One-step, two-step, network-step?

Complementary perspectives on communication flows in Twittered citizen protests

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Abstract

The article analyzes the nature of communication flows during social conflicts via the digital platform Twitter. We gathered over 150,000 Tweets from citizen protests for nine environmental social movements in Chile, and use a mixed-methods approach to show that longstanding paradigms for social mobilization and participation are neither replicated nor replaced, but reshaped. In digital platforms, long standing communication theories, like the 1955 two-step flow model, are still valid, while direct one-step flows and more complex network flows are also present. For example, we show that it is no contradiction that participants mainly refer to intermediating amplifiers (39 % of the mentions from participants go through this two-step flow), while at the same time traditional media outlets and official protest voices receive 80-90 % of their mentions directly through a direct one-step flow from the same participants. While non-intuitive at first sight, Bayes' theorem allows to detangle the different perspectives in the arising communication channel. We identify the strategic importance of a group of amplifying intermediaries in local positions of the networks, who coexist with specialized voices and professional media outlets at the center of the global network. We also show that direct personalized messages represent merely 20 % of the total communication. This shows that the fine-grained digital footprint from social media enable us to go beyond simplistic views of a single all-encompassing step-flow model for social communication. The resulting research agenda builds on longstanding theories with a new set of tools.

Keywords: two-step flow; Twitter; social movement; protest; big data; Bayes' theorem.

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This study uses the digital footprint of digital social media to contribute to the currently revived discussion about step-flow models in communication networks, with a focus on social movements and citizen protests. One of the most well-known theories of social communication, media effects and personal influence is the six decade old "two-step flow model of communication" by Katz and Lazarsfeld (1955). It identified communication flows in two steps, from mass media over opinion leaders to audiences. Initially, the model was set up as a counter-theory to reject what is known as the so-called hypodermic needle model or magic bullet theory, which holds that media messages are directly received and consumed by audiences (e.g. Lasswell, 1938; Horkheimer and Adorno, 1944). Developments in digital communication networks have led authors to revive this older model, which is nowadays known as "one-step flow of communication" (Bennett and Manheim, 2006). At the same time, others have suggested and identified different models of communication in digital media (e.g. Stansberry, 2012; Smith et al., 2014; Feng, 2016). This article article contributes to the ongoing discussion about communication flows in digital media by analyzing 150,000 Tweets from citizen protests for nine environmental social movements in Chile.

Introduction

Based on previous work by Lazarsfeld (Lazarsfeld, 1940; Lazarsfeld, Berelson, and Gaudet 1944), it was the much renowned chapter XIV (starting at the unsuspicious page 309) of their 1955 book on *Personal Influence* that sparked a discussion that has spanned generations of scholars. The two-step flow proposed that ideas flow from mass media to opinion leaders first, who put them into context, and from them to a wider population. As soon as two years later, the very same Elihu Katz observed that "opinion leaders themselves often reported that their own decisions were influenced by still other people", which we dubbed "opinion leaders of opinion leaders" (Katz, 1957; p.68). There seemed to be more to it than two straightforward steps. The ensuing decades since then saw a myriad of empirical tests and theoretical discussions (Stansberry, 2012), which might be best summarized by the term "multi-step flow models" with many different flow directions and iterations (e.g. Weimann, 1982; Iyengar, 1994; Turow, 1997). As a result of the data scarcity in the social sciences at the time and the unfathomable complexity of possible flow combinations, no clear understanding could be obtained. Instead, scholars rather pursued parts of the picture separately. It was suggested that there are "two distinct patterns of mass media and interpersonal influence at work" (Robinson, 1976; p. 304), which resulted in two largely separate bodies of studies in mass-communication and interpersonal communication (Rogers, 1999). By the end of the century, the emerging science of social networks contributed an entire new dimension of analytical tools and conceptual language, which significantly increased the complexity of the related discussion by quantifying the roles of "opinion leaders", "opinion brokers", and "network entrepreneurs in social capital research" (Burt, 1999; p.37).

Between Confusion, Resignation and Complexity

More recently, it seems that this collective intellectual *tour de force* came back full circle, proposing a return to a model of "one-step flow of communication" (Bennett and Manheim, 2006). The difference to the original hypodermic needle model lies in the increased fragmentation, differentiation, and message targeting technologies of the digital age allows spinning refined messages targeted directly at specific audiences. The result is a direct message that already contains the required context, and therefore can readily be consumed and mobilize citizens to take action (political or otherwise). The social media revolution of Web 2.0 (O'Reilly, 2005; Kelly, 2011) combined with the phenomena of big data (Mayer-Schönberger and Cukier, 2013; Hilbert, 2015) has resulted in practical applications of mass-customization and micro-targeting. The driver are "massive databases aimed at identifying and characterizing individual members of the mass audience and at delivering messages directly to these individuals through the most efficient and narrowest possible channel" (Bennett and Manheim, 2006; p.215-216).

On the one hand, the fact that an increasing number of people receive their news directly from social networks such as Facebook and Twitter (Kwak et al., 2010; Mitchell et al., 2011) has been taken as evidence for real-world effectiveness of data-mining informed context provision. On the other hand, empirical research on social media found evidence for a clear two-step flow structure, for example in Twitter networks (Choi, 2014). Again other studies of online communities started to question the basic assumption that information still originates in the media in the digital age. For example, Stansberry (2012) found that "a core group of primary influencers who act as conduits within the network are more influential in developing shared attitudes and cognitions among members of active publics online than traditional mass media sources are". The result is a star-shaped communication structure with core influencers in the center surrounded by other types, which she calls radial model of communication. Going firther, Feng (2016) creates a series of new types of communicators, which results in an intricate multistep model, including influencer, active engager, and information bridge. All of this suggest a new mix of old ideas, as it for example revives Katz' (1957) idea of "opinion leaders of opinion leaders", who use digital channels to side-step media outlets, which results in a mixed model between direct communication with audiences and with other intermediaries.

The Silver Lining: The Digital Footprint of Online Platforms

In short, the discussion seems to have gone almost in full circle and we are currently not much more along than we were when we started this journey six decades ago. Shedding light on this questions on how digital platforms matter not only for marketing companies, who currently do not have "effective metrics for deciding who are the most influential players" (Gillin, 2008; p. 16), but also for other forms of social communication. Questions of political mobilization, engagement and participation hinge on the underlying communication flows. Are citizen movements driven by the instigation of mass-customized personalized messages from particularly vocal actors? Do intermediators mobilize the masses by putting messages into the required context? If so, do they take those messages from traditional media outlets, leading voices, or from a wide choice of participants in a decentralized fashion? Or is intermediation following a more intricate network logic, where context is an emergent phenomena that arises as a result of a back and forth between different intermediators?

The current silver lining to the clouds of these questions is that this time technological change is not only the catalyst for a change in the intermediation of social communication patterns, but will also help us to understand it better. Every digital communication inevitably leaves a digital footprint which can potentially be used to study the underlying network structure (Manyika et al., 2011; Mayer-Schönberger and Cukier, 2013; Hilbert, 2015). This digital footprint provides vast amounts of empirical evidence that can be analyzed. A natural choice of method to analyze the digital footprint of social media seems to be social network analysis (in the sense of Monge and Contractor, 2003; Easley and Kleinberg, 2010; Barnett, 2011; Hanneman and Riddle, 2015). This is because "opinion leadership is not a trait which some people have and others do not, but rather… an integral part of the give-and-take of… potential networks of communication" (Katz and Lazarsfeld, 1955; p. 33). In this article we use the digital footprint left behind by 108,618 messages sent through the micro-blogging social network Twitter during a period of 6 months in 2014. The database consists of 9 separate cases of environmental protests in Chile. Use use social network analysis and create a summarizing picture of the existing communication channel between different kinds of communicators in the network.

Social Media Citizen Protests in Chile

During recent years, there have been growing discussions of internet activism and how social media have been used effectively by a variety of social movements (Harlow & Harp, 2012; Kahn & Kellner, 2004). This approach has considered the Internet as a tool for greater public participation (Harp, Bachmann, & Guo, 2012), arguing that Internet use leads to increased interpersonal communication about political issues (Shah et al., 2005; Sotirovic & McLeod, 2001). While Web 1.0 was more similar to traditional mass media in the sense that there were few content provider, Web 2.0 provided social media services in which every individuals could easily become content provider themselves. Existent research has mainly given two reasons to explain why social media may be strengthening activism (Harlow & Harp, 2012; Karpf, 2010; Reber & Kim, 2006; Wall, 2007). First, scholars argue that the use of social media is helping social movements to publicize local causes to distant audiences at low cost. And second, through these new tools activists can improve their logistical communication to organize more and better protests on the ground. The idea of the so-called "Twitter revolution" has become a much studied phenomenon (e.g. Morozov, 2009; Lotan et al., 2011).

Case Study

In Latin America, online social networking services are particularly popular. The region represents less than 8 % of global internet users, while it for example represents 12 % of the world's Twitter users. Chile in particular has the world's 6^{th} highest per capita usage of Twitter worldwide in 2013 (after Kuwait, Netherlands, Brunei, UK, USA; Mocanu et al., 2013). Additionally, in contrast with social movements in North America and Europe, public protest in Chile has been quite successful at accomplishing legal and policy changes (Valenzuela, Arriagada & Schermann, 2014). Both of these facts make Chile a particularly interesting case study.

One subject that has been specifically sensitive to its citizens is the environmental awareness and the moral fight against major energy projects that can put in jeopardy the country's natural ecological equilibrium. Scholars have considered the August 2010 protest against the Barrancones power plant as the turning point in that sense (García & Torres, 2011; Valenzuela et al. 2012). García and Torres (2011) explain that in the two days following the environmental agency's approval of the project, 118 Facebook Groups against Barrancones were created, which together garnered more than 25,700 'Likes' and 177,450 'Fans'. At the same time, 3,000-plus citizens — coordinated via Facebook and Twitter—marched to the presidential palace in Santiago, demanding the President to fulfill his campaign promise to build no power plants in environmentally sensitive areas. The next day the President announced that he had overridden the agency's approval and personally asked the company to relocate the plant (Valenzuela et al., 2012). The ensuing year, green movements mobilized against a planned power plant in Chilean Patagonia, HidroAysén, through large street demonstrations in Santiago. Social media played a pivotal role in the organization of collective action in response to this project that meant flooding nearly 6,000 hectares in Patagonia (Scherman, Arriagada, & Valenzuela, 2015).

Data Collection

After observing the major environmental projects in Chile during 2013, we decided to select nine environmental conflicts that presented the highest movement in Twitter based on the number of tweets observed. The selected conflicts included protests against the installation of hydro power plants, mining and thermal power plants, and included discussions as diverse as the protection of flora and fauna, contamination, and employment effects. During January and February 2014 we revised the most relevant words associated with each conflict based on: geographic location (e.g. "Patagonia"), type of project (e.g. "Central termoeléctrica"), issues raised by activists (e.g. glazers), authorities involved and main actors. These words were combined to be used as input keys, to set up the platform Analitic.cl to retrieve text based on Twitter API.[1] We collected messages for 6 months, between 15 February and 14 August 2014.

We chose the conflicts to be in various stages of their life-cycle: movements “in crisis” consisted of initiatives in current development that face high active opposition. “Frozen” movements refer to projects that are not currently operating due to some kind of legal or political stand-still. Finally, the projects that are “asleep” refer to ongoing and operational initiatives that have a have a lower and constantly ongoing opposition (see Table 1).

Table 1: Conflicts according to sector and life-cycle stage in 2014. Note: projects marked with the superscript $^{(-v)}$ do not count with ‘Voices’.

	Crisis	**Frozen**	**Asleep**
Hydro Power	Alto Maipo Central Mediterraneo	Hidro Aysén	Santa Barbara$^{(-v)}$ Central Pangue$^{(-v)}$
Mining		Pascua Lama	Dominga
Thermal Power			Puerto Ventanas$^{(-v)}$ Bocamina$^{(-v)}$

Alto Maipo is a project that includes the construction of two hydroelectric passings and one water reservoir. Central Mediterranean installs a river hydroelectric plant. Both projects were in full development in 2014 and have been subject to severe questioning and accusations that over time have gained prominence. Hidro Aysen and Pascua Lama are two flagship large scale projects that were completely paralyzed in 2014, and this is due at least in part to the rejection by the citizenry. Pascua Lama's ambition was to be the first binational mining project, while Hidro Aysen made global headlines by contemplating the construction and operation of five hydroelectric plants in the heart of Patagonia (e.g. see the documentary Malloy, 2011). We chose to also track five smaller projects that were not under much dynamic activity during 2014.

For the subsequent analysis, we defined Twitter users to be the nodes of the network and the links to be mentions or citation of other users (“@user”).[2] This means that links do not represent if one account follows the other, but whether information flows, since this is what matters in the step flow model of communication. This results in a directed network in which the link points into the direction of the user mentioned in the Tweet. It is important to note that a mention might mean “@receiver here is some information for you about #topic” or “everybody: look at @source who has great information about #topic”. If we would be able to distinguish between those two cases we would certainly be able to expand our analysis. However, for our purposes we are satisfied with the fact that even a simple mention allows us to state that somebody is active (sender) and somebody passive (receiver).

It is also important to point out that working with direct mentions does not allow to track a specific mention over more than one step, as we only track direct mentions. We were evaluating to work with retweet networks, but after looking at the data, rejected this option, as it comes with all the well-known potential confounders that influence retweet networks (e.g. Suh, et al., 2010; Boyd et al, 2010; Macskassy & Michelson, 2011). We therefore focus on the magnitude of the different proportions of very clearly defined and easily interpretable direct mentions.

One of our first findings was that during these 6 months, most users either actively sent messages at least once mentioning others (outgoing tie), or were explicitly mentioned by others (incoming tie). So most participated in some way. The share of truly passive audiences in our cases was small, representing 14 % of the total number of individuals scraped by the algorithm. For our final network analysis, we eliminated these passive audiences, since they are isolates in the resulting network. The reason for this is simply methodological, as isolates easily confound average network metrics (e.g. the closeness of an isolate to other nodes is undefined). We also exclusively worked with the giant component, which assures that information flows within the entire sample. This eliminated another 8.5 % of the nodes, leaving us for the 9 cases with a total of 31,112 nodes with 150,114 directed degrees, consisting of 75,906 links.

Analysis

We opted for a mixed methods approach that combines qualitative insights with quantitative metrics. First we used a qualitative classification scheme to distinguish among four different types of communicators. Then we calculated quantitative network metrics to confirm differences in these categories and to better understand their role in the network. In other words, we assign each node an attribute that describes its nature (qualitatively, ‘by hand’) and then test the effects through the metrics of social network analysis (quantitatively). Finally we looked at the intensity of information flow between each of these four groups.

Qualitative Attribute Metrics: Communicator Types

We oriented ourselves on the more traditional literature on step-flow models and more recent findings based on quantitative (González-Bailón, et al., 2013; Smith et al., 2014) and qualitative insights (Bennett and Segerberg, 2012) to distinguish between four types of nodes: “Voice”, “Media”, “Amplifier”, and “Participants”.

“Voices” are defined as Twitter accounts that belong to organizations or individuals that are dedicated (almost) exclusively to the conflict and accompanying social movement. They are experts in the subject and are often involved in the foundation of the movement, or are assigned their position as a result of the movement. Examples include the account @sinrepresas, dedicated to lobby against the construction of Hidro Aysen (with 86,400 followers), and @puelosintorres, dedicated to the protection of flora and fauna in Puelo and against the Central Mediterraneo 33,600 followers). In terms of Bennett and Segerberg's (2012) three-part typology of collective vs. connective action, most of the Voices belong to the middle category of "organizationally enabled networks of connective action".

"Media" are organizations (not individuals) that self-identify as media outlets, such as radio, web portals, television channels, newspapers and state institutions. Examples include @t13 of *Canal 13* (national television network with 2,200,000 followers), @latercera of the national newspaper *La Tercera* (1,300,000 followers), and the radio station @biobio (1,140,000 followers). The content of their tweets is mainly following journalistic guidelines of neutrality with few opinions or judgements. Naturally, the related subnetworks follow strong organizational coordination, and therefore are rather of the character of "organizationally brokered networks of collective action" (Bennett and Segerberg, 2012).

"Amplifiers" belong to individuals or organizations that do not belong to the previous two categories and make part of the Chilean public sphere. Their public status might stem from formal authority (politicians, non-specialized organizations or organization with a focus besides the conflict or media, general activists, union leaders, etc.) or public visibility (actors, artists, musicians, celebrities, bloggers, athletes, etc.). Examples include @giorgioJackson (Member of Congress for Central Santiago with 568,000 followers); @GreenpeaceCL (generic environmental protection NGO with 110,000 followers); and @tv_mauricio (journalist and TV news anchor who tweets personal views, with 1,810,000 followers). Amplifiers often also share personal expressions over social networks, and are therefore rather akin to the category of "self-organizing networks of connective action" (Bennett and Segerberg, 2012). "Participants" consist of all other natural person (excluding truly passive audiences who have not sent at least one Twitter message during the 6 month study period).

This results in a classification scheme based on our in-depth knowledge of the Chilean context (i.e. for "Voices" and "Amplifiers"). There are two reasons why we are confident that this classification is robust. For one, Chile is a rather small country (with 17 million inhabitant) and therefore has a quite manageable scene of organizations and celebrities. Besides, even if individual cases might be at the borderline or even wrongly classified, the mere size of our dataset should make it robust against individual reclassifications.

One of the results of this qualitative classification scheme was that most of the "asleep" movements do not count with anybody who could in some way be classified as "Voice" (see those projects marked with the superscript [-v] in Table 1. These networks only count with "Media", "Amplifiers", and "Participants" (and passive audiences). It can be expected that his would have an important effect on the communication flow in the network. Any quantitative classification scheme would not have revealed this fact as clearly. This justifies our option for a mixed method approach and emphasizes the usefulness of the considerable effort to classify over 30,000 nodes by hand.

Quantitative Network Metrics: Network Centralities

Different metrics have been suggested to identify opinion leaders and social influencers of message diffusion (e.g. Burt, 1999; Lee and Cotte, 2009; Banerjee et al., 2012; Dubois and Gaffney, 2014; Choi, 2014). Based on insights from almost four decades of research on network centrality (e.g. Freeman, 1978; Mullen et al., 1991; Costenbader and Valente, 2003; Lee and Pfeffer, 2015), we chose the four most typical centrality metrics; namely degree centrality (the average number of degrees per node), betweenness centrality (the number of times a node acts as a bridge along the shortest path between two other nodes), closeness centrality (the inverse of the sum of the shortest distances between the node and all other nodes) and eigenvector centrality (i.e. PageRank, which gives weight to second-degree links maintained by first-degree links of the node).

Figures I and II give a first graphic appreciation of the networks. The Santa Barbara network (Figure I a) is small enough to reveal some of the underlying network structure. This network is "asleep" during the period of our inventory (and does not contain "Voices"). Media outlets such as the national news network BioBio occupy a central role. The AltoMaipo movement in Figure I b, which is in plain "crisis" during the period of study, seems to present a mix with regard to the nature of the central nodes.

Figure I. Nodes by color. (a) left, Santa Barbara (asleep movement; n = 348). (b) Alto Maipo (crisis movement; n = 5,071). Presented with Gephi.

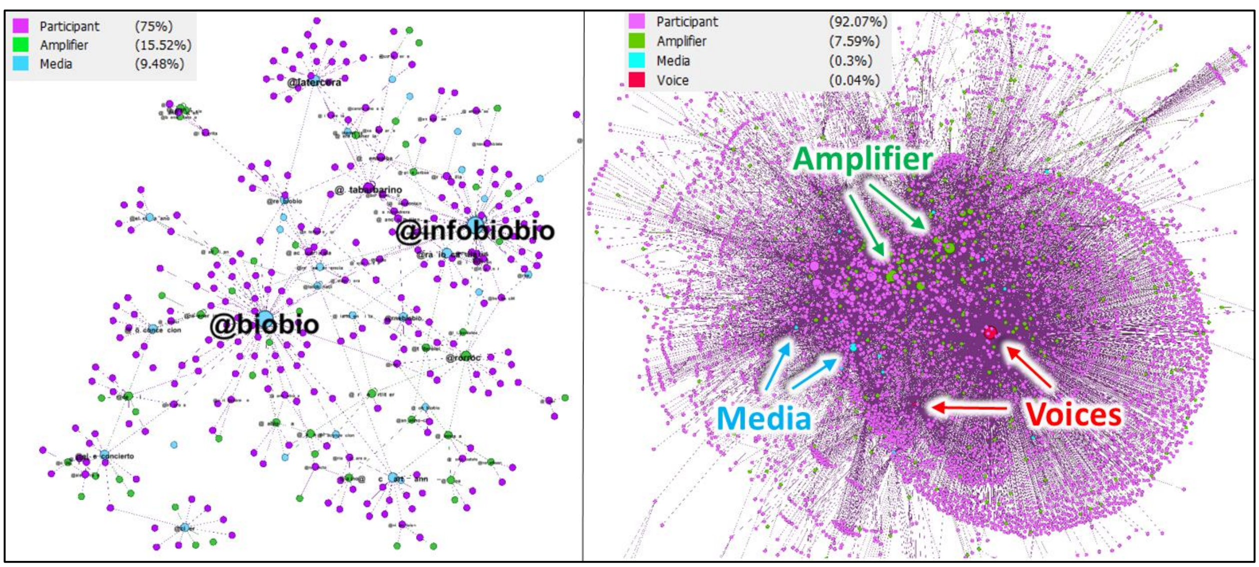


Table 2 quantifies these first impressions by representing the centrality measures for each one of the groups and movements. A clear pattern emerges throughout the samples, which confirms the usefulness of our classification scheme based on the attributes of communicators. Voices are the most central types of communicators. They are fewest in numbers, but exhibit the highest concentration in terms of being mentioned (in-degree of Tweet mentions) and their intensity of communicating actively (mentioning others in Tweets, out-degree). They also lie most often on the shortest path between all nodes, and therefore act as bridges and potential filters and gatekeepers (betweenness). Additionally they are on average closest to all other nodes (closeness) and are in the best position to act as agents of change through potentially breaking loose information cascades in which contacts quickly reach other contacts (PageRank). This would confirm a star-like network structure (Stansberry, 2012), where Voices act as a primary source to inform others. The second most central type of communicator are traditional Media outlets, followed by Amplifier and Participants (which would naturally be followed by passive audiences, which would obtain measures of 0, as they do not have links). Small exceptions to this general logic are identifiable in Table 2, but do not change the general tendencies.

The first conclusion is that Voices play a central role, especially in cases of some kind of urgent social interest (our networks in ‘crisis’). In this case these kinds of actors seem to undertake such tremendous effort that they can even displace the traditionally all-powerful Media industry. In cases of ‘asleep’ movements, it seems that these actors disappear, potentially due to a lack of social justification, legitimation, or funding. In these cases we find communication networks in the traditional style with traditional Media outlets as the most central communicator type.

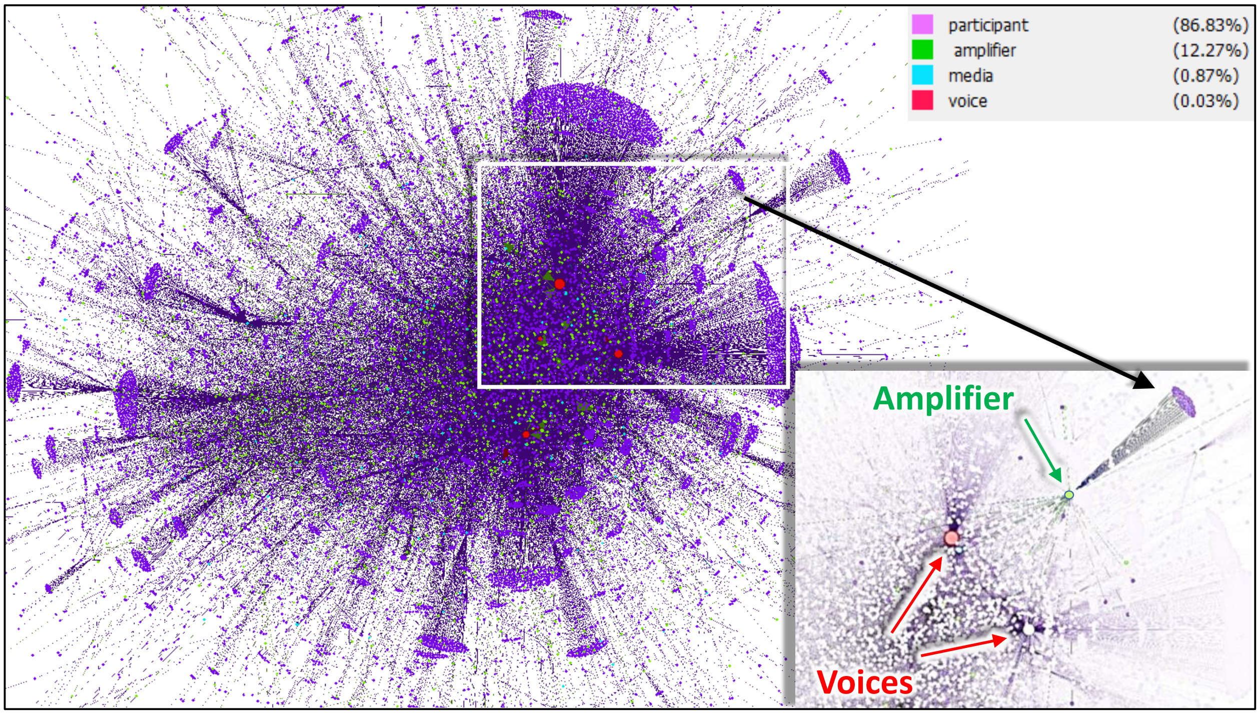
Amplifiers play a clearly different role in comparison to ordinary Participants. In some cases, they can even rise to a more central role than traditional Media outlets, such as in the case or Puerto Ventana (although not significant). This clearly confirms the role of intermediaries played by Amplifiers. The zoomed in insert of the case of HidroAysen in Figure II demonstrates this intermediary role example visually for one case. Voice takes a more central role in the overall network, but the Amplifier take a central role in a local part of the network, being directly connected to a considerable group of participants in this local area. This would suggest Voices as “opinion leaders of opinion leaders” (Katz, 1957; p.68).

This leaves us with a clear communication hierarchy, with official protest Voices taking the most central role, followed by traditional Media outlets, then Amplifiers, and finally Participants. It is important to notice that these metrics represent averages per node, and that the number of nodes present behaves inversely with this hierarchy. It is therefore important to analyze if the sheer number of types also plays a role in the overall communication flow.

Table 2: Centrality measures for all 9 networks (calculated with NodeXL). Averages refer to members of the communication type group. Note: we ran pairwise significance tests between between the metrics. Pairs of measures marked with the same superscript^{number} indicate that no statistical significance could be found at the p=0.1 level between the two measures with the same number.

		Nodes	Avg. Degree	Avg. In-degree	Avg. Out-degree	Avg. Betweenness	Avg. Closeness	Avg. Page Rank
AltoMaipo	Voice	2	1,968	1,894	74	10,799,089	0.00012	376
	Media	15	110	102	8	259,744	0.00008[1,2,3]	16
	Amplifier	385	20	14	6	25,313	0.00008[1]	3
	Participant	4,669	4	1	3	1,898	0.00007[2,3]	1
	TOTAL	**5,071**	**6**	**3**	**3**	**8,697**	**0.00007**	**1**
Central Mediterraneo	Voice	3	1,304	1,145	158	4,192,692	0.00052	250
	Media	58	9	8	-	6,076[4]	0.00011	1
	Amplifier	334	15	10	5	4,012[4]	0.00012[5]	2
	Participant	3,245	4	1	3	696	0.00012[5]	1
	TOTAL	**3,640**	**6**	**3**	**3**	**4,541**	**0.00012**	**1**
HidroAysen	Voice	4	1,668	1,529	139	32,638,604	0.00003[7]	310
	Media	113	35	34	1	394,898[6]	0.00002[7]	7
	Amplifier	1,600	12	9	4	107,588[6]	0.00002[7]	2
	Participant	11,328	3	1	2	12,086	0.00002[7]	1
	TOTAL	**13,045**	**5**	**2**	**2**	**37,119**	**0.00002**	**1**
PascuaLama	Voice	4	465	409	56	4,034,183	0.00006[11,12,13]	87
	Media	108	39	38	1	285,086	0.00004[12]	9
	Amplifier	648	12	8	4	58,347	0.00004[11]	2
	Participant	5,700	3	1	2	6,004	0.00004[13]	1
	TOTAL	**6,460**	**4**	**2**	**2**	**18,415**	**0.00004**	**1**
Dominga	Voice	1	224	176	48	230,945	0.00075	55
	Media	18	10	9	1[8]	7,070	0.00044[9]	3
	Amplifier	97	9	6	3	5,505	0.00047[10]	2
	Participant	531	2	1	2[8]	422	0.00043[9,10]	1
	TOTAL	**647**	**4**	**2**	**2**	**1,725**	**0.00044**	**1**
SantaBarbara	Voice	-	-	-	-	-	-	-
	Media	33	9	8	1[14]	6,881	0.00067[15]	3
	Amplifier	54	3	2	1[14]	1,368	0.00060[15]	1
	Participant	261	2	-	1[14]	551	0.00064[15]	1
	TOTAL	**348**	**3**	**1**	**1**	**1,278**	**0.00064**	**1**
Central Pangue	Voice	-	-	-	-	-	-	-
	Media	64	10	9	1[16]	15,216	0.00028[17]	3
	Amplifier	81	6	4	2	9,913	0.00028[17]	2
	Participant	669	2	-	1[16]	942	0.00027[17]	1
	TOTAL	**814**	**3**	**1**	**1**	**2,957**	**0.00027**	**1**
PuertoVentana	Voice	-	-	-	-	-	-	-
	Media	18	3	3[18]	-	980[19]	0.00175[20]	1
	Amplifier	26	5	3[18]	2	1,318[19]	0.00175[20]	2
	Participant	96	2	1	1	133	0.00170[20]	1
	TOTAL	**140**	**2**	**1**	**1**	**462**	**0.00172**	**1**
Bocamina	Voice	-	-	-	-	-	-	-
	Media	60	15	15	1	27,271	0.00025[21]	5
	Amplifier	72	4	2	2	6,015	0.00024[21]	1
	Participant	815	2	-	1	1,363	0.00024[21]	1
	TOTAL	**947**	**3**	**1**	**1**	**3,358**	**0.00024**	**1**

Figure II. Nodes by color. HidroAysen (frozen movement; n = 13,045). Presented with Gephi.



Average Flow Proportions

We now ask about the relative proportions of the flow between these different types of communicators.[3] To obtain the most fundamental view, Table 3 represents the joint links from one communicator type to others for the five cases that contain all four types of communicators, including 72,971 of the total of 75,906 links. This matrix can be read as a network among supra-nodes, where the different supra-nodes represent communicator types, and the weighted ties are the sum of the binary ties between individual communicators. The raw data in Table 3 allows us to calculate joint and conditional proportions of the between-type link distribution. This enables us to analyze which percentage of the communication of one type flows to another type, and vice versa. The result can be understood as a communication channel, much in the tradition of formal information theory (see for example Cover and Thomas, 2006; Ch. 7).

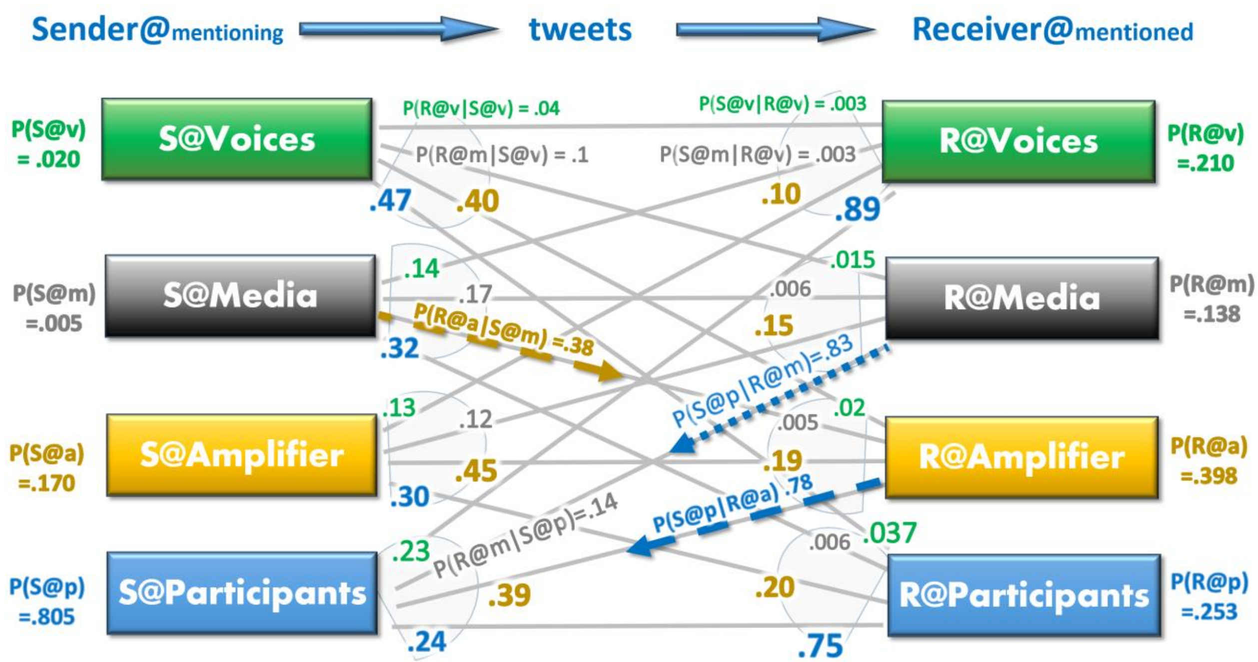
Table 3. Joint distribution of tweets among types of communicators for the five cases that contain all four types of communicators. S@... refers to mentioning sender type, R@... refers to mentioned receiving type. Total number of mentions and in parentheses (percentage %) of total 72,971 mentions.

	R@Voice	R@Media	R@Amplifier	R@Participant	
S@Voice	52 (0.07%)	149 (0.20%)	582 (0.80%)	690 (0.95%)	**1,473 (2.0%)**
S@Media	51 (0.07%)	63 (0.09%)	144 (0.20%)	119 (0.16%)	**377 (0.5%)**
S@Amplifier	1,606 (2.20%)	1,511 (2.07%)	5,536 (7.59%)	3,749 (5.14%)	**12,402 (17.0%)**
S@Participant	13,618 (18.66%)	8,375 (11.48%)	22,805 (31.25%)	13,921 (19.08%)	**58,719 (80.5%)**
	15,327 (21.0%)	**11,849 (13.8%)**	**29,766 (39.8%)**	**18,964 (25.3%)**	**72,971 (100%)**

A first insight from Table 3 refers to the general proportions of mentions (the marginals of the presented joint distribution). While recent research has emphasized how media outlets and other key communicators of collective and connective actions use the available tools of personalization to address participants in social movements directly (e.g. Bennett and Manheim, 2006; Bennett and Segerberg, 2012), the Table shows that personalization from central communicators does not present the lion's share of mentions. Participants only receive 25.3 % of the mentions, and Voices, Media, or Amplifiers only contribute 19.5 % of all mentions (most of them produced by Amplifiers, with 17 %). This means that personalized addressing of individual Participants done by Voices, Media or Amplifiers represents only a small fraction of all communication flows. Most mentions consists of Participants mentioning Amplifiers (31.25 %).

In order to facilitate further interpretation, it is useful to analyze the conditional distributions that can be calculated from the joint distribution in Table 3. Figure III presents those conditional distributions in form of a visual representations of a communication channel between mentioning senders and mentioned receivers.

Figure III. Conditional frequencies of the five networks that contain all four types of communicators, i.e. AltoMaipo, CentralMediterraneo, HidroAysen, Dominga, PascuaLama. Shown is the simple average of the five movements for the proportions within each movement.



The conditional frequencies from left to right (normalized on the right-hand marginal of Table 3) show the constitution of the average mentions in a message (how frequently does the type on the left-hand side in Figure III mention the type on the right-hand side). The conditional frequencies from right to left (normalized on the bottom-line marginal of Table 3) show the constitution of the average number of mentions from the point of view of the mentioned type (how frequently does the type on the right-hand side get mentioned by the type on the left-hand side). Both conditional frequencies are naturally related by Bayes' theorem:

$$Bayes'theorem\colon\ P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

For example, for the communication link between sending participants (S@p) and receiving media outlets (R@m), we get (compare with Figure III):

$$0.14 = P(R@m|S@p) = \frac{P(S@p|R@m) * P(R@m)}{P(S@p)} = \frac{0.83 * 0.138}{0.805}$$

This refers to the same communication flow (in which the participants send/mention and media outlets receive/ are mentioned), but links the two complementary perspectives on it: one from the perspective of the sending/mentioning participant (conditioned on |S@p), and the other one from the perspective of the receiving/mentioned media outlet (conditioned on |R@m). These complementary views of looking at communication flows reveals that many of the common step-flow communication paradigms can easily be confounded by the conditioning perspective, leading to seemingly contradictory statements.

For example, Figure III showcases that it is no contradiction to state that most media outlets receive their mentions from participants directly, P(S@p|R@m) = 83% (from the perspective of a media outlet, which would suggest a one-step flow, see the dotted arrow in Figure III); while at the same time most media outlet communications refer to amplifying intermediaries, P(R@a|S@m) = 38 %, and most amplifiers receive their mentions from participants, P(S@p|R@a) = 78 % (implying a two-step flow, see the two dashed arrows in Figure III). Additionally, Voices most frequently mention participants directly, P(R@p|S@v) = 47 % (implying a one-step flow from the perspectives of these communicators of often original content), while Amplifiers most frequently mention other Amplifiers P(R@a|S@a) = 45 %. This last fact implies that the creation of context communicated by Amplifiers (in a sense of the two-step flow) is actually more involved multi-step back and forth, where the context arises as an emergent result of the interactions between intermediating Amplifiers.

As non-intuitive as these claims might sound, the important but subtle differences of conditioning perspectives quickly gets lost in natural language, while the mathematical logic of Bayes' theorem assures that there is no contradiction in them.

As indicated by the nature of Bayes' formula, differences in the marginal shares can confuse the outlook (as their ratio is what relates the two complementary perspectives on the same communication flow). Figure III shows that the distribution of senders is much more skewed than the distribution of receivers, which are more uniformly distributed. 80 % of all tweets originate from Participants, while they only receive 25.3 % of the mentions. On the contrary, Voices are mentioned ten times more frequently than they send tweets, and Media even thirty times more (see also Table 3). The weight of Participants on the sender-side of the channel (P(S@p) ≈ 80.5 %) leads to the fact that all different communication types are most often mentioned by participants, P(S@p|R@...) ≈ 80%. The weight of Amplifiers on the receiver-side of the channel (P(R@a) ≈ 39.8 %) leads to the fact that they are the most frequently mentioned types, P(R@a|S@...) ≈ 40 %. While the omnipresence of participants simply stems from the fact that participants are the largest group (88 % of nodes are Participants, compare Table 2), the mentions of Amplifiers is overrepresented, as they merely represent 10.6 % of nodes.

The combination of this finding with the network centrality metrics from Table I seems to suggest that Amplifiers occupy a kind of sweat spot between the network position of each individual and the reaching of a critical mass as a type. On the one hand, one particular Amplifier is not as central as Voices or Media. Their degree-centrality, betweenness-centrality, and closeness-centrality is lower (Table 2). On the other hand, there is a considerable number of them, many more than Voices and Media outlets. The effect is that one of them (not the same one, but of the same kind) is frequently mentioned by any other communicator type, leading to a high average number of mentions for the group of Amplifiers. The importance of Amplifiers stems from have a somewhat central position in the network structure (more so than Participants), but being enough in numbers to be distributed among different local network structures. As a result, almost every third mention consists of a Participant mentioning an Amplifier (see joint frequencies in Table 3, with 31.25 %). This implies that Amplifiers act as local intermediaries.[4]

At the same time, digital social networks also clearly allow for several kinds of direct one-step flow communications. Participants are not only the core cliental of Media outlets, but social networks allow official Voices to frequently bypass any kind of intermediary, to directly communicate with Participants (88 % of mentions of Voices are done directly by participants). The other way around, Participants are also the second most important type that is being mentioned. 45 % of the Tweets sent out by official movement Voices mention some kind of Participant directly. We can conclude that these kinds of messages provide an adequate context for direct consumption, while being directly sent by ‘opinion leaders of opinion leaders’. This again provides evidence for a one-step flow.

Our analysis suggests that Voices do not act exclusively as opinion leaders of opinion leaders, but rather act from a centralized star-shaped position in the network. Voices seem to concentrate even more to send messages to Participants than to Amplifiers (47% vs. 40%, see Figure III). Their interaction with traditional Media outlets is low and they are most frequently mentioned directly by Participants (89%). This reconfirms the previously detected high centrality of official Voices in the network.

The smallest role in the resulting flow of communication are traditional Media outlets. It turns out that message senders do not mention them very frequently (only 13.8 % of all Tweets mention Media sources), and they are almost negligible from the point of actively engaging communicators in the flow, with less than 1 % of tweets originating from Media outlets. In terms of relative share, the type that mentions Media outlets most frequently are other Media outlets, MAX[P(R@m|S@...)] = P(R@m|S@m) = 0.17). This means that the mass-customization paradigm promised by the one-step flow model does not seem to be implemented in these cases. From a glass-half-full outlook from the perspective of the Media, this could also mean that traditional Media outlets still have lots of potential to better exploit communication flows in online social media settings, especially by engaging audiences more directly.

Discussion

So which ones of the proposed step-flow models fits our empirical findings: one-step flow, two-step flow, three- or multi-step flow, or some kind of intricate network-step flow? The short answer is: all of the above, depending on the perspective. Communication flow via digital platforms can be looked at from different perspectives and the digital footprint left behind by social media allows to distinguish clearly between them.

Our analysis of centrality metrics has revealed that the average Voice is the most intense communicator (highest centrality), followed by Media outlets and only then Amplifiers. However, our flow analysis has shown that pervasiveness and presence relates inversely with intensity. This leads to the fact that Amplifiers are more omnipresent and maintain the strongest communication link with Participants. They act as pervasive local intermediaries in conflict situations, while specialized Voices and professional Media outlets act as global intermediaries of the entire network. The result is that there is no contradiction that participants mainly refer to intermediating amplifiers (39 % of the mentions from participants go through this two-step flow), while at the same time traditional media outlets and official protest voices receive 80-90 % of their mentions directly through a direct one-step flow from the same participants. From the perspective of a traditional media it is correct to state that they most frequently mention Amplifiers, while from the perspectives of both Amplifiers and Participants, their mutual communication flow the strongest tie for each of them (Figure III). At the same time, Amplifiers most frequently mention other Amplifiers, which suggests some kind of intermediate step flow that goes beyond two steps. Our analysis does not ask for the reasons behind these characteristic communication patterns. It might be that Amplifiers mention Amplifiers frequently because they simply strive for personal visibility, while Voices focus directly on Participants because they aim for support for the cause. More research will be needed to better understand the details.

It is important to underline that our data only referred to one specific case of political communication (citizen protests) through one specific digital platform (Twitter). Even here we have already seen differences. For example, asleep movements seem to present communication flows much more akin to the traditional two-step flow than hotter social movements in crisis, which evidence more intricate radial and multi-step flows with a notable tendency toward communication flow concentration in a more centralized manner. Context surely influences communication structures. It is very likely that other settings will feature different structures, including other communication contexts (e.g. Smith et al., 2014).

This being said, one of the main messages of this article is that this does not even need to be a question of communication in different settings, but can simply be a question of perspective (as evidenced by Figure III). Our intuition is notoriously bad with switching conditioning perspectives mentally (see for example the famous Monty Hall problem (2015)). Taking different perspectives into account, we have seen that it can very well be at the same time that official Voices play the central role in a radial flow model, while from the perspective of traditional Media outlets, a one-step flow model is implemented, and from the perspective of Participants, intermediating Amplifiers are the most frequent go-to source. It would be straightforward to confirm any of these hypothesis in favor of another. This makes clear that any partial view on this dynamic can be deceiving.

This leads us to the final conclusion that it is unlikely that even at its 60th anniversary, the discussion about different step flow model of communication will retire any time soon. Today's big data communication landscape allows us to strive for what Katz and Lazarfeld could only dream of. The first phrase of their prominent chapter XIV states that: "Ideally, we should have liked to trace out all of the interpersonal networks in the community to see how they link up with each other…" (Katz and Lazarsfeld, 1955; p. 309). The provision of such networks by the digital footprint has two benefits, one short-term, and one longer-term. In the short term we can put current hypothesis to the immediate test. For example, our findings showed that only a small percentage of direct mentions in social movements consists of direct personalized messages from more central communicators to ordinary participants (some 20 %). This allows us to put recently voiced hypotheses of personalized direct engagement into a quantitative perspective. They do exist and do matter, but only that much. The challenge for the longer-term research agenda consists of using the digital footprint of social media to develop and test for more elaborate network flow mechanisms that goes beyond a simple one-size fits all hypothesis. Six decades into the discussion of step-flow models the work on the issue just seems to begin.

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[1] Index search terms for conflicts: **(1) Alto Maipo:** AES Gener, No a Alto Maipo, Salvemos el Cajón del Maipo, Hidroeléctrica Alto Maipo, Luksic socio Proyecto Alto Maipo, PHAM, Laguna Negra, Laguna Lo Encañada, Coordinadora Ciudadana Ríos del Maipo; **(2) Bocamina:** Bocamina Endesa, Muerte masiva de peces Bocamina ll, Paralización Bocamina ll, Bocamina Coronel, Superintendencia del Medioambiente (SMA), Central Bocamina ll, Termoeléctrica Coronel, Recurso de protección pescadores artesanales; **(3) Central Mediterráneo:** Central de paso Mediterráneo, Río Manso, Río Puelo, Lago Tagua Tagua, Cochamó, Edgard Wilhelm, Seremi Medioambiente región de Los Lagos, @PueloSinTorres; **(4) Central Pangue:** Río Pangue, Bíobío, Ralco, Presidente Aylwin, Nicolasa Quintreman, Lago artificial de Endesa; **(5) Dominga:** Andes Iron, Proyecto Minero Doña Dominga, Carta contra Proyecto Dominga, Minera Andes Iron, Concentrado de hierro, Proyecto minero y portuario, CEAZA, Modema; **(6) Hidro Aysén:** Patagonia, Sin represas, Energía sustentable, Endesa, Colbún, Aprobación ilegal Hidroaysén, 5 obras paralizadas de Endesa, Corrupto Hidroaysén; **(7) Pascua Lama:** Barrick Gold falsifica datos, Tribunal Ambiental, SEA Atacama, Región de Atacama, OLCA, Greenpeace; **(8) Puerto Ventanas:** Bahía de Quintero, AES Gener, Segunda muerte masiva de sardinas, Nueva Varazón de sardinas, Varamiento de sardinas, Falla Central termoeléctrica Ventanas, Central termoeléctrica Ventanas; **(9) Santa Bárbara:** Central hidroeléctrica Angostura, Embalse Puente Piulo, Daniel Salamanca, Alcalde de Santa Bárbara, Colbún.

[2] Since we are interested in the general flow of information among the widest possible audience, we dichotomized the network by eliminating duplicate mentions (this eliminates biases that might arise from dyads and triples with very high tweeting activity).

[3] We also conducted an analysis of variance test with a structural block model option between these four blocks in UCINET, as executed by Choi (2014). However, the results of the correlation were low and often insignificant. This is also to be expected, as the test was originally designed for homophily testing (within and between group ties of cohesive groups) (Hanneman and Riddle, 2015), not for spread out types, like in our case (see Figures I – III). It is our suspicion that the test worked as nicely in Choi's case because of small networks with only two groups, while one consists of very few and extremely highly connected nodes.

[4] It is important to remember that in the presentation of Figure IV passive audiences are omitted. We recorded them (14 % of our total sample), but excluded them form the analysis as they do not form direct network ties through explicit mentions.