens who used Twitter therefore represent a particular group, which may only partially account for the success of populist parties in wider German population. A second limitation is that the collection approach that uses the hashtag as a collection selector, which may affect the representativity of the sample, since hashtags are usually only used by experienced Twitter users, who know how to use the function to link their messages to wider discourses (Grandjean, 2016). A third limitation of representativity that is related to resources available to this study, is the collection method used. Only the commercial access through the ‘Gardenhose’ API of Twitter guarantees unbiased results, which means a collection of all Tweets that used a certain hashtag (Marres and Weltevrede, 2013). Moreover, the limitation to German language Tweets was critical in order to control for political content, since the party hashtags are only in the German language consistently used for political Tweets. Thus, Tweets in other languages that were supposed to contribute to the hashtag debates could not be analysed.

The second type of limitations also relates to Twitter’s data-sharing policy, which only allows publishing the Tweet ID of the sample, but not the complete dataset (Stier et
Moreover, computational challenges related to the large size dataset made it necessary to use Gephi and R for data analysis, which may have limited the reproducibility of the results and required a more practical approach to the analysis.

With respect to this study, the statement of Rogers (2013) that collecting and analysing big data demands high computing power and programming skills were another limiting factor. One possible method for reconfirming the results would be the analysis of different modularity assignments similar to Conover (2011), to control for variation within the community detection algorithm. This method however, exceeds the technical resources being available for this Master’s dissertation. Lastly, there is a risk of “treating software for network visualization as black box” (Bruns, 2012:1331), which the researcher aimed to minimize by contemplating aspects as the prior limitation related to the modularity based community detection algorithm in Gephi. Furthermore, all steps of the analysis were chosen in lien with the interpretability of the network data. To conclude, these limitations will be thoughtfully considered for the interpretation of the results.
4. Analysis & Findings

This chapter introduces the steps and findings of the explorative network analysis. Since the analysis is based on an explorative approach the theoretical considerations and sequence of the analysis will be outlined for the reader. The analysis is organized into two main parts that each address one of the practical research questions.

The first part of the analysis finds that the AfD Retweet network is divided into two main clusters that represent communities of users with opposed political alignments in terms of support or opposition to the AfD. The analysis derives that 30.23% of the nodes in the AfD Network are in AfD Support, while the majority of 67.93% nodes are assigned to AfD Opposition. However, the nodes in AfD Support generate more Tweets due to a remarkably higher average activity in respect of outgoing edges.

The second segment of the analysis is organized into a sequence of three steps with an increasing depth of analysis. These steps derive the other main finding that on average more than half of the nodes of X Network are co-occurring in the AfD Support. The first step discovers that nodes from AfD Support are much more likely to co-occur in other party networks. The second step investigates the coherence of assignments and finds that members of AfD Support are also much more likely to be assigned to the AfD support clusters in the other party networks called X Support. This results in a much higher share of co-occurring nodes in X Support than in X Opposition, which emphasizes the high similarity between the AfD Support and X Support. The last finding of the analysis is that on average 50.70% of nodes in the other party networks X Network co-occur in X Support and AfD Support. This final finding underlines the extent of coherent co-occurrence as an indicator for strategic hashtag use by AfD supporters on Twitter.

4.1. The AfD Network and politically aligned clusters

This section presents the findings and steps of explorative analysis of the AfD Network and the co-occurrence of its most retweeted users in X Network. First, the community detection algorithm, which was introduced in Section 3.5.1 is applied and followed by the qualitative content analysis to identify the political alignment of the clusters and control the meaningfulness of the clustering. Thereafter, the analysis contrasts the two clusters
of the AfD Network and identifies a co-occurrence of the most retweeted official AfD party accounts in XNetwork.

4.1.1 Modularity clustering

After a first visual inspection shows a clustered structure of the AfD Network the community detection algorithm is applied to the retweet networks in Gephi. Besides, Table B4.1 displays the network overview in terms of network nodes and edges for all parties and Table B4.2 in the appendix depicts the cluster assignments of the two largest communities for all parties. The result of the modularity clustering for the AfD Retweet network is shown graphically in Figure A4.1 in the appendix. The network graph shows the network clearly separated into a red and a blue coloured cluster. It is important to note that the application of the modularity algorithm does not change the structure of the network graph, but only assigns the individual nodes to communities and colours them pertaining to their community membership. The nodes in the blue cluster are expected to be in support of the AfD, which is therefore called AfD Support, while the opposed red cluster is called AfD Opposition. The next step controls and affirms the expectation that politically aligned Retweeting behaviour is responsible for the clustering of the network by using a qualitative content analysis.

4.1.2 Is there political alignment?

To triangulate the approach and control the meaningfulness of the clustering and interpretability as political alignment a qualitative content analysis of the fifty most retweeted accounts is conducted (Neuendorf, 2017). This identification is chosen, because the Indegree distributions are highly positively skewed, which signifies that these most retweeted accounts have a high share of the overall retweets. The content analysis investigates the profile information and if the accounts are officially associated with a political party. For the accounts where this is not stated the ten most recent Tweets are analysed to determine if the account has a political line that is supportive of the AfD (or right-wing) or opposed to the AfD (left-wing or moderate).

The findings emphasise the suggestion that the clustering in the AfD network is caused by political alignment in the Retweeting behaviour of its users that causes the clustering. The blue cluster is identified as AfD Support, while the red cluster called AfD Opposition. Of the 50 most retweeted accounts 33 were assigned to the AfD Support and 17
to the AfD Opposition. Of these 33 nodes in the blue AfDSupport cluster, 24 are official AfD party accounts representing politicians, the party magazine or the party’s state associations from different German federal states. Moreover, the vast majority of 97% of the investigated users that were assigned to the AfDSupport are classified to have a pro-AfD political alignment, which means being openly against migration and Islam in Tweets or profile information. Only one user in the AfDSupport has a clear anti-AfD profile and cannot be interpreted as correctly represented by the clustering. This account however, could be evaluated as an exemption, because it retweeted official AfD accounts frequently, although opposed to the content. Nevertheless, the identification of 97% of the investigated accounts as supportive of or associated with the AfD indicates a high degree of right-wing and pro-AfD political alignment in AfDSupport.

The investigation of the 17 accounts in the red AfDOpposition showed a more heterogeneous group of 5 journalists or media accounts, only one other party politician (SPD) and 10 accounts that were clearly identified to be anti-AfD. Thus, the red cluster is called AfDOpposition in the continuing analysis and the study suggests it to be less strictly politically aligned than AfDSupport. Consequently, the qualitative content analysis has supported the expected political alignment in the two clusters of the AfDNetwork. The next section introduces the findings of the comparison of the AfDClusters.

4.1.3 Cluster analysis
The network graph in Figure 4.2 shows that the official AfD accounts represented by the orange nodes are embedded in AfDSupport and sized according to their high Indegree as the number of times a user has been retweeted by others. Consequently, table 4.1 contrasts the results of the basic network measures for the AfDNetwork and the two clusters. The cluster analysis finds that AfDOpposition contains 13,894 nodes, whereas 6,321 nodes were assigned to AfDSupport. This translates to 67.93% of all nodes in AfDNetwork are in AfDOpposition, while 30.23% of the nodes are assigned to AfDSupport.
However, the Indegree and Outdegree in AfD Support is remarkably higher, which links to the findings of the qualitative content analysis that identified the majority of the 50 most retweeted users in AfD Support. In terms of outgoing retweets, the AfD Support, although containing only about half of the nodes of AfD Opposition, represents the majority of the retweets, which underlines the higher activity of nodes in AfD Support. In terms of activity, as the number of outgoing edges, the AfD Support cluster represents 63.89% of retweets of the AfD Network. Moreover, table 4.1 depicts a very low density of the network and the clusters, which could be explained by the large network sizes.
<table>
<thead>
<tr>
<th>Summary</th>
<th>AfD Network</th>
<th>AfD Opposition</th>
<th>AfD Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nodes</td>
<td>20583</td>
<td>13894</td>
<td>6321</td>
</tr>
<tr>
<td>In %</td>
<td>100</td>
<td><strong>67.93</strong></td>
<td><strong>30.23</strong></td>
</tr>
<tr>
<td>Edges (outgoing)</td>
<td>100431</td>
<td>36269</td>
<td>64162</td>
</tr>
<tr>
<td>In %</td>
<td>100</td>
<td><strong>36.11</strong></td>
<td><strong>63.89</strong></td>
</tr>
<tr>
<td>Density</td>
<td>0.00024</td>
<td>0.00019</td>
<td>0.00160</td>
</tr>
<tr>
<td>Mean Indegree</td>
<td>4.88</td>
<td>2.62</td>
<td>10.13</td>
</tr>
<tr>
<td>Median Indegree</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Mean Outdegree</td>
<td>4.88</td>
<td>2.61</td>
<td>10.15</td>
</tr>
<tr>
<td>Median Outdegree</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 4.1: Summary of the AfD retweet network and the two largest clusters

Concluding, the AfD Support and AfD Opposition clusters are structurally different and AfD Support is more densely connected and thus has a much higher activity than the AfD Opposition. Furthermore, AfD Support appears more hierarchically structured with higher outliers to the top. Due to the large network size of the AfD Network and the possible strategic hashtag use, a co-occurrence of these most retweeted users in the AfD Support in the other networks seems probable. Thus, the findings of the investigation will be presented in the next section.

4.1.4 Co-occurrence of the most retweeted accounts from the AfD Network

The community detection for the other networks also detects two large clusters, which contain the majority of network nodes. When comparing the co-occurrence of the most retweeted accounts from the AfD Network it shows that the official AfD account for the majority of the most retweeted and co-occurring nodes. Furthermore, figure A4.2-A4.7 illustrate the network graphs for all XNetwork with the modularity cluster colouring and the AfD official accounts in orange. The position of these official accounts in the more connected cluster of each network stresses the suggestion that these are also in support
of the AfD called XSupport. Table 4.2 depicts the number of most retweeted users that co-occur in the AfD Network and XNetwork. The majority of the most often-retweeted nodes that co-occur in the AfD and other networks are found to be official AfD accounts.

<table>
<thead>
<tr>
<th>Co-occurrence of the most retweeted accounts in X_{Network} (n=50)</th>
<th>Linke</th>
<th>Gruene</th>
<th>SPD</th>
<th>CDU</th>
<th>CSU</th>
<th>FDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>In Top 50 AfD</td>
<td>4</td>
<td>8</td>
<td>13</td>
<td>11</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>From AfD support cluster</td>
<td>4</td>
<td>8</td>
<td>13</td>
<td>10</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Of which official AfD</td>
<td>2</td>
<td>5</td>
<td>10</td>
<td>7</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Network content share</td>
<td>29%</td>
<td>49%</td>
<td>33%</td>
<td>46%</td>
<td>23%</td>
<td>14%</td>
</tr>
</tbody>
</table>

Table 4.2. Co-occurrence between the 50 most retweeted accounts in the AfD_{Network} and X_{Network}

The results illustrate that almost exclusively AfD officials and supporters co-occur in the most retweeted accounts of X_{Network}, because they used multiple party hashtags. Moreover, the official AfD accounts and supporters have an over-proportional impact on the content belonging to the other hashtags discourses. In particular for the #GRUENE and #CDU network in which 8 or 10 accounts from the AfD_{Support} issued almost half of the content that emerged under these party hashtags. Consequently, the further analysis focuses on the co-occurrence of all nodes between the AfD_{Network} and X_{Network} to investigate whether the co-occurring nodes represent AfD supporters or opponents.
4.2 Measuring node co-occurrence

In the previous the findings that resulted from the AfD network analysis and the qualitative content analysis were presented. Moreover, the co-occurrence of AfD politicians in X\text{Support} and their relatively high network share indicate a wider co-occurrence of nodes between the networks. This finding motivates a more in-depth analysis of node co-occurrence as a representation of cluster and network similarity between different party networks. Consequently, this section presents the findings of the sequential steps of co-occurrence analysis.

4.2.1 Co-occurrence between \text{AfD_{Network}} and \text{X_{Network}}

The first analysis of co-occurrence of the most retweeted users in Section 4.1.4 implied high proportions of node co-occurrence in terms of \text{X_{Network}}. This section supports this finding, by measuring high levels of co-occurrence on the network level. The fractions of co-occurring nodes between \text{AfD_{Network}} and \text{X_{Network}} are depicted in table 4.3, which presents the highest value of node co-occurrence for \text{GRUENE_{Network}} where 83.81\% of the nodes also occur in \text{AfD_{Network}}. In contrast, \text{SPD_{Network}} has the lowest value of co-occurrence with 74.20 \% of the nodes that are also part of the \text{AfD_{Network}}.

<table>
<thead>
<tr>
<th>Node co-occurrence of \text{X_{Network}} and \text{AfD_{Network}}</th>
<th>FDP</th>
<th>CSU</th>
<th>CDU</th>
<th>SPD</th>
<th>GRUENE</th>
<th>LINKE</th>
</tr>
</thead>
<tbody>
<tr>
<td>in % of \text{X_{Network}}</td>
<td>80.78</td>
<td>78.65</td>
<td>83.07</td>
<td>74.20</td>
<td>83.81</td>
<td>82.32</td>
</tr>
</tbody>
</table>

Table 4.3: Node co-occurrence between \text{AfD_{Network}} and \text{X_{Network}}

This underlines the connection or high co-occurrence between the \text{AfD_{Network}} and \text{X_{Network}}. However, solely co-occurring in other party networks is no sufficient indication for strategic hashtag use in a politically aligned manner. The cluster membership in the \text{AfD_{Network}} however, indicates if a user is in support or opposition of the AfD. Thus, the next section will present the findings in respect to the \text{AfD_{Cluster membership}} and the likelihood of co-occurrence of nodes from the politically aligned AfD Clusters.
4.2.2 Co-occurrence between AfD Clusters and XNetwork

This section presents the findings of co-occurrence between the networks while also taking into account if the co-occurring nodes are from AfDSupport or AfDOpposition. Figure 4.3 graphically illustrates the approach of the analysis that first focuses on the cluster membership in the AfDNetwork.

Figure 4.2: Illustration of the co-occurrence analysis between AfD Clusters and XNetwork

Assuming that there is no pattern in the co-occurrence the expectation would be that the nodes of the two AfD Clusters occur in XNetwork with the same proportions as they occur in the AfDNetwork. Since AfDSupport contains 30% of the nodes the expectation would be that also 30% of the co-occurring nodes in XNetwork are from AfDSupport and 68% from AfDOpposition. However, figure 4.3 illustrates the AfD Cluster membership of co-occurring nodes and shows that the majority of the co-occurring nodes in XNetwork are nodes from AfDSupport represented by the blue bars.
Thus, the observed co-occurrence between $X_{\text{Network}}$ with $\text{AfD}_{\text{Support}}$ or $\text{AfD}_{\text{Opposition}}$ is much higher than expected, while it is lower than expected for $\text{AfD}_{\text{Opposition}}$ and $X_{\text{Network}}$. To allow a more intuitive comparison Table 4.4 presents the ratios between the observed and expected co-occurrence and the last column expresses the likelihood of co-occurrence for a random node from $\text{AfD}_{\text{Support}}$ relative to the likelihood of co-occurrence of a node from $\text{AfD}_{\text{Opposition}}$. The analysis shows that nodes from the $\text{AfD}_{\text{Support}}$ are remarkably more likely to use other party hashtags and therefore co-occur in the other party networks. In fact, a user who used the $\#\text{AfD}$ and $\#\text{Gruene}$ in the observation period is 12.09 times more likely to be located in $\text{AfD}_{\text{Support}}$ than to be from the $\text{AfD}_{\text{Opposition}}$. 

Figure 4.3. Co-occurrence between $X_{\text{Network}}$ with $\text{AfD}_{\text{Support}}$ or $\text{AfD}_{\text{Opposition}}$
Table 4.4: Probability of co-occurrence, if nodes from AfD Cluster are expected to co-occur with the same probability as in AfD Network

<table>
<thead>
<tr>
<th>Probability of co-occurrence</th>
<th>( P(AfD_{Support}) )</th>
<th>( P(AfD_{Opposition}) )</th>
<th>Likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPD</td>
<td>2.04</td>
<td>0.55</td>
<td>3.70</td>
</tr>
<tr>
<td>CDU</td>
<td>2.30</td>
<td>0.44</td>
<td>5.27</td>
</tr>
<tr>
<td>CSU</td>
<td>1.84</td>
<td>0.64</td>
<td>2.85</td>
</tr>
<tr>
<td>FDP</td>
<td>2.29</td>
<td>0.44</td>
<td>5.19</td>
</tr>
<tr>
<td>GRUENE</td>
<td>2.77</td>
<td>0.23</td>
<td>12.09</td>
</tr>
<tr>
<td>LINKE</td>
<td>2.46</td>
<td>0.36</td>
<td>6.91</td>
</tr>
</tbody>
</table>

In summary, nodes from AfD Support are much more likely to co-occur in other party networks, but yet the cluster assignment in X Network has not been investigated. Thus, the next section presents the findings of the analysis of coherent co-occurrence.

4.2.3 Coherent cluster co-occurrence between the AfD Cluster and X Cluster

The previous section has shown that users from the pro AfD cluster in the #AfD network are much more likely to use other party hashtags. However, it is not yet clear in which cluster these nodes appear in the other networks. Only if nodes from AfD Support are also appearing in the clusters dominated by AfD politicians X Support it could be interpreted as a measure for strategic hashtag usage and a projection of AfD Support network on the other hashtag networks. Figure 4.4 illustrates the four options of co-occurrence as four arrows, of which the co-occurrence between AfD Support and X Support is found to be much higher than between the other options. However, there is also a high co-occurrence between AfD Opposition and X Opposition.
The results in table 4.5 show the values for each arrow in figure 4.4 and find a high rate of co-occurrence between AfDSupport and XSupport. In fact, 95.17% of users from the AfDSupport that used other party hashtags are also assigned to XSupport, while the rate is lower for co-occurrence between AfDOpposition and XOpposition. This value is weighted mean of node co-occurrence between the AfD clusters and all other party clusters and allows for a collective interpretation. Besides, the values for the co-occurrence between all XNetwork and the AfDClusters are depicted in table A4.X in the appendix.

<table>
<thead>
<tr>
<th></th>
<th>AfDSupport</th>
<th>AfDOpposition</th>
</tr>
</thead>
<tbody>
<tr>
<td>XSupport</td>
<td>95.17%</td>
<td>37.43%</td>
</tr>
<tr>
<td>XOpposition</td>
<td>1.60%</td>
<td>71.78%</td>
</tr>
</tbody>
</table>

Table 4.5: Weighted mean of cluster co-occurrence between AfDClusters and XClusters

The co-occurrence between AfDSupport and XSupport appears highly coherent and only 1.6% of nodes are co-occurring in the opposed cluster. For the co-occurrence between AfDOpposition and XOpposition the value is with 71.78% lower and the mean of incoherently assigned nodes is much higher, 37.43%. The next steps will show the high
cluster share and network share of the nodes that are coherently assigned to the clusters in support of the AfD.

4.3. Impact of co-occurring nodes
After finding nodes from AfD_Support to be much more likely to co-occur in X_Network and additionally to be with 95.17% coherently assigned to X_Support, this section of the analysis presents the impact of the two AfD_Clusters measured by their network or cluster share of all nodes in the X_Clusters and finally in X_Network.

4.3.1 X_Cluster share of co-occurring nodes
The results of the node co-occurrence show high values between X_Support and AfD_Support, which signify that X_Support consists to a very high degree of the same users as AfD_Support. The blue bars in Figure 4.5 represent the share of nodes from AfD_Support and illustrate, that in most X_Support about 90% of the nodes co-occur in AfD_Support. For the co-occurrence in X_Opposition however, the red bars in Figure 4.6 on the right hand side illustrate a lower co-occurrence and more party variation. The exact values for all parties are depicted in Table 4.6 and underline the variation between the politically aligned clusters and the different parties especially for co-occurrence in X_Opposition.

![Co-occurrence in X_Support](image)

Figure 4.5: Cluster share of nodes from AfD_Support in X_Support
Figure 4.6: Cluster share of nodes from $\text{AfD}_{\text{Opposition}}$ in $X_{\text{Opposition}}$

<table>
<thead>
<tr>
<th>$X_{\text{Network}}$</th>
<th>$X_{\text{Support}}$</th>
<th>$X_{\text{Opposition}}$</th>
<th>Others</th>
<th>AfD Support</th>
<th>AfD Opposition</th>
<th>Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>FDP</td>
<td>94%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
<td>30%</td>
<td>67%</td>
</tr>
<tr>
<td>CSU</td>
<td>81%</td>
<td>3%</td>
<td>16%</td>
<td>2%</td>
<td>70%</td>
<td>28%</td>
</tr>
<tr>
<td>CDU</td>
<td>89%</td>
<td>3%</td>
<td>8%</td>
<td>1%</td>
<td>75%</td>
<td>24%</td>
</tr>
<tr>
<td>SPD</td>
<td>87%</td>
<td>3%</td>
<td>10%</td>
<td>2%</td>
<td>61%</td>
<td>37%</td>
</tr>
<tr>
<td>GRUENE</td>
<td>91%</td>
<td>3%</td>
<td>6%</td>
<td>1%</td>
<td>52%</td>
<td>48%</td>
</tr>
<tr>
<td>LINKE</td>
<td>89%</td>
<td>2%</td>
<td>9%</td>
<td>2%</td>
<td>60%</td>
<td>39%</td>
</tr>
<tr>
<td>W. Mean</td>
<td><strong>88%</strong></td>
<td><strong>3%</strong></td>
<td><strong>9%</strong></td>
<td><strong>2%</strong></td>
<td><strong>63%</strong></td>
<td><strong>35%</strong></td>
</tr>
</tbody>
</table>

Table 4.6: Cluster share of co-occurring nodes for different cluster combinations (sum of rounded values may be >100%)
4.3.2 XNetwork share of co-occurring nodes

The prior section showed the high node similarity or co-occurrence of nodes between AfDSupport and XSupport and a lower share of nodes from AfDOpposition in XOpposition. This section relates these findings to the overall network size to show the impact in terms of network share that the coherently assigned nodes from AfDNetwork have on XNetwork. Figure 4.6 illustrates the network share of co-occurring nodes in XNetwork and allows for a differentiation of co-occurrence with AfDClusters by color. The blue bars represent again the nodes that are coherently assigned to AfDSupport and XSupport.

Figure 4.7 Network shares of co-occurring nodes for different cluster combinations

Additionally, Table 4.7 depicts the exact values for all parties and combinations of cluster membership. The results underline that on average 50.70% of the nodes in XNetwork are co-occurring in AfDSupport. Furthermore, the network shares of coherently assigned nodes differ between the different parties. The network share of nodes that are in both networks assigned to the cluster in support of the AfD is highest for GRUENE and LINKE, followed by the CDU and FDP. For SPD and CSU the shares are lower than for the other parties. The share of nodes that were coherently assigned as oppositional is lower and on average 17.87%. The network share or impact of incoherently assigned nodes however, is very low and supports the suggestion that other party hashtags are mostly
used in a politically aligned way. The findings furthermore, support the initial assumption of a significant impact of the AfDSupport on the structure of XNetwork and in particular XSupport and will be interpreted in the following chapter.

<table>
<thead>
<tr>
<th>Network share of XNetwork for different cluster combinations</th>
<th>AfDSupport &amp; XSupport</th>
<th>AfDSupport &amp; XOpposition</th>
<th>AfDOpposition &amp; XSupport</th>
<th>AfDOpposition &amp; XOpposition</th>
</tr>
</thead>
<tbody>
<tr>
<td>FDP</td>
<td>50%</td>
<td>2%</td>
<td>2%</td>
<td>4%</td>
</tr>
<tr>
<td>CSU</td>
<td>36%</td>
<td>1%</td>
<td>1%</td>
<td>25%</td>
</tr>
<tr>
<td>CDU</td>
<td>56%</td>
<td>1%</td>
<td>2%</td>
<td>20%</td>
</tr>
<tr>
<td>SPD</td>
<td>43%</td>
<td>1%</td>
<td>2%</td>
<td>22%</td>
</tr>
<tr>
<td>GRUENE</td>
<td>68%</td>
<td>0%</td>
<td>3%</td>
<td>8%</td>
</tr>
<tr>
<td>LINKE</td>
<td>57%</td>
<td>1%</td>
<td>1%</td>
<td>16%</td>
</tr>
<tr>
<td><strong>W. Mean</strong></td>
<td><strong>51%</strong></td>
<td><strong>1%</strong></td>
<td><strong>2%</strong></td>
<td><strong>18%</strong></td>
</tr>
</tbody>
</table>

Table 4.7: Network Share of co-occurring nodes regarding their cluster memberships in AfDNetwork and XNetwork

5. Discussion
The reviewed literature and findings of the analysis underline the meaningfulness to apply network visualisation and analysis in order to investigate how social media plays a crucial role in the rise of right wing populism in Germany. In that respect, analysis and literature review have evidenced how the right wing populist party AfD has been successful in promoting their own party hashtag (Stier et al., 2018). For this reason the political party hashtag use on Twitter and the respective retweet networks, were systematically analysed during an index period of eight days. Moreover, the introduction formulated three research questions, which the discussion of the findings will further illuminate:

1. Why are populists so successful on social media?
2. To what extent does the high frequency of the #AfD on Twitter express support of or opposition to the right-wing populist party?
3. Is there indication that the AfD uses hashtags strategically?

This chapter will discuss the findings with respect to the practical literature on strategic behaviour on Twitter and to the existing literature on populism on social media to provide answers for the research questions. Section 5.1 briefly reiterates the research problem and summarises the major findings of the analysis pertaining to the research questions. Section 5.2 and Section 5.3 proceed with discussing the findings relating to research question 2 and 3 in more detail. This will highlight two main findings, which are that the AfD hashtag is mostly used in support of the party and that these supporters use other party hashtags strategically. Thereafter, Section 5.4 considers these findings and theoretical literature to debate research question 1. Concluding, Section 5.5 briefly evaluates the relevance of the study for politics and directions for future research.

5.1 Research problem and major findings
The aim of this study is to shed light on the success of populist parties and politicians on social media, which is identified here as a crucial factor for their rise in recent years. Thus, the analysis focused on the case of German political party hashtag use on Twitter where the #AfD was found to be the most used hashtag before the 2017 elections (Stier et al., 2018). Although earlier studies did investigate the social media use of the AfD on Facebook or Twitter and found the AfD to generate a lot of activity, in particular the
studies on Twitter have not analysed the networked structure that underlie the data. Therefore this study analysed in detail the connection between the Retweet networks that emerge around the #AfD and the political hashtags of all other parties that are represented in the German federal parliament.

Regarding the second research question the findings show that the #AfD hashtag is used by two distinct communities of Twitter users of which one group of shared Tweets opposed to the AfD and whereas the others were in support of the AfD. This indicates a strategic retweeting strategy since the clustering evolves if only politically aligned Tweets are retweeted. While the opposed group contained twice as many accounts, the AfD support community generated a much higher activity in terms of the absolute number of retweets. Thus, the findings indicate that the #AfD is mostly used in support of the AfD, but underlines the necessity to distinguish between the number of Tweets and the number of accounts using a hashtag, when investigating the use of political party hashtags.

The final major finding of the study relates to the first and third research questions. The analysis strongly suggests strategic hashtag use or ‘hashjacking’ by AfD-supporters as crucial in the AfD’s success on Twitter. Indeed, the analysis found that on average half of the users of the opposed political party hashtags are AfD-supporters. This was shown by the analysis of node co-occurrence between the different party networks and clusters and will be discussed further. The following section will discuss the findings that relate to the second research question in greater detail.

5.2 Supportive or opposed usage of the AfD hashtag?

The first graphical representation of the modular clustering for the AfD network in Figure 4.1 presented a network graph with a clear partisan structure similarly to the findings and graphical illustrations of Conover et al. (2011). The qualitative content analysis of the fifty most retweeted accounts however, supported this suggestion only partially. While the AfDSupport cluster is dominated by official AfD party accounts and shows a more hierarchically structure, AfDOpposition contains media accounts and clearly opposed accounts that mention their opposition to the AfD in the profile information or user names. These result question an interpretation as partisanship in relation to political parties, since the opposed group of Twitter accounts is supposedly much more
diverse. This notion affirms Bode et al. (2015), who suggested that partisan models are not sufficient to show the diverse use of political hashtags on Twitter.

The major finding that the #AfD is used more often to support the party indicates that the AfD uses Twitter efficiently to promote their party hashtag and politicians. Furthermore, the successful use shows in the content domination of official party accounts in AfDSupport. But also the finding that 24 of the 50 most retweeted accounts in the whole AfDNetwork are officials AfD accounts underlines the importance of a closely connected support network that has arguably also contributed to the high #AfD frequency prior to the 2017 general elections (Stier et al., 2018). The observation of a much higher activity of AfD supporters is moreover in line with earlier studies on Twitter use in the US, that identified right-wing users to be more politically active on Twitter and embedded in tighter communication networks (Conover et al., 2012). These findings also support concerns articulated by Krämer (2017) that social media users could adapt right-world views or alternative interpretations of news and politics in polarized environments. While the AfD retweet network showed a very polarized structure it is hard to evaluate how many users interact with each other, but an extension of the investigation that would include the mention network might clarify these interpretations. However, the strategic behaviour of the AfDSupport cluster that mainly retweeted AfD propaganda raises concerns, since even the official Tweets are often xenophobic or islamophobic (Schmid et al., 2018).

As a surprising finding the group of accounts that used the AfD hashtag in opposition, or perhaps neutral in case of the media, contained about twice as many accounts as the AfD support community. However, this more heterogeneous group of users was outnumbered by the AfD support community, in terms of activity per individual account and total activity as already discussed before. Furthermore, the findings of the second part of the analysis underline the impression that AfDOpposition uses less other party hashtags than AfDSupport.

In terms of the success of the AfD on social media and Twitter, the findings confirm the suggestion of Stier et al. (2018) and in particular the comparison of the political party hashtag frequencies emphasises the over-representation of the AfD on Twitter. Although the party for a long time preferred Facebook, because of the possibility of moderation in open and closed groups (Stier et al., 2017), the findings
indicate that the party has established a closely connected supporter network on Twitter.

5.3 Strategic hashtag use as a coordinated effort?

The main finding with respect to the third research question is that on average almost 51% of the users of all other party hashtags are supporters or officials of the AfD. This indicates, that most of the content pertaining to the political party hashtags is politically aligned with the AfD and implies strategic hashtag use of other party hashtags. This finding relates to Conover et al. (2011), who call the coordinated action using politically opposed group hashtags ‘content injection’. Considering the network graphs it would also be possible to call the result a projection of the AfD Support cluster onto the other networks. Referring to Bode et al. (2015) the findings underline the strategic hashtag use and find in particular the AfD supporters to use this strategy. This is also affected by the higher political alignment of the AfD cluster and the higher influence of the elite accounts and AfD officials. Besides, the study suggested a more graphical term for content injection or ‘hashjacking’, since these strategies resulted in a projection of AfD Support on the other party networks.

The term of a projection seems in a graphical understanding reasonable for all $X_{\text{Support}}$ and is illustrated in the network graphs in Figure A4.1-A4.6. Moreover, Table 4.6 depicted the very high similarity of members between a minimum of 81% for CSU Support and a maximum of 94% for the FDP Support. These cluster similarities or share of co-occurring AfD supporters, however, are difficult to interpret in terms of strategic targeting. Therefore the final results related the impact of AfD supporters to the overall network size to allow for a careful interpretation, which parties are affected the most by strategic hashtag use of AfD officials and supporters (Table 4.7). The analysis showed that a high number of about 68% #Gruene users and 57% of #LINKE users are AfD supporters and therefore expected to use these hashtags strategically. While these findings make sense according to the political spectrum where LINKE and GRUENE are the most left-wing parties in the parliament, it is surprising that the centre-right CDU is more affected than the centre-left SPD. With respect to this, 56% of #CDU users were classified as AfD supporters in comparison to only 43% of the #SPD users.
These major findings of this study link to wider debates of populism and social media or politics on the Internet, which are discussed in the next section. Furthermore, the findings and wider theoretical interpretations provide answers to the first research question.

5.4 The crux of the populist success on social media

The findings of this study implied that the German right wing party AfD employs Twitter successfully to boost their party hashtag and promote official party accounts. While a former study by Stier et al. (2018) has equated success to the sheer quantity of retweets this might express some of the nature of many frequency-based social media platforms, but does not take into consideration the supportive or opposed character that Tweets using the same hashtag can have. Thus, this study applied methods that allow a distinction between different groups of users based on their retweeting behaviour, which indicated support or opposition to the AfD.

Furthermore, the findings support the hypothesis according to which the AfD is successful on social media, since the official party accounts dominate the content in a closely connected retweet support network. This supporter group might share or increasingly adapt the AfD’s nationalist worldview that has in Germany before only been politically represented by the extreme-right party NPD that due to the 5% threshold never made it into the federal parliament (Arzheimer, 2015). This support network is particularly remarkable when considering the size and impact on other party networks. Additionally, the other party networks did not show any similarly densely connected clusters. The strategy employed by the officials and supporters of the AfD to use other party hashtags strategically to confront politically opposed users and spread their content is successful in terms of the impact on the other party networks.

The content spread although not subject of the analysis is often based on party memes or media reports about migrant criminality. With respect to this, the intensity of the migration and refugee debate has been extraordinarily high in Germany since 2015, which must also be interpreted as a push factor for the AfD on social media and in recent elections (Lux, 2018).
Consequently, the other parties should take the overrepresentation of the AfD on social media seriously and themselves engage more with citizens, party members and their colleagues on social media (Ausserhofer, 2013). Moreover, the Internet undoubtedly has a participative effect and social media such as the opportunities Twitter gives to citizens to engage in public discourse and address politicians directly (Krämer, 2017). This however, does not imply a change towards a ‘public sphere’-like state, but the findings rather support the echo-chamber interpretation since the AfDSupport cluster is clearly dominated by official AfD accounts. While right-wing populist parties have existed before, their opinions and political communication find more attention on social media, where citizen can often anonymously participate in debates and communication battles with political opponents (Bode et al., 2015).

The reviewed literature and the findings of this study provide two suggestions to answer this question. Firstly, social media benefit populist communication, because both have a sensationalistic nature. Secondly, supporters and official representatives of right-wing populist parties use strategies to maximize their influence in terms of spreading their content and to attack the other parties.

Regarding the first suggestion, the main objective of populist communication is to construct ‘the people’ and foster this construct and the belief in it by anti-elitist and anti-out-group ideology (Reinemann et al., 2016). To achieve this messages often simplify complex problems and use emotional arguments to relate to citizens (ibid). This style of political communication largely benefits from social media communication and especially from Twitter, where the length of text messages is limited to 140 characters. This matches with populist communication as defined by Reinemann et al. (2016) since the medium is described as “insufficient for reasoned discourse and debate, instead privileging haste and emotion” (Yardi and Boyd, 2010:325). Consequently, populist messages may be sensationalistic or emotional as a condition to spread, but at the same point serve their political objectives. These objectives are in case of the AfD and many other right-wing populist parties compromising political elites and the media, de-humanising migrants and refugees and constructing a nationalist construct of ‘the people’ (Engessler et al., 2017). Furthermore, these messages often provoke a media response or initiate counter-reactions of political opponents on social media, which increases the attention for populists and their opinions. In summary, the first reason
why populists are so successful on social media is because their messages are short, emotional and sensationalistic and still serve their purposes.

The other reason for the success of populist parties and politicians on social media relates to the findings of this study that imply effective strategic behaviour by party officials and supporter. The high importance that right wing populist parties and their supporters pay to social media communication shows in the high activity of AfD Support in this study and was also found for American right wing supporters by Bode and Dalrymple (2016). This makes sense since they might not be able to spread their opinions through traditional media channels, which was discussed in the literature review as the ‘gatekeeper’ function that journalists and traditional media have (Arzheimer, 2015; Engesser et al., 2017; Stier et al., 2017). Furthermore, the support of right wing populist politicians is organised in right-wing online networks and Facebook groups, in which individuals coordinate, communicate and self-radicalize (Krämer, 2017; Nagle, 2017). Due to the German language selection this study does not take into consideration English Tweets that could have been issued by international alt-right communities, thus the increasing connectedness of the international populists extreme right will be subject of further study. Lastly, this study has shown the high extent of strategic hashtag use by the AfD and its supporters, which supports the interpretation of communication strategies as a crucial factor for the success of populist parties on social media. The following section, will interpret the relevance of the findings for politics and future research on populism and social media.

5.5 Relevance for politics and future research
It follows from the findings and discussion that the success of populist parties and politicians on social media should not exclusively be understood as a result of current political affairs or the media transformation, but also as a consequence of political communication strategies. The high extent of strategic behaviour of AfD politicians and supporters underlined the over-representation of the AfD on Twitter as a direct result of political communication and hashjacking of other party hashtags. This however, indicates that established parties need to intensify their social media communication and engagement with citizen on social media, to not leave the field to right wing populist and their supporters.
The findings of the study also imply that academic work on populism on social media, but also on the theorization of populism should adapt methods of computational sociology and social media studies. The analysis and collection of this study were based on a innovative network approach and allowed the visualization and investigation of the structural features of retweet networks that emerged around political party hashtag use. Further research, on populism on Twitter and social media may adapt existing methodologies for network research and continue the analysis of this study based on an extended collection period. Moreover, the empirical study of social media demands advanced analytic and programming skills, which emphasizes the necessity of extended interdisciplinary collaboration between computational scientists, sociologists and political scientists to investigate politics online and the increasing problem of right-wing networks and populism on social media.

6. Conclusions

This study has empirically explored the use of German political party hashtags on Twitter in order to make sense of the success of populist parties like the on social media. A large sample of Tweets (n=173,612) was collected and the retweet networks investigated with a network approach to investigate strategic behaviour in retweeting and hashtag use. The main findings are that AfD politicians and supporters generate the majority of the frequency of the AfD hashtag. Moreover, the findings strongly indicate a large extent of strategic hashtag use by AfD supporters and officials. Thus, the study suggests understanding the success of populist parties on social media as a result of their political communication strategies that need to be further investigated and should be tackled by established moderate parties.
Bibliography


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Appendix A – Figures

Figure A3.1: Daily frequencies of German political party hashtags

Total Tweets per day using different party hashtags
Figure A4.1: Modularity clustering for the AfD retweet network shown as blue for AfDSupport and red for AfDOpposition
Figure A4.2: Retweet network graph of CDU with modularity clustering
Blue: XSupport. Black: CDUOpposition. Orange: AfD officials in 50 most retweeted

Figure A4.3: Retweet network graph of CSU with modularity clustering
Blue: \(X_{\text{Support}}\). Light blue: \(CSU_{\text{Opposition}}\). Orange: AfD officials in 50 most retweeted.

Figure A4.4: Retweet network graph of FDP with modularity clustering
Blue: \(X_{\text{Support}}\). Yellow: \(FDP_{\text{Opposition}}\). Orange: AfD officials in 50 most retweeted.

Figure A4.5: Retweet network graph of SPD with modularity clustering
Blue: \(X_{\text{Support}}\). Red: \(SPD_{\text{Opposition}}\). Orange: AfD officials in 50 most retweeted.
Figure A4.6: Retweet network graph of GRUENE with modularity clustering
Blue: $X_{support}$. Green: GRUENE_opposition. Orange: AfD officials in 50 most retweeted

Figure A4.7: Retweet network graph of LINKE with modularity clustering
Blue: $X_{support}$. Pink: LINKE_opposition. Orange: AfD officials in 50 most retweeted
Appendix B – Tables

<table>
<thead>
<tr>
<th>Network</th>
<th>AfD</th>
<th>CDU</th>
<th>CSU</th>
<th>FDP</th>
<th>SPD</th>
<th>Gruene</th>
<th>Linke</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nodes</td>
<td>20583</td>
<td>4411</td>
<td>3002</td>
<td>1748</td>
<td>5778</td>
<td>2805</td>
<td>1889</td>
</tr>
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<td>Edges</td>
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<td>5244</td>
<td>2547</td>
<td>13700</td>
<td>6039</td>
<td>2905</td>
</tr>
</tbody>
</table>

Table B4.1: Retweet network overview of AfD_{Network} and X_{Network}

<table>
<thead>
<tr>
<th>In % of total nodes</th>
<th>#AfD</th>
<th>#CDU</th>
<th>#CSU</th>
<th>#FDP</th>
<th>#SPD</th>
<th>#GRUENE</th>
<th>#LINKE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Support</td>
<td>30.23</td>
<td>63.11</td>
<td>44.90</td>
<td>53.72</td>
<td>50.00</td>
<td>75.04</td>
<td>64.06</td>
</tr>
<tr>
<td>Sum</td>
<td>98.16</td>
<td>89.82</td>
<td>81.28</td>
<td>67.56</td>
<td>86.66</td>
<td>89.66</td>
<td>90.26</td>
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</tbody>
</table>

Table B4.2: The two largest clusters detected with the modularity algorithm

<table>
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<th>X_{Network}</th>
<th>XSupport</th>
<th>XOpposition</th>
<th>Others</th>
<th>XSupport</th>
<th>XOpposition</th>
<th>Others</th>
</tr>
</thead>
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<td>AfD</td>
<td>94%</td>
<td>3%</td>
<td>3%</td>
<td>3%</td>
<td>30%</td>
<td>67%</td>
</tr>
<tr>
<td>AfD</td>
<td>81%</td>
<td>3%</td>
<td>16%</td>
<td>2%</td>
<td>70%</td>
<td>28%</td>
</tr>
<tr>
<td>AfD</td>
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<td>3%</td>
<td>8%</td>
<td>1%</td>
<td>75%</td>
<td>24%</td>
</tr>
<tr>
<td>AfD</td>
<td>87%</td>
<td>3%</td>
<td>10%</td>
<td>2%</td>
<td>61%</td>
<td>37%</td>
</tr>
<tr>
<td>AfD</td>
<td>91%</td>
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<td>6%</td>
<td>1%</td>
<td>52%</td>
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<tr>
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<td>60%</td>
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</tr>
<tr>
<td>AfD</td>
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<td>3%</td>
<td>9%</td>
<td>2%</td>
<td>63%</td>
<td>35%</td>
</tr>
</tbody>
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Table B4.3: Cluster share of co-occurring nodes for different cluster combinations