An Analysis of Interactions Within and Between Extreme Right Communities in Social Media

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Abstract. Many extreme right groups have had an online presence for some time through the use of dedicated websites. This has been accompanied by increased activity in social media platforms in recent years, enabling the dissemination of extreme right content to a wider audience. In this paper, we present an analysis of the activity of a selection of such groups on Twitter, using network representations based on reciprocal follower and interaction relationships, while also analyzing topics found in their corresponding tweets. International relationships between certain extreme right groups across geopolitical boundaries are initially identified. Furthermore, we also discover stable communities of accounts within local interaction networks, in addition to associated topics, where the underlying extreme right ideology of these communities is often identifiable.

Keywords: network analysis, social media, community detection, topic modelling, Twitter, extreme right

1 Introduction

Groups associated with the extreme right have maintained an online presence for some time [12], where dedicated websites have been employed for the purposes of content dissemination and member recruitment. Recent years have seen increased activity by these groups in social media platforms, given the potential to access a far wider audience than was previously possible [31]. In this paper, we present an analysis of the activity of a selection of these groups on Twitter, where the focus is upon groups of a fascist, racist, supremacist, extreme nationalist or neo-Nazi nature, or some combination of these. Twitter’s features enable extreme right groups to disseminate hate content with relative ease, while also facilitating the formation of communities of accounts around variants of extreme right ideology. Message posts (tweets) by members of these groups, to which access is usually unrestricted, are often used to redirect users to content hosted on external websites, including dedicated websites managed by particular groups, or content sharing platforms such as YouTube.
For the purpose of this analysis, we have retrieved data for a selection of identified extreme right Twitter accounts from eight countries. Our initial objective is the identification of international relationships between certain groups that transcend geopolitical boundaries. This involves the analysis of two network representations of the accounts from the eight country sets, based on reciprocal follower and interaction relationships. Here, interactions are derived from observations of mentions and retweets between accounts. It appears that a certain amount of international awareness exists between accounts based on the follower relationship, while interactions indicate stronger relationships where linguistic and geographical proximity are highly influential.

This leads to our next objective of analyzing communities of extreme right accounts found within local interaction networks, where locality is considered in terms of nationality or linguistic proximity. Tweet content is also analyzed for the purpose of generating interpretable descriptions for the detected communities, in addition to the discovery of latent topics associated with interactions between the member accounts. We find that matrix factorization techniques are more suitable for topic analysis of these particular data sets. By using the same account profile document representation for both community description generation and topic discovery, it is possible to generate a mapping between the detected communities and their associated topics. Each community description and corresponding topic mapping can then be used in conjunction with manual analysis of the account profiles, tweets and external websites to provide an interpretation of the underlying community ideology. While we observe some community division along electoral and non-electoral lines, this is not clear in all cases. Other notable findings include communities of a more traditional conservative nature, opposition to bodies such as the EU, and the influence of concerns such as counter-Jihad on international relationships.

In Section 2, we provide a description of related work based on the online activities of extremist groups. The collection of the Twitter data sets is then discussed in Section 3. Analysis of the international relationships between extreme right groups from the eight countries is presented in Section 4. Next, in Section 5 we describe the discovery of extreme right communities within local interaction networks, including the methodology used for network derivation, community detection, stability ranking, description generation and topic analysis. We focus on two case studies using English and German language networks, where we offer an interpretation of a selection of these communities. Finally, the overall conclusions are discussed in Section 6 and some suggestions for future work are made.

2 Related Work

The online activities of different varieties of extremist groups including those associated with the extreme right have been the subject of a number of studies. Burris et al. used social network analysis to study a network based on the links between a selection of white supremacist websites [2]. They found this network to
be relatively decentralized with multiple centres of influence, while also appearing to be mostly undivided along doctrinal lines. Similar decentralization and multiple communities were found by Chau and Xu in their study of networks built from users contributing to hate group and racist blogs [5]. They also found that some of these groups exhibited transnational characteristics. In a similar approach to that of Burris et al., Tateo analyzed groups associated with the Italian extreme right, using networks based on links between group websites [6]. Caiani and Wagemann studied similar Italian groups along with those from the German extreme right, where they found the German network to be structurally centralized to a greater extent than that of the Italian groups [7]. The contents of websites belonging to central nodes within Russian extreme right networks were analyzed by Zuev [8]. In their review of the conservative movement in the USA, Blee and Creasap [9] discuss the engagement in online activity as part of an overall mobilization strategy by the more extremist groups within it.

The potential for online radicalization through exposure to jihadi video content on YouTube was investigated by Bermingham et al., where it was suggested that a potentially increased online leadership role may be attributed to users claiming to be women, according to centrality, network density and average speed of communication [10]. Sureka et al. also studied the activity of extremist users within YouTube, investigating content properties along with hidden network communities [11]. Bartlett et al. performed a survey of European populist party and group supporters on Facebook [3], while Baldauf et al. also investigated the use of Facebook by the German extreme right [4]. As the majority of this work involved the study of dedicated websites managed by extreme right groups, we believed that an analysis of their activity in social media, focusing specifically on extreme right Twitter communities, would complement this by providing additional insight into the overall online presence of these groups.

### 3 Data

Twitter data was collected to facilitate the analysis of contemporary online extreme right activity. We identified initial sets of relevant accounts for a selection of countries, where the country selection was informed by prior knowledge of extreme right groups. Based on earlier studies [4,7], the criteria used to identify relevant accounts included profiles containing references to known groups or employing extreme right symbols; recent tweet activity; similar Facebook/YouTube accounts; reciprocal follower relationships with known relevant accounts; accounts with self-curated Twitter lists containing relevant accounts; extreme right media accounts such as record labels and concert organisers. Details of these country sets can be found in Table 1.

Certain accounts were not included, such as inactive accounts, or those that were not deemed to be related to the extreme right. These included traditional conservative (e.g. centre-right) accounts, non-conformists/anti-establishment accounts considered to be left-wing, and conspiracy theorists. As we were initially interested in non-electoral extreme right groups [12], higher-profile politicians or
Table 1. Data set sizes for eight countries of interest.

| Country  | Number of Accounts |
|----------|--------------------|
| France   | 25                 |
| Germany  | 53                 |
| Greece   | 45                 |
| Italy    | 17                 |
| Spain    | 43                 |
| Sweden   | 21                 |
| UK       | 32                 |
| USA      | 32                 |

Political parties were ignored for the most part, with a minor number of these accounts included where it was felt that there was a close association with relevant accounts. An obstacle was the language barrier, where the use of online translation tools did not always prove helpful in the interpretation of ambiguous profiles. In cases where the relevance of an account profile was inconclusive, that account was ignored. Twitter data including followers, friends, tweets and list memberships were retrieved for each of the selected accounts during the period March – August 2012, as limited by the Twitter API restrictions effective at the time.

4 International Relationships

We began with an analysis of the international relationships between the identified extreme right groups, based on interactions between the accounts from the eight country sets. An interaction is defined as one account “mentioning” another account within a tweet, or an account “retweeting” a tweet generated by another account. Both types of event were included in order to address issues of data sparsity and incompleteness. We were particularly interested in reciprocal activity between accounts, where such activity can potentially indicate the presence of a stronger relationship. For example, previous work has used reciprocal mentions between accounts to represent dialogue [13]. An interactions network was created with n nodes representing accounts, and m undirected weighted edges representing reciprocal mentions and retweets between pairs of accounts, with weights corresponding to the number of interactions. All observed interactions found in the retrieved data sets were considered. Any connected components of size < 5 were filtered. In addition, we were also interested in international follower relationships, and a similar undirected unweighted network was created to capture reciprocal follower links between the accounts in different country sets. Throughout this analysis, due to the sensitivity of the subject matter, and in the interest of privacy, individual accounts are not identified; instead, we restrict discussion to known extreme right groups and their affiliates.
4.1 International Follower Awareness

The international followers network can be seen in Fig. 1. As might be expected, most of the follower relationships are between accounts from the same country, although a certain number of international relationships are evident. It would appear that linguistic and geographical proximity is influential here, for example, we can observe relationships between the Spanish and Italian (and to a lesser extent, French) accounts, with strong connections also between the UK and USA. Similar behaviour with respect to social ties in Twitter has been identified by Takhteyev et al. and Kulshrestha et al. [14,15]. However, there appear to be some exceptions to the influence of geographical proximity, most notably, Swedish (yellow) and Italian (green) accounts that are not co-located with their respective country nodes. In both cases, the majority of tweets from these accounts are in English, which presumably ensures a wider audience. The former account is a Swedish representative of a pan-Scandinavian group espousing national socialist ideas, who appears to be interacting with many international accounts, particularly from the USA. The Italian account is a national socialist whose tweets often contain URLs to music or video content hosted on external websites, but it is unclear if a direct association exists with any particular group. From an analysis of other central nodes in the network (using betweenness centrality), it would seem that those involved in the dissemination of material via external URLs, or media platforms such as extreme right news websites and ra-

![Fig. 1. International reciprocal followers network, containing 257 nodes and 2,100 edges. Node size is proportional to degree.](image-url)
dio stations, are attempting to raise awareness amongst a variety of international followers. This is particularly the case when the English language is used.

4.2 International Interactions

The follower-based relationship between international accounts could be considered as passive when compared with that of the interaction networks, where such interactions can be indicative of actual dialogue between accounts. The interactions network in Fig. 2 is somewhat smaller than the corresponding network in Fig. 1. We also observe that the Greek community is now disconnected from the largest connected component. Apart from this, the network has a similar structure to that of the followers network, in that most interaction occurs within individual country-based communities. Connections between these communities do exist, but are fewer than in the followers network. The influence of linguistic proximity appears to take precedence here, with the use of English playing a major role as mentioned in the previous section. For example, a relatively large number of connections remain present between accounts in the UK and USA. In the case of the German community, while the followers network contains a variety of connections with other international accounts, this has now been reduced to connections between two German accounts and a small number of UK accounts, in addition to an account acting as an English language Twitter channel for a Swedish nationalist group. Similarly, the Swedish account co-located with the USA community is the same account as that in the followers network, who appears to be involved in many English-based interactions with international accounts.

![Figure 2](image-url)

**Fig. 2.** International reciprocal interactions network, containing 218 nodes and 1,186 edges. Node size is proportional to degree.
5 Local Analysis

Following the analysis of international relationships described in the previous section, we then proceeded to analyze interactions within local networks with the objective of detecting specific communities of related accounts, focusing on two data sets as case studies. Based on our observation of linguistic proximity at the international level, we merged the UK and USA data sets to produce a single English language data set for one case study, while the second focused on the German language data set. In both cases, we created expanded versions of the initial data sets to facilitate a more detailed analysis, where all available data were also retrieved for those accounts having a reciprocal follower relationship with more than one of the original identified accounts. As Twitter follower relationships tend to exhibit lower reciprocity than other social networking sites [16], the understanding was that this action would be largely isolated to accounts having a relatively stronger relationship with those from the original data sets. This process resulted in the inclusion of 1,513 and 448 accounts respectively in the expanded English and German language data sets.

5.1 Community Detection in Interaction Networks

For the purpose of community detection based on account interactions, we constructed undirected interaction networks \((G)\) from the expanded data sets. As with the international analysis, only reciprocal edges were used in order to capture stronger relationships, all observed interactions were included, and connected components of size \(< 5\) were filtered. We used our variant of the work by Lancichinetti & Fortunato to generate a set of stable consensus communities from such a network \([17,18]\), where 100 runs of the OSLOM algorithm \([19]\) were used to generate the consensus communities. Following this, the consensus communities were ranked based on the stability of their members with respect to the corresponding consensus matrix \(M\). For a given consensus community \(C\) of size \(c\), we computed the mean of the values \(M_{xy}\) for all unique pairs \((L_x, L_y)\) assigned to \(C\); this value has the range \([0, 1]\). We then computed the mean expected value for a community of size \(c\) as follows: randomly select \(c\) unique nodes from \(G\), and compute their mean pairwise score from the corresponding entries in \(M\). This process was repeated over a large number of randomised runs, yielding an approximation of the expected stability value. The widely-used adjustment technique introduced by \([20]\) was then employed to correct for chance agreement:

\[
\text{CorrectedStability}(C) = \frac{\text{Stability}(C) - \text{ExpectedStability}(C)}{1 - \text{ExpectedStability}(C)}
\]  

(1)

A value close to 1 will indicate that \(C\) is a highly-stable community. As higher values of the threshold parameter \(\tau\) used with the consensus method resulted in sparser consensus networks, and having tested with values of \(\tau\) in the range \([0.1, 0.9]\), we selected \(\tau = 0.5\) as a compromise between node retention and
more stable communities. The resolution of communities found by OSLOM is
directly controlled by the associated parameter $P$, which has a default value
of $0.5$ in the implementation. Although Lancichinetti et al. state that $P = 0.1$
delivered an excellent performance on the benchmark graphs used in the OSLOM
paper, they also suggest that it would be more appropriate to estimate $P$ on
a case by case basis [19]. We found that using $P = 0.1$ tended to detect a
larger number of relatively small communities. Increasing values of $P$ ([0.1, 0.9])
produced smaller numbers of larger communities having higher stability scores
(with $\tau = 0.5$). Given this, for both data sets, we used the corresponding value
of $P$ that produced the highest mean stability score to generate communities
for detailed analysis. Further details of the $P$ values used can be found later
in the case study sections. For the purpose of this analysis, we focus on larger
consensus communities having $\geq 10$ members.

5.2 Community Descriptions

The content of tweets was also analyzed for the purpose of (1) generating inter-
pretable descriptions for the detected communities, and (2) identifying latent
topics associated with interactions between the accounts assigned to these com-
munities. Following the approach of Hannon et al. [21], we generated a “profile
document” for each node in an interactions network, consisting of an aggregation
of their corresponding tweets, from which a tokenized representation was pro-
duced. Our initial experiments used all available terms in the account documents,
where the tokenization process involved the exclusion of URLs and stopwords
(additional social networking stopwords such as “ff”, “facebook” etc. were in-
cluded with multiple language stopword lists), normalization of diacritics, and
stemming of the remaining terms. Low-frequency terms (appearing in < 4 ac-
count documents) and documents containing < 10 terms were excluded. These
profile documents were then represented by log-based TF-IDF term vectors,
which were subsequently normalized to unit length.

However, we encountered two issues with the use of all available tweet terms
as candidates for this representation. It transpired that the expansion of this
data set through the addition of reciprocal follower accounts of the original
accounts resulted in the inclusion of accounts whose mother tongue was not En-
lish, for example, accounts from South Africa and Sweden. As a result, generic
non-English terms were treated as highly discriminating due to their relative low
frequency within the full set of English terms across all documents. Separately,
the use of all terms required extensive maintenance of a multilingual stopword
list. To address these issues, we excluded all terms apart from hashtags when
generating the account documents, which greatly reduced the number of re-
quired stopwords, while also promoting more discriminating non-English terms
in subsequent analysis. As it was possible to generate hashtag-based account
documents for 96% of English language accounts and 92% of German language
accounts present in the corresponding interaction networks, it was felt that suf-
cient coverage of the accounts was retained. In addition, the dimensionality
of the vector representations was also considerably reduced by the sole use of
hashtags. Having produced these TF-IDF vectors, each community description was generated by selecting the subset of vectors for the accounts assigned to the community, and calculating a mean vector $D$ from this subset matrix. The final community description consisted of the top ten hashtags from $D$. For the remainder of this paper, all hashtags are presented without the preceding “#” character.

5.3 Topic Analysis

Topic modelling is concerned with the discovery of latent semantic structure or topics within a set of documents, which can be derived from co-occurrences of words and documents [22]. This strategy dates back to the early work on latent semantic indexing by Deerwester et al. [23]. Popular methods include probabilistic models such as latent Dirichlet allocation (LDA) [24], or matrix factorization techniques such as Non-negative matrix factorization (NMF) [25]. These have previously been successfully applied in social media analytics, for example, the work of Ramage et al. [26], Weng et al. [27], and Saha and Sindhwani [28]. We initially evaluated both LDA and NMF-based methods with the account document representations described above, where NMF was found to produce the most readily-interpretable results. This appeared to be due to the tendency of LDA to discover topics that over-generalized [29].

The observed connections between the countries at the international level suggested that specific topics associated with smaller groups of accounts were present in the extended English and German language data sets. Given this, in the trade-off between generality and specificity, we opted for the latter in this particular analysis, and so used NMF with the same TF-IDF account vectors as before for topic analysis. Here, the IDF component ensured a lower ranking for less discriminating terms, thus leading to the discovery of more specific topics. Having constructed an $n \times m$ term-document matrix $V$, where each column contained a TF-IDF account vector, NMF produced two factors; $W$, an $n \times T$ matrix containing topic basis vectors and $H$, a $T \times m$ matrix containing the topic assignments for each account document. To address the instability introduced by random initialization in standard NMF, we employed the NNDSVD method proposed by Boutsidis and Gallopoulos [30], which is particularly suitable for sparse matrices.

Although the interactions network topology and general topic analysis provided two different views on a particular data set, in this analysis, we were primarily interested in the communities within the interactions networks, where the associated topics could be used for further interpretation of the account membership. As the same hashtag-based account document TF-IDF vectors were used for both community description generation and topic detection, it was possible to generate a mapping between the detected communities and topics. For each community, we ranked the topics according to the cosine similarity between its mean community hashtag description vector $D$ and the topic basis vectors $W$. This method occasionally detected multiple similar topics for a particular community, which was to be expected given that individual account documents
could themselves be associated with multiple topics. To avoid redundant mappings, we ignored any topics having a cosine similarity < 0.1 with each $D$ vector, as using this threshold appeared to produce relevant community-topic mappings in general for both data sets.

5.4 Case Study: English language

![English language interactions network](image)

**Fig. 3.** English language interactions network with 1,034 nodes and 9,429 edges. Node size is proportional to degree. Consensus communities ($P = 0.4$, #members $\geq 10$) are labelled.

An interactions network (Fig. 3) was created for the English language data set, consisting of 1,034 nodes and 9,429 edges. Due to the effect of the resolution parameter $P$ on the communities found by OSLOM, we measured the mean stability score ($\tau = 0.5$) and number of communities found for values of $P$ in $[0.1, 0.9]$, using the consensus community method previously described. A plot of the mean score and sizes can be found in Fig. 4, where it can be seen that the highest mean score was generated for $P = 0.4$, while the number of communities found had also stabilized at $\sim 34$. Eight communities having at least ten members were found for $P = 0.4$ (86% of total network account nodes), and their corresponding hashtag descriptions and stability scores can be found in Table 2. These communities have been manually annotated with identifiers for reference in the subsequent discussion, based on an analysis of the account
member composition (for example, EAST, LONDON). Topic analysis was also performed using NMF, with number of topics \( T = 15 \). Having experimented with a range of values for \( T \), we used \( T = 15 \) as this was the smallest value which led to the emergence of non-English language topics.

The accounts in the SA community appear to be white South Africans, with some profiles containing racist and national socialist references. Many tweets from these accounts relate to perceived cultural threats from black South Africans that are often retweeted by international accounts. Most of the description hashtags are related to South Africa, such as anc (African National Congress, the current governing party) and onswiloorleef (“We want to sur-

Table 2. Consensus communities found in the English language interactions network (\( \tau = 0.5, P = 0.4, \text{#members} \geq 10 \)), representing 86% of all network nodes.

| Id | Description                                                                 | Size | Score |
|----|-----------------------------------------------------------------------------|------|-------|
| SA | anc, onswiloorleef, southafrica, ancyl, onssaloorleef, zuma, stopabsa, zuma, | 13   | 1.00  |
|    | nua, svpol                                                                  |      |       |
| EAST| presstv, sv, wpww, metal, estonia, 666, polska, ww2, edl, ukraine            | 11   | 0.95  |
| WPWW| wpww, tcot, whitepower, nigger, p2, niggers, teaparty, gop, obama, whitepride | 240  | 0.88  |
| TCOT| tcot, teaparty, p2, obama, gop, israel, tlot, inyhbt, sgp, islam             | 91   | 0.74  |
| NO2EU| no2eu, ukip, bbcqt, labour, edl, leveson, newsnight, euro2012, eurovision, | 214  | 0.74  |
|     | london2012                                                                  |      |       |
| EDL | edl, uaf, islam, bbcqt, lfc, bnp, muslim, tcot, mufc, israel                 | 290  | 0.62  |
| RANGERS| watp, rangersfamily, nosurrender, gersfollowback, wedont | 16   | 0.58  |
|     | dowalkingaway, rfc, taintedtitle, rangersfamily, rangers, rangerfamily       |      |       |
| LONDON| edl, coys, stgeorgesday, londonriots, whys, savages, bbcqt, stfc, tottenham, | 10   | 0.53  |
|      | dench                                                                      |      |       |
vive”), associated with a campaign highlighting alleged violent attacks against Afrikaners. This community is associated with a single South African topic, which is to be expected given the discriminating nature of these hashtags. The EAST community includes white power/national socialist accounts from Eastern European countries such as Estonia, Poland and Ukraine, who occasionally tweet in English. Notable description hashtags include wpww (white pride world wide) and metal, where the latter refers to a music sub-genre known as nationalist socialist black metal. Of similar interest is presstv, the Iranian state-owned English language news network. This has previously been accused of propagating anti-Semitic content, while also hosting Holocaust-deniers and white nationalists. The most similar topic for this community is one connected to white pride ideology that includes media references, for example, wpradio (white pride radio).

The WPWW community would appear to be national socialist/white power in nature, with the appearance of hashtags such as wpww and whitepower. An

Table 3. English language communities and associated NMF topics ($T = 15$, hashtag description cosine similarity $\geq 0.1$).

| Community | Similarity | Top 10 Topic Terms |
|-----------|------------|--------------------|
| SA        | 0.56       | anc, onswiolorleef, stopabsa, ancyl, southafrica, zuma, nuus, afrikaans, zumaspear, genocide |
| EAST      | 0.12       | wpww, whitepride, wpradio, contest, staywhite, whitesiright, white, whiteunitey, genocide, skinhead |
| WPWW      | 0.14       | wpww, whitepride, wpradio, contest, staywhite, whitesiright, white, whiteunitey, genocide, skinhead |
|           | 0.10       | tcot, teaparty, p2, gop, tlot, obama, sgp, ocra, inyhtbt, twisters |
| TCOT      | 0.48       | tcot, teaparty, p2, gop, tlot, obama, sgp, ocra, inyhtbt, twisters |
|           | 0.17       | israel, islam, sharia, muslim, jihad, iran, gaza, syria, egypt, nadarkhani |
|           | 0.15       | prolife, abortion, tcot, prochoice, personhood, god, octoberbaby, 912, gingrich, preborn |
| NO2EU     | 0.16       | labour, leveson, occupylsx, cameron, ukuncut, bnp, greece, bbc, syria, olympics |
|           | 0.13       | bbcqt, newsnight, eurovision, london2012, euro2012, closingceremony, pmqs, teamgh, leveson, olympics |
|           | 0.12       | no2eu, lab11, english, labour, england, eurozone, euro, eurocrash, euro2012, london2012 |
| NO2EU     | 0.12       | ukip, voteukip, christappin, uk, greece, ronpaul, freegary, tories, richardo, extradition |
| EDL       | 0.42       | edl, uaf, islam, bnp, casualsunitcd, luton, rochdale, mdl, bristol, praetorian |
| RANGERS   | 0.50       | rangersfamily, watp, nosurrender, rangers, gersfollowback, rfc, wedontdowalkingaway, taintedtitle, rangersfamilly, celtictaintedtitle |
| LONDON    | 0.15       | edl, uaf, islam, bnp, casualsunitcd, luton, rochdale, mdl, bristol, praetorian |
analysis of the accounts and associated profiles finds references to the American Nazi Party, along with other related terms such as 14 (a reference to a 14-word slogan coined by the white supremacist David Lane), and 88 (“heil hitler”) in account names. There are also references to skinhead groups, including a website where related media and merchandise can be found for sale. Accounts appear to be mostly associated with the USA, although a small number of European accounts are also present. References to tcot (top conservatives on Twitter) and gop (US Republican Party) can also be seen, indicating the presence of more traditional conservative accounts. However, this does not necessarily point to any official link between these groups. Two topics are most closely associated with this community, mirroring the account and description hashtag division between wpww and tcot. The TCOT community is largely composed of traditional conservatives, where the description contains a number of hashtags commonly used by these groups such as gop and teaparty. However, we also note the presence of p2 (progressives, Tweet Progress), effectively the polar opposite of tcot. A number of anti-Islamic counter-Jihad accounts are also present [31]. This community is strongly linked to the tcot topic, with the counter-Jihad and pro-life/anti-abortion topics also of interest.

Opposition to the EU appears to be the binding theme of the NO2EU community, which contains several political or electoral accounts, including a number affiliated with British Eurosceptic parties such as the United Kingdom Independence Party (UKIP). Non-electoral British nationalist accounts are also present, where their tweets and profiles often contain anti-EU statements and imagery. We also see references to British media such as BBC current affairs programmes (bbcqt, newsnight). Accordingly, topics linked to this community appear to be concerned with politics and the EU in general. The EDL community consists mostly of accounts associated with the English Defence League (edl), a counter-Jihad movement opposed to the alleged spread of radical Islamism within the UK [31,32]. Other accounts include those associated with Casuals United, a protest group linked with the EDL that formed from an alliance of football hooligans (references to football clubs can also be observed). The uaf hashtag refers to the Unite Against Fascism group; a staunch opponent of the EDL. Accounts from the USA are also present, acting as a further reminder of the international relationships within the counter-Jihad movement [31]. The final two small communities appear to consist of soccer fans, and are associated with Rangers Football Club from Scotland, and London-based soccer clubs respectively. The latter also contains a number of accounts affiliated with the EDL.

5.5 Case Study: German language

An interactions network (Fig. 5) was created for the German language data set, consisting of 208 nodes and 630 edges. As before, we measured the mean stability score ($\tau = 0.5$) and number of communities found for values of $P$ in $[0.1, 0.9]$. The corresponding plots found in Fig. 6 show that the highest mean score was generated for $P = 0.9$, while the number of communities found had also stabilized at $\sim 15$. Five communities having at least ten members were found for
Fig. 5. German language interactions network with 208 nodes and 630 edges. Node size is proportional to degree. Consensus communities ($P = 0.9$, #members $\geq 10$) are labelled.

$P = 0.9$ (74% of total network account nodes), and their corresponding hashtag descriptions, stability scores and manually annotated identifiers can be found in Table [4]. Topic analysis was also performed with NMF, with number of topics $T = 10$, as lower values of $T$ led to topics associated with relatively few account documents.

Fig. 6. German language mean stability scores (left) and number of communities found (right) for $P$ in $[0.1, 0.9]$. 
The first community consists of accounts associated with the Nationaldemokratische Partei Deutschlands - National Democratic Party of Germany (NPD) that appear to be localized to western regions of Germany. Hashtags such as landtagswahl/ltw... (regional election) and flugblatt (flyer/leaflet/pamphlet) along with analysis of the tweet content may indicate mobilization prior to elections. Two topics most closely associated with this community include a Germany-wide NPD topic in addition to a general topic appearing to be related to street demonstrations. For example, stolberg refers to the town where a German teenager was killed by non-Germans in 2008, which has been the focus of annual extreme right commemorations. The EU community appears to be somewhat analogous to the NO2EU English language community, in that its membership is composed of a mixture of moderate and more extreme nationalist accounts bound by general opposition to the EU and related entities such as the European Stability Mechanism (stopesm), in addition to domestic German political parties (cdu, fdp, spd). Other notable members include a number of counter-Jihad accounts, along with others associated with relatively high-profile external media and blog websites.

The NPDE community is the second that can be associated with the NPD, which, in contrast to the NPDW community, appears to be largely localized to eastern German regions. In addition to NPD politicians, various Freies Netz (neo-Nazi collectives - FN) and "information/news portal" accounts are also present. Similar variants of the landtagswahl hashtag and corresponding tweets to those of NPDW can also be observed. Other issues of interest include references to Thilo Sarrazin, a German politician and former Bundesbank executive who has criticized German immigration policy and proposed the abolition of the euro currency. As might be expected, the general NPD topic is linked to this community, while the anti-EU/political system topic is also prominent.

The remaining two communities contain accounts associated with a variety of non-electoral groups and individuals within the German extreme right. An analysis of the accounts in the NE-E community finds them to be associated with eastern regions of Germany, in particular, the town of Geithain near Leipzig in Sachsen. Accounts associated with various extreme right groups are present, such as FN and the Junge Nationaldemokraten (Young National Democrats, Table 4. Consensus communities found in the German language interactions network (τ = 0.5, P = 0.9, #members ≥ 10), representing 74% of all network nodes.

| Id    | Description                                                                 | Size | Score |
|-------|-----------------------------------------------------------------------------|------|-------|
| NPDW  | npd, bochum, nrw, landtagswahl, wassenscheid,.ovg, flugblatt,bamberg        | 10   | 0.92  |
| EU    | euro, esm, stope, spd, islam, cdu, piraten, fdp, berlin, griechenland        | 26   | 0.82  |
| NPDE  | npd, ltwlsa, deutschland, ltw2011, berlin, linke, isa, ltwmv, guttenberg, sarrazin | 28   | 0.80  |
| NE-E  | geithain, apw, emwall, widerstand, jena, unsterblichen, gera, leipzig, volkstod, tdi | 44   | 0.71  |
| NE-APW| apw, gema, denkdran, volkstod, demokraten, dresden, hannover, spreelichter, 130abschaffen, unsterblichen | 45   | 0.64  |
youth wing of the NPD). References to Aktionsbüros (coordination of activist activities) are also made. The emwall hashtag was popularly used during the 2012 UEFA European Football Championship, and accounts in this community used it to promote tweets suggesting that players having non-German ancestry should be excluded from the national squad. Separately, the unsterblichen (immortals) hashtag refers to anti-democratic flashmob marches that previously occurred sporadically throughout Germany in 2011 and 2012. These protests were linked to Spreelichter, an organization that was banned by the German authorities in 2012, whose account was also a member of this community. They used social media to propagate national socialist-related material, including professional-quality videos of the marches themselves. In general, the accounts in this community appear to be quite active, with many tweets containing URLs linking to content hosted on external platforms such as YouTube or other dedicated websites.

### Table 5. German language communities and associated NMF topics ($T = 10$, hashtag description cosine similarity $\geq 0.1$).

| Community | Similarity | Top 10 Topic Terms |
|-----------|------------|---------------------|
| NPDW      | 0.35       | npd, landtagswahl, ltwlsa, ltwmv, nrw, sachsenanhalt, bochum, linke, wahlen, wattenscheid |
|           | 0.14       | stolberg, dortmund, nrw, demonstration, demo, aachen, koln, brd, rheinland, munster |
| EU        | 0.39       | esm, euro, stopesm, spd, cdu, deutschland, fdp, piraten, stoppesm, islam |
| NPDE      | 0.26       | npd, landtagswahl, ltwlsa, ltwmv, nrw, sachsenanhalt, bochum, linke, wahlen, wattenscheid |
|           | 0.14       | esm, euro, stopesm, spd, cdu, deutschland, fdp, piraten, stoppesm, islam |
| NE-E      | 0.17       | emwall, geithain, tdi, leipzig, imc, linksunten, arbeiterkampftag, lvz, hof, dd2012 |
|           | 0.16       | widerstand, unsterblichen, altermedia, israel, wuppertal, hannover, dieunsterblichen, repression, abschiebar, spreelichter |
|           | 0.15       | jena, raz10, gera, thuringen, volkstod, kahla, altenburg, demokraten, dresden, apw |
|           | 0.13       | apw, volkstod, hannover, heldengedenken, demokratie, spreelichter, cottbus, guttenberg, dresden, vds |
|           | 0.10       | stolberg, dortmund, nrw, demonstration, demo, aachen, koln, brd, rheinland, munster |
| NE-APW    | 0.40       | apw, volkstod, hannover, heldengedenken, demokratie, spreelichter, cottbus, guttenberg, dresden, vds |
|           | 0.19       | gema, denkdran, chemnitz, 5maerz, dresden, magdeburg, 13februar, 130abschaffen, demokraten, akt |
|           | 0.14       | widerstand, unsterblichen, altermedia, israel, wuppertal, hannover, dieunsterblichen, repression, abschiebar, spreelichter |
|           | 0.13       | jena, raz10, gera, thuringen, volkstod, kahla, altenburg, demokraten, dresden, apw |
The second non-electoral community, NE-APW, appears to contain accounts from regions throughout Germany. The concept of *apw* (außerparlamentarischer Widerstand - non-parliamentary resistance) is prominent here, referring to actions taken outside of the democratic process. Other relevant hashtags include 13februar, denkdran, dresden and gema, which all refer to the bombing of Dresden which began on February 13, 1945. The anniversary of this event is usually commemorated by extreme right groups each year. Also relevant is *volksstod*, which refers to the perceived destruction of the German race and traditions since World War II. This concept has separately featured in material distributed by alleged supporters of the National Socialist Underground [35], a group linked to a series of murders throughout Germany. The official account of the *Besseres Hannover* organization is present here; an initial ban by the German authorities was followed by this account being blocked by Twitter within Germany [36,37]. Both NE communities are associated with a variety of topics, perhaps reflecting the fragmented nature of non-electoral groups in the German extreme right. Relevant themes include street demonstrations (*stolberg*), some form of resistance (*apw, widerstand*) and media references such as *altermedia* (a collective of politically-incorrect/nationalist-oriented news websites).

### 5.6 Case Studies Discussion

For both the English and German language case studies, identifiable communities of accounts and related topics are clearly observable. When creating the original data sets, we purposely focused on non-electoral accounts and excluded electoral accounts affiliated with political parties. However, in both cases, the expansion of the data sets using reciprocal follower relationships resulted in the inclusion of electoral accounts, such as those affiliated with UKIP or the NPD. This potentially indicates the presence of some form of relationship between these two categories, if only at a passive level. Other similarities include the presence of distinct anti-EU communities and topics, in addition to the use of media accounts such as those associated with extreme right news websites and radio stations, along with external websites hosting media content. While geographical proximity is evident in most communities, linguistic proximity is a key factor in the existence of international connections such as those between certain counter-Jihad groups and individuals. Although the underlying ideology of certain communities can often be identified, this is less clear in other cases, especially when the mappings between communities and their associated topics are considered. Here, multiple topic mappings suggest a complexity and diversity in both the membership composition and interests of the corresponding community. However, this may also be related to data incompleteness, variances in Twitter usage patterns between different countries, and the fact that an opinion that may be legally voiced in one country may not be permitted in another.

We should mention that this sample of accounts does not provide full coverage of all extreme right Twitter activity, and the accounts and subsequent communities and topics are greatly dependent on the initial selection of relevant accounts. In this domain, the random sampling of Twitter accounts is unlikely
to yield a representative data set, as it is probably safe to assume that the total number of extreme right accounts merely constitutes a small percentage of all accounts. The fact that we did not rely on hashtags for data selection, coupled with the expansion using reciprocal follower relationships goes some way to avoid “selecting on the dependent variable” [38]. However, as suggested by Boyd and Crawford, it is important to acknowledge all known data set limitations [39]. At the same time, the authors also recognize the value of small data sets, where research insights can be found at any level. In this case, in spite of data sampling and coverage issues, it is still possible to detect the presence of extreme right communities and topics on Twitter. In addition, they emphasize the importance of results interpretation, which we have addressed here in our discussion of the communities and topics. In relation to this, care should be taken when inferring conclusions from results. It is unclear as to how representative they may be of offline extreme right network activity. It may be the case that social media platforms are merely used by these groups to disseminate related material to a wider audience, with the majority of subsequent interaction occurring elsewhere, but it is naturally difficult to quantify the extent to which this occurs. Separately, Boyd and Crawford also raise the issue of ethics in relation to publicly accessible data, emphasising the need for accountability on the part of researchers. Here, we address this by restricting discussion to known extreme right groups and their affiliates without identifying any individual accounts.

6 Conclusions and Future Work

Extreme right groups have become increasingly active in social media platforms such as Twitter in recent years. We have presented an analysis of the activity of a selection of such groups using network representations based on reciprocal follower and interaction activity, in addition to topic analysis of their corresponding tweets. The existence of stable communities and associated topics within local interaction networks has been demonstrated, and we have also identified international relationships between groups across geopolitical boundaries. Although a certain awareness exists between accounts based on follower relationships, it would appear that mentions and retweets interactions indicate stronger relationships where linguistic and geographical proximity are highly influential, in particular, the use of the English language. In relation to this, media accounts such as those associated with extreme right news websites and radio stations, along with external websites hosting content such as music or video, are a popular mechanism for the dissemination of associated material.

In future work, we will address the issues of sampling and incompleteness in the data sets, where the emergence of new extreme right groups should also be considered. The temporal properties of these networks will also be studied to provide insight into the evolution of extreme right communities over time. Separately, we plan to investigate the use of probabilistic topic models that support the discovery of more specific topics similar to those found in this analysis.
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