Audiencing through Social Media

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Abstract

Social Media provide a rich source of data for analysing ‘the audience’. Whether the audience for a TV show, movie, sporting event or political debate, we are able to use social media platforms and their publicly available APIs to understand not only what is being shared, but also by whom, and develop a number of key post-demographic insights into the userbase. In this chapter, we outline a number of methods for social media analysis across three major platforms: Twitter, Facebook and Instagram, and consider what each tells us about the social media audience. We also highlight the limitations of this type of study, from both technical and practical perspectives.

Introduction

In most developed and many developing nations, general-purpose social media platforms such as Facebook and Twitter, as well as more application-specific tools such as YouTube, Instagram, and Vine, have by now become a key and central part of the media repertoires of the wider population. They are used for practices ranging from everyday phatic engagement with friends[1] through crisis communication[2] to political debate,[3] but an especially important practice which has emerged over recent years has been their use as ancillary and backchannel media alongside mainstream, mass media channels such as radio and television, as well as during major live events. Many broadcast and live events now advertise 'official' Facebook pages and Twitter accounts and hashtags for viewers to engage with, for example, while in the absence (or even in the presence) of such official offerings social media users are also frequently establishing their own *ad hoc* alternatives.

Such forms of audience participation through social media are now frequently described as "second-screen” viewing[4] or more narrowly as "social TV".[5] They constitute a new form of the active engagement of audiences with the shared texts of mainstream media content which earlier cultural studies work has recognised as a form of "audiencing",[6] but in using social media for the first time make such practices widely visible beyond the living room or other loci of mass media reception, as well as offering a greater opportunity for further engagement by fellow audience members well beyond the immediate "personal public"[7] of the individual listener or viewer. This therefore also constitutes a shift away from what, in the tradition of Benedict Anderson,[8] we might be able to describe as an "imagined" audience or community around the shared media text, and towards a more tangible and indeed more measurable audience (which may or may not also constitute a community, in any meaningful sense of the term).

This is not to say that – other than utilising new communication platforms – television audiences are necessarily doing anything dramatically different today, compared to previous practices. Research into the uses of television, especially from cultural studies perspectives,[9] has long recognised that "audiences are far from passive":

> We are not consuming a product but using the imaginative resources of story, song, sight, and sound … to think about identity, relationship, and community, in real time and space … . We make ourselves up as we watch.[10]

But when we do so *and* use social media to share that process with others as it happens, it becomes amplified – we think aloud, or at least louder than previously, and we think with others beyond the familiar space of the living room. Watching television is already an inherently social process, as Hartley's reference to the key social concepts of "identity, relationship, and community" indicates, and television itself is a social medium in this sense; its combination with what we have now come to call "social media" in a narrower sense simply makes the active audience described by television scholars for the past half-century considerably more visible, and tangible.

This more tangible sense of the active audience emerges most centrally through the tracing, capturing, and quantification of audience activities which state-of-the-art social media analytics make possible.[11] By gathering and evaluating potentially large datasets on the audiencing practices of individual listeners and viewers it becomes possible to identify the patterns of audience responses to media texts, both to examine their engagement with individual broadcasts and events and to compare and benchmark such individual observations against each other. This is valuable in the first place as a significant extension of conventional audience measurements (such as television ratings), providing a substantially more fine-grained and detailed picture of audience responses, but indeed also has substantial value well beyond the assessment of conventional media audiences; such engagement metrics also have applications in areas from brand communication to political campaign management, in fact.

As part of an ongoing effort to establish and standardise rigorous, robust, and reliable methods and metrics for the assessment and evaluation of audience engagement with broadcast content and live events (and to facilitate their extension and application to other fields beyond these core uses), this chapter presents an overview of relevant approaches and outlines the potential for further methodological advancement. We focus here especially on the development of audience engagement metrics that draw on Twitter activity in the Australian television context, but these principles are transferable and extensible to other social media platforms, mainstream media texts, and national contexts as well.

Measuring the Audience

While there is an ever-increasing range of social media platforms, both generally targetting global audiences (e.g. Facebook, Twitter, Instagram, YouTube) and specific to particular countries (e.g. Sina and Tencent Weibo, VKontakte), the ease with which data on the public activities of their users can be collected and analysed through their various Application Programming Interfaces (APIs) varies widely. For example, many of the metrics that would be useful for analysing YouTube, such as the view count over time for a video, are only available to the channel owner. Even those platforms with relatively open access have their quirks.

Facebook, for example, limits the ability of automated software accounts (as opposed to regular human-operated accounts) to access a number public pages which would otherwise have age limits, such as those for R-Rated movies. This is because application accounts do not have an "age" associated with their profile, and thus the Facebook age-verification algorithm denies the application access to the page data. Instagram provides a far more limited range of data than the other platforms (for instance, it does not provide information such as the account creation date for a given user account), and throttles requests more aggressively.

A comparison between API access limits for Twitter and Instagram illustrates this. Using the Twitter API it is possible to make 180 calls to retrieve user profile data in every 15-minute window, and each of these calls can query up to 100 user accounts; this enables researchers to query up to 18,000 accounts in each quarter-hour, or up to 72,000 accounts per hour. Other types of queries (for example for tweets themselves) are subject to a different limit, and can be made in parallel to retrieving user profile data. Instagram, on the other hand, has instituted a general limit of 5,000 API calls per hour, across all types of data, and each such call can only query one individual user profile, rather than a list of accounts. Compared to Twitter's up to 72,000 user profile queries per hour, Instagram thus allows only 5,000 such queries.

It is not least for this reason that most scholarly and commercial social media research has focused on Twitter: a platform which is public by default and shares a comparatively large volume of information through the public API. However, Twitter, Inc., too, is increasingly limiting access to publicly available information as it continues to revise its API functionality; for example, it is now only possible to retrieve detailed information on the previous 100 retweets by a user. This tightening of API capabilities is having significant chilling effects on scholarly research that draws on the Twitter API.[12]

However, there is still a large volume of data available, and even data which appear not to be immediately publicly available can often be gathered through a combination of other data sources. Here, we outline a range of methods developed for studying public communication on Twitter, Facebook and Instagram, outlining how such data may be useful for studying the social media activities of audiences.

Activity over Time

Perhaps the most obvious metric for analysing social media data is time-series data, or the volume of posts over time. This metric allows both comparisons of the long-term performance of specific events and topics, and the identification of key periods (e.g. of intense activity, or no activity at all) that warrant further attention. The data could be drawn from a myriad of use cases, including in the first instance discussion around a particular keyword or hashtag, or posts from or mentioning specific accounts. However, more complex time-series tracking is also possible, to show for example the volume of images or videos posted to Twitter through Instagram, the split between retweets, @mentions, and original posts, or other measures of activity.

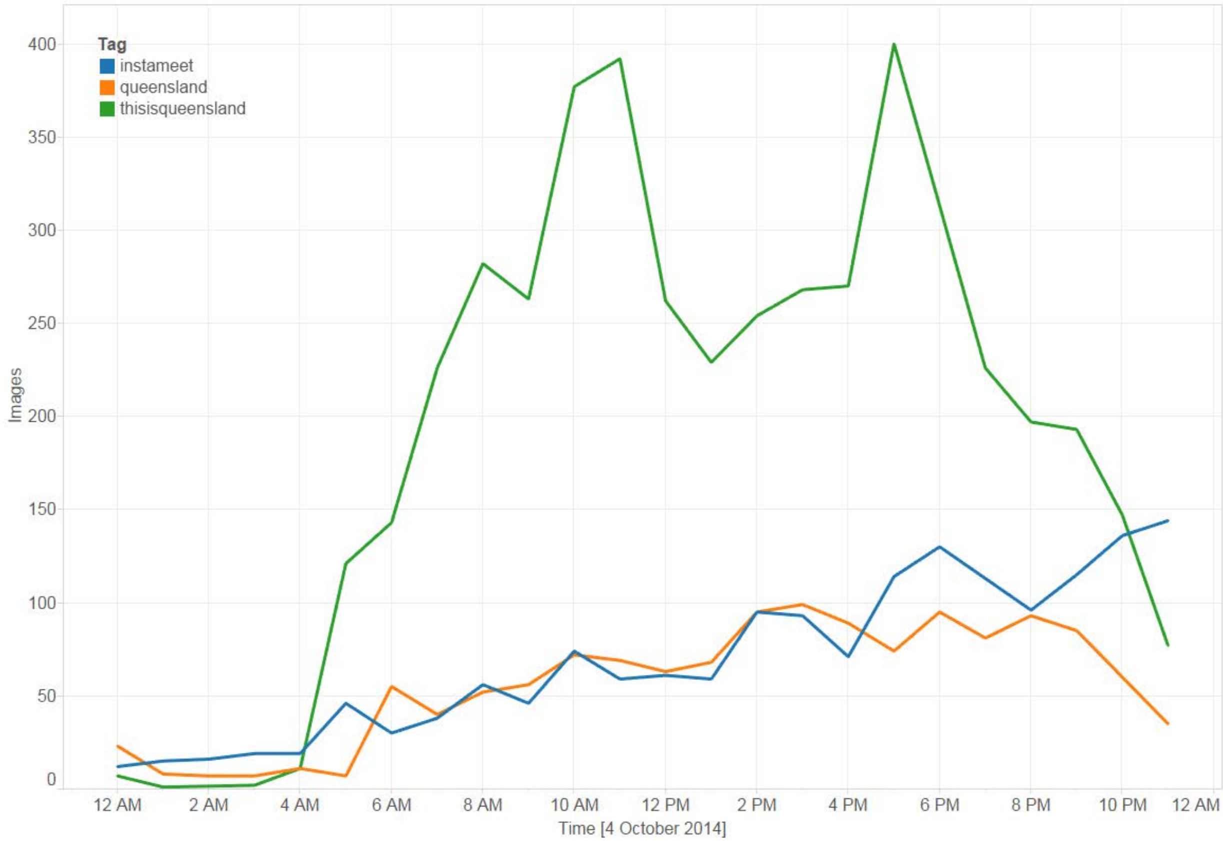

Fig. 1: Total volume of the #instameet, #queensland, and #thisisqueensland hashtags for Tourism and Events Queensland Instameet Campaign on Instagram (4 October 2014).

However, time-series charts can also be based on a further processed version of the data. For example, by running tweets through a sentiment engine,[13] it is possible to generate sentiment scores for each tweet. While the accuracy of sentiment analysis, particularly for social media data where sarcasm and humor can be difficult to detect, is still in question, often such an approach does at least provide a general trend of the sentiment within a conversation. Having performed this classification, it is then possible to graph tweets where sentiment is above or below particular levels, in order to track the shape of the conversation over time.

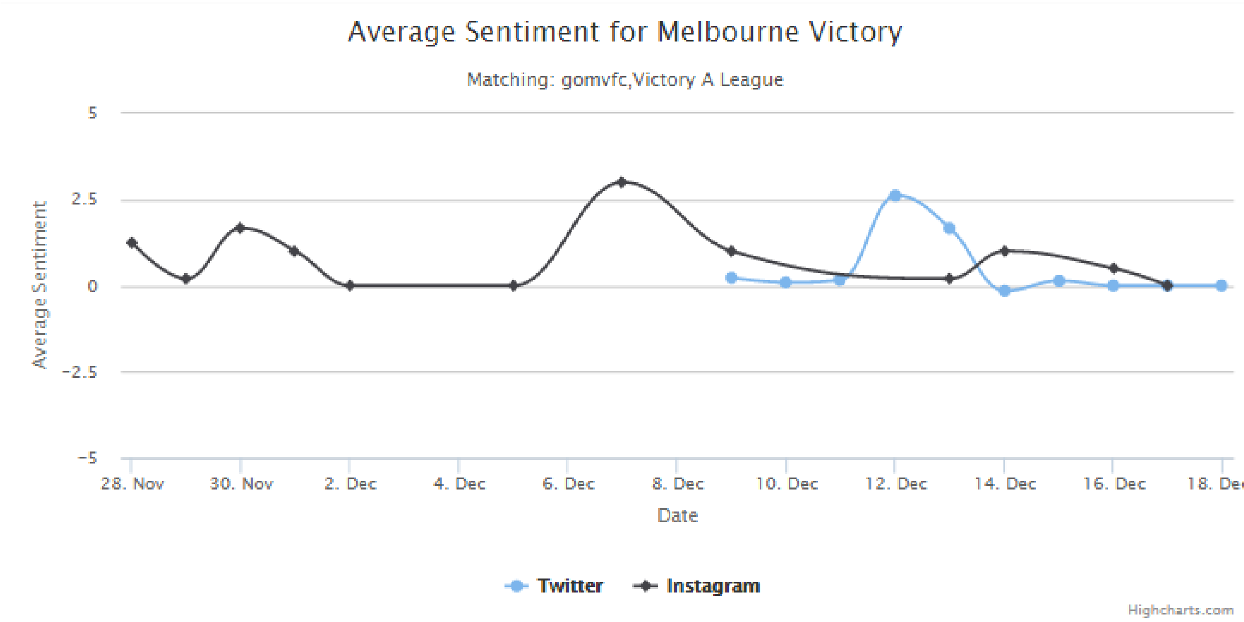

Fig. 2: Average Twitter and Instagram sentiment over time for posts containing #gomvfc and 'Victory A League', referring to the Melbourne Victory football team in the Australian A-League

Finally, these data streams can also be used to measure the activity of particular users, for example to find the most active users within a keyword or hashtag community. It is then possible to graph the activity of particular users or groups of users within the community over time, and to apply the same filters as discussed previously (e.g. images, retweets, sentiment) to gain deeper insight, and to drill down into the details of their engagement.

Such time-series analyses thus illustrate audience engagement with television content as viewers encounter the shows live; they trace viewers' interpretive practices as they read media texts, and indeed can highlight the evolution of such practices from minute to minute and episode to episode, as social media users explore and establish their own conventions for interpreting and critiquing a shared text (on Twitter for example in the form of common hashtags and memes surrounding show and cast). In doing so, they can point to both the gradual development of individual audience members' practices, and the establishment of an interpretive community[14] with commonly held readings, as individual viewers connect and share their interpretations through social media.

While time-series data in the forms discussed above is widely covered in existing literature, it is mentioned here as it can also be further refined to provide metrics which give an insight into the underlying nature of the conversation. Two examples of this are the Weighted Tweet Index and Excitement Index,[15] both of which take data over time as core inputs. In the case of the Excitement Index, we measure the volatility of a conversation over time so as to generate a measure of 'excitement' within the conversation, following an approach developed by Burke[16] for excitement around NFL games.

As we apply the Weighted Tweet Index to analysing social media activity around television broadcasts, we measure the tweet volume not only during the show itself, but also in between shows. In doing so, we not only capture those who are talking about the show as it airs, but crucially also those who are communicating some form of anticipation for the show. We use these data in combination with other factors, such as the network on which a show aired, the time of day, day of week, month of year, position within the season, and country of broadcast, to compare the social media engagement for different shows. By accounting for the impact of each of these contextual factors, it is possible to place each show into a 'neutral' environment and normalise the observed tweeting activity by eliminating the effects of such factors. This allows for more direct comparisons between shows across timeslots, channels, and seasons, and offers an opportunity to develop more sophisticated social media strategies around these broadcasts.

Audience Overlap

Given that we are able to filter time-series data by users, we can thus also determine which users have contributed to which particular conversations. This enables us to map the overlap between audiences, both between specific cases (e.g. *Masterchef* vs. *My Kitchen Rules* or *National Football League* vs. *Major League Baseball*) and on a wider scale, across the Twittersphere. In its most simplistic form, this enables us to visualise overlaps in the social media audience, based on the users taking part in particular hashtag- or keyword-based communities (Fig. 3).

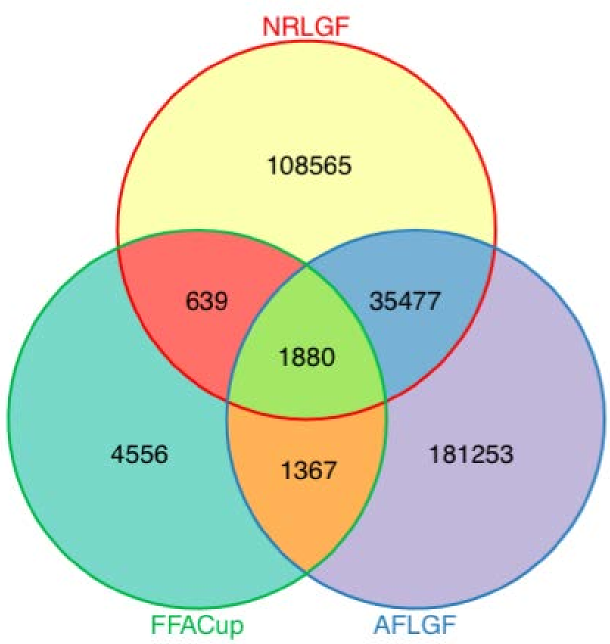

Fig. 3: Twitter audience overlap between the #NRLGF, #AFLGF, and #FFACup hashtags in 2014.

In the above example, the overlap between three Australian sporting conversations on Twitter is mapped; the 2014 Australian Rules (AFL) Grand Final, the Rugby League (NRL) Grand Final, and the opening rounds of the FFA Cup Soccer tournament. Due to the differences in audience size, the image is not proportional, but serves to identify those 1,880 users who could be considered to be ‘hardcore’ sports fans, those who are dedicated to a specific sport, and perhaps those who watch on only major occasions such as the grand finals.

Similarly, we are able to map the conversations around television shows such as the political talk show *Q&A*, public affairs show *60 Minutes*, and evening news panel *The Project*, drawing on data gathered over several weeks in 2014 for each case (Fig. 4).

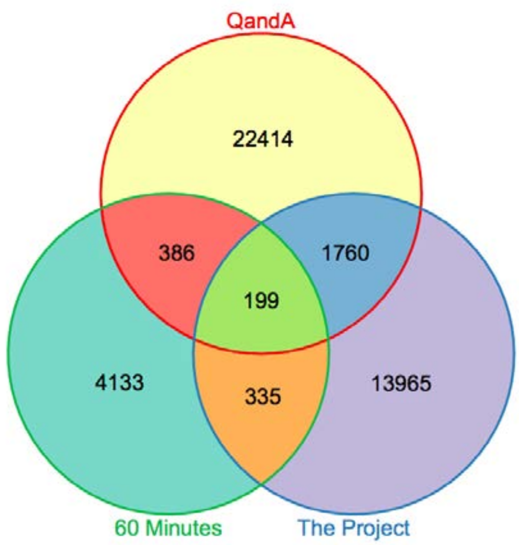

Fig. 4: Twitter audience overlap between the hashtag use for Q & A (#qanda), 60 Minutes (#60mins, #ExtraMins) and The Project (#theprojecttv) over several weeks in 2014.

Within a particular broadcast context, this approach also allows a measurement of continued engagement, in the television example for instance by contrasting the audience for the premiere of a show with that of subsequent episodes. In this way, audience retention can be measured, and those users who have dropped from a conversation can be targeted for further study, for example by identifying whether they constitute a particular segment of the audience. A key tool in such further analysis is the study and mapping of user profiles across the Twittersphere, as we discuss it below.

Such analyses, then, enable further research into the contextual factors which influence audience activities – from the impact that programming decisions and the broader political economy of the contemporary television industry may have on the formation of interpretive communities around specific TV shows to the strategic and tactical choices made by viewers as they consider which broadcasts to engage with, and how. They place the active audience within the context of the wider mediasphere, including both broadcast and social media and their operators.

Mapping the Twittersphere

What is still missing from the analytical approaches we have outlined so far is any further background information about the users participating in the social media conversations relating to one or more television broadcasts. For example, it would be of considerable value to determine whether users participating around any given topic or event have well-established social media presences with a substantial following in the network, or are relative newcomers with very limited visibility; from a broadcaster's perspective, it is no doubt important to attract at least a sizeable number of well-connected lead users to its shows, as their engagement is likely to attract further participants. Additionally, it would also be desirable to develop a better understanding of the day-to-day interests of participating users in order to determine whether a show managed to attract only the 'usual suspects', or reached a broader audience – a political talkshow addressing a crucial controversial topic would aim to reach a broad audience beyond the "political junkies",[17] for example, while other programming might be more interested in narrow but deep engagement by its target audience.

Such an assessment of the quality, reach, and depth of a broadcast audience depends crucially on the availability of sufficient background data on the overall make-up and structure of the social media population in the broadcast region, then. The development of such background knowledge is often difficult and time-consuming, but not impossible; as part of our long-term effort of researching the Australian Twittersphere, for example, we have developed a comprehensive database and map of Australian Twitter users, their interests and networks.[18]

We present the outcomes of this work here in the form of an annotated network map of follower/followee relationships in the Australian Twittersphere, which is current to September 2013 (Fig. 5). The map comprises the 140,000 Australian Twitter accounts which had a total of 1,000 or more follower and/or followee connections by that point, and plots them as a network graph that locates densely connected areas of the network close to each other (as network clusters) while showing less connected areas at greater distance. We further examined the user population in each cluster to infer from the lead users' profile descriptions what the guiding themes of each cluster are. This does not imply that users in each cluster tweet *only* about the cluster's key topics, but that they largely define their Twitter presence by this guiding theme.

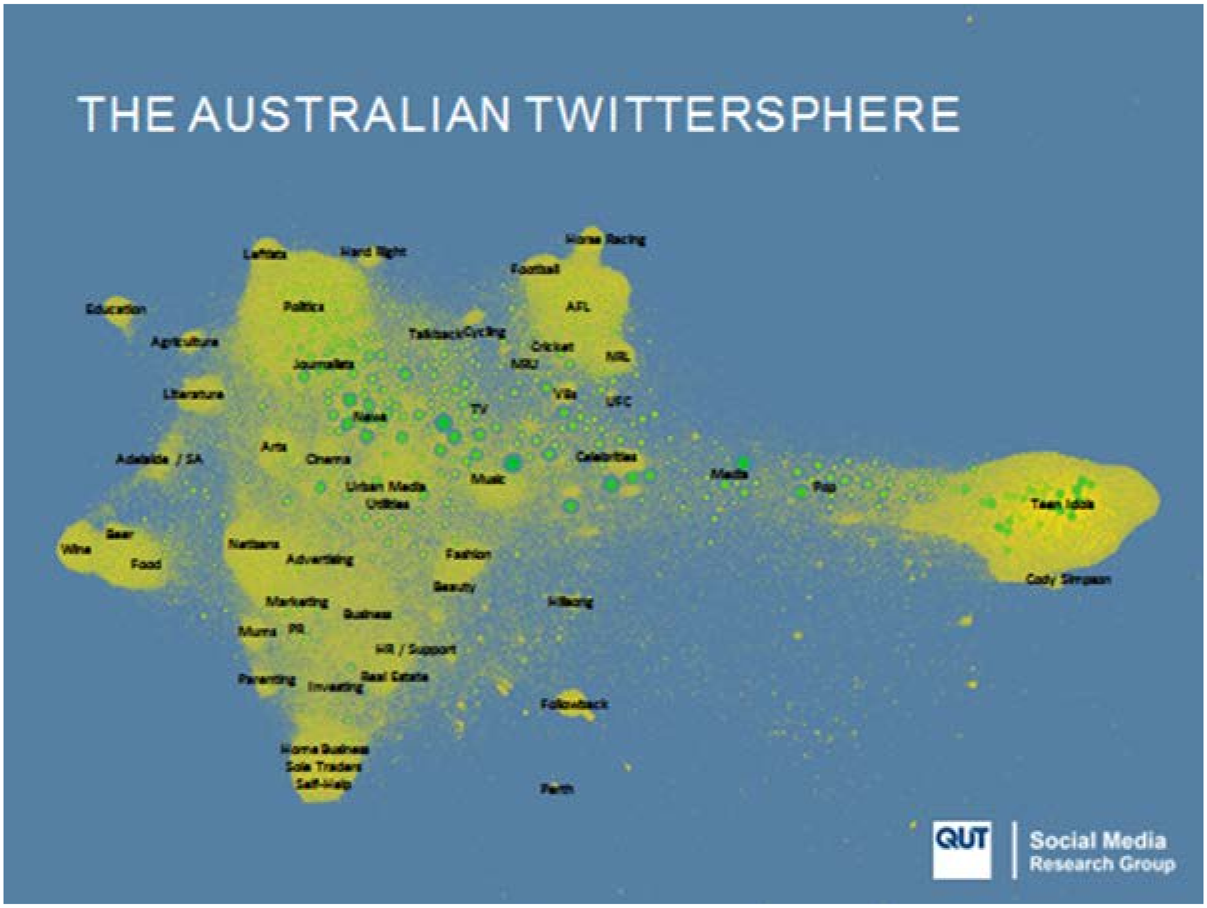

Fig. 5: Network map of follower/followee relations in the Australian Twittersphere, as of September 2013. 140,000 accounts with 1,000 or more network connections shown, out of a total of 2.8 million identified Australian accounts. Cluster topics identified through manual analysis.

This map is valuable in its own right as it provides detailed information about the structure of the Australian Twittersphere and documents the key thematic areas and communities of interest represented in or missing from the overall network. However, it also becomes important background information to the further analysis of audiencing practices: given the overall map of follower/followee connections in Fig. 5, for example, it now becomes possible to overlay the patterns of actual Twitter activity for any one given broadcast or event, and to compare these patterns across a number of datasets, as the comparison in Fig. 6 illustrates. This enables an assessment of the relative breadth and depth of social media activity around such broadcasts, and an identification of the prominence of specific pre-existing interest clusters in the follower network as participants in the Twitter conversation.

Fig. 6: Location of #qanda and #AFLGF participants in the overall Australian Twittersphere.

Fig. 6, for example, compares the Twitter footprints of the weekly political talkshow Q&A (#qanda) and the 2014 Australian Football League Grand Final (#AFLGF). Perhaps unsurprisingly, the core areas in the overall Twittersphere that engage with these events are, respectively, the clusters centred around politics and sports, but it is also obvious that the AFL Grand Final finds take-up well beyond this core cluster; indeed, as a result of teen band One Direction showing their interest in Australian Football by wearing Hawthorne Football Club jerseys on a number of occasions, there is even considerable engagement with the #AFLGF hashtag within the network cluster related to teenage culture, which shows practically no interest in *Q&A*.

Further, much more detailed analysis is possible here (but beyond the scope of this chapter), of course: we may query whether such out-of-cluster participation was sustained throughout the broadcast, or related only to specific moments; we may examine whether the most influential (e.g. the best-connected) users in the core cluster were also activated as participants during the broadcast; and we may examine the extent to which user participation manifested in original tweets, @mentions, or retweets, for instance. Such more in-depth analyses reveal further patterns that may be used to assess and distinguish between different forms of audience engagement.

This further positions the active audiencing practices already described in existing cultural studies research within the context of specific media environments (here, especially, the Twittersphere), and can examine the impact that pre-existing social structures – such as established follower networks – can have on the interpretive and participatory practices of individual audience members. It thus also adds to the consideration of social context as a factor in viewers' development of reading practices for media texts, but does so not primarily by examining generic, demographic markers of socioeconomic status as previous studies might have done, but instead by considering post-demographic aspects relating to positioning of audience members within their personal social networks, at least to the extent that such networks have been made visible by and in social media.

Constructing a Panel

Building on the measurement of the overlap between audiences, and their spread across the Twittersphere, is the idea of developing a ‘panel’ of users that can stand in for the wider userbase. This operates on a similar basis to the way that market research companies such as Nielsen seek to build a representative panel of users to measure TV audiences, and is subject to similar limitations. Combining our knowledge from these previous metrics, we are able to select a panel which is representative of the Australian Twittersphere geographically, by interests and by volume.

What is missing in comparison to the approaches taken by firms such as Nielsen is detailed demographic information, which is difficult – but possible – to extract from Twitter.[19] Already, we have developed an estimate of the probable gender of each account holder, which is calculated using a user’s stated real name and also takes into account their likely location (for example, ‘Kim’ may be predominantly a female name in Australia, but in Scandinavian countries is also used for males). The development and testing of additional methods to estimate the age and socio-economic status of account holders is the next step towards establishing robust demographic estimates for a given userbase. Such approaches have clear limitations – not least that users cannot always be relied upon to provide accurate profile details – but are necessary in order to enable further demographically informed social media analytics.

A panel-based approach to social media analytics also addresses and works around important technical limitations for social media research. We have already highlighted the limits of social media APIs; for instance, Twitter limits the tracking of larger groups of users, and a single streaming API connection is able to collect the tweets from a maximum of 5,000 accounts only. For researchers who are unwilling to pay the significant access fees demanded by commercial social media data resellers such as GNIP, and who are therefore limited to Twitter’s public, freely available API, tracking 5,000 users at a time is therefore a hard limit. The panel-based approach works well within such limitations, and given that the OzTam service in Australia uses a sample of 3,500 homes to derive its free-to-air national television ratings, for a national population of over 23 million, it is reasonable to suggest that 5,000 accounts out of a total userbase of some 2.8 million Australian Twitter accounts would provide a very workable approximation of overall tweeting patterns in the country.

Constructing such a panel allows for the real-time analysis and reporting of Twitter usage patterns by a representative sample of the Australian userbase, enabling researchers to identify trends in conversation beyond the hashtag- or keyword-level analyses which have dominated scholarly Twitter research to date. Combining such an approach with methods to dynamically identify conversations and begin tracking new keywords enables the gathering of a much larger percentage of the social media conversation around given topics. The same approach of building panels of users could also be applied to Instagram, where it is possible to gather a limited amount of user-level and relationship data, although ensuring such a panel is representative would be a more significant challenge here. By contrast, comparable user-level information is not readily available through the Facebook API.

Content Analysis

In discussing volume over time, we have already detailed a number of ways in which the time-series data could be processed and analysed, including sentiment analyses. However, there are other forms of analysis that are possible through natural language processing. Content analysis is possible both on a hashtag- or keyword-based stream, such as the conversations about a television show or around a political debate or crisis, and at the user level, analysing the archived tweets of a user to determine the subjects that particular users are interested in.

In its simplest form, this may be identifying and counting keywords, bi-grams (combinations of two words) and tri-grams (combinations of three words) within the social media conversation. By doing this, common phrases and keywords can be identified, providing a first indication of the overall shape of a conversation, which can be further filtered to a particular group of users, to a specific period of time, or to a given hashtag or keyword community.

A more advanced extension of this approach is topic modelling, which uses machine learning techniques to automatically categorise segments of text according to a particular theme. This moves current practice beyond the simple word-based analysis to begin to account for the context in which those terms are used, enabling us, for example, to separate conversations around sporting events into sub-communities (e.g. home team, away team, gambling, popular culture, etc.), which can then be further studied using the other techniques discussed in this chapter.

There are also other means of presenting data. One famous example of sentiment is the ‘worm’, which is often used in televised political debates to assess the immediate response of the audience. We have developed a similar approach using sentiment analysis techniques on popular Australian political hashtags (e.g. #auspol, #qldpol) to measure – in real time – the popularity of Australian politicians, and will use this to track sentiment during the 2015 Queensland and New South Wales election campaigns.

Whether condensed to such simple measures, or forming the basis of a much more detailed study of the key terms, themes, and topics of social media conversation amongst a television audience, such approaches draw on the way that electronic media such as Twitter provide a space for the public expression and exchange of viewers’ readings and interpretations of the televisual text. From a textual point of view, the picture of audience practices that emerges from this analysis can be considerably richer and more detailed than that which can be solicited through participant observation during the viewing, or through interviews and surveys with viewers after the fact, as it draws on first-hand evidence of audience responses as contributed by a potentially very large audience itself, without being prompted by a researcher. On the other hand, however, it should also be noted that the actively posting social media community constitutes only a fraction of the total television audience in most cases, and that its observable activities are therefore not simply and directly representative of the full range of interpretive processes taking place amongst the overall audience. A combination of such social media analytics with more conventional research methods in audience studies will be able to generate an even richer and more detailed perspective on audiencing practices.

Follower Accession

Elsewhere, we have detailed a methodology for examining what we describe as "follower accession": the growth in followers of specific Twitter or Instagram accounts.[20] Importantly, our method enables such an assessment retrospectively, without a need to take regular snapshots of follower numbers; this is facilitated for example by the user-level information provided through the Twitter API, such as the order in which accounts followed a particular user, and the account creation date for the various following accounts. Such an analysis enables both a benchmarking of the popularity of different Twitter accounts, and an identification of specific moments of particularly strong follower growth (which may be traced to particular events surrounding such accounts). Again, beyond the evaluation of audience activities themselves, such analyses may provide useful and important further background data.

Such approaches may also be valuable beyond Twitter, for example to understand which events lead to a growth in Instagram followers. In Figure 7, for example, we see a large increase in growth linked to the 'Instameet' event on 4 October 2014,[21] which brought together Instagram users across Queensland to meet up and take photos that were ultimately used by Tourism Queensland for promotional purposes.

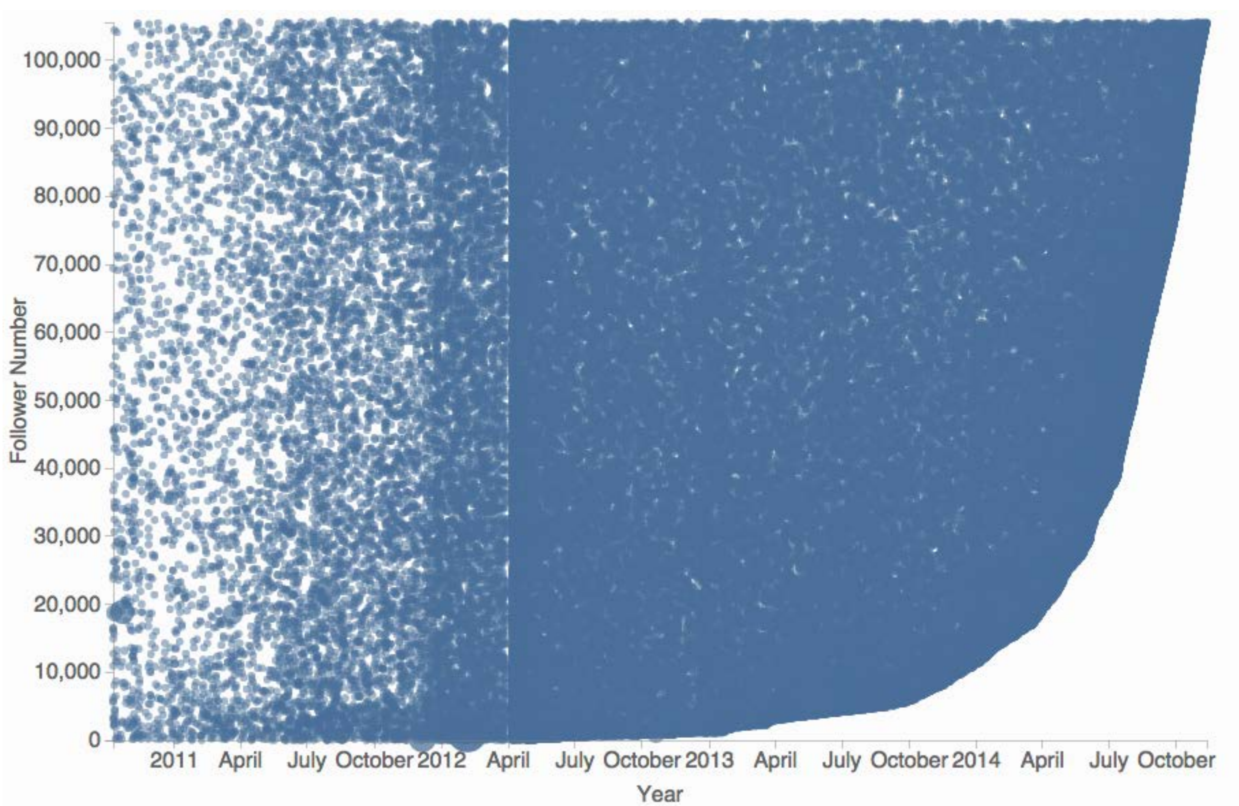

Fig. 7: Follower accession for the Tourism Queensland account on Instagram

As discussed previously, the Instagram API provides more limited user-level data, and most notably for our purposes does not include the date at which a given account was created. However, it is relatively simple to identify the date at which a user first posted an image, which provides a good proxy for their sign-up date. The precision of this can be further enhanced by collecting the first photo date for a sample of Instagram accounts, and thus building up a pairing of account IDs – which are allocated sequentially – and dates. As discussed in Bruns & Woodford (2014), we are thus able to build a list of dates before which we know the user could not have signed up.

The Instagram API also provides a chronologically ordered list of followers (except for a small number of the account’s most recent followers, which are listed alphabetically). As with Twitter, using this ordered list (the accession number) and the first photo date (as a proxy for date on which an account was created), we can generate accession charts for Instagram users. As illustrated by Fig. 7, such charts provide a useful set of indicators about the growth dynamics of a given account’s follower base, and provide a tool to evaluate the success or otherwise of specific promotional campaigns.

Longer-Term Engagement with Social Media Content

Beyond the assessment of an audience's immediate activities in relation to broadcast content and live events, it is often also important to examine the longer-term resonance of and engagement with specific topics and issues, potentially on a post-per-post basis. On Twitter, this may manifest for example in the longevity of a specific hashtag, or the period of time over which new retweets of or @replies to relevant posts continue to be made; on Facebook, similar observations may be made about the length of time during which specific posts are liked, shared, or commented on.

Collectively, we define such longitudinal patterns as the lifecycles of posts. By plotting the temporal distribution of activity around a given post we are able to distinguish a range of engagement patterns, ranging from rapid but brief engagement to slower but more sustained responses. Fig. 8, which shows these temporal data for posts on the Facebook page of the *Captain America* movie, is one example of this. It charts the percentage of comments which have been posted by a specified point in time after the post itself, and shows that approximately 60% of engagement with posts on the *Captain America* page comes within the first 400 minutes (6 hours, 40 minutes) of new content being posted.

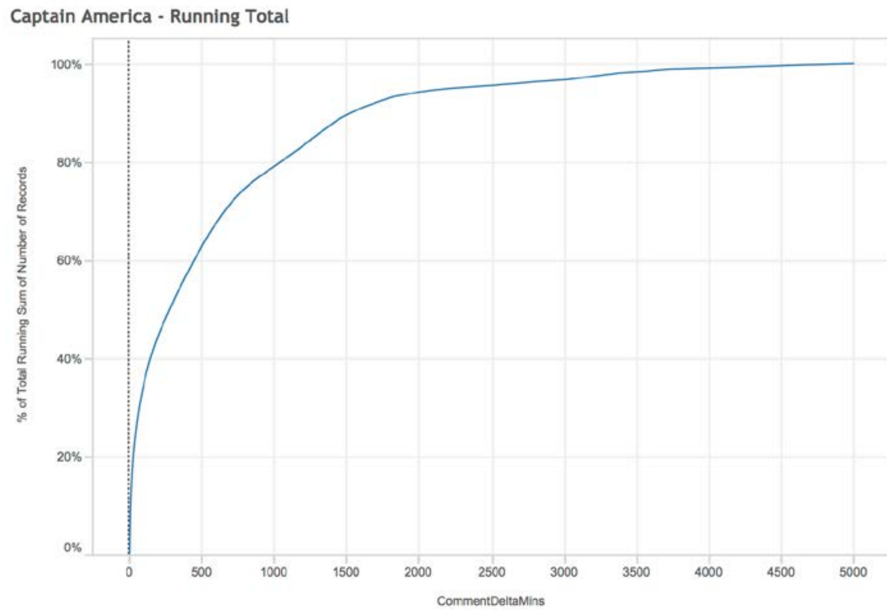

Fig. 8: Lifecycle of posts on the *Captain America* Facebook page

Given a sufficient number of observations, these individual patterns may also be compared and benchmarked against an aggregate baseline that describes the ‘typical’ dynamics of engagement with content on each platform, and can thus highlight especially strongly or poorly performing posts and pages. Further, this approach also enables us to compare typical user engagement patterns across different genres of content. Fig. 9, for example, compares aggregate longitudinal audience engagement patterns with two movies to engagement with a television show and an online newspaper, and points to notable differences in the dynamics of such audience engagement.

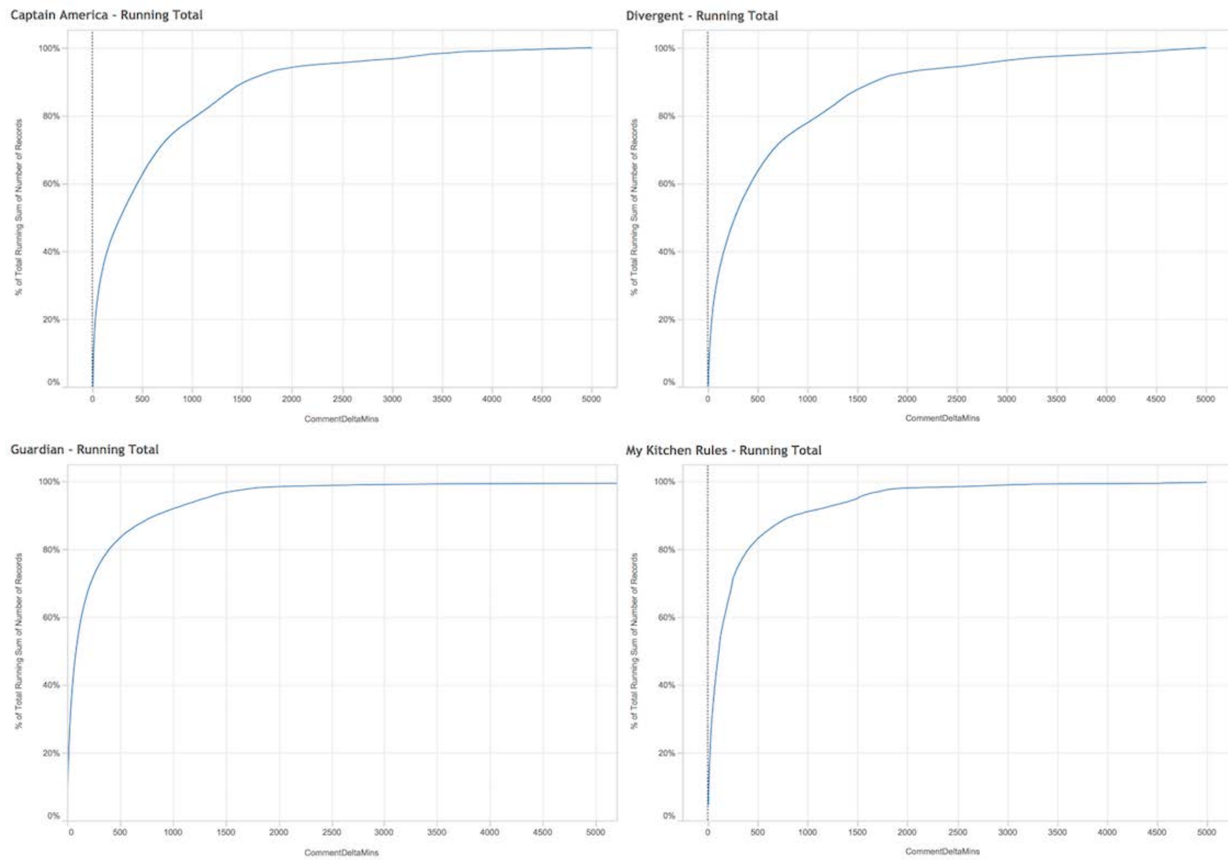

Fig. 9: Comparison of post lifecycles on the Facebook pages for movies *Captain America* and *Divergent*, for reality TV show *My Kitchen Rules*, and for online newspaper *Guardian Australia*

As this comparison shows, engagement with *Guardian Australia* content tends to be significantly faster (and shorter-lived) than engagement with movies, for example, reflecting the divergent shelf-life of such content. Such observations also provide valuable information to the content providers and may be used for further developing their social media strategies: most simply, the different speeds of engagement which emerge here suggest that the frequency of posting new updates on these providers' official Facebook pages should also differ.

Public-Facing Tools

While the purpose of the methods discussed here may not always be readily apparent to the general public, a number of them can easily be adapted to public-facing applications. One example of this is our ‘Hypometer’ application, which was originally developed to generate daily indicators showing the social media hype around upcoming television shows. The application now also reports daily and weekly engagement figures for television; this includes both raw numbers and the more complex measures (e.g. Weighted Tweet Index, Excitement Index) we have discussed above. Beyond generic uses related to television, the tool has also been adapted to show engagement with and around individual contestants on reality television shows, sentiment and volume for politicians, and user engagement with global events such as the G20 Summit held in Brisbane in November 2014 (fig. 10).

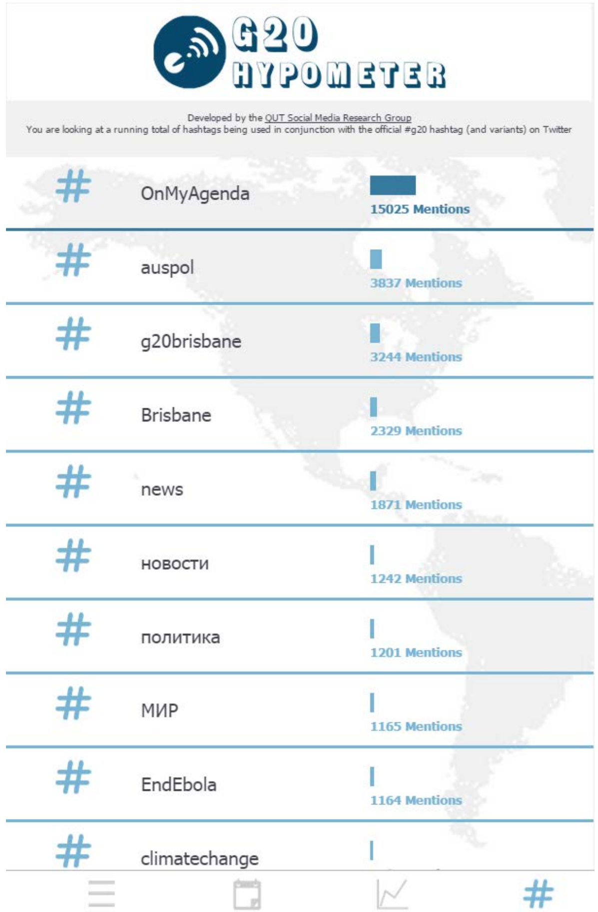

Fig. 10: G20 Hypometer showing the most prominent hashtags used in association with #G20, 'G20', #g20cultural, #g20brisbane, or colourmebrisbane.

Such applications serve two primary purposes: first, they are a way of communicating engagement metrics to the general public in a meaningful manner; for example, assigning a 'hype' score to television shows immediately makes it clear which shows are receiving significant audience attention beyond the context of their expected performance (based on broadcast network, time of day, day of week, etc.) in a way that neither displaying raw tweet totals, nor the results of the Weighted Tweet Index and Excitement Index would. Second, they could be used as active interventions, for either industry or research purposes. We might examine, for example, whether viewers are more likely to watch a particular show if they know that their social network has been discussing it and is likely to watch and discuss it in real time.

Conclusion

It is possible to ascertain a wide range of post-demographic information through social media. That information can be used to describe, analyse, and target audiences at a range of levels, from the global userbase of a platform through geographically bounded audiences, as shown in the case of the Australian Twittersphere, to the audiences of specific TV shows or sporting events. In each case, such information is valuable to researchers, but also to marketers, sales teams, and others who seek more detailed information on the social media users whom they engage with on a day-to-day basis.

In this chapter we have outlined a collection of interrelated methods and metrics for assessing social media-based audience engagement with broadcast media and live events, focussing for purposes of illustration mainly on Twitter, but also flagging the translatability of such approaches to other key social media platforms, especially including Facebook and Instagram. This is part of an ongoing effort to promote a broader conversation about new approaches to tracking, measuring, and evaluating audience engagement with media texts, and to develop new standardised metrics for audience engagement which may complement (and in some instances perhaps eventually replace) conventional television ratings and similar existing metrics.

The methods and metrics we have presented here are intended to further, not to curtail, that conversation. Not least also because of the continuing changes to the functionality of current social media platforms, the fluctuating overall popularity of specific platforms, and the growing sophistication of content providers in their engagement with social media, some of the metrics we have presented here may come to be obsolete within years, while new content provider and audience practices may enable the development of new engagement evaluation methods that we are unable to foresee at this stage. This means that there is considerable need for further methodological innovation, building on the work we have presented here as well as on other initiatives in both scholarly and industry contexts, and for the continued sharing and testing of these new approaches.

It must be noted here, of course, that these approaches to studying television audiencing practices as they take place on Twitter and in other social media spaces are not intended to replace the existing arsenal of research methods in audience studies, which has already generated significant insight into how television viewers engage and interpret the broadcast content they encounter. Rather, the methods we have outlined here further complement and enhance that collection of methods, and address some of its traditional weaknesses: while the interpretation of TV content remained a largely internal or oral practice, it was best researched through small-group data-gathering methods which generated rich insights, but could not easily be generalised across larger audiences.

Social media (and other online media before them), however, have contributed to the greater externalisation and public expression of audience readings of televisual texts, and combined with the growing sophistication in methods for gathering and analysing social media data at large scale, this has enabled researchers to generate much more comprehensive datasets on audiencing practices at least to the extent that they are taking place in such spaces. Further, data gathering here is unobtrusive and can be done without affecting the contexts in which audience responses are generated; social media analysis is able to observe audiencing *in situ*, rather than in the more artificial setting of an interview or focus group.

But given the comparative ease with which such data may now be gathered from social media, there is also a danger that the most vocal social media users, who will be most visible in the dataset, are going to be seen as representative of all participants in social media environments, or even that social media-supported audiencing practices are going to be regarded as straightforwardly representative of all other, offline as well as online, internal as well as externalised, interpretive practices. Such misrepresentations must be avoided by continuing to employ the entire range of audience studies methods, rather than relying only on now comparatively readily available social media analytics tools, and by comparing the observations made by using these different methods against each other. We also stress, therefore, that our contribution here should not be misread in any way as an argument for an increased emphasis on quantitative over qualitative methods – instead, the analytical approaches we have outlined here will indeed often help to pinpoint the most promising areas for further in-depth qualitative research (for example by highlighting participants to be approached for follow-up interviews, or by identifying a corpus of social media messages that should be studied further through close reading).

What is required next, then, is the rigorous application and evaluation of the methods we have outlined here in production-grade contexts, and the sharing and benchmarking of results in order to develop a more comprehensive picture of, in the first place, social television audiencing practices. We must also pursue the application and extension of these methods to address a broader range of audiencing practices well beyond television, to test whether similar social media user activity patterns exist across areas as diverse as brand communication and political debate. And finally, we must work to more fully integrate these methods with the existing research toolkit employed by audience studies research. It is our hope that the eventual outcome of such research will be not only a range of important domain-specific insights, but also a stable and flexible toolkit of research methods and metrics for the study of social media engagement.

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