American Behavioral Scientist
57(7) 943–965

DOI: 10.1177/0002764213479371
abs.sagepub.com
SAGE

Broadcasters and Hidden Influentials in Online Protest Diffusion

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Abstract

This article explores the growth of online mobilizations using data from the *indignados* (outraged) movement in Spain, which emerged under the influence of the revolution in Egypt and as a precursor to the global Occupy mobilizations. The data track Twitter activity around the protests that took place in May 2011, which led to the formation of camp sites in dozens of cities all over the country and massive daily demonstrations during the week prior to the elections of May 22. We reconstruct the network of tens of thousands of users and monitor their message activity for a month (April 25, 2011, to May 25, 2011). Using both the structure of the network and levels of activity in message exchange, we identify four types of users and analyze their role in the growth of the protest. Drawing from theories of online activism and research on information diffusion in networks, this article centers on the following two questions: How does protest information spread in online networks? And how do different actors contribute to the growth of activity? The article aims to inform the theoretical debate on whether digital technologies are changing the logic of collective action and to provide evidence of how new media facilitates the emergence of massive offline mobilizations.

Keywords

networks, information diffusion, protests, collective action, social media

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The year 2011 was punctuated by the emergence of protests in several countries around the world. The January uprisings in Tunisia were soon followed by social unrest in many other countries of the Middle East and North Africa (MENA) region, leading to the revolutions of Egypt and Libya and shaking the foundations of several other dictatorial regimes, a set of uprisings that has come to be known as the Arab Spring. This wave of dissent in authoritarian states soon extended to liberal democracies, with citizens in Spain, Greece, and Chile staging massive demonstrations against their political leaders; Israel protesters advocating for greater social justice; and U.S. demonstrators setting camp sites in the squares of several cities, following the original occupation of Zuccotti Park in New York. These mobilizations paved the way for the global Occupy movement that brought, toward the end of the year, thousands of protesters to the streets of hundreds of cities worldwide under the slogan "We are the 99%." In the process, protesters consolidated new tactics in the social movement repertoire, such as camping in public spaces and creating on-site media centers to use online networks for information diffusion.

The prominence of these events was epitomized by the decision of *Time* magazine to dedicate its 2011 Person of the Year issue to the protester. According to the editors, the word *protest* appeared in newspapers and online "exponentially more in 2011 than at any other time in history." Because the leadership of these movements came from the bottom up, not from the top of an organization, the editors chose the anonymous protester rather than a particular individual, highlighting the role that technology played as a crucial aide in the mobilizations: Internet-enabled forms of communication, claims the report, allowed people to watch what was happening in real time and helped spread "the virus of protest" (Stengel, 2011). Although online networks did not cause the movements, the report states, they kept them alive and connected.

This decision to nominate the anonymous protester as Person of the Year closes a cycle of news reporting where online technologies have been repeatedly identified as the backbone of the protests. Most news reports highlight the prominent role of social media in the emergence and the coordination of offline mobilizations, consolidating as conventional wisdom the idea that new media is inherently linked to social unrest and popularizing expressions such as "Facebook Revolution" and "Twitter Revolution" as shorthand for the uprisings. However, there are many open questions about how these and other online networks facilitate the emergence and diffusion of protests: How does information spread in online networks? How fast? Do online networks really promote a decentralized diffusion of information? And if not, who are the most influential users? Journalistic accounts of the protests provide valuable insights into the personal stories of the protagonists and the narratives of the events they contributed to trigger. But understanding how social media drives the emergence of collective action on a large scale requires going beyond the contingencies of each case to the general principles that drive those dynamics.

This article offers that type of analysis, providing an empirical examination of the diffusion mechanisms that drove online activity in one instance of mass mobilization: the protests that erupted in Spain in May of 2011. The study draws theoretical insights from previous research on networks and collective action, paying special attention to how new media has changed the costs of mobilization and coordination. Our analyses focus on the diffusion of protest activity through an online network (Twitter). The Spanish *indignados* movement offers a particularly good example of how online diffusion is often accompanied (and can even drive) the offline diffusion of behavior: The movement that mobilized tens of thousands of people arose from the fringes of online networks, and these networks also facilitated the coordination of the logistics involved in setting up camp sites in public spaces (Mackey, 2011; Minder, 2011). The main question we aim to answer with this research is, Who are the actors who led the diffusion of protest information? Or, put differently, can we identify gravity centers in the network that help explain how the movement grew?

Our main unit of analysis is the messages that protesters sent during the mobilizations. They allow us to determine the time when a given user joined the curve of protest growth (by contributing to the flow of messages) and how far the cascades of protest information went (in terms of number of users involved at any given time). Ours is a case study of information diffusion where information is broadly defined as any message related to the mobilizations. As explained below, we identify these messages using the metainformation that users themselves created to label the stream of protest-related content (in the form of *hashtags*). Our data contain information on several levels of analysis: We track activity at the individual and group level, identifying the position of users in the overall communication network; and we follow changes on those measures over time, using the time stamps of messages to reconstruct the longitudinal trail of events. The aim of analyzing these data is to shed novel light into the dynamics of protest diffusion and the self-organization of political movements.

The analysis of protest activity through the lens of diffusion links the study of collective action to broader studies of social influence and interdependence in networks, which are—we argue—better equipped to make sense of digital protests than classic approaches to the logic of collective action. Our analyses suggest that the growth of digitally born protests depends on the strategic deployment of preexisting networks and on the ability to capitalize on the visibility of the best-connected actors. Furthermore, our analyses suggest that some of the benefits of using communication networks derive from the cumulative effects brought about by chain reactions, which amplify the reach of messages and the size of audiences. The mechanics of this process are consistent with more generic principles of diffusion; the peculiarity of online protests is that they scale up faster (by exposing people to bursts of information within shorter time windows) and that they can adapt in a more responsive manner to shifting circumstances (such as a change of strategy in the response of authorities). The following two sections elaborate on the generic principles of collective action in networks, and the specificities of online communication, before moving to the details of the Spanish case.

Networks, Diffusion, and Collective Action

The analysis of collective action as a diffusion process shifts the focus of attention from the nature of social dilemmas, and the conditions in which they are solved, to the effects of interdependence in decision making. One of the key questions that has puzzled researchers for decades is what makes people contribute to the public good when, by virtue of being public, it can be enjoyed without having to contribute to its provision. The problem arises from the assumption that individuals are rational actors motivated by self-interest (Olson, 1965). Pondering the costs and benefits of participation, rational actors find strong incentives to free ride: They know they would be better off if the public good were produced, but they would rather have others make the effort to actually produce it. When everybody reasons along these lines, no public good is provided and everybody is worse off.

This social dilemma has received attention from a number of fronts (Downs, 1957; Hardin, 1982; Ostrom, 1990). In the study of social movements, the question is what makes people participate in protests and take part in the organization of collective demands when they could enjoy the benefits without having to sustain the efforts and invest the time. Something that the recent wave of mobilizations illustrates quite powerfully is that free riding does not always become the dominant strategy—but what explains participation when rational behavior works in the direction of defection?

Research considering the question of why people engage in collective action assumes a deviation from rationality and its predictions, such as acting under the effects of norms, group pressure, or social influence (Coleman, 1990; Elster, 1989). The assumption is that actors are not isolated decision makers but are instead embedded in networks of social interactions that allow the efficient enforcement of norms. Many models of diffusion rely on the effects of social influence: They are built on the premise that individual decisions are contingent on the decisions of others, which creates paths of influence through which behavior diffuses (Rogers, 2003). Networks shape choice by altering the probability that an actor will adopt a given practice; influence is one of the mechanisms through which these network effects take place, along with externalities and learning (DiMaggio & Garip, 2012). This focus on network effects relaxes rationality demands of classic approaches by assuming that actors learn through experience, "adapting their decisions in response to social feedback" (Macy, 1991, p. 731); and it is consistent with the importance of social norms: Individuals often respond to normative principles, such as fairness, for instance, when actors are willing to contribute only in proportion to what others are contributing (Gould, 1993, p. 183). Although networks do not solve the initial "volunteer's dilemma"—that is, who decides to take part first—they help spread participation by exposing individuals to examples of previous behavior.

The question that, according to this view, actors pose themselves is not whether it is beneficial to join a collective effort but whether it is efficient, which depends on how many other actors are already involved (Gould, 1993; Macy, 1991; Marwell & Prahl, 1988; Oliver & Marwell, 1988; Oliver, Marwell, & Teixeira, 1985). In most empirical settings, actors decide not in parallel but sequentially; this allows them to see how many others are contributing before deciding whether to contribute as well. Since actors are heterogeneous in their inclination to participate (they have different thresholds with respect to how many others need to be participating; see Granovetter, 1978, and Valente, 1996), sequential decisions allow actors who did not consider joining in a given time to join later, when their own critical mass has been reached. Collective action emerges out of the concatenation of these individual decisions: When a sufficiently large number of actors have been activated, the adoption curve crosses a point of no return and diffusion becomes self-sustaining (Schelling, 1978, chap. 3). Networks have a central role in defining when that critical point is reached.

The chain reactions activated by social influence reduce the need for selective incentives. Under the effects of social influence, collective action becomes more a process of contagion than of incentive design. This contagious dimension makes collective action similar to other diffusion processes (Young, 2003, 2009). Networks are crucial to understand those processes because they define the group of reference that individuals monitor prior to making a decision. Two actors with the same threshold might join the collective effort at different times if they are embedded in different personal networks (Valente, 1996; Watts & Dodds, 2010). Because of this, networks not only provide a structure of interdependence; some of their features, such as size, density, or centralization, also affect the speed and overall reach of chain reactions (Gould, 1993; Marwell & Prahl, 1988; Oliver & Marwell, 1988; Siegel, 2009). A minority of highly motivated actors is necessary to start the chains, but their position in the network, and the position of those to whom they are connected, is also relevant to understand the course of those chains—and ultimately the success or failure of the diffusion attempt. This leads back to the question motivating this article: Who are the actors who trigger the spread of protest information? And how does their success relate to the way in which they are embedded in online communication networks?

Empirical examples of how networks mediate diffusion dynamics include insurgencies, political demonstrations, the growth of unions, contentious action, and voting (Biggs, 2005; Gould, 1991; Hedström, 1994; Lohmann, 1994; Rolfe, 2010). These examples provide compelling evidence of the interdependence of individual decisions and discuss the importance of taking into account the structure of interactions of which individuals are part. The wave of protests that took place in 2011 provides an excellent empirical ground to assess these dynamics in the context of online mobilizations and, in the process, dissect the logic of collective action in the digital era.

The one common denominator connecting these recent protests (which, in all other respects, differ widely in the contingencies imposed by their local contexts) is that they emerged without the structure of formal organizations, which have often been the focus of network approaches to social movements (Baldassarri & Diani, 2007; Bearman & Everett, 1993; Wang & Soule, 2012). In the case of recent protests, large numbers of people were recruited and mobilized in a decentralized, horizontal way, using preexisting networks of communication that were not necessarily, or not exclusively, political. The leaders of the movement (the "initial volunteers") managed to seed those networks with protest messages that snowballed until they reached global proportions. But how did they manage to trigger that collective reaction? Or put differently, what were the conditions that, in hindsight, facilitated the growth of the movement from the original minority of leaders?

Classic approaches to collective action are in a bad position to answer these questions, first, because they are built on the assumption that the costs of participation give incentives to free ride when, in fact, digital technologies have reduced many of those costs to the point of rendering them negligible (Bimber, Flanagin, & Sthol, 2005; Earl & Kimport, 2011; Lupia & Sin, 2003); and, second, because they suggest that only formal organizations and interactions in small groups can dissuade free riding and enforce contributions, whereas recent events demonstrate that thousands of loosely connected individuals can coordinate their actions in the absence of formal structures or sanctions ("loosely connected" if one assumes that online networks offer a pale substitute for strong ties, as suggested by, for instance, Gladwell, 2010). The classic approach to collective action breaks actors off the social structures that contextualize their actions and obliterates the effects that social feedback and information dynamics, as channeled through those structures, have on their decisions.

A diffusion approach, by contrast, shifts attention from the individual to the group, that is, to the dynamics of a process that cannot be pinned down to any individual-level attribute or decision-making mechanism. Interdependence diffuses responsibility: Things turn out the way they do because of the cumulative effects piled up through networks rather than because of any individual decision taken along the way—hence the unpredictability of the outcomes and the necessity of hindsight to understand the way in which the process unfolded. The logic of these dynamics is unique not to the eruption of political protests (which have long been known to escape predictability) but to a wider range of examples where social systems self-organize without central planning or authority. An increasing body of research is using online interactions to analyze how networks mediate diffusion and the cascading effects of social influence; the following section reviews some of these recent contributions to contextualize the role that social media played in the recent wave of protests.

Social Influence and Diffusion in Online Networks

Two aspects of diffusion in networks are central to understand its dynamics: One is the structure of the network (that is, the paths for diffusion the network creates); the other is the relative position that leaders and followers occupy within that network (in other words, how those who trigger diffusion, and those who help disseminate it, are placed along the network paths). Research on online networks has accumulated fast during the past few years, identifying regularities that are relevant for the dynamics of diffusion (Easley & Kleinberg, 2010; Newman, 2010). We know, for instance, that most online networks have very skewed degree distributions, with a small percentage of nodes concentrating the vast majority of connections; and that there are higher levels of local clustering than one would expect by chance, brought about by transitivity or the tendency to forge connections with those already connected to neighbors. Two snapshots of the Facebook and Twitter networks show that these structural features bring about other network properties, such as close-to-full connectivity and a short distance between any two users: Even though these networks have millions of nodes, a random pair of users can be connected on average through no more than four to six intermediaries (Kwak, Lee, Park, & Moon, 2010; Ugander, Karrer, Backstrom, & Marlow, 2011). These platforms encourage different types of interactions (i.e., Twitter allows asymmetrical connections whereas Facebook, excluding the recent introduction of the "subscriptions" feature, is based on mutual connections), but they create structures of communication that share similar characteristics. The relevant question, if we are to understand the role that social media played in the recent wave of mobilizations, is: How do these structural features relate to the effervescence of activity that characterized the protests?

Research on the collective dynamics that take place on networks has established the importance of bridges (or the shortcuts that central actors create with their connections) and local clusters for a fast and efficient diffusion of information: Bridges facilitate global spread by connecting parts of the network that would be apart otherwise, and clusters encourage a fast local diffusion by making connections with neighbors redundant (Watts, 1999; Watts & Strogatz, 1998). Online networks exhibit these characteristics, which means that they can facilitate a fast and efficient diffusion of information. And yet the evidence suggests that long cascades, or the ability to spread information on a large scale, is the exception rather than the rule (Adar & Adamic, 2005; Bakshy, Hofman, Mason, & Watts, 2011; Bakshy, Karrer, & Adamic, 2009; Goel, Watts, & Goldstein, 2012; Leskovec, Adamic, & Huberman, 2007; Sun, Rosenn, Marlow, & Lento, 2009). The reason for this is twofold: First, for cascades to grow, actors still need to decide to pass the message along and overcome the resistance or indifference of their neighbors in the network; and second, cascades have less chances of success if they do not start rolling from the right place in the network, that is, from a junction of users and connections that can maximize the chances of reaching the spring for global growth.

So what are the most advantageous positions in online networks for diffusion seeds to succeed? Studies on offline diffusion have often concluded that more central actors or actors connected with equally central (or structurally equivalent) neighbors can be more consequential for diffusion processes because of the distribution channels that their local networks grant them (Burt, 1987; Iyengar, Van den Bulte, & Valente, 2011; Marwell & Prahl, 1988; Valente, 1996). Research on social movements has also highlighted the importance of network centrality to reach and mobilize resources that are essential for the success of a movement (Diani & McAdam, 2003). Costs are not as relevant online as they are offline, and classic resource mobilization theories are ill suited to explain most instances of online mobilizations (Earl & Kimport, 2011), but attention still matters, particularly when it comes to mobilizing people for a political cause; and attention is equally scarce in the realms of social media.

Research on online influentials has tried to find the actors with more chances of spurring global attention. Theoretical models suggest that there are two possibilities: Either there is a small subset of special individuals who can influence a disproportionate number of others, or influence derives from a critical mass of smaller people who, on the aggregate, will make chain reactions converge in global cascades (Watts & Dodds, 2007). Empirical studies of diffusion in Facebook and Twitter suggest that it is the latter that applies in most cases or at least that influence takes place in the immediate neighborhood of average users (Bakshy et al., 2011; Cha, Haddadi, Benevenuto, & Gummadi, 2010; Sun et al., 2009). This line of research aims to test the claim, assumed in many diffusion studies, that local, peer-to-peer influence is more relevant for diffusion than common exposure to global information, but the fact is that both are likely to exert an influence on behavior (Onnela & Reed-Tsochas, 2010). In the context of political protests, mass media offers access to that global source of information.

The common assumption in most accounts of the 2011 protests is that they were driven by online communication; however, big media outlets, such as Al Jazeera, the BBC, or CNN, were also covering the events and sending signals in parallel to those transmitted through online networks. There is evidence of past riots and protest waves that underscores the importance of mass media for the diffusion of protests (Myers, 2000). Disentangling the effects of these exogenous forces vis-à-vis peer effects in networks is one of the greatest methodological challenges in social influence research (Aral, 2011). And yet, social media has added a new element in the way mass media interacts with diffusion networks: It is not only an exogenous source of global influence but also an active part of the network itself. Analyses of Twitter reveal that broadcasters and news organizations are core to the way in which information flows online (Cha, Benevenuto, Haddadi, & Gummadi, 2012; Wu, Hofman, Mason, & Watts, 2011). This brings the discussion back to the original questions: Who are the actors who led the diffusion of protest information and the growth of the movement? Are news organizations and broadcasters as relevant as diffusion studies in online networks suggest? And if so, what does this say about the role that online networks play in the organization of collective action? The protests that emerged in Spain in 2011 give us the empirical setting to answer these questions.

The Spanish Case in the 2011 Wave of Protests

The Spanish *indignados* (outraged) movement is a step in the sequence of events that went from the Arab Spring in the MENA region at the beginning of 2011 to the global Occupy movement toward the end of the year. The movement emerged as a civic initiative with no party or union affiliation that protested against political alienation and demanded better channels for democratic participation. The first big demonstration took place on May 15, and it was organized by the digitally coordinated platform Democracia Real Ya (Real Democracy Now), a web-based initiative created about 3 months before the first demonstration day to gain support for the protests. Hundreds of entities joined the platform, from local associations to territorial delegations of groups such as ATTAC (an international antiglobalization organization) or Ecologists in Action. Signatories of the original call included student associations, bloggers, and people from the arts but also hundreds of individual citizens of different ages and ideologies. The motto of the movement was “Take the streets”; other slogans included “We are not goods in the hands of politicians and bankers” and “We don’t pay [for] this crisis.”

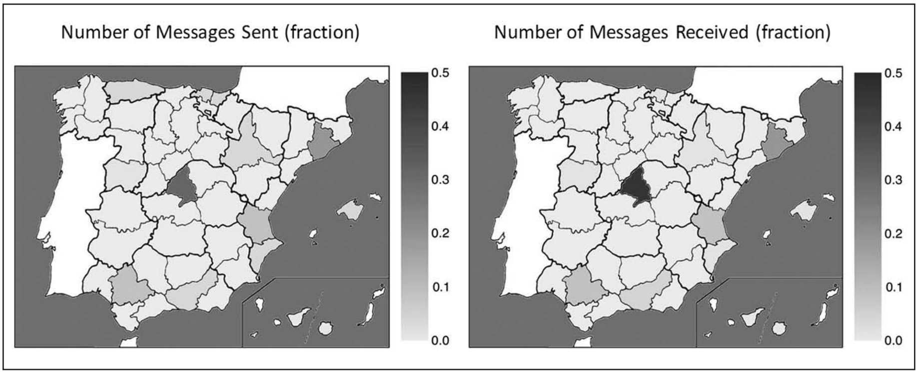

Figure 1. Geographical distribution of the protests.
Note: The maps are based on profile location information. See Data and Method for further details on data and collection method.

The protests of May 15 brought tens of thousands of people to the streets of more than 50 cities all over the country. Figure 1 gives a snapshot of the online (Twitter) activity generated by users in different regions of Spain: The most active cities were, in order, Madrid, Barcelona, Seville and Valencia, in terms of number of protest messages both emitted and received. After the march, some demonstrators decided to continue the protests by camping on the squares of the main cities until the following Sunday, May 22, the date for regional and local elections. During that week, the authorities tried to evict camped protesters by force, and the Electoral Committee declared the protests illegal, but these events only increased the media visibility of the movement and boosted popular support. After the elections, the movement remained active, organizing another big demonstration later in the year, on October 15, 2011, and more recently on May 13, 2012, to celebrate its first anniversary, this time part of the global Occupy movement and under the motto "United for Global Change."

The Spanish protests were greatly inspired by the Arab Spring. In the words of one of the protesters,

> after seeing what happened in the Arab countries, you ask yourself, why not here? If they can do it there, where things are so much worse, don't we, with our supposed democracy, have a responsibility to try to make things better as well? (Andersen, 2011)

The Spanish protests inspired, in turn, subsequent mobilizations in Greece and Chile and the Occupy movement originating in New York, soon replicated in other cities. In the process, strategies and tactics were exchanged through online networks (Andersen, 2011). This suggests that there was a spatial diffusion driven by overlapping channels of communication that spanned geographical borders. However, within each country, there were also large volumes of online activity that allowed each of these instances of mobilization to brew and ultimately explode. By focusing on one of these local networks, the Spanish movement, we aim to open an avenue for research that can ultimately be expanded to understand the global patterns of diffusion of which the Spanish experience offers just one case.

The analyses that follow center on two main questions: How did protest messages diffuse in the population of online users who were mobilized? And who were the most prominent actors in that diffusion? In the light of the discussion held in the previous section, there are two aspects that are important to understand the growth of this movement: One is the structure of the communication network (and the position that different actors have within that structure); the second is the type of chain reactions triggered by protest messages (or how long the trail runs when different actors start those chains). In line with previous research, there are three possible explanations behind the success of this movement: One is that better connected users, that is, the broadcasters or celebrities acting as the hubs of the network, led the diffusion process, triggering a snowball effect that quickly reached global proportions thanks to their larger personal networks; another is that the movement grew out of numerous focuses of action, started by random users, that expanded through smaller local networks to ultimately converge on a global cascade; and a third explanation—which our analyses support—is that the movement benefited from a mixture of these two dynamics, creating synergies between the minority of hubs and the majority of common or grassroots users. The following section introduces the data collected to examine these alternative explanations and gives details of the way in which we measured cascades and reconstructed networks.

Data and Method

Our data consist of Twitter activity around the protests for the period April 25 to May 25. This observation window goes back a few weeks before the first big mass demonstrations, which allows tracking of online activity before the movement became visible in mainstream media. The method to monitor Twitter activity around the protests was applied in two stages. First, we selected hashtags that were relevant to the protests, coming up with a list of 70 keywords. Figure 2 shows the most prominent tags in terms of frequency of use prior and after the demonstration of May 15. The size of each tag is proportional to the number of messages (in the log scale) that used it on a given day, so sizes along the timeline cannot be directly compared, but they help assess how different issues rose in salience as the movement progressed, giving some exploratory insights into how protesters framed their actions during the phases of emergence and growth. Before "15-M" (used as shorthand for the *indignados* movement), most protest messages are tagged with a reference to the demonstration (*15m; tomalacalle*, or "take the streets"), the online platform promoting it (*democraciarealya*, or "real democracy now"), and the main message of the protest, which in this case was to the demand for new forms of democratic representation (*nolesvotes*, or "don't vote for them"). On May 15, the day of the first mass demonstrations, other hashtags gained prominence: *spanishrevolution, acampadasol, acampadabcn, acampadasevilla*, and

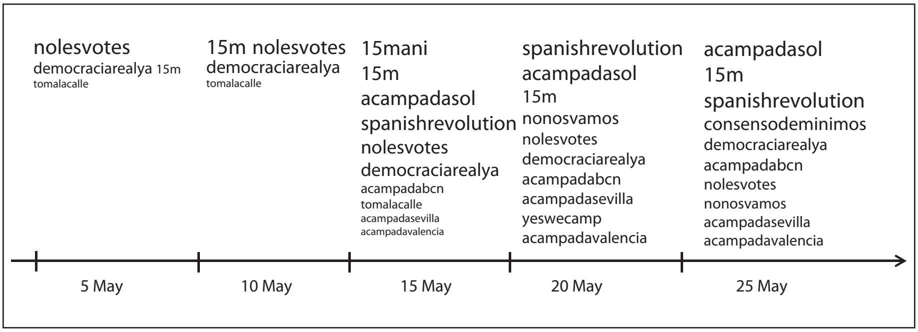

Figure 2. Most popular hashtags before and after the first demonstration day (in bold).
Note: The size of each tag is proportional to the number of messages (logged) that used it on a given day. Sizes cannot be directly compared along the timeline, but they help assess the salience of different issues as the movement grew (see main text for translations and further explanation).

acampadavalencia (the last four as an explicit reference to the camps set up in Madrid, Barcelona, Seville, and Valencia, respectively). Other tags (*nonosvamos*, or "we don't leave," and *yeswecamp*) emerged later as a response to authorities' attempts to evict the squares. Toward the end of the observation window, when the elections had already taken place, new hashtags (i.e., *consensodemininos*, or "minimum consensus") signal the evolution of the movement into a new, more deliberative stage.

We collected messages that used any of the hashtags included in our list, with the constraints that we archived only messages written in Spanish and sent from Spanish territory. Using publicly available data on aggregated volume of activity, we estimate that our sample captures about a third of the total number of tweets related to the protests, amounting to a total of more than half a million messages. The second stage of data collection used those messages to reconstruct the network of users involved in the mobilization. We used the IDs (i.e., unique identifiers) of the authors of the messages as the starting point of a crawl that applied a one-step snowball sampling procedure, which allowed us to identify their network neighbors (users following or being followed). More details of data collection can be found in these related articles (Borge-Holthoefer et al., 2011; González-Bailón, Borge-Holthoefer, Rivero, & Moreno, 2011).

With this information, we reconstructed two types of networks. The first is the baseline *following-follower network*, which creates the basic infrastructure for information flow and on which traditional measures of influential users have often been calculated (i.e., Cha et al., 2010). The hubs in these networks are users who accumulate a disproportionate number of followers. The second network is formed by the more direct communication channels that users create by mentioning, or targeting, other users in their messages. We reconstructed this network using the subset of messages that, in addition to protest hashtags, also used the @ symbol followed by a handle to identify other users. The following-follower network creates possible

Table 1. Network Statistics for the Following-Follower and Mentions Network.

Variable	Following-Follower Network	Mentions Network
N (number of nodes)	87,569	87,569
M (number of arcs)	6,030,459	206,592
$<k>$ (average degree)	69	2.36
max(k_{in}) (maximum indegree)	5,773	29,155
max(k_{out}) (maximum outdegree)	31,798	289
C (clustering)	0.22	0.034
l (average path length)	3.24	1.7

channels for information flow, but the *mentions network* is based on actual instances of communication—the difference between both is important because not all existing connections serve as channels for diffusion, and users who are prominent in one information domain might not necessarily be prominent in another.

Table 1 gives a summary of the structural properties of these two networks. Overall, the characteristics of the following-follower network fall in line with what has been found in other online networks and, more specifically, in larger samples of Twitter (Kwak et al., 2010): It is locally clustered, the degree distribution is right skewed, and the minority of disproportionately connected users keep the network small (in terms of path length or average distance between any two nodes). The mentions network is much sparser because only a fraction of the users we tracked engaged in direct communication with each other, and it has significantly lower levels of clustering, but it is also skewed in the number of mentions users receive: Some of them are disproportionately more visible.

In addition to the networks, we also reconstructed information cascades using the structure of the following-follower network and the time stamps of the messages sent. Our data set does not keep track of the messages that were retweeted, so we could not reconstruct information cascades following the method employed by previous research (Bakshy et al., 2011; Cha et al., 2010; Liben-Nowell & Kleinberg, 2008). Instead, we followed a different approach based on the assumption that messages that are sent within short time spans are part of the same chain. We followed this logic: For any given user that acts as a seed, there is a neighborhood of followers that act as the audience; of these, some will send a message shortly after being exposed to the original message and expose in turn their own neighbors in the network; shortly after, some of these neighbors will send a message as well, exposing their immediate audience, and so on. The size of the cascade is computed as the sum of all nodes that are part of the direct audience of messages sent, that is, the sum of all neighbors directly connected to users who spread information; where nodes are connected to two or more spreaders, they are counted only once. This applies to all protest messages, regardless of the hashtags used.

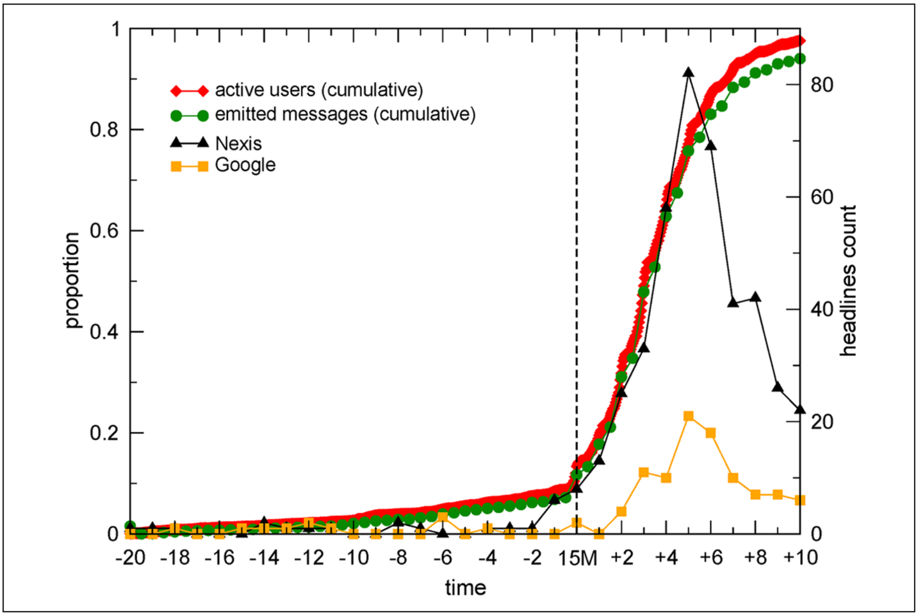

Figure 3. Online growth of the movement and offline media coverage.

There are two crucial decisions in this reconstruction of cascades: One is who sends the original message (or how we determine who acts as the seed and who counts as part of thein spite of the old reservations chain); the second is the width of the time window used to decide when to stop counting nodes toward the same chain. The final calculation of cascade sizes are averages of several setups that make the measurement robust to different seeds and to different time windows (more details can be found in Borge-Holthoefer, Rivero, & Moreno, 2012). For the purposes of the analyses below, we used a time window equal to 1 hr. This method does not guarantee that the chains are diffusing the same message, but to the extent that all messages are related to the same event, we can interpret these cascades as bursts of activity directly relevant to the protests and the growth of the movement.

Overall, these data track a substantive volume of online activity around the protests, but they inevitably account for only one part of the story: This mobilization had a very strong presence in the streets and high visibility in mainstream media, particularly after protesters decided to set up camps prior to Election Day. Since we are analyzing only what happened in an online network, we are missing many channels for diffusion, for instance, those opened by offline networks or exposure to mass media. However, to the extent that the platform behind the movement (Real Democracy Now) was born online, our data allow us to analyze its origins before it got the overwhelming attention of mass media. As a way of contextualizing online activity within the focus of offline news coverage, Figure 3 displays the chronological growth of the movement as measured by number of active users and protest messages (left axis) compared to the number of headlines in traditional newspapers mentioning the protests (right axis). Media coverage was assessed by querying the database Nexis and Google News for headlines in Spanish for three main keywords linked to the protests (*15-M* or *indignados* or *Democracia Real*). The number of users and emitted messages are expressed as proportions and in cumulative form to highlight that the growth of protests follows the traditional *S*-shaped curve of diffusion dynamics. By the first big day of demonstrations, about 10% of users (or 9,000 nodes in the network) had sent at least one protest message, but the protests had received scarce media attention compared to what followed after the protesters were already on the streets.

Analyses

The platform behind these protests was born online as a virtual assembly of otherwise dispersed actors and organizations. Our question is how their message was diffused to the larger population and whether and how online networks helped in that diffusion. As explained above, we pay attention to both the structure of the Twitter network and to the dynamics of message exchange this network facilitated. The former creates the possibility of communication; the latter offers a direct assessment of explicit exchange in the context of these mobilizations. Following the discussion of previous studies on diffusion in online networks, the structural position of actors can be used to assess their influence or, at least, their prominence in global trends of information diffusion. Most of these previous studies focus on the number of followers, retweets, or mentions that users get to rank them in the influential scale and then identify cutoff points in those ranks to classify users (see, for instance, Cha et al., 2012). These cutoff points are, however, somehow arbitrary, and the categories they create do not help discriminate between a user's potential to disseminate information and the user's actual influence in that process.

We propose using the network of targeted messages in conjunction with the underlying network of communication to create a typology of users that can help us make that distinction and identify who was more relevant in the growth of this political mobilization. The assumption is that influence is domain specific and that a mere approach to the network structure of Twitter is not informative enough to determine who is more consequential in this particular context. The following-follower network offers the potential for diffusion; our question is how that potential is realized.

The scatterplot in Figure 4 summarizes that typology. Both axes are expressed as ratios so that it is easier to identify outliers. The vertical axis tracks the number of protest messages that users received by the number of protest messages they sent; the most visible users (those who were mentioned more often) are above the dashed line. The horizontal axis tracks the number of other accounts a user is following by the number of followers the user has; the most central and popular users in this baseline network are on the left of the dashed line. Again, users who are central in the overall communication network are not necessarily the most visible users in the stream of

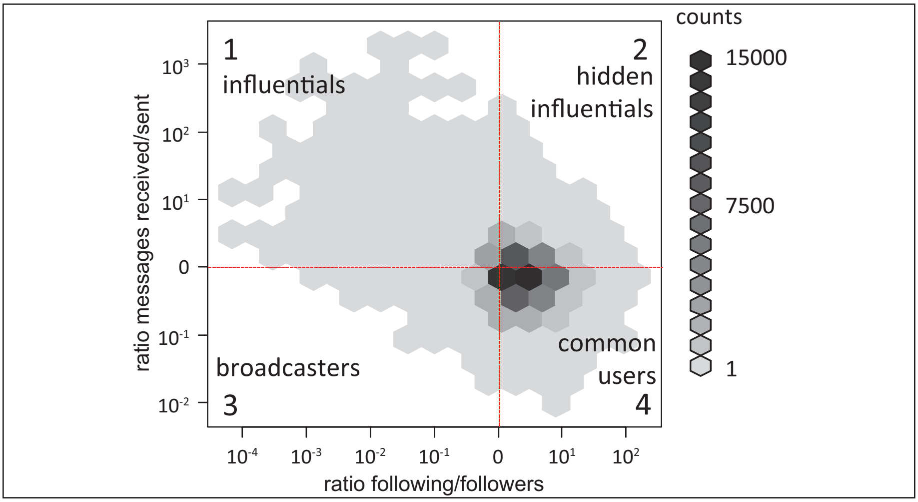

Figure 4. Distribution of users according to network position and message activity.

protest information flow. Comparing these two distributions helps us identify who these users are.

The color of bins is proportional to the number of users who fall in the binned area. What the scatterplot shows is that most users active in these protests receive roughly the same number of messages that they send, and they have roughly the same number of followers that they follow (although their networks tend to be asymmetrical in favor of hubs or celebrities). This larger group of users falls around the intersection of the dashed lines. The second thing the scatterplot shows is that hubs receive more targeted messages than normal users; most of the activity goes toward celebrity accounts, identified in Quadrant 1. We call these users "influentials" (n = 4,048) not only because they are central in the overall communication network (following the standard in previous research) but also because they are prominent targets in the domain-specific communication exchange of protest messages: Other users direct their tweets to them in the hope, we assume, that they will pass them on and help them reach a larger number of people. Since the number of followers any user has is, by default, public information in Twitter, it is relatively easy to assess the impact that some users may have if they decide to pass a message along or if messages are displayed in their feeds.

However, global visibility is not enough to make some users the preferred target of protest messages, a fact that is illustrated by the amount of users who fall into Quadrants 2 and 3. Users in Quadrant 3 (n = 3,309) also have a more-central-than-average position in the following-follower network but are more prominent at sending messages than at receiving them. Their network positions grant them larger audiences, and they can potentially influence a larger number of users (hence our decision to call them "broadcasters"), but they are not deemed the most influential actors by other participants in the protests. By contrast, users located in Quadrant 2 (n = 8,472) do not have

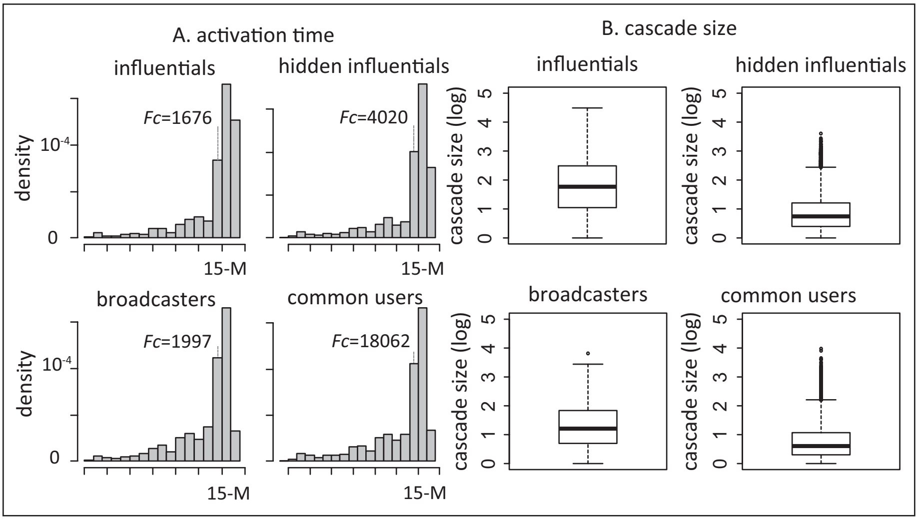

Figure 5. Distribution of activation time and cascade sizes.

network positions that would a priori identify them as globally visible, and yet they are very prominent in the context of this mobilization. They are the explicit target of more protest messages than the average user. This is why we call them "hidden influentials": They are at the center of this flow of information, but they are at the margins of the underlying communication network.

The largest set of users (n = 30,173) falls into Quadrant 4. They send more messages than they receive and have relatively smaller audiences. They are the "common users" or grassroots activists that contributed the gross of the activity to the protests without standing out. The question is, were these users more important for the diffusion of information, or did the protests grow because of the minority of influential people? As expected, users in the top ranks of network centrality and message visibility are celebrities or established news organizations. However, some accounts created as part of the protests, for instance, *acampadasol* (which refers to the camp set up by protesters in the main square of Madrid, the epicenter of the movement), also made it to the top ranks of visibility in terms of both number of followers and targeted messages, and most accounts created to promote the protests (within the hidden-influentials category) jumped in a matter of days from none to global visibility in this flow of information. Who pushed them there?

Figure 5, Panel A, shows the histograms of activation times for each of the four types of users we identify. We define activation time as the moment when a user sent his or her first protest message. To ease comparison, the vertical axes are expressed as densities. The comparison of activation times across types of users suggests that most of them, regardless of their position in the network, joined en masse the mobilization around the same time, that is, during or immediately after May 15. However, a disproportionate fraction of the users who were active prior to that day (when the protests were mostly invisible in traditional mass media) came from the echelons of common or grassroots accounts, as the cumulative frequencies annotated in the histograms indicate. The distributions of cascade sizes initiated by each of these types of users are shown in Panel B. As explained in the previous section, the assumption behind our reconstruction of cascades is that users are more likely to send a message if they are exposed to protest activity through their network neighbors. This form of influence activates a chain reaction that might unfold to ultimately reach a large number of people. The length of all the chains initiated by each type of user is summarized by the box plots in the figure.

On average, influential users triggered the largest cascades, followed by broadcasters—that is, the two groups with more central positions in the network, as defined by number of followers. Common users are less successful in starting long chain reactions, but they have the power of numbers. For purely statistical reasons, more trials means more chances of success, and in some instances (the outliers depicted in the upper region of the box plots), they were at the starting point of cascades as large as those initiated by influential users.

These differences in cascade sizes explain why influentials are such a prominent target for message exchange: It makes strategic sense to try to trigger their reaction because they can make the message reach a large number of people and potentially motivate them to join the movement as well. What this means is that, echoing the basic argument of resource mobilization theories, protesters also try to mobilize resources in online networks, where resources take the form of access to a wider audience. Hidden influentials give the movement identity and framing (hence their visibility in the exchange of protest messages), and influentials help project their message; in other words, protesters employ online networks both to frame the movement and to maximize outreach. But it would be misleading to identify a single group responsible for the explosion of activity. Instead, our data suggest that this protest managed to mobilize so many people in such a short time span because of the reinforcing interactions between opinion leaders and grassroots users and because of the constant information transfer between the periphery and the core of the network.

Discussion

This article departed from the puzzle that digital activism has created for social movement researchers. New forms of political mobilization, channeled and coordinated by means of online networks, do not conform to traditional models of collective action. The costs of participation are not as relevant online, and copresence is no longer necessary to activate the wheels of protest (Earl & Kimport, 2011). Because of this, the mechanisms to restrain selfish rationality and to encourage participation (e.g., selective incentives and reputation in small groups) lose their explanatory power. We argued that a better approach to understand how those movements come to be is to focus on group dynamics and on the chain reactions that network effects generate.

Although our data do not help us discriminate the actual mechanism underlying those chain reactions (or unmistakably pin down social influence), we could still analyze diffusion dynamics and track the origins of the most successful chains. We found that, on average, users who are more central in the network (celebrities and broadcasters) are more likely to start long cascades of information. However, we also found that grassroots or common users provide the disproportionate majority of early protesters; by the time the protests exploded in the streets, there were about 10 times more active users in this group than users classified as influential. Most common users were unsuccessful at triggering global cascades, but the sheer number of them means that sometimes they managed to activate reactions that reached as many people as the minority of influentials.

These findings demystify two common assumptions about online networks: that they are horizontal structures and that they are very good at diffusing information. Although online networks such as the one we analyze here are horizontal in the sense that there are no formal organizations coordinating the protests in a centralized, top-down fashion, our analyses suggest that the actual structure of communication on which protesters rely is very centralized and hierarchical. This is not surprising, given previous research on digital networks, but it qualifies metaphorical uses of network talk, abundant in recent literature on digital protests. Our analyses also show that online networks can be very efficient when diffusing information, but they do not always serve that purpose as efficiently as they could, not even in the context of collective effervescence created by political protests. Again, this is not surprising; research on information cascades in online networks shows that diffusing information on a global scale is the lucky exception (Goel et al., 2012). We find that this is also the case in the unusual context of massive mobilizations.

One immediate conclusion of these findings is that research on digital movements can benefit greatly from the larger body of work on diffusion in online networks, which provides the tools and evidence to understand the dynamics and mechanics of online collective action. Another conclusion is that more research is needed on diffusion dynamics, especially to test whether the same mechanisms apply in different information domains. Political protests are effervescent by nature, and it remains to be seen whether the same dynamics apply when the information diffused is of a different nature, as already suggested by recent research (Romero, Meeder, & Kleinberg, 2011). Finally, more work is also needed to determine how traditional media affects the process in its dual role of exogenous source information and active part of online networks. Previous research on the blogosphere suggests that traditional media still dominates information diffusion (Leskovec, Backstrom, & Kleinberg, 2009). Although our analyses suggest that this was not the case in the context of these protests, more detailed analyses would be needed to determine who led information flows.

A very significant finding of our analysis is that accounts such as *acampadasol* (the tag labeling activity at the epicenter of the protests) managed to gain global significance only a few weeks after it was brought into existence and to compete with prominent media outlets in terms of centrality and visibility. The fact that an account created by protesters gets so prominent in a matter of days provides evidence of the extent to which online networks can help challenge the competitive advantage of traditional players. The chances of unknown actors to be projected to the spotlight of global visibility are slim, but this exceptionality highlights a central property of the protests we analyze here and, by extension, of those that rolled all over the world during 2011: that they are built on an unlikely alignment of circumstances, and it is this uniqueness that grants them political power.

Overall, this study sees collective action as a diffusion process driven by two main factors: the number of people who already joined the process and the exposure of actors who did not yet join to those already participating. To the extent that networks define that exposure, they offer the key to understand the emergence of collective action. Online networks are not unique in facilitating this process, but they can be more efficient than their offline counterparts. At the very least, they generate the data to, in hindsight, trace back how networks help a movement grow out of nowhere and shed light onto why, in spite of the reservations of some (Gladwell, 2010), the revolution was indeed tweeted only a few months down the line. How general the mechanisms we identify here are to other instances of dissent is, however, a question that will require further research.

Acknowledgement

We thank Cristina Viñas and Alejandro Rivero for their help in preparing the data and the three anonymous reviewers for their insightful comments.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was partly supported by the John Fell OUP Research Fund (Project 102/671), the Spanish MICINN (Projects CSO2009-09890, CSD2010-00034, and FIS2011-25167), and the government of Aragon (DGA) through a project to the research group FENOL.

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