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Big Data: Methodological Challenges and Approaches for Sociological Analysis

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Abstract

The emergence of Big Data is both promising and challenging for social research. This article suggests that realising this promise has been restricted by the methods applied in social science research, which undermine our potential to apprehend the qualities that make Big Data so appealing, not least in relation to the sociology of networks and flows. With specific reference to the micro-blogging website Twitter, the article outlines a set of methodological principles for approaching these data that stand in contrast to previous research; and introduces a new tool for harvesting and analysing Twitter built on these principles. We work our argument through an analysis of Twitter data linked to political protest over UK university fees. Our approach transcends earlier methodological limitations to offer original insights into the flow of information and the actors and networks that emerge in this flow.

Keywords

Big Data, information flow, methodology, networks, Twitter, Web Science

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Introduction

The current emergence of 'Big Data' is both promising and challenging for social research. Originally coined to describe digital data sets so large that they required non-standard computational facilities and software for storage and analysis (Manovich, 2011), the term has now come to encompass a wider range of remarkable properties inherent in these data. Beyond the scale of these data attention is drawn to their proportionality – these are 'whole' data sets, capturing everything within a particular field (e.g. utility records) or on a particular platform (e.g. Twitter) (Hale and Margetts, 2012); they are dynamic – capturing social activity in real-time, over time; and they offer information on what people do and say 'in the wild', rather than what they say they do in interviews and surveys.[1] The digital nature of these data also opens up new potentials for data mining and data linking, allowing connections to be made between diverse data (boyd and Crawford, 2011; Halford et al., 2013).

However, Big Data also raises some challenges for social research. These are emergent, but it is clear that there are new and important ethical issues to deal with (Neuhaus and Webmoor, 2012). Furthermore, in between the enthusiasm of some – Latour suggests '… it is as if the inner workings of private worlds have been pried open' (2007: 2) – and the scepticism of others, for whom these data are ephemeral froth distracting us from more serious sociological endeavours, lie some important ontological and epistemological questions: what do these data represent and what claims can be made from them? Finally, before we can address either of these issues fully, there are methodological challenges. Indeed, until we know how to apprehend and analyse Big Data, we cannot appreciate the range or scale of ethical and epistemological questions that may arise; and will arise variously across different forms of Big Data. For although the term may imply coherence and uniformity, 'Big Data' is not one thing but many, differentiated inter alia by content, structure, ownership and availability. Whilst much has been made of the potential of Big Data for social research (e.g. Savage and Burrows, 2007), for reasons of privacy and/or commercial sensitivity, many of these datasets remain in the hands of governments and private corporations.

One significant exception to this is Twitter, the micro-blogging website whose content is (almost entirely)[2] public, visible to anyone who chooses to search and follow users, and available via Twitter's own Application Programming Interface (API), which – depending on the methods used – allows access to (1) a small selection of the tweets via the search or streaming service, (2) the 'garden-hose', a 10 per cent random sample, or (3) the 'firehose' of all tweets made. Not surprisingly, Twitter has generated a considerable amount of interest amongst social scientists: since its launch in 2008, there have been over 110 scholarly publications about Twitter.[3] Whilst little of this has been published in mainstream sociology (Murthy, 2012), there is much here to interest sociologists, for instance in attention to practices of impression management, micro-celebrity and personal branding (Hargittai and Litt, 2011; Jackson and Lilleker, 2011; Marwick and boyd, 2011); and to questions of participatory democracy and political mobilisation (Grant et al., 2010; Larsson and Moe, 2011; Segerberg and Bennett, 2011; Tufekci and Wilson, 2012).

However, to date, the scope for pushing this research forward has been methodologically limited because social scientists have approached Big Data with methods that cannot explore many of the particular qualities that make it so appealing to use: that is, the scale, proportionality, dynamism and relationality described above. Rather, Big Data has commonly been approached with *small-scale* content analysis – looking at small numbers of users – or larger scale *random or purposive samples* of tweets. Rendering Big Data manageable in this way overrides its nature as 'big' data, bypassing the scale of the data for its availability or imposing an external structure by sampling users or tweets according to a priori criteria, external to the data themselves. Furthermore, most previous social science studies are snapshots, categorising content and user-types rather than following the data as it emerges dynamically or exploring the nature of the social networks that constitute Twitter.

In what follows, we elaborate our claim that Twitter research remains limited by its methodological approaches. Specifically, we suggest not only that social scientific approaches have failed to capture the most interesting qualities of Big Data but also that, because of this, we cannot make the most of these data to address currently emblematic sociological concerns for networks, mobilities and flows. In this article we present a new tool for harvesting and analysing Twitter data, underpinned by a broader set of methodological considerations, which together begin to address some of these limitations. Working our case through an analysis of the Twitter activity surrounding the recent student fees protests in the UK, we show how the combination of quantitative and qualitative analysis within a broader methodological approach that draws on 'wide data' might help to connect Twitter research more firmly with sociological analysis.

Sociological and Methodological Challenges

The past decade has seen an extraordinary proliferation of user-generated content on the World Wide Web as platforms from Facebook to YouTube and Wikipedia have captured the popular imagination and become embedded in the daily practices of people, businesses and governments around the world. Twitter was established in 2006 as a microblogging website, allowing individuals to 'tweet' 140 character messages made immediately visible in the timelines of their 'followers' and to anyone searching the Twitter website. By 2011 Twitter had over 300m users and 200m daily tweets (http://blog.twitter.com/2011/06/200-million-tweets-per-day.html). The emergence and success of Twitter resonates with some of the recent cutting-edge concerns of sociology. At the meta-level, it is symptomatic of a wider transition away from the 'social as society' – at least, as society bounded by nation states – towards the 'social as mobility', emergent in dynamic flows of people, objects, images and information (Urry, 2000). More specifically, this can be characterised as a 'network society' (Castells, 1996) in which information – now the key commodity – flows across time and space between loosely connected individuals and groups that form and re-form fluid identities and connections transcending older ties of place, time, class, gender, race and so on. Networks, in this sense, do not reflect society but rather shape or even produce society (Urry, 2000). The social is assembled (Latour, 2006) in the everyday practices that constitute the 'global networks' of multinational enterprises and the heterogeneous, uneven and dynamic 'global fluids' '…

of people, information, objects, money, images and risks that move chaotically across regions in strikingly faster and unpredictable shapes' (Urry, 2000: 190). For Urry (2000) these fluids have no clear point of departure or arrival, no necessary end-state and are characterised by '… emergent, unintended and non-linear consequences' (2000: 195) *that sociology, as a discipline, should find better ways of interrogating*.

Big Data in general, and Twitter as a specific example, offer hitherto unexplored potential for empirical work of this type. Twitter holds promise not least because of its availability to researchers but also its openness. It is easy to access and the conversations between users are relatively easy to follow as are the users' networks of 'friends'. Unlike other social networking websites such as Facebook, Twitter does not enforce reciprocal relations between users, enabling registered users to 'follow' as many others as they wish, whether or not they 'follow back'. Bill Gates, for instance, follows 140 Twitter users, but has nine million followers. Anyone can observe any post on Twitter, even without being an identified 'follower'; messages can be sent to any other user using their unique @username (known as 'mentions') – and these are displayed publicly on all profiles and tweets; and users can pass on any tweet – via the 'retweet' function. Users may also choose to group their discussions around particular topics or events using hashtags (e.g. #election2012) within the body of the tweet. In short, Twitter offers a small number of defined structures: the tweet (140 characters), the 'follow' function, direct messages and the retweet. Beyond this – the content, the flows of information and connections of people are entirely undetermined. In principle then, we can follow the emergent flow of information – what is tweeted, retweeted and hashtagged, and the evolving networks that form and reform between people over time.

Twitter has already been the subject of some fascinating research, particularly in political science, but the methods used mean this work is somewhat limited in scope and, understandably, this research has not engaged with the issues raised by the sociology of networks, mobilities and flows. For instance, research on the role of Twitter in grassroots activism and its potential for enhancing participatory democracy, either pre-selects the important actors (elected politicians especially) and/or takes a sample of tweets or users within a defined area of activity, often a hashtag stream. Of course, if the aim of the research is to explore how elected politicians use Twitter then pre-selecting these actors is an entirely consistent choice. Furthermore, it is inevitable that the quantity of Twitter data will require some management, and since hashtags emerge from user practices this makes them a sampling frame. However, if the aim is to explore which actors are active and influential on Twitter during election debates, or what kinds of networks emerge between actors at this time, we need to take *the network itself* at the starting point. Sampling tweets, whether purposively or randomly, denies the opportunity to trace which actors and information emerge as important over time. Rather, this method predefines which actors are important and/or renders all actors equal as members of a random sample. Nothing can be said about what the network itself produces.

Similarly, small-scale content analysis of selected tweets or studies of particular users (for instance, 30 tweets from each of 60 Twitter accounts [Waters and Williams, 2011] or following the Twitter stream of 51 MPs [Jackson and Lilleker, 2011]) allows in-depth analysis but no possibility of understanding where and how this content or these users are positioned within the broader Twitter stream. More generally, previous research has neglected the dynamic nature of information flows and network connections on Twitter. In one exception, the number of tweets around a hashtag is reported at 13 weekly intervals (Segerberg and Bennett, 2011) but the wider temporality of the network itself – who is connected with whom via direct messages or retweets – is not reported. Notably, however, in explaining Twitter temporality, Segerberg and Bennett (2011) make links to contemporaneous events offline, highlighting the value of making links across data sources, flagging up the importance of following hyperlinks within tweets, whilst others (Hargittai and Litt, 2011; Marwick and boyd, 2011) have begun to use mixed methods to evaluate Twitter usage. These are important methodological developments to which we return in a moment. For now the point we want to make is this: whilst the key characteristics of Big Data are its scale, proportionality, dynamism and relationality, the methods used in social science have fallen short of enabling us to explore this.

Meanwhile, Twitter has also attracted attention from computer scientists. Compared with the 110 articles on IBSS there are over 350 articles with a primary focus on Twitter listed in the Association for Computing Machinery (ACM) Digital Library. In contrast to social science research, computational approaches endeavour to capture data at scale, through the development of algorithms and technical solutions (Cohen et al., 2009) that aim to reduce the computational times of data processing (Dean and Ghemawat, 2004) or improve mechanisms for aggregation and storage to enable faster and more efficient access (Herodotou et al., 2011). However, interest from the computer sciences has not been confined to technical concerns. As Manovich (2011) suggests, the advent of Big Data makes it easier for those with programming skills and knowledge of social media APIs to ask social questions. Indeed, there is a stream of such research on Twitter from computer science exploring, for instance, friendship networks (Macskassy and Michelson, 2011), political orientations (Conover et al., 2011) and the diffusion of information (Bakshy et al., 2012). At first sight, this might seem to support Savage and Burrows' (2007) claim that the availability of new forms of data is moving the centre of gravity for social research away from sociology, although it is important to note that attention is more often to observing patterns and network structures per se rather than exploring meaning or explanation. Where claims to social knowledge are made these take the form of 'big' claims about the patterns in Twitter, for example using Natural Language Programming and sentiment analysis to search for key words to determine the 'happiness' of a tweet (Dodds et al., 2011), or an individual's political affiliations (Rao et al., 2010). Notably, these approaches favour computational techniques over theoretically informed or conceptually nuanced sociological analysis, let alone fine-grained qualitative analysis, and tend to treat the data as 'naturally occurring' rather than paying any attention to their social and technical constitution.

Nonetheless, computational research brings relevant methods to Twitter research; in particular, the capacity to apprehend Big Data and analyse network structures, and to measure the volume of data and the flow of information and relations between actors. These techniques are not untried in sociology. Indeed, from the application of graph theory to social ties (Moreno, 1953), which gained momentum from the quantitative 'revolution' of the 1960s (Barnes, 1969), to John Scott's pioneering work to embed Social Network Analysis (SNA) in the sociological methods repertoire (1998, 2000) these techniques have a long history in the discipline. However, whilst some of these techniques have been used by political scientists to research Twitter (Larsson and Moe, 2011) they remain untried in its sociological analysis. Further, the established SNA techniques have some limitations. As Scott (2008) has argued, the power of SNA would be improved if it were to move beyond static metrics and statistical measures of network structures and connectivity, to expose the temporal nature of the data and this, we suggest, is particularly pertinent here. In what follows we present a new software tool, developed to meet these challenges.

The Method

Our tool provides a dynamic visualisation of the Twitter information flows and social networks that emerge over time. Its development was driven by the following underlying principles. First, *begin with the network*. If we are interested in the actors and outcomes that are produced in the ongoing flow of information, we need tools that can explore how these emerge within the network, rather than imposing a priori assumptions about who or what is important, or using sampling frames from beyond the network to make the data manageable. Second, we must *capture the dynamic flow* of tweets, to explore the network as it grows. Third, we must *overcome methodological polarisation between macro and micro analysis*: between large-scale metrics – which measure the structures and patterns of Big Data – and analysis of micro-level interactions – the communications of individuals (see also Larsson and Moe, 2011; Edwards, 2010), allowing the combination of technical capabilities with in-depth qualitative research methods.

From these principles we have developed a computer-based tool that enables the metrics, dynamics and content of Twitter information flows and network formation to be explored in real-time or via historic data. This uses some common techniques and metrics from SNA, for example measuring static properties such as number of nodes (users), edges (directed communications between one user and another), in-degree (the number of directed tweets or retweets towards an individual user) and out-degree (measuring the mentions made or retweets by that user of another user). Beyond this, our tool also enables us to (1) examine the dynamic properties of Twitter networks, incorporating an adaptable graphical user interface to visualise this; (2) develop associated metrics to measure the flow of information at scale and over time; and 'zoom in' to examine the content of conversations and communications between individuals.

Remaining true to these principles does *not* mean that we have to engage with the whole Twittersphere. Although some have done this (Ahn et al., 2007), the scale and heterogeneity makes this difficult. Rather, our tool filters the data stream following the primary principle: that is, starting with the network itself, drawing on user-generated hashtags. Hashtags are produced to link a tweet to a particular topic, effectively a 'bottom-up' curation of tweets around a particular topic into a single stream of data. Second, the tool uses an algorithmic filtering solution to reduce the volume of data based on the characteristics that individuals display within the network: the number of times they have tweeted, the number of times they have retweeted or been retweeted, their connectivity within the network and the role that they play in the diffusion of information.

It is important to focus on the retweet function because it is the means by which information is diffused across Twitter. User ‘A’ tweets: this is seen by their followers and anyone else who searches Twitter for that user or topic, or happens to come across the tweet serendipitously. If User ‘B’ retweets the original post, then this is seen by all User B’s followers (etc.), who may in turn retweet. And so on. Following retweets allows us to trace the *flow of information*, rather than simply observe individuals or tweets, which we have no way of knowing whether anyone has read, let alone passed on to anyone else. The retweet also offers a way to observe which information and which actors become important as the network evolves: what the network produces, rather than using the network as a data source to observe actors or tweets selected in advance. In what follows we demonstrate our method through an analysis of the #feesprotest Twitter network that draws together tweets around the rise of student fees and a protest that took place in November 2011.

Political Activism on Twitter

There has been much interest in if and how Twitter might be used to facilitate political activism and, perhaps, engender new forms of grass-roots mobilisation and enhance participatory democracy. Some dramatic claims have been made in public debate, not least about the ‘Obama paradigm’ of social media electioneering (Theocharis, 2011), ‘Twitter revolutions’ in the Arab Spring (Sullivan, 2009) and the role of Twitter in the 2011 UK riots.[4] However, there is relatively little concrete or detailed evidence about the actual role of Twitter in these events, leading to calls for systematic research beyond ‘anecdotal evidence and sweeping generality’ (Segerberg and Bennett, 2011: 199). We need to know more about how Twitter is used in practice and avoid the abstraction fallacy (Segerberg and Bennett, 2011) that ascribes political features to a technology, rather than exploring these with rigorous investigation. Rising to this challenge, Theocharis (2011) and Segerberg and Bennett (2011) provide theoretically informed and empirically detailed accounts of Twitter use in political protest, showing that Twitter is used to both mobilise and inform over sustained periods as well as more tactically during actual demonstrations; and that Twitter plays an important role in connecting diverse networks of people, although this is done in different ways in different hashtag streams and changes over time. Both studies conclude that Twitter expands the portfolio for political organisation in an increasingly sophisticated repertoire.

This emphasis on the place of Twitter in the broader political ecology is important, but previous research remains methodologically limited by its focus on a small number of tweeters, pre-defined on the basis of institutional affiliation (Theocharis, 2011) or random samples of a larger set of data (Segerberg and Bennett, 2011). Thus, whilst these studies might begin with the data generated by a hashtag, they impose their own external criteria on this to sample data, rather than tracing the actors and relationships that emerge in the network. Second, the analysis is based on static properties of the network and the user – for example, snapshots of the ‘friends’ and ‘follower’ metrics for key actors – rather than analysis of the relations that emerge within the network over time. Even though Segerberg and Bennett take counts at several points in time, we cannot see the dynamics that produce these statistics. Finally, whilst there is some inclusion of qualitative data – illustrative tweets for example – the methods employed cannot allow us to see what information (which tweets) is moving across the network or linking users together. To redress these concerns, in what follows we present our approach, which allows us to explore which users, information and linkages emerge within the network over time.

#feesprotest[5]

Our dataset is the tweets using the hashtag #feesprotest, linked to political protest against the rise in university tuition fees in England and in particular the demonstration that took place in London in November 2011. The total collection contains 12,831 tweets made by 4737 Twitter users from 8 October to 21 November 2011. These data identify the author, time of tweet and tweet content. Figure 1 provides the basic metrics from this data stream, showing an uneven flow of activity, with a big increase around the day of the protest that then tails off.[6]

Over 54 per cent of the tweets are retweets – passing on others' messages – whilst only 18 per cent of all tweets direct messages to another user, showing a high recirculation of information intended for a general, rather than specific, audience.

From these metrics a series of questions emerge. What information is flowing? Which actors are most widely cited? How well connected are the tweeters? And do these change over time? In our analysis we focus primarily on the retweet network because this allows us to trace the information in flow, the actors involved and the networks that emerge as a consequence, although – as will become apparent – this also engages us with direct messaging between users and with other sources of data, beyond the tweet itself. We use our tool to filter the data archived from #feesprotest to trace tweets that have been retweeted 100+ times.[7] This is a simplification of our data based on network metrics that allows

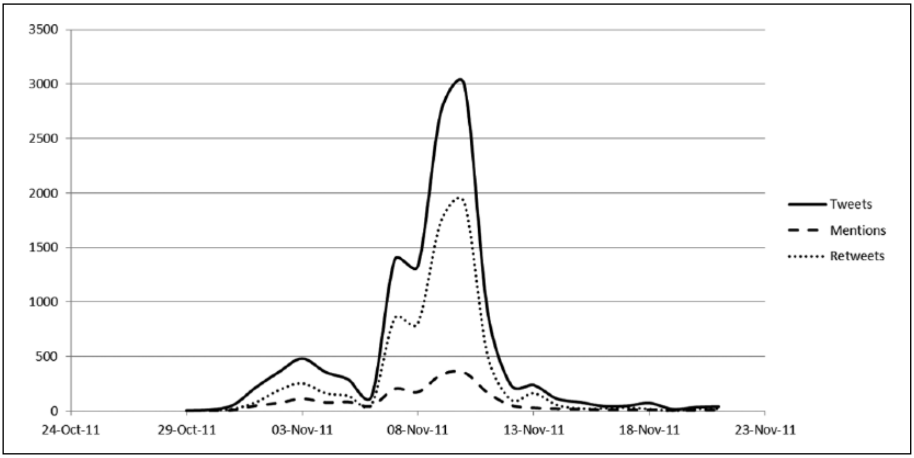
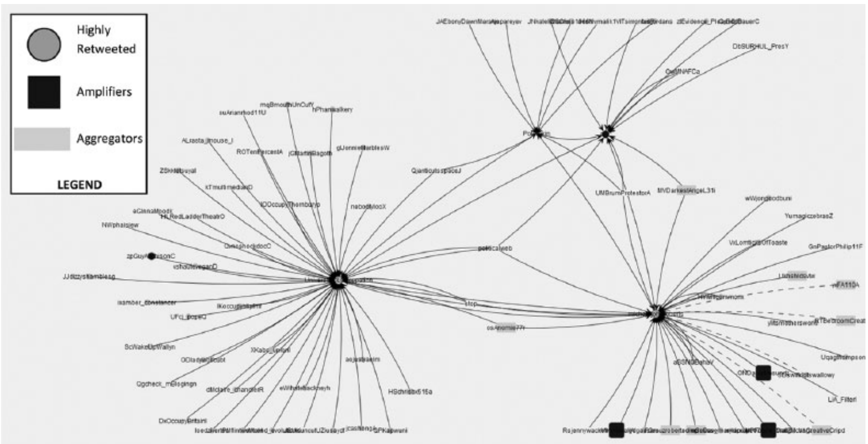


Figure 1. Number of #feesprotest Tweets, re-tweets and mentions, 30 October to 19 November 2011.

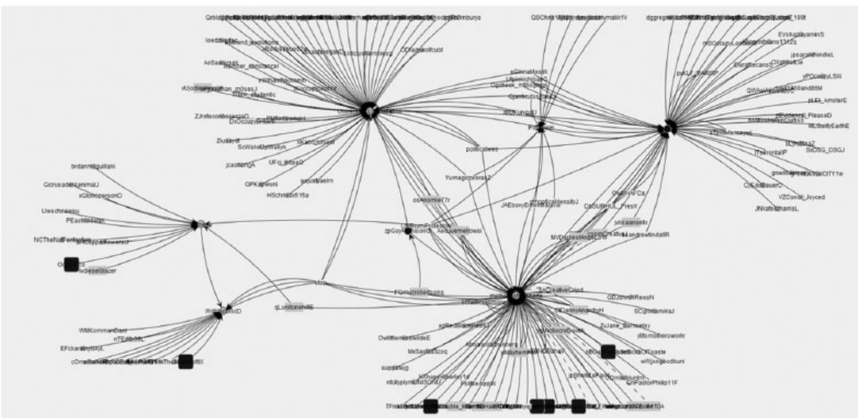
us to trace the most widely flowing streams of information. Figure 2 shows a series of static snapshots taken from the six days surrounding the protest, visualising the growth of the retweet network over this time whilst the conversation playback video at http://eprints.soton.ac.uk/358941/ shows a dynamic visualisation of the network over the same period that can be paused at any point in time.[8] We strongly recommend viewing this video for the best visualisation of our data. In what follows, we explore the flow of information across this retweet network and examine the roles that emerge in the network over the time.

In the Flow: Information and Actors

The large circular nodes in Figure 2 (red nodes in the conversation playback video) identify the users who have received a significant number of retweets within the data being

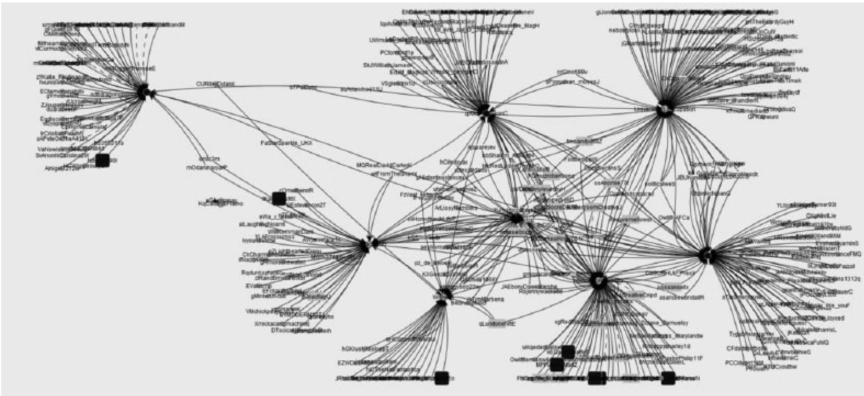


6 days before protest at 21:00

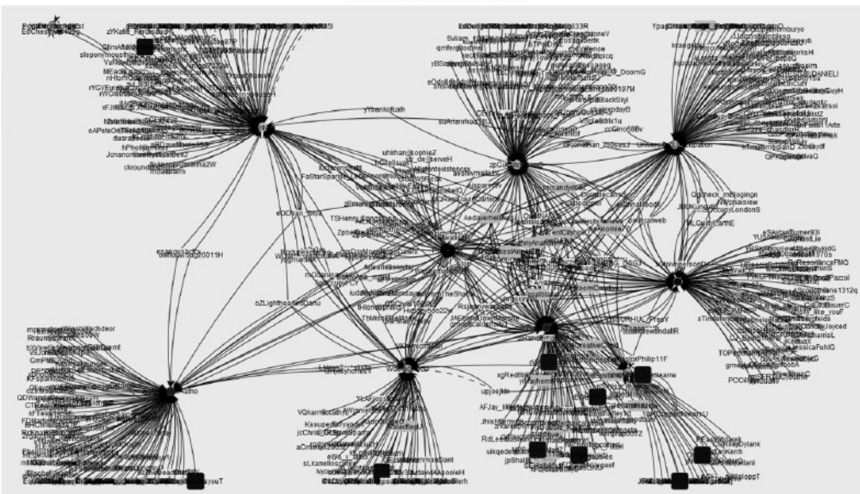


2 days before protest at 21:00

(Continued)



1 day before protest at 21:00



During protest at 21:00

Figure 2. #feesprotest re-tweet network.

examined, whilst the ‘edges’ (or links from these red nodes) show who has been retweeting them, and any subsequent retweets of this message.

It is immediately obvious that there are only a small number of highly retweeted users (in these data, only 0.26 per cent or 12 individuals were retweeted more than 100 times). These are not necessarily the most prolific tweeters – their average tweet-retweet ratio is 1:12 – so they would not have been identified on these grounds alone, but their place in the flow of information is clearly significant. Four of these users were already apparent almost a week before the protest, and by 9am on the morning of the protest, nine of the 12 were already present, showing the emergence of consistent key players who, indeed, only consolidate their role as central nodes in the network over the period. In contrast to previous research that identifies the interesting actors as a way of sampling data, our method means that these key players are derived from the network itself. Significantly, whilst several of these users might be characterised as 'the usual suspects' there are also some less known figures.

'@UniversityOccupation' for instance, linked to students at the University of London and highly retweeted in our network also features in Theocharis' (2011) chart of Twitter accounts associated with university student politics. Similarly, '@AFC' represents the 'Against Fees and Cuts', a coalition of students and workers who actively protest against student tuition fees. On the other hand, '@Potemkin', 'and '@michaeljohnroberts' are individuals, one linked to a grass-roots group working towards improved democratic engagement and the other with no apparent organised affiliations. These tweeters became important in the network, but would not have been captured by sampling well-known actors and, given the number of tweeters in the network, might not be selected by random sampling methods.

As the network grows, and new highly retweeted users emerge, this heterogeneity narrows. By two days before the protest, the most highly retweeted messages are from known anti-cuts tweeters and these users maintain their ranking throughout the remainder of our analysis. This phenomenon can be described by the concept of preferential attachment (Albert et al., 1999). The noise of total information flow is often dominated by the voices of a few, who, once they have gained a voice, increase their audience and therefore volume over time. As the network of communication grows, it becomes harder to become popular. Prior to the day of protest itself, four individuals were identified as highly retweeted, and this number quickly rose to double that within five days. However, subsequently, the rate of growth of individuals to become highly retweeted decreased and, instead, the already highly retweeted individuals reinforced their voice within the network, although they were not necessarily adding new tweets. As Figure 2 illustrates, 24 hours after the protest, the nodes with the highest amount of edges (here, retweets) become more popular and gain more edges. At this stage, the flow of information within the network becomes saturated with the tweets of these highly retweeted individuals, overshadowing the unknown users and their tweets.

Alongside this temporal pattern in user popularity, we see a temporal turn in the content of the highly circulated information around #feesprotest, from calls to participation to discussion of police tactics and apparent evidence of police brutality.

> *[Wed 02 Nov 2011 20:40:49] "RT @michaeljohnroberts: There is a march of 10000 students to the city of London on November 15th come! #barricades #feesprotest"*
>
> *[Tue 01 Nov 2011 12:36:38] "RT @UniversityOccupation: @abc_union will you and your members join and support the demonstration http://t.co/LTpspyra #feesprotest"*
>
> *[Sat 05 Nov 2011 20:27:52] "RT @Witness: More disgusting police behaviour. We need to think about #feesprotest and how to defend ourselves. #abca"*
>
> *[Mon 07 Nov 2011 16:55:40] "RT @Cityears: In case you missed it The Police have given the go ahead to use bullets on the kids if they misbehave too much at the student demo #feesprotest"*

Of the top 10 most retweeted posts, nine concerned policing and allegations of brutality. Figure 3 shows the retweet chains for these top 10 posts. The single most retweeted post, from @Potemkin – a user with no apparent political affiliation and a relatively small number of followers (*c*.600) – begins 'I got told not to post these pictures …' suggesting an appetite amongst retweeters for using Twitter as a mechanism of direct defiance, although the chain dies away within 24 hours. In comparison, the longest chain, also highlighting policing tactics sustains itself over four days, and was posted by a journalist with over 8000 followers.

Attention to the number of followers of an individual (re)tweeter is important, since any post will show up in the timelines of all those followers. The more followers, the more widely the information is circulated. This point is compounded if we consider the URLs embedded in many of the tweets above. A hyperlink – if opened – extends the information circulated via Twitter way beyond the original 140 character tweet. For instance, the URL embedded in the UniversityOccupation tweet above links to a Facebook page which itself contains over 31,000 users. Making use of this 'wide data' underscores points made elsewhere about the importance of placing Twitter within a broader ecology of tactics available for political mobilisation (Segerberg and Bennett, 2011) and enables us to place specific political mobilisations on a broader canvas.

Emergent Network Roles

In our analysis so far, we have concentrated on the users that emerged as highly retweeted as the network grew, and the content of their messages: the information that flowed. It is not, however, the actions of these original tweeters which cause the information to flow. In this section, we turn our attention to the role of the retweeters: the users who pass on information and who may come to occupy a particularly significant role in the emergent network. Figure 2 and the conversation playback video http://eprints.soton.ac.uk/358941/ show that the pattern of retweets is not random or evenly spread across the network. Specifically, there are users who – whilst not particularly active in generating content themselves – play an important role in passing information on, being the first to retweet, pushing information on to new audiences, often very swiftly (these are identified as the square nodes in Figure 2 and as blue nodes in the online visualisation, Figure 3 shows the speed of retweeting). Retweeting is not spread evenly across users, but, rather, the flow of information is strongly shaped by these 'amplifiers'. Analysis of the #feesprotest network reveals one particularly active user in this respect. Throughout the lifetime of the network, '@politicalweb' was the first to retweet three of the four most highly retweeted messages, initiating the wider circulation of these original posts. However, this amplification role was *selective*, with emphasis on the organisation and coordination of the protest:

> *[Sun 30 Oct 2011 16:47:01] "RT @UniversityOccupation: http://t.co/7D8jFsRE debut is in common room – 9 pm Thursday #politicalweb #feesprotest #solidarity"*

> *[Tue 01 Nov 2011 16:39:36] "RT @AFC: London regional meeting TONIGHT at 6pm in UniversityLondon. Also remember @politicalweb also here from 6pm. #politicalweb #feesprotest"*

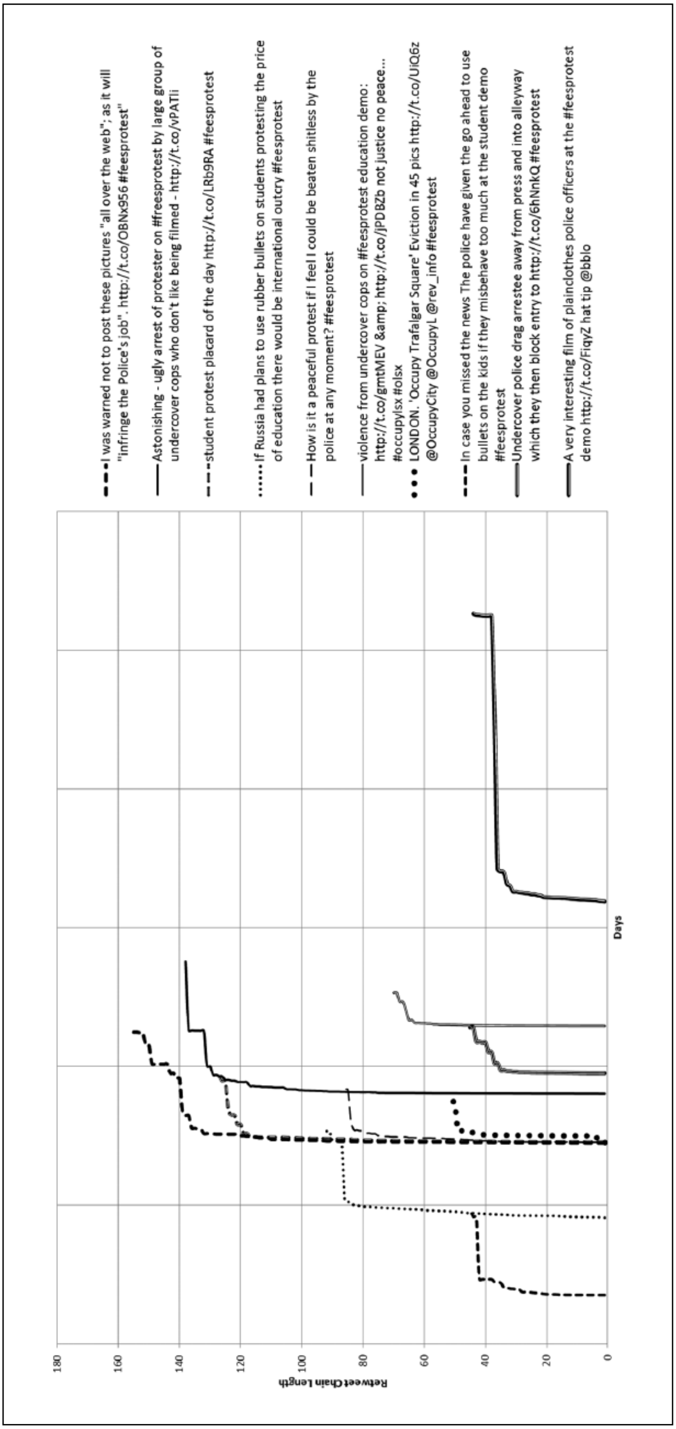


Figure 3. #feeprotest ten longest retweet chains.

In each case, the retweeter promoted their *own* activities, thorough links to other hashtags and websites. Whilst the action extends the flow of the original tweet it also piggy-backs other interests onto this. As the original tweeters gain dominance in the network, they carry with them the retweeter's information, gaining a wider audience for this too.

A second important role that emerges in the network is that of 'aggregator', (identified by the oblong nodes in Figure 2 and as yellow nodes in the online visualisation). This is also a retweet activity, but here the contribution is not in being the first to retweet, but in retweeting posts from diverse streams of information, building bridges between discrete networks, pulling threads of information into a single channel.[9] This works in two ways. First, the aggregators are compiling a selected stream of #feesprotest tweets for their followers who are not themselves following #feesprotest, pushing the information on to a wider audience. Second, the aggregators are doing this across multiple hashtag data streams, operating as a node in the wider Twitter network beyond #feesprotest. Some individuals such as '@politicalweb' take on both the role of the 'amplifier' and 'aggregator', for example '@stop' who is a first retweeter and aggregates posts from a number of highly retweeted individuals, assimilating potentially valuable information.

> *[Sat 05 Nov 2011 21:50:41] "RT @michaeljamesroberts: New November Student Demo (and more) website launched! http://t.co/j6rmFmpy Please RT! #feesprotest #occupysx"*
>
> *[Wed 09 Nov 2011 22:05:03] "RT @Potemkin: I was warned not to post these pictures "all over the web"; as it will "infringe the Police's job". http://t.co/OBNx956 #feesprotest"*

In sum, the combined effects of these emergent roles in the network led to a complex interconnected network, dominated by a few highly retweeted individuals, whose position strengthens over time, narrowing down the information in flow, specifically, in this case, to concentrate on concerns about the policing of this protest. Our analysis shows that this patterning to the flow of information emerges from multiple iterative actions, not only those of the original tweeters – although these are clearly important – but also by the retweeters and aggregators whose selections come to shape the dominant discourse of the network.

Conclusions

The primary aim of this article has been to consider the methodological challenges that face those interested in engaging with Big Data and to demonstrate a new research tool designed to address some of these challenges, specifically related to scale, proportionality and dynamism. The same principles and method could be applied to any web-based system of dynamic information diffusion from emails, to YouTube, Facebook or Flickr. In this article we have worked through an illustrative case based on Twitter and the #feesprotest data stream and our findings extend previous research in the following ways. Rather than selecting users either purposively or randomly, we examine the emergence of a communications network, and have explored which users and which information rise to the surface as a result of the dynamic flow of information. To achieve this, our method enables us to 'zoom' from analysis of the macro-structure of the network – where our analysis is based on quantitative algorithmic methods – to the micro-level of individual users and tweets. This allows us to see how information diffuses and flows between users over time, and to explore the networks that emerge as a consequence. Whilst previous research concentrates on content and aims to link this to offline activities, our research shows for the first time how specific pieces of information flow and how the incremental actions of individual users produce social roles and networks inside Twitter.

This shows, very clearly, that Twitter is not one thing but many. Twitter is neither a medium for news nor a method of organising but both: its form is contingent produced in the multiple iterations of users. In the spirit of Science and Technology Studies we might say that Twitter is in an ongoing process of becoming. We mean this in a double sense. First, the technical platform itself is evolving over time, with the formal adoption of the hashtag function into the Twitter repertoire, following its informal invention by users, being the best example. Second, the flows of information and the networks that form, however temporary or permanent, small or large, are undetermined and emergent. Original tweeters cannot know the fate of their posts, whether they will capture a wider imagination, or be selected by the influential retweeters and aggregators. Similarly, the retweeters and aggregators can aim to promote particular information but once they have done this the fate of their retweets will be in the hands (or thumbs) of others. Nonetheless, dominant discourses may emerge within a hashtag stream, even if they dissipate and disappear just as quickly as they appear. Although the #feesprotest hashtag was used extensively previous and subsequent to the demonstration, overall this was only a short period of time; the networks themselves are dynamic, fluid and changing (Urry, 2000); the topics that the #feesprotest hashtag represented at the time of the protest no longer resonate through the Twitter network; and the hashtag itself is barely used and then only for apparently disconnected tweets from disconnected individuals.

In methodological terms, this is just the beginning. Whilst this approach offers some important advantages over previous methods, there is clearly more that we can do. Thinking just of Twitter, we might explore the relationship between retweets and followers to trace flows of information and emergent linkages between users. That is, are retweets only made by those who are *already* followers of a particular user, or by others who come across the tweet either through the hashtag or in other more serendipitous ways? And how, or do, tweeters gain or lose followers in relation to particular tweets? We might also aim to develop methods that connect hashtag streams, rather than following one stream only. Indeed, there are still questions that need to be asked about who actually sees this information: retweets only offer one way to explore the exposure of information within a communications network. Thinking beyond Twitter, we have argued for a 'wide data' approach, making links across digital sources e.g. from Twitter to Facebook or online corporate media – this would allow us to explore the relationality of these data. Furthermore, as others have suggested, we need to move beyond the digital, making links to print media as well as data from interviews and observations to develop fuller understandings.

These methodological developments have epistemological, ethical and disciplinary implications. Our capacity to engage with whole data sets at scale, and to combine qualitative with quantitative analysis may go some way to allaying concerns about the status of Twitter data, by allowing us to position individual tweets/tweeters, or samples, within the whole network; by allowing us to follow the flow of data – where it goes – rather than simply commenting on the existence of these data; and by allowing us to engage with detailed content as well as overall patterns. This is 'wide data' rather than Big Data and we suggest that this methodological approach will also serve to strengthen our claims to knowledge. Meanwhile, however, a wide data approach raises some new ethical questions. Building links across data sets can pose profound threats to individual privacy (Bizer et al., 2009). Whilst individuals posting on Twitter are likely to be aware that this will be publically available, they may not consider the composite picture that can be built up about them by combining multiple sources. This is not something that we have done in this article, but it will become increasingly possible and challenges us to find ways to govern our practice in ethical ways. Finally, our argument suggests that sociological concepts, theories and methods are critical to Big Data analysis. As the zeitgeist shifts towards 'data driven' research we must be clear that data are not naturally occurring or unmediated but are sociotechnically constructed: produced and represented in the artefacts that have been designed for particular platforms and through the users' adoption and adaption of these. Furthermore, the meaning of these data is not self-evident but requires robust methodologies, nuanced conceptual vocabularies and theoretical frameworks drawn inter alia from sociology. However, the existing sociological repertoire of methods (and perhaps theories) will not be sufficient in this endeavour. Indeed, as Savage concludes more generally, in his analysis of post-war British sociology, the future of the social sciences may depend on building 'intellectual and technical alliances' (2012: 249) with other ways of knowing, not least of which – we suggest – in the context of Big Data will include the computational sciences.

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Notes

1. This is not to suggest that Big Data is somehow 'pure' or 'free' of social norms and constraints simply that these data are produced beyond rather than through sociological research methods.
2. It is possible to 'protect' tweets from other users unless they are identified followers. We are aware of no information on how often this is done, but it appears to be very rarely indeed.
3. International Bibliography of Social Sciences (IBSS), accessed 8 October 2012.
4. http://www.huffingtonpost.co.uk/2011/08/08/london-riots-twitter-that_n_920791.html
5. These are publically available data, however we have anonymised them by changing hashtag and user names (checking that they are not currently in use by other Twitter account holders) and making minor inconsequential changes to the tweets, so that they are not discoverable.
6. It is worth noting that there are no constraints on the use of a particular hashtag for any specified purpose. #feesprotest has been used more recently to refer to a range of events and topics, not only the student fees protest. However, since our tool allows us to view the content of the tweets using this hashtag over the archived time period and to see which information 'rises to the top' in terms of number of retweets we can be confident that the vast majority of the data collected refers specifically to the student protests.

7. Our tool allows us to set this filter at any level. We have chosen 100+ here to allow us to see the detail in this particular set of data and address the questions that we are focussing on in this article. For other data or other questions the level might well be set lower, or indeed higher.
8. This conversation playback video can also be accessed at http://youtu.be/F12oZpasFPk.
9. Please note that in Figure 2 some of nodes identified as aggregators (oblongs) remain at the margins of the graph because their role as aggregators has yet to emerge at this point in the evolution of the network.

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