Uncovering the Wider Structure of Extreme Right Communities Spanning Popular Online Networks

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ABSTRACT

Recent years have seen increased interest in the online presence of extreme right groups. Although originally composed of dedicated websites, the online extreme right milieu now spans multiple networks, including popular social media platforms such as Twitter, Facebook and YouTube. Ideally therefore, any contemporary analysis of online extreme right activity requires the consideration of multiple data sources, rather than being restricted to a single platform. We investigate the potential for Twitter to act as one possible gateway to communities within the wider online network of the extreme right, given its facility for the dissemination of content. A strategy for representing heterogeneous network data with a single homogeneous network for the purpose of community detection is presented, where these inherently dynamic communities are tracked over time. We use this strategy to discover and analyze persistent English and German language extreme right communities.

Author Keywords

Social network analysis; extreme right; heterogeneous online networks.

ACM Classification Keywords

J.4 Social and Behavioral Sciences: Sociology

INTRODUCTION

The online presence of the extreme right has come under greater scrutiny in recent years, particularly given events such as the Oslo killings by Anders Behring Breivik in July 2011, Wade Michael Page's attack on a Sikh temple in Wisconsin in August 2012 and the uncovering in November 2011 of the German National Socialist Underground (NSU)'s multi-year murder campaign. While initially the extreme right relied upon dedicated websites for the dissemination of their hate content [7], they have since incorporated the use of social media platforms for community formation around variants of extreme right ideology [15]. As Twitter's facility for the dissemination of content has been established [2], our previous work [27] provided an exploratory analysis of its use by extreme right groups. Here we extend this analysis to investigate its potential to act as one possible gateway to communities located within the online extreme right milieu, which spans multiple platforms such as Twitter, Facebook and YouTube in addition to other websites. Our analysis is focused on two case studies, involving the investigation of English and German language online communities.

We infer network representations of heterogeneous nodes and edges to capture the relations between four different extreme right online entities: (a) Twitter accounts, (b) YouTube channels, (c) Facebook profiles and (d) all other websites. The inclusion of such platforms allows us to identify extreme right communities that would otherwise not be apparent when considering Twitter data alone. As online extreme right networks are inherently dynamic, we are also interested in tracking the evolution of the associated groups over an extended period of time. Following work by Lehmann et al. [23], we apply the community finding process to a single network representation where all node types are treated as peers. When interpreting the output of the process, the use of heterogeneous data provides us with a rich insight into the composition of the communities, and serves to differentiate between them.

We initially provide a description of related work on the online activities of extremist groups, along with discussion of relevant network analysis methods. The generation of two data sets using English and German language tweets is then discussed. Next, we describe the methodology used to derive network representations and subsequently track detected communities. This is followed by an analysis of selected persistent dynamic communities found in both data sets, where we discuss the merits of the network representation and provide characterizations of the membership composition in terms of the extent to which they span multiple online platforms. Finally, the overall conclusions are discussed, and some suggestions for future work are made.

RELATED WORK

Online Extremism

A number of studies have investigated the online presence of extreme right groups. An early example is that of Burris et al. [7], where social network analysis of a white supremacist website network found evidence of decentralization, with little division along doctrinal lines. Gerstenfeld et al. [14] analyzed the content of various extremist websites, and described the potential for forging a stronger sense of community between geographically isolated groups. Chau and Xu [9] studied networks built from users contributing to hate group and racist blogs. Caiani and Wagemann [8] analyzed the website networks of German and Italian extreme right groups.

More recent work has included the study of online social media usage by the extreme right. Bartlett et al. [4] performed a survey of European populist party and group supporters on Facebook. Baldauf et al. [3] investigated the use of Facebook by the German extreme right, exploring the strategies employed for promoting associated ideology along with the use of certain themes designed to attract new unsuspecting followers, such as stated support for freedom of speech and opposition to child sex abuse. Goodwin and Ramalingam's [16] analysis of the radical right in Europe discussed the importance of online social media, and separately found a shortage of research on non-electoral forms of right-wing extremism. A set of reports commissioned by the Swedish Ministry of Justice and the Institute for Strategic Dialogue [15] analyzed the use of social media such as Facebook and YouTube by a number of European extreme right groups.

These related studies suggest that communities within the online extreme right milieu span multiple networks, which provides a motivation for the current work to analyze their structure and temporal persistence, while also investigating the potential for popular social media platforms such as Twitter to act as gateways to this activity.

Network Analysis

An appropriate network representation is required in order to analyze the multi-network online activity of the extreme right. The *inference* and *relevance* problems discussed by De Choudhary et al. [12] are applicable here, where the former is attributed to the fact that "real" social ties are not directly observable and must be inferred from observations of events (in our case, tweets from identified extreme right accounts on Twitter), while the lack of one "true" social network is associated with the latter, due to the potential existence of multiple networks each corresponding to a different definition of a tie. Separate *incompleteness* issues also exist given the nature of the extreme right. These issues are similar to those encountered by Sparrow [30] and Krebs [20] in their respective studies of criminal and terrorist networks, where references are made to the inevitability of missing nodes and links, the difficulty in deciding who to include and who not to include, and the dynamic quality of the networks. As our current work uses Twitter as a starting point for analyzing online extreme right activity, the notion of missing nodes and links is realized with the unavailability of older tweet data, relevant Twitter accounts that have been suspended, profiles that are not publicly accessible and extreme right entities that do not maintain a presence on Twitter.

Our proposed representation of heterogeneous node types with a single homogeneous network is also motivated in part by previous work in cluster analysis and community finding, where nodes with different semantics have been treated equally during the clustering phase, and subsequently treated separately to support the interpretation of the resulting clusters. For instance, Dhillon [13] produced a bipartite spectral embedding of words and documents, which allowed both to be clustered simultaneously. Lehmann et al. [23] proposed an extension of the well-known clique percolation method for community finding to identify communities of nodes in bipartite graphs. The use of multiple node types avoids the loss of important structural information, which can occur when performing a one-mode projection of a graph.

For the analysis of communities in temporal networks, a variety of approaches have been proposed. Greene et al. [18] described a general model for tracking communities in dynamic networks. Communities are identified on each individual *time step* network, which provides a snapshot of the data at a particular interval. These communities are then matched together to form timelines, representing long-lived dynamic communities that exist over multiple successive steps. This work was extended in [17] to address the problem of clustering dynamic bipartite networks, where a clustering is produced on a spectral embedding of both types of nodes simultaneously at each time step before matching.

DATA

In our previous analysis [27], we collected a number of Twitter data sets, each associated with a particular country, to facilitate the analysis of contemporary activity by extreme right groups. One of our findings was the influence of linguistic proximity on relationships within the detected extreme right communities, in particular, the use of the English language. Given this, we merged two of our data sets associated with the USA and the United Kingdom respectively. This data set, along with that associated with German extreme right Twitter accounts, are the starting points for this current work. Both data sets were extended to include additional accounts that were identified as relevant, using criteria such as profiles containing extreme right symbols or references to known groups; follower relationships with known relevant accounts; similar Facebook profiles/YouTube channels; extreme right media accounts; a propensity to share links to known extreme right websites. Similar criteria were employed in earlier studies [3, 8], and further details can be found in our previous analysis [27]. In total, 1,267 English language and 430 German language accounts were identified. Profile data including followers, friends, tweets and list memberships were retrieved for these accounts, as limited by the Twitter API restrictions effective at the time, between June 2012 and November 2012.

We are interested in the potential for Twitter to act as one possible gateway to online extreme right activity through the dissemination of links to external websites; for example, dedicated websites managed by particular groups, content sharing websites such as YouTube, or mainstream websites hosting content that could be used to promote associated concerns. Accordingly, the account tweet content is analyzed to extract all external URLs. YouTube URLs are further processed, where profile data is retrieved for any detected video and channel (account) identifiers. Similarly, profile data is retrieved for any user, group and page identifiers detected within Facebook URLs. In both cases, we are restricted to data that is publicly accessible. We also extract Twitter account identifiers from any URLs that point to content such as photos or other images that are hosted directly on Twitter. Regarding interactions within Twitter itself, we extract all *mention* and *retweet* events between the identified accounts. Statistics of the final data sets used in the analysis can be found in Table 1.

METHODOLOGY

Network Representation

In this work, we use a single network representation consisting of four node types: (a) Twitter accounts, (b) YouTube channels, (c) Facebook profiles and (d) other websites, where we refer to the latter three as *external* nodes (with respect to Twitter). Heterogeneous edges are also employed to reflect the variety of possible interactions; (a) a Twitter account mentioning another Twitter account, (b) a Twitter account retweeting another Twitter account and (c) a Twitter account linking to an external node through the inclusion of a corresponding URL in a tweet. For the purpose of this analysis, no distinction is made between mention or retweet events. In a similar approach to the ingredient complement network used by Teng et al. [33], we infer edges between external nodes whose URLs have appeared in tweets from the same Twitter account, in order to further tackle the issue of data incompleteness. At this point, we filter any YouTube and website nodes whose URLs have appeared in tweets from a single account only. As the number of unique profiles found in tweets containing Facebook URLs tends to be lower, these nodes are not filtered. We do not filter external nodes that could be considered as mainstream (for example, newspapers or TV channels), as we are also interested in references to such entities by extreme right accounts. All edges are treated as undirected, with raw weights based on the frequency of the edge event in question. These weights are normalized with the use of pointwise mutual information (PMI) as suggested by Teng et al. [33], where we extend this process for heterogeneous node pairs (a, b) as follows:

$$\text{PMI(a,b)} = log\left(1 + \frac{p(a,b)}{p(a)p(b)}\right)$$

For Twitter-Twitter mentions|retweets edges, the PMI is the probability that two Twitter accounts a and b have a mention|retweet relationship against the probability that their respective mentions|retweets are separate:

$$p(a,b) = \frac{\#\text{ of mentions}|\text{retweets between } a \text{ and } b}{\#\text{ of mentions}|\text{retweets}}$$

$$p(a) = \frac{\#\text{ of mentions}|\text{retweets featuring } a}{\#\text{ of mentions}|\text{retweets}}$$

$$p(b) = \frac{\#\text{ of mentions}|\text{retweets featuring } b}{\#\text{ of mentions}|\text{retweets}}$$

For Twitter-external URL edges, the PMI is the probability that a URL external entity b has been tweeted by a particular Twitter account a against the probability that their respective URL tweet occurrences are separate:

$$p(a,b) = \frac{\#\text{ of tweets from } a \text{ with URL of } b}{\#\text{ of tweets with URLs}}$$

$$p(a) = \frac{\#\text{ of tweets from } a \text{ with URLs}}{\#\text{ of tweets with URLs}}$$

$$p(b) = \frac{\#\text{ of tweets with URL of } b}{\#\text{ of tweets with URLs}}$$

For inferred external-external edges, the PMI is the probability that two URL external entities a and b have been tweeted by a particular Twitter account against the probability that they have been tweeted by separate accounts:

$$p(a,b) = \frac{\#\text{ of accounts that tweeted URLs of both } a \text{ and } b}{\#\text{ of accounts that tweeted URLs}}$$

$$p(a) = \frac{\#\text{ of accounts that tweeted URL of } a}{\#\text{ of accounts that tweeted URLs}}$$

$$p(b) = \frac{\#\text{ of accounts that tweeted URL of } b}{\#\text{ of accounts that tweeted URLs}}$$

The addition of inferred edges between external nodes can occasionally lead to dense networks, particularly with the inclusion of accounts that are prolific tweeters. As the PMI weights for these edges tend to be normally distributed, we filter any such edges with PMI $< \mu + 2\sigma$. All other edges are retained.

Community Detection

As with our previous analysis [27], we use our variant [19] of the Lancichinetti and Fortunato consensus clustering method [21] to generate a set of stable consensus communities from an inferred network instance, based on 100 runs of the OSLOM algorithm [22]. As before, we selected a value of 0.5 for the threshold parameter τ used with the consensus method, as a compromise between node retention and more stable communities. Although we previously detected communities within a static graph representation, these networks are inherently dynamic, and so we are interested in the topology of these communities over an extended period of time. Using the method of Greene et al. [18], we represent this dynamic network as a set of l time step networks $\{g_1, \ldots, g_l\}$, employing a sliding window approach to generate snapshots of the nodes and edges in the overall network at successive intervals.

The selection of the sliding window size has a direct impact on the topology of the generated network snapshots. In their

Data set	*Tweets*	*Mentions*	*Retweets*	*All URLs*	*YouTube URLs*	*Facebook URLs*
English language	1,517,339	539,181	162,042	972,444	71,049	23,007
German language	54,873	14,263	11,028	88,309	3,868	6,924

Table 1: Data set statistics for the period of June 1st, 2012 to November 16th, 2012.

discussion of dynamic proximity networks, Clauset and Eagle [10] claim that dynamics are a multi-scale phenomenon, with variation taking place at several distinct time scales. However, they also suggest that a natural time scale exists with which important temporal variation is preserved. In this analysis, we consider this natural time scale to be related to the activity of the identified extreme right Twitter accounts. We calculated the mean percentage of accounts active in each data set within a series of increasing time scales ranging from one day up to a duration of eight weeks; a plot of these values can be seen in Figure 1. Although the accounts in the English language data set seem to be more active than those of the German language data set, the relative activity trends are highly similar. In both cases, there is a sharp increase in the percentage of active accounts between the daily and weekly time scales, with a lesser increase between the weekly and bi-weekly scales. At this point, the rate of increase slows down, which suggests that using a window size of two weeks is appropriate for meaningful analysis rather than a larger size whereby the corresponding snapshot networks become increasingly static. When using non-overlapping sliding windows, we found that the generated step networks exhibited a certain amount of volatility, potentially due to data incompleteness or a variance in Twitter usage patterns in different countries, for example, the use of Twitter tends to be more prevalent in the UK and the USA than in other countries such as Germany. We use overlapping sliding windows in an attempt to smooth this volatility, where the overlap is a period of one week.

Another factor that can influence volatility is related to nodes that are intermittently present in the step networks. For example, an offline extreme right event may lead to increased activity from certain Twitter accounts or references to external media nodes. As a dynamic community timeline is created by matching step communities to existing dynamic communities over successive steps, we address this issue as follows:

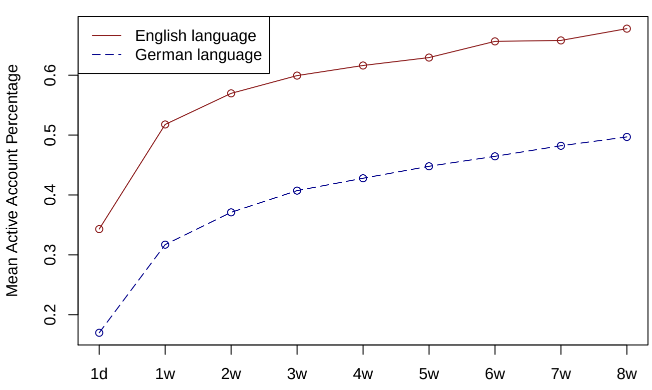


Figure 1: Mean percentage of Twitter accounts active at increasing time scales (1 day up to 8 weeks) for English and German language data sets, between June 2012 and November 2012.

1. Rather than solely relying on the most recent observation (referred to as the *front*) in an existing dynamic community timeline for comparison with the set of step communities at each step, we consider all historical step communities in a timeline as comparison candidates. This permits the consideration of those nodes that are intermittently active.

2. We use a modified version of the Jaccard coefficient for binary sets to calculate the similarity between a step community C_{ta} and a single candidate historical step community D_{tb} belonging to an existing dynamic community timeline, based on the *undirected cluster representativeness* metric suggested by Bourqui et al. [6]:

$$\mathrm{sim}(C_{ta}, D_{tb}) = \sqrt{\frac{|C_{ta} \cap D_{tb}|}{|C_{ta}|} \times \frac{|C_{ta} \cap D_{tb}|}{|D_{tb}|}}$$

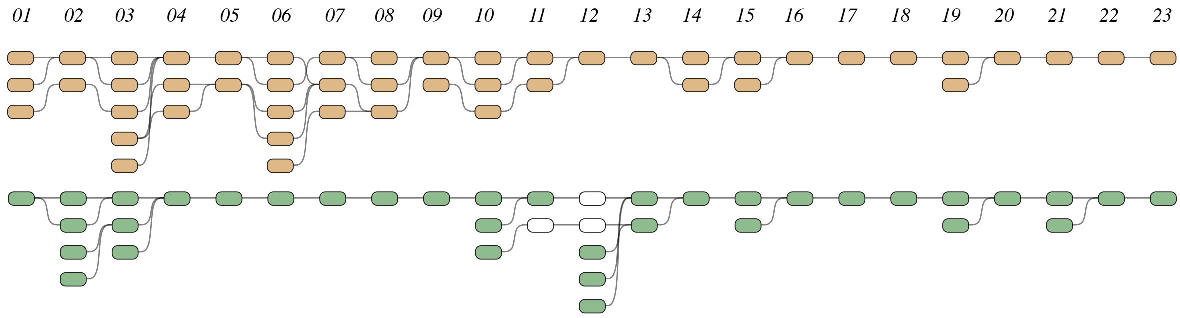
3. The overall similarity of a step community with the entire set of candidate communities belonging to an existing dynamic community timeline is calculated as an exponential weighted moving average of the individual similarities, with a decay factor $\alpha = 0.5$. A match occurs if the overall similarity ≥ 0.25. This is in line with the range of threshold values used in the original Greene et al. method evaluation [18].

ANALYSIS

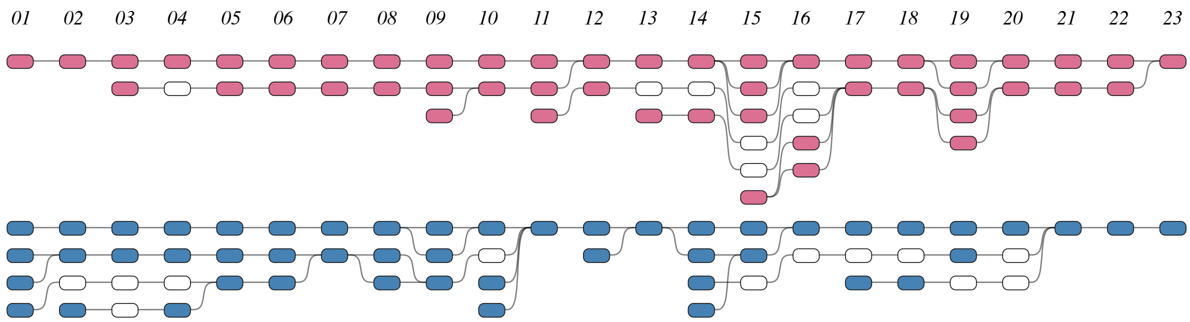
Persistent Dynamic Communities

The method described in the previous section was applied to our two case study data sets, on data collected from June 1st, 2012 to November 16th, 2012. Using a sliding window length of two weeks with a one week overlap resulted in twenty-three time steps. A network representation was derived for each of these steps, and the dynamic community matching process was then applied to these step networks. In our analysis, we are particularly interested in *persistent dynamic communities*, where a community is defined as persistent if it has members active in all time steps. The total number of such dynamic communities found in the English language and German language data sets were fifteen and four respectively. We have selected two persistent communities from each data set for detailed analysis, and timeline diagrams of the constituent step communities can be found in Figures 2a and 2b.

From an initial inspection of these timeline diagrams, it can be seen that these dynamic communities exhibit a certain amount of volatility, with numerous *merge* and *split* life-cycle



(a) EDL (top) and BNP (bottom) communities, containing an average of 14.9% of the nodes in each step network ($\sigma = 2\%$)



(b) German non-electoral (top) and NPD (bottom) communities, containing an average of 50% of the nodes in each step network ($\sigma = 7\%$)

Figure 2: Timelines of selected persistent dynamic communities for the (a) English and (b) German language datasets, from June 2012 (step $t = 1$) to mid-November 2012 (step $t = 23$). Each step corresponds to a two week window, with one week overlaps. White rectangles indicate that the associated dynamic community was not matched in the corresponding step.

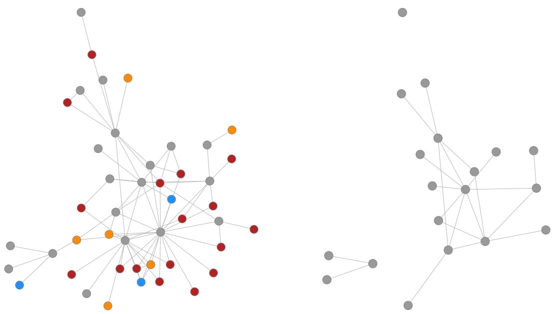
events occurring. As in [18], a merge occurs if multiple existing dynamic communities are matched to a single step community at time t. A split occurs if a single dynamic community is matched to multiple step communities at time t. On occasion, we have found that an existing dynamic community may be a candidate for both a merge and a split event at a particular time t. In this scenario, we give precedence to merge events and a new dynamic community is created for the step community that generates the split. Both timeline diagrams also include branches of step communities that are distinct upon initial creation, but become merged in a subsequent step.

An analysis of the nodes in the first English language community in Figure 2a shows that it is associated with the *English Defence League* (EDL), a street protest movement opposed to the alleged spread of radical Islamism within the UK. This community also contains nodes associated with the *British Freedom* party, a splinter group from the *British National Party* (BNP) that formed an alliance with the EDL in 2012 [16, 25]. We observe the presence of *Casuals United*, a protest group formed from an alliance of football hooligans, also linked with the EDL. The second English language community is primarily associated with the BNP, with nodes from other groups such as *Combined ex-Forces* (CxF), *Infidels* and *The British Resistance* also present [15]. Other notable persistent dynamic communities from this data set include two white power/national socialist communities largely consisting of North American and South African nodes respectively.

The first of the selected German language communities shown in Figure 2b appears to be associated with a variety of non-electoral groups. These include *außerparlamentarischer Widerstand* (non-parliamentary resistance) entities, *Freies Netz* (neo-Nazi collectives), along with various "information/news portals" [26]. Two organizations banned by the German authorities in 2012, namely *Spreelichter* [29] and *Besseres Hannover* [32], are also present. The second German language community is electoral in nature, associated with the *Nationaldemokratische Partei Deutschlands* (National Democratic Party of Germany - NPD), and includes nodes representing regional NPD offices and individual politicians. Although this community appears to be associated with regions across Germany, a smaller persistent NPD community, localized to the federal state of Thüringen can also be observed. This smaller community contains a mixture of electoral (NPD) and non-electoral nodes.

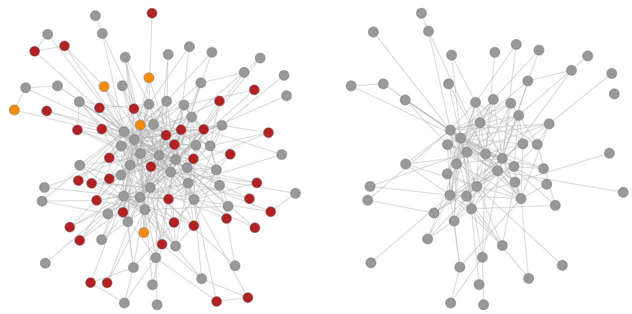
Community Structure

In this section, we discuss the merits of using a single network representation of heterogeneous node types in our analysis of extreme right communities. As the online presence of these groups extends beyond individual networks such as Twitter or Facebook, the proposed representation permits the structure of these wider communities to be revealed, which would otherwise not be evident if analysis was restricted to a single network.



(a) All nodes (b) Twitter nodes

Figure 3: BNP community. Filtering results in central node loss and disconnection (grey=Twitter, blue=Facebook, orange=YouTube, red=other websites).

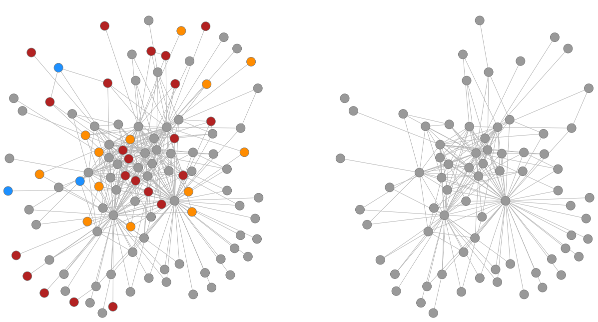


(a) All nodes (b) Twitter nodes

Figure 5: German non-electoral community. Filtering results in central node loss (grey=Twitter, orange=YouTube, red=other websites).

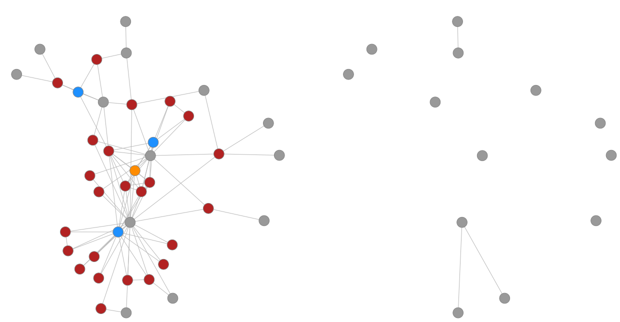
We illustrate this by visualizing individual step communities belonging to the persistent dynamic communities selected from the data sets, as described in the previous section. Network diagrams of these communities were created with Gephi [5], using the Yifan Hu layout. Figure 3 contains diagrams for a BNP step community, with Figure 3a presenting the community with all nodes, while non-Twitter nodes have been filtered in Figure 3b (42% of nodes and 28% of edges are retained), resulting in the loss of important central nodes such as the official BNP website and YouTube channel. The contrast between Figures 3a and 3b illustrates the important linking role played by non-Twitter nodes, as the observable network is disconnected when they are not considered. In addition, the use of heterogeneous nodes enables us to immediately identify this community as being associated with the BNP. Similar diagrams for an EDL step community can be seen in Figure 4, with 66% of nodes and 56% of edges retained with filtering (Figure 4b). Although disconnection is not introduced, it nevertheless results in the loss of central nodes such as the official EDL and British Freedom websites.

We also present examples from the selected German language communities. The filtering of the non-electoral community in Figure 5 (58% of nodes and 46% of edges are retained) produces a similar effect to that of the EDL community, where important central nodes such as the *Besseres Hannover* website and those associated with other relevant information portals are removed. Our last example in Figure 6 demonstrates the potential for severe loss of community structure when filtering is applied (32% of nodes and 3% of edges are retained). In this example, although there is almost no communication (in terms of mentions and retweets) between the Twitter nodes, they are considered members of the same community within the wider network.



(a) All nodes (b) Twitter nodes

Figure 4: EDL community. Filtering results in central node loss (grey=Twitter, blue=Facebook, orange=YouTube, red=other websites).

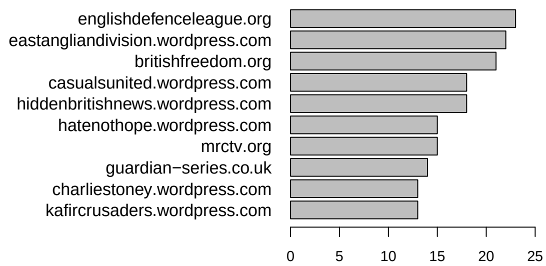


(a) All nodes (b) Twitter nodes

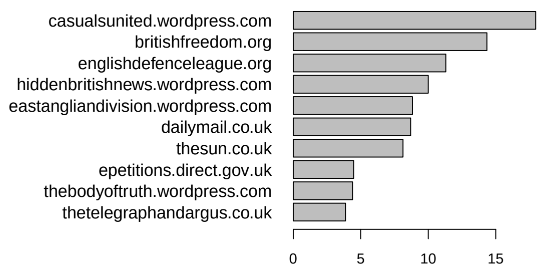
Figure 6: NPD community. Filtering results in central node loss and disconnection (grey=Twitter, blue=Facebook, orange=YouTube, red=other websites).

Community Characterization

We now provide a characterization of the selected persistent dynamic communities shown in Figure 2, with a detailed analysis of the member nodes; in particular, those associated with external (non-Twitter) websites. Due to the sensitivity of the subject matter, and in the interests of privacy, individual accounts and profiles from networks such as Twitter, Facebook and YouTube are not explicitly identified. Instead, we restrict discussion to known extreme right groups and their

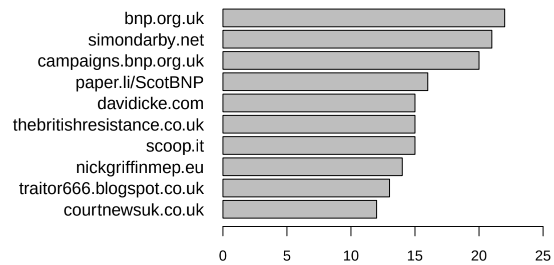


(a) Membership frequency

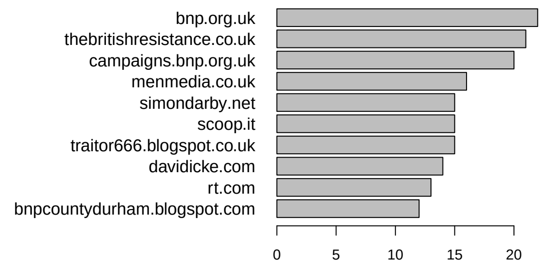


(b) Normalized degree

Figure 7: EDL community characterization, based on two alternative rankings of website nodes.



(a) Membership frequency



(b) Normalized degree

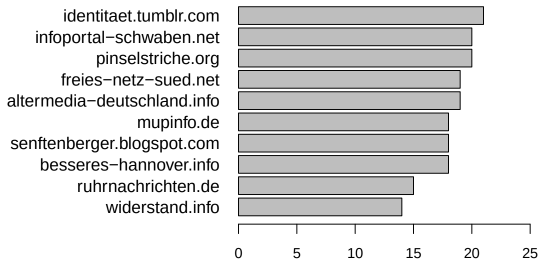
Figure 8: BNP community characterization, based on two alternative rankings of website nodes.

affiliates. For each of the selected communities, we provide two alternative top ten rankings of the website nodes; the first ranks the nodes in terms of their frequency of step membership, while the second ranks them in terms of their total degree across all steps, normalized with respect to the total number of steps. In both cases, the membership ranking distribution tends to be positively skewed, with a set of core community members assigned in the majority of steps, accompanied by a larger set of peripheral members who were assigned intermittently.

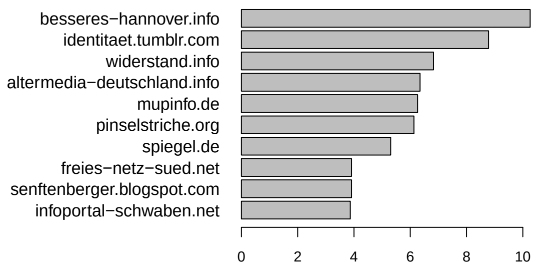
Figure 7 presents the two rankings of website nodes for the EDL community. As might be expected, the frequency ranking includes the official EDL and British Freedom websites. Other websites and blogs affiliated with the EDL are also present, including a Casuals United blog. Of similar interest is a blog that appears to be a mocking reference to the established anti-extremist organization, *HOPE not hate*. The degree ranking produces broadly similar results, with notable exceptions being the appearance of mainstream media websites. An analysis of the original URLs finds them to be associated with populist newspaper articles on topics such as the existence of UK sex grooming gangs, Muslim integration, and immigration in general. Separate studies have found interest in these topics by other extreme right groups [3], and it would appear that mainstream media may unwittingly play a role in the occasional promotion of material that coincides with extreme right ideology. Other articles that are interpreted as perceived media persecution of groups such as the EDL are also promoted. Looking at the non-website nodes, official EDL Twitter and Facebook accounts can be observed, along with those purporting to be affiliates. Similar YouTube channels are also present, including a British Freedom channel that was suspended in late 2012 (this has since been replaced with a new channel according to their website).

We find similar membership composition in the BNP community, where the website rankings are presented in Figure 8. The frequency ranking highlights websites associated with the BNP and that of its current leader, Nick Griffin. As mentioned in an earlier section, this community also contains members associated with The British Resistance, a white nationalist group whose website banner contains the 14-word slogan coined by the American white supremacist David Lane (*"We must secure the existence of our people and a future for White Children"*). As with the EDL community, mainstream media websites appear in the degree ranking, where the corresponding article topics are similar to those promoted by the EDL. The presence of additional groups such as Combined ex-Forces (CxF) and the Infidels can be found when the Twitter and Facebook nodes are inspected. The latter group originally splintered from the EDL, and although it has a minor presence within the EDL community, it would seem that the BNP's efforts to court this group [24] may partly explain its more significant role in this community. The most prominent YouTube node is the official BNP channel, with other channels of a nationalist nature appearing sporadically.

In the case of the German language website rankings, Figure 9 shows blogs and websites from a variety of disparate groups for the non-electoral community. The majority of these are associated with known non-electoral groups, although mainstream media websites are also present. An analysis of the associated articles demonstrates once again the promotion of perceived persecution, for example, the banning of the *Spreelichter* and *Besseres Hannover* groups features heavily here. We also see a connection to electoral

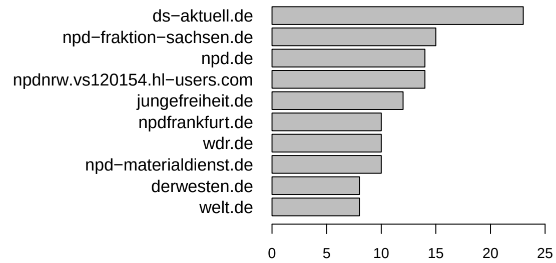


(a) Membership frequency

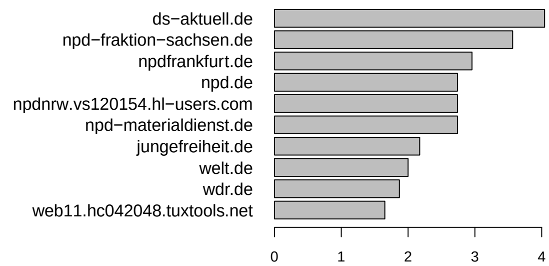


(b) Normalized degree

Figure 9: German non-electoral community characterization, based on two alternative rankings of website nodes.



(a) Membership frequency



(b) Normalized degree

Figure 10: NPD community characterization, based on two alternative rankings of website nodes.

groups with the appearance of the NPD-affiliated MUPInfo website. Further connections to the NPD are visible as various NPD Facebook page nodes are also intermittent members of this community. A notable temporary Facebook member node was a page (no longer available) encouraging "solidarity" with Nadja Drygalla, a member of the 2012 German Olympic rowing team who left the tournament early due to the neo-Nazi connections of her boyfriend, who was a former NPD election candidate [31]. The website rankings for the NPD community in Figure 10 are primarily composed of NPD-affiliated websites, with a minor number of mainstream websites also appearing for the same reasons as before. Both communities feature a moderate YouTube presence, with nodes such as NPD channels, music channels and individual channels featuring videos of demonstrations, including some of the *Unsterblichen* (immortals) marches that were orchestrated by *Spreelichter* [3, 29].

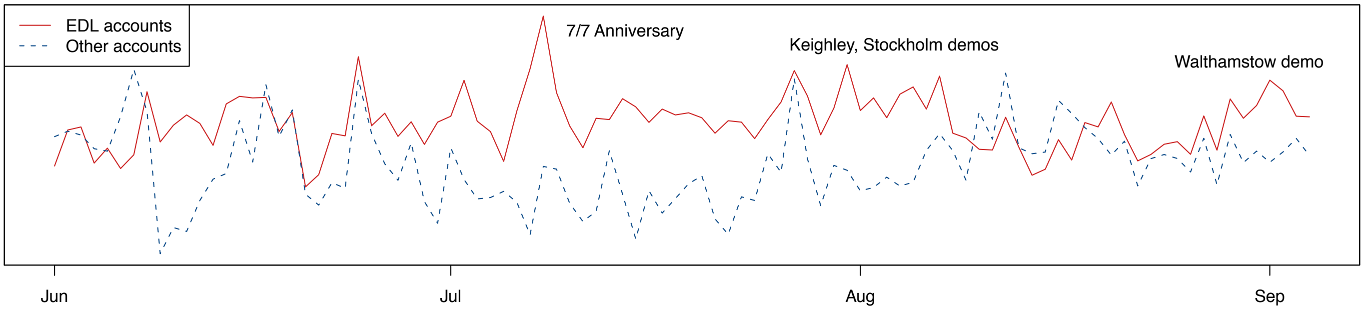
Twitter Activity and External Events

We also perform a brief inspection of community Twitter activity, providing examples for a single persistent dynamic community from both data sets. Based on knowledge of external offline events associated with these communities, we generate three month plots of the daily total tweet counts for (a) the accounts assigned in the corresponding two-week step community and (b) the remaining accounts in the data set, where the raw counts are z-score normalized. In both cases, we find that peaks in tweeting activity by the community accounts may be associated with external events. For example, the EDL activity plot in Figure 11a highlights increased activity around the times of street demonstrations, with other events such as the anniversary of the July 7th, 2005 London bombings being of particular interest to this community. Although the German non-electoral community plot in Figure 11b also contains raised activity for a demonstration, other events such as the *Besseres Hannover* ban (initially banned by the German authorities [32]; their account was subsequently blocked by Twitter within Germany [11]) have a similar impact. These peaks may introduce temporary community members, for example, a file-sharing site containing an archive of the besseres-hannover.info website appears for a number of days at the time of the initial ban.

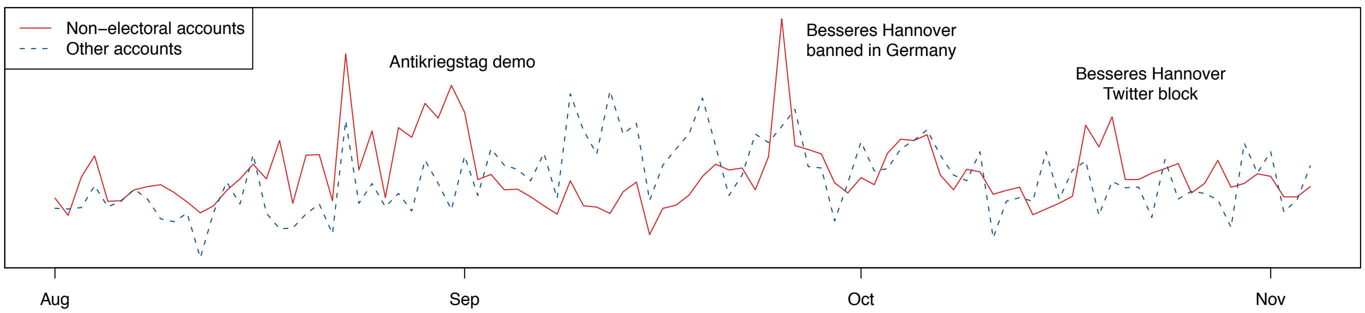
Summary Discussion

In general, the membership composition of the selected communities would appear to broadly correspond with contemporary knowledge of these groups; for example, the distinction between the EDL and the BNP [24]. To a certain extent, we also see divisions according to the four-fold typology suggested by Goodwin et al. [16], where these communities could be characterized by three of the four types; organized political parties (BNP, NPD), grassroots social movements (EDL) and smaller groups (German non-electoral). However, it could also be suggested that some overlap between these types can occur, for example, the presence of the Infidels and British Resistance in the BNP community, or NPD-affiliated nodes in the German non-electoral community. In addition, the finding of Bartlett et al. [4] that online supporters of groups such as the EDL are more likely to demonstrate than the national average may partly explain the increased levels of community Twitter activity at the time of external protests.

We also note the use of official Facebook profiles and YouTube channels by electoral parties and grassroots movements in addition to those maintained by related individuals, while general blogging websites (often hosted in other countries)



(a) EDL community tweet activity from June to September 2012.



(b) German non-electoral community tweet activity from August to November 2012.

Figure 11: Tweet activity plots of communities, produced via z-score normalization of tweet counts, for selected time periods.

appear popular with most groups. Separately, all groups appear to selectively reference mainstream media, directing traffic to material that coincides with associated ideology. At this point, we also emphasize that the network representations used in this analysis do not provide coverage of all online extreme right activity. As mentioned earlier, data collection from Twitter, YouTube and Facebook was restricted to publicly accessible content. Given existing knowledge of the use of online platforms such as Facebook by the extreme right [3, 15], a certain level of incompleteness is to be expected. In addition, the fact that we use Twitter to infer structure within the wider online network of the extreme right may also introduce incompleteness, where the network representations are dependent on the initial identification of relevant profiles.

CONCLUSIONS AND FUTURE WORK

The online activity of extreme right groups has progressed from the use of dedicated websites to span multiple networks, including popular social media platforms such as Twitter, Facebook and YouTube. As its role in the general dissemination of content has previously been established, we have investigated the potential for Twitter to act as one possible gateway to communities located within this wider network. By representing relations between the heterogeneous network entities with a single homogeneous network, we are able to identify extreme right communities that would otherwise not be evident when considering a single online network alone. The use of heterogeneous data provides us with a rich insight into the composition of the resulting communities. Our analysis has focused on the investigation of English and German language communities using two separate data sets, where we have tracked community evolution in these inherently dynamic networks over an extended period of time. Two persistent communities found in each of the data sets were selected for detailed analysis. We have discussed the impact of heterogeneous nodes on community topology, and used these nodes to provide community characterizations, particularly in terms of the extent to which these communities span multiple online platforms.

In our dynamic community analysis of both data sets, we have found that the individual step networks tended to exhibit a considerable level of volatility. Although this may be due in part to data incompleteness, it is possible that such volatility may simply be a feature of the online extreme right presence. It is likely that this corresponds to factors such as the continual emergence of new groups [25], while events such as the jailing of the EDL's Tommy Robinson [28] or a potential ban of the NPD [1] are also likely to impact volatility. We would like to address this issue in future work, which may involve an extension of the process currently used to track dynamic communities. In addition, it would be worthwhile to investigate the potential for other social media platforms such as Facebook to act as gateways to online extreme right activity, where a comparison could be made with the current results. This should also help to address the issue of data incompleteness.

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REFERENCES

1. Arzheimer, K. Why trying to ban the NPD is a stupid idea. *Extremis* (01 2013).
2. Bakshy, E., Hofman, J. M., Mason, W. A., and Watts, D. J. Everyone's an Influencer: Quantifying Influence on Twitter. In *Proceedings of the fourth ACM international conference on Web search and data mining*, WSDM '11, ACM (New York, NY, USA, 2011), 65–74.
3. Baldauf, J., Groß, A., Rafael, S., and Wolf, J. Zwischen Propaganda und Mimikry. Neonazi-Strategien in Sozialen Netzwerken. *Amadeu Antonio Stiftung* (2011).
4. Bartlett, J., Birdwell, J., and Littler, M. The New Face of Digital Populism. *Demos* (2011).
5. Bastian, M., Heymann, S., and Jacomy, M. Gephi: An open source software for exploring and manipulating networks. In *Proc. 3rd Int. Conf. on Weblogs and Social Media (ICWSM'09)* (2009), 361–362.
6. Bourqui, R., Gilbert, F., Simonetto, P., Zaidi, F., Sharan, U., and Jourdan, F. Detecting Structural Changes and Command Hierarchies in Dynamic Social Networks. In *Proc. Int. Conf. on Advances in Social Network Analysis and Mining (ASONAM'09)* (2009), 83–88.
7. Burris, V., Smith, E., and Strahm, A. White Supremacist Networks on the Internet. *Sociological Focus 33*, 2 (2000), 215–235.
8. Caiani, M., and Wagemann, C. Online Networks of the Italian and German Extreme Right. *Information, Communication & Society 12*, 1 (2009), 66–109.
9. Chau, M., and Xu, J. Mining communities and their relationships in blogs: A study of online hate groups. *Int. J. Hum.-Comput. Stud. 65*, 1 (Jan. 2007), 57–70.
10. Clauset, A., and Eagle, N. Persistence and periodicity in a dynamic proximity network. In *DIMACS Workshop on Computational Methods for Dynamic Interaction Networks* (2007).
11. Connolly, K. Twitter blocks neo-Nazi account in Germany. *The Guardian* (10 2012).
12. De Choudhury, M., Mason, W. A., Hofman, J. M., and Watts, D. J. Inferring Relevant Social Networks from Interpersonal Communication. In *Proc. 19th Int. Conf. on World Wide Web (WWW '10)* (2010), 301–310.
13. Dhillon, I. S. Co-clustering documents and words using bipartite spectral graph partitioning. In *Knowledge Discovery and Data Mining* (2001), 269–274.
14. Gerstenfeld, P. B., Grant, D. R., and Chiang, C.-P. Hate Online: A Content Analysis of Extremist Internet Sites. *Analyses of Social Issues and Public Policy 3*, 1 (2003), 29–44.
15. Goodwin, M., Jungar, A.-C., Jupskås, A. R., Kreko, P., Meret, S., Pankowski, R., Učeň, P., and Witte, R. Preventing and Countering Far-Right Extremism: European Cooperation. *Ministry of Justice, Sweden and Institute for Strategic Dialogue* (2012).
16. Goodwin, M., and Ramalingam, V. The New Radical Right: Violent and Non-Violent Movements in Europe. *Institute for Strategic Dialogue* (2012).
17. Greene, D., and Cunningham, P. Spectral co-clustering for dynamic bipartite graphs. In *Workshop on Dynamic Networks and Knowledge Discovery (DyNAK'10)* (2010).
18. Greene, D., Doyle, D., and Cunningham, P. Tracking the Evolution of Communities in Dynamic Social Networks. In *Proc. Int. Conf. on Advances in Social Networks Analysis and Mining (ASONAM '10)* (2010), 176–183.
19. Greene, D., O'Callaghan, D., and Cunningham, P. Identifying topical twitter communities via user list aggregation. In *Proc. 2nd International Workshop on Mining Communities and People Recommenders (COMMPER'12)* (2012).
20. Krebs, V. E. Mapping Networks of Terrorist Cells. *Connections 24*, 3 (2002), 43–52.
21. Lancichinetti, A., and Fortunato, S. Consensus clustering in complex networks. *Sci. Rep. 2* (03 2012).
22. Lancichinetti, A., Radicchi, F., Ramasco, J., Fortunato, S., and Ben-Jacob, E. Finding Statistically Significant Communities in Networks. *PLoS ONE 6*, 4 (2011), e18961.
23. Lehmann, S., Schwartz, M., and Hansen, L. Biclique communities. *Physical Review E 78*, 1 (2008), 016108.
24. Lowles, N. Where now for the British far-right? *Extremis* (09 2012).
25. Mulhall, J. Beginner's guide to new groups on Britain's far right. *Extremis* (10 2012).
26. Netz Gegen Nazis. Nach den Portal-Sperren im Internet: Hier geht der Hass weiter. *netz-gegen-nazis.de* (2012).
27. O'Callaghan, D., Greene, D., Conway, M., Carthy, J., and Cunningham, P. An Analysis of Interactions Within and Between Extreme Right Communities in Social Media. In *Proc. 3rd Int. Workshop on Mining Ubiquitous and Social Environments (MUSE'12)* (2012), 27–34.
28. Press Association. EDL leader jailed for using friend's passport to travel to New York. *The Guardian* (01 2013).
29. Radke, J. Das Ende der Nazi-Masken-Show. *Die Zeit* (06 2012).
30. Sparrow, M. K. The application of network analysis to criminal intelligence: An assessment of the prospects. *Social Networks 13*, 3 (1991), 251 – 274.
31. Sport. Ruderin Drygalla verlässt Olympiateam wegen NPD-Kontakten. *Die Zeit* (08 2012).
32. Störungsmelder. Nach Razzia bei Neonazi-Gruppierung "Besseres Hannover" folgt ein Verbot. *Die Zeit* (09 2012).
33. Teng, C.-Y., Lin, Y.-R., and Adamic, L. A. Recipe recommendation using ingredient networks. In *Proc. 3rd Annual ACM Web Science Conference (WebSci'12)* (2012), 298–307.