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Social Action on Social Media

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Abstract

People try to help others in a wide number of ways. Taken together this is social action - the heart of civil society, and the foundation of a healthy one. However, some social action is hard to spot. It may be unregistered, be carried out with little or no income, or have little formal governance. This paper examines a new way of detecting and measuring social action – especially that which takes place below the radar. It uses a new methodology developed by CASM to use social media to spot, collect and measure social action that normally is carried out below the radar. It uses natural language processing algorithms to analyse, and sort large quantities of Tweets related to two key events: the flooding of 2014, and the launch of the Step up to Serve Campaign.

It finds:

- Disasters, accidents and catastrophes are likely to create a explosions of Tweets too large to manually read.
- Some people will use Twitter to either offer or ask for help. This will often be specific to the disaster, spontaneous, and by people operating outside of any organization or charity.
- Twitter is a significant new forum which people will use in response to events to try to help each other.

It recommends:

- An Ebay for social action on social media': Connecting social action supply with demand: When social action information is found, it could be centralized onto a real-time online platform, information exchange or brokerage hub, clearly related to a specific event and segmented either into the type of help that people are offering, or where the help is being offered.

Key Words: Social media, social action, big data

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Part 1 – Introduction

People try to help others in a wide number of ways. They volunteer, organize, share skills, mentor, fundraise and donate, participate in local civic projects and work as activists to change laws and minds. Taken together this is social action - the heart of civil society, and the foundation of a healthy one. This paper scopes a new way to measure and understand it by researching social media. It is part of a broader attempt to make our understanding of social action more data-driven.

Social action is, of course, a vital social good. A wide body of research points to the valuable social benefits that it brings to both the people taking part and the wider community that they help.ⁱ It improves and makes people feel more connected to the people and institutions that surround them, and also gives people skills - problem solving, resilience, compassion, determination – to succeed in other parts of their lives.

To promote social action, it is important to understand it, to know where it happens and why, who is doing it, and what problems it is directed towards. We need to know what helps or hinders social action in order to craft the right kinds of public policies and messages to support and sustain it and, ultimately, to ensure that we live in a society where, in a variety of circumstances, people help each other as much as possible.

Some social action – especially when undertaken on a large scale and in a formal and structured way – is easy to spot. In 2010, 12 charities in Britain received over £100 million in voluntary donations, and hundreds more than £10 million.ⁱⁱ Around 20 million people formally volunteer for a charity at least once a year, and 15 million once a month.ⁱⁱⁱ Activity carried out by these large organizations is generally well understood and measured by a network of agencies, including the Charity Commission, Companies House, the Registrar of Community Interest Companies and Guidestar.^{iv}

However, some social action is much harder to spot. Around half of charities are local, run by volunteers, and with annual incomes under £10,000 a year. Other social action takes place entirely outside of any organizational structure. Activity can happen ‘below the radar’ when:

- *It is unregistered:* with the Charity Commission, Companies House or other regulatory bodies the Registrar of Community Interest Companies, NCVO Almanac or Guidestar.^v

- *It is carried out with little or no income:* roughly, with an annual income of less than £25,000 per annum.^{vi}
- *It has little formal governance:* such as leadership, management, legal structure and staff involvement.^{vii} There are practically different forms of radar: the policy and influence radar, the information technology, and so on. Organizations may be above some, yet below others.^{viii}

Whether helping a vulnerable neighbor or putting up sandbags, this kind of activity is important and significant, but is notoriously difficult to measure or understand. It is also difficult to know how much of this type of activity is currently being missed. Estimates of the number of below the radar groups range from 5,500^{ix} to 900,000.^x

This paper examines a new way of detecting and measuring social action – especially that which takes place below the radar. By improving how we measure social action, we become better at understanding it, and making the right decisions to protect and promote it.

Spotting social action through studying social media

Over the last five years, the way we communicate and engage with each other has changed dramatically. Around the world, 1.2 billion people use an app or website to generate as well as consume information.^{xi} This new ‘social’ media is now the most popular way the Internet is used.^{xii} In the UK, 48 per cent of British adults use a social networking site, and this number is growing rapidly.^{xiii}

The explosion of social media has radically changed where we live our lives, and how we talk about the experiences we have had and the attitudes that we hold. There is growing evidence that it is also changing the face of social action. Recent research by Demos has indicated that social media is a place where people discuss, encourage, promote, coordinate and solicit offline social action, and is also an important venue for a new kind of online social action. It is an arena now important for political discussion and debate,^{xiv} social action, activism and volunteering,^{xv} and concerted petitions and collective action,^{xvi} where new political groups form and organize.^{xvii}

The rise of social media has also opened up a new way of understanding society. The recent Demos paper *Vox Digitas* laid out a new method for studying Twitter, called Digital Observation. Twitter allows its users to ‘tweet’ short messages, pictures or links. It has been operating since 2006 and its 200 million active

users have posted over 170 billion Tweets since the platform was first created. Around ten million of these users are British.^{xviii} Twitter makes many of these Tweets available for researchers.

Of course, large parts of society never use social media, and even more use it only infrequently. Many of the least wealthy and most vulnerable individuals are either under-represented on social media platforms, or not represented at all.^{xix} However, *Vox Digitas* found that social media platforms, and especially Twitter, created datasets that were both unprecedentedly large and sociologically rich. Digital Observation was designed to begin to ethically and robustly unlock these datasets, to form them new windows on society that could be used and understood alongside other forms of social research.^{xx}

The aim of this paper is to test whether Digital Observation can spot, collect and measure social action that normally is carried out below the radar (henceforth abbreviated to 'BTR'). It scopes whether Twitter contains information about social action that cannot be picked up through other means, and, overall, whether this is a promising new avenue through which social action can be tracked and supported.

This is broken down into four key research questions about social action on Twitter:

- (a) *Is social action mentioned on Twitter?* And if so, on what scale, of what quality, and in which contexts?
- (b) *Who carries out the social action?* Does it tend to be large, structured organizations, or informal and less organized? Where does it come from?
- (c) *Who does the social action benefit?* Who is it directed towards, and what problems
- (d) *Can it be reliably measured?* To what extent can all of the above be collected and measured accurately?

Research Method

This section describes the new method – Digital Observation – that was used to identify Tweets related to BTR social action.

Data Collection – the ‘API’

This paper collected one set of Tweets for each case study. These were via Twitter’s ‘stream’ and ‘search’ application programming interfaces (APIs). These allow researchers to collect publically available Tweets. The ‘search’ API returns a collection of relevant Tweets from an index that extends up to roughly a week in the past. The stream API continually produces Tweets that contain one of a number of keywords to the researcher, in real time as they are posted onto Twitter.^{xxi}

For each case study, a set of words was created to collect as many Tweets as possible related to the event in question, but as few irrelevant Tweets as possible.

Data Analysis - the ‘classifier’

The Twitter data collected was too large to be manually analysed or understood in its totality. Digital Observation was developed as a method capable of handling datasets of this kind. It uses Natural Language Programming (NLP) ‘classifiers’ that are trained by analysts to recognise the linguistic difference between different categories of language. This training is conducted using a technology developed by CASM to allow non-technical analysts to train and use classifiers called ‘Method 51’.^{xxii} For a full description of Method 51 and the training of classifiers, see the methodology annex.

Classifiers are built to analyze two kinds of text, (a) the content of the Tweet itself, and (b) the profile of the Tweeter. Both pieces of information are contained in every Tweet produced by Twitter’s API.

Practically, classifiers were built to work together. Each is able to perform a fairly simple task at a very large scale: to filter relevant Tweets from irrelevant ones, to sort Tweets into broad category of meanings, or to separate Tweets containing one kind of key message with those containing another. When classifiers work together, they are called a ‘cascade’. Cascades of classifiers were used for both case studies.

Evaluation and Assessment

Each classifier trained and used for this paper was measured for accuracy. In each case, this was done by (a) randomly selecting 100 Tweets, (b) coding each Tweet using the classifier (c) each same Tweet being read and coded by an

analyst, and (d) comparing the results and recording whether the classifier got the same result as the analyst.

There are three outcomes of this test. Each measures the ability of the classifier to make the same decisions as a human in a different way:

Recall: This is number of correct selections that the classifier makes as a proportion of the total correct selections it could have made. If there were 10 relevant Tweets in a dataset, and a relevancy classifier successfully picks 8 of them, it has a recall score of 80 per cent

Precision: This is the number of correct selections the classifiers makes as a proportion of all the selections it has made. If a relevancy classifier selects 10 Tweets as relevant, and 8 of them actually are indeed relevant, it has a precision score of 80 per cent.

Overall: All classifiers are a trade-off between recall and precision. Classifiers with a high recall score tend to be less precise, and vice versa. The 'overall' score reconciles precision and recall to create one, overall measurement of performance for the classifier.

Case Studies

A tweet is overwhelmingly a reaction to an event that the user has otherwise encountered – either online or offline – in their lives.^{xxiii} Two events were selected because, in two different ways, they could possibly influence, require or cause social action to take place. They were:

(1) The January-February flooding: After a period of extremely wet weather, widespread floods hit the UK in January and February 2014, causing millions of pounds of damage, and severe disruption to Britain's transport networks. This was selected as a largely unanticipated event that caused widespread hardship and disruption to communities throughout the UK. Communities often react spontaneously to emergencies, helping each other to respond and recover from emergencies.^{xxiv} Twitter-activity related to the flooding was studied to see whether it reflected 'community resilience' social action.

(2) The launch of the Step up to Serve Campaign: This was a high-profile call to get over half of young people regularly conducting social action by 2020. It was launched in Buckingham Palace by Prince Charles, David Cameron and Nick Clegg, received major support from businesses and third sector organizations and was widely covered in the media. It was selected both because it was an opportunity to study an event that has caused many people to speak about social

action, and because it was an explicit, planned and coordinated attempt to try to increase the amount of social action undertaken.

Ethics

Conducting research using Twitter data presents new ethical challenges for how researchers should collect, store, analyse and present publicly posted tweets. It is a new field of research and there are no widely accepted protocols and approaches for ethical social media research. Some useful recent guidance has been issued by the *New Social Media New Social Science* academic working group, which recognises that a number of outstanding ethical questions for research of this kind remain.^{xxv}

The Economic and Social Research Council has 6 principles of ethical research.^{xxvi} After reviewing these principles, two were judged to be important to consider:

1) Was informed consent necessary?

Informed consent is widely understood to be required in any occasion of 'personal data' use when research subjects have an expectation of privacy. Determining the reasonable expectation of privacy someone might have is important in both offline and online research contexts. How to do this is not simple. The individual must (a) expect the action to be private and this expectation must (b) be societally accepted as objectively reasonable.

Within this frame, an important determinant of an individual's expectation of privacy on social media is by reference to whether the individual has made any explicit effort or decision in order to ensure that third parties cannot access this information.

Applying these two tests to Twitter, it is reasonable to conclude that there is a very low expectation of privacy. (This is not true of all social networks). A Tweet is a public statement. Twitter's Terms of Service^{xxvii} and Privacy Policy^{xxviii} state: "What you say on Twitter may be viewed all around the world instantly. We encourage and permit broad re-use of Content. The Twitter API exists to enable this". Societal expectation of privacy on Twitter, we believe, is also relatively low given recent court cases that have determined Tweets are closely analogous to acts of publishing, and can thus also be prosecuted under laws governing public communications, including libel.

2) *Are there any possible harms to individual participants entailed in this form of research?*

The chief burden on researchers is to make sure they are not causing any likely harm to the people being researched, especially if those people have not given a clear, informed, express consent.

Whilst harm to an individual is difficult to measure in respect of social media research, Digital Observation poses little possibility of inflicting individual harm. It gathers and analyzes large bodies of aggregate data; and does not focus on the individuals contained within it. However, individual harm is possible when individual Tweets are taken from this dataset and quoted within the research.

It was judged that individual harm to participants was possible through quoting individual Tweets – especially those that contained a message that was critical, offensive or obscene. It could be traced back to the individual, possibly with negative consequences. For other users, simply having their details published might be distressing or upsetting, especially if used in a context they had not consented to.

There is material value to the research in directly quoting Tweets. As a general principle, it is considered good practice where possible to quote research subjects directly and faithfully. This is because a) it is more accurate as a research method and b) it allows other researchers to more closely scrutinise and potentially replicate your research work. However, in this case, it was decided to ‘cloak’ direct quotes, and retain the essence of the meaning whilst changing small parts of the text so that no one can be easily identified.^{xxix} Links contained within Tweets were depersonalized to <http://t.co/XXX>. Institutional Twitter accounts have been maintained, personal account names have been depersonalized as ‘@XXX’.

PART 2 – CASE STUDY RESEARCH

Case Study (1) – The 2014 Floods

At one of the crisis points during the UK floods in 2014, people across the country used Twitter to quickly share information – travel disruption, weather reports and first-person reportage - to help others react and stay safe. Especially in affected areas, people used Twitter to both offer and request help for finding animal feed,

moving livestock to dry fields, building sandbag defences, and to donate to relief agencies.

From January 2014 onwards, following the wettest weather on record, the UK suffered widespread flooding. Southern England, and Wales were particularly affected, but flood warnings were issued throughout wide areas of England and Wales. The flooding damaged over 7,800 homes and nearly 3,000 commercial properties, causing around £400 million pounds of damage, and caused serious damage to the road and rail infrastructure of some affected areas.^{xxx}

The paper studied Tweets related to the floods during one of its crisis points: 5 – 10 February 2014. On the 5th, David Cameron convened a COBRA meeting – the first of the year – as severe flood warnings were given to residents in Somerset. On the 7 and 9 of February, the Thames burst its banks across Surrey, Berkshire and Oxfordshire, causing additional flooding continuing up to the 10th and beyond.

Data Collection & Analysis

116,123 Tweets between the 5th and 10th of February were collected that contained the keyword ‘flooding’. This dataset contained many Tweets related to flooding in the UK, but also Tweets that related to floods elsewhere, and Tweets that used the word ‘flooding’ in a variety of other senses and contexts. A multi-stage Digital Observation system was built to peel away successive layers of irrelevant data, eventually producing a kernel of Tweets related to social action.

Step 1 – Finding Tweets relevant to the flooding: The first classifier was built to distinguish between Tweets related to flooding as a natural phenomenon within the UK – and all other Tweets. Of the initial dataset of 116,123 Tweets, 84,711 were judged to be relevant to the UK floods, and 31,412 were not. The Tweets that were not relevant to the English floods were discarded. The Tweets that were relevant were further analyzed during step 2.

Step 2 – Finding Tweets related to social action: People were using Twitter to respond to the floods in a number of ways. These were divided into two broad categories – ‘social action’ and ‘non-action’. ‘Social action’ Tweets were those that broadly contained any communication or activity aimed at trying to help other people respond to the flooding, or to appeal for help to respond to the flooding. This included circulating important general information, first person reporting on conditions on the ground and organising responses. Non-action included all other Tweets.

At this stage, no attempt was made to discern whether the action was above or below the radar. Hence, various large organisations such as the police, fire and train services were included. Local media outlets were included in addition since it was clear that much of their content, when locally oriented, was driven by submissions from local residents. 39,327 Tweets were analysed as containing social action' and the rest - 45,384 - did not contain an action, and were discarded.

Step 3 – Separating online and offline social action: A key distinction was found in the kind of social action that Tweets contained. People were using Twitter to help each other by sharing information, updates, warnings and advice, such as:

Despite flooding the Hampshire Bowman IS OPEN AS NORMAL. Dundry lane has been closed at the Bishops...<http://t.co/XXX>

This was classed as 'online social action'. People also used Twitter to promote, advertise, talk about or volunteer for social action that would be *primarily carried out offline*:

Flood fighting Chichester District Council praised: THE EFFORTS of people combating tidal flooding... <http://t.co/XXX> #Chichester

A third category – commercial – covered Tweets about commercial activity related to the floods, or where individuals had appealed to private companies for help:

Flooding @sculthorpemoor but still open for business. Bullfinches and bramblings in abundance. <http://t.co/XXX>

A classifier was trained to divide Tweets along these lines. 28,564 Tweets were identified as online social action, 3,612 Tweets as offline social action and 195 as commercial.

Step 4 – Identifying 'below the radar' social action: Some of these Tweets contained social action conducted by large and formal 'above the radar' organizations, or members of them. These included public organizations like the Environment Agency, train companies, local and national charities, politicians and councillors.

A classifier was built to separate Tweets sent from users who, in their profile, were affiliated with large, structured organizations whose remit extended to flooding relief or humanitarian assistance. These were classed as ‘above the radar’. Other Tweets, either where the user was unaffiliated, or affiliated with a company not involved in flooding relief, were classed as BTR. This, of course, was an imperfect way of distinguishing between above and below the radar social action (see conclusion). A final category removed Tweets that were irrelevant.

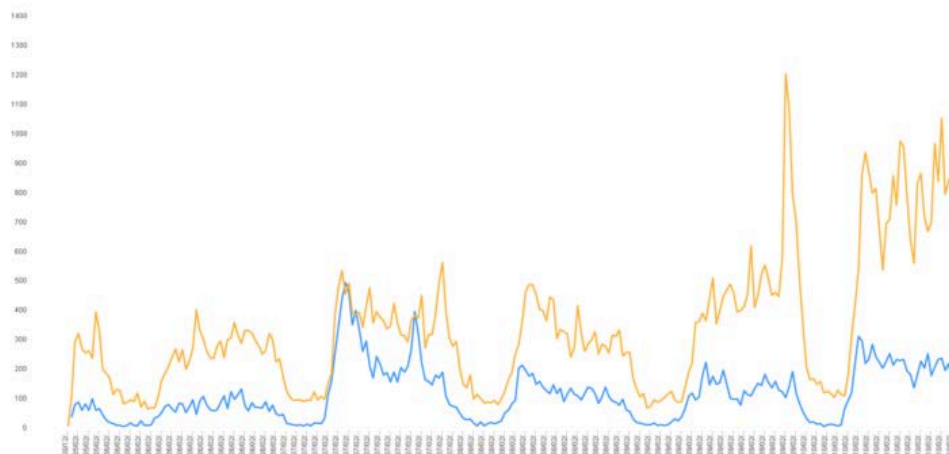
Both the online and offline social action datasets were analysed by this classifier. The final classifier produced the following results:

Type of social Action	Above the radar Tweets	Below the radar Tweets
Online social action	6,488	8,681
Offline social action	209	2,990

Results

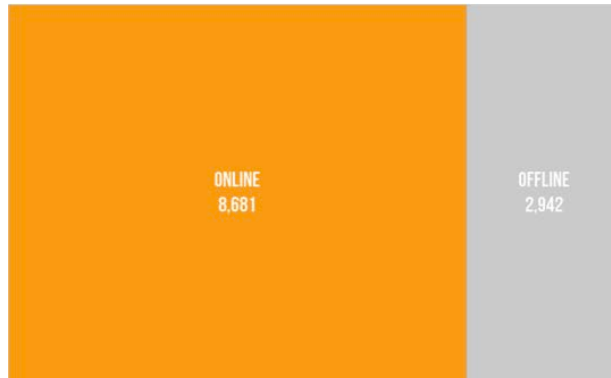
Twitter reflected significant amounts of social action conducted in response to the floods: Of the initial dataset of 116,123 Tweets, 18,320 were judged to either indicate or represent social action. 11,671 Tweets were judged to possibly be below the radar. As the graph below demonstrates, social action Tweets formed an important and consistent way that people used Twitter to respond to the flooding during one of its crisis points.

Social action vs Total Tweets about the flooding

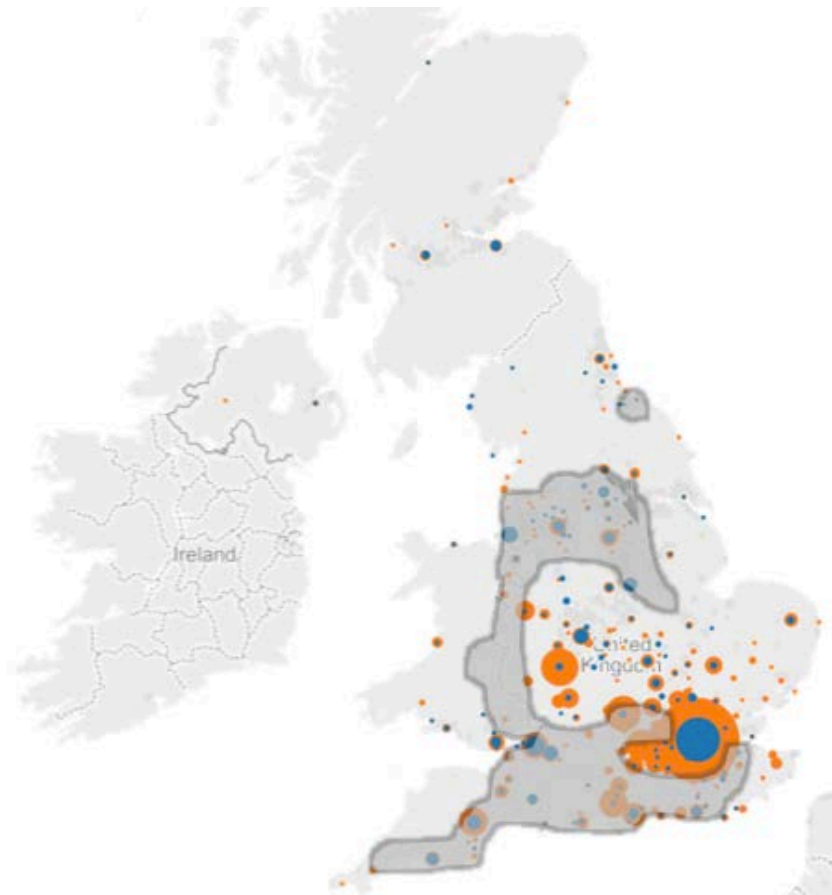


Most of the social action was principally ‘online’: Most Tweets – 8681 - fell into a wide category of ‘online’ social action. People used Twitter to share information,

and updates that helped others to make smarter decisions about how to react to the floods, to get where they needed to go, and to keep safe. A smaller number of Tweets mentioned or reflected social action that would be primarily carried out offline.



Tweets mentioning offline social action tended to be sent from areas directly affected by the floods. Online social action tended to be sent outside of affected areas: Of those that could be geographically located, a very broad pattern emerged. Tweets reflecting offline social action – of volunteering, donations and offers of help, tended to come from areas affected by the flooding. Tweets reflecting online social action – of sharing information and advice – tended to come from areas – especially London and central England – that were not affected by the flooding, but were densely populated.



As online social action, people helped others by sharing information about transport and the weather: 100 examples of online BTR social action were randomly selected, and broken down by the kind of information that was being shared.

Roads (25 per cent): the most common category was Tweets sharing information about the state of the road network. Some were general warnings:

Drivers are urged to check their route b4 Monday rush hour after wkend of flooding & adverse weather <http://t.co/XXX>

But most were updates on specific disruptions or problems:

A417 at Maisemore is currently closed due to flooding #floodglos #floodalert

#Eastleigh on high flood alert. Road flooding in many parts. Deep flood on exit of filling station located at the end of Allington Lane west End

Railways (16 per cent): The second most common form of information shared was to report on the operation of the rail network. As with the roads category, Tweets focussed on specific updates regarding emerging disruptions:

Train delays between Reading and Paddington due to flooding betw Maidenhead and Twyford <http://t.co/XXX>

West Country completely cut off by rail after flooding #somesetfloods <http://t.co/XXX> <http://t.co/XXX>

Weather (13 per cent): After transport disruption, the next most common category were people sharing updates about the weather and its likely impact on the floods:

Heavy rain causing surface water, flooding & spray Please drive to the road conditions SLOW DOWN, BE SAFE

Tides not so high this weekend but large waves expected in the SW. Risk of coastal flooding e.g. #Pembrokeshire<http://t.co/XXX>

Official (9 per cent): Some Tweets mentioned or helped to spread the warnings and advice issued from central institutions or authorities:

@EnvAgencySE has issued another Flood warning (flooding expected) for R. Medway betwn HampsteadLock + AllingtonLock <http://t.co/XXX>

@DubCityCouncil the advice on high tides & flooding measures put in place are at <http://t.co/XXX>

First Person Reportage (6 per cent): These were Tweets that, whilst addressing topics covered by the other categories, clearly reported on the extent, damage or disruption of the flooding first-hand, often linked to a photo of the scene:

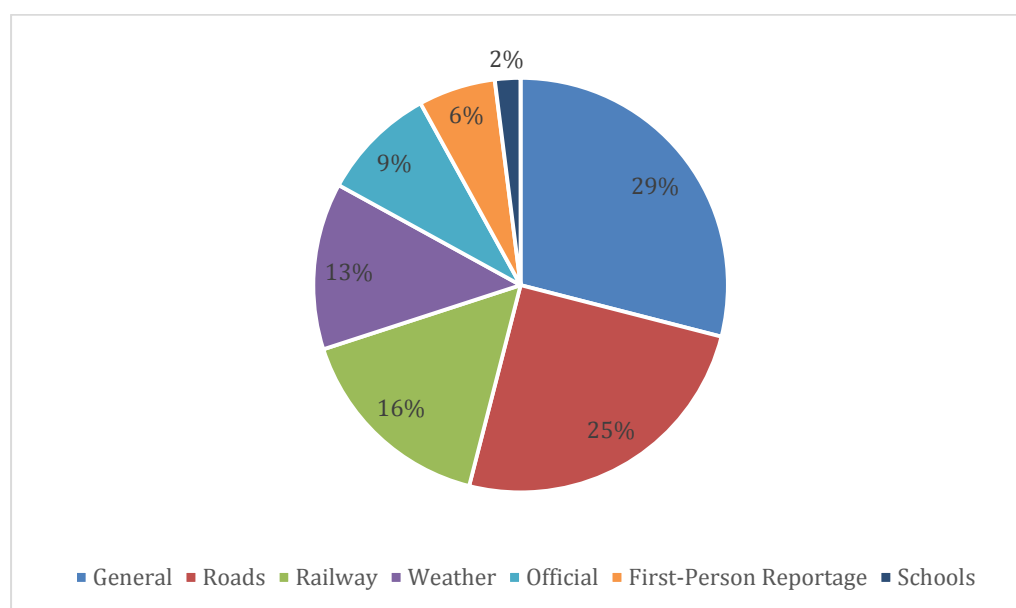
Flooding of Chester Street this evening #shrewsbury @ShropshireStar <http://t.co/XXX>

Flooding on Green Street Chorleywood #wd3 as bad as it's ever been, water very muddy now, and yet another car stuck <http://t.co/XXX>

When they said there was a bit of flooding down by Walton Bridge, I didn't expect it to be like this #blimey <http://t.co/XXX>

Schools (2 per cent): A small number of Tweets announced the closure of schools due to the floods:

SCHOOL CLOSURE: Fairfield High School in #Peterchurch is closed today because of flooding preventing access to the site



People used Twitter to mention offline volunteering, and to connect people offering help with those that needed it. 100 examples of offline BTR were randomly selected, and broken down by the kind of information that was being shared.

Volunteering (42 per cent): the most common Tweets were those that referred to or coordinated a broad range of non-specialist, or unspecified volunteering:

Am at @tfbalerts #Aylesbury w/ officers working out flooding support for #TheWillows , they are beyond stretched but support is coming!

Teams busy with temporary pump being lowered into to basin. Keeping properties at #Jurys Gap safe frm #flooding. <http://t.co/XXX>

Animals (33 per cent): Were those Tweets related to animals, and especially the rescue and movement of livestock (or in one case a hedgehog). This involved both appeals for help, and responses to those appeals

@XXX Farmers like @XXX desperate for feed/forage for cattle on #SomersetLevels due to flooding anything u can do to help?!!

Appeal: can anyone stable 6 horses UFN. #SomersetLevels #flooding Please R/T. Horses currently at #Fordgate

Amazing rural community spirit @XXX: Farmer @XXX flooding nightmare as friends help save 550 cattle <http://t.co/XXX>

@SkyNews @BBCNews I am able to help with minding small pets from cats to chickens to rabbits {no dogs}if people do need assistance #flooding

@larymary60: kennels have collapsed due to flooding in Cornwall, can you offer a temp foster home to a dog? URGENT! call 01872 XXXXXX

10 per cent of Tweets related to the coordination of **specialist responses** to the flooding, such as sewage treatment, the provision of fodder or relief using 4X4 vehicles:

#forageaid live again if you have feed forage bedding spare plz tel 01278 XXXXXX #flooding #somersefloods #SomersetLevels

CALLOUT We are receiving requests for our assistance in relation to the Thames Flooding #4x4r #volunteer @bbcsurrey @eagleradio @radiojackie

9 per cent of Tweets were **donations**, or people appealing for donations, to help the victims of the flooding

@ToneFMKate @TauntonsToneFM To help those hurt most by the flooding donate to Somerset Community Foundation by texting to XXX NOAHXX £10

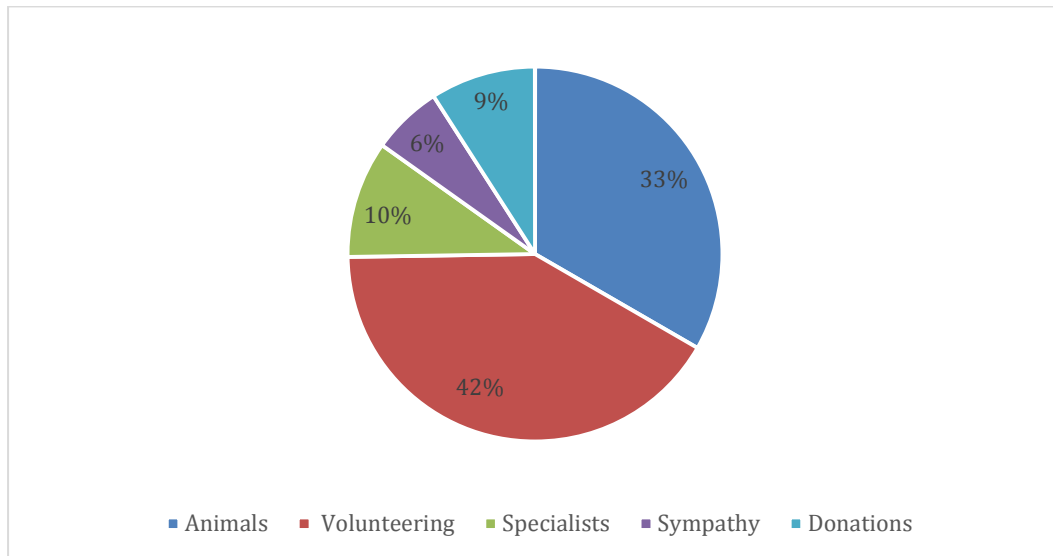
Can u help the #somersefloods affected farmers? Details of how to donate money and fodder are on @NFUtweets <http://t.co/XXX>

@Farmer_wheeler @RoyalAgRAG @FarmBolus @westyeo Go to <http://t.co/XXX> for details of how to donate fodder, time or money

6 per cent of Tweets extended **sympathy or solidarity** with the flooding. They were not, therefore social action per se, but reflected an underlying sense of connection or mutual reliance to those affected:

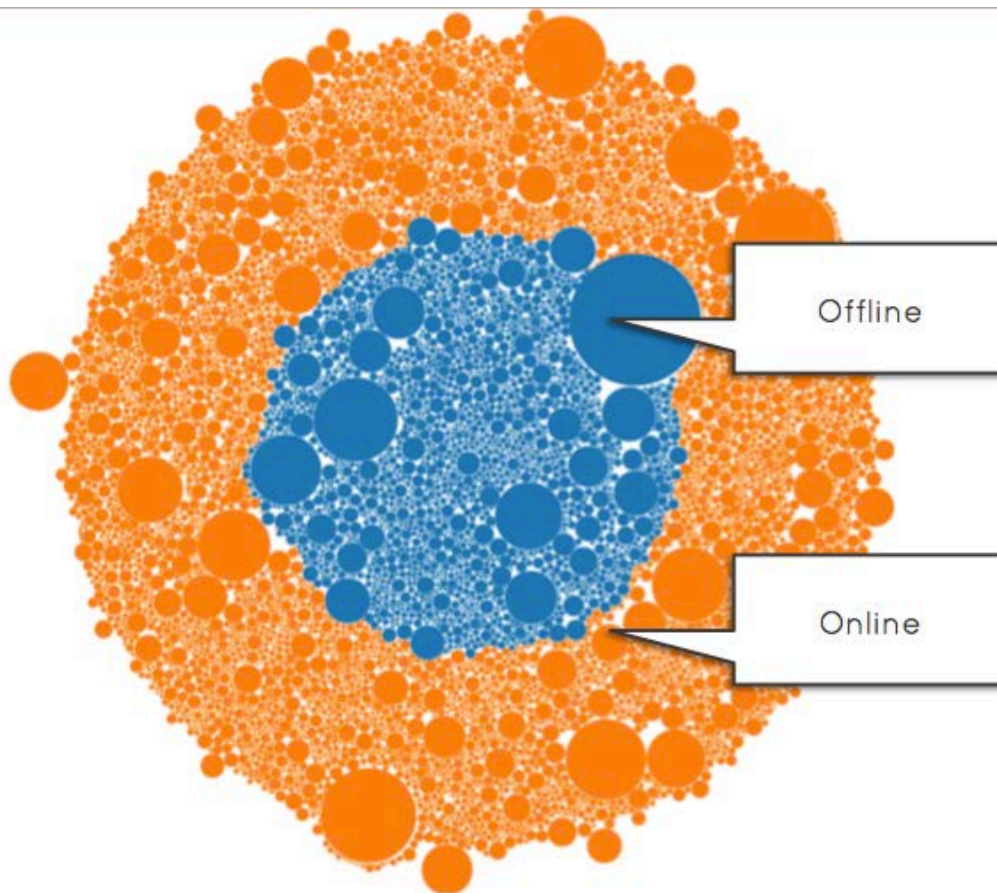
My heart goes out to everyone who is affected by the storms and flooding

Thoughts go out to the communities affected by flooding in Bucks. Please check on any vulnerable neighbours and offer support.



Who was doing the social action?

In addition to the kind of social action that was being done, it is important to know who is doing it. Every user who contributed a Tweet that was classed as either offline or online BTR social action was analysed for their number of followers, graphed below (the larger the circle the more followers).



It shows that a small number of accounts with very large followings were tweeting, from both the online and offline datasets. These were likely to be institutions or celebrities. However the large majority of accounts did not have very large followings.

How many were Retweets?

People use Twitter not only to post Tweets themselves, but to re-post other Tweets to their followers. These are called 'Retweets'. 2903 Tweets of the total 2990 in the offline BTR dataset were Retweets. There were therefore only 87 original messages; the other Tweets were, as copies of these original messages, attempts to increase their reach and audience.

Many of the most retweeted messages included an appeal for help in evacuating cattle:

@XXX Is #flooding. Must evacuate 550 cattle today. Has anyone got spare buildings/feed? Please RT #clubhectare (41 Retweets)

Appeal: can anyone stable 6 horses UFN.#SomersetLevels #flooding Please R/T. Horses currently at #Fordgate (41 Retweets)

Other retweeted messages were indications of other volunteer work:

Volunteers are working with fire service and council in Wraysbury Berks to move vulnerable nursing home residents to safety after flooding. (15 Retweets)

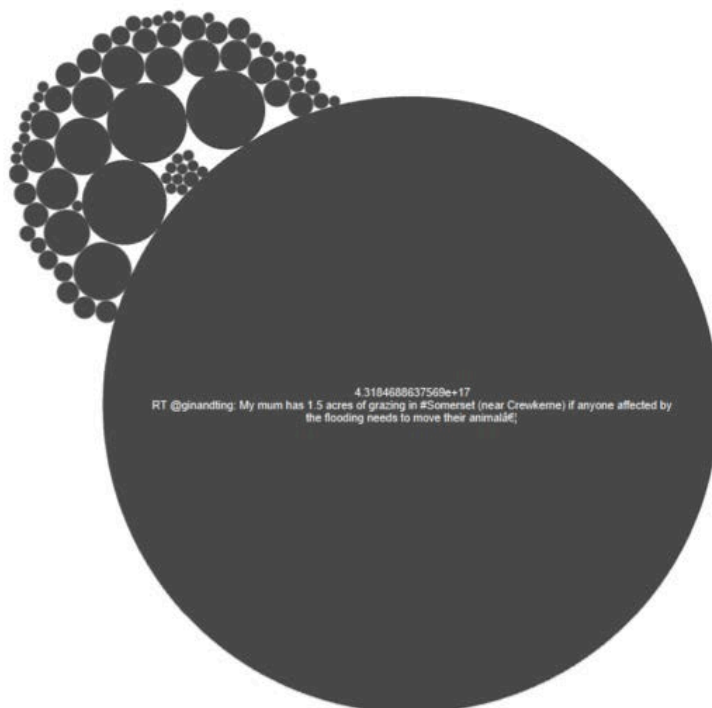
Amazing rural community spirit @XXX: Farmer @XXX flooding nightmare as friends help save 550 cattle <http://t.co/XXX> (8 Retweets)

Beds volunteers off to help deliver community meals in Herts in our 4x4, for people not accessible due to flooding <http://t.co/XXX> (8 Retweets)

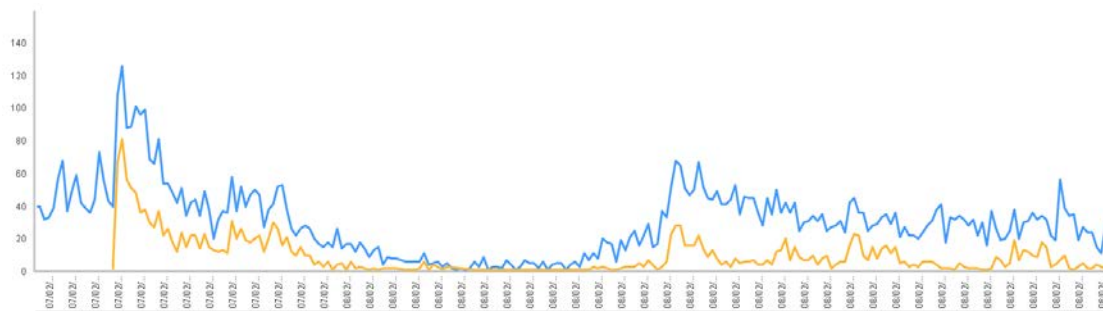
However, With 2583 Retweets, one message dominated this dataset:

My mum has 1.5 acres of grazing in #Somerset (near Crewkerne) if anyone affected by flooding needs to move their animals. Pls RT

The image below, shows each of the original contained within the dataset by the number of Retweets that they received. The larger the circle, the more Retweets that the message received. It shows the dominance of a single message within the dataset.



This key message was heavily Retweeted as soon as it was posted was then consistently Retweeted for at least the next five days. The graph below shows the total number of BTR social action Tweets (in blue) posted between 5 and 10 of February, and the total number (in orange) of the message:



Key Lessons:

- Disasters, accidents and catastrophes are likely to create a explosions of Tweets too large to manually read.
- Some people will use Twitter to either offer or ask for help. This will often be specific to the disaster, spontaneous, and by people operating outside of any organization or charity.
- Some of this help will be 'online-only': information, updates and advice intended to help others react to the emergency. But people will also use Twitter to ask for or provide help on the ground – especially if they are in areas affected by the event.
- Offers for help will constitute some of the most shared, re-Tweeted messages related to the event. However, they will be surrounded by a deluge of other Tweets – including wider commentary, jokes, and discussion.
- Overall, therefore, Twitter is a significant new forum which people will use in response to events to try to help each other. However, for the reasons above, it is not clear that Twitter is currently being leveraged effectively to promote social action in this context. Much of the social action needed

is local and specific, and is difficult to find given the scale and variety of information available on Twitter.

Case Study (2) – The Step up to Serve Campaign

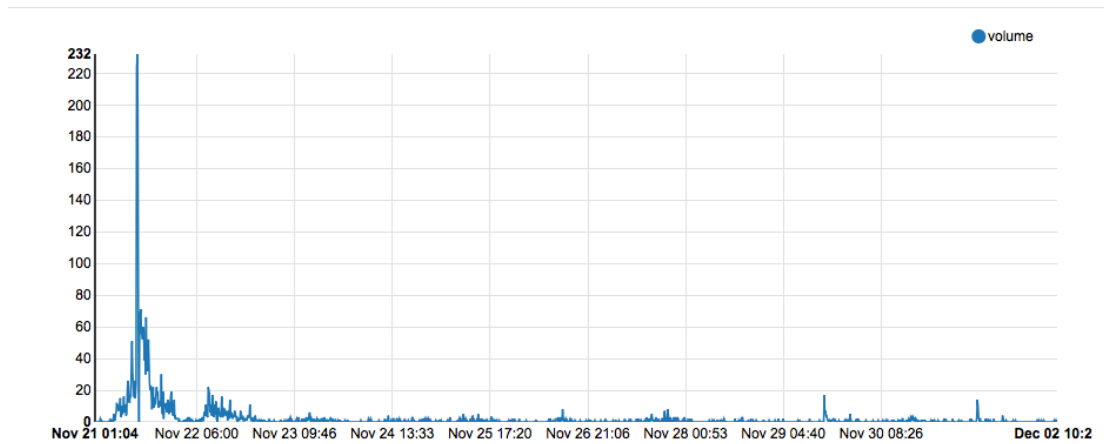
During the 2013 launch of the Step Up to Serve campaign, a number of people used Twitter to pledge to support or conduct social action for a wide range of causes; helping young people to find employment, help the local community, work with disadvantaged groups, improve the education system, even to make volunteering itself more visible and celebrated.

The Step up to Serve Campaign was launched on November 21, 2013. Supported by Prince Charles and the leaders of all three main political parties, a number of large private and third sector organization made specific pledges for how they were going to support the aim of getting at least half of young people routinely involved in social action by 2020. It was widely covered in the media, and on social media was promoted by the hashtag #iwill.

This case study looks at the social media reaction of the campaign, to see whether its message and example prompted people to take to Twitter to also pledge to do social action or help others to do so.

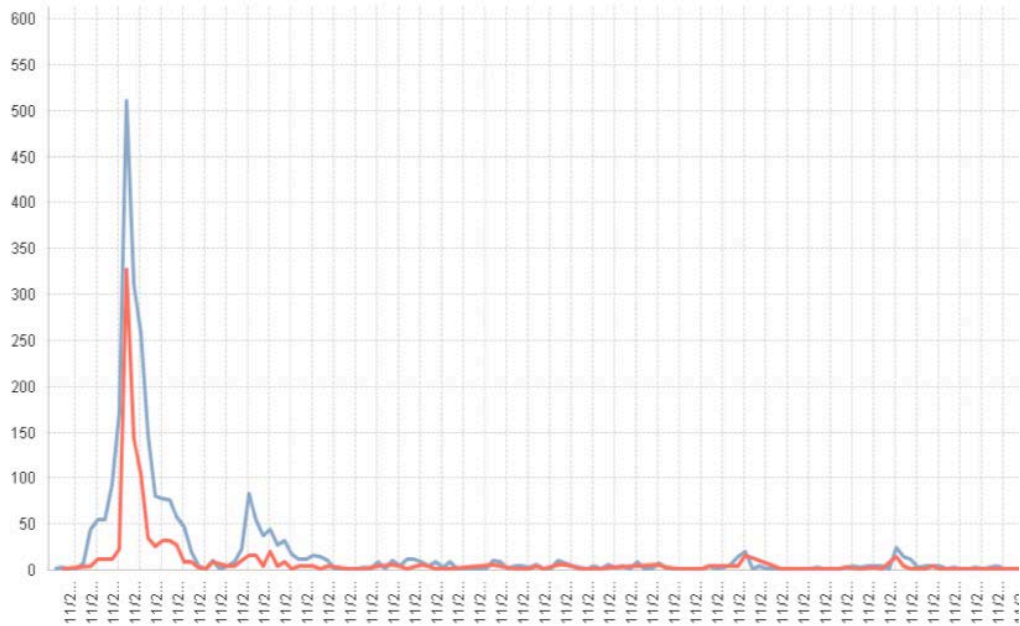
Between the 1st of November and December 1st, 10665 Tweets contained “#iwill”. These were collected and analyzed.

Step 1 – find all Tweets related to the Step up to Serve Campaign: The hashtag #iwill was also used within promotional advertising campaigns not related to Step Up to Serve. Of the 10,665 Tweets in total containing #iwill, 3780 were relevant to the Step up to Serve Campaign. These represented a sharp spike in volume over the day of the launch itself, and quickly declined thereafter.



Step 2 – find Tweets mentioning social action: People used Twitter to respond to the campaign in a number of ways. Some Tweets were attempting to increase awareness of the campaign, and sharing links to news stories covering it. Others spoke about the campaign, discussing its objectives and intentions. Importantly, some people used Twitter to make pledges to conduct social action or help others to do so.

A classifier was trained to identify Tweets that contained this form of pledge from other forms of social action. The classifier identified 1884 Tweets that were considered to contain a ‘pledge’ to support or conduct social action. The graph below shows (in blue) the total number of Tweets related to the Step up to Serve campaign and (in red) the number of pledges made. It shows how making pledges was a key way that people used Twitter to react to the campaign’s launch.

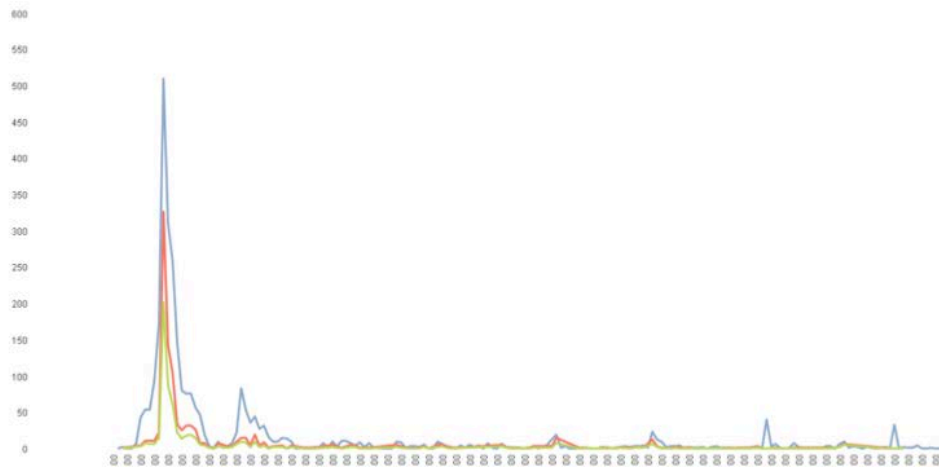


Step 3 – Remove organizations and charities: A number of different organizations participated in Step up to Serve and made pledges to support its aims. This included very large ‘above the radar’ national organizations. A classifier was built to identify those Tweeters contained within the dataset that contained explicit affiliation with a large, structured charity. Of the total of 1073 Tweeters, 476 were considered to not be charities. These 476 Tweeters were responsible for 690 Tweets containing #iwill.

Step 4 – Identify ‘below the radar’ social action: The content of these 690 Tweets were then analyzed to see whether they contained social action that was above or under the radar. 252 Tweets were considered to be below the radar social action.

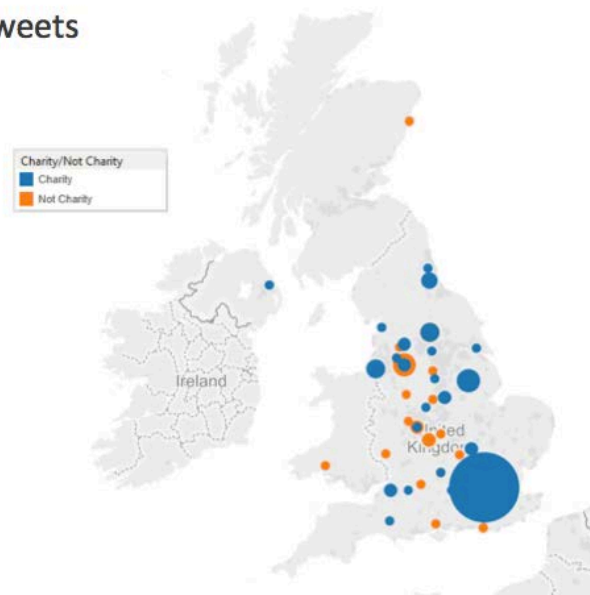
When plotted over time, the results show that the Step up to Serve Campaign did prompt social action to be spoken about on Twitter, and that some of these pledges did not explicitly come from large organizations or institutions. These pledges possibly represented commitments to social action that would exist, otherwise, below the radar.

Total vs Pledges vs non-Charity-only Pledges



Geographically, of those Tweets that could be located, both charity and non-charity pledges came from across the UK, but were heavily weighted towards London.

Step up to Serve Charity vs Non Charity Tweets



What did the Tweets pledge?

Tweets considered to be BTR social action were analyzed in greater detail. 100 Tweets were randomly selected, and following a review, they were analyzed on

two dimensions: (a) the nature of the social action pledged, and (b) the people the pledge aimed to help conduct social action.

The nature of social action

Generic (49 per cent): The highest proportion of Tweets were pledged a commitment to social action in general. They contained pledges that supported the concept of social action and generally promised to help, but did not specify what this help would be:

Help youngsters volunteer #iwill @stepuptoserve @XXX

#iwill step up to serve + help all young people to have every opportunity to serve others

#IWILL empower youngsters to be involved in #socialaction to achieve their full potential, through personal and skills development @stepuptoserve

#iwill continue to invest in organisations that use tech to engage young people in social action. @stepuptoserve

Even if it's by promoting and supporting the #iwill campaign from @stepuptoserve through social media we can all do a little bit to help

Work and employability (17 per cent): Some Tweets contained offers to help young people to find work as a form of social action, or to allow young people to improve their employability through volunteering themselves:

XXX already helps 2 young people to gain work experience and support their learning as our pledge #iwill @stepuptoserve

#iwill @nationalgriduk will encourage and value young peoples social action by making it part of our recruitment criteria @stepuptoserve

#iwill use youth #socialaction to encourage others to #continuevolunteering on return from int. dev internships

We pledge to increase the employability of #careleavers by piloting Plan.Do the #socialaction app #iwill

#iwill further raise the aspirations of more young people and help them find ways into training, gain employability skills and a career.

Local Community (11 per cent): A smaller number of Tweets pledged to support young people to specifically help their local community:

@stepuptoserve My pledge: #iwill continue to support student volunteers + carry on volunteering both in my local and wider communities

Disadvantaged groups (11 per cent): Some Tweets contained pledges to help especially disadvantaged groups to do social action:

#iwill digitalise #socialaction to unlock potential of disadvantaged young people

#iwill celebrate diversity, focusing our offer to engage 50per centof participants from disadvantaged backgrounds of high deprivation

#iwill engage young people from our most challenged communities

We pledge to increase the employability of gang-involved young people by piloting Plan.Do the #socialaction app #iwill

Education (9 per cent): These Tweets pledged to work with teachers and the education system to promote social action:

We pledge to help our teachers develop practical ways to share the value of #socialaction with pupils #iwill <http://t.co/XXX>

We're supporting @stepuptoserve - #iwill give young people new opportunities through music. Make your pledge now!!

#IWill Cultivate. One of our backers will be receiving this piece of art created by students in RATCo. <http://t.co/XXX>

#IWILL continue to teach my students & myself to never stop analyzing & critically engage w/ the world around them to promote selfjustice

.@StephenCurry30 I will work hard 2 help teachers be empowered to use tech w/students&help create positivity in general. #IWill #TeamCurry

Prestige and reputation (3 per cent): Were those Tweets that pledged to increase how social action is understood and appreciated:

#IWILL make volunteering cool and acceptable by highlighting and celebrating young people who do it to the media as role models @stepuptoserve

#iwill celebrate role models as young people and volunteers that support them

Who were being helped to do social action?

These same Tweets were then coded for whom the pledges were intended to benefit:

Generic (58 per cent): Most Tweets did not specify who they were intending to help, but rather made a general commitment to encourage social action.

Prince Charles is starting a new youth campaign #iwill to reduce crime, encouraging 10-20 yr. olds to take up volunteering #cool ill help

We're supporting @stepuptoserve to raise youth #socialaction to over 50% by 2020 #iwill <http://t.co/XXX>

The launch of @stepuptoserve today! Exciting - #iwill help make full-time voluntary service a reality, to make Britain a better place.

What an exciting day for @stepuptoserve #iwill encourage young people to @StepUpToServe between now & 2020 will you? <http://t.co/XXX>

Very proud to be part of Step Up To Serve campaign today #iwill pledge to do my bit thru volunteering and research

Disadvantaged groups (11 per cent): These were Tweets that aimed to benefit disadvantaged young people:

#iwill celebrate diversity, focusing on our offer to engage 50% of participants from disadvantaged backgrounds or areas of high deprivation.

New initiative Working with local @barnardos to offer @DofE to young people with Learning and physical disabilities @Dudley_College #iwill

@stepuptoserve #iwill empower young people with the knowledge to fight racial hatred and prejudice

Students (11 per cent): Were Tweets that pledged to help students to conduct social action:

We pledge to double the number of young people we help to progress from social action in school to social action outside school #iWill

We pledge to survey England's FE and 6th form colleges about student service to others & involve college principals in @stepuptoserve #iwill

Job Seekers (10 per cent): Were Tweets who pledged to help job seekers to volunteer:

By 2020 we pledge to use social action to increase the employability of young people that might be considered unemployable #iwill.

#iwill further raise the aspirations of more young people and help them find ways into training, gain employability skills and a career.

The young employed (5 per cent): Were Tweets that pledged to help the young employed, especially the employees of the pledger

RT @XXX: Today we say #iwill step up to make youth social action more recognised & valued element of responsible biz practice...

Therefore, most Tweets lacked detail of the social action that they pledged: Overall, therefore, most Tweets lacked detail either about the kind of social action that they aimed to encourage, or who they aimed to encourage to do it. However, some natural associations were clearly present: social action related to employment jobs were directed towards job seekers, and social action related to diversity and access were targeted at disadvantaged young people. The table below shows the comparison of the Tweets analyzed above, across the two dimensions that they were coded on.

Category 2	Category							
	Generic	Work Experience/ Jobs	Local Community Action	Diversity	Education	Campaign Support	Recognition	Crime
General Youth	41	2	11	1	2	3	3	
Disadvantaged Youth	1			8				2
Students	3	1			7			
Jobseekers		10						
Young Employed	1	4						

Key Lessons

- The Step up to Serve campaign was a highly publicised media event that attracted a significant response from Twitter.
- The nature of this response was markedly different from the first case study. In responding to the Step up to Serve campaign, people did not use Twitter to look for, or offer, specific help. Instead, people offered their longer term views and plans related to social action.
- This shows that Twitter can be studied to gain insight into attitudes towards social action – its prestige and sense of importance, the kinds that people think are a priority and how they intend to do it.

Overall Conclusions

This section outlines the general conclusions about social action on Twitter drawn from both case studies, and the ability of Digital Observation to identify, collect, and measure them.

Overall, Twitter is a significant new forum of social action. It was found to reflect volunteering, mobilize it, and unlock new forms of it.

Of the 126,788 Tweets collected for the two case studies of this report, 41,211 were judged relevant to social action. Some of these reflected, indicated and pointed to social action that happened offline. However, Twitter does not just reflect, promote or indicate social action. It also opens up new opportunities for it.

Case Study	Total Tweets collected	Total social action	Judged above the radar	Judged below the radar
1 - Flooding	116,123	39,327	6,697	11,671
2 - Step up to Serve	10,665	1884	1,632	252
Total	126,788	41,211	8,329	11,923

This included Tweets that:

Mentioned specific acts of volunteering, both of themselves and others: Twitter is used to talk about people's experiences, what they have done that day. It is also used to mention what people find inspiring and laudable. Hence, some Tweets contained information about specific acts of volunteering that the person had done themselves, or had seen happen.

Making Specific offers of help: Some people used Twitter because they had help to offer, but didn't know who needed it. They therefore launched these appeals on Twitter, hoping that the platform would connect them with the people who needed it. This was especially prevalent for the Step up to Serve case study.

Appeals for help: The reverse was also true. Some people needed help, and didn't know who could provide it. Strictly, of course, these Tweets did not represent social action, but instead the opportunity for it to be done. This was especially prevalent for the flooding case study.

Pledges to do social action, and help others to do it: In addition to specific offers or or calls for help, more longstanding commitments to doing social action Twitter was used to make more general and longstanding commitments.

Sharing, brokering and giving information to help others: People shared information, warnings and advice on Twitter to help others make better decisions. This included first-person reportage of the situation on the ground, and links to further information.

Helping all of the above to spread: Social action, in the widest and loosest sense, also happened when people used Twitter to help all of the above spread, be amplified and reach new people. Indeed, clear acts of social action tended to be heavily shared as people, as each shared, Retweeted, and relayed the information.

Twitter data on social action has new significant strengths and weaknesses

Large amounts of data - 41,211 pieces of data relevant to social action were found. Within the limited context of a short report, this is a significant quantity of relevant data – and far larger than what could be gathered using conventional sociological methods under the same time and resource constraints.

Real or near-real time: Relevant tweets were collected almost immediately after they were posted and Digital Observation, as an automated method, analysed the Tweets almost immediately after they were collected. This opens the possibility for the real-time analysis of social action as it happens.^{xxxii}

Reactive and event-specific: In this and other recent research, it was broadly become understood that a tweet is overwhelmingly a reaction to an event that the tweeter has otherwise encountered – either online or offline – in their lives. The method used in this report is therefore broadly better able at spotting and understanding social action when it occurs in reaction to an event or in the context of an event. It is less able to understand social action outside of the context of a specific scenario. Social action is likely to be spoken about on Twitter when events prompt people to.

However:

This information is not comprehensive: either of the whole of Twitter or, of course, of all the social action being undertaken. Many under the radar organizations or practices would not be reflected, and possibly could never be reflected in research of this kind, including some of the most important, and that require the most support.

Much of the information lacked detail: Tweets are only short statements, and, especially when read out of context, they often lack detail about either the person conducting social action, or the nature of the social action itself. Whilst Twitter is good to research at scale to find behaviours that would not be found, it does not provide great detail about what these behaviours are.

Digital Observation sometimes gets it wrong: The technology required to analyze very large quantities of data is not perfect. On average, the classifiers used in this paper made the correct answer 78 per cent of the time. However, the technology was more accurate when making some decisions than others. It was:

- *Best at separating data related or not related to a particular event:* In both case studies, the classifier was able to tell whether the Tweet related to the event in question with a high degree of accuracy
- *Acceptable at identifying incidents of social action:* The classifier was generally able to tell whether a Tweet reflected, mentioned, represented or called for social action between 75-80 per cent of the time.
- *Worst at identifying whether the social action contained within the Tweet was above or below the radar:* this was where the classifiers were least accurate, given the lack of context (see below) that the Tweets contained.

It was difficult to distinguish above and below the radar social action using Twitter alone

Given the lack of detail, it was not possible to reliably determine whether the social action would have been picked up by conventional forms of monitoring. There was, therefore, significant uncertainty in the final distinctions between above and below the radar Tweets. Manual analysis was (and will continue to be) necessary to get a more nuanced view of what kind of social action exists. To establish more accurately the extent of Tweets that were found and were below the radar, they should be cross-referenced with the relevant databases, registers and almanacs.

Recommendations and Future Research

This scoping paper points to a number of research areas that would be both help us to better understand the emerging relationship between BTR social action and social media, and also help to promote, strengthen and support social action using social media.

(1) Using social media to support social action

The case studies, especially the first, demonstrate that social media is becoming an important forum where social action is both sought and offered. However, research here suggests that this process is *ad hoc* and chaotic, especially when the social action is spontaneous and especially when it occurs, 'below the radar', outside of an organizational setting.

There are a number of different interventions that social action organizations and charities could make to better support the growth and increase the effect of below the radar social action on social media.

(a) Lifting social action activity above the radar: Create a social action triage capacity

Times when people need the help of others – especially disasters, accidents and catastrophes – create explosions of Tweets. The flooding case study demonstrated that people were taking to social media to both ask for help, and also to offer it. However, the amount of information appearing on twitter during these times will be very large, certainly too large to manually read. It will crucially contain information of radically varying degrees of usefulness to those who need help: most will not be useful at all, a small kernel may be very useful indeed.

There is no simple way to sort information relevant to social action posted on Twitter from the irrelevant. However, there are ways of finding this information. Tweets offering help are likely to be more highly shared, and contain different language from other kinds of Tweets. The technology used in this report has shown that it can reliably differentiate social action Tweets on this basis.

This technology could be practically deployed to create an 'information triage' capacity, especially in the aftermath of a major event. This would allow social action Tweets to be quickly identified, collated and publicized. In other words, it would allow spontaneous, non-organized offers of help to be lifted above the radar, and leveraged by charities in their own relief or response efforts, and to be publicized or engaged with by their own support networks.

This would represent an important force multiplier for social action: allowing existing offers and calls for help to be more easily and readily found and used. The development of this capacity should be seriously considered by organizations involved in the promotion and support of social action.

(b) 'An Ebay for social action': Connecting social action supply with demand

A powerful application of digital platforms in other areas – especially commerce and the provision of services – has been to directly connect people providing something with those who need it. When social action information is found, it could be centralized onto a real-time online platform, information exchange or brokerage hub, clearly related to a specific event and segmented either into the type of help that people are offering, or where the help is being offered. This would allow people to find and help, and also know what help is needed and who needs it. This is likely to significantly increase the practical contribution of social media platforms to social action.

(2) Studying social media to understand social action

The case studies, especially the second, also suggest that social media can be researched to better understand BTR social action. This study suggests a number of important new research coalfaces that could be explored:

(a) What different types of event cause different social media reactions?

The two case studies showed people taking to social media in contrasting ways, related to social action. During the floods – an emergency event and largely unanticipated – people spontaneously took to social media to try to find and offer help in the immediate aftermath. During the planned Step up to Serve campaign launch, people used Twitter to – as requested – pledge longer-term commitments to supporting volunteerism. This suggests that different kinds of events will elicit different kinds of reaction on Twitter.

The relationship between event-type and social media reaction must be more clearly understood. If it is, the specific usefulness of the data that Twitter produces – and therefore the value of the kind of research used in this paper – will be better known. This will allow social media research to more directly and specifically plug current knowledge gaps around BTR social action.

(b) Who conducts BTR social action?

A straightforward extension of the research conducted here would be to learn more about the people who use social media to conduct BTR social action, and how they relate to charities and other social action organizations. This could ethically be progressed in a number of ways, including (a) analyzing the public profile information of those who conduct BTR social action to understand their interests and priorities, (b) a closer geographic analysis of where BTR social

action is offered, (c) a longer-term longitudinal analysis of the contexts when BTR social action are offered on social media, and (d) social network analysis to understand whether these individuals follow, Retweet, respond to or support formal social action organizations.

This research would represent a vital step forwards for organizations to mobilise volunteers, and leverage the informal, spontaneous and unstable networks that form online at the times of heightened need.

(c) Extend beyond Twitter as a data source

Twitter was used as the sole data source for this project. Given the technical ease of collection, this was considered appropriate for a relatively small scope. However, a very large variety of other social media platforms exist, often with different functions and used by different groups of people. Much of this data could also be acquired.

A data scope should be conducted to identify which platforms contain information related to BTR social action, and the availability, quantity, quality and nature of data that they produce. Initial platforms that should be considered include, of course, Facebook, but also Sina Weibo, Wordpress, Tumblr, Instagram and Disqus.

(d) Contextualise social media with other forms of research

Social media research is novel, and the methodologies and technologies that it uses are young, untried and usually experimental. In order to influence important decisions, this kind of research needs to be conducted alongside more mature, more trusted conventional forms of research. This would allow the results of social media research to be corroborated and verified.

A comparative trial should be conducted, where an event is studied using both social media and conventional research techniques. This would allow us to know better the 'value added' from social media research: how accurate it is, its resource implications versus other research techniques, its accuracy, and whether there are specific kinds of measurements possibly only through social media research.

Technical and Methodology Annex

1. Data Collection

APIs

All data from Twitter was collected from its Application Programming Interfaces. Twitter has three different APIs that are available to researchers. The 'search' API returns a collection of relevant Tweets matching a specified query (word match) from an index that extends up to roughly a week in the past. Its 'stream' API continually produces Tweets that contain one of a number of keywords to the researcher, in real time as they are made. Its 'sample' API returns a small number (approximately 1 per cent) of all public Tweets in real time. Each of these APIs (consistent with the vast majority of all social media platform APIs) is constrained – or 'rate-limited' - by the amount of data they will return. This limit was not exceeded by any collection used in this report.

2. Data Analysis

Natural language processing

The Twitter data that was collected was too large to be manually analysed or understood in its totality. Language such as this, as it naturally occurs on social media, can be automatically understood at great scale and speed using 'natural language processing' (NLP). A long-established sub-field of artificial intelligence research, natural language processing combines approaches developed in the fields of computer science, applied mathematics, and linguistics. It is increasingly used as an analytical 'window' into 'big' datasets, such as ours.

The value of NLP in the context of this work is its ability to create 'classifiers'. Classifiers are algorithms that automatically place tweets in one of a number of pre-defined categories of meaning. To build classifiers, the study makes use of a web-hosted software platform, developed by the project team, called Method51.^{xxxii} Method51 uses NLP technology to allow the researcher to rapidly construct bespoke classifiers to sort defined bodies of Tweets into categories (defined by the analyst). The process to create each classifier was to go through the following phases. Each phase is undertaken via a user interface within Method51.

- *Phase 1: Definition of categories.* The formal criteria explaining how tweets should be annotated is developed. Practically, this means that a

small number of categories – between two and five – are defined. These will be the categories that the classifier will try to place each (and every) Tweet within. The exact definition of the categories develops throughout the early interaction of the data. The categories are not arrived at *a priori*, but only through an iterative interaction with the data – wherein the definition of each category can be challenged by the actual data itself. This is to ensure that the categories reflect the evidence rather than the preconceptions or expectations of the analyst. This is consistent with a well-known sociological method called grounded theory.^{xxxiii}

- *Phase 2: Creation of a Gold-standard test dataset:* This phase provides a baseline of truth against which the classifier performance is tested. A number of Tweets (usually 100, but more are selected if the dataset is very large) are randomly selected to form a gold standard test set. These are manually coded into the categories defined during Phase 1 – above. These Tweets are then removed from the main dataset, and are not used – in the Phase 3 - to train the classifier.
- *Phase 3: Training:* This phase describes the process wherein training data is introduced into the statistical model, called ‘mark up’. Through a process called ‘active learning’, each unlabelled Tweet in the dataset is assessed by the classifier for the level of confidence it has that the Tweet is in the correct category. The classifier selects the Tweets with the lowest confidence score, and these are presented to the human analyst via a user interface of Method51. The analyst reads each tweet, and decides which of the pre-assigned categories (see Phase 1) that it should belong to. When 10 have been selected, these are submitted as training data, and the NLP model is recalculated. The NLP algorithm looks for statistical correlations between the language used and the meaning expressed to arrive at a series of rules-based criteria.
- *Phase 4: Performance Review and modification:* The updated classifier is then used to classify each Tweet within the gold standard test set. The decisions made by the classifier are compared with the decisions made (in Phase 2) by the human analyst. On the basis of this comparison, classifier performance statistics – ‘recall’, ‘precision’, and ‘overall’ (see ‘assessment of classifiers’, above) - are created and appraised by a human analyst.
- *Phase 6 – Retraining:* Phase 3 and 4 are iteratively repeated until classifier performance ceases to increase. This state is called ‘plateau’, and, when reached, is considered the practical optimum performance that a classifier can reasonably reach. Plateau typically occurs within 200-300 of

annotated Tweets, although it depends on the scenario: the more complex the task, the more training data that is required.

- *Phase 7 – Processing:* When the classifier performance has plateaued, the NLP model is used to process all the remaining Tweets in the dataset into the categories defined during Phase 1 along the same, inferred, lines as the examples it has been given. Processing creates a series of new databases – one for each category of meaning – each containing the Tweets considered by the model to most likely fall within that category.
- *Phase 8 – Creation of a new classifier (phase 1), or post-processing analysis (phase 9).* Practically, classifiers are built to work together. Each is able to perform a fairly simple task at a very large scale: to filter relevant Tweets from irrelevant ones, to sort Tweets into broad category of meanings, or to separate Tweets containing one kind of key message with those containing another. When classifiers work together, they are called a ‘cascade’. Cascades of classifiers were used for both case studies. After Phase 7 is completed, a decision is made about whether to return to Phase 1 to construct the next classifier within the cascade, or, if the cascade is complete, to move to the final phase – 9, post-processing analysis.
- *Phase 9 – Post processing analysis:* After Tweets have been processed, the new datasets are often analysed and assessed using a variety of other techniques. These are:
 - **Metadata Analysis:** There are around 150 pieces of metadata attached to every Tweet.^{xxxiv} This includes (a) information about the Tweeter, such as their public profile, the number of followers they have, and their screen name, (b) about the Tweet’s context, such as whether it was a retweet, or a reply, (c) possible geographic information about where the Tweet was sent from, or where the Tweeter has stated they are from, and (d) whether the Tweet contains objects like links, hashtags, or media content. The metadata of processed datasets are often analysed to understand better their nature and meaning, such as the most retweeted tweets, the users with the most followers, and geographic distributions of Tweets.
 - **Time series analysis:** The datasets are often graphed over time. This is typically done to understand their relationship to offline events, and to identify significant moments when volume sharply increased or decreased.

- **Qualitative Analysis:** a random sample of Tweets are often drawn from processed datasets and analysed using qualitative sociological coding methodologies. These techniques attempt to draw out the detail, nuances and subtleties of meaning contained within the dataset that automated analysis is not able to identify.

3. Performance of the Classifiers

Case Study 1

These tables detail the specific measured performance of the classifiers used for this paper.

Classifier	Decision	Precision	Recall	F-score
Tweet about the British floods?	Relevant	0.944	0.826	0.881
	Irrelevant	0.303	0.606	0.404
	Overall Accuracy: 0.801			
Does a Tweet contain social action?	Yes	0.647	0.805	0.717
	No	0.837	0.695	0.759
	Overall accuracy: 0.740			
What kind of social action?	Online	0.575	0.943	0.714
	Offline	1.000	0.841	0.914
	Commercial	1.000	0.200	0.333
	Irrelevant	0.706	0.300	0.421
	Overall Accuracy 0.704			
Is the social action above or below the radar?	Above	0.423	0.891	0.573
	Below	0.961	0.685	0.800
	Overall accuracy: 0.728			

Case Study 2

Classifier	Decision	Precision	Recall	F-score
Relevant to the Step Up to Serve Campaign?	Relevant	0.902	0.982	0.940
	Irrelevant	0.993	0.958	0.975
	Overall Accuracy: 0.965			

Does the Tweet contain a pledge?	Pledge	0.782	0.832	0.806
	No Pledge	0.838	0.790	0.814
	Overall accuracy: 0.810			
Does the Tweeter identify as a member of a charity?	Charity	0.786	0.898	0.838
	Not Charity	0.828	0.667	0.738
	Overall Accuracy: 0.800			
Above or below social action?	Charity	0.791	0.773	0.782
	Not Charity	0.476	0.625	0.541
	Irrelevant	1.000	0.600	0.750
	Overall accuracy: 0.714			

ⁱ Service Generation; Jonathan Birdwell and Mona Bani, *Introducing Generation Citizen*, Demos: 2014; Ally Paget and Jonathan Birdwell, *Giving Something Back*, Demos: 2013

ⁱⁱ Britain's Top 1,000 charities ranked by donations. Who raises the most money?
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