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Quantification of Echo Chambers: A Methodological Framework Considering Multi-party Systems

by

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QUANTIFICATION OF ECHO CHAMBERS: A METHODOLOGICAL FRAMEWORK CONSIDERING MULTI-PARTY SYSTEMS

Research paper

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Abstract

The possibility of distributing user-generated content through online social networks (OSNs) has had liberating effects on society, with prominent examples such as the Arab Spring. Yet, since then, many dark sides of OSNs have been brought up. An example is the echo chambers phenomenon. Theory suggests that cognitive dissonance causes individuals to associate themselves with groups of like-minded individuals that are only exposed to content that confirms their previously held beliefs. In turn, deliberation amongst segregated groups increases social extremism and causes polarization, rather than moderation. Previous research endeavors to identify echo chambers in OSNs have scarcely investigated the community structures of a network on a fine granular level, specifically in the context of multi-party systems. To contribute to the scientific body of knowledge, we propose a framework that summarizes existing work and outlines a way for future research to fill this void. We further propose a new way to measure homophily in multi-party systems based on the cosine similarity between users. We evaluate our framework through real world data and find that members of the political right experience the least amount of crosscutting communication and the highest degrees of homophily.

Keywords: Echo Chambers, Community Detection, Multi-party System, Homophily, Twitter

1 Introduction

The emergence of the web 2.0 and the possibility to create user-generated content, especially in online social networks (OSN), have had liberating effects on society with high profile examples such as the Arab spring and the recent #metoo movement. These examples show the mobilizing potential for political actions and the power of OSNs for individuals to raise societal issues, known as hashtag activism (Bonilla and Rosa, 2015). Moreover, we are experiencing a substantial increase in the usage of OSNs. Facebook has well surpassed 2 billion active users (Statista, 2018) and Twitter has been subject to great media attention with many politicians using the platform as a social broadcasting network (Shi et al., 2014). Most prominently, Donald Trump, who considers his Twitter usage “modern day presidential” (Trump, 2017) has become a highly active user of Twitter. The readership of tweets is further increased through extensive media coverage. A detailed study on the consumption patterns of OSNs has been performed by Newman et al. (2017). It shows that almost a quarter of the global population with access to the internet considers OSNs their primary news source (Newman et al., 2017). Many western countries, though, surpass those numbers substantially.

On the flipside, however, we see that the change in media and news consumption affects how individuals discuss politics in a way that has intensified “cultural polarization of democratic societies” (World Economic Forum, 2017, p. 24). The increasing polarization of politics in general has been particularly evident in the US, where Republicans move to the right under Trump and Democrats move to the left with the emergence of Bernie Sanders as an important political figure. In addition, all over Europe we see populist and nationalist parties emerge on the far right, further emphasizing a general trend towards polarization. Undoubtedly, it would be far too easy to attribute this trend exclusively to OSNs, however, it seems clear that the diminishing gate keeper role of traditional media influences the type of content that individuals are exposed to in OSNs (Garimella et al., 2018). A potential result is an increasingly noticed number of scandals around fake or deceptive news spread by individuals and even politicians (Lazer et al., 2018).

A main talking point when it comes to the dangers of OSNs towards society have been echo chambers, which are groups of like-minded individuals that are only exposed to content that confirms their previously held beliefs (Shore et al., 2018). Such a tendency of individuals to prefer interacting with similar others is known as homophily (McPherson et al., 2001). Amongst other things, echo chambers have the power to perpetuate false or misleading information, and extreme views as they go unchallenged in a network of like-minded individuals. Furthermore, deliberation amongst segregated like-minded individuals is said to create more extreme views (Sunstein, 2001). While many scientific contributions have since looked into the issue of echo chambers, the results remain inconclusive. This is in part because of a black-and-white look on the phenomenon. Yet, homophilous behavior has been shown to occur at different degrees among different groups (Barberá, 2014). As Shore et al. (2018) point out, there is little evidence that the echo chambers phenomenon is widespread, but individual areas of a network experience significantly different levels of homophily than others. Therefore, we call for research endeavors that take a closer and more granular view at the echo chambers phenomenon while taking the network structure into account.

To contribute toward this, we present a four-step analytics framework and lay out the design decisions when conducting echo chambers research in OSNs based on previous literature. We do this to point out where adjustments to the application in multi-party systems are necessary. We then extend upon the existing approaches and propose a way of measuring homophily in multi-party systems based on the cosine distance between the user's ideologies. Additionally, we apply our framework and modifications to a data set from the German Federal Election of 2017 to evaluate the approach and show that echo chambers do indeed occur at different levels of echofication. We find that followers of far-right parties experience the least amount of crosscutting communication and the highest degree of homophily.

The remainder of this paper is structured as follows: Section 2 gives an overview of theoretical foundations of echo chambers and their causes and effects, as well as previous research on the subject. In Section 3, we present the general approach to identify echo chambers and discuss several design decisions that researchers need to make. In Section 4, we propose modifications based on previous research to study multi-party systems. Subsequently, we evaluate these modifications and our framework with a data set from the German Federal Election of 2017 in Section 5. In Section 6, we discuss the results before Section 7 concludes the paper by presenting limitations and opportunities for further research.

2 Theoretical Background

2.1 The Phenomenon of Echo Chambers

The phenomenon of echo chambers and the accompanying discussion regarding the dangers that the internet and OSNs hold towards democracy, have been kick started by Sunstein's *republic.com* (2001). In his book, Sunstein (2001) makes a point that the personalization of the internet - be it through algorithms or personal choice - leads to an increase in fragmentation and limits the individuals' exposure to diverse content. He paints a picture where echo chambers lead to group polarization and deliberation amongst like-minded people leads such groups to move to a more extreme position. This phenomenon has since found its way into many academic research contributions. In recent literature, a number of different definitions have emerged for the echo chambers phenomenon that are similar, yet slightly different (table 1).

Source	Definition
Bakshy et al., 2015, p.1130	"Echo chambers in which individuals are exposed only to information from like-minded individuals"
Colleoni et al., 2014, p.319	"The echo chamber effect is due to a tendency of individuals to create homogeneous groups and to affiliate with individuals that share their political view"
Garimella et al., 2018, p.931	"Situations where users consume content that expresses the same point of view that the users themselves hold or express"
Garrett, 2009, p. 676 based on Sunstein, 2001	"Individuals use the Internet to construct 'echo chambers' in which the only viewpoints they encounter are their own"
Shore et al., 2018, p.850	"The fragmentation of users into ideologically narrow groups in which people are only exposed to information that confirms their previously held opinions"
Zollo et al., 2015, p. 6	"Users interact only with information that conforms with their system of beliefs and ignore other perspectives and opposing information"

Table 1: Echo chamber definitions

To shed light on the commonalities between the definitions, we extract the prerequisites that make up an echo chamber. This is congruent with Garimella et al. (2018), who differentiate between the two main aspects: echo and chamber. However, based on the definitions derived from the literature, we suggest that there are three aspects: the first aspect are limits to the discourse within a network, such as narrow groups (Shore et al., 2018) or chambers (e.g. Bakshy et al., 2015). We refer to this as the *Social Boundaries* of echo chambers**.** Further, the definitions describe the exposure to (Bakshy et al., 2015), interaction with (Zollo et al., 2015), or consumption of (Garimella et al., 2018) information that only conforms to their beliefs (Zollo et al., 2015), confirms their previously held opinions (Shore et al., 2018), and express the same point of views (Garrett, 2009; Garimella et al., 2018). We refer to this as the *Information Homogeneity* aspect. Third, in an echo chamber, this information is provided by like-minded (Bakshy et al., 2015), ideologically similar others (Shore et al., 2018), that share their political views (Colleoni et al., 2014). We refer to this as the *User Similarity* aspect of the definition. Lastly, some definitions contain the restriction that "only" such information is present in echo chambers. However, this strong limitation is difficult to achieve in the real world and contradicts previous empirical observations (e.g. Adamic and Glance, 2005; Williams et al., 2015).

2.2 Cause and Effect of Echo Chambers

As a theoretical foundation from the social sciences to explain the appearance of echo chambers, cognitive dissonance theory has been cited frequently. It suggests that individuals feel uncomfortable when there is dissonance between themselves and other members of a group regarding their beliefs. As a result, a person will be attracted to situations where other peoples' opinions are close to his or hers (Festinger, 1954). Generally, there are multiple options for an individual to cope with this situation when they experience cognitive dissonance. First, an individual can reduce cognitive dissonance by changing his or her own opinions to reduce the discrepancy and increase conformity with the group's beliefs (Festinger, 1954). Alternatively, an individual may seek groups that show little dissonance with their personal beliefs (Lazarsfeld and Merton, 1954). Hence, this effect leads individuals to expose themselves to information that is congruent with their own opinions (Colleoni et al., 2014). This mechanism is also known as selective exposure theory (e.g. Frey, 1986). The theory has long experienced inconsistent empirical results, in part because of a limited understanding of the theory and problematic experimental designs (Cotton, 1985). A more recent meta-study has confirmed a moderate preference for congenial (agreeable) information, especially when individuals feel they need to defend their existing beliefs (Hart et al., 2009). In a highly divisive political environment, such as the current political landscape in the US, it thus seems intuitive that this effect may appear. Recent work suggests that such selective exposure has started to see measurable increase with the emergence of biased news outlets, such as Fox News (Iyengar and Hahn, 2009). This is also congruent with Cotton (1985) who states that selective exposure is particularly relevant in the context of mass communication. The selection of news outlets and the personalization of news feeds has become even easier with the emergence of OSNs, where individuals can follow news outlets and other users without establishing formal reciprocal relationships and thus at very low transactional cost (Kane et al., 2014). In regards to the echo chambers phenomenon, the confirmation bias has also been cited (Shore et al., 2018). This refers to the search and interpretation of information in a way that conforms to existing personal opinions (Nickerson, 1998). No matter which mechanism is at work, theory suggests that there are good reasons to expect the emergence of ideologically narrow groups, such as echo chambers, in social media and beyond.

A segregated partisan structure is present, when there is very little discourse between individuals of different ideologies (Conover et al., 2011), cf. figure 1. When individuals are “disconnected and ignorant of opposing views” (Shore et al., 2018, p. 851), healthy political discourse is minimal and thus democratic principles suffer (Sunstein, 2001). Because of the laid out urge to reduce cognitive dissonance, such deliberation amongst alike individuals can create more extreme views than before (Sunstein, 2001). Thus, segregation can foster social extremism and can contribute to further political polarization (Barberá, 2015). Political networks in OSN have long been described to be rather segregated (e.g. Adamic and Glance, 2005; Conover et al., 2011). On the contrary, exposure to political diversity has a positive effect on the adoption of moderate positions (Barberá, 2014). The internet in general has long been argued to have positive effects on political discourse as it brings together people from all corners and ideologies of the world (e.g. Dahlgren, 2005). This argument was also made for OSNs (Barberá, 2014).

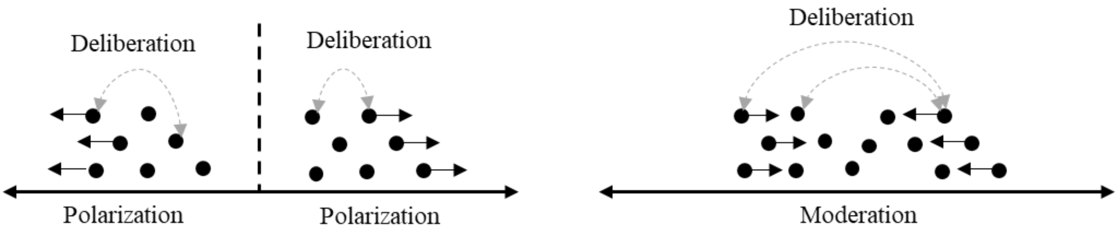

Figure 1: Polarization as a result of segregation and political moderation as a result of cross-ideological discourse

2.3 Related Work Regarding Echo Chamber Quantification

As Sunstein (2001) introduced the topic of echo chambers with the accompanying effects on political discourse, several other researchers also studied this field including Barberá (2014), who investigates the *Information Homogeneity* aspect. He studied the political discussion on Twitter in Germany, Spain and the US. In his empirical study, he found that individuals interact with a large share of others that do not share the same ideology (on average: Spain 45%, Germany 44%, US 33% of the users). These results imply that OSNs reduce political polarization, the author concludes. However, Barberá (2014) studied the overall situation on an aggregated level but does not consider differences within certain areas of the network – thus, he disregards *Social Boundaries*. Quattrociocchi et al. (2016) have brought forward a similar approach, while focusing on Facebook users in Italy and the US. In their study, they investigate how scientific information and conspiracy theories spread. In contrast to Barberá (2014), their empirical study implies that users focus on a single type of narrative and thus the discussion is mainly polarized. Bakshy et al. (2015) also find substantial polarization by studying the content shared by users on Facebook and observe high proportions of friends who share the same ideology.

Other approaches in the area of echo chambers rely on network graphs utilizing digital trace data. In contrast to Facebook, Twitter provides a publicly accessible API which enables a more efficient way of gathering these data. Therefore, most of the research in this area refers to Twitter. Among those studies are Colleoni et al. (2014) who support Quattrociocchi et al.(2016) as they provide evidence that in general, Democrats tend to interact with themselves even more likely than Republicans. Yet, this changes when limiting the analyzed users to those who follow official parliamentarian’s accounts on Twitter. Adamic and Glance (2005) use network graphs differently to study the *Information Homogeneity* as they investigate the interactions between liberal and conservative blogs. As a result of their empirical study they provide evidence that conservative blogs reference each other more often than liberals.

Most recently, Shore et al. (2018) provide an extensive empirical review of several theories revolving around echo chambers. In their study, they find that areas of high density within the network experience modestly more homophily than others. They conclude that there is no evidence for “widespread echo chambers” (Shore et al., 2018, p. 863). Their findings are based on an analysis of tweets containing links to politically biased news outlets. While this study advances the area of research substantially, it investigates the network in its entirety and does not differentiate between different communities within it. Thus, while the problem might not be widespread, it may still exist within certain areas of the network.

To address the aspect of *Social Boundaries* in more detail, Conover et al. (2011) analyze tweets from the 2010 US midterm elections. They apply a community detection algorithm to find secluded groups of users. As their subject of research is the political system in the US, Conover et al. (2011) predetermine that there can only be two of such groups, consisting of Democrats and Republicans respectively. Their findings imply that there is high political segregation in the retweet network. Williams et al. (2015) perform a network analysis in regards to tweets about climate change. Although they also categorize users dichotomously, they find multiple clusters of both activists and sceptics. They attain comparable results and identify echo chambers in the retweet graph.

All these scientific results have in common that they deal with dichotomous groups of individuals - whether this is due to the subject of interest or due to a simplification introduced by the scientists. A rare exception are Takikawa and Nagayoshi (2017), who investigate echo chambers in the context of the Japanese multi-party system. However, they concentrate on the content that individuals within a community talk about, while disregarding the users’ views and ideologies.

In summation, there are several different approaches that identify echo chambers in OSNs of which many include some sort of network component. Yet, to date there are few studies that investigate communities of like-minded individuals within the network on a fine granular level, specifically in multi-party systems. To contribute to the scientific body of knowledge, we propose a framework that summarizes existing work and point out where current research insufficiently addresses the special nature of multi-party systems. Subsequently, we propose modifications based on previous research for future research to address the gap in empirical studies regarding multi-party systems.

3 Framework to Quantify Echo Chambers

To contribute to the existing scientific body of knowledge, we developed a framework (cf. table 2) to identify echo chambers following the three aspects of echo chambers derived from their definition. In doing so, we reveal design considerations that researchers have to make in each of the steps and state which choices previous research has made in those regards. Furthermore, we address why the current methodological approaches are not fully applicable to multi-party systems.

Data Set & Network Graph - The first step to identifying echo chambers in OSNs lies in gathering and preparing the data. In order to do that, preliminary decisions have to be made. OSNs vary widely concerning adoption rate by individual demographics as well as content-related usage (Newman et al., 2017). Previous studies emphasize the two big OSNs, Facebook (e.g. Bakshy et al., 2015; Quattrociocchi et al., 2016) and Twitter (e.g. Barberá, 2014; Colleoni et al., 2014; Conover et al., 2011; Williams et al., 2015), but are mainly concentrated on Twitter due to its publicly accessible API. The platform in question should be chosen based on the respective research question; however, data availability plays a role in the decision. Due to data limitations, empirical studies often refer to certain events rather than the entirety of all status updates (Colleoni et al., 2014). An exception to this rule are data sets collected in 2009, where Twitter adoption was small enough and the API restrictions lenient enough to allow for a collection of wide ranges of status updates. Such data sets were collected by Kwak et al. (2010), Yang and Leskovec (2011) or Galuba et al. (2010) and have been used by a number of researchers in the context of echo chambers (e.g. Colleoni et al., 2014; Shore et al., 2018). However, those data sets have a number of limitations, such as missing follower data or constraints regarding the way tweets were collected, which limit the selection of possible research approaches.

Step	Design Consideration
Collect data set & construct network graph	- Select OSN, time frame and event based on research quest (Colleoni et al., 2014) - Decide on social ties to construct edges (Borgatti et al., 2009; Kane et al., 2014) - Perform appropriate data collection, e.g. via APIs (e.g. Anonymous, 2018)
Perform community detection	- Select community detection algorithm (Lancichinetti and Fortunato, 2009; Yang et al., 2016) - Evaluate quality measures of detection (Kumpula et al., 2007; Newman and Girvan, 2004; Traag et al., 2011)
Infer user ideology	- Determine information source - e.g. page likes (Quattrociocchi et al., 2016) or follower data (Colleoni et al., 2014) - Employ method to estimate users' ideology - e.g. machine learning (Colleoni et al., 2014) or manual assessment (Conover et al., 2011) - Handle undefined users and non-dichotomous categories (Halberstam and Knight, 2016) - Chose measures for similarity based on the previous decisions - e.g. bipolar (Halberstam and Knight, 2016), gradations between two extremes (Barberá, 2015)
Evaluate degree of echofication	- Evaluate *Social Boundaries* (e.g. Lancichinetti and Fortunato, 2009), *User Similarity* (e.g. Williams et al., 2015) and *Information Homogeneity* (e.g. Halberstam and Knight, 2016)

Table 2: Framework to identify Echo Chambers

Research in the area of echo chambers has been successfully conducted without relying on network graphs (e.g. Bakshy et al., 2015) but these papers mainly refer to the *Information Homogeneity* and *User Similarity* aspect of echo chambers. However, when also considering the *Social Boundaries* aspect of echo chamber network graphs are essential (e.g. Shore et al., 2018; Williams et al., 2015). In a graph, nodes represent users and edges represent the ties between two users. In general, there are four types of tie types in social networks: proximities, relations, interactions, and flows (Borgatti et al., 2009).

Kane et al. (2014) lay out the specifics of social network analysis for OSN, such as Twitter. They state that while the emergence of OSNs and its formal data structure has enabled researchers to measure and analyze ties more easily, the interpretation of such ties has become a challenge (Kane et al., 2014). Interactions (such as retweets, replies or quote tweets) are well documented and have been used frequently to build social networks in the context of political studies on Twitter (e.g. Conover et al., 2011; Anonymous, 2018; Williams et al., 2015). In contrast, recent studies have also used the status updates posted by the Twitter accounts a user follows to approximate what content they were potentially exposed to (e.g. Shore et al., 2018). While this approach is intriguing, it requires a large amount of user-based Twitter data, which is difficult to acquire through the public Twitter API. In addition, there is no feasible way of knowing if these tweets where actually seen or read by an individual (e.g. Bakshy et al., 2015). The data collection step is well applicable to multi-party systems.

Community Detection - Another aspect of the definition of echo chambers are *Social Boundaries* that limit an individual's exposure to content from opposing views. In previous studies, such boundaries have been identified by detecting communities within the social network (e.g. Quattrociocchi et al., 2016; Williams et al., 2015). A community is a part of a graph containing a group of nodes that are connected sparsely to the rest of the graph (Fortunato, 2010) but are heavily connected among themselves (Newman and Girvan, 2004; Yang et al., 2016). Thus, evaluating if a group of nodes is a community has two main components; the density among its nodes and the ties towards nodes outside of the group. The identification is usually accomplished algorithmically by minimizing the mixing parameter μ (Lancichinetti and Fortunato, 2009). The mixing parameter expresses the fraction between external connections and the total connections of a group. Network theory has developed many approaches to detect communities within graphs. Addressing the issue of choosing the right community detection algorithm, Lancichinetti and Fortunato (2009) and Yang et al. (2016) compare and evaluate several of them. For this purpose, they refer to benchmark graphs consisting of up to 32,000 nodes.

Bakshy et al. (2015) point out that many previous research endeavors regarding echo chambers have had reliability and generalizability issues with their data sets. As investigating the whole network compared to an analysis of the network's core leads to completely different results, reducing the amount of nodes is not recommendable (Shore et al., 2018). As graphs derived from OSNs often include more nodes than the tested 32,000, researcher cannot rely exclusively on the findings of Lancichinetti and Fortunato (2009) and Yang et al. (2016) when choosing an algorithm.

Detecting communities within a graph with more than 32,000 nodes has been successfully accomplished by Williams et al. (2015) who applied the *Louivan method* (Blondel et al., 2008). This algorithm is a greedy approach to maximize the modularity by moving nodes between communities in order to find their local optimum. Apart from the Louivan method the *Fastgreedy method* is another algorithm to identify communities in very large graphs (Clauset et al., 2004). This algorithm uses a greedy hierarchical agglomerative procedure to maximize the modularity of a graph.

Greedy approaches are not deterministic and thus, multiple algorithms may come to different results. The quality evaluation of the community detection results can be measured by their final *modularity* (Newman and Girvan, 2004). It assesses the result by comparing the fraction of edges within the communities to the same measure in a setting where nodes are allocated randomly to the same number of groups. Although algorithms which maximize modularity generally accurately identify communities (Lancichinetti et al., 2008), they seem to have weaknesses in finding small communities in large graphs (Kumpula et al., 2007). Therefore, Traag et al. (2011) present several approaches improving modularity that are still open to be empirically verified. Consistent with the data collection and construction of the graph, the community detection works equally well for multi-party systems and the results of this section can thus be applied to that context.

User Ideology - To ultimately address the aspect of *User Similarity*, the ideological views of the users need to be assessed. This is a prerequisite to study whether like-minded individuals do indeed communicate with one another more frequently than with others. However, this step has posed difficulties to researchers as many networks do not provide direct information on the ideology (Halberstam and Knight, 2016). Thus, the ideology needs to be derived or approximated through other information available to the researchers. Potential concerns for this process include that the derived ideology may be under- or overestimated due to factors such as social norms, peer-pressure, public exposure, or regional political slants (Halberstam and Knight, 2016). Yet, many approaches do exist where researchers have estimated political ideology based on data from OSNs.

Quattrociocchi et al. (2016), for instance, referred to „liked" Facebook posts to approximate a user's ideological view. When 95% of a user's *likes* are on posts of a certain category, the user is labeled a supporter of this category. Barberá (2015, pp. 10–11) propose that "the decision to follow [politicians on Twitter] provides information about an individual's ideology". Thus, Colleoni et al. (2014) categorize users as Democrats or as Republicans, if they only follow politicians on Twitter of either of these parties. For the remaining users, they use the previously categorized users as a training data set and apply a machine learning approach to assign the rest to the two ideologies. Halberstam and Knight (2016) categorize users as supporter of Democrats or Republicans if they follow a larger share of politicians of one party. Williams et al. (2015) show textual content of the users consisting of tweets and profile information to experts in order to manually classify the users.

All these procedures have in common that the subject of interest is predetermined to be classifiable dichotomously. However, even in bipolar systems like in the US, there are so-called swing voters or independents, changing to favor either the Republicans or Democrats. Hence, a dichotomous categorization represents the real world only oversimplified. This constrained becomes even more evident, when regarding the political systems across the world, for instance in Europe, where multi-party systems are prevalent. For example, in Germany, the largest democracy in the European Union, six parties form the federal parliament. Thus, there is a clear need to get away from the dichotomy assumption.

A possible solution is proposed by Barberá (2015), who develops a Bayesian model to classify Twitter users in a continuous model from liberal to conservative based on Twitter follower data. Furthermore, Shore et al. (2018) use content, rather than user preferences or followers, to derive ideology. In their study, they asses the links to news outlets shared by individuals and use the political slant (or bias) of the news source to approximate the users' ideological views. Yet, both approaches have in common that they only consider liberals and conservatives. However, more diverse ideologies exist, that become accentuated in multi-party systems (Geoghegan, 2003). However, neither of the previous approaches enables the proper representation of the full spectrum of political views innate in multi-party systems. Addressing this issue, we introduce another way to express users' ideologies in Section 4.

Degree of Echofication - Referring to the definition of echo chambers there are three aspects to consider, namely *Social Boundaries*, *User Similarity* and *Information Homogeneity*. To evaluate to what degree a community qualifies as an echo chamber, measures need to be evaluated.

Regarding *Social Boundaries* well-studied community detection algorithms accompanied by evaluation measures have been discussed (e.g. Lancichinetti and Fortunato, 2009). As the resulting communities vary widely, Fortunato (2010) recommends to evaluate them individually. To the best of our knowledge, no thresholds have yet to be established for this. However, it may be reasonable that if $\mu > 0.5$ meaning that more than half of the connections are outgoing this group of users cannot be considered a strong community (Yang et al., 2016).

The aspects *User Similarity* and *Information Homogeneity* aim at the degree to which communication among the community happens between like-minded individuals that share similar political views (Halberstam and Knight, 2016). A principle that has been proposed in this context is homophily, which is based on the idea that "contact between similar people occurs at a higher rate than among dissimilar people" (McPherson et al., 2001, p. 416). It measures a user's exposure to diversity by specifying the similarity between a user's personal view and the views he or she is confronted within their own personal network (Barberá, 2014). Currarini et al. (2009) define this measure as the fraction of interactions with the same type of individuals.

Previously, researchers have frequently utilized the measure *homophily* in the context of echo chambers (e.g. Colleoni et al., 2014; Williams et al., 2015). To adequately assess the values of homophily, they need to be put in perspective. Thus, Colleoni et al. (2014) assessed their findings regarding a *baseline homophily* rate that would be expected for a randomized graph based on the same characteristics. If larger groups within a network generally experience higher degrees of homophily than smaller groups, the network satisfies *relative homophily* (Halberstam and Knight, 2016). In other words, larger groups form more ties with members of their own type (Currarini et al., 2009), which may simply be because of a greater availability of such individuals within a network. In studies related to the US, a fine granular view of the baseline homophily is not necessarily needed, as the shares of Liberals and Conservatives are close to equal. However, this is different in a multi-party system where parties of the political middle have traditionally had higher numbers of supporters than smaller parties.

While homophily works well and has been used in many research contributions, it does come with limitations regarding echo chambers. This is because *Information Homogeneity* can only be assessed in such a way under the assumption that like-minded others share ideologically similar information. Especially for the context of retweet networks on Twitter, this assumption seems to hold true (Wong et al., 2016). Yet, further analysis into the content that was shared within homophile communities may provide additional insights. Shore et al. (2018) do this by analyzing links to political news outlets. Text mining and approaches, such as word2vec may help in that regard too (Mikolov et al., 2013). This approach has also been successfully utilized in the context of OSNs, such as Twitter (e.g. Dickinson and Hu, 2015).

4 Modification in Multi-party Systems

As outlined, previous research has focused on two-party systems rather than multi-party systems. To identify echo chambers in multi-party systems, we propose a number of modifications to the methodological approach, which we describe in this section.

User Ideology - Assigning users to a single ideology seems to be the preferred procedure in the literature (e.g. Colleoni et al., 2014; Halberstam and Knight, 2016; Quattrociocchi et al., 2016) and can theoretically also be done in a multi-party system. However, Barberá (2015) and Shore et al. (2018) make a point that a continuous assessment of voter ideology within the spectrum from left to right is desirable. Although they may be categorized in this spectrum, there are parties in multi-party systems, that refer to other ideologies, such as ecologism (Geoghegan, 2003). Consequently, supporters of these ideologies cannot be properly displayed in a simple spectrum between left and right. As outlined, neither of the previous approaches is appropriate to handle ideological views in multi-party systems. Therefore, we propose to refer to a m-dimensional vector $v_u \in V \subseteq (\mathbb{N}_0)^m$, when modeling the ideology of a user $u \in U$. The m dimensions represent the different ideologies and its values specify how strongly the user is linked to them. Using this procedure, users do not need to be classified into a specific category or single ideology. As multiple ideologies exist (Geoghegan, 2003), the users' views can be estimated and differentiated between more accurately. For instance, a user with a pure socialist ideology may follow different parties than a socialist who also supports ecologism.

Degree of Echofication - In order to evaluate *User Similarity* and *Information Homogeneity* the users' ideological views are investigated. As previous research used dichotomous categorization of such views, the comparison of the views is simple: it is either the same or different (e.g. Halberstam and Knight, 2016). However, when we address a more complex representation, namely the proposed vector, there is a need to differentiate more accurately, because two users are very unlikely to be exactly the same. For this purpose, we propose using a similarity measure fulfilling the following three requirements: (1) the similarity between two users' views shell not be determined by the lengths of the representing vectors (e.g. number of politicians a user follows). Regardless of the similarity measure, we can ensure this by normalizing the vectors' length. (2) Similar to dichotomous categorizations, the measure must be symmetric and within a fixed interval (such as [0;1]) to allow an estimation of a consistent and thus, interpretable homophily across the whole network. (3) Clearly, the measure needs to be sensitive to differences in the intensity of the vectors' values.

The cosine similarity $\psi(v_1, v_2)$ - where $v_{i\in\{1;2\}} \in V$ - meets all these requirements. This measure quantifies the cosine of the angle between two vectors (Manning et al., 2008). As the vectors' lengths are greater than 0 and they only include non-negative values, the angle between two of such vectors can only reach a maximum of 90° (corresponding to a ψ value of 0) when there is no dimension in which both vectors have a value greater than 0. Contrarily, if ψ amounts to its maximum of 1 (corresponding to an angle of 0°) the vectors point in the same direction. Further, ψ can be calculated by using the dot product between the two vectors as the numerator, and the products of their magnitudes as the denominator: $\psi(v_1, v_2) = \frac{v_1 \cdot v_2}{\|v_1\| \; \|v_2\|}$ (Manning et al., 2008).

We introduced homophily as the measure to approximate *Information Homogeneity*. As stated, Currarini et al. (2009) define this measure as the fraction of interactions with the same type of individuals. Therefore, we determine $\phi(u_i)\colon U \to \mathbb{R}$ by the average similarity of user u_i to his or her neighbors in the network graph $N_i \subseteq U$.

$$\phi(u_i) = \frac{\sum_{u_j \in N_i} \psi(u_i, u_j)}{|N_i|}$$

When considering a weighted graph, edge weights $w(u_i, u_j)\colon U \times U \to \mathbb{R}$ between u_i and one of his or her neighbors $u_j \in N_i$ indicate how strongly these users affect each other. The intensity of interactions between users can be represented through weighted edges in a graph (Howison et al., 2011). In order to consider weights, we propose the weighted counterpart $\phi_w(u_i)\colon U \to \mathbb{R}$.

$$\phi_w(u_i) = \frac{\sum_{u_j \in N_i} \psi(u_i, u_j) w(u_i, u_j)}{\sum_{u_j \in N_i} w(u_i, u_j)}$$

These continuous measures enable the estimation of the homophily for users in a multi-party system. As communities $C \subseteq U$ consist of multiple users, their homophily comprise its members' homophily measures. In order to calculate this, we average ϕ or rather ϕ_w over the community's members, $\overline{\phi}$ and $\overline{\phi_w}$. However, as the distribution of the different ideological views among the users of the graph is rarely balanced, for users of some ideologies it is more statistically likely to achieve a higher homophily. Let us assume that 75% of all IS researchers are male and 25% are female. If a male researcher collaborates with three men and one woman, his ϕ is 75% even though the composition of his collaborator network represents the statistically expected distribution among IS researchers. Therefore, a male researcher with a ϕ of 50% is less homophile than expected, whereas a female researcher with a ϕ of 50% is more homophile than expected. To accommodate this, we follow the idea of relative homophily by Currarini et al. (2009) and include the probability of interacting with similar others. Transforming this to our vectorized multi-party approach, we estimate the expected homophily for the user u_i, $E(\phi(u_i))$ or rather $E(\phi_w(u_i))$ by calculating the user's ψ to the average ideological view of all users and compare it to his or her homophily. We express this consideration through the measure $\Delta: U \rightarrow \mathbb{R}$ and its weighted counterpart $\Delta_w: U \rightarrow \mathbb{R}$.

$$\Delta(u_i) = \phi(u_i) - E(\phi(u_i))$$

$$\Delta_w(u_i) = \phi_{w(u_i)} - E(\phi_w(u_i))$$

5 Evaluation

To evaluate the introduced framework and the modification in multi-party systems, we apply it to a data set of the German Federal Election 2017. In contrast to the US, many different parties characterize Germany's legislature. As of 2017, six of them are represented in the federal parliament.

Data Set & Network Graph - In this study, we mainly rely on the data collected by Gimpel et al. (2018). The researchers used Twitter's Streaming API to collect publicly accessible data, which includes all status updates from August 2, 2017 until September 24, 2017 (closure of polling stations) that refer to the German Federal Election. The data set contains 2,932,148 status updates by a total of 305,529 distinct users. Using Twitter's REST API, we extended these data by collecting the followers of the 544 accounts of all former and newly elected (current) members of the federal parliament in March 2018. The selection of the 544 accounts was done through lists of Twitter accounts provided by the parties (Gimpel et al., 2018). Based on the interactional data, namely *retweets*, *replies* and *quote tweets*, we modeled a network graph representing the OSN. While studies have shown that people are more likely to retweet status updates that contain similar political views (e.g. Wong et al., 2016), we use all interactions equally and do not differentiate between them in this study. This is because in the context of echo chambers, it is of vital importance that users are exposed to other users' views rather than the manner of this recognition.

Community Detection - Although Germany has a low Twitter adoption rate (Newman et al., 2017), the graph we analyze is rather large. Thus, we apply the Louvain method as well as the Fastgreedy method and calculate the modularity in order to assess their performance. We use the igraph module 0.7.1 for Python 3.6.2 to calculate our results. We proceed with the Louvain method, as its modularity score is slightly higher (0.576 versus 0.572). Values greater than 0.7 are considered rare, therefore these scores are in the upper range and indicate good performance (Newman and Girvan, 2004).

User Ideology - As Germany has a multi-party system, we apply the approach developed in this paper. Through this procedure, we refer to the follower data and represent the users' ideological views by six-dimensional vectors - one dimension for every national party represented in the federal parliament. We use the gathered follower data to fill these vectors.

5.1 Descriptive Statistics

By mining the data set, we identified that 2,153,878 of the 2,932,148 status updates present interactions between 258,048 users - which are either replies (146,469), retweets (1,848,625) or quote tweets (158,784). We found that the follower data and identified 94,292 distinct users who follow at least one of our 544 politicians on Twitter. Table 3 states further descriptive statistics regarding follower data.

Descriptive statistics		**AfD**	**CDU/CSU**	**FDP**	**Grüne**	**Linke**	**SPD**
Distribution of the politicians on Twitter		82	123	54	72	64	149
Average normalized vector of politicians followed from each party		0.10	0.13	0.10	0.21	0.21	0.25
Number of users' subscriptions	Min/Mean/Max	0/0.79/79	0/1.44/122	0/0.76/53	0/1.47/72	0/1.47/63	0/2.40/140
	0.5/0.75/0.95-quantile	0/0/3	0/1/6	0/1/3	0/2/9	0/1/6	0/2/9

Table 3: Descriptive statistics of the follower data

5.2 Evaluating Communities

Using our outlined approach, we identified 7,800 communities. We filter these communities and present those with a minimum of 500 members. If users do not follow national politicians on Twitter, we cannot estimate the users' ideological views reliably. Thus, we do not report communities from which we can infer less than 20% of the users' ideologies. The remaining six communities are shown in table 4. To relate these communities' measures to the entire data and enable their interpretation, we calculate the overall $\overline{\phi}$ amounting to 59.9%. This means that if two users are connected, their ideological views match to 59.9% on average. The measure only marginally increases to $\overline{\phi_w}$ = 60.3% when taking the edges' weights into account, which means that users are stronger connected to users to whom they agree more ideologically.

Id	**#User**	**Users following politicians**	**Politicians**							**In %**				
			#	**AfD**	**CDU/CSU**	**FDP**	**Grüne**	**Linke**	**SPD**	**μ**	μ_w	$\overline{\phi}$	$\overline{\phi_w}$	$\overline{\Delta_w}$
A	69,890	38.2%	60	2	4	1	1	47	5	22.1	20.7	55.3	55.6	-7.9
B	34,110	49.2%	213	-	76	39	2	3	93	36.1	30.0	63.3	63.9	4.9
C	16,516	48.4%	43	39	2	-	-	-	2	18.3	11.6	68.2	69.2	28.1
D	9,999	51.8%	69	1	1	1	61	-	5	44.6	36.5	68.7	69.4	5.4
E	3,861	42.6%	0	-	-	-	-	-	-	43.8	32.8	55.1	55.7	-9.1
F	551	32.3%	0	-	-	-	-	-	-	35.5	29.5	60.2	60.6	-0.3

Table 4: Results and measures for the identified communities

In the table, it is notable that the politicians that belong to the communities A, C and D mainly belong to a single party. Community B is more diverse in that regard. There is no well-defined range to determine whether a community's μ fulfills the aspect of enclosed *Social Boundaries* or not but all meet the minimum requirement of being smaller than 0.5, which means that users mainly interact with users' inside their community (Yang et al., 2016). As the weighted measure $\overline{\mu_w}$ is smaller than $\overline{\mu}$ the users also interact with the users inside their community more frequently than with other users. Regarding $\overline{\phi}$ and $\overline{\phi_w}$, A and E are about 5% below average. Similarly, $\overline{\Delta_w}$ is below zero, which indicates that these communities have a lower homophily than expected. Thus, all measures suggest a low degree of echofication for A and E. Contrarily, the average homophily of the members of community C are 28.1 percentage points above the expected, providing indications for a high degree of echofication. To gain a deeper understanding of the communities, we analyze the ideological views further. For this purpose, we normalized the users' political vectors and aggregated them across each community (c.f. table 5).

Community	A	B	C	D	E	F
AfD	0.02	0.03	0.60	0.01	0.02	0.02
CDU/CSU	0.10	0.20	0.09	0.11	0.15	0.26
FDP	0.08	0.18	0.06	0.06	0.10	0.14
Grüne	0.24	0.14	0.05	0.47	0.23	0.14
Linke	0.30	0.13	0.11	0.12	0.28	0.11
SPD	0.26	0.32	0.09	0.23	0.21	0.33

Table 5: Percentage of politicians from each party followed by each community

Interestingly, community A hosts a large number of politicians from the Linke (47 of 60). However, that slant is not nearly as skewed in the follower share, where three different left-leaning parties are represented quite equally. While the community has the second lowest mixing coefficient, its homophily is below average in all measures. Community B is diversified in both followers and accounts of politicians, but favors parties from the political middle, namely SPD, FDP and CDU/CSU. The distribution of followers is particularly lopsided for community C, where politicians belong to the AfD with a probability of 60%. The community exhibits the highest degrees of homophily, particularly when compared to the baseline, with a delta of +28.1%. Congruently, the mixing parameter is very low, with a $\overline{\mu_w}$ of 11.6%. Politicians from the Grüne dominate community D, which also matches the political slant in the percentage of followers. While the absolute homophily is similar to community C, the $\overline{\Delta_w}$ to the expected baseline is only +4.9%. The mixing parameter is high with a $\overline{\mu_w}$ of 36.5%. Lastly, communities E and F are rather diverse, but do not host any politicians. The homophily measures are below the baseline.

In summation, users of the communities B, D and C favor one party heavily. C and D exhibit the greatest homophily and can be associated to parties from the political left (Grüne) and the far right (AfD). By far the largest homophily relative to the baseline is found in a community dominated by the AfD.

6 Discussion

As a theoretical contribution, in this study we propose a four-step framework to analyze the phenomenon of echo chambers in the political context of multi-party systems and tackle three aspects of echo chambers in doing so. We suggest a network approach to address the *Social Boundaries* aspect of echo chambers. To give guidance to other researchers, we present literature on how to select appropriate community detection algorithms and discuss measures to assess their performance.

In addition, we address the unique characteristics of multi-party systems to infer user ideology by suggesting a vector-based approach. This step is essential for the calculation of *User Similarity*, for which we suggest the cosine distance. This allows us to calculate homophily in the context of multi-party systems, which may serve as a proxy for *Information Homogeneity*. However, further analysis into the content of the conversations may be necessary.

To demonstrate our modifications for multi-party systems, we conduct a case study based on Twitter data from the German Federal Election of 2017. The results show that different communities do indeed show different degrees of the mixing coefficients and the homophily measure. This exemplifies the need to differentiate between the sections of a network when investigating echo chambers and provides evidence that different degrees of echofication do exist within a network.

As many studies have proposed before, our research suggests that there is frequent interaction between heterogeneous users in OSNs. The overall observed levels of homophily seem to be relatively low but are congruent with previous research. Barberá (2014), for example, find that on average, 56% of the individuals in a German Twitter user's network favor the same ideology comparing well with our $\overline{\phi}$ of 59.9%. However, some chambers exhibit substantially higher values (up to 69.4%). These communities can be associated with individual parties relatively clearly. This generally speaks for an antagonistic, not segregated political discussion on Twitter (Shore et al., 2018). That being said, the degree of homophily varies between the communities. We find that communities comprised of users following far-right politicians show particularly high levels of homophily. This effect becomes particularly visible, when analyzing the delta between the expected homophily and the actual observed homophily. When assessing our empirical results, we need to bear in mind that this research was conducted in Germany, where polarization of the political landscape is known to be rather low (Munzert and Bauer, 2013).

To put the homophily values into perspective compared to a dichotomous categorization, we need to consider how it was calculated. Reaching values close to one is very unlikely with our vector-based approach. This is because two users who overwhelmingly follow the same party, but both also follow a few other individuals from different parties, will not be assigned the same ideology value. In other words, the ideology values are not categorical but continuous and may differ slightly, even when two users are likely followers of the same party. This is not necessarily a bad thing, as it allows us to assess ideology more granularly. For instance, with this approach we can differentiate between users who follow multiple parties who form a coalition and those that follow only one party.

For practitioners, our results provide a way of identifying and quantifying echo chambers in multi-party systems. In practice, this could be done continuously to find groups of people who are particularly exposed to previously held beliefs. Based on those insights, individual users could then be targeted by the platforms to disrupt echo chambers. Treviranus and Hockema (2013) as well as Gillani et al. (2018) suggest such measures. For example, utilizing platform-provided recommendations that are contrary to the users' ideological views seems promising in promoting diversity. Another suggested approach are structured discussion boards in OSNs for comparing opposing arguments from different ideological views. These ideas may offer reference points for future research on solutions.

7 Limitations, Further Research & Conclusion

In this study, we presented a framework suitable for multi-party systems to investigate the echo chambers phenomenon in OSNs based on a network approach that allows an investigation of different communities. As a structure to our framework, we propose that there are three aspects of the definition of echo chambers: *Social Boundaries*, *User Similarity*, and *Information Homogeneity*. Our framework shows different design choices that need to be made when conducting echo chambers research. We argue that continuous measures for political ideology are preferable in multi-party systems and introduce cosine distance as a way to quantify it. Subsequently, we adjust well-established homophily measures to accommodate our similarities. To evaluate the framework and demonstrate its outcomes, we further conduct a case study based on data from the German Federal Election of 2017. Previous empirical analyses on the echo chamber phenomenon were dominated by studies in a bipolar context such as the political system of the US. Thus, this paper helps advance studies in multi-party systems, which are prevalent in Europe. Our empirical findings are in line with previous research in showing that OSN users may be antagonistic rather than segregated. Future research should consider that this phenomenon might not be caused by OSNs, but that it becomes measurable through the unique trace data provided by OSNs. Thus, OSNs open up manifold opportunities for IS researchers to gain a deeper understanding of social issues which have yet to be fully exploited.

Certainly, our study has a number of limitations and leaves room for further research. First, our results of the case study are supposed to demonstrate the application of our framework. Thus, the quantitative findings need to be verified in future studies with different data sets and more in-depth investigations. Additionally, we expect to gain a better understanding of the political discussion when the content of the tweets and the members of the communities are analyzed in greater detail. For content-related research endeavors, machine-learning technics, such as word2vec, seem promising and may help shed light on the *Information Homogeneity* aspect of echo chambers. Furthermore, it would be insightful for future research to investigate whether different approaches yield the same results with identical data sets. For instance, some previous work has been based on measurable interactions while others have focused on potential exposure to information.

In summation, our findings suggest that when echo chambers are supposed to have any practical relevance in data-driven approaches, they cannot be binary, and their definition cannot be absolute. Many researchers have addressed this by reporting the average homophily of a network's users while neglecting the idea of separate communities that host particularly homophile users. This may have led to an underestimation of the problem in communities that host groups of political extremes.

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