

immigration on twitter

understanding public attitudes online

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April 2015

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Jamie Bartlett
Richard Norrie
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INTRODUCTION

Over the last fifteen years, immigration has become an increasingly important political issue in the United Kingdom – with growing concern among the settled population about its economic and cultural impact. In 2012, 60 per cent of citizens viewed the rate of settlement of migrants in the United Kingdom negatively, and three quarters wanted an overall reduction in immigration levels – scores which are consistently among the most negative in Europe.¹ The 2014 Ipsos MORI report on attitudes toward immigration found that, along with sustained concern toward immigration into the UK, there are significant misconceptions in the UK about the nature and scale of the issue, for example over-estimating the number of asylum seekers as a proportion of all immigrants.² It is not our purpose to untangle the various reasons for these figures, which are numerous and complex.³ But some research suggests that the way immigration is reported in the media is likely to play a role. The 2013 Oxford Migration Observatory report ‘Migration in the News’ found that the most common descriptor accompanying the word immigrant in the mainstream print media was ‘illegal’.⁴ Other common terms associated with immigration often had a dramatic quantity (‘thousands’, ‘million’, ‘influx’ and ‘flood’) or security and legality implication, such as ‘terrorist’, ‘suspected’ or ‘sham’.⁵

There has been a change over the last decade in the way people access, consume and produce media: a shift away from mainstream media and toward internet-based content and social media. Social media is a new, dynamic and less hierarchical space which has opened up the public portrayal of immigration.⁶ In total, 37 million people – more than two thirds of the UK’s internet users – use social media (30 million Facebook users and over ten million Twitter users).⁷ This is changing the way people get their news, because the public now considers the internet to be the most reliable source of information. As a result, 77 per cent of British internet users access the internet in order to access news information, and more than half of social media users use social media sites to receive news and information.⁸

This social media activity also presents a novel way to research and understand attitudes, trends and media consumption. There are a growing number of academic and commercial efforts to make sense of social media data sets for research or (more typically) advertising and marketing purposes.⁹ This short scoping exercise

examines the potential of listening to conversations taking place about immigration on Twitter. Based on meetings with policy specialists at the outset of this project, we determined five areas to study in detail:

- a. the frequency and type of conversations taking place on Twitter relating to immigration
- b. the traffic flows of those conversations, such as what sort of stories get picked up by Twitter users and shared
- c. the demographic and topographic features of these conversations
- d. the effectiveness of automated data collection and analysis
- e. the ethical and methodological considerations in doing work of this nature

Below we set out the methodology used; present four case studies; and then conclude with a series of conclusions in relation to the challenges and opportunities of using Twitter as a source of data for research of this type.

Method

The potential of social media as a source of attitudinal insight was tested using four practical case studies, each examining discussions held by Twitter users relating to immigration.

Data collection

The data were collected using the publically available live Twitter feed, via its 'stream' application programming interface, which allows researchers to collect data directly from Twitter as they are published.

We collected one set of data for each case study. For the purposes of this study, we collected data based on keyword matches, which means collecting all tweets which contain a word or group of words selected by the researcher. For each case study, a hand-crafted set of words were created based on a manual review of Twitter conversations prior to data collection. Each case study reflects a response to a specific event.

The data were collected between October 2013 and January 2014. All of the messages in our samples were publically available to any Twitter user as a live comment (ie at the time the tweet was published) if the user was either a follower of the sender, or was searching Twitter using keywords and the tweet contained one of those keywords. Typically, a tweet can be accessed by any user of Twitter

for up to seven days after the time of publication, provided neither Twitter nor the original sender has deleted it.

The tweets were then passed through an English language filter to exclude non-English tweets.

Data analysis

We used three types of analysis, which covered both automated and manual methods:

- **Trend analysis:** examining the general volume of tweets over the time period
- **Content analysis:** examining the nature and type of tweets over time, usually using both automated classifiers and manual analysis
- **Profile analysis:** examining the users that were contributing to the data set

In each case study (usually for the content analysis) we used an automated approach involving ‘natural language processing’ (or NLP). This allows researchers to build models that detect patterns in language use that can be used to undertake meaning-based analysis of large data sets. These were built and applied in different contexts to see where they worked, and where they did not. These models are called ‘classifiers’. Classifiers are built by researchers who train an algorithm to automatically recognise patterns in the text through annotating examples (this is based on linguistic, grammatical and rules-based patterns – not simply word matches). The classifiers then begin to recognise certain patterns and can then automatically spot the same patterns in much larger data sets. NLP is widely used in the analysis of language in ‘big data’ sets, which are too big for humans to manually analyse, for example, to perform sentiment analysis. The methodology annex includes details of our NLP-based methods.

The research team built several classifiers and tested how well they performed against human analyst decisions. Each classifier was designed according to patterns found in the data. The performance of the classifiers is discussed in the conclusion. Manual analysis of smaller, random samples of the data was undertaken for more detailed insight, both of the tweet texts and the tweeter’s profiles.

We conclude by setting out the strengths and weaknesses of using Twitter data as a source of insight and research, and where it might be usefully employed by research and campaign groups.

CASE STUDY 1: IMMIGRATION BILL

Background

The 2013—14 Immigration Bill proposes to place a requirement on landlords, banks and healthcare providers to check people's immigration status.¹⁰ Students from outside Europe would have to pay a £200 levy before getting NHS access while foreign criminals will no longer be able to use the Human Rights Act to try to avoid deportation.¹¹ The Coalition government argues that the Bill will stop abuse of public services, reduce illegal immigration, and make it easier to deport foreign criminals.¹² Labour has given broad support to the Bill, but has criticised it for not containing provisions to prevent exploitation or the undercutting of the wages of British citizens and for potentially leading to discriminatory treatment of ethnic minorities.^{13 14} The Immigration Bill had its first reading in parliament on 10 October 2013. It had its second reading on 22 October 2013, and has been through its committee stage.¹⁵

Data collection

From 22 October to 19 November 2013, we collected all mentions of the Bill, using the following key words: 'immigration', 'immigrationbill', 'stoptheimmigrationbill'. The data were then filtered to include only UK-related data about the Immigration Bill. In total 553,060 tweets were collected, but when filtered for UK-only tweets (and once we created a classifier to remove tweets about immigration but not the Immigration Bill) this fell to 5,321. The reason this was such a dramatic reduction is that a very high proportion of the data were from, and about, the United States and Australia.

Trend analysis

The overall number of relevant tweets referencing the Immigration Bill is graphed in figure 1. The highest number of tweets occurs on 22 October at 11:18 as the Bill receives its second reading in parliament. Thereafter the number of tweets declines sharply with minor spikes of around 150—200 at various moments. After this time period, the number of tweets referencing the Immigration Bill is negligible. (This is not a very significant volume of tweets. During, for example, the second Nick Clegg versus Nigel Farage European debate there were approximately 1,000 tweets on the subject of the debate per minute.)¹⁶

Figure 1: Tweets referencing the Immigration Bill

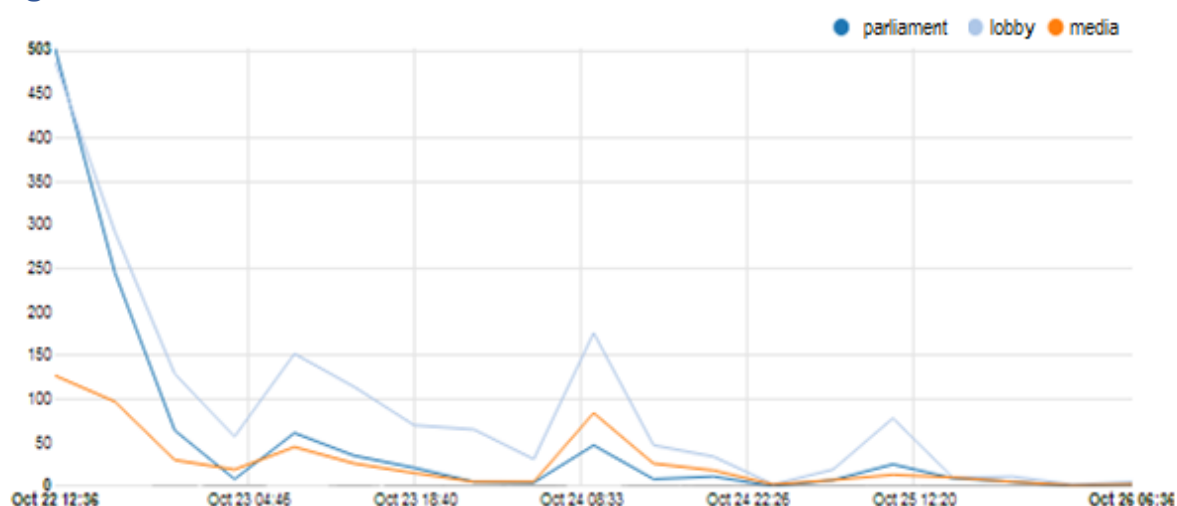


Content analysis

On manual review of the data, we determined that there appeared to be three general types of tweet. We therefore built a three-way classifier in order to distinguish between tweets that were: (a) ‘parliament’: reflecting communication from parliament or MPs, or communications addressed to MPs or soliciting communications to them; (b) ‘lobby’: which we defined as expressing opinions or relaying information in an attempt to influence the parliamentary process; (c) ‘media’: reflecting communication from or interaction with the media. Overall, there were 1,724 parliament tweets, 2,771 lobbying tweets, and 826 media tweets.

Figure 2 presents the volume of tweets in each of these three categories between 22 and 26 of October, which was the most active period. These three types of tweets tend to track each other closely. Twitter users are exchanging information about the parliamentary process and trying to influence it. Initially, direct exchange via parliamentary tweets and indirect exchange via lobbying tweets are roughly equal. However, around 23 October, lobbying is greater than parliamentary communication and this remains the case for the rest of the period.

Figure 2



We undertook a manual analysis of 358 randomly selected tweets from this data set. Tweets were classified according to whether they were expressing in relation to the Immigration Bill, (a) positive sentiments; (b) neutral sentiments; or (c) negative sentiments.

Of this sample, 47 per cent were hostile towards the Immigration Bill; 51 per cent were neutral. Many of these tweets stemmed from the All-Party Parliamentary Group which was scrutinising the Bill and communicated its evidence via Twitter. Only 2 per cent were supportive and these mostly came from government itself (table 1).

Table 1

	Sentiment	Sample	Extrapolated
Immigration Bill	Positive	2.2%	117
eg <i>Immigration Bill ensures GB welcomes the brightest from across the world and ensures the law is on the side of those who respect it.</i>			
	Neutral	50.8%	2,703
eg <i>"@xxxK: This is how many MP's turned up to #ImmigrationBill. http://t.co/HAowxXLbWU" Is this really true?</i>			
	Negative	46.9%	2,496
e.g. <i>My parents are immigrants. My grandfather, like many, fought for this country. I am extremely worried about the #ImmigrationBill.</i>			

The near-complete lack of support on Twitter for the Bill stands in contrast to a poll which found that the UK public tend to be in favour of the kinds of restrictions placed on immigrants proposed: 89 per cent support denying

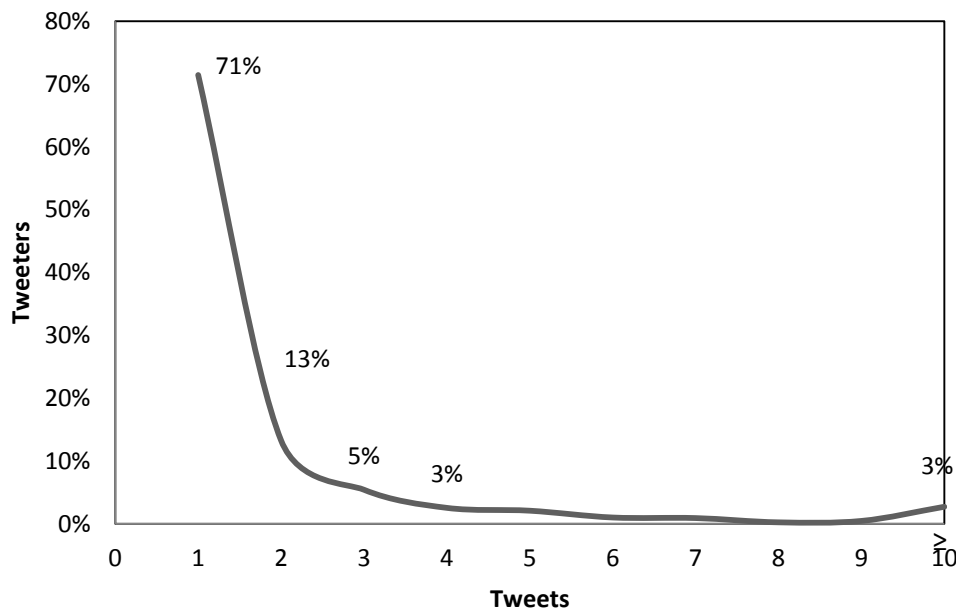
unemployment benefits to migrants in the first three months after their arrival; 83 per cent support withholding jobseeker's allowance after six months for those who do not find a job; 80 per cent support repatriation of begging or homeless migrants; 56 per cent said the proposed changes were not harsh enough.¹⁷

Profile analysis

We undertook what is called a 'power law' analysis on the overall sample data in order to establish how many unique users contributed to the data set (figure 3). This sort of analysis calculates how many unique users tweeted on the subject, and how many times each user tweeted. This provides a greater understanding of the overall number of people who were involved in the data set.

We found 71 per cent of users tweeted once; 13 per cent twice; 5 per cent tweeted three times and 3 per cent tweeted ten times or more. Although most people make single contributions, there are a small but substantial minority who are much more engaged in the political process through Twitter. These people tend to be either professional commentators or at least keen amateurs. The most active user tweeted 472 times about the Immigration Bill.

Figure 3



We took a closer look at the same random sample of profiles of tweeters (n=358) which were manually analysed to determine their background.

We found that 56 per cent came from members of the public, 9 per cent came from MPs, and 31 per cent came from either organisations or individuals in some way concerned expressly with immigration, asylum seekers or ethnic minorities. For each of these groups it is worth looking at the differences between mean and median in order to get some idea of how much the contributions are dominated by a few highly active users. For the general public, the mean number of tweets for each unique user was 1.84; the median was 1. The typical member of the public on Twitter was only contributing one tweet but there were a small number who were more active, thus skewing the mean upwards. For MPs and the immigration lobby, this is also the case: for MPs the mean was 2.13 while the median was 1; for the immigration lobby the mean was 2.02 and the median was 1 (see table 2).

Table 2

	Tweets	Extrapolated	Tweeters	Mean	Median	Mean - median
Public	56.4%	3,001	58.0%	1.84	1	0.84
eg Left winger, atheist, dislikes HS2, pro-NHS						
MPs	9.4%	500	8.3%	2.13	1	1.13
eg. AS Plaid Cymru dros Ddwyrain Caerfyrddin a Dinefwr / Plaid Cymru MP for Carmarthen East and Dinefwr						
Immigration/ethnic/asylum lobby	30.7%	1,634	28.7%	2.02	1	1.02
eg Academic anthropologist who researches deportation, families and privacy. Used to work on immigration, asylum and detention. Trustee of an immigration charity.						

CASE STUDY 2: COMPAS TERMS AND COLLOCATES

Background

The University of Oxford-based Centre on Migration, Policy, and Society (COMPAS) conducted a major research effort entitled ‘Migration in the Media and Public Opinion’ in Britain, which ran from June 2012 to May 2013. It researched prominent portrayals of migration in the media and how this influences public understanding and attitudes.¹⁸ The research team collected a sample of 58,000 news stories and other news-related material connected to migration. Newspapers represented in the sample included all the major broadsheets, mid-markets, and tabloids from across the political spectrum. They used bespoke technologies to analyse the material in order to see how the media covered migration as stories developed. They examined the usage of the words ‘migrant’, ‘immigrant’, ‘refugee’, and ‘asylum seeker’ and in what contexts they tended to be used. They were interested in which words appeared immediately before these words and within five words before or afterwards.

Data collection

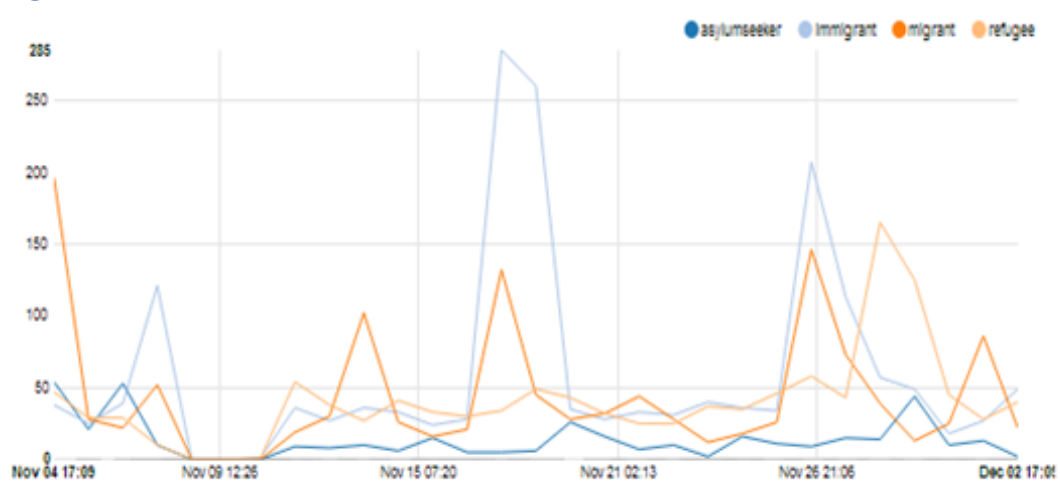
We used the same restricted sample terms as used by COMPAS to determine what terms co-occurred with them: ‘migrant’, ‘immigrant’, ‘asylum seeker’, ‘refugee’.

We collected 247,291 tweets between 4 and 23 November and November. When this was filtered for UK-only cases, this number fell to 9,116. (There was a very significant number of US-specific conversations on the subject.)

Trend analysis

We found 1,710 mentions of ‘immigrant’, 1,281 of ‘migrant’, 1,169 of ‘refugee’, and 397 of ‘asylum seeker’ over the period. Trends in the use of these four terms are graphed in figure 4. Generally it seems there is some degree of inter-relationship but, equally, some independence between these four terms. For instance, usage of all four terms tends to rise in varying degrees around 26 November. Between 16 November and 19 November, there is a large rise in the number of mentions of ‘immigrant’ met with a smaller rise in the number of mentions of ‘migrant’ but no accompanying rise in the use of ‘asylum seeker’ and ‘refugee’. It is of note that the spikes occur concurrently, which suggests a high degree of interchangeability in the terms used.

Figure 4



Content Analysis

The results of the COMPAS study showed that media coverage tended to place the emphasis firmly on the more negative aspects of migration. Across all types of newspaper, the word most commonly associated with ‘immigrants’ was ‘illegal’. Country of origin was often linked to how immigration is written about across all newspapers, with a particularly recurrent theme being Eastern Europe and the EU. Newspapers tended to speak of ‘immigrants’ in terms of large numbers – ‘million’ and ‘thousands’ being popular collocates. The word ‘migrants’, across all newspapers, was associated with the word ‘economic’, whilst ‘jobs’ and ‘benefits’ were particular favourites of the tabloids and mid-markets. Tabloids often talked about ‘immigration’ in terms reflective of dishonesty and criminality – ‘terrorist’, ‘suspected’, ‘sham’. Regarding asylum seekers, the most common collocate across all newspapers was ‘failed’. Mid-markets linked them to criminality and long-term residence. Broadsheets did this to some extent but were also more likely to stress vulnerability.¹⁹

In table 3 are presented the most common words or phrases in our data that are linked to the words ‘migrant’, ‘immigrant’, ‘asylum seeker’ and ‘refugee’. These were selected as being the most frequent non-stop unigram/bigrams in the tweets which contained the target term. Also presented are the corresponding most popular co-locates from newspapers as revealed by the COMPAS study.²⁰

Regarding the word ‘migrant’, the most popular collocate in our data was ‘workers’. Then came a cluster of collocates specifying origins: ‘Qatar’, ‘Saudi’, ‘Roma’. Then

we have a cluster of words that seem to be related to discussion of migrant issues: ‘support’, ‘lies’, ‘reform’, ‘lies pro’, ‘gain support’. There is also a cluster of words/phrases reflecting Nick Clegg’s intervention in the debate on Roma in Sheffield. The collocates from the COMPAS study for ‘migrants’ suggest a discussion in the media that is characterised by large swathes of illegal immigrants coming to the UK for economic reasons. Our data are different. The discussion on Twitter is more news-focused and focused on the political debate, although it seems that each debate is charged with some sympathetic voices while others feel politicians have not been especially honest with them.

Common collocates of ‘immigrant’ mostly reflect then-recent events in Greece and in particular the murder of a young activist. There is also some mention of the Conservatives reflecting their position on immigration. COMPAS’ results revealed a strong interest, in the newspapers, in illegal immigration and the origins of immigrants. Our results reflect a stronger interest in events tied to the word ‘immigrant’ with no stress placed on the legality of immigrants.

The most common collocates for ‘asylum seeker’ were ‘hunger’, ‘failed’, and ‘hunger strike’, relating to notable cases in the news of asylum seekers going on hunger strike. Most of the other popular co-locates relate to the story of an asylum seeker who was awarded costs to pursue his education as a pilot by his local authority. What is not apparent in these data is the tone of the newspapers that the COMPAS study revealed. COMPAS found that collocates of ‘asylum seeker’ tended to express illegality, criminality, and vulnerability.

The common collocates of ‘refugee’ were more often than not tied to the Syrian crisis. They suggest a focus of concern for the most vulnerable, ie children. They suggest attempts to do something to help these people: ‘provide’, ‘support’, ‘school’. The impression left by these collocates is broadly similar to the COMPAS study in that there is no sense of hostility and that coverage is broadly factual. COMPAS’ study differs from ours in that there is some marginal concern regarding large influxes.

Below are the results of both studies (presented in order of prevalence). It is important to stress that our data were collected over a much shorter time period than the COMPAS study, which will account for some of the different themes which were associated with each of the terms. Moreover, COMPAS’ collocates

were ‘consistent collocates’, meaning they appeared in each year of the sample, which ruled out event-specific terms.

Table 3

Migrant							
Demos	COMPAS	Demos	COMPAS	Demos	COMPAS	Demos	COMPAS
workers	EU	Greek	illegal	hunger	failed	Syrian	thousands
Qatar	Britain	anti-immigrant	Jewish	failed	immigrants	children	asylum
Saudi	illegal	party	African	hunger strike	illegal	camp	fleeing
Roma	economic	group killed	European	flying lessons	criminals	#Syria	borders
support	number	members Greek	non-EU	Isa Muazu	migrants	Syria	fled
lies	non	Greek anti-immigrant	EU	removed	refugees	crisis	Palestinian
reform	jobs	Anti-immigrant party	Polish	bill	number	work provide	Jewish
lies pro	UK	killed	Irish	fly	stay	children work	UN
Gain support	Eastern	2 members	Eastern European	taxpayers	detention	provide families	camp
nonprofits	benefits	guerrilla	Muslim	mail	child	camps	help
pro migrant	thousands	previously unknown	undocumented	bill teach	thousand	families	high
Clegg urges	skilled	leftist	Italian	10,000 billion	treatment	Lebanon	return
sensitivity	Europe	Party previously	recent	teach	deportation	Palestinian	across
Arabia	Influx	unknown leftist	skilled	side story	housing	work	Turkey
pro	African	members	Asian	lawyers	Australia	camp HTTPLINK	number
Nick	European	group	Russian	Daily Mail	refused	#FutureofSyria	Commission
urges Roma	countries	Texas	Turkish	lawyers failed	countries	support	seekers
Clegg Roma	numbers	immigrant game	Mexican	side	destitute	impossible	millions
Nick Clegg	coming	Conservative	legal	lessons caused	whom	morning	camps
Roma immigrants	stop	young Conservatives	Caribbean	caused fuss	vulnerable	school	influx

CASE STUDY 3: AN 'UNEXPECTED EVENT – DAVID CAMERON'S ARTICLE IN THE *FINANCIAL TIMES*

Background

David Cameron addressed the subject of immigration in an article in the *Financial Times* published on 26 November 2013.²¹ In this article, Cameron outlined his views on immigration in the light of the impending lifting of restrictions on the freedom of movement of European Union citizens from Romania and Bulgaria. Cameron argued that greater integration with Eastern European countries was good for prosperity and security on both sides but that integration had been mismanaged by Labour. He wrote that nobody should be able to come to the UK and start claiming benefits immediately. EU foreign nationals would only be able to claim benefits after three months and would only be paid for a maximum of six months if they were unable to demonstrate a genuine prospect of finding work. Beggars and homeless migrants would be removed and barred from returning for 12 months unless they could show they had employment. Fines of up to £20,000 were to be introduced for employers paying below the minimum wage. Cameron called for reform of the European Union so that the right to freedom of movement within it would be qualified, giving member states the right to restrict access to their labour markets if they feared inequalities would lead to mass movements of people. He suggested that there could be a threshold of economic output before free movement was allowed and that caps on migration should be allowed.

Data collection

The data were collected between 04:01 on 27 November and 03:30 on 28 November 2013. In total, 11,050 relevant tweets were collected. Search terms used were: 'EU', 'Bulgaria', 'Romania', 'Bulgarian', 'Romanian', 'Cameron', 'Immigrants', 'Immigration', 'Benefit Tourism'.

Analysis of trends

As we can see from figure 5, there is one initial spike with a peak of 102 tweets at 5:41 on 27 November. This spike is short lived. Thereafter, the number of tweets rises to a peak at around 9:00 before gradually declining until the conversation effectively ceases at about 03:30 on 28 November. This trend of decline is bucked by a spike at 22:31 on 27 November, peaking at 158 tweets.

Figure 5



Content analysis

A classifier was trained on this sub-section of the data covering the time span 5:21 to 11:30 on 27 November (see figure 6). Based on a manual review of the data, tweets appeared to fall into either ‘report’ (tweets that were for the most part neutrally sharing information) or ‘comment’ (reaction to this news and people’s judgement of what Cameron wrote, along with any other comments relating to the subject of immigration that the article may have provoked). Some tweets contained content that could very easily lead to their being classified as either ‘report’ or ‘comment’. We therefore built a classifier to separate the data in this way. Overall 1,873 tweets were classed as ‘report’, and 9,176 were classed as ‘comment’. Initially, the time series begins with people reporting Cameron’s article. The prominent spike at 5:21 is entirely made up of reports. At around 8:00, comments overtake reports and reports start to decline.

Figure 6

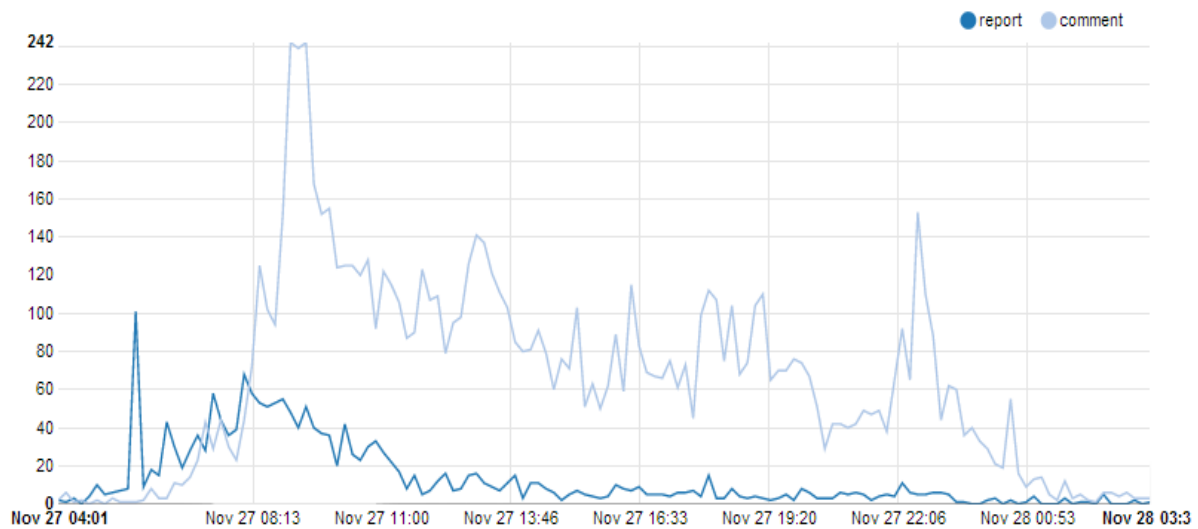


Figure 6 shows that an initial spike in ‘report’ tweets – people sharing the story – was quickly overtaken by broader comment and discussion. A random sample of 342 of the tweets identified as ‘comment’ tweets was taken, and these were manually analysed by a researcher. They were classified as to whether or not they made reference to immigration and whether the tone was: (a) positive; (b) neutral; or (c) negative.

In total, 5 per cent of tweets were hostile to immigration while 23 per cent were supportive. Forty six per cent were neither openly hostile nor supportive. However, these tweets were mostly information sharing and the type of information shared could be interpreted in some sense as being supportive of immigration. Most often, tweets in this category were sharing information on the number of British people enjoying the benefits of migration, which can be interpreted as a rejoinder to criticism of it. The lack of negative opinions on immigration is not in line with opinion polling on the subject. In the sample we also picked up a lot of hostility towards David Cameron himself and criticism of the media’s handling of immigration.

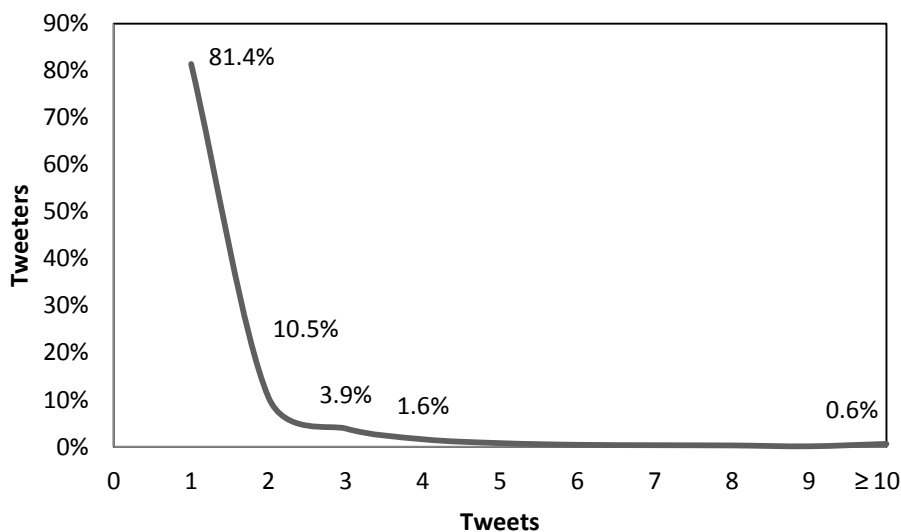
Table 4

Reference	Sentiment	Sample	Extrapolated
Immigration	Positive	23.4%	2,569
eg <i>Reasons not to worry about Romanian and Bulgarian immigration: http://t.co/ICdXf5bZxj</i>			
	Neutral	45.6%	5,006
eg <i>under 2 million EU migrants live in the UK. Over 2.2 million British migrants live in other EU countries http://t.co/dgPkPa9DDz</i>			
	Negative	4.7%	516
eg <i>@^^^ stop immigration now we in [xxxx] have enough already, they don't integrate and it feels like we're in a foreign country</i>			

Profile analysis

As we can see from figure 7, the vast majority of the discussion concerning Cameron's article was made up of individual users making small contributions. Overall, 9,759 unique users tweeted: 81 per cent of tweeters tweeted only once; 11 per cent tweeted twice; 3 per cent tweeted 3 times. The most prolific user tweeted 32 times.

Figure 7



We manually analysed the profile data for both 'report' and 'comment' tweets. Profiles were classified by a researcher according to whether or not they: (a) made some reference to politics; (b) expressed some form of connection to the media; (c) expressed some form of belonging to an organisation and (excluding having a job), to which their tweets might be linked; or (d) were members of the public.

An analysis of a random sample of 288 user profiles from the ‘report’ stream showed that 73 per cent of users were from the general public; 21 per cent were overtly political, 14 per cent were tied to the media; while 22 per cent were connected to some kind of organisation.

An analysis of a random sample of 334 user profiles from the ‘comment’ stream showed that 85 per cent of users were from the general public; 30 per cent were expressly political; 6 per cent were connected to the media; while 15 per cent were connected to an organisation.

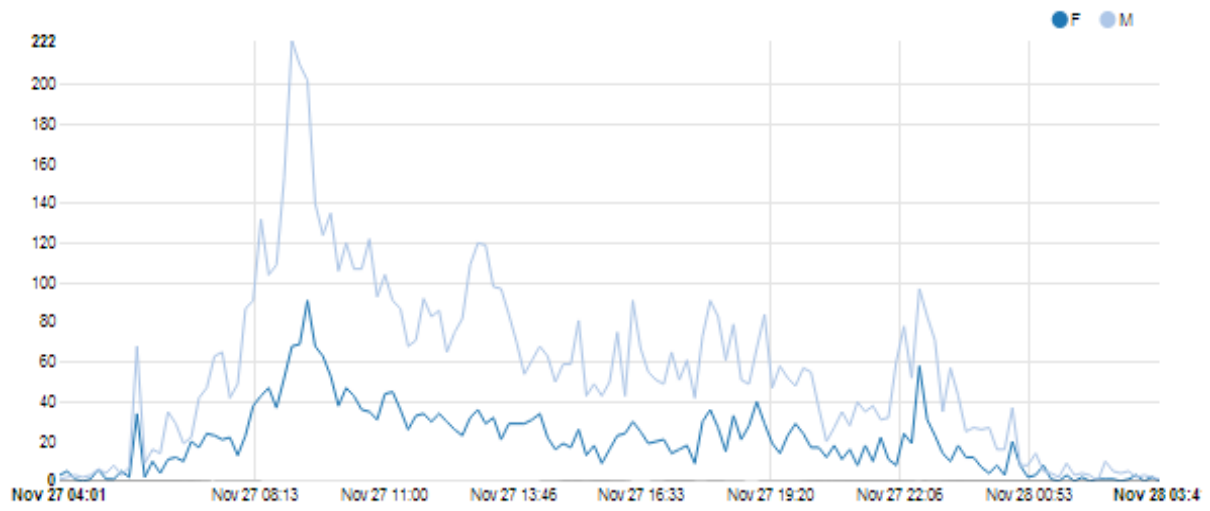
Members of the public made up most of the contributors to the sharing and discussion of Cameron’s article. However, they were more inclined to comment than to report. Whilst they were doing most of the sharing overall, traditional media representatives still had a role to play in reporting, and were less inclined to pass comment.

Table 5

	Report		Comment	
	Sample	Extrapolated	Sample	Extrapolated
Member of the public	73.2%	840	85.3%	2,162
eg <i>Say what I think.</i> Football fan. Supports Liverpool.				
Political	20.5%	384	30.2%	766
eg <i>I’m a ranty left wing type.</i>				
Media	13.9%	260	6.0%	152
eg <i>Journalist with Dow Jones and the Wall Street Journal. Greek immigrant. All views categorically my own.</i>				
Organisational	21.9%	410	15.0%	379
eg <i>Programme Manager, Prince’s Charities’ International Sustainability Unit, London; Labour Councillor candidate for Riverside Ward, SE16, 2014. All views my own.</i>				

A gender classifier was applied to the Cameron data, as seen in figure 8. 3,003 tweets were made by women, 7,974 were made by men. The general traffic trends were similar, but on the whole, men tweeted more often on this subject. This is surprising, given that the demographic background of Twitter users in the UK is marginally skewed toward there being more female than male users (women aged 15—24 make up the largest user group on Twitter, although whether men or women tweet more is not known).

Figure 8



CASE STUDY 4: THE LIFTING OF TRANSITIONAL CONTROLS

Background

On 1 January 2014 controls on the movement of Romanians and Bulgarians into the United Kingdom were lifted. When Romania and Bulgaria first joined the European Union in 2007, the then Labour government imposed restrictions on their entry into the UK.²² Prior to the lifting of restrictions, some had expressed fears that there would be mass migration into the United Kingdom from these two countries. The *Mail on Sunday* for instance suggested the lifting of transitions could 'lead to strain on public services, to housing problems and even to social cohesion issues among different migrant groups'.²³ Others took a more placid approach – an editorial in *The Guardian* admitted the restrictions posed economic and social questions but called for a debate grounded on fact rather than conjecture.²⁴ Around the same time, a cross-party group on Roma warned of the dangers of increasingly anti-Roma rhetoric.²⁵ Polling found that British people were largely supportive of Romanians and Bulgarians coming to the UK provided they found jobs and integrated into British society.²⁶

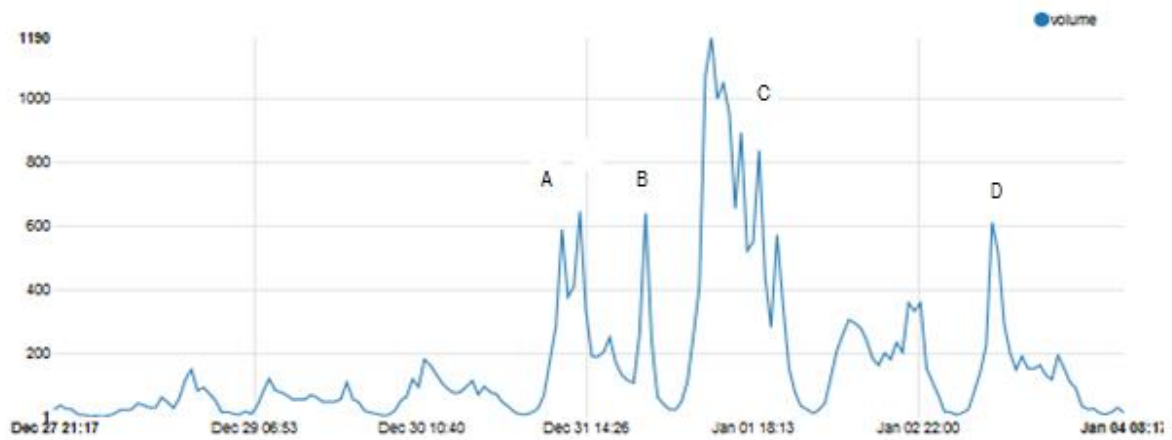
The political parties took different approaches. David Cameron announced that his government would introduce restrictions on benefits and tough penalties on anyone found begging or homeless. The Liberal Democrat and business secretary Vince Cable criticised the Conservatives for adopting alarmist policies, while Shadow Home Secretary Yvette Cooper warned of the danger of employers using immigration to undercut British wages.²⁷ Keith Vaz, the (Labour) chairman of the Home Affairs Select Committee, along with his (Conservative) committee colleague Mark Reckless went to Luton Airport in order to witness the process of immigration under the new rules.²⁸ Since the restrictions were lifted, no large scale influxes of migrants have been registered.²⁹

Data collection

Tweets were collected that contained the search terms 'EU', 'Bulgaria', 'Bulgarian', 'Romania' and 'Romanian' between 21:17 on 27 December 2013 and 15:10 on 3 January 2014. In total 29,509 relevant tweets were collected.

Trend Analysis

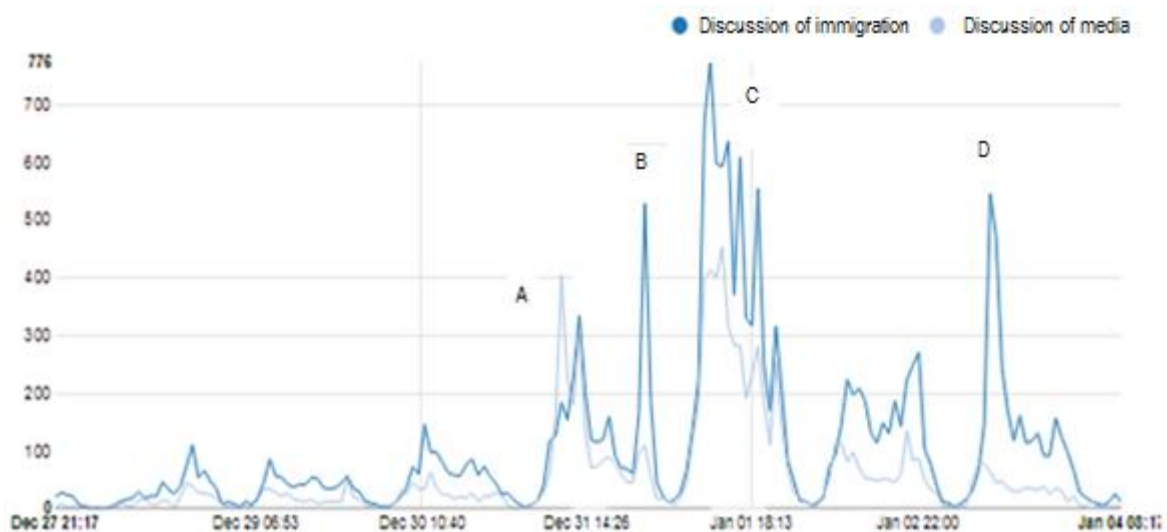
Figure 9



Content analysis

Looking at the data, it was apparent that there were two inter-related conversations. The first was relating to the actual lifting of transitional controls and the immigration it invited. The second was to do with the media and what was perceived as its alarmist reporting of the issue. Thus, a classifier distinguishing between 'media' related tweets and 'non-media' was trained on a subset of the data around 1 January and then applied to the complete data set (see figure 10).

Figure 10



In order to explore the tone of the conversation, a random sample was taken from clusters A, B and C (n=710). Results are presented in table 6. Tweets were classified by a researcher according to whether they made some reference to immigration and if they were: (a) positive; (b) neutral; (c) negative – these categories are mutually exclusive. Most tweets made some reference to immigration. Generally, people were non-committal in their tweets about whether or not they approved of immigration. Those tweets that did have some expression of positive or negative sentiment were relatively few, with more negative than positive.

Table 6

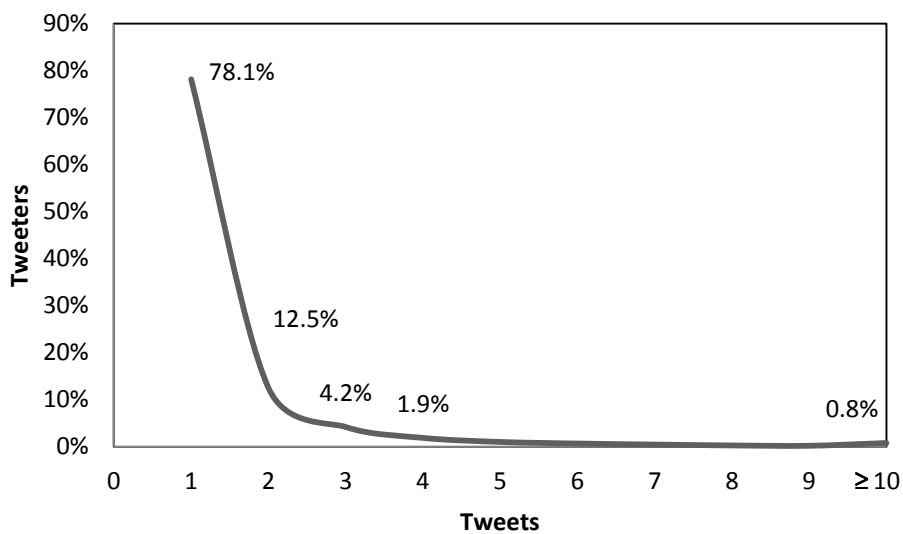
Immigration		Sample	Extrapolated
	Positive	4.6%	488
<i>eg It's 2014 in the UK. Dear Romanians – we're sorry about our racist media and prime minister. You're very welcome here!</i>			
	Neutral	66.1%	6,935
<i>eg Woke up this morning, came down to the kitchen and didn't see a single Romanian or Bulgarian. I feel let down.</i>			
	Negative	9.9%	1,035
<i>eg Hope you've all been practicing your Romanian and Bulgarian because the invasion is about to start. It's gonna get messy.</i>			

(Note: it is extremely difficult to accurately know if irony is positive or negative in intent, hence the above example falling under 'neutral', which is likely to come from a broadly pro-immigration stance. We discuss this problem further in the conclusion.)

Profile analysis

In figure 11, power law analysis is presented for these data. There were 29,986 unique users: 78 per cent of these tweeted just once; 12 per cent twice; 4 per cent three times; 1 per cent more than ten times. The most prolific tweeted 118 times. Contributions made on Twitter on the subject of the lifting of transitional controls were mostly small and made by a large number of individuals. A small minority of individuals were more engaged, making multiple tweets.

Figure 11



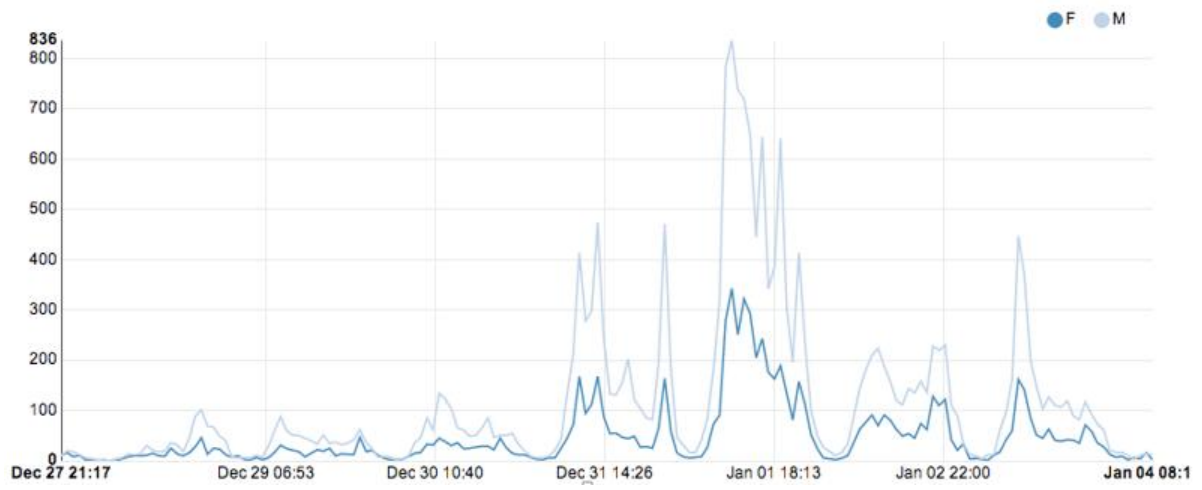
A random sample of 379 profile descriptions was taken. Profiles were classified by a researcher according to whether or not they: (a) made some reference to politics; (b) expressed some form of connection to the media; (c) expressed some form of belonging to an organisation, to which their tweets might be linked. Results are presented in table 7. Nearly one in five users were political while, the vast majority were not connected to the media and were tweeting in an individual capacity.

Table 7

	Sample	Extrapolated
Member of the public	85.8%	25488
eg <i>Alcohol researcher, Everton fan, love music. Always tweet in a personal capacity.</i>		
Political	19.0%	5,697
eg <i>Manager in health and social care Performance manager. Standing for the Labour Party. Father and long distance commuter.</i>		
Media	6.1%	1,820
eg <i>We're proud to provide you with all the latest Politcal news from the UK and around the world</i>		
Organisational	8.7%	2,611
eg <i>Work for and tweet about trade union issues</i>		

As seen in figure 11, a gender classifier was applied to the data. In total, there were 8,416 from women, 20,839 from men. In the UK, women tweeters outnumber male tweeters.³⁰

Figure 12



CONCLUSION

Overall, there is a considerable amount of relevant and useful data available from conversation on Twitter relating to the subject of immigration. Twitter data sets are ‘social big data’. The quantity of the data gathered even for this pilot is far larger than comparative data sets gathered through conventional polling, interviewing and surveying techniques. Attitudinal research is often expensive. It is expensive to employ interviewers and to manage and incentivise panels of willing participants, to mail surveys to thousands of people and to hire rooms, technology and people to conduct focus groups.

These techniques are very economic in comparison. Acquiring tweets is free (although accessing historic data or accessing all tweets published in real time does cost money) and the technology, once in place, can be trained and purposed in a matter of minutes. Commercial technology to collect and analyse tweets can be expensive, but there are a number of cheap or free open source pieces of software available. This lowers the threshold for attitudinal research – many more organisations will be able to listen more often to more conversation that they care about.

In addition, the data come from a relatively large volume of people, including users who do not appear to have any specific organisational or political affiliation. Another benefit of these data sets is that they are non-intrusive and naturalistic (although with limitations which we discuss below). A well-known weakness in most attitudinal research is that data are collected in ‘non-real world’ settings. Most ways of gathering attitudes require a researcher intervening in someone’s life – asking them questions, and recording what they say. This introduces ‘observation effects’ that may change the attitudes expressed and views offered in a number of ways.³¹ By listening to digital voices as they naturally arise in the public debate, rather than asking directly for responses, Twitter data avoid this well-known observation bias.

However, Twitter, as a new public space, creates new types of observation bias. Because all the tweets we collected are public, users who posted them are aware that other users are able to access their output, which also creates an observational effect of its own. Twitter may also create new types of platform-specific observational biases. For example, although there are roughly the same number of male and female users on Twitter overall, our data finds that men are more likely

to tweet on the subject of immigration than women. Precisely how significant these effects are, and the likely impact on the quality of a sample, is an area that requires further work.

Features of the data

Twitter data sets are very different to traditional types of attitudinal data sets. This is important for how to best understand and analyse them.

Real or near-real time

Relevant tweets are collected almost immediately after they are posted. By using automated technologies, this draws meaning from this data very quickly after collection. It is therefore possible to understand attitudes about an event as the event happens, and as the public debate evolves. The ability to discern real-time reactions to events is a powerful tool for institutions to have. It allows them to be agile, and react to groundswells of anger, support or criticism quickly enough to influence the underlying developments and events that drive these attitudes.

Reactive and indirect

Our case studies and classifier tests revealed that people do not in general express generic sentiment on Twitter about immigration. A tweet is overwhelmingly a reaction to an event that the tweeter has otherwise encountered – either online or offline, whether through reading mainstream media or being told by their friend. Very specific and unprompted expressions of opinion are relatively rare, and much appears to be indirect expression of opinion or immediate reaction to particular events. Therefore it is best used as a way of gaining insight into how people respond to events, rather than a continuous ‘poll’ of opinion. For example, much of the data relating to the lifting of transitional immigration controls were a comment on media reporting rather than directly expressed personal opinions. Our data tell us very little on what people think about immigration directly. Most people were holding back from expressing opinions directly concerning the pluses and minuses of immigration but were content to either attempt to refute claims made in the press or to mock them.

Adversarial

Twitter data appeared strongly adversarial – people tended to respond negatively to anything politicians said concerning immigration. While there are very few unprompted expressions of attitude, both Cameron’s article and the Immigration Bill appeared to enliven the ‘pro-immigration’ attitude. It is possible that the

reverse would happen: a very pro-immigration article may provoke a significant anti-immigration response on Twitter. Other research conducted by Demos supports the idea that Twitter is often used as a way to critique or complain about those in positions of power. In analysis we conducted for the Nigel Farage and Nick Clegg debates of Spring 2014, we found almost 90 per cent of tweets were negative (irrespective of which candidate they related to). We term this the ‘boo and cheer’ phenomenon.³²

Media driven

There is an interesting and dynamic relationship between media reports and stories and broader conversations which take place afterward. In the case of David Cameron’s article in the *Financial Times*, the piece was published before people began to share news of this article along with the article itself. They then began to discuss the article and the wider topic of immigration, and the debate took off at the same time as they stopped sharing information with each other. What is most interesting is that people often tended to turn on both media and politician. People were for the most part hostile to Cameron but also to the media that was bringing them the story. Twitter has an ambivalent relationship to the media. On the one hand it feeds off it – as was seen in the Cameron article study; on the other hand it holds the media to account – as we saw in the lifting of transitional controls study.

Limitations

Our research found a number of interesting insights relating to immigration attitudes on Twitter. However, for campaigners and researchers considering whether to use the results of this paper, or to develop and employ these techniques for other areas of research, there are a number of important caveats about what can be generalised from Twitter-driven research.

Twitter is a new type of data: short, produced in large volume, and above all driven by events rather than the decisions of the researcher. There are demographic and other biases in the data sets collected. Established ways of researching attitudes have long histories of use. This experience has consolidated into a body of good practice – dos and don’ts – that, when followed, ensures the quality of the research. Twitter research doesn’t have a long history of use, or a collective memory of what works and what doesn’t. It uses new technologies in new ways that are unfamiliar to the social sciences, often with new and important implications for research. Below we list some of the main limitations of these data

sets in respect of how far they allow us to make generalisations about attitudes and views toward immigration.

Demographic and self-selection biases

Twitter users do not demographically represent wider populations (they remain slightly younger, and more urban than average). Anecdotal and small-scale research suggests they might also be more liberal than average. In our research, one recurring theme we identified was the overall lack of negative sentiment toward immigration. Given that we selected words or themes that would allow for a relatively broad array of conversations, we conclude that people posting on Twitter explicitly about immigration tend to be broadly more in favour of immigration than the general public (although there may be other ways through which they express dissatisfaction that wasn't picked up by us). This stands in line with previous research conducted by Pew Research Center, which found that in the aftermath of a high school shooting in Connecticut, the reaction on Twitter was largely in favour of greater gun controls while the overall population was closely split on the issue.³³ In this paper, we have demonstrated certain ways these skews can be presented, although not necessarily corrected.

Moreover, even collected tweets often do not represent all Twitter users, because it appears that many users go on to Twitter to express an reaction to an event if they have a particularly strong opinion about it, and so they are not necessarily a representative sample even within Twitter. This is called a self-selection bias. We have noted, for example, that men appear far more likely than women to comment directly on the subject of immigration on Twitter.

Technology performance

The technology sometimes performed very successfully, and at other times very poorly. In the research, the best performing classifiers were almost always correct, and the worst performing classifiers performed no better than chance. The performance of classifiers depends on the context of the task (full results below).

Non-random missing data

Data are typically acquired through Twitter by being matched to keywords. Because data are collected based on conversations rather than demographic or what we call 'topographic' details (for example, the power law features), there is a high degree of uncertainty regarding the demographic background of any collected data set. The case studies show that these keywords can produce different kinds of

problems – sometimes they are over-inclusive (and collect tweets on other irrelevant topics), and sometimes they are under-inclusive (and miss relevant tweets). In both these ways, keyword matching is inherently prone to systemic bias – meaning that the data collected, and therefore the conclusions drawn, are affected in a non-random way by the search terms employed. In these studies, keywords were selected using a trial and error approach: collecting data based on a series of keywords, reviewing and selecting further terms from the data, and continually spidering out. In other research work, we have identified the need for more robust systems for selecting sample terms as a key methodological innovation necessary to improve the discipline as a whole.³⁴

Unpredictable

It can be extremely difficult to predict in advance the likely volume and data quality of Twitter conversations on any given subject. This can make it difficult to plan in advance what topics and subjects can be researched.

Forum specific biases

Twitter is a new social space. It is characterised by its own norms and mores. For example, based on our research, it is a medium characterised by humour, sharing stories, and anti-establishment sentiment. One example is the use of irony and anti-establishment humour, which is a feature of many conversations that take place on Twitter. For a human analyst not habituated to certain memes or group-specific language it can be very difficult to determine likely sentiment or underlying attitude. This is even more difficult, if not impossible, when training a classifier to recognise these very subtle distinctions. These reflections are based on an analysis of conversations which involve a high proportion of political, public policy, and news-related subjects. There are many other sets of conversations and themes which are likely to follow their own norms of use.

Discussion on methods and ethics

In this study we employed a system of automated data collection and analysis. This created quite specific ethical and methodological considerations.

Classifier performance

The performance of all the classifiers used in the project was tested by comparing the decisions that they made against a human analyst making the same decisions about the same tweets. Classifier training involved, for each classifier, the creation of a ‘gold standard’ data set containing around 100 tweets annotated by a human

annotator into the same categories of meaning as the algorithm was designed to do. The performance of each classifier could then be assessed by comparing the decisions that it made on those 100 tweets against the decisions made by the human analyst. There are three outcomes of this test, and each measures the ability of the classifier to make the same decisions as a human – and thus its overall performance - in a different way:

Recall: This is the number of correct selections that the classifier makes as a proportion of the total correct selections it could have made. If there are ten relevant tweets in a data set, and a relevancy classifier successfully picks eight 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 ten tweets as relevant, and eight of them are indeed relevant, it has a precision score of 80 per cent.

Overall, or 'F1': All classifiers are a trade-off between recall and precision. Classifiers with a high recall score tend to be less precise, and vice versa. 'F1' is the harmonic mean of precision and recall, and equally reconciles precision and recall to create one, overall measurement of performance for the classifier.

The results are displayed in the table below. Importantly, the performance of each of the decisions that a classifier makes can be drastically different: it can much more reliably select 'relevant' rather than 'irrelevant' tweets, or 'negative' rather than 'positive' ones. Only the scores for a tweet being 'relevant', 'attitudinal', and then either 'positive', or 'negative' are included below.

In total we created four classifiers, one for each case study.

Table 8 Classifier scores

		Precision	Recall	F-score
Immigration Bill	Parliament	0.758	0.758	0.758
	Lobby	0.733	0.804	0.767
	Media	0.606	0.476	0.533
Four terms	Migrant	0.923	0.980	0.950
	Immigrant	0.928	0.975	0.951
	Asylum seeker	0.938	0.938	0.938
	Refugee	0.891	0.953	0.921
	Irrelevant	1.000	0.231	0.375
Cameron speech	Report	0.678	0.930	0.784
	Comment	0.979	0.879	0.926
Transitional control	Media	0.728	0.756	0.742
	Non-media	0.840	0.820	0.830

(Gender classifiers were not subject to the same gold standard analysis, because they are based on a pre-prepared name match dictionary. These classifiers tend to work at between 85—95 per cent accuracy.)

Overall classifiers tended to work well. It was only in the case of the Immigration Bill data that there was anything troubling. As we can see in table 8, it was the label ‘media’ that produced relatively low scores on all three fronts. This was to do with there not being enough examples of media tweets to train the classifier in order to make improvements. The classifiers that work the best tend to be those that are based on very clear distinctions visible in the text. For the four terms data set, a classifier was trained that just focused on individual words rather than complex phrasing and thus provided much higher measures of fit. The more complex and nuanced the distinctions, the more difficult it is for the classifiers to lock onto plain distinctions in the text.

Ethics

Conducting research using Twitter data presents new ethical challenges in respect of how researchers should collect, store, analyse and present publicly posted tweets. Because it is a new field of research, there are no widely accepted protocols and approaches for how to do this ethically. Some useful recent guidance has been issued by the New Social Media, New Social Science network, which recognises that remain a number of outstanding ethical questions for research of this kind.³⁵

However, the Economic and Social Research Council principles of ethical research are an excellent guide for conducting research of all kinds – and can be usefully applied to online research as well as offline.

After reviewing these principles, we considered that the most important and relevant principles for this research paper were whether informed consent is necessary to collect, store, analyse and present participants' public tweets; whether there are any possible harms to participants in including and possibly re-publishing their tweets, as part of a research project; and whether directly publishing personal information about an individual that might make them identifiable was important for the research purpose (including where material might identify an individual via a search engine).

There are no hard and fast rules when making these decisions. Research ethics is rather a series of judgements that a researcher needs to make, balanced against the possible benefits of conducting the research. Below we discuss each.

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 whether the individual has made any explicit effort or decision in order to ensure that third parties cannot access the information in question. In the UK, there are a number of polls and surveys that have gauged public attitudes on this subject, including a small number of representative, national-level surveys. Taken together, they similarly find that citizens are increasingly worried about losing control over what happens to their personal information, and the potential for misuse, by both governments and commercial companies. These surveys also show, however, that it is less clear what people actually understand online privacy to entail. They found that there is no clear agreement on what constitutes personal or public data on the internet.³⁶

Applying these two tests to Twitter in respect of our work, we believe that there is, in general, a low level of expectation of privacy for those who tweet publicly available messages. (This is not true of all social networks). Twitter's Terms of Service³⁷ and Privacy Policy³⁸ 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 that tweets are closely analogous to acts of publishing, and can thus also be prosecuted under laws governing public communications, including libel.

That said, it is possible that different users have quite different views about reasonable expectations of privacy in respect to Twitter. For example, a user posting from an official account of an organisation might have a different expectation from someone posting in a personal capacity with a small number of close followers.

In this study we considered that although there is a generally low expectation of privacy for those who post publicly on Twitter, this could vary across users and is not always very easy to determine.

2. Whether or not identifying a user might result in any harm to the research subject

The chief burden on researchers is to make sure they are not causing any likely harm to users, if those users have not given a clear, informed, express consent that they might be identified. Harm is difficult to measure in respect of social media research. For example, posting an offensive or obscene tweet that could be traced back to the user might result in them receiving abuse or other 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.

In our study, we considered that the use of profile data (the description given by users of themselves) was potentially problematic as we categorised users based on their profile data into different categories. Profile data are arguably more personal than tweets because they can also more easily and quickly be linked back to the user.

However, these considerations also had to be balanced against the social benefits of this research:

3. The material value to the research of directly quoting social media.

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, where the conditions (a) or (b) are judged by the researcher to be unmet, it is considered acceptable to ‘cloak’ direct quotes or data. (This means retaining the essence of the data, but changing small parts so that no-one can be easily identified.) This is especially the case where cloaking of quotes does not negatively affect the material value of the research.³⁹

Finally, there are some further considerations, such as whether it is realistic to contact research subjects to seek explicit consent; and whether there are any other obligations involved in quoting a research subject directly, such as copyright infringement.

Overall, we determined that, given the sensitive subject matter and the fact that the precise, identifiable data was not materially important for the rigour of the research work, it was acceptable to ‘cloak’ (sometimes called ‘mask’, meaning slightly change the content so it could not be linked to an individual but without losing the overall meaning) any tweets and profile names, except those from well-known public figures – such as a Member of Parliament who was tweeting in his or her public capacity.

Future applications and recommendations for researchers

Overall, we have found that Twitter offers a novel way of understanding citizens’ reaction to events as they unfold, in a way that can be powerful and useful for academics, researchers, advocacy groups, policy makers, and others. Discerning real-time reactions is a useful capability for institutions to have, especially where it can be undertaken at low cost.

In respect of the application of automated technology, on the whole we believe that generic, long-term classifiers perform less well than bespoke and short-term classifiers which are based on very specific conversations and subject matter. This means that ‘off the shelf’ data analytics tools are likely to be less valuable than systems which allow researchers and analysts control over how the system

operates. Language-use – the kinds of words used and the meanings these words have – changes quickly on Twitter and is specific to a particular conversation at a particular time. Automated algorithms struggle to accurately find generic meaning independent of a particular event or discussion, and become less accurate over a long period of time. We are therefore sceptical about the value of existing ‘off the shelf’ commercial social media analytics software for research and campaign work.

In respect of data quality overall, it is important to make a distinction between internal and external validity. At present, Twitter is not a valid instrument to conduct reliable, population level opinion surveys. There are significant problems with several types of self-selection bias and no clear way to correct for them. Therefore, statements making generalisations about overall public attitudes based on Twitter data sets – ‘external validity’ – should be made with extreme caution. Twitter data sets are not a valid alternative to population level surveys. They provide a different sort of data.

However, with careful analysis, research can be conducted which produces high levels of internal validity – that is, our data analysis produces an accurate and robust insight into overall traffic and trends on Twitter. In short, it is possible to have a good idea of what subjects and themes are being discussed on Twitter, and in what way.

Therefore, we would suggest researchers and campaigners use these technologies in order to:

- gauge immediate responses to online or offline events (whether the volume, nature or source of those responses) from a quite specific, but attentive, active and important portion of the public
- begin to understand why and how certain messages and campaigns spread beyond sector-specific Twitter users, and are picked up a wider audience
- longitudinal analysis of terms, phrases or words and how they are used over time, for example specific derogatory instances
- identification of individuals or groups that comment on and discuss issues of interest to better understand communities of interest (this requires careful ethical consideration, as above)

We recommend that campaign groups, third sector organisations and research institutes investigate the free, open source software that can allow them to

undertake in-house research to analyse social media. Analysis of Twitter data is most valuable where subject matter specialists are able to use and adapt technology to their own purposes.

As it stands, these sorts of capabilities cannot replace existing research methods. If the data are presented with due caveats outlined above, this type of research does provide a valuable method of understanding how people communicate using social media, and the reactions of certain groups on Twitter to certain events, identifying patterns of influence and information dissemination, all of which is important and useful in its own right.

METHODOLOGY ANNEX

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 ‘filter’ API continually produces tweets that contain one of a number of keywords, 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 by the amount of data it will return.

Keywords

Acquiring data from Twitter on a particular topic through the use of keywords is a trade-off between ‘precision’ and ‘comprehensiveness’. A precise data collection strategy will only return tweets that are on-topic, but will likely miss some.

The Twitter data set 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’ data sets, 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. The process of creating a classifier – machine-learning – is achieved through ‘mark up’. Messages are presented to the analyst via an interface. The analyst reads each tweet, and decides which of a number of pre-assigned categories it should belong to. The machine-learning algorithm looks for statistical correlations between the language used and the analyst’s markup to derive an association between the features of the language and the categories of meaning. Having learned these associations, the computer applies this criteria to additional (and unseen) tweets and categorises them along the same, inferred, lines as the examples it has been given.

Our study makes use of a web-hosted software platform, developed by the project team, called Method51.⁴⁰ 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 using this technology:

- **Phase 1 – Definition of categories:** The formal criteria explaining how tweets should be annotated were developed. This, importantly, continued throughout the early interaction of the data: categories and definitions of meaning were not arrived at a priori, but through relating the direct observation of the contours of the data to the overall research aims. These guidelines were provided to all the annotators working on the task.
- **Phase 2 – Creation of a gold-standard baseline:** On the basis of these formal criteria, analysts manually annotated around a ‘gold standard’ set of around 100 Tweets using Method51. This phase provides ‘gold-standard’ tweets, providing a base-line of truth against which the classifier performance is tested. A human analyst and the classifier both classify 100 random tweets, and it is the performance of the classifier compared to the human analyst that provides the accuracy scores, above. (For large scale studies it is typical to have more than one analysts creating the gold standard data sets, and presenting the results of inter-annotator agreement, to determine how accurate the gold standard data standard is, and subsequently the classifier itself.)
- **Phase 3 – Training:** The analyst manually annotated a set of tweets to train the machine-learning classifier, through web access to the AAF interface. The number of tweets that were annotated depended on the performance of the classifier, which itself depended on the scenario. Between 200 and 500 Tweets were analysed for each stream.
- **Phase 4 – Performance review and modification:** The performance of the classifier was reviewed, and examples of its outputs were read. Where feasible and necessary, the algorithm was modified to improve its performance

NOTES

- ¹ 'British Social Attitudes 29', NatCen Social Research, http://www.bsa29.natcen.ac.uk/media/13421/bsa29_full_report.pdf (accessed 11 November 2013).
- ² Duffy, B and Frere-Smith, T, *Perceptions and Reality: Public attitudes to immigration*, London: Ipsos MORI, 2014.
- ³ For a detailed discussion of these trends and further reading, see: <http://www.compas.ox.ac.uk/>
- ⁴ *The Migration Observatory*, 'Migration in the News: Portrayals of Immigrants, Migrants, Asylum Seekers and Refugees in National British Newspapers 2010-2012', <http://www.migrationobservatory.ox.ac.uk/sites/files/migobs/Report%20-%20migration%20in%20the%20news.pdf> (accessed 10 November 2013).
- ⁵ Ibid.
- ⁶ comScore, UK Digital Future in Focus 2013', http://www.comscore.com/Insights/Presentations_and_Whitepapers/2013/2013_UK_Digital_Future_in_Focus, (accessed 10 November 2013).
- ⁷ <http://econsultancy.com/uk/blog/9072-of-people-with-active-social-media-profiles-infographic>, (accessed 19 November 2013); <http://battenhall.net/blog/iab-releases-2013-uk-social-media-ad-spend-stats/>, (accessed 19 November 2013); <http://inforrm.wordpress.com/2013/06/16/social-media-how-many-people-use-twitter-and-what-do-we-think-about-it/> (accessed 19 November 2013).
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- ²⁸ <http://www.theguardian.com/uk-news/2014/jan/01/luton-romanian-arrival-mps-media>
- ²⁹ <http://www.independent.co.uk/news/world/europe/romanian-and-bulgarian-migrants-have-not-flocked-to-britain-says-eu-chief-9057296.html>
- ³⁰ <http://www.beevolve.com/twitter-statistics/#a1>
- ³¹ Attitudinal research itself can often change the context of what is said, and in doing so introduce 'measurement effects', where the very act of measuring changes the measurement itself. People involved in a poll are often seen to change their behaviour in consistent ways, to make it more acceptable in general or to the researcher specifically. Respondents will 'acquiesce' or consistently agree or disagree with a set of questions. Sometimes, people who knew they were being observed or were asked
- ³² <http://www.demos.co.uk/blog/nickvignellive>
- ³³ <http://www.journalism.org/2014/03/26/8-key-takeaways-about-social-media-and-news/>
- ³⁴ Bartlett et al (2014) *Vox Digitas*, Demos 2014
- ³⁵ <http://nsmnss.blogspot.co.uk/2014/02/new-social-media-new-social-science-and.html>
- ³⁶ Bartlett, J, *The Data Dialogue*, Demos, 2011. This is based on a representative population level poll of circa 5,000 people. Also see Bartlett, J and Miller, C, *Demos CASM submission to the Joint Committee on the Draft Communications Data Bill*, Demos, 2012.
- ³⁷ <http://www.twitter.com/tos> (accessed 27 March 2013)
- ³⁸ <http://www.twitter.com/privacy> (accessed 27 March.2013)
- ³⁹ <http://nsmnss.blogspot.co.uk/2014/02/new-social-media-new-social-science-and.html>
- ⁴⁰ The Agile Analysis Framework is a software suite developed by the project team over the last 18 months. It is based on an open source project called DUALIST: Settles, B., 'Closing the Loop: Fast, Interactive Semi-Supervised Annotation With Queries on Features and Instances' in *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pp. 1467—78. It enables non-technical analysts to build machine-learning

classifiers. The most important feature of it is the speed at which accurate classifiers can be built. Classically, a natural language processing (NLP) algorithm would require roughly at least 10,000 examples of 'marked-up' examples to achieve 70 per cent accuracy. This is both expensive, and takes days to complete. However, DUALIST innovatively uses 'active learning', an application of information theory that can identify pieces of text that the NLP algorithm would learn most from. This radically reduces the number of marked-up examples from 10,000 to a few hundred. Overall, in allowing social scientists to build and evaluate classifiers quickly, and therefore to engage directly with big social media data sets, the AAF makes possible the methodology used in this project.

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Immigration has become an increasingly important political issue in the United Kingdom. The way it's reported in the media plays a vital role in how immigration is felt and understood by citizens.

But media is changing: and an increasing number of us now either access - or even create - news on social media. Social media sites like Twitter are a new, dynamic and less hierarchical space which has opened up the public portrayal of immigration. What's more, social media activity also presents a novel way to research and understand attitudes, trends and media consumption.

Immigration and Twitter is a groundbreaking study that examines how people use the social media platform to talk about immigration. By applying new 'big data' methodologies such as machine learning algorithms, the study analyses hundreds of thousands of tweets about immigration in the UK to understand what they are saying, what drives online conversations, and who is behind it. It finds significant differences in the way the subject is discussed online compared to traditional media outlets, and argues social media is an important new public space for conversations that people care about.

The study also examines in detail the strengths and weaknesses of new big data research methods to understand public attitudes online, and where it might - and might not - be usefully employed by research and campaign groups.

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