Echo Chamber? What Echo Chamber? Reviewing the Evidence

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Abstract

The success of political movements that appear to be immune to any factual evidence that contradicts their claims – from the Brexiteers to the 'alt-right', neo-fascist groups supporting Donald Trump – has reinvigorated claims that social media spaces constitute so-called 'filter bubbles' or 'echo chambers'. But while such claims may appear intuitively true to politicians and journalists – who have themselves been accused of living in filter bubbles (Bradshaw 2016) –, the evidence that ordinary users experience their everyday social media environments as echo chambers is far more limited.

For instance, a 2016 Pew Center study has shown that only 23% of U.S. users on Facebook and 17% on Twitter now say with confidence that most of their contacts' views are similar to their own. 20% have changed their minds about a political or social issue because of interactions on social media (Duggan and Smith 2016). Similarly, large-scale studies of follower and interaction networks on Twitter (e.g. Bruns *et al*., 2014) show that national Twitterspheres are often thoroughly interconnected and facilitate the flow of information across boundaries of personal ideology and interest, except for a few especially hardcore partisan communities.

Building on new, comprehensive data from a project that maps and tracks interactions between 4 million accounts in the Australian Twittersphere, this paper explores in detail the evidence for the existence of echo chambers in that country. It thereby moves the present debate beyond a merely anecdotal footing, and offers a more reliable assessment of the 'echo chamber' threat.

Keywords

echo chamber, filter bubble, social media, Twitter, Australia, network analysis

Introduction

The success of political movements that appear to be immune to any factual evidence that contradicts their claims – from the Brexiteers to the 'alt-right', neo-fascist groups supporting Donald Trump – has reinvigorated claims that social media spaces constitute so-called 'filter bubbles' (Pariser 2011) or 'echo chambers' (Sunstein 2009). But while such claims may appear intuitively true to politicians and journalists – who have themselves been accused of living in filter bubbles (Bradshaw 2016) –, the evidence that ordinary users experience their everyday social media environments as echo chambers is far more limited. For instance, a 2016 Pew Center study, conducted in the lead-up to that year's presidential election, showed that only 23% of U.S. users on Facebook and 17% on Twitter now say with confidence that most of their contacts' views are similar to their own. 20% have changed their minds about a political or social issue because of interactions on social media (Duggan and Smith 2016; fig. 1). At the same time, 39% of social media users say they have changed their settings to filter out political posts or block certain users in their network; this could certainly be seen as an attempt to build a personal echo chamber, but in itself is also a clear sign that those filtering mechanisms are as yet far from effective.

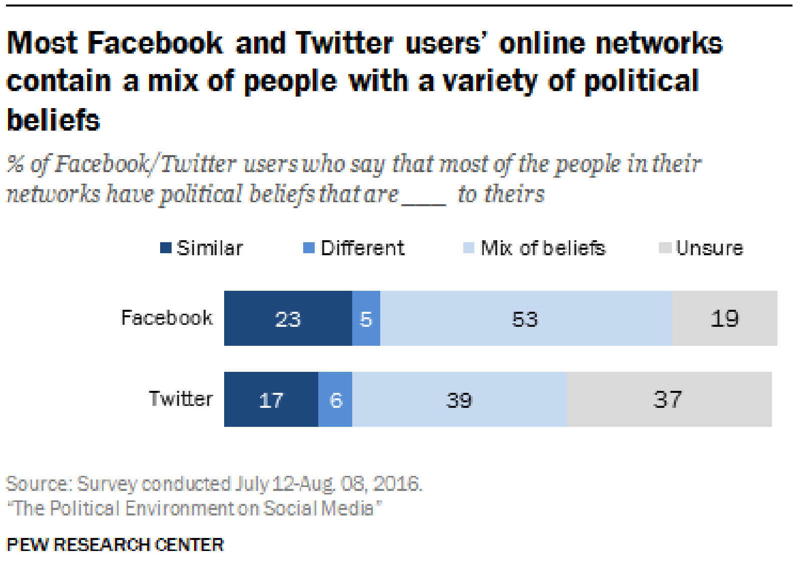

Fig. 1: U.S. social media users' assessment of their social network connections' political beliefs. (Duggan and Smith 2016)

Further, the *Reuters Institute Digital News Report 2017* finds "that on average social media users access more brands (4.34 per week) than non-users (3.10 per week). Likewise, those who use search engines for news, or news aggregators, use more online news brands than those who don't" (Newman *et al*. 2017: 43). This might be seen as evidence that the use of digital media for news is actively dissolving rather than strengthening users' filter bubbles.

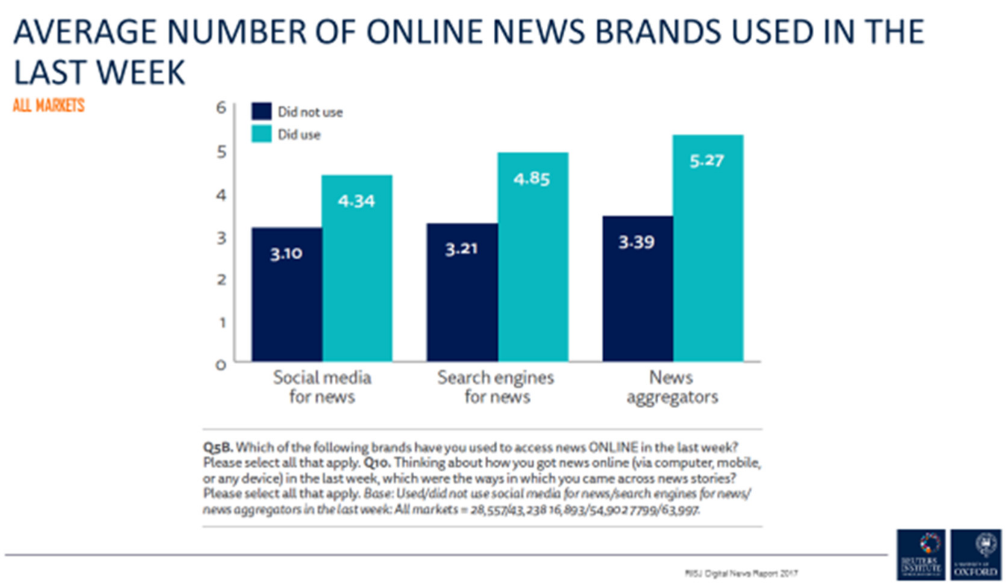

Fig. 2: Average number of online news brands used by users and non-users of online services (Newman et al. *2017: 43)*

There is a pressing need for more empirical assessments of the actual presence and impact of echo chambers and filter bubbles, then; in the absence of reliable data on these phenomena, there is a considerable danger that these terms (along with 'fake news') simply represent the latest in a long line of moral panics associated with new media technologies, embraced for various reasons by journalists and politicians who may indeed live in their own professional filter bubbles but for that reason falsely assume that their experience is shared by ordinary social media users. This paper explores the empirical evidence for the existence of such exclusionary network structures, therefore; it focusses on one of the social networks most frequently cited as part of the problem, *Twitter*, and draws on a large dataset of network structures and account interactions in the Australian Twittersphere as its test case.

Defining the Key Terms

One central problem in testing for the existence of echo chambers and filter bubbles is the rather loose definition of these key terms; indeed, in much public discourse they are used almost interchangeably. For the purposes of this study, the two terms are treated as describing distinct but interrelated patterns that are able to be operationalised in the empirical analysis of network structures, on social media and beyond:

1. An **echo chamber** comes into being where a group of participants *choose to preferentially connect* with each other, to the exclusion of outsiders. The more fully formed this network is (that is, the more connections are created within the group, and the more connections with outsiders are severed), the more isolated from the introduction of outside views is the group, while the views of its members are able to circulate widely within it.
2. A **filter bubble** emerges when a group of participants, independent of the underlying network structures of their connections with others, *choose to preferentially communicate* with each other, to the exclusion of outsiders. The more consistently they adhere to such practices, the more likely it is that participants' own views and information will circulate amongst group members, rather than information introduced from the outside.

The important distinction that these definitions seek to make is one between the structural properties of a network of participants on the one hand, and between the behavioural patterns amongst participants on the other. This does not mean that there is no linkage between the two concepts, of course: the existence of a strongly established echo chamber means that it becomes much easier for a filter bubble to emerge, for instance. However, one does not automatically imply the other: for example, in a well-connected network that shows few echo chamber tendencies, and which would therefore enable the widespread circulation of information from a diverse range of sources, it is nonetheless possible for groups of participants to form strong filter bubbles by engaging with and re-circulating the contributions of only a select number of in-group members.

It should be noted here that these two definitions may be applied to a range of networks, both offline, online, and across different channels. For the purposes of the following analysis, they will be used to study communicative patterns on social media, and especially on Twitter. Here, the two key terms translate directly to two different types of networks, which can be captured in distinct datasets: the connections between participants that are relevant for the assessment of echo chamber tendencies are represented by data on whom each account friends or follows (and by whom it is friended or followed in turn), while the interactions between participants that determine the presence of filter bubbles are shown by acts of public communication between two accounts (such as liking, commenting, sharing another user's post on Facebook, or @mentioning and retweeting another account on Twitter). The following analysis examines these networks of connection and communication, in the Australian Twittersphere.

Dataset

This study draws on a comprehensive dataset of network structures and public communication in the Australian Twittersphere, described in more detail in Bruns *et al*. (2017): this comprises data on some 3.7 million Australian Twitter accounts identified by February 2016, on the follower/followee relationships between them, and on their public tweeting activities in subsequent months. For the purposes of this analysis, the focus here is limited to the 255,000 Australian accounts with at least 1,000 connections in the global Twitter network (followers + followees), and to the 55 million public tweets that this group posted during the first quarter of 2017, collected using the TrISMA project (Bruns *et al*. 2016). For obvious reasons, tweets from the small percentage of 'private' accounts (whose posts are visible only to approved followers) as well as any direct, private messages between accounts, are absent from this dataset.

Our focus on the 255,000 accounts with the largest number of overall connections in the global Twittersphere might appear to skew the analysis away from the detection of echo chambers: given the high overall connectedness of these accounts, it may appear less likely that all of their connections would be directed at other members of their own group only. This is true to some extent; however, it should also be noted here that Twitter accounts with considerably fewer connections in the network may predominantly belong to very occasional users of the platform, or may indeed have been abandoned. For instance, an account with only a dozen followers or followees might display considerable echo chamber tendencies in its choice of network connections; however, if that account is inactive or used only very rarely, the actual impact of such echo chamber membership on the individual user's worldview is likely to be negligible. By contrast, Twitter accounts with higher levels of connectedness and activity should be understood as belonging to considerably more engaged, regular Twitter users, and any echo chamber or filter bubble tendencies detected here have the potential to exert a much greater influence on their users' information diet and understanding of current events. Further, Bruns *et al*. (2017) employ the same selection strategy in their analysis, so that the present study serves as a further extension of the findings reported there.

Analysis

Echo Chambers

The 255,000 accounts selected for analysis here are connected by some 61 million follower/followee relationships between them; as is standard for the specific implementation of social networking in the Twitter platform, contrary to user friendship relations on Facebook these relationships are directed and not necessarily reciprocal. A visualisation of this network using the Force Atlas 2 algorithm (Jacomy *et al*. 2014) as implemented in the open-source network analysis software *Gephi* (Bastian *et al*. 2009) results in a network map that displays obvious tendencies towards the formation of dense clusters of interconnection amongst groups of accounts, separated by sparser areas with fewer connections; the existence of such clusters is further confirmed by an application of the Louvain community detection algorithm (Blondel *et al*. 2008, implemented in Python in Aynaud 2016). Such algorithms may be used at different levels of resolution (resulting variously in fewer, larger clusters or more, smaller clusters); fig. 3 shows the results of a community detection exercise at a modularity resolution level of 0.25.

A qualitative evaluation of the best-connected accounts in each of the major communities detected through this process results in an interpretation of the guiding themes for these clusters, as outlined in more detail in Bruns *et al*. (2017); we have therefore assigned a descriptive label to each of the thirty largest clusters. Further, this process identifies not only the *raison d'être* for each individual cluster, but also reveals the logic behind their positioning relative to each other: a group of clusters in the top centre of the network, for instance, all relate to a range of sports popular in Australia, while the clusters in the top left represent various political and news-related interests.

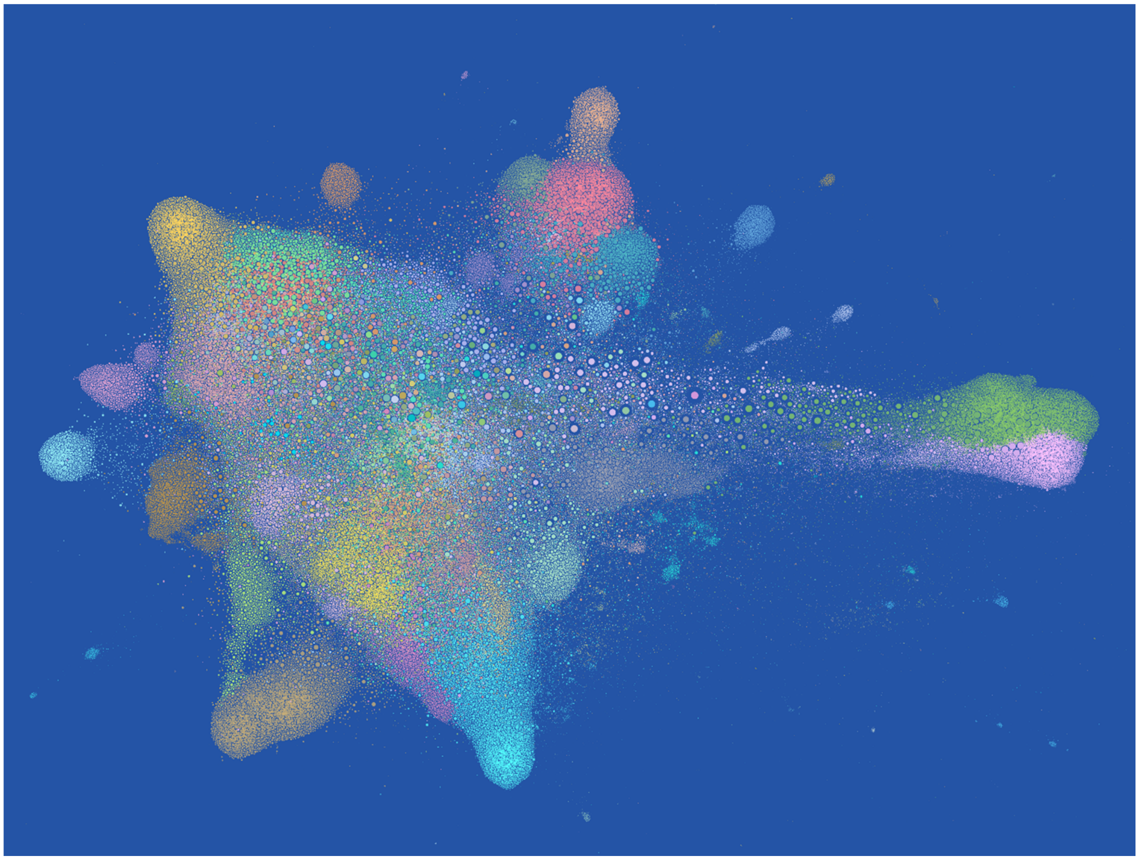

Fig. 3: 2016 Australian Twittersphere network. Nodes with global degree ≥1000 shown only (n = 255,362); edges not shown. Nodes positioned using Force Atlas 2 algorithm in Gephi (Jacomy et al*. 2014); node colour using Louvain community detection algorithm (modularity resolution 0.25; Blondel* et al*. 2008) as implemented in Python (Aynaud 2016).*

Although *prima facie* the mere existence of preferentially connected network clusters could therefore be understood as pointing to the existence of echo chambers, in the definition employed here, further analysis is required: the question is not simply whether social (media) networks exhibit clustering tendencies, but to what extent these cluster communities also result in the exclusion of outsiders. It is unsurprising, for example, that users with an interest in a specific sport might connect with fellow enthusiasts; however, it does not follow automatically that these users may not *also*, if to a somewhat lesser extent, connect with accounts representing a very different range of interests. By themselves, the network clusters visualised in fig. 2 are a necessary but not sufficient condition for the presence of echo chambers.

To measure the balance between internal and external connections for each cluster, we therefore draw on the E-I Index, a network measure proposed by Krackhardt & Stern (1988). For each of the major clusters identified at a Louvain network resolution of 0.25, we count the number of follower/followee connections internal to that cluster (that is, directed from one member of the cluster to another), as well as those external to it (directed from a cluster member to an external account). The E-I Index converts these two counts into a normalised measure that assesses the balance between external and internal focus, and thus the extent to which – in the present definition – the cluster constitutes an echo chamber:

$$E\text{-}I\ Index = \frac{\#\ External\ Links\ -\ \#\ Internal\ Links}{\#\ External\ Links\ +\ \#\ Internal\ Links}$$

Using this calculation, a group of accounts that exclusively connect to (i.e. follow) accounts outside of the group would receive an E-I Index value of +1; a group that exclusively connect amongst themselves would receive -1. Both these extremes are comparatively unlikely; however, the relative placement of each cluster on the E-I continuum from +1 to -1 provides a reliable normalised assessment of its inward or outward focus. In the present context, then, lower E-I Index values point to stronger echo chamber tendencies.

Importantly, for the purposes of the present analysis, we will consider only follower/followee connections amongst the best-connected Australian Twitter accounts, in order to obtain more meaningful E-I Index values. Many of these accounts do of course also follow others from outside of this group of 255,000 accounts that constitutes our core dataset here – they may follow other Australian accounts that have fewer than 1,000 follower/followee connections and are therefore absent from our dataset, for instance, or follow non-Australian Twitter accounts that are excluded by definition from the TrISMA dataset on which we draw. Connections to these accounts could be classed as external to the source account's cluster, of course, but this would serve to systematically overestimate each cluster's external connections: after all, although not present in our core dataset of 255,000 accounts, a target account may still represent interests related to those of the cluster, and connecting to it should therefore not be seen as breaking out of the echo chamber. Our limitation to studying only the connections between the core group of 255,000 accounts, on the other hand, removes this uncertainty: here, it is possible to clearly assign each account to one cluster.

A calculation of the E-I Indices for the fifty largest clusters in the Australian Twittersphere (fig. 4) points to a considerable amount of outward focus in most of the clusters; except for two clusters relating to teen culture, a cluster addressing fine food and gourmet culture, and a cluster of pornographic accounts, the E-I Indices for all major clusters are near or above zero. This indicates an even balance between internal and external follower/followee connections for such clusters, and for some clusters even a substantial preference for following external accounts. Indeed, the likelihood of strongly positive E-I Index values (indicating an external focus) appears to increase for smaller clusters; on the one hand, this is unsurprising as the members of such clusters only have a more limited opportunity to connect to in-group peers, yet on the other hand it also demonstrates that small, isolated networks of accounts appear to be rare in the Australian Twittersphere.

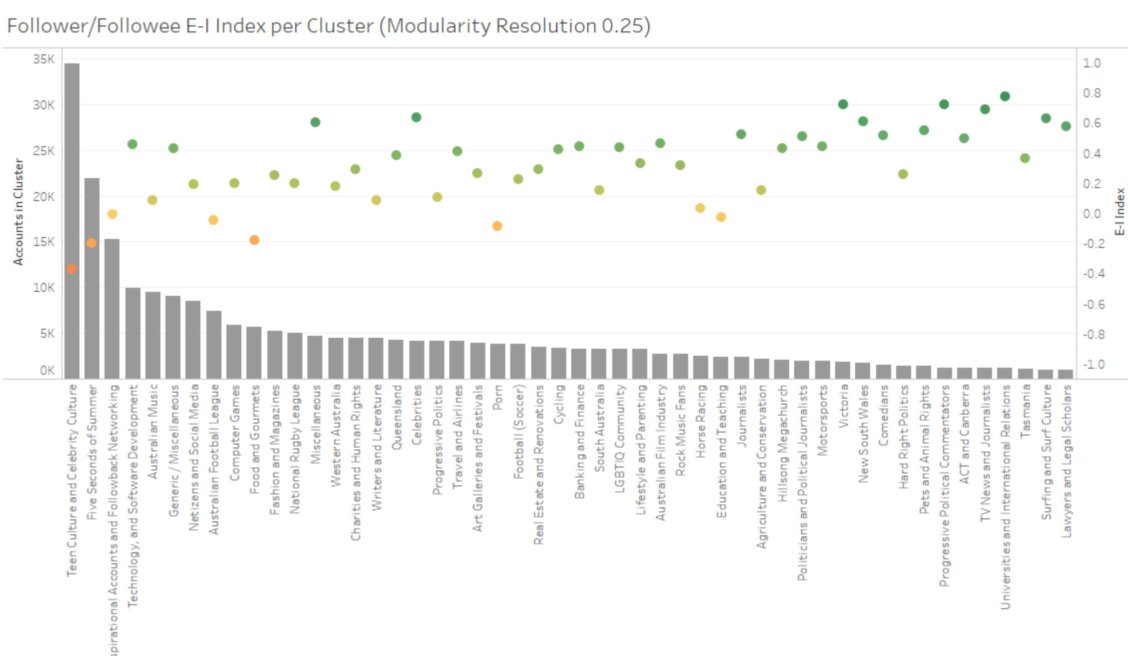

Fig. 4: E-I Index values for the fifty largest clusters in the Australian Twittersphere (at modularity resolution 0.25), amongst accounts with a global degree ≥1000. Clusters arranged by number of member accounts (bar graph); E-I Index shown by dot graph. Cluster labels based on qualitative evaluation of leading members.

This finding should not be misunderstood as negating the existence of network clusters altogether, of course. A neutral E-I Index of zero still means that of all the follower/followee connections emanating from a group of accounts, fully half are directed to other group members; this represents considerable preferential attachment within the group, and is the reason that the Louvain community detection algorithm did identify the group as a distinct cluster in the network. But at the same time it also means that the other half of all connections are directed elsewhere within the Twittersphere (or in the present analysis, to other accounts in the underlying dataset of the 255,000 most connected Australian Twitter accounts). As a result, through these follower/followee connections, there is considerable opportunity for new content to enter the cluster and become visible to its members, provided that those members do in fact take note of the tweets that appear in their timelines. From this perspective, then, the analysis presented here does not indicate any strong echo chamber tendencies amongst this core component of the Australian Twittersphere; even the most inward-looking groups still have substantial connections to the outside.

Filter Bubbles

The network structures observed so far point at least to the possibility of a relatively unrestricted circulation of information (in the form of tweets) between and across thematic clusters in the Australian Twittersphere: as far as their approaches to following others are concerned, Australian Twitter users have put themselves in a position to see tweets from a wide variety of sources. The question then becomes whether and to what extent they engage with and act on the content they encounter, by @mentioning or @replying to other accounts or by retweeting their posts. This question addresses the potential for filter bubbles to exist even in the absence of prominent echo chamber tendencies: although they connect to a wide variety of external accounts, for instance, users might still choose only to respond to and retweet the posts originating from within their own cluster, for example.

To detect the presence of such filter bubbles, this paper draws on a dataset available from the TrISMA project, which tracks the tweets posted by Australian Twitter accounts on a continuous basis (Bruns *et al*. 2016). For the purposes of the following analysis, we selected all tweets posted by our core userbase of the 255,000 most connected Australian Twitter accounts during the first quarter of 2017; in their tweets, we identified all @mentions and retweets of other accounts within the same userbase. Drawing on the clusters already utilised for the analysis of follower/followee connections amongst this userbase in the previous section, this makes it possible to calculate a further set of E-I Indices: for each cluster, this assesses in general how many of the total number of references to other accounts in its tweets were directed to internal or external accounts, but it also provides two separate E-I Indices specifically for @mentions and retweets only. The distinction between retweets and @mentions, in particular, makes it possible to explore whether filter bubble tendencies manifest differently as users are merely talking to, at, and about others (@mentions) or as they are actively disseminating the messages of others (retweets).

Fig. 5 shows these three E-I Indices for the most active clusters during Q1/2017, as well as highlighting the differential between the retweet and @mention E-I Indices and indicating the total volume of tweet interactions for each cluster. It is immediately obvious that for the majority of the most active clusters, these tweeting interaction E-I Indices are considerably more negative than their follower/followee connection results. This indicates that, in spite of a connection repertoire that usually featured a substantial number of external links, a substantial amount of day-to-day interactions in the form of @mentions or retweets remain focussed on users' immediate network neighbourhoods.

At the same time, there are also considerable divergences between the E-I Index values when calculated for @mentions or retweets only: for the Progressive Politics cluster, for instance, the @mentions E-I Index is slightly positive (0.102), indicating a mild preference for @mentioning accounts outside the home cluster, while its retweets E-I Index is -0.196 and indicates a somewhat stronger preference for amplifying messages from within the cluster. This indicates, not unsurprisingly, that Twitter users make distinct choices about whom they simply interact with (through @mentions), and whose messages they actively promote (through retweets).

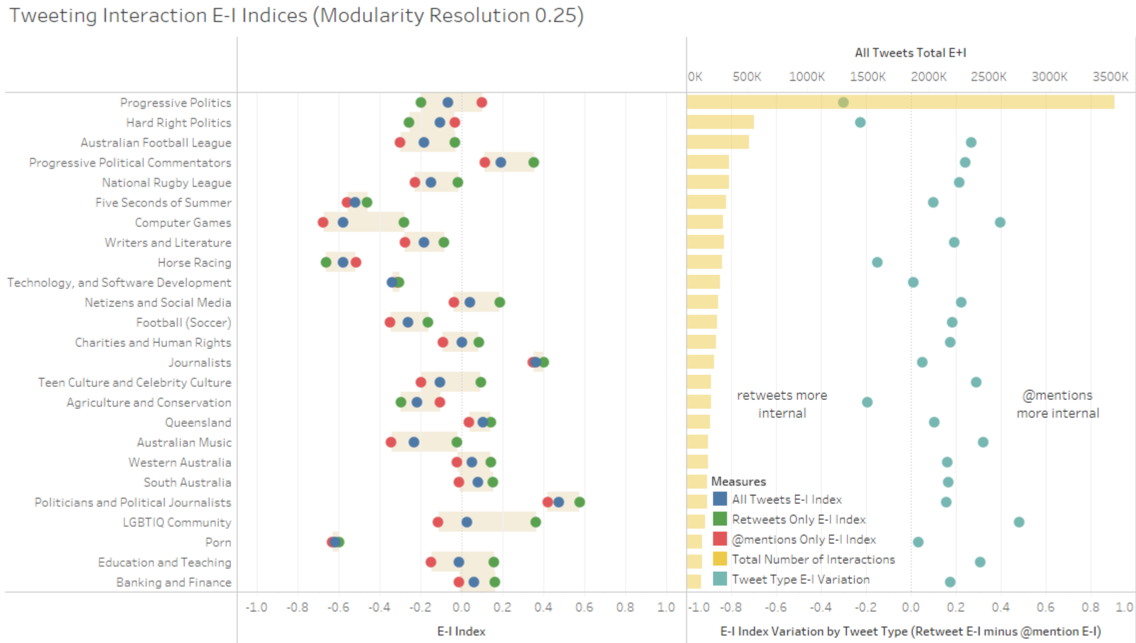

Fig. 5: E-I Index values for the 25 most active clusters in the Australian Twittersphere (modularity resolution 0.25), amongst accounts with a global degree ≥1000. Clusters arranged by total number of tweet interactions (@mentions + retweets: bar graph in right panel); E-I Indices shown by dot graph in left panel (all interactions: blue; retweets: green; @mentions: red); differential between retweet and @mention E-I Indices shown by dot graph in right panel. Cluster labels based on qualitative evaluation of leading members.

Further, the differential between the E-I Indices for these different tweet types shows that the members of most clusters are more prepared to retweet outside of their own group than to otherwise engage with external accounts, sometimes by a considerable margin. This hints at a shared sense of cluster membership: users might have preferentially followed others with shared interests and are now engaging with them through @mentions and @reply discussions on an everyday basis, but also occasionally feed new information into these networks by retweeting material from the general Twittersphere beyond these clusters. Notably, however, a small number of clusters (including the two clusters most active in Q1/2017, Progressive Politics and Hard Right Politics) diverge from this pattern: here, @mentioning is more outwardly focussed while retweeting remains more strongly in-group. This reversed pattern might indicate that members of these clusters more frequently talk to, about, or at outsiders (targetting for instance the accounts of journalists or politicians), but work together predominantly to amplify the visibility of messages originating from within their cluster by retweeting them to the outside world. We might loosely understand these divergent behaviours as *pulling information into the cluster* (where @mentions are more inwardly and retweets more outwardly focussed) and *pushing information out of the cluster* (where @mentions are more outwardly and retweets more inwardly focussed), respectively.

Overall, then, this paints a complex and multifaceted picture of filter bubble tendencies within the Australian Twittersphere: although interactions between accounts within the most active clusters are for the most part privileging fellow cluster members rather than external interlocutors, their overall E-I Indices largely remain within a moderate range, indicating a comparative balance between internal and external engagement. Only a handful of clusters – most prominently Computer Games, with an overall E-I Index of -0.577 – are strongly negative, and could be considered to exhibit substantial filter bubble tendencies; indeed, some others – such as the Politicians and Political Journalists cluster, with an overall E-I Index of 0.479 – are predominantly interacting with accounts outside of their own cluster, in effect bursting any filter bubbles that could exist around them.

At the same time, the differences in @mentioning and retweeting behaviours also indicate that filter bubble tendencies might manifest differently for different activities on the same platform, and the consequences of these diverging behaviours need to be considered further. If they should emerge more strongly, filter bubbles built on @mentions represent cliques of communicative interaction that could serve to exclude non-members and ossify into elitist networks of frequent interlocutors, but fresh, external information could still circulate through these networks in the form of retweets from external sources that are then evaluated through in-group discussion within the clique. Filter bubbles built on retweets, on the other hand, might present a more significant problem in the context of recent debates about the circulation of 'fake news' and other undesirable (mis)information: here, the preferential retweeting of in-group messages could initiate a feedback loop that continuously amplifies ideologically orthodox messages and drowns out any opposition, creating "spiral of silence" effects (Noelle-Neumann 1974). In this case, a greater external focus in the group's @mentions might merely indicate that these self-affirming retweets are *also* directed at others (e.g. journalists, politicians, activists) outside of the cluster, perhaps in order to influence them. In this context it is unsurprising that the two communities in the Australian Twittersphere where this configuration appeared most prominently (if still with relatively balanced E-I Index values) represented partisan political clusters of the left and right.

Conclusion

Overall, this paper has demonstrated that the Australian Twittersphere – or at least that component of the Twittersphere that is represented by the 255,000 most highly connected accounts within the overall network – exhibits only very limited tendencies towards the emergence of echo chambers or filter bubbles, in the definitions we have utilised here. Although an analysis of the network of follower/followee relations between these accounts clearly points to the existence of a number of distinct clusters, formed by the preferential attachment of individual accounts to each other on the basis of shared interests and ideologies, those connections have not been made to the exclusion of all others, and the individual clusters also remain widely interconnected with each other. In order to be able to describe any of these clusters as true echo chambers, they would have to appear far more disconnected from the remainder of the network, and this is not the case here; the E-I Index calculated from follower/followee connections points only to moderate variations in the likelihood that the members of each cluster will encounter tweets from the outside in their Twitter feeds.

Meanwhile, the analysis of @mention and retweet interactions between these accounts during the first quarter of 2017 similarly provides only limited evidence of filter bubble tendencies. Although cluster members do largely prefer to engage with their in-group peers, this behaviour is usually more pronounced for @mentions than for retweets; retweet E-I Indices are mostly positive or only very mildly negative, indicating the recirculation of considerable volumes of external content into the cluster in-groups. But notably, the two most prominent partisan clusters diverge from this pattern, and their more strongly inward-focussed retweeting behaviours offer some support for the filter bubble thesis in these cases; however, at -0.196 and -0.255, respectively, even their retweet E-I Indices reveal only a moderate imbalance between inward and outward focus, and their filter bubbles, to the extent that they exist at all, remain highly permeable to outside information.

Especially in these two cases, the specific timeframe chosen for the tweet dataset must also be taken into account, of course. The first quarter of 2017 covers the inauguration of Donald Trump as U.S. President, as well as a variety of international as well as domestic political crises; variously, these might have contributed to greater outward *or* inward focus in @mentioning and retweeting activities at times. A comparison of the findings presented here with equivalent analyses for different timeframes (taking in, for example, an Australian federal or state election or covering a period of heightened partisan debate) might well show that the strength of echo chamber or filter bubble tendencies waxes and wanes in response to external stimuli.

The present analysis could also be extended further by comparing the E-I Index patterns at different levels of modularity resolution. As noted above, these would result in a smaller number of larger or a greater number of smaller clusters, respectively, and thus re-draw the boundaries between in- and out-groups for each cluster community. Available space does not permit the in-depth exploration of such differences in the present paper, but a repeat of the present analysis at a Louvain modularity resolution 0.5 does indeed create a larger Politics cluster that receives lower E-I Index ratings than do the smaller clusters we have encountered here (-0.153 for the E-I Index based on follower/followee connections, indicating very moderate echo chamber tendencies, and -0.417 based on tweet interactions, showing greater filter bubble proclivities); however, as a larger cluster that combines multiple previously separate communities this larger cluster is now also more internally diverse, which is likely in turn to counteract trends towards homogeneity.

Finally, in further analysis it will also be important to better incorporate additional information on the accounts comprising each cluster. As presented here, the E-I Index simply draws on the total count of internal and external connections from cluster members; it treats any such connections as equal. It would be possible instead to adjust this measure to give more weight to follower/followee connections made by the most important members of a cluster, or to repeated rather than merely one-off @mention and retweet interactions between two accounts. This would enable it to measure not just the extent to which cluster communities are generally focussing inwards or outwards, but also whether such focus originates from the centre or the periphery of the group.

However, the analysis presented here already shows that to date there is only scant empirical evidence at network level for the existence of well-developed, exclusive echo chambers or filter bubbles, at least within the Australian Twittersphere. This does not deny that it remains possible for individual users to "design [their] own filter bubble", as Bradshaw (2016) has put it, and that at that individual level such choices can have considerable consequences for the user's information diet; collectively, however, it appears likely that the various overlaps between the "personal publics" (Schmidt 2014) created by the individual networking choices of each social media user, and the accumulation of such personal publics into the superstructures formed by network clustering tendencies, serve to counteract rather than amplify echo chamber and filter bubble tendencies. Patterns in other national Twitterspheres – for instance in the hyperpartisan political context of the United States – may also vary considerably, however, and it would be valuable to repeat the present study for a number of such cases in order to assess the polarisation of public debate on social media platforms such as Twitter.

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