When a Movement Becomes a Party: Computational Assessment of New Forms of Political Organization in Social Media

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Abstract

Social media has become a key mechanism for the organization of grassroots movements. In the 2015 Barcelona City Council election, Barcelona en Comú, an emerging grassroots party, was the most voted one. This candidacy was devised by activists involved in the Spanish 15M movement in order to turn citizen outrage into political change. On the one hand, the 15M movement is based on a decentralized structure. On the other hand, political science literature postulates that parties historically develop oligarchical leadership structures. This tension motivates us to examine whether Barcelona en Comú preserved a decentralized structure or adopted a conventional centralized organization. In this article we propose a computational framework to analyze the Twitter networks of the parties that ran for this election by measuring their hierarchical structure, small-world phenomenon and coreness. The results of our assessment show that in Barcelona en Comú two well-defined groups co-exist: a cluster dominated by the party leader and the collective accounts, and another cluster formed by the movement activists. While the former group is highly centralized like traditional parties, the latter one stands out for its decentralized, cohesive and resilient structure.

Introduction

In the last years a new global wave of citizen protests has emerged: the Arab Spring, the 15M movement in Spain, Occupy Wall Street, #YoSoy132 in Mexico, Occupy Gezi in Turkey, the Brazilian movement #VemPraRua, Occupy Central in Hong Kong, etc. All these movements share common characteristics such as the claim for new models of democracy, the strategic usage of social media (e.g. Twitter), and the occupation of physical spaces. Also, all of them have encountered difficulties in modifying the institutional agenda and, hence, the public policies. The 2015 Barcelona City Council election is one of the first cases in which one of these movements has got to "occupy" the public institutions by building Barcelona en Comú (BeC), a political party that won the elections. BeC was conceived as the confluence of (1) minor and/or emerging parties and, to a large extent, (2) collectives and activists, with no political party affiliation, who played a prominent role in the 15M movement.

The 15M movement, also referred to as #SpanishRevolution or the "Indignados" Movement, emerged in May 2011 and has been defined as a "networked social movement of the digital age" (Castells 2013). Networked social movements, like the Arab Spring, the 15M and Occupy Wall Street, are claimed to be "a network of networks, they can afford not to have an identifiable center, and yet ensure coordination functions, as well as deliberation, by interaction between multiple nodes" (Castells 2013). Other authors have formulated similar hypotheses defining this new model of social movement as a "change from logic of collective action, associated with high levels of organizational resources and the formation of collective identities, to a logic of connective action, based on personalized content sharing across media networks" (Bennett and Segerberg 2012). We should note that some voices have refused these theoretical assumptions and argued that "a handful of people control most of the communication flow" and, consequently, the existence of leaders in such movements could not be denied (Gerbaudo 2012). Empirical studies revealed that the 15M network on Twitter is characterized by its "decentralized structure, based on coalitions of smaller organizations" in spite of "a small core of central users is still critical to trigger chains of messages of high orders of magnitude" (González-Bailón et al. 2011). Decentralization has been also observed in Toret et al. (2015) in which the 15M network is defined as polycentric.

The 15M network properties (i.e. decentralization, polycentrism) could be perceived as a striking contrast to conventional political organizations, in particular, political parties. The Iron Law of Oligarchy (Michels 1915) postulates that political parties, like any complex organization, self-generate an elite (i.e. "Who says organization, says oligarchy"). Although some scholars have criticized the idea that organizations will intrinsically build oligarchical leadership structures (Lipset et al. 1956; Rothschild-Whitt 1976; Edelstein and Warner 1979), many political and social theorists have supported that, historically, small minorities hold the most power in political processes (Pareto et al. 1935; Mosca 1939; Mills 1999). Regarding Spanish politics, a study of the 2011 national election campaign on Twitter revealed that "minor and new parties tend to be more clustered and better connected, which implies a more cohesive community" (Aragón et al. 2013). Nevertheless, all the diffusion networks of parties in that study were strongly centralized around their candidate and/or party profiles. Later studies analyzed the interactions on Twitter between the 15M nodes and political parties and conclude that networked social movements are *para-institutions*: perceived as institutions but preserving an internal networked organization (Peña-López, Congosto, and Aragón 2014). However, these conclusions were formulated by analyzing the networks when no elections were held, before institutionalization began. Campaigns are competitive processes that might favor the centralization of an organization around candidates. Indeed, it has been proven that the network properties of political parties change when elections arrive (Garcia et al. 2015).

Given that Barcelona en Comú emerged from the 15M and this networked movement is characterized by a decentralized structure, the research question of this study is the following: *Has Barcelona en Comú preserved a decentralized structure or has it adopted a conventional centralized organization ruled by an elite?*

Previous hypotheses (Toret 2015) about Podemos, a member party of the Barcelona en Comú candidacy and as well inspired by the 15M movement, postulate an organization formed by a *front-end* ("spokesmen/spokeswomen who are visible from the media perspective") and a *back-end* ("muscle of the organization, barely visible from the media perspective"). However, there are no empirical validations of this hypothesis.

Motivated by our research question, we propose a computational framework to (1) identify the Twitter networks of political parties running for elections and (2) characterize their organizational structures by comparing their online communication topologies. The identification of the subnetwork corresponding to each party is made possible by the highly divided partisan structure of the information diffusion network. This assumption relies on previous studies of political discussions on social media (Adamic and Glance 2005; Conover et al. 2011). Data-driven political science has revealed the recurrent existence of boundaries between ideological online communities, in particular, political parties. A study of the 2004 U.S. Presidential election depicted a divided blogosphere in which liberals and conservatives barely generated links between the two communities (Adamic and Glance 2005). Similarly, the network of retweets for the 2010 U.S. congressional midterm elections exhibited a highly segregated partisan structure where connections between left- and right-leaning users were extremely limited (Conover et al. 2011). Both studies have been taken as relevant empirical validations of the so-called *cyber-balkanization*, a social phenomenon that occurs when Internet users form isolated groups around specific topics (e.g. political interests). This concept is closely related to the idea of *echo chambers*, in which people are "mainly listening to louder echoes of their own voices" (Sunstein 2009) and, therefore, reinforce division in social media. Indeed, online polarization is not only a particular feature of U.S. politics but also a social behaviour observed in a diverse range of countries, e.g. Canada (Gruzd and Roy 2014) and Germany (Feller et al. 2011). In Spain, previous studies of the Twitter networks related to recent elections also showed evidence of online polarization, e.g. in the 2010 Catalan election (Congosto, Fernández, and Moro 2011) and in the 2011 Spanish elections (Borondo et al. 2012).

In this study, we first describe our computational framework to (1) detect the online diffusion sub-network of each party, and (2) characterize these sub-networks. Then, we apply our framework to a dataset of tweets related to the 2015 Barcelona City Council election. We strongly believe that the answer to the above research question through our framework will provide relevant insights into the assessment of new forms of political organization in social media.

Computational framework

Here we describe the computational framework that, given a network of retweets, detects the major clusters (i.e. political parties) and characterizes their social structures along three dimensions: hierarchical structure, small-world phenomenon and coreness.

Community detection

Community detection is performed by applying a clustering algorithm. Previous studies have relied on the Louvain method (Blondel et al. 2008) because of its high performance in terms of efficiency and accuracy. This method is based on a greedy algorithm that attempts to optimize the modularity of a partition of a given network. The modularity measures the density of edges inside communities in comparison to edges between communities (Newman 2004). The modularity value, between -1 and 1, is defined as:

$$Q = \frac{1}{2m}\Sigma_{ij}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta(c_i, c_j)$$

where A_{ij} is the edge weight between nodes i and j; k_i and k_j are the degrees of the nodes i and j, respectively; m represents the total number of edges in the graph; c_i and c_j are the indexes of communities of those nodes and δ is the Kronecker delta.

The Louvain method follows a two-step approach. First, each node is assigned to its own community. Then, for each node i, the change in modularity is measured for moving i from its own community into the community of each neighbor j:

$$\Delta Q = \left[\frac{S_{in} + k_{i,in}}{2m} - \left(\frac{S_{tot} + k_i}{2m}\right)^2\right] - \left[\frac{S_{in}}{2m} - \left(\frac{S_{tot}}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)^2\right],$$

where S_{in} is the sum of all the weights of the intra-edges of the community where i being moved into, S_{tot} is the sum of all the weights of the edges to nodes of the community, k_i is the degree of i, $k_{i,in}$ is the sum of the weights of the edges between i and other nodes in the community, and m is the sum of the weights of all edges in the network. Once this value is measured for all communities that i is linked to, the algorithm sets i into the community that produces the largest increase in modularity. If no increase is possible, i remains in its original community. This process is applied until modularity cannot be increase and a local maximum of modularity is achieved. Then, the method groups the nodes from the same community and builds a new network where nodes are the communities from the previous step. Both steps are repeated until modularity cannot be increased.

Adapted version to enhance the robustness of the largest clusters Like many community detection methods, the Louvain method is a greedy algorithm and has a random component, so each execution produces a different result. To obtain robust results, avoiding dependency on a particular execution of the algorithm, we introduce the following method to identify the main clusters of the network in a stable way. First, we run N executions of the Louvain algorithm, which produce N different partitions of the network into clusters. Then we select the bigger clusters for each partition, and identify each cluster through its most representative nodes. In particular, as we expect that the main clusters will represent the political parties, we identify each cluster with the most relevant node according to its centrality measure PageRank (which we expect to be the account of a political party or a political party leader). Finally, we assign to each cluster all the nodes that appear in that cluster in at least a fraction of ε of the partitions created, where ε represents the confidence interval.

This procedure allows us to validate the results of the community detection algorithm, and to guarantee that all the nodes that are assigned to a cluster do actually belong to it with high confidence. The remaining nodes, that cannot be assigned in a stable way to any of the main clusters, are left out from all the clusters (in our study, $\varepsilon = 0.95$).

Cluster characterization

Inspired by the social dimensions and corresponding metrics suggested in Garcia et al. (2015) we propose an extended framework to compare the topology of the intra-network of each cluster.

Hierarchical structure: To evaluate the hierarchical structure we apply the Gini coefficient, a statistical metric to quantify the level of inequality given a distribution (Gini 1912). It was initially formulated in Economics to measure the income distribution by using the Lorenz curve. The Gini coefficient is equal to

$$G_{in} = A/(A+B),$$

where A is the area between the line corresponding perfect equality and B is the area under the Lorenz curve. If the Lorenz curve is expressed by the function $y = L(x)$, B is calculated as $B = 1 - 2\int_0^1 L(x)dx$ and $A = 1/2 - B$. In the context of network topology, the Gini coefficient is applied to characterize the hierarchical structure of a network based on the inequality of its in-degree distribution.

Small-world phenomenon: The small-world phenomenon states that most nodes of a network are reachable from any other node in a small number of steps and explains information efficiency in social networks. To assess the small-world phenomenon in each cluster we compute the clustering coefficient and the average path length. Small-world networks tend to have a small average shortest path length and a clustering coefficient significantly higher than expected by random chance Watts and Strogatz. The clustering coefficient measures the extent of nodes to cluster together by calculating the number of triangles in the network. For every node i we set N_i to be the neighborhood, i.e. $N_i = \{j \in V : (i,j) \in E\}$, and define the local clustering coefficient as

$$Cl_i = \frac{2|(j,k) \in E : j,\ k \in N_i|}{k_i(k_i - 1)}.$$

Then, following (Watts and Strogatz 1998) the clustering coefficient is just the average of the local clustering coefficients: $Cl = \sum_i Cl_i/n$, where n is the number of nodes in the network. To calculate the average path length, for every pair of nodes i and j we set d_{ij} to be the smallest number of steps among all paths between i and j. This metric is applied to the clusters identified by our community detection algorithm and, by definition, there is always a path between any pair of nodes in every cluster. The average path length is defined as follows: $l = \sum_{i \neq j} d_{ij}/n(n-1)$.

Coreness: Coreness has been employed in previous literature as a metric of the resilience of a network (Garcia, Mavrodiev, and Schweitzer 2013). The resilience of a social network is the ability of a social group to withstand external stresses. To measure coreness of the intra-network of each cluster we apply the k-core decomposition and then evaluate the distributions of the nodes within each k-core. Given a network, we define a sub-network H induced by the subset of users C. H is a k-core of the network if and only if for every user in C: $deg_H(i) \geq k$, and H is the maximum sub-graph which fulfils this condition. With $deg_H(i)$ we denote the degree of the node i in the sub-graph H. A user has k-index equal to k if it belongs to the k-core but not to the $(k+1)$-core.

Data preparation

Data were collected from Twitter in relation to the campaign for the 2015 Barcelona City Council election (May 1-26, 2015). We defined a list of Twitter accounts of the seven main political parties:

- Barcelona en Comú (BeC)[1],
- Convergència i Unió (CiU)[2],
- Ciudadanos (Cs)[3],
- Capgirem Barcelona (CUP)[4],
- Esquerra Republicana de Catalunya (ERC) [5],
- Partit Popular de Catalunya (PP)[6],
- Partit dels Socialistes de Catalunya (PSC)[7].

[1] `http://wki.pe/Barcelona_en_Com%C3%BA`

[2] `http://wki.pe/Convergence_and_Union`

[3] `http://wki.pe/Citizens_(Spanish_political_party)`

[4] `http://wki.pe/Popular_Unity_Candidates`

[5] `http://wki.pe/Republican_Left_of_Catalonia`

[6] `http://wki.pe/People%27s_Party_of_Catalonia`

[7] `http://wki.pe/Socialists%27_Party_of_Catalonia`

Table 1: Twitter accounts of the selected political parties and candidates.

Political Party	Party account(s)	Candidate account
BeC	@bcnencomu @icveuiabcn @podem_bcn @equobcn @pconstituentbcn	@adacolau
CiU	@cdcbarcelona @uniobcn	@xaviertrias
Cs	@cs_bcna	@carinamejias
CUP	@capgirembcn @cupbarcelona	@mjlecha
ERC	@ercbcn	@alfredbosch
PP	@ppbarcelona_	@albertofdezxbcn
PSC	@pscbarcelona	@jaumecollboni

We also added the Twitter accounts for corresponding candidates for Mayor and each member party for the coalitions CiU, BeC and CUP. The users of that list can be found in Table 1. From the Twitter Streaming API, we extracted 373,818 retweets of tweets that (1) were created by, (2) were retweeted by, or (3) mentioned a user from the list.

We should remark that our sampling criteria are based on specific accounts instead of hashtags. Previous studies have detected differences in the tagging practice of politicians (Lietz et al. 2014). We have observed that some parties adopt a small set of hashtags during campaigns and some other parties generate new hashtags every day in order to locate them in the list of trending topics. Therefore, sampling messages from a list of campaign hashtags would likely lead to an unbalanced dataset. For this reason, we consider that our sampling criteria represent a better approach to capture the diffusion practices of the communities around parties.

From the collection of retweets, we build a directed weighted graph comprising a set of nodes (users) and a set of edges (retweets between any pair of users). Each edge in the graph represents that the source user retweeted a message posted by the the target user. To exclude anecdotal interactions between users which might not be enough of a signal to infer endorsement (Garimella et al. 2015) and to highlight the structure of the expected clusters, we only keep the interactions between any pair of nodes that occurred at least 3 times: an edge from user A to user B implies that user A has retweeted at least 3 times user B in the dataset. Nodes without edges after this process are removed. The resulting network comprises 6,492 nodes and 16,775 edges.

Results

Below we describe the results of our computational framework for community detection and characterization of the major clusters.

Community detection

We first execute the standard Louvain method once and find 151 clusters achieving a remarkable value of modularity ($Q = 0.727$).

We note a clear difference between the 8 largest clusters (size $\in [232, 1981]$) and the remaining 143 clusters (size $\in [2, 62]$). In order to label these 8 clusters, we manually inspect the most relevant users from each cluster according to their PageRank value within the full network (the top five users for each cluster are listed in Table 2). The results indicate that the standard Louvain method identifies a single cluster for almost each party: BeC = c_1, c_4; ERC = c_2; CUP = c_3; Cs = c_5; CiU = c_6; PP = c_7 and PSC = c_8. The only exception for such rule is that BeC is composed of two clusters. The manual inspection of the users from these two clusters reveals that cluster c_1 is formed by the official accounts of the party (e.g. @bcnencomu, @ahorapodemos), allied parties (e.g. @ahoramadrid), the candidate (@adacolau) and a large community of peripheral users. Cluster c_4 is composed of activists engaged in the digital communication for the campaign (e.g. @toret, @santidemajo, @galapita). That is to say that the most visible accounts from the media perspective belong to c_1 while c_4 is formed by party activists, many of whom are related to the 15M movement. For this reason, from now on, we distinguish these clusters as *BeC-p* and *BeC-m*: *party* and *movement*, respectively.

In this single execution of the standard Louvain method, accounts related to media appear in almost every political party cluster. As we noted above, our adapted version of the Louvain method is designed to study the ecosystem of each political party, i.e including only nodes that are reliably assigned to them. We apply our adapted version by running the algorithm 100 times and assigning to each cluster only the nodes that fall into that cluster more than 95 times ($N = 100, \varepsilon = 0.95$). By inspecting the results of the 100 executions, we find the constant presence of 8 major clusters much bigger than the other clusters. The composition of these clusters is also quite stable: 4,973 nodes (82.25%) are assigned to the same cluster in over 95 executions.

The boundaries between ideological online communities are visible in Figure 1. For a better readability of the network, we only consider the giant component of the graph and apply the Force Atlas 2 layout (Jacomy 2011) to enforce cluster graph drawing. As one could expect in any polarized scenario, the largest number of interaction links occur within the same cluster. There exists, however, a notably large number of links between the two clusters of BeC (BeC-p and BeC-m). To further prove the low levels of interactions between major parties we define an interaction matrix A, where $A_{i,j}$ counts all retweets that accounts assigned to cluster i made for the tweets from users of cluster j. Since the clusters are of the different size, we then normalize $A_{i,j}$ by the sum of the all retweets made by the users assigned to cluster i. From Figure 2, where we show matrix A for all the clusters, we confirm that a vast majority of retweets were made between users from the same cluster (main diagonal). This is also true in the case of the two clusters of Barcelona en Comú although we find a presence of communication between movement and party clusters, with a prevalence from the movement to the party (BeC-m $\rightarrow$ BeC-p $= 0.18$, the largest value out of the main diagonal).

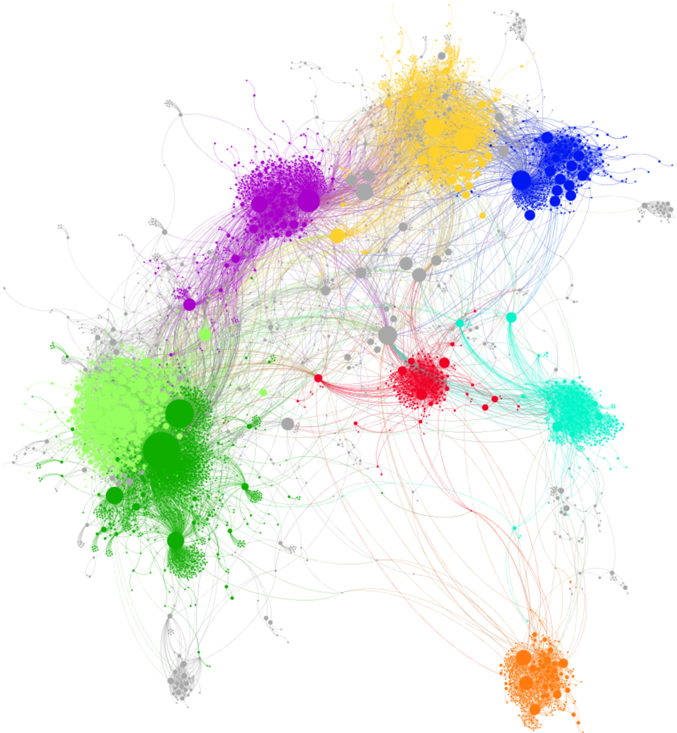


Figure 1: Network of retweets (giant component). Clusters are represented by color: BeC-p (dark green); BeC-m (light green); ERC (yellow); PSC (red); CUP (violet); Cs (orange); CiU (dark blue); PP (cyan). The nodes out of these clusters are gray-colored.

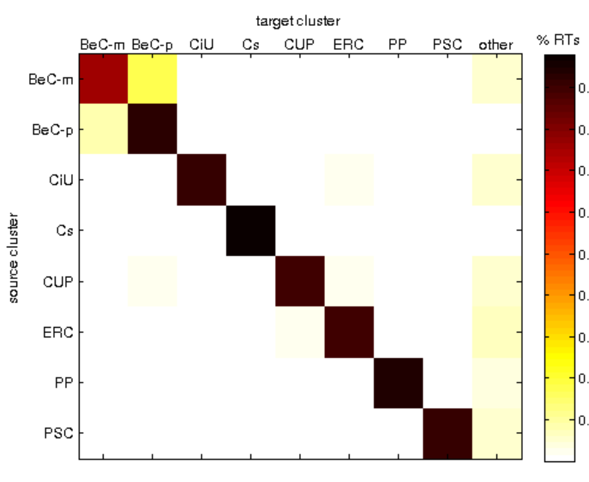


Figure 2: Normalized weighted adjacency matrix of the network of clusters.

Table 2: Top 5 users for the 8 largest clusters in the first execution of the standard Louvain method according to their PageRank (PR) value (clusters are ordered by size).

Id	Label	User	PR	Role
c_1	BeC-p	@bcnencomu	0.092	BeC party
c_1	BeC-p	@adacolau	0.029	BeC candidate
c_1	BeC-p	@ahoramadrid	0.009	BeC allied party
c_1	BeC-p	@ahorapodemos	0.009	BeC member party
c_1	BeC-p	@elperiodico	0.005	media
c_2	ERC	@ercbcn	0.016	ERC party
c_2	ERC	@alfredbosch	0.011	ERC candidate
c_2	ERC	@naciodigital	0.009	media
c_2	ERC	@arapolitica	0.007	media
c_2	ERC	@esquerra_erc	0.004	ERC party
c_3	CUP	@cupbarcelona	0.016	CUP party
c_3	CUP	@capgirembcn	0.008	CUP party
c_3	CUP	@albertmartnez	0.005	media
c_3	CUP	@encampanya	0.003	media
c_3	CUP	@mjlecha	0.002	CUP candidate
c_4	BeC-m	@toret	0.014	BeC member
c_4	BeC-m	@santidemajo	0.005	BeC member
c_4	BeC-m	@sentitcritic	0.005	media
c_4	BeC-m	@galapita	0.005	BeC member
c_4	BeC-m	@eloibadia	0.005	BeC member
c_5	Cs	@carinamejias	0.007	Cs candidate
c_5	Cs	@cs_bcna	0.006	Cs party
c_5	Cs	@ciudadanoscs	0.004	Cs party
c_5	Cs	@soniasi02	0.003	Cs member
c_5	Cs	@prensacs	0.002	media
c_6	CiU	@xaviertrias	0.012	CiU candidate
c_6	CiU	@ciu	0.004	CiU party
c_6	CiU	@bcn_ajuntament	0.003	institutional
c_6	CiU	@ramontremosa	0.002	CiU member
c_6	CiU	@cdcbarcelona	0.002	CiU member party
c_7	PP	@btvnoticies	0.011	media
c_7	PP	@cati_bcn	0.003	media
c_7	PP	@albertofdezxbcn	0.003	PP candidate
c_7	PP	@maticatradio	0.002	media
c_7	PP	@ppbarcelona_	0.002	PP party
c_8	PSC	@elsmatins	0.006	media
c_8	PSC	@pscbarcelona	0.003	PSC party
c_8	PSC	@sergifor	0.003	media
c_8	PSC	@jaumecollboni	0.002	PSC candidate
c_8	PSC	@elpaiscat	0.002	media

Network of weak ties

Among the nodes which could not be reliably assigned to any of the major clusters, we find that many accounts correspond to traditional mass media outlets. To analyze this finding in more detail we take an execution of the standard Louvain method and identify the most relevant users, according to PageRank, in the sub-network formed only by edges between nodes from different clusters, i.e. "weak ties" (Granovetter 1973).

Table 3 presents the 25 most relevant users in this sub-network and confirms that media played a key role in connecting different clusters. Since media accounts rarely retweet content from other accounts, a great amount of weak ties consists of users from political party clusters retweeting content published by media accounts. To deepen how media built bridges among clusters, we analyze the ego-networks of four of the most relevant media accounts within the networks of retweet. Figure 3a corresponds to the ego-network of @btvnoticies, the local and publicly owned television channel, that is retweeted by users from every cluster. This behaviour might be explained by the fact that this TV channel organized the debate among most of the candidates. In contrast, the other three accounts are private media: @elpaiscat, @arapolitica, and @naciodigital. We clearly see in Figure 3b that tweets from @elpaiscat, progressive media, are mostly diffused by users from BeC and PSC, progressive parties. On the other hand, Figures 3c and 3d reveal that @arapolitica and @naciodigital, Catalan nationalist media, are mainly retweeted by users from the pro-independence Catalan parties CUP and ERC.

Cluster characterization

The eight clusters detected by our framework are then characterized in terms of hierarchical structure, small-world phenomenon and coreness. The values of the metrics of these three dimensions are presented in Table 4.

Hierarchical structure From Table 4 we see that the movement cluster of Barcelona en Comú BeC-m emerges as the most equal one ($G_{in} = 0.811$) while the party cluster BeC-p forms the most unequal cluster ($G_{in} = 0.995$). The inequality values of the other party clusters are between these two values. We also plotted the Lorenz curve of the in-degree distribution of the clusters in Figure 4 to visually validate the different levels of inequality among clusters that were presented in Table 4.

Small-world phenomenon We observe in Table 4 that BeC-m has the highest clustering coefficient ($Cl = 0.208$) closely followed by PP and PSC, the two smallest clusters by size. On the contrary the clustering coefficient of BeC-p is almost 0. This finding could be explained by the topology of BeC-p, roughly formed by stars whose center nodes are the most visible Twitter accounts of Barcelona en Comú: the party official accounts and the candidate. We do not observe a remarkable pattern regarding the average path length. It is lower than 3 for the majority of the party clusters with the PSC cluster having the lowest value ($l = 2.29$). In the same time ERC, CiU and BeC-m present the longest average path length (5.43, 4.66, and 3.35, respectively).

Table 3: Most relevant nodes by PageRank in the sub-network formed by edges between nodes from different clusters.

User	Page Rank	Role
@btvnoticies	0.014	media
@bcnencomu	0.012	party
@sicomtelevision	0.010	media
@cupbarcelona	0.007	party
@elsmatins	0.007	media
@capgirembcn	0.006	party
@tv3cat	0.006	media
@324cat	0.006	media
@xaviertrias	0.005	candidate
@puntcattv3	0.005	media
@revolucio1984	0.004	citizen
@sergifor	0.004	media
@nuriapujadas	0.004	media
@annatorrasfont	0.004	media
@arapolitica	0.004	media
@maticatradio	0.003	media
@cati_bcn	0.003	media
@elpaiscat	0.003	media
@encampanya	0.003	media
@albertmartnez	0.002	media
@naciodigital	0.002	media
@adacolau	0.002	candidate
@ramontremosa	0.002	party member
@alfredbosch	0.002	candidate
@directe	0.001	media

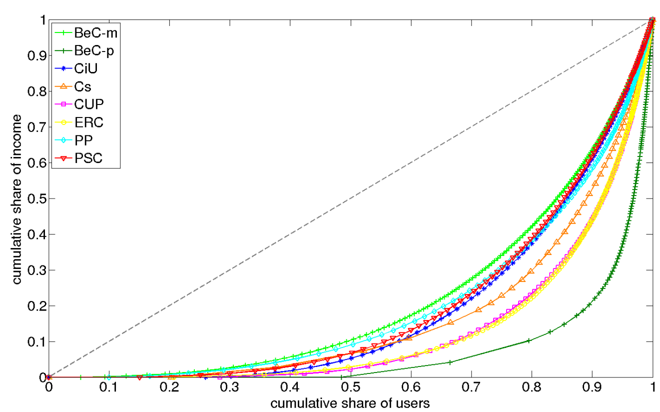
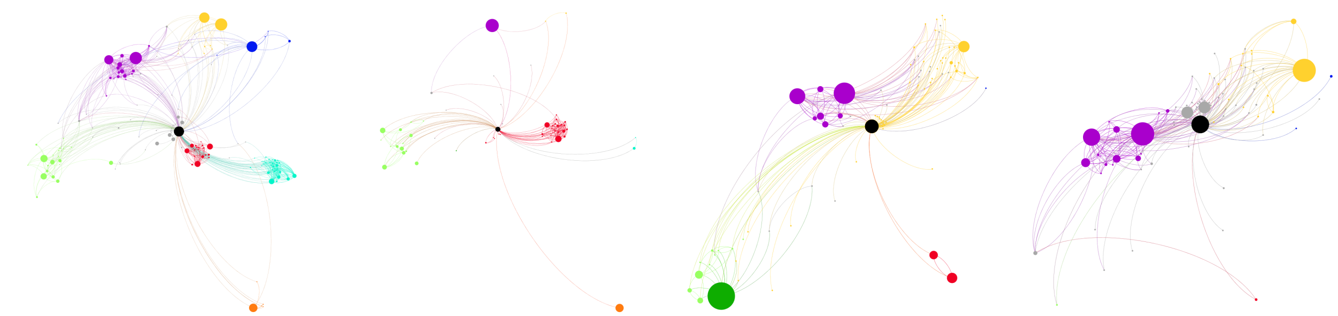


Figure 4: Lorenz curve of the in-degree distribution of each cluster.



(a) @btvnoticies (public media) (b) @elpaiscat (private progressive media) (c) @arapolitica (private Catalan nationalist media) (d) @naciodigital (private Catalan nationalist media)

Figure 3: Ego-networks of 4 media accounts within the network of retweets. Central nodes (i.e. corresponding media accounts) are black-colored. Clusters are represented by color: BeC-p (dark green); BeC-m (light green); ERC (yellow); PSC (red); CUP (violet); Cs (orange); CiU (dark blue); PP (cyan). The nodes outside of these clusters are gray-colored.

Table 4: Number of nodes (N) and edges (E), Gini coefficient of the in-degree distribution (G_{in}), clustering coefficient (Cl) and average path length (l), maximum k-index (k_{max}) and average k-index (k_{avg}, standard deviation in parentheses) of the intra-network of each cluster.

Cluster	N	E	G_{in}	Cl	l	k_{max}	k_{avg}
BeC-m	427	2 431	0.811	0.208	3.35	17	5.90 (5.46)
BeC-p	1 844	2 427	0.995	0.002	2.48	5	1.33 (0.71)
CiU	337	1 003	0.893	0.114	4.66	13	3.10 (3.44)
Cs	352	832	0.964	0.073	2.57	10	2.42 (2.42)
CUP	635	1 422	0.953	0.037	2.57	10	2.19 (2.22)
ERC	866	1 899	0.954	0.027	5.43	8	2.25 (1.85)
PP	301	1 163	0.876	0.188	2.73	12	4.02 (3.99)
PSC	211	810	0.818	0.182	2.29	11	3.85 (3.55)

Coreness In Table 4 we present maximum and average k-indices for each cluster and Figure 5 visually shows the corresponding distributions. As in the case of measuring the hierarchical structure and the small-world phenomenon we observe a remarkable difference between BeC-m ($k_{max} = 17$, $k_{avg} = 5.90$) and BeC-p ($k_{max} = 5$, $k_{avg} = 1.33$), that are the highest and lowest values respectively. In comparison to the other parties we see clear differences between node distributions for both, BeC-m and BeC-p, and the rest (the largest concentration of the nodes is in the first k-cores and considerable part is in the inner most cores). In terms of resilience, the results show the movement group of Barcelona en Comú as an online social community with a strong ability to withstand or recover. In the same time the party group of Barcelona en Comú seems to only focus on its central users.

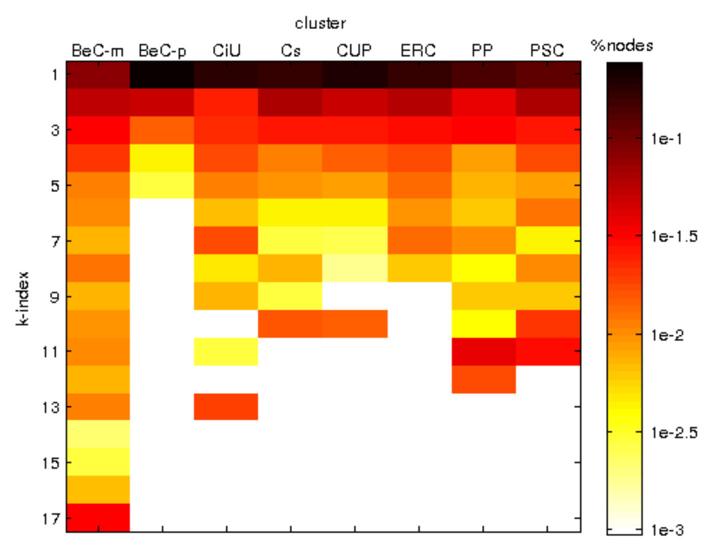


Figure 5: Distribution of the nodes per cluster (column) and k-index (row). Cells are colored to form a heat map indicating the density (log scale).

Discussion

In this section, we discuss our computational framework and the results on the Twitter networks of the political parties for the 2015 Barcelona City Council election.

Institutionalization of movement

Our framework has been designed to provide an answer to our research question that deals with the kind of organizational structure that Barcelona en Comú developed for the election campaign. On the one hand, the cited literature (González-Bailón et al. 2011; Toret et al. 2015) provided evidence of the decentralization of the 15M movement, which inspired the Barcelona en Comú candidacy. On the other hand, many political scientists (Michels 1915; Pareto et al. 1935; Mosca 1939; Mills 1999) argued that parties are historically ruled by elites and, therefore, result in centralized organizations. Furthermore, the historical models of political parties reviewed in Katz and Mair (1995) (i.e. *Caucus parties*, *Mass parties*, *Catch-all parties*, and *Cartel parties*) always assumed organization around elites. All of these observations motivated us to study whether Barcelona en Comú preserved a decentralized structure or adopted a conventional centralized organization.

Our results depict a movement-party structure in which the two components form well-defined clusters. In comparison to the clusters of the rest of political parties, we find the BeC movement community as the least hierarchical, best clustered and most resilient one. In contrast, the BeC party community emerges as the most hierarchical, least clustered and least resilient one. The centralization of the party cluster points to the candidate and official accounts, the subjects that are commonly associated with the elite. However, unlike the rest of political parties, there is a co-existence of both party and movement clusters. This co-existence is consistent with the hypothesis expressed in Toret (2015) when defining Podemos, member party of Barcelona en Comú, as the conjugation of a front-end and a back-end.

In this article we have characterized the organization of political parties according to their online diffusion networks. Some authors have reported that the Internet played a key role in the organization of the 15M movement for building "a hybrid space between the Internet social networks and the occupied urban space" (Castells 2013). According to Toret et al. (2015), this hybrid space is the result of *techno-political practices*: "the tactical and strategic use of technological devices (including social networks) for organization, communication and collective action". Are techno-politics the origin of this particular movement-party partition of Barcelona en Comú? Recently, political scientists have postulated the emergence of *cyber parties* "with its origins in developments in media and information and communication technologies" (Margetts 2001). Although we cannot ensure that the Internet and social media are the only reason behind this new form of political organization, in this particular context some party activists reported that ICT becomes essential for campaigning (Sandiumenge 2015). Therefore, a close link between techno-politics and the structure of Barcelona en Comú might exist.

Polarization in social media

The identification of the different clusters was made possible by the high level of polarization that the network exhibited, as we initially expected. We observe that bridges between clusters (i.e. "weak ties" (Granovetter 1973)) were mostly built by accounts related to media. As we noted above, media do not retweet messages from other accounts, therefore most of weak ties correspond to tweets from media accounts that were retweeted by users from political party clusters. This means that media play a key role in generating messages that build a public sphere. Some theorists suggest that the best response to group polarization is the usage of "mechanisms providing a public sphere" (Sunstein 1999). We found that the most relevant account in the sub-network of weak ties was @btvnoticies, the local and publicly owned television. Indeed, according to its ego-network, @btvnoticies was retweeted from every party while the other three private media were mostly retweeted by users from like-minded parties. This finding might indicate that public television became more plural than the other three analyzed private media, and pluralism is an effective tool in order to get "people exposed to a range of reasonable competing views" (Sunstein 1999).

We should note that some steps of the data preparation process may have accentuated the polarization effect: (1) tweet collection criteria were focused on parties/candidates, (2) the graph only comprises edges of interactions that occurred at least 3 times and (3) the community detection algorithm was adapted to enforce the robustness of the clusters. Moreover, retweeting has been proven as a common mechanism for endorsement (boyd, Golder, and Lotan 2010) and Twitter itself presents considerable levels of homophily (Kwak et al. 2010). Therefore, we find of interest to discuss whether polarization based on retweets is an effect of the own characteristics of this particular microblogging service. An analysis of the 2011 Spanish election on Twitter revealed that polarization measured in retweet networks was more intense than polarization measured in reply networks (Aragón et al. 2013). This indicates that diffusion/support networks exhibit segregation to a greater extent than discussion networks. Similar findings are also reported in a study of a Swiss political online platform which concluded that "interactions with positive connotation (supports and likes) revealed significant patterns of polarization with respect to party alignment, unlike the comments layer, which has negligible polarization" (Garcia et al. 2015). Another analysis conducted on Wikipedia, online platform in which users have to collaborate, discuss and reach agreement on editing articles, did not find a strong preference to interact with members of the same political party (Neff et al. 2013). We conclude that polarization in diffusion/support networks (e.g. microblogging) does not imply a segregated society.

Improvements of the Computational Framework

The results of this work were obtained through the computational framework that has been described in this article. The first step of the framework was to detect the major clusters that correspond to the political parties. The fuzzy membership of some nodes in certain communities (e.g. media accounts) motivated our adaptation of a standard community detection algorithm (Louvain method) by setting a confidence parameter to enhance the robustness of the clusters.

The characterization of the clusters was inspired by the metrics proposed in Garcia et al. (2015) to compare political party networks. The original dimensions of this framework were hierarchical structure, information efficiency, and social resilience. We believe that the redefinition of these three dimensions and the inclusion of new metrics in our framework constitute an improvement of the characterization of political networks:

- *Hierarchical structure*. In-degree centralization (Freeman 1979) was originally applied in Garcia et al. (2015) to measure the hierarchical structure of a network. This metric is based on (1) how the centrality of the most central node exceeds the centrality of all other nodes and (2) the comparison to a star network. It is easy to demonstrate that for networks with a heavy tailed in-degree distribution (as the ones of this study) the in-degree centralization is approximately equal to the ratio between the maximum in-degree and the number of nodes. This is caused by the differences of several orders of magnitude between the maximum and average in-degree, common situation for social graphs. Therefore, the in-degree centralization is not a good metric to capture hierarchical structure for social diffusion graphs, and the Gini coefficient for in-degree inequality represents a more reliable measure of the hierarchical structure of a network.
- *Information efficiency*. Information efficiency in social networks is closely related to the *small-world phenomenon*. We then propose the average path length, as the previous framework does (Garcia et al. 2015), and clustering coefficient to characterize efficiency in social networks.
- *Social Resilience*. Previous studies indicated the suitability of the k-core decomposition to measure the resilience of social networks (Garcia, Mavrodiev, and Schweitzer 2013). In our framework we use the term *coreness* which represents a more precise definition of this metric and we believe that showing the distribution of nodes along k-cores does capture resilience better than maximum k-core as done by Garcia et al. (2015).

Conclusions

In this study we have proposed a computational framework to examine new forms of political organization in social media. Our results focus on the Twitter networks of Barcelona en Comú in comparison to the other parties for the 2015 Barcelona municipal elections. We note that our findings rely on a dataset from Twitter. Social networks are only a slice of the structure of political organizations and not every party member has a Twitter account. Furthermore, some experts are sceptical with the digital forms of activism because of the “loss of coherence, morality or even sustainability” (Morozov 2012) and pointed out the rise of a low commitment and feel-good form of activism. Nevertheless, online platforms are playing a key role in political discussion and campaigning, and social media data are leveraging the capacity of revealing patterns of individual and group behaviours (Lazer et al. 2009; Golder and Macy 2014). Recent studies about the communication dynamics in social media for collective action have demonstrated that “relatively low commitment participants are potentially very important as a collective” (Barberá et al. 2015) and, therefore, we see Twitter as an informative and valuable data source to examine collective behaviour and self-organization in social and political contexts.

In our results we have observed that the tension between the decentralization of networked movements and the centralization of political parties results into a movement-party structure: both paradigms co-exist in two well-defined clusters. From this result, we find of interest to further investigate the origin of this particular structure: (1) Did the online structure of Barcelona en Comú result from the confluence of minor parties and the 15M activists? (2) Instead of evolving into a centralized organization, did the 15M networked movement implement a party interface over its decentralized structure? Our framework could be refined by adding longitudinal analyses of the formation of the clusters in order to provide answer to these open questions.

Finally, it is interesting to note that city council elections were held in every Spanish city in May 2015 and candidacies similar to Barcelona en Comú were built. Moreover, after these elections, the city councils of several of the largest Spanish cities are ruled by similar new organizations (e.g. Ahora Madrid, Zaragoza en Común). For this reason, future work should apply our framework to examine whether the characteristics that we observed in Barcelona en Comú are also present in these other grassroots movement-parties.

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