Are we always in strife? A longitudinal study of the echo chamber effect in the Australian Twittersphere

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Abstract
Contrary to expectations that the increased connectivity offered by the internet and particularly Online Social Networks (OSNs) would result in broad consensus on contentious issues, we instead frequently observe the formation of polarised echo chambers, in which only one side of an argument is entertained.

These can progress to filter bubbles, actively filtering contrasting opinions, resulting in vulnerability to misinformation and increased polarisation on social and political issues. These have real world effects when they spread offline, such as vaccine hesitation and violence. This work seeks to develop a better understanding of how echo chambers manifest in different discussions dealing with different issues over an extended period of time.

We explore the activities of two groups of polarised accounts across three Twitter discussions in the Australian context. We found Australian Twitter accounts arguing against marriage equality in 2017 were more likely to support the notion that arsonists were the primary cause of the 2019/2020 Australian bushfires, and those supporting marriage equality argued against that arson narrative. We also found strong evidence that the stance people took on marriage equality in 2017 did not predict their political stance in discussions around the Australian federal election two years later. Although mostly isolated from each other, we observe that in certain situations the polarised groups may interact with the broader community, which offers hope that the echo chambers may be reduced with concerted outreach to members.

Keywords
echo chambers, polarisation, misinformation, partisanship, Twitter

Introduction
The increased connectivity and relative anonymity offered by the internet and especially social media platforms (aka online social networks, or OSNs) was once hoped to provide a mechanism for a more inclusive society, especially with regard to political involvement, “promot[ing] more civic engagement and participation in elections” (p.40, Hwang, Pearce, & Nanis, 2012). OSNs in particular allow people to connect with friends, family and like-minded individuals to form and maintain communities with shared beliefs, values and interests. Observers of modern social media will note, however, that, like with any complex system, there are unintended consequences of making reaching out to others so easy, including the broad spread of conspiracies (e.g., QAnon and the Flat Earth Society) (The Soufan Center, 2021; Brazil, 2020), increased polarisation (Garimella & Weber, 2017), especially in political discussions (Garimella, Morales, Gionis, & Mathioudakis, 2018b), providing environments for radicalization (Badawy & Ferrara, 2018) and extremism (Baumann, Lorenz-Spreen, Sokolov, & Starnini, 2021), and coordinated aggression (Bot Sentinel, 2021; Mariconti et al., 2019). The general consensus on contentious issues expected by classical opinion modelling theory (DeGroot, 1974; Baronchelli, 2018) has instead been replaced by communities focused around competing stances on those issues, echo chambers in which only one opinion is entertained (Pariser, 2012; Bruns, 2019), entrenched by online recommender systems preventing contrary voices from entering, thus forming filter bubbles (Pariser, 2012), which leaves us vulnerable to misinformation (Nikolov, Flammini, & Menczer, 2021) and disinformation (Starbird, 2019). When this misinformed aggression moves beyond the online sphere it has real world effects such as vaccine hesitancy and anti-lockdown movements in a time of pandemics (Broniatowski et al., 2018; Loucaides, Perrone, & Holnburger, 2021; Loomba, de Figueiredo, Piatek, de Graaf, & Larson, 2021), and violence (Samuels, 2020), some of which is politically motivated (Scott, 2021; Mackintosh, 2021).

The dynamics of these echo chambers is of particular interest, because their entrenchment of particular viewpoints drives the in-group/out-group mentality behind polarisation, which, left unchecked, can lead to fundamental difficulties

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in cooperation, with particular implications for democratic political systems (Bail et al., 2018). Not all are convinced of their danger, however (Bruns, 2019), because individuals are known to be members of many social circles, each with their own common attributes and interests (e.g., family, friends, work, or sports, referred to as foci by Feld, 1981), and each of these circles will provide new and potentially contrasting viewpoints on a variety of overlapping issues. Questions remain over how these social circles and echo chambers influence social behaviour, both online and offline (Bruns, 2019; Nasim, 2019), but it is known that there is alignment between some sets of opinions (Baumann et al., 2021), particularly with regard to political viewpoint (Jost, Glaser, Kruglanski, & Sulloway, 2003; Jost, 2017).

Given the relative youth of OSNs, longitudinal studies of online polarisation are only just beginning to appear, but often seek to follow polarisation on specific contentious issues over time (Garimella & Weber, 2017; Garimella, Morales, Gionis, & Mathioudakis, 2017). Our focus, instead, is on investigating communities that remain polarised over time across a variety of issues. Furthermore, it is important to study their activities in the context of the broader discussion to determine not just to what degree the groups isolate themselves from each other, but also how isolated the groups remain from the surrounding community. For these reasons, we require datasets in which known polarised groups are known to be active that are collected over a reasonable period of time and relate to a variety of discussion topics. The issue of political alignment is also relevant, due to vulnerability to misinformation introduced by increased partisanship (Nikolov et al., 2021) and the fact that political alignment has been observed to correlate with different personal values (Jost et al., 2003), for example, right-aligned people value tradition more than left-aligned people while left-aligned people value egalitarianism more (Jost, 2017).

Although OSNs share many features (Weber, Nasim, Mitchell, & Falzon, 2021), the openness of micro-blog platforms, such as Twitter, Parler and Gab, where one account can directly connect to any other (via, e.g., mentions, replies and retweets and their equivalents), provides the best opportunity for accounts in polarised communities to bridge the gaps. Doing so enables new and different information to flow between the communities, enabling the potential to grow consensus. In contrast, participants in Facebook, Instagram, Reddit and WhatsApp discussions can usually only refer to others in the same discussion thread or channel. We use Twitter data in this study, as it is the longest established of the three microblogs mentioned, and has the largest and most representative user base. It also provides a freely available rich data model, which includes information on the directed interactions between accounts, resulting in an up-to-date window into the direction and degree of information and influence flow between Twitter accounts (Weber et al., 2021).

In this work, we examine the roles played online by members of two identified polarised communities in the context of three separate online discussions, each focused on different topics and themes, over the period of almost a year. The polarised groups had been identified in discussions of contentious issues:

- Those using #VoteYes and those using #VoteNo (mutually exclusively) during the same sex marriage (SSM) debate during the Australian postal survey on the matter in late 2017 (Nasim, Tuke, Bean, & Mitchell, 2019), dubbed the YES and NO communities, respectively; and
- Those debating the role of arson and climate change during the 2019/2020 Australian bushfires (Weber, Nasim, Falzon, & Mitchell, 2020), in which Supporters of the arson theory were countered by an Opposer community.

Notably, we have found these polarised groups to overlap and, at times, align, in the three datasets inspected. Our aim is to study the activities of these groups over time in different contexts to determine whether they remain polarised, and to characterise the nature of that polarisation using network and content analysis. Our network analysis relies upon accounts’ interactions (i.e., retweets, replies, mentions and quotes) and the associations between topics they discuss as represented by partisan hashtags as proxies for clear stances on the issues at hand.

**Research questions**

We will guide our investigation of these groups’ behaviour with the following research questions:

**RQ1** Do polarised accounts continue to be active in the Australian Twittersphere over a period of years?

**RQ2** Is their polarisation reflected in a range of their interactions (on Twitter) and discussion topics, or is it limited to just a particular type of interaction?

**RQ3** Are accounts found to be polarised in one dataset still polarised in later datasets, including ones discussing different topics? In particular is there any alignment between partisan communities and those that were found to be polarised over other issues (e.g., SSM, bushfires)?

Our expectation is that the Australian Twittersphere is sufficiently well established to support persistent communities of accounts over long periods of time, ones which discuss related issues, and though they may be polarised on some issues, that polarisation may not be so pronounced on others and the communities may, at times, overlap. If this is found to be true, we can conjecture that the filter bubble effect is not as strong as it was thought to be, and the echo chambers constantly reconfigure and reorganise, allowing interaction between the members of different communities. Such an observation will also be inline with previous social interaction theories that established that people are a part of various overlapping social circles (Feld, 1981).

We also expect that the degree of polarisation will vary across interaction types because different interaction types are used for different purposes. Interactions between accounts may be direct, requiring that one account be aware of the other’s identity (e.g., with an @mention, a reply or retweet), while others are indirect, requiring only knowledge of intermediary data and perhaps an associated common stance (e.g., common use of a partisan hashtag or URL).
direct interactions, there is the possibility that the connection is made because of a personal connection (e.g., a friendship or indication of personal respect) in addition to an agreement on stance. Furthermore, different direct interactions have different audiences: while a reply or a mention may be directed at the replied to or mentioned account, a retweet or quote tweet is aimed at the poster’s followers despite the reference back to the originator of the retweeted or quoted tweet. For this reason, networks built from different interactions can be expected to exhibit different degrees of polarisation.

Contribution

This work provides the following contributions to the literature:

1. Two original datasets on the 2017 SSM debate in Australia, and the 2019 Australian federal election;*
2. A methodology for the analysis of online polarisation between two non-overlapping groups based on their behaviour and discussion content; and
3. A longitudinal study of two sets of such polarised communities and their degree of alignment over a series of three Twitter datasets.

Related work

Due to the breadth of related work in this field, we structure this section as follows. We first elaborate on dangers caused by allowing polarisation to flourish online, then consider the difficulties of opinion formation in real world environments where contentious issues and opinions on them abound. We then touch on related polarisation research, before clarifying where our work makes its contribution.

The broken promise of social media

As mentioned, OSNs allow people to easily form communities with shared ideas, ideals and beliefs. This notion of people connecting based on similarities is known as homophily (Rogers & Bhownik, 1970; McPherson, Smith-Lovin, & Cook, 2001). The open nature of the internet and social media was expected to facilitate broader engagement in society, allowing ordinary folk to communicate directly with elites (S. Woolley & Guilbeault, 2018), leading to what Habermas referred to as deliberative democracy (Habermas, 1996), where people could more easily come to a consensus on issues of interest, or gain an understanding of opposing views (as discussed by Graham & Ackland, 2017). Instead, social media users have found a plethora of explicit and implicit ways to use the features of OSNs beyond their intended functions.

These include:

- the creation of echo chambers and subsequent filter bubbles (Pariser, 2012; Bruns, 2019) leading to opportunities for anti-social groups to form (Massanari, 2016), incite and radicalise their members, and conduct organised raids on other online communities (Datta & Adar, 2019; Burgess & Matamoros-Fernández, 2016; Mariconti et al., 2019)—this radicalisation can move offline also, ultimately resulting in terrorist attacks (Brooking & Singer, 2016; CREST, 2017; Waldek, Ballsun-Stanton, & Droogan, 2020; Scott, 2021);
- the use of automation, big data holdings, and organised inauthentic effort to influence both domestic and foreign politics (S. C. Woolley, 2016; Shorey & Howard, 2016; King, Pan, & Roberts, 2017; Dawson & Innes, 2019) as far back as 2010 (Metaxas & Mustafaraj, 2012);
- the realisation that misinformation can be monetised (without the requirement for malicious intent exhibited by scammers), such as when Macedonian teenagers found they could generate revenue from GoogleAds when they created highly conservative but entirely fictional news articles in the lead up the US 2016 presidential election (Subramanian, 2017);
- that public support can be manufactured with the use of employees and motivated volunteers (King et al., 2017; S. Woolley & Guilbeault, 2018; Jamieson, 2020) or, failing that, simply faked with automated follower accounts (Aggarwal & Kumaraguru, 2015; Aggarwal, Kumar, Bhargava, & Kumaraguru, 2018; Confessore, Dance, Harris, & Hansen, 2018); and
- coordinated anonymous malicious campaigns against prominent individuals (e.g., Bot Sentinel, 2021; Nasim, Nguyen, Lothian, Cope, & Mitchell, 2018), groups (Pacheco, Flammini, & Menczer, 2020; Starbird, Arif, & Wilson, 2019; Graham, Bruns, Angus, Hurcombe, & Hames, 2020) or countries (Graham, Bruns, Zhu, & Campbell, 2020; Strick, 2021; Schlies, Bailey, Bright, & Howard, 2021) for ideological reasons or simply for the lulz (Drenten & Gurrieri, 2018; Hine et al., 2017).

Some of these dangers have been foreseen, however, as recent revelations from whistleblowers have revealed that Facebook knew an increase in inflammatory content would be a likely consequence of its policy to weight Reactions five times more than Likes (Merrill & Oremus, 2021). In some cases the OSNs have even facilitated the spread of misinformation through favourable treatment of prominent accounts (Timberg, Dwoskin, & Albergotti, 2021). These are all factors contributing to the increased aggression and polarisation observed not only in the online space (Garimella & Weber, 2017), but also offline as a direct result of those online events. These have real world effects, such as vaccine hesitancy in a global pandemic (Broniatowski et al., 2018), coordinated anti-lockdown movements (Loucaides et al., 2021), extremism facilitated by conspiratorial thinking (The Soufan Center, 2021; Brazil, 2020) and exacerbated by bias in the media (e.g., Barry, 2020) and its online amplification (Huszár et al., 2021), radicalisation (Badawy & Ferrara, 2018) and violence (Samuels, 2020; Scott, 2021; Mackintosh, 2021).

Opinion formation in a complex opinion space

Classical opinion modelling theory tells us that, assuming people have an opinion on any matter, increased interaction...
will shift the population towards consensus (DeGroot, 1974; Baronchelli, 2018) as people find more reasons that they are similar (the concept of homophily, Rogers & Bhowmik, 1970) than different. Despite the increased opportunity for interaction provided by the internet and social media, what we observe is the contrary: an increase in polarisation on some issues (Garimella & Weber, 2017), which then spills from one issue to sets of issues and from the online world to the offline world. Although it might be reasonable to assume that accounts highly polarised on certain issues are unlikely to change their stance on those issues over time, they may be more receptive to alternative viewpoints on a variety of other topics. The online opinion space is complex as it consists of many competing diverse, often incompatible, often orthogonal, sets of opinions. For example, in the recent COVID-19 coronavirus pandemic, healthcare and economics experts’ opinions on lock-downs were consistently contested and undermined by conflicting information on social media and in the news media (Ali & Kurasawa, 2020; Tasnim, Hossain, & Mazumder, 2020). Studies have shown that online polarisation can persist even across conceptually unrelated issues (Häussler, 2018), and that stances on some issues seem to align (Baumann et al., 2021), which may contribute to online friendships, consolidating the social groups and the polarisation between them. These findings highlight the need to better understand how humans respond to multiple and sometimes conflicting opinions, particularly in the online context.

**Polarisation research**

Online polarisation is a broad and well studied topic (Garimella, Morales, Gionis, & Mathioudakis, 2018a; Kliger-Vilenchik, Baden, & Yarchi, 2020), particularly in the context of politics and from a variety of analytical perspectives and disciplines.

As social media has increasingly been used for political communications, election-related discussions have become rich sources of study of polarisation (Bessi & Ferrara, 2016; S. Woolley & Guillebault, 2018; Morstatter, Shao, Galstyan, & Karunasekera, 2018; Garimella et al., 2018b)). The primary fear associated with online polarisation and the echo chambers and filter bubbles that contribute to it is that, by their very nature, they may constrain the opportunities to exchange views, let alone establish common ground. They reinforce existing opinions, risking extremism and radicalisation (Bruns, 2019; Baumann et al., 2021; Jiang, Ren, & Ferrara, 2021).

The concern around echo chambers creating filter bubbles is not shared by all, however: Bruns argues that although a group may form an echo chamber in an online space, the individuals have many opportunities to obtain information via other communication channels, both online and offline (Bruns, 2019). Nevertheless, online polarisation appears to be increasing (Garimella & Weber, 2017) and can be costly to those attempting bipartisanship (Garimella et al., 2018b). This is in part due to the dynamics between social media, and traditional and alternative media, along with political pressures (Benkler, Farris, & Roberts, 2018; Jamieson, 2020; Badham, 2021), leaving us vulnerable to the influence of misinformation and disinformation (Wardle, 2019; Carley, 2020).

This work seeks to provide empirical evidence from an Australian perspective, providing not just a longitudinal study of opinion polarisation over a number of distinct contentious and non-contentious topics, but also considering whether polarisation extends through different methods of online interaction. Baumann et al. considered homophily and heterophily based on political opinion from surveys (2021), whereas we infer opinion based on users’ interactions and their use of partisan hashtags, and Garimella and Weber studied polarisation on Twitter in a longitudinal setting (2017), but did so by focusing on particular issues rather than the communities around them.

**Datasets**

We analysed the following four datasets of tweets collected between 2017 and 2020. Two of those datasets were compiled on the contentious social issues of marriage equality and federal elections.

1. **Same sex marriage (SSM)** We label users based on their preferential hashtags during the Australian 2017 SSM postal survey: YES accounts were those that used only #VoteYes, NO accounts used only #VoteNo, and BOTH accounts used both hashtags.
2. **Election** A collection of tweets of the labelled users in the SSM dataset, close to the Australian federal election in 2019.
3. **ArsonEmergency** This dataset was collected by Weber et al. (2020) during the 2019-2020 Australian bushfires. They found two polarised communities in the retweet network, which we refer to here as the Arson groups. One community strongly supported the arson narrative (Supporters), claiming arson was the cause of the bushfires, while the other community opposed that narrative with fact-check articles and official announcements (Opposers).
4. **AFL** A three-day collection of Australian Football League (AFL) discussions was conducted over a weekend in March, 2019.

Further information is available in Table 1. Detailed statistics and in-depth contextual information on these datasets is provided in the supplementary material.

**Specific Hypotheses**

We are now in a position to guide our investigation with specific hypotheses regarding these labelled groups.

Direct and indirect interactions can be expected to exhibit polarisation differently. Content-based connections made through hashtag use are based on what the hashtag expresses rather than who else is using it. For direct interactions, where the other account is known (at least by name), that other identity may influence a user’s decision to interact or not. For these reasons, we might expect that the polarisation evident in the Arson groups might spread across other interactions (e.g., from retweets to mentions, replies and quotes) because the accounts know each other, whereas polarisation across hashtags (as themes) might be more diffuse, because they relate to opinions and are not directly associated with individuals. People’s opinions (which guide their hashtag use) may have more variety and overlap differently from the
Table 1. Data Statistics

| Dataset        | Tool          | Twitter API       | Duration                      | Tweets | Accounts | Method of Collection | Keywords                        |
|----------------|---------------|-------------------|-------------------------------|--------|----------|----------------------|---------------------------------|
| SSM            | GNIP          | 10% academic API  | 1 Sep to 20 Nov 2017          | 79,725 | 54,855   |                      | #MarriageEquality, #SSM, #auspol, #VoteYes, #VoteNo |
| Election       | TWINT         | Web UI            | 1-21 May 2019                 | 398,352| 4,429    |                      | Timeline scraping of seed accounts |
| ArsonEmergency | Twarc         | Standard Search API | 31 Dec 2019 to 17 Jan 2020   | 27,546 | 12,872   |                      | Keyword: ArsonEmergency         |
| AFL            | RAPID         | Standard Streaming API | 22-25 Mar 2019              | 21,799 | 11,573   |                      | Keyword: afl                     |

individuals they interact with regularly. Thus, we may expect polarisation in one type of interaction to persist into others, but less polarisation in content as the discussion changes to different topics.

Now knowing our labelled groups, our hypotheses moving forward are that:

1. Because the SSM groups are so tightly tied to the use of #VoteYes and #VoteNo and the previously mentioned strong association between political outlook at progressive issues (such as marriage equality), we expect their interactions to be moderately homophilic and their discussion topics to be strongly homophilic, as they disagree strongly on SSM and have no evidence of other socialisation in the original SSM dataset.

2. For the Arson groups, their retweet network strongly defines their communities based on shared opinions, so we expect strong homophily to be visible in their interactions, however it may be only moderate for mention and quote networks, which can be used to refer to non-community members without much risk of engagement or confrontation (compared with a more direct reply interaction). Furthermore, given the political and, to some degree, ideological nature of the ArsonEmergency discussion, we expect the Arson groups to also remain strongly polarised in the hashtags they use.

Methods

We used a variety of measures to uncover polarised groups in social networks, identify their extent and characterise their connectivity and their content. We did this by building networks of accounts linked by interactions (retweets, mentions, replies, and quotes) and the common use of partisan hashtags, and then systematically considering a variety of measures of homophily of the polarised communities within those networks.

Constraints of OSN data

Despite the appeal of social media as a rich data source for sociological research, a number of questions and challenges remain. For example, restricted access to OSNs’ data via their Application Programming Interfaces (APIs) limits the social networks built from such data (Nasim, Charbey, Prieur, & Brandes, 2016), the retrieved data may have inconsistencies (Weber et al., 2021), reproducibility of results is not always possible (Assenmacher et al., 2021), and there is a lack of robust sociological theories about social media interaction (e.g., Schroeder, 2018).

That said, interactions on social media, limited in data model though they may be, provide the best portal we have to relevant data and therefore the best opportunity to understand the degree and nature of activity between particular actors at a particular time on a given topic of discussion.

Social networks

Social networks of accounts can be built with a variety of information to define the edges in the network. In traditional SNA, relations are evidence of long-standing relationships between actors, such as familial or friend relations, or organisational structures, such as supervisory or collaborative relations, but online connections differ (Wasserman & Faust, 1994; Nasim, 2016; Borgatti, Mehra, Brass, & Labianca, 2009). Beyond follower relations, which are very easy to create but very quickly can become stale, rendering them of limited meaningful value, Twitter, for example, provides no other data on long-standing relations between accounts. Instead, direct interactions between accounts, such as retweets, mentions, replies, and quotes, can provide evidence of the currency of connectivity, the degree of interaction activity and its direction, and thus we use these interactions to study the communities in these datasets. We also use hashtags as proxies for content, and consider networks of accounts that use the same hashtags, though given the prevalence of some hashtags, we constrain the set of hashtags used.

Interaction network construction To build an interaction network, which we define as a weighted directed network of accounts, \( G = (V, E) \), where \( V \) is the set of nodes, and \( E \) is the set of edges between them, representing when they retweet, mention, quote, or reply to each other. Nodes have a label attribute for the name of the polarised group to which they belong (if they belong to no group, it is given the value ‘OTHER’). The frequency of the interactions in the dataset is recorded as the weight of the edge.

Hashtag co-mention networks The hashtag co-mention (account) network also consists of nodes representing accounts, but they are linked with an undirected weighted edge when the accounts use the same hashtag. The edge weights are the sums of the product of the number of uses each account made of a given hashtag, for each hashtag they both used. So, for example, if accounts \( \{u, v \in V\} \) use a set of common hashtags, \( \{h_1, h_2, \ldots, h_n \in H\} \), we create an undirected edge \( \{u, v\} \). If \( h_i \) indicates how often user \( u \) used hashtag \( h_i \), the weight of the new edge is the given by

\[
    w_{(u,v)} = \sum_{i=0}^{n} h_i^u \cdot h_i^v. \tag{1}
\]

Others (e.g., Magelinski, Ng, & Carley, 2021) use the minimum of \( u \) and \( v \’s \) usages of each hashtag, but their aim was to reduce computational overheads, whereas our datasets are small enough that that is not a limitation. Instead our
weight calculation emphasises links from quiet (i.e., those with a small number of uses of a hashtag) accounts to loud accounts (i.e., ones with many uses), highlighting links that might otherwise be obscured or filtered out.

Some hashtags appear frequently in social media datasets, especially ones used as query terms to create the dataset in the first place (in which case it may appear in every single post). Creating a hashtag co-mention network using such popular hashtags will result in a very dense network in which many edges may lack any significant meaning. Instead, we can examine the distribution of hashtag use in a dataset and remove the most widely used hashtags.

Further meaningful filtering can be employed by considering the content of the hashtags; in political datasets, partisan hashtags are usually indicative of (1) an opinion on an issue (2) that potentially creates an axis of polarisation depending on how strongly it divides accounts, and (3) an association with one of the polarised groups.

**Structural analysis and visualisation** Social theories of friendship indicate that not all ties are equal, and we have options to define the strength of ties in our networks. For networks based on interactions and content, it is possible to use frequencies as edge weights, but agnostic of the edge semantics, we can use the quadrilateral Simmelean backbone to identify the strongest ties in a given social network (Nick, Lee, Cunningham, & Brandes, 2013; Nocaj, Ortmann, & Brandes, 2014). This approach gives high weight to edges embedded in cycles of length 4. The intuition behind this approach is that dyads that share more common neighbours (meaning they are part of a triangle, $K_3$, or cycle, $C_4$, Nastos & Gao, 2013) are more strongly tied – this weight is therefore referred to as the backbone strength of the edge. This can be used in the rendering of edges, but also the layout of network nodes.

![Figure 1](image.png)

**Figure 1.** The largest component of the network of follow relations of the YES (blue), NO (red) and BOTH (green) accounts. The directed edges are coloured according to the following (i.e., source) node. Although BOTH accounts are primarily embedded in the YES community, the YES and NO communities are clearly polarised. (Visualised with Gephi.)

Some partisan hashtags are usually indicative of (1) an opinion on an issue (2) that potentially creates an axis of polarisation depending on how strongly it divides accounts, and (3) an association with one of the polarised groups.

**Homophily metrics**

Beyond simple frequency metrics of numbers of accounts, interactions, and comparisons of internal to external connection counts (i.e., how many connections are between members inside a polarised group versus connections between members of different groups), we rely on two primary measures of homophily: the assortativity coefficient (Newman, 2003) and a variation on the Krackhardt E-I Index (Krackhardt & Stern, 1988). Assortativity is the tendency for nodes to be connected to similar nodes, for a given value of ‘similar’, similar to homophily but agnostic of network semantics. Here, it is defined by the node’s label attribute. This measure makes no use of edge weights. The Krackhardt E-I Index is a simple ratio of edges internal to a community, $I$, (i.e., between community members) and edges external to that community, $E$, (i.e., edges which have only one endpoint within the community):

$$E-I \text{ Index} = \frac{|E| - |I|}{|E| + |I|}. \tag{2}$$

Our variation takes into account the weights of edges, because the weights represent the frequencies of individual interactions. This ensures that the strength of connections between nodes is considered, rather than simply their count. Both measures lie within $[-1, 1]$, but their meaning is reversed: an assortativity score close to 1 implies high polarisation, with the majority of edges connecting nodes with the same label, whereas an E-I Index of 1 implies that all edges reach outside the group and no edge joins members of the same group. A value of 0 for both metrics implies a balance between internal and external edges.

Binomial tests are used to test the statistical significance of the homophily measures. We consider $p$ value thresholds of 0.05, 0.01, 0.001, and 0.0001 to express the confidence in the significance.

**Results**

We address the research questions posed in the Introduction through the lens of the polarised groups identified in the SSM
and Bushfires datasets. Initially, we confirm the presence of polarisation between the SSM groups (polarisation in the ArsonEmergency dataset has already been confirmed by Weber et al., 2020). We then consider the activity of the polarised accounts over an extended period of ten months, whether the polarisation spans interaction types and discussion topics, and then whether the polarisation remains regardless of the topic of the discussion.

**Polarisation in the SSM discussion**

In the SSM tweets, as mentioned above, one set of hashtag filter terms were general in nature, referring to the marriage equality voting activity and politics, namely #MarriageEquality, #SSM, and #auspol, while the second set reflected users’ opinions about marriage equality, namely #VoteYes and #VoteNo. These last two are the defining feature of YES, NO and BOTH accounts. We hypothesised a lot of repulsion between these YES and NO accounts, in particular; specifically, we anticipated relatively high structural cohesion within the groups of accounts who used the same hashtag, and relatively low cohesion among accounts who used opposite hashtags.

To consider this, we retrieved as many followers of YES, NO, and BOTH accounts as possible and constructed a network of their follower relations, ignoring accounts outside the YES, NO and BOTH groups. The resulting network consisted of 2,973 YES nodes, 3,417 NO nodes, and 473 BOTH nodes, and 22,139 directed follower edges, where \( \{u, v\} \) indicates that account \( u \) follows account \( v \). Considering only edges adjacent to a YES or NO node, we find a E-I index of \(-0.84\), implying a high degree of homophily, as expected. Further confirmation of this polarisation is evident in a visualisation of the largest component of the follower network, which includes BOTH nodes (in green) for completeness, shown in Figure 1. On this basis, we can confirm the YES and NO groups are polarised, as not only do they use disjoint sets of hashtags but they mostly only follow fellow community members.

Previous work have revealed alignment between people’s political leaning and their support for egaliatarism and inclusivity (e.g., Jost et al., 2003; Jost, 2017; Albada, Hansen, & Otten, 2021), so it is a reasonable to expect a similar pattern on a progressive issue, such as marriage equality. To examine whether the SSM groups corresponded with political alignment, a manual review of 1,000 random samples from YES and NO Election tweets was conducted. Tweets were labelled at two resolutions, one aiming for a simple two-way left-wing or liberal (LEFT), or right-wing or conservative (RIGHT) alignment label, and the other also permitting NEUTRAL and UNCLASSIFIED labels. Tweets were judged on their content, and if that were not sufficiently clear, the profile of the tweet’s author would be inspected (such content was preserved in the metadata of collected tweets). The results presented in Figure 2 indicate that YES members were almost exclusively LEFT-aligned, while the alignment of NO members varied much more. On deeper inspection, many tweets could be labelled only as NEUTRAL, which is not unexpected in a wide-ranging political discussion, as they often include simple statements of fact. Furthermore, a significant number could not be reasonably classified due to a lack of content. The implications are that the NO members are much more politically diverse than the YES members, who are mostly LEFT-aligned and that the polarisation observed in their use of #VoteYes and #VoteNo may not be sustained in other political discussions.

Based on this identification of polarised YES and NO accounts, and the analysis of their political stance, we then observed those accounts’ behaviour in the lead up to the 2019 Australian federal election, with the aim of testing whether their polarisation on SSM also led to polarisation over the political issues being discussed. Prior to presenting those results, however, we discuss a significant overlap between the SSM groups and the Arson groups.

**A chance finding**

It was observed that 1,015 SSM accounts from YES, NO and BOTH groups were active in the ArsonEmergency discussion, and that they appeared to still be polarised. Furthermore, of those 1,015 accounts, a full 995 of them appeared in the retweet network, in which the Supporters and Opposers appeared. We highlighted the SSM accounts in a reproduction of the original retweet network visualisation (Figure 3) and observed that the groups appeared to have remained polarised. To examine this statistically, one-tail probability tests for each group were used to confirm that Supporters \( \mapsto \) NO accounts and Opposers \( \mapsto \) YES accounts by rejecting the null hypothesis that the polarised groups were independent, at \( \alpha = 0.01 \).

With this encouragement, we used the ArsonEmergency dataset and earlier Australia-focused datasets, to determine if the SSM and Arson accounts were present and active, and whether the polarisation observed elsewhere was maintained across interaction types and in the content they discussed.

**Enduring polarisation**

There is some evidence to suggest that if people have strong moral convictions, then they are likely to continue engaging

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*An account’s followers may be unavailable for a variety of reasons, such as the account being protected, suspended or deleted.*
politically (Skitka & Bauman, 2008), and so it is possible, if not likely, that those who participated in the SSM discussion and the ArsonEmergency discussion (both topics with a strong political element) would also have been active in the Australian Twittersphere in the intervening period.

We therefore now turn to examine the presence and polarisation across all four datasets. To do this, from these datasets we construct and examine retweet, reply, mention and quote interaction networks, as well as content-related networks based on hashtag co-mentions.

Continued presence Table 2 shows the number and proportion of SSM and Arson accounts in the four datasets. Although some of the proportions drop considerably from the original groups, there are still sufficient absolute numbers to draw conclusions regarding their behaviour (the smallest presence still has 42 members, nearly 10% of the original community). The considerable drop in SSM accounts, especially in the NO group, does raise the question of how these accounts have been used, despite the time between the SSM collection (late 2017) and the earliest of the other datasets (the AFL, in early 2019). Given so many accounts did not participate in these discussions, was it because they were still active but discussing other topics, or is it that they were used only or mostly for the SSM discussion and then left inactive. The great number of YES accounts active in the Election dataset indicates that perhaps NO accounts were used in this single-purpose manner.

Table 2. Sizes and proportions of the presence of the polarised groups in the datasets. Bolded figures belong to the original datasets.

|            | SSM     | AFL     | Election | ArsonEmergency |
|------------|---------|---------|----------|----------------|
|            | Late 2017 | March 2019 | May 2019 | January 2020    |
| YES        | 8,623   | 376     | 3,390    | 698            |
|            | (100.0%) | (4.4%)  | (39.3%)  | (8.1%)         |
| NO         | 7,880   | 53      | 631      | 148            |
|            | (100.0%) | (0.7%)  | (8.0%)   | (1.8%)         |
| Supporter  | 93      | 42      | 72       | 497            |
|            | (18.7%) | (8.5%)  | (14.5%)  | (100%)         |
| Opposer    | 240     | 73      | 156      | 593            |
|            | (40.5%) | (12.3%) | (26.3%)  | (100%)         |

Summary of interaction network findings In almost all circumstances, the echo chamber effect appears to be maintained to some degree, with internal networks preferred over external ones, especially between Supporters and Opposers. The only circumstance where that effect is reduced is in the NO groups’ use of replies and mentions and Opposers’ use of mentions in the ArsonEmergency dataset, where they more even in their connections. It is possible that some of these mentions were used for aggressive, rather than collegiate, interactions, but analysis of their content is required for this judgement and there were relatively few of these interactions, so any such judgement is unlikely to be indicative of a broader pattern of behaviour.

The results of a systematic examination of the presence and interactivity between the YES and NO and Supporter and Opposer accounts in the AFL, Election and ArsonEmergency datasets are presented in Table 3.

The polarisation in the Election dataset is statistically significant across all groups and interactions, and it is homophilic in all but one condition; NO accounts mention YES accounts more frequently than other NO accounts. This marked polarisation is also immediately apparent in visualisations of the interaction networks (Figure 4).
Table 3. Summary details of the inter- and intra-group interactions by the SSM and Arson polarised groups in networks built from three datasets. Significance $p$-values are based on using binomial tests with the null hypothesis that the groups had no connection preference.

| Network | Source | Election | ArsonEmergency | AFL |
|---------|--------|----------|----------------|-----|
|         | Target | Target | Target |       |
|         | YES | NO | Sig. ($p <$) | YES | NO | Sig. ($p <$) | YES | NO | Sig. ($p <$) |
| Retweets | YES | 55,792 | 2,359 | 0.0001 | 349 | 27 | 0.0001 | 45 | – | 0.0001 |
|          | NO   | 2,091 | 4,677 | 0.0001 | 17 | 96 | 0.0001 | – | 6 | 0.05 |
| Mentions | YES | 5,337 | 209 | 0.0001 | 9 | 2 | – | – | 23 | 1 | 0.0001 |
|          | NO | 749 | 261 | 0.0001 | 24 | 21 | – | – | – | 1 |
| Replies  | YES | 2,231 | 106 | 0.0001 | 5 | – | – | – | 21 | 1 | 0.0001 |
|          | NO | 133 | 175 | 0.05 | 10 | 10 | – | – | – | – |
| Quotes   | YES | 3,303 | 183 | 0.0001 | 10 | 3 | – | – | 10 | – | 0.01 |
|          | NO | 250 | 335 | 0.01 | 1 | 9 | 0.05 | 1 | – | – |
| Hashtags | YES | 42,683,122 | 79,068,551 | 0.0001 | 381 | 1,258 | 0.0001 | 652 | 1,577 | 0.0001 |
|          | NO | 79,068,551 | 258,579 | 0.0001 | 1,258 | 611 | 0.0001 | 1,577 | 105 | 0.0001 |

| Network | Source | Supporters | Opposers | Sig. ($p <$) | Supporters | Opposers | Sig. ($p <$) | Supporters | Opposers | Sig. ($p <$) |
|---------|--------|------------|----------|--------------|------------|----------|--------------|------------|----------|--------------|
| Retweets | Supporters | 5,725 | 23 | 0.0001 | 3,603 | 23 | 0.0001 | 4 | – | – |
|          | Opposers | 12 | 11,878 | 0.0001 | 13 | 3,006 | 0.0001 | – | 6 | 0.05 |
| Mentions | Supporters | 509 | 14 | 0.0001 | 567 | 343 | 0.0001 | 4 | – | – |
|          | Opposers | 12 | 562 | 0.0001 | 28 | 30 | – | – | 1 |
| Replies  | Supporters | 81 | 5 | 0.0001 | 288 | 144 | 0.0001 | 6 | – | 0.05 |
|          | Opposers | 6 | 250 | 0.0001 | 11 | 33 | 0.01 | – | 1 |
| Quotes   | Supporters | 183 | 27 | 0.0001 | 212 | 50 | 0.0001 | – | – | – |
|          | Opposers | 9 | 568 | 0.0001 | 6 | 62 | 0.0001 | – | – | – |
| Hashtags | Supporters | 173,488 | 977,889 | 0.0001 | 106,433 | 106,922 | – | 60 | 553 | 0.0001 |
|          | Opposers | 977,889 | 5,941,413 | 0.0001 | 106,922 | 7,875 | 0.0001 | 553 | 37 | 0.0001 |

Figure 4. Polarisation in interaction networks: The largest components in interaction networks of Supporter (red) and Opposer (blue) accounts (top row) and YES (blue) and NO (red) accounts (bottom row) active in the Election dataset. Edge width describes the backbone strength. Polarised accounts from Arson and SSM datasets remain significantly polarised in elections dataset for various types of interactions.

Addressing the research questions

We now directly consider the research questions posed in the Introduction.
**Table 4.** Summary details of SSM and Arson polarised groups in networks built from three datasets. The ‘Hashtag’ networks are the hashtag co-mention accounts, and the number in parentheses is the total count of the partisan and co-occurring hashtags.

| Group  | Dataset | Network | Category 1/2 Nodes | Category 1/2 Edge Weights | Homophily | Assortativity | E-I Index | Nodes | Edge Weights | E-I Index |
|--------|---------|---------|---------------------|---------------------------|-----------|---------------|-----------|-------|--------------|-----------|
| RQ1 Do Twitter accounts remain involved in Australian discussions for extended periods?  
We have shown that a significant number of accounts have remained active in the Australian Twitterosphere over a number of years, with nearly 40% of SSM YES accounts active nearly two years later in the lead up to the federal election and some hundreds still active in early 2020 during the Australian “Black Summer” bushfires. Conversely, some hundreds of ArsonEmergency group members had also been active during the SSM discussion in 2017, exhibiting a high degree of alignment with 65 of 93 Supporters using #VoteNo (24 of them also used #VoteYes) and 152 of 240 Opposers using #VoteYes (33 of them also used #VoteNo).  

**RQ2 Is polarisation observed in one interaction type present across other interaction types?**  
To the greater extent, the echo chambers observed in the Arson and SSM groups persisted through most interaction types according to E-I Index scores, at least moderately. E-I Index scores rose dramatically (towards heterophily) when the broader network was considered, indicating that the polarised groups were primarily polarised with regard to one another, and did, in fact, interact strongly with those outside their groups.  

**RQ3 Do accounts found to be polarised in some discussions maintain their polarisation in different discussions, and does the theme of the discussion impact this polarisation?**  
In contrast to the interaction networks, analysis of the common use of partisan hashtags revealed more heterophily in the Election dataset (in which a great variety of political issues were discussed), leading to the conclusion that although the groups mostly...
interacted amongst themselves, they discussed similar partisan topics and so probably also held similar positions on those topics (as described by the stance of the hashtags). The mix of political leanings exhibited by the NO accounts in the Election may have contributed to the overall greater heterophily in the Election dataset.

In contrast to the Election, homophily remained very high in the topics discussed in the other datasets. For the ArsonEmergency discussion, this is likely due to the high alignment between the SSM and Arson groups, and for the AFL discussion, it is likely due to the match-specific nature of parts of the discussion.

Figure 6. Polarisation in hashtag co-mention networks: The largest components in hashtag co-mention networks of YES (blue) and NO (red) accounts and Supporter (red) and Opposer (blue) accounts active in the Election, ArsonEmergency and AFL dataset. Green nodes represent accounts that used both #VoteYes and #VoteNo, and yellow nodes represent OTHER nodes co-mentioning hashtags with affiliated accounts. Node size is determined by the sum of the backbone strength values on incident edges, i.e., degree weighted by backbone strength, indicating each node’s embeddedness. Edge width describes the backbone strength.
When considering the broader network, heterophily in discussions topics was mostly very strong across all datasets, except for when it was moderately homophilic and heterophilic amongst the SSM groups in the Election and the Arson groups in the ArsonEmergency datasets, respectively. This implies the SSM groups had their own distinct discussion topics during the election, which they shared amongst themselves but not with the broader community, and which might also provide an avenue for further integration.

The interaction- and content-based E-I Index scores of the polarised groups revealed the groups interacted differently to how they discussed topics, raising the important question why. We summarise the E-I Index scores for each group and dataset in Figure 7, averaging the interaction network scores and contrasting them with the scores from the corresponding partisan hashtag co-mention networks. First, as mentioned above, polarisation varies from moderate to high across all interaction types for both SSM and Arson groups in all datasets, but is particularly pronounced between the Arson groups in the Election and AFL datasets. Second, the use of partisan hashtags during the Election was remarkably even compared to the other datasets. In fact, partisan hashtag use was almost entirely homophilic in the ArsonEmergency and AFL datasets. This could be explained in at least two ways. The first is that, although the partisan hashtags clearly align with political camps, the hashtags that co-occur with them in tweets might overlap significantly between the groups. Given the large number of them in the Election dataset (200), it is possible that there are many opportunities for accounts in different groups to use the same one. We might expect that, if this were the case, then the number of co-occurring hashtags in the other datasets should be low, however this is not what we find. Both had hundreds of co-occurring hashtags (see the counts next to the ‘Hashtags’ labels in Table 4). The second possibility is that the polarisation between the SSM and Arson groups is less to do with political opinions and more to do with social circles. People may have used \#VoteNo in the SSM dataset for a variety of non-political reasons and factors, including religion, culture or general conservatism, and therefore may share the political opinions of many in the YES group. This orthogonality is perhaps less likely in the Arson group, given the motivation for being a Supporter or Opposer is easier to attribute to political outlook (Weber et al., 2020), and we can see that the partisan hashtag use E-I Index score of the Arson groups in the Election dataset reflects this, being slightly more homophilic than that of the SSM groups.

Addressing the hypotheses

The statistical support shown in Table 4 for the hypotheses presented at the end of the Datasets section is mixed. SSM groups were very polarised in discussion topics in the ArsonEmergency and AFL datasets, but much less so in the Election dataset, and their interactions varied from moderately to highly homophilic (especially amongst the few present in the AFL dataset). In this way, the interactions observed indicate socially connected groups, while the content connections suggest they shared discussion topics strongly, even when they may have been partisan in nature.

Similarly, Arson groups interacted in strongly polarised ways in the Election and AFL datasets, but were only strongly homophilic in retweets and quotes in the ArsonEmergency dataset, where they were initially identified. Their connections were only weakly to moderately homophilic in their mentions and replies, respectively, in that dataset. Their use of content, however, was strongly polarised in all but the Election, where again they seemed to often share partisan discussion topics, but only within established social groups. The lower homophily in the reply and networks seems to suggest that Supporters and Opposers were willing to bridge the gap between the groups, but this may be a reflection of direct conflict, rather than genuine debate, based on the degree of aggressive behaviour observed in the tweets by Weber et al. (2020).

Discussion

This work touches on a variety of research questions, including how people decide their position in a social space when presented with conflicting opinions about contentious topics, how political ideology drives people’s stance on issues, and what could make an echo chamber transient or persistent. How behavior is affected by the social relations is described as one of the classic questions of social theory (Granovetter, 1985). A listener who is not an active part of the conversation experiences the occurrences of the others’ actions as “events occurring in outer time and space” (Garfinkel, Rawls, & Lemert, 2005). This view on shared events is a motivating factor for studying interactions which do not share physical presence, such as those in the online space. Studies have shown that people are influenced by online interactions, for instance, when it comes to making decisions about vaccination, opinions about vaccination on Twitter can act as a precursor to making a practical decision (Dunn, Leask, Zhou, Mandl, & Coiera, 2015).

Our analysis of the structural properties of a variety of networks based on their follower relations, interactions and hashtag use suggest that accounts expressing positive opinions about marriage equality (in the SSM dataset) or the arson narrative (in the ArsonEmergency dataset) were more closely connected in some parts of these networks.
leading to greater statistical homophily. Similar patterns held for those arguing against marriage equality and the arson narrative. A number of factors could be involved in causing this connection preference, some of which have been previously identified in the literature (Rogers & Bhowmik, 1970). These include that communication is more effective amongst those who share common meanings, attitudes and beliefs. Use of common information sources leads to a perception of greater trustworthiness and credibility within a community, while heterophilic interaction risks distortion of the message and potential for cognitive dissonance inasmuch as new messages can conflict with current beliefs. Such interactions can be valuable, however, helping to break the filter bubbles, exposing people to new ideas and points of view and challenging them to critically evaluate their own.

Based on our observations, the primary cause for persistent polarisation may be the existence of social groups more so than differences in opinions. As discussed above, a reason for homophilic connections is similarity between conversants, but that similarity may be due to being friends or acquaintances, rather than on less personal attributes, such as education or social status (as noted elsewhere in the literature, e.g., Rogers & Bhowmik, 1970). This is reinforced by the fact that the use of partisan hashtags in the Election dataset was so evenly distributed, suggesting that although the accounts interacted in what might be called echo chambers, they often discussed similar topics and held similar partisan views. In that sense, they may be more accurately described as social circles. That said, in other discussions, not only did they not interact, but they did not share content either, particularly in the ArsonEmergency dataset, so concerns that people are cutting themselves off from alternative viewpoints remain. Evidence from heterophilic connections in the ArsonEmergency dataset also aligns with observations of a high degree of antagonism (Weber et al., 2020).

More broadly, Bruns’ criticism of lack of clear definitions for the terms ‘echo chamber’ and ‘filter bubble’ (2019) is well-founded, but these labels still hold value for communicating high level concepts. We offer a conceptual definition of an echo chamber as a community formed around a shared opinion on a particular issue or discussion topic, within which that same opinion is reinforced as part of the community’s interactions and discussion. This is consistent with the literature (Garimella et al., 2018a). The members still interact with those outside the echo chamber, but may do so by also discussing other issues, which is in line with Georg Simmel’s theory of intersecting ‘social circles’ (Simmel, 1908). Echo chambers can be identified as communities whose content, when analysed, is highly focused and of a similar opinion (e.g., through the use of partisan hashtags, which declare a stance on an issue), but whose members still interact frequently with those outside the community. The members of a filter bubble, in contrast, lack significant interaction with those outside the community (i.e., instigated from within). This situation is often blamed on OSN recommendation algorithms in pursuit of personalised information offerings (Pariser, 2012; Massanari, 2016; Bruns, 2019). This kind of connectivity can be observed with network analysis and the discussion topics and stances can be identified with content analysis, but hard and fast rules such as ‘filter bubble members never interact with new content’ are too strict to be of use in the highly varied world of social media. Of course, these definitions are limited to the OSNs (and other communication environments) available for analysis. A person might only ever tweet about arson, but will still interact with family, friends and workmates outside of Twitter, so a filter bubble is only likely to occur in the most extreme of circumstances (e.g., isolated cults).

Critique and future work

There are a number of ways to improve the approaches we have taken in this study, including the following considerations.

The weights in the hashtag co-mention networks are calculated as the sum of the products of each pair of accounts’ uses of a common hashtag, which may potentially inflate weights and not reflect imbalanced use between the members of the pair. Others (e.g., Magelinski et al., 2021) have used the minimum instead, or a more sophisticated calculation may be warranted.

In fact, there may be benefit in additionally scaling edge weights by user activity: if an account is very active, they might co-use a hashtag more often just by chance, which will connect them to other users of the hashtag with very heavy edge weights. Taking relative activity into account may lighten these edges.

The manner in which partisan hashtags are chosen is also, to some degree, a subjective activity. Furthermore, the faux partisan hashtags are highly likely to generate polarised groups, after all that is how they are chosen. We have, however, revealed interesting findings in the hashtags that co-occur with them, so there is merit in the approach but deeper investigation is required. For example, these commonalities could be studied separately by ignoring the specifically partisan hashtags as the hashtag co-mention network is created from the filtered tweets.

The assumption that homophilic and heterophilic interactions are all equally representative of civil communication is lacking, and deeper examination is required to determine to what degree the interactions are positive or negative. Weber et al. (2020) found high degrees of aggression between the Arson groups, so it is possible that that aggression exists in the heterophilic connections in the other datasets. Methods exist for examining online group conflict that could be applied for this purpose (e.g., Kumar, Hamilton, Leskovec, & Jurafsky, 2018; Datta & Adar, 2019). An analysis of URL-sharing behaviour in these datasets may also reveal shared or divided stances on issues, as defined by what the URLs refer to.

Conclusion

Echo chambers on OSNs provide fertile ground for misinformation and polarisation on social and political issues, which can influence offline behaviour with real world effects such as vaccine hesitation and even violence. This study begins by identifying the SSM groups, a pair of polarised groups in the Twitter discussion surrounding the 2017 Australian postal survey on marriage equality. The activities of the SSM groups and of the previously
identified Arson groups (Weber et al., 2020) are tracked over several Twitter datasets spanning a long period and a variety of discussion topics. The aim of the study has been to characterise the nature of their polarisation in terms of the interactions used and the topics discussed to determine if such communities are persistently polarised, or whether they mix over time as the issues at hand change.

Our findings reveal that persistent communities of Australian Twitter users exist and remain polarised in the social groups they form over periods of several years, but that the topics they discuss are often common, even in the context of partisan topics. Furthermore, these polarised groups interact strongly with those outside their groups even while they avoid each other, which offers hope that the echo chambers they form between themselves can be pierced and infiltrated through further encouraging and facilitating engagement with the broader online community.

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Ethics
All data was collected, stored and analysed in accordance with Protocols #170316 and H-2018-045 as approved by the University of Adelaide’s human research ethics committee.

Supplementary material: Datasets
The marriage law postal survey (late 2017)
In late 2017, the Australian federal government conducted an optional national postal survey asking Australian voters “Should the law be changed to allow same-sex couples to marry?” On the basis of a majority affirmative result, the government would commit to passing legislation to change the Marriage Act accordingly. From August, when the survey was announced, through to the final acceptance date of the ballots in November and beyond, discussions and debate raged on social media with strong opinions both for and against marriage equality. Ultimately, over 60% of the nearly 13 million responses voted ‘yes’ and the Australian Parliament changed the law to permit marriage between any two individuals.

During three months of the campaign, we collected tweets from Twitter’s 10% academic sample stream based on the keywords #MarriageEquality, #SSM, #auspol, #VoteYes, and #VoteNo, capturing close to 80k tweets (and associated metadata) by almost 55k unique accounts.

The hashtags used as keyword filters belonged to two categories: general marriage equality-related terms (#MarriageEquality, #SSM, and #auspol), and ones clearly reflecting an opinion (#VoteYes and #VoteNo). We focused on the 17.3k accounts which used the opinion-linked hashtags, which we hypothesised would have relatively high structural cohesion around users of the same hashtag, and low structural cohesion among users of different hashtags. YES accounts were those that used only #VoteYes, NO accounts used only #VoteNo, and BOTH accounts used both hashtags. Of these, there were slightly more YES accounts than NO accounts (8.6k to 7.9k), and those using both made up just under 5% of the accounts using opinion hashtags (778). YES accounts contributed more tweets (18,621) than NO accounts (11,261) and BOTH accounts (7,246).

Some cleaning of the data was required due to international overlap with #VoteNo, which was also used in American discussions surrounding a medical insurance-related bill before the US Congress at the time. These tweets were identified through the use of a hashtag network. The network is visualised in Figure 8 with a force-directed layout clearly showing a minimally linked cluster of hashtags on the left that relate to the foreign discussion. 6,295 tweets posted by 5,366 accounts mentioning the hashtags in the orange coloured Louvain cluster (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008) to the left (other than #VoteNo) were identified as pollution and removed.

This dataset is referred to herein as the SSM dataset, and the YES and NO accounts as the SSM accounts (BOTH accounts are not included in the analysis as their position on the matter is just as obscure as OTHER accounts).

The Australian federal election (May 2019)
A total of 4,429 of the YES, NO and BOTH accounts (3,390, 631 and 408, respectively) were active during the election period surrounding the Australian federal election held on the 18th of May, 2019. Their activity was tracked, resulting in a dataset of nearly 400k tweets spanning three weeks. These activities were obtained, post-election, by retrieving their timelines via Twint (a tool that obtains Twitter data directly from its web UI avoiding any recommender influence or constraint present in the APIs). Nearly 3.4K YES accounts were active during the campaign, compared to only 631 NO accounts. The data includes a variety of politically-relevant hashtags, and in particular we have identified 44 partisan hashtags.

Australia’s “Black Summer” (2019-2020)
During the 2019-2020 southern summer, referred to as Australia’s ‘Black Summer’, bushfires burnt over 16 million

*https://www.abs.gov.au/ausstats/abs@.nsf/mf/1800.0
†The Decahose: https://developer.twitter.com/en/docs/twitter-api/enterprise/decahose-api/overview/decahose
‡All hashtag analysis was performed ignoring case, but capitals are included here for readability.
§https://github.com/twintproject/twint
hectares of the Australian mainland, destroyed over 3,500 homes, and caused at least 33 human and a billion animal fatalities (NSW Bushfire Inquiry, 2020). While scientists attributed these bushfires to natural causes such as lightning, an alternative theory labelled arson as the cause of bushfires. At the peak of the bushfires season the hashtag #ArsonEmergency started trending on Twitter and was observed to include a high proportion of bot and troll activity (Stilgherrian, 2020; Graham & Keller, 2020). Weber et al. (2020) collected a dataset of tweets during that period, both before and after news of bots and trolls reached the mainstream media. The dataset consisted of 27.5k tweets containing the term ‘ArsonEmergency’ posted by 12.9k unique accounts over 18 days in early January 2020. The Tweets were obtained with Twitter’s Standard Search API using Twarc.* Weber et al. (2020) found two polarised communities in the retweet network, which we refer to here as the Arson groups. One community strongly supported the arson narrative (Supporters), claiming arson was the cause of the bushfires, posting 6,972 tweets, while the other community opposed that narrative with fact-check articles and official announcements in 3,587 tweets (Opposers). A second study on this hashtag and contemporary news media reports found evidence of a disinformation campaign conducted by trolls, which appeared coordinated with the help of prominent public figures (Keller et al., 2020).

This dataset provides our second set of polarised accounts.

AFL (March 2019)

A further, non-political dataset that could also exhibit patterns of polarisation was sought as a contrast. Australian Rules Football is a national pastime in Australia, particularly following the national competition run by and synonymous with the Australian Football League (AFL). A three-day collection of AFL discussions was conducted over a weekend in March, 2019, just as the annual season began (previously published in Weber et al., 2021). Although a federal election was expected around this time, it was not called for another two weeks, and so little political content was expected to be captured. The collection tool RAPID (Lim et al., 2018) was used to stream all tweets from the Standard Twitter v1.0 Streaming API (up to rate limits) using the keyword ‘afl’ and a language filter for English and undefined (i.e., a ‘lang’ value of ‘und’, which captures text too short to inform Twitter’s language detection).

Polarisation labelling

Different methods were used to identify polarised communities in the SSM and Bushfires datasets due to the different ways in which they were collected. The sizes of the groups discovered are shown in Table 5 and their relative contributions in Figure 9.

Generalising our terminology, we refer to YES and Supporter groups as Category 1 accounts and NO and Opposer groups as Category 2 accounts later in this work. Any unaffiliated accounts appearing in networks are given the label OTHER.

A summary of the content of the datasets and the extent of the polarised group presence in them is shown in Table 6.
Polarisation leading up to the federal election. The polarisation in the Election dataset is statistically significant across all groups and interactions, and it is homophilic in all but one condition: NO accounts mention YES accounts more frequently than other NO accounts. This is not necessarily surprising given there are more than five times more YES accounts than NO accounts active in the dataset.

Amongst the Arson groups, in particular, the echo chamber effect (with relation to each other, at least) is stark, with both groups preferring internal to external connections by several orders of magnitude. The smallest ratio of homophilic to heterophilic connections was Supporters’ use of quotes (at ≈ 6.8), but most were much greater than that. This marked polarisation is also immediately apparent in visualisations of the interaction networks (Figures 4a to 4d).

The results amongst SSM groups were also all statistically significant, and in all but one case were homophilic, as mentioned above, but the pattern of polarisation differs due to the relative sizes of the groups present (Figures 4e to 4h). The imbalance in use of interactions is immediately apparent, with the greater number of active YES accounts (presented in Table 2) contributing more proportionally than NO accounts across all interaction types. YES accounts outnumber NO accounts five to one, but posted 8.2 times as many retweets, 10.5 times as many mentions, 8.4 times as many replies and 6.9 times as many quotes, so more YES accounts were present in the Election dataset but they were also more active. Furthermore, their echo chamber effect was more pronounced, retweeting, mentioning, replying to and quoting each other over 95% of the time, while NO accounts interacted with each other slightly less than half the time. These findings indicate that: 1) polarisation detected amongst one type of interaction can be present across other types of interaction; and 2) polarisation detected in one issue-related discussion can be found in other issue-related discussions, including across a variety of interactions.

The issues discussed in the ArsonEmergency and Election datasets can be regarded as at least partially political in nature, so the question remains whether the above phenomena persist in non-political discussions. We use the AFL dataset for this contrast, assuming that, whatever their political opinions, any alignment with people’s political opinions is likely to be coincidental. Political discussion in the AFL dataset is minimal, and even the most prominent political hashtag is the non-partisan #auspol.

Polarisation discussing the AFL. Very few Arson accounts interacted with other accounts in the AFL dataset, but where they did it was strongly homophilic relative to each group. The majority of their connections were to the broader network as sources of interactions (i.e., they reached out to others).

SSM accounts also interacted rarely in the AFL dataset, but the much greater number of YES accounts were strongly homophilic in the connections they made, with respect to the two groups. Again, both groups interacted strongly with the broader network, with some accounts frequently the recipient of interactions rather than just the instigator, as was the case with the Arson group members.

Summary of interaction network findings. In almost all circumstances, the echo chamber effect appears to be
maintained to some degree, with internal connections preferred over external ones, especially between Supporters and Opposers. The only circumstance where that effect is reduced is in the NO groups’ use of replies and mentions and Opposers’ use of mentions in the ArsonEmergency dataset, where they more even in their connections. It is possible that some of these mentions were used for aggressive, rather than collegiate, interactions, but analysis of their content is required for this judgement and there were relatively few of these interactions, so any such judgement is unlikely to be indicative of a broader pattern of behaviour.

**Networks based on content**

Results so far indicate the echo chamber effect is strongly maintained across most interactions in most datasets, especially where there is reasonable amount of activity. Here we consider whether the topics also under discussion also exhibit similar patterns of polarisation, and we use hashtags as an indicator of those topics.

First, however, we must cull the hashtags under consideration, as the high frequency of popular hashtags can hamper the discovery of the structures underlying their use. Instead, as discussed above, we explicitly filter the most frequent hashtags and we additionally make use of partisan and faux partisan hashtags. Examining the distributions of hashtag use in each of the dataset revealed that removing the ten most frequent hashtags in each would be sufficient to avoid the majority of their binding effects (shown as the dashed red vertical lines in Figure 5).

Second, we developed the (faux) partisan hashtag sets. In the Election dataset, we identified 44 hashtags of the 200 most frequent as clearly partisan (e.g., #corrupt<party> or #<party>liars). For the AFL and ArsonEmergency datasets, we identified the ten most frequently used hashtags unique to each group. We considered the tweets containing these hashtags and created hashtag co-mention networks using all the hashtags that appeared in them (save for the most frequently occurring hashtags, as mentioned above). The number of hashtags considered for each group and dataset is shown in parentheses next to the “Hashtags” label in Table 4, which also shows the number of SSM and Arson group accounts present in the resulting networks, and their respective connectivity.

Above, Table 3 shows that although the connectivity between the polarised groups was often statistically significant, it was often heterophilic rather than homophilic, meaning the groups often used the same hashtags. That said, there were large imbalances between the homophilic connections of the groups: YES accounts used YES-specific hashtags far more frequently than NO accounts used NO-specific hashtags in the Election dataset, while the same applied for Opposer accounts. In the other datasets, only Opposers’ use of Opposer-specific hashtags in the ArsonEmergency dataset stand out, and that is because there are so few connections, relatively (there were 7,875 Opposer–Opposer connections, compared with 106,433 Supporter–Supporter connections and 106,922 Supporter–Opposer connections). Opposers strongly shared hashtags with Supporters, while Supporters also connected internally strongly to a similar degree. In all other cases, heterophilic connections dominated. This suggests that although the groups tended to interact amongst themselves, they often discussed similar topics, even with similar partisan leanings. A deeper exploration of which particular hashtags accounted for these heterophilic connections could reveal further insights regarding the axes of polarisation and agreement between the groups.

**Visualisation reveals deeper community structures.** Using the backbone layout to visualise the hashtag co-mention networks (Figure 6) makes clear the extent of the isolation of the groups despite their heterophilic connections, as well as the implications of the homophily measures. Nodes are sized according to weighted degree, using the backbone strength for edge weights. Edges are also coloured and sized according to backbone strength.

The relatively low homophily of the YES and NO groups during the Election (Figure 6a) is primarily due to the relatively small number of NO-only connections (see Table 3), which is evident from the NO nodes’ dispersed placement throughout the network. Despite the placement, their size indicates they have high centrality and are therefore deeply embedded in the network. In contrast, the Supporter nodes active in the Election in Figure 6b are not deeply embedded in the network (according to their sizes) but they clearly form a cluster of their own (to the bottom of the figure). The majority of Opposer nodes reside in a large cluster (top left) and are deeply embedded. The relatively moderate E-I Index and assortativity scores in Table 4 (−0.207 and 0.055, respectively) indicate that the Supporter nodes are highly connected to the Opposer nodes, which outnumber them, one to two (72 to 156).

Both SSM and Arson groups formed mostly homophilic tight clusters in the ArsonEmergency dataset (Figures 6c and 6d, respectively), but NO accounts were more often associated with BOTH accounts, which suggests they shared views on the arson narrative, given the alignment between NO and Supporter groups mentioned previously. Opposers and Supporters formed multiple separate clusters, but the most deeply embedded Opposers are clearly strongly concentrated in a single cluster (bottom left), while the deeply embedded Supporters form several groups. Deeper analysis is needed to examine which hashtags bound each different cluster.

Similar patterns of hashtag co-use are present in the AFL dataset (Figures 6e and 6f), but unaffiliated
accounts contributed more structure. The nature of the AFL discussion is relatively clustered in general, however, as sports fans discuss specific games, each of which has its own hashtag, which they use along with the #afl hashtag – the top five used hashtags after #afl were #aflPiesCats, #aflDogsSwans, #aflLionsEagles, #aflFreoNorth and #aflDeesPower, all of which refer to the AFL and two teams that played each other in that round of the competition. It is therefore unsurprising to see some significant degree of clustering in these networks, but the fact that accounts from different groups do not seem to mix in each is notable, and may suggest a strong degree of influence from social circles.

Homophily measures and the broader network

The homophily measures in Table 4 provide a more nuanced view of the groups’ homophily or heterophily in different circumstances than the statistics in Table 3. The SSM groups remained moderately to strongly polarised among all interactions except for mentions in the Election and ArsonEmergency datasets and the few quotes they posted in the AFL dataset. The Arson groups were mostly highly polarised in all cases except in replies (moderately) and mentions (mildly) in the ArsonEmergency dataset. Regarding their content, polarisation remained in the Arson groups, respectively) during the Election.

Considering the broader network (as defined above), it is clear that all groups interacted and shared discussions with each other, albeit with some differences across contexts. For example, the AFL discussion is relatively clustered in general, however, as sports fans discuss specific games, each of which has its own hashtag, which they use along with the #afl hashtag – the top five used hashtags after #afl were #aflPiesCats, #aflDogsSwans, #aflLionsEagles, #aflFreoNorth and #aflDeesPower, all of which refer to the AFL and two teams that played each other in that round of the competition. It is therefore unsurprising to see some significant degree of clustering in these networks, but the fact that accounts from different groups do not seem to mix in each is notable, and may suggest a strong degree of influence from social circles.

References

Aggarwal, A., Kumar, S., Bhargava, K., & Kumaraguru, P. (2018, April). The follower count fallacy: Detecting Twitter users with manipulated follower count. In Symposium on Applied Computing (SAC 2018). ACM. doi: 10.1145/3167132.3167318

Aggarwal, A., & Kumaraguru, P. (2015, July). What they do in shadows: Twitter underground follower market. In Annual Conference on Privacy, Security and Trust (PST). IEEE. doi: 10.1109/pst.2015.7232959

Albada, K., Hansen, N., & Otten, S. (2021, April). Polarization in attitudes towards refugees and migrants in the netherlands. European Journal of Social Psychology, 51(3), 627–643. doi: 10.1002/ejsp.2766

Ali, S. H., & Kurasawa, F. (2020, March). #COVID19: Social media both a blessing and a curse during coronavirus pandemic. The Conversation. Retrieved from https://thecoveration.com/covid19-social-media-both-a-blessing-and-a-curse-during-coronavirus-pandemic-133596

Assenmacher, D., Weber, D., Preuss, M., Valdez, A. C., Bradshaw, A., Ross, B., . . . Grimme, C. (2021, May). Benchmarking crisis in social media analytics: A solution for the data-sharing problem. Social Science Computer Review. doi: 10.1177/0894393211012268

Badawy, A., & Ferrara, E. (2018, April). The rise of Jihadist propaganda on social networks. Journal of Computational Social Science, 1(2), 453–470. doi: 10.1007/s42001-018-0015-z

Badham, V. (2021, October). No, Australia is not actually an evil dictatorship. The New York Times. Retrieved from https://www.nytimes.com/interactive/2018/01/27/technology/social-media-bots.html

Bail, C. A., Argyle, L. P., Brown, T. W., Bumpus, J. P., Chen, H., Hunzaker, M. B. F., . . . Volfovsky, A. (2018, August). Exposure to opposing views on social media can increase political polarization. PNAS, 115(37), 9216–9221. doi: 10.1073/pnas.1804840115

Baronchelli, A. (2018, February). The emergence of consensus: a primer. Royal Society Open Science, 5(2). doi: 10.1098/rsos.172189

Barry, P. (2020, February). Media Watch: News Corps Fire Fight. Australian Broadcasting Corporation. Australian Broadcasting Corporation. Retrieved from https://iview.abc.net.au/show/media-watch/series/0/video/FA1935H001S00 (Broadcast 2020-02-03)

Baumann, F., Lorenz-Spreen, P., Sokolov, I. M., & Starnini, M. (2021, January). Emergence of polarized ideological opinions in multidimensional topic spaces. Physical Review X, 1(1). doi: 10.1103/physrevx.11 .011012

Benkler, Y., Farris, R., & Roberts, H. (2018). Network propaganda. Oxford University Press. doi: 10.1093/oso/9780190923624.001.0001

Bessi, A., & Ferrara, E. (2016, January). Emergence of polarized attitudes towards refugees and migrants in the netherlands. European Journal of Social Psychology, 51(3), 627–643. doi: 10.1002/ejsp.2766

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. Journal of Statistical Mechanics: Theory and Experiment, 2008(10). doi: 10.1088/1742-5468/2008/10/p10008

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. Science, 323(5916), 892–895. doi: 10.1126/science.1165821

Bot Sentinel. (2021, October). Twitter hate accounts targeting Meghan and Harry, Duke and Duchess of Sussex (Tech. Rep.). Bot Sentinel Inc. Retrieved from https://botsentinel.com/reports/documents/duke-and-duchess-of-sussex-report-10-26-2021.pdf

Brazil, R. (2020, July). Fighting flat-Earth theory. Physics World. Retrieved from https://physicsworld.com/a/fighting-flat-earth-theory/

Broniatowski, D. A., Jamison, A. M., Qi, S., AlKulaib, L., Chen, T., Benton, A., . . . Dredze, M. (2018, October). Weaponized health communication: Twitter bots and Russian trolls amplify the vaccine debate. American Journal of Public Health, 108(10), 1378–1384.
Seen

Garfinkel, H., Rawls, A., & Lemert, C. C. (2005). Seeing sociologically: The routine grounds of social action (1st ed.). Taylor & Francis Ltd.

Garimella, K., Morales, G. D. F., Gionis, A., & Mathioudakis, M. (2017, June). The effect of collective attention on controversial debates on social media. In WebSci. ACM. doi: 10.1145/3091478.3091486

Garimella, K., Morales, G. D. F., Gionis, A., & Mathioudakis, M. (2018a). Polarization on social media. In WWW (Tutorial Volume). ACM.

Garimella, K., Morales, G. D. F., Gionis, A., & Mathioudakis, M. (2018b). Political discourse on social media: Echo chambers, gatekeepers, and the price of bipartisanship. In WWW. ACM Press. doi: 10.1145/3178876.3186139

Graham, T., & Ackland, R. (2017). Do socialbots dream of popping the filter bubble? The role of socialbots in promoting participatory democracy in social media. In R. W. Gehl & M. Bakardjieva (Eds.), Socialbots and their friends: Digital media and the automation of sociality (pp. 187–206). London: Routledge.

Graham, T., Bruns, A., Angus, D., Hurcombe, E., & Hames, S. (2020, December). #IStandWithDan versus #DictatorDan: the polarised dynamics of Twitter discussions about Victoria’s COVID-19 restrictions. Media International Australia, 1329878X2098178. doi: 10.1177/1329878x20981780

Graham, T., Bruns, A., Zhu, G., & Campbell, R. (2020, May). Like a virus: the coordinated spread of coronavirus disinformation (Tech. Rep.). Centre for Responsible Technology, The Australia Institute. Retrieved from https://apo.org.au/node/305864

Habermas, J. (1996). Between facts and norms: Contributions to a discourse theory of law and democracy. Cambridge, Mass: MIT Press.

Hine, G. E., Onaolapo, J., Cristofaro, E. D., Kourtellis, N., Leontiadis, I., Samaras, R., . . . Blackburn, J. (2017). Kek, cucks, and God Emperor Trump: A measurement study of 4chan’s politically incorrect forum and its attention on controversial debates on social media. In WWW (pp. 187–206). London: Routledge.

Hinze, J., & Wolfram, N. (2015, June). Associations between exposure to and expression of negative opinions about human papillomavirus vaccines on social media: An observational study. Journal of medical Internet research, 17(6), e144. doi: 10.2196/jmir.4343

Hussár, F., Ktena, S. I., O’Brien, C., Belli, L., Schlaikjer, A., & Hardt, M. (2021, October). Algorithmic amplification of politics on Twitter (Tech. Rep.). Twitter. Retrieved from https://cdn.cms-twdigitalassets.com/content/dam/blog-twitter/official/en_us/company/2021/rml/Algorithmic-Amplification

Huszár, F., Nasim, I., & Gionis, A. (2020, November). Social cybersecurity: an emerging science. Computational and Mathematical Organization Theory, 26(4), 365–381. doi: 10.1007/s10588-020-09322-9

Huszar, F., Ktena, S. I., O’Brien, C., Belli, L., Schlaikjer, A., & Hardt, M. (2021, October). Algorithmic amplification of politics on Twitter (Tech. Rep.). Twitter. Retrieved from https://cdn.cms-twdigitalassets.com/content/dam/blog-twitter/official/en_us/company/2021/rml/Algorithmic-Amplification
Kumar, S., Hamilton, W. L., Leskovec, J., & Jurafsky, D. (2022, March). SocialBots: Voices from the fronts. *Interactions, 19*(2), 38–45. doi: 10.1145/2090150.2090161

Häussler, T. (2018, July). Heating up the debate? Measuring fragmentation and polarisation in a German climate change hyperlink network. *Social Networks, 54*, 303–313. doi: 10.1016/j.socnet.2017.10.002

Jamieson, K. H. (2020). *Cyberwar*. Oxford University Press. doi: 10.1093/oso/9780190058838.001.0001

Jost, J. T., Glaser, J., Kruglanski, A. W., & Sulloway, F. J. (2017, March). Ideological asymmetries and the essence of political psychology. *Psychological Bulletin*, *129*(3), 339–375. doi: 10.1037/0302-9900-129.3.339

Keller, T., Graham, T., Angus, D., Bruns, A., Marchal, N., Neudert, L.-M., . . . de Oliveira, V. V. (2020, October). ‘Coordinated inauthentic behaviour’ and other online influence operations in social media spaces. Panel presented at the Annual Conference of the Association of Internet Researchers, AoIR 2020. Retrieved from [https://spir.oair.org/ojs/index.php/spir/article/view/11132/9763](https://spir.oair.org/ojs/index.php/spir/article/view/11132/9763)

King, G., Pan, J., & Roberts, M. E. (2017). How the Chinese government fabricates social media posts for strategic distraction, not engaged argument. *American Political Science Review, 111*(3), 484–501. doi: 10.1017/S0003055417000144

Kligler-Vilenchik, N., Baden, C., & Yarchi, M. (2020). Interpretative polarization across platforms: How political disagreement develops over time on Facebook, Twitter, and WhatsApp. *Social Media + Society, 6*(3). doi: 10.1177/2056305120944393

Krackhardt, D., & Stern, R. N. (1988, June). Informal Networks and Organizational Crises: An Experimental Simulation. *Social Psychology Quarterly*, *51*(2), 123–140. doi: 10.2307/2786835

Kumar, S., Hamilton, W. L., Leskovec, J., & Jurafsky, D. (2018). Community interaction and conflict on the Web. In *WWW* (pp. 933–943). ACM. doi: 10.1145/3178876.3186141

Lim, K., Jayasekara, S., Karunasekera, S., Harwood, A., Falcon, L., Dunn, J., & Burgess, G. (2018). RAPID: Real-time Analytics Platform for Interactive Data Mining. In *ECML/PKDD* (3) (Vol. 11053, pp. 649–653). Springer. doi: 10.1007/978-3-030-10997-4_44

Loomba, S., de Figueiredo, A., Piatek, S. J., de Graaf, K., & Larson, H. J. (2021, February). Measuring the impact of COVID-19 vaccine misinformation on vaccination intent in the UK and USA. *Nature Human Behaviour*. doi: 10.1038/s41562-021-01056-1

Loucaides, D., Perrone, A., & Holnburger, J. (2021, June). How Germany became ground zero for the COVID infodemic — openDemocracy. Retrieved from [https://www.opendemocracy.net/en/germany-ground-zero-covid-infodemic-russia-far-right/](https://www.opendemocracy.net/en/germany-ground-zero-covid-infodemic-russia-far-right/)

Mackintosh, E. (2021, October). Facebook knew it was being used to incite violence in Ethiopia. It did little to stop the spread, documents show. *CNN, The Facebook Papers*. Retrieved from [https://edition.cnn.com/2021/10/25/business/ethiopia-violence-facebook-papers-cmd-intl/index.html](https://edition.cnn.com/2021/10/25/business/ethiopia-violence-facebook-papers-cmd-intl/index.html)

Magelinski, T., Ng, L. H. X., & Carley, K. M. (2021, May). A synchronized action framework for responsible detection of coordination on social media. *CoRR, abs/2105.07454*.  

Mariconti, E., Suarez-Tangil, G., Blackburn, J., Cristofaro, E. D., Kourtellis, N., Leontiadis, I., . . . Stringhini, G. (2019, November). “You know what to do”: Proactive detection of YouTube videos targeted by coordinated hate attacks. *PACMHCI, 3* (CSCW), 207:1–207:21.

Massanari, A. (2016, July). #gamerGate and the Fappening: How Reddit’s algorithm, governance, and culture support toxic technocultures. *New Media & Society, 19*(3), 329–346. doi: 10.1177/1461444815608807

McPherson, M., Smith-Lovin, L., & Cook, J. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology, 415–444*. doi: 10.1146/annurev.soc.27.1.415

Merrill, J. B., & Oremus, W. (2021, October). Five points for anger, one for a ‘like’: How Facebook’s formula fostered rage and misinformation. *The Washington Post*. Retrieved from [https://www.washingtonpost.com/technology/2021/10/26/facebook-angry-emoji-algorithm/](https://www.washingtonpost.com/technology/2021/10/26/facebook-angry-emoji-algorithm/)

Metaxas, P. T., & Mustafaraj, E. (2012). Social media and the elections. *Science, 338*(6106), 472–473. doi: 10.1126/science.1230456

Morstatter, F., Shao, Y., Galstyan, A., & Karunasekera, S. (2018). From Alt-Right to Alt-Rechts: Twitter analysis of the 2017 German federal election. In *WWW Companion Volume* (pp. 621–628). ACM. doi: 10.1145/3184558.3188733

Nasim, M. (2016). Inferring social relations from online and communication networks (Doctoral dissertation, University of Konstanz, Computer and Information Science). Retrieved from [http://nbn-resolving.de/urn:nbn:de:bsz:352-0-422190](http://nbn-resolving.de/urn:nbn:de:bsz:352-0-422190)

Nasim, M. (2019, November). *Polarisation on social media: Modelling and evaluation*. Talk presented at the Australian Social Network Analysis Conference, ASNAC’19.

Nasim, M., Charbey, R., Prieur, C., & Brandes, U. (2016). Nasim, M. (2019, November). *Polarisation on social media: Modelling and evaluation*. Talk presented at the Australian Social Network Analysis Conference, ASNAC’19.

Nasim, M., Charbey, R., Prieur, C., & Brandes, U. (2016). Investigating link inference in partially observable networks: Friendship ties and interaction. *IEEE Transactions on Computational Social Systems, 3*(3), 113–119. doi: 10.1109/TCSs.2016.2618998

Nasim, M., Nguyen, A., Lothian, N., Cope, R., & Mitchell, L. (2018, April). Real-time detection of content polluters in partially observable Twitter networks. In *WWW Companion Volume* (pp. 1331–1339). doi: 10.1145/3184558.3191574

Nasim, M., Tuke, J., Bean, N., & Mitchell, L. (2019).
Emergence of echo chambers in social relations and sentiments on Twitter: An observational study. *NetSci.*

Nastos, J., & Gao, Y. (2013, July). Familial groups in social networks. *Social Networks, 35*(3), 439–450. doi: 10.1016/j.socnet.2013.05.001

Newman, M. E. J. (2003, February). Mixing patterns in networks. *Physical Review E, 67*(2). doi: 10.1103/physreve.67.026126

Nick, B., Lee, C., Cunningham, P., & Brandes, U. (2013). Simmelian backbones: Amplifying hidden homophily in Facebook networks. In *ASONAM* (pp. 525–532). doi: 10.1145/2492517.2492569

Nikolov, D., Flammini, A., & Menczer, F. (2021, February). Right and left, partisanship predicts (asymmetric) vulnerability to misinformation. *Harvard Kennedy School (HKS) Misinformation Review.* Retrieved from https://misinforeview.hks.harvard.edu/article/right-and-left-partisanship-predicts-asymmetric-vulnerability-to-misinformation/(2021-02-15) doi: 10.37016/mr-2020-55

Nocaj, A., Ortmann, M., & Brandes, U. (2014). Untangling hairballs. In *International symposium on graph drawing* (pp. 101–112). doi: 10.1007/978-3-662-45803-7_9

NSW Bushfire Inquiry. (2020, July). *Final report of the NSW Bushfire Inquiry (State Inquiry Report).* NSW State Government. Retrieved from https://www.dpc.nsw.gov.au/assets/dpc-nsw-gov-au/publications/NSW-Bushfire-Inquiry-1630/Final-Report-of-the-NSW-Bushfire-Inquiry.pdf

Pacheco, D., Flammini, A., & Menczer, F. (2020, April). Unveiling coordinated groups behind White Helmets disinformation. In *WWW (Companion).* ACM. doi: 10.1145/3366424.3385775

Pariser, E. (2012). *The filter bubble.* Penguin LCC US.

Rogers, E. M., & Bhowmik, D. K. (1970). Homophily-heterophily: Relational concepts for communication research. *Public opinion quarterly, 34*(4), 523–538. doi: 10.1086/267838

Samuels, E. (2020, February). How misinformation on WhatsApp led to a mob killing in India. *The Washington Post.* Retrieved from https://www.washingtonpost.com/politics/2020/02/21/how-misinformation-whatsapp-led-deadly-mob-lynching-india/

Schliebs, M., Bailey, H., Bright, J., & Howard, P. N. (2021, May). China’s inauthentic UK Twitter diplomacy: A coordinated network amplifying *DRC* diplomatys (Working Paper No. 2021.2). Oxford, UK: Programme on Democracy and Technology, Oxford University. Retrieved from https://demtech.oii.ox.ac.uk/china-public-diplomacy-casestudy-uk

Schroeder, R. (2018). *Social theory after the internet.* UCL Press. doi: 10.14324/111.9781787351226

Scott, M. (2021, January). *Capitol Hill riot lays bare what’s wrong with social media.* POLITICO. Retrieved from https://www.politico.eu/article/us-capitol-hill-riots-lay-bare-whats-wrong-social-media-donald-trump-facebook-twitter/

Shorey, S., & Howard, P. N. (2016). Automation, Algorithms, and Politics—Automation, Big Data and Politics: A Research Review. *International Journal of Communication, 10,* 5032–5055. Retrieved from http://ijoc.org/index.php/ijoc/article/view/6233/1812

Simmel, G. (1908). *Das Geheimnis und die geheime Gesellschaft.* *Soziologie. Untersuchungen über die Formen der Vergesellschaftung,* 256–304.

Skitka, L. J., & Bauman, C. W. (2008, January). Moral conviction and political engagement. *Political Psychology, 29*(1), 29–54. doi: 10.1111/j.1467-9221.2007.00611.x

Starbird, K. (2019, July). Disinformation’s spread: bots, trolls and all of us. *Nature, 571*(7766), 449–449. doi: 10.1038/d41586-019-02235-x

Starbird, K., Arif, A., & Wilson, T. (2019, November). Disinformation as collaborative work: Surfacing the participatory nature of Strategic Information Operations. *PACMHCI, 3*(CSCW), 1–26. Retrieved from https://doi.org/10.1145/3359229 doi: 10.1145/3359229

Stilgherrian. (2020, January). Twitter bots and trolls promote conspiracy theories about Australian bushfires. *ZDNet.* Retrieved from https://www.zdnet.com/article/twitter-bots-and-trolls-promote-conspiracy-theories-about-australian-bushfires/

Strick, B. (2021, August). Analysis of the pro-China propaganda network targeting international narratives (Research Report). Centre for Information Resilience. Retrieved from https://www.info-res.org/post/revealed-coordinated-attempt-to-push-pro-china-anti-western-narratives-on-social-media

Subramanian, S. (2017, February). Inside the Macedonian fake-news complex. *Wired.* Retrieved from https://www.wired.com/2017/02/veles-macedonia-fake-news/

Tasnim, S., Hossain, M. M., & Mazumder, H. (2020, May). Impact of rumors and misinformation on COVID-19 in social media. *Journal of Preventive Medicine and Public Health, 53*(3), 171–174. doi: 10.3961/jpmph.20.094

The Soufan Center. (2021, April). *Quantifying the Q Conspiracy: A Data-Driven Approach to Understanding the Threat Posed by QAnon* (Special Report). The Soufan Center. Retrieved from https://thesoufancenter.org/research/quantifying-the-q-conspiracy-a-data-driven-approach-to-understanding-the-threat-posed-by-qanon/

Timberg, C., Dowskin, E., & Albergotti, R. (2021, October). How Facebook played a role in the Jan. 6 Capitol riot. *The Washington Post.* Retrieved from https://www.washingtonpost.com/technology/2021/10/22/jan-6-capitol-riot-facebook/
Waldek, L., Ballsun-Stanton, B., & Droogan, J. (2020, November). *After Christchurch: mapping online right-wing extremists*. The Lowy Institute. Retrieved from https://researchers.mq.edu.au/en/publications/after-christchurch-mapping-online-right-wing-extremists

Wardle, C. (2019, September). A new world disorder. *Scientific American, 321*(3), 88–93. doi: 10.1038/scientificamerican0919-88

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8). Cambridge University Press.

Weber, D., Nasim, M., Falzon, L., & Mitchell, L. (2020, April). #ArsonEmergency and Australia’s “Black Summer”: Polarisation and misinformation on social media. In *Disinformation in open online media* (pp. 159–173). Springer International Publishing. doi: 10.1007/978-3-030-61841-4_11

Weber, D., Nasim, M., Mitchell, L., & Falzon, L. (2021, July). Exploring the effect of streamed social media data variations on social network analysis. *Social Network Analysis and Mining, 11*(1). doi: 10.1007/s13278-021-00770-y

Woolley, S., & Guilbeault, D. (2018). United States: Manufacturing consensus online. In P. Howard & S. Woolley (Eds.), *Computational propaganda: Political parties, politicians, and political manipulation on social media* (pp. 185–211). Oxford University Press. doi: 10.1093/oso/9780190931407.001.0001

Woolley, S. C. (2016, March). Automating power: Social bot interference in global politics. *First Monday, 21*(4). doi: 10.5210/fm.v21i4.6161