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Evolution and structuration of opinion communities in social conflicts

Trabajo Fin de Máster
Máster en Investigación e Innovación en Tecnologías de la Información y las Comunicaciones

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Contents

Abstract

Traditionally, political polarization has been an important topic of analysis on the social and political sciences, but in recent years, due to the paradigm shift of political participation and the digital record that it generates associated to the universalization of the Internet and the emergence of online social networks, it can be seen that different scientific disciplines related to complex networks have focused on the study of political polarization, elections predictions or protests.

In this context, this work consists of an extense analysis of the society behavior on a social network when there is a tense situation, using as case of study an ongoing conflict in Spain, the catalan independence. This conflict, besides the political tension that generates, provides us a unique ground truth for user classification. Taking advantage of this fact, we perform two strategies to classify ideologically opposite users and several analyses to detect political communities, study the political polarization underlying this great amount of data and evaluate temporal dynamics.

Acknowledgements

El presente trabajo ha sido fruto de casi un año de esfuerzo y dedicación, un año en el que la ayuda y apoyo de mi tutor han sido imprescindibles. Gracias Manuel por compartir conmigo tus conocimientos y por las conversaciones que han inspirado gran parte de los análisis que juntos hemos desarrollado. Pese a no haberte sufrido mucho en las clases puedo decir, sin lugar a dudas, que has sido el mejor profesor que he tenido estos años.

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A todos, gracias.

Chapter 1

Introduction and motivation

Political polarization and participation have been old topics of interest, studying how people get involved in politics or elections and the social tensions politics impose on the overall society. Traditionally, these types of studies were conducted by other scientific fields such as sociology and political science, using statistical tools to process data collected in surveys [Balaguer and Cazorla, 2010].

In the last years, the universalization of Internet and the apparition of new communication tools have changed the way people express, participate and debate about politics, exporting, amplifying and changing political trends in the online space and adding a new dimension to political participation and its study [Anduiza et al., 2010].

Timidly beginning with blogs [Adamic and Glance, 2005] and strongly followed with online social networks, the Internet has become a crucial tool for political participation and engagement and both society, political parties and organizations are now beginning to realize its potential. Campaigns such as Barack Obama's 2008, which changed the way politicians looked at online social networks in the same way John F. Kennedy changed in the sixties the way they looked at TV [Times, 2008] [Cogburn and Espinoza-Vasquez, 2011], social movements such as Occupy Wall Street, the Arab Spring and the 11-M or the recent and challenging apparition of Podemos party in Spain are just but examples of how the online world is changing and redefining political participation worldwide.

Besides the political changing force behind online social networks, this new type of participation also generates a digital record of the whereabouts of politics, social participation, political tensions, reactions and awareness of an unprecedented scale and granularity, thus changing too the way politics are studied. This can be seen in the recent interest of different scientific disciplines related to complex networks focusing on the study of political polarization [Conover et al., 2011], elections prediction [Tumasjan et al., 2010][Jungherr et al., 2012][Telegraph, 2008], social movements [Lotan et al., 2011][Borge-Holthoefer et al., 2014] [Lotan et al., 2011] or protests [González-Bailón et al., 2013][González-Bailón et al., 2011].

In this context, this work presents a step forward in understanding the possibilities and challenges of analyzing the digital exhaust to evaluate and predict social tensions in political scenarios. In this sense, we examine and extend previous works against a unique dataset focused on an ongoing conflict in Spain: the catalan separatist movement.

During the last decades, and with a tipping point in the financial crisis of 2008, the separatist movement has seen a significant growth within the catalan society, with an increase in the polarization, tension and attention in Catalonia and in the spanish society as a whole (see figure 1.1). During 2013 *Diada*, the catalan holiday of September 11th, separatist parties, organizations and supporters performed a crowded demonstration, lining up in a single human line all over Catalonia. This demonstration, called *Via Catalana*, and its specific location and time, provides a unique ground truth for group classification, with which to analyze and extend previous works on political polarization, detecting political communities and evaluating temporal dynamics.

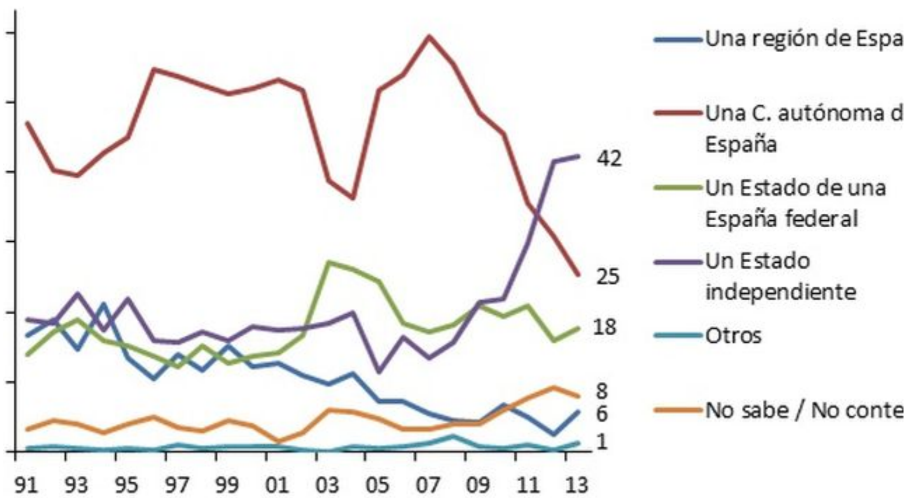

Figure 1.1: Evolution of the preferences about relations between Catalonia and Spain [Diario, 2013] based on the results of the ICPS

Structure of the document

The present document describes the analysis we have performed about political polarization based on the political tensions of the catalan society around the *Vía Catalana*. It is divided into the following chapters:

- In chapter 2 we present the main approaches to analyze political polarization, networks structure theoretical concepts as well as a more extensive explanation of the fields studied.
- In chapter 3 we describe the data used for the study.
- In chapter 4 we introduce the two strategies to classify users we use in the analysis of the problem.
- In chapter 5 we present the conducted analysis on political polarization, hashtags spreading and temporal dynamics.
- In chapter 6 we finish with the conclusions of the analysis and the further work.

Chapter 2

State of the art

Political polarization has been an important topic of analysis on the social and political sciences and more recently of the computational sociology and the complex networks communities, due to paradigm shift of political participation and its digital record brought by the universalization of the Internet and the emergence of online social and information networks.

The computer science communities have handled this problem with two main approaches:

- **Opinion mining and sentiment analysis.** Studying people's opinions by analyzing the content of the information they publish online. Its aim is to detect what people talk about and the sentiment behind them [Pang and Lee, 2008] [Pak and Paroubek, 2010]. As every semantic approach, it is language specific, relying on specific semantic corpuses and, despite the recent advances and the availability of strong corpuses for more and more languages, minority languages such as catalan are still far behind the main trends, mainly focused on english.

- **Complex networks properties.** This second approach focuses on the structural properties of the social network as a language independent proxy to the underlying opinions, trends and sentiments shaping the social fabric. The structural properties of a network have in addition an important role in understanding the actors and processes affecting society, from information epidemics to behavioral dynamics or influence [Hanneman and Riddle, 2005]. Studying users relevance in the network, detecting how users group together in communities or understanding how information is propagated and which role is played by each type of tie in the network gives us an indirect view of the underlying forces driving the society behind the network.

This work lies among the latter, structure-based language-independent studies, mainly due to the complexity of performing natural language processing in catalan as well as looking forward to obtain results that can be applied to other political settings, regardless of the underlying language.

In the first part of this section we briefly introduce the most relevant theoretical aspects and properties of social networks, emphasizing those concepts that will be later used in this work. In the second part, we review two previous studies in political polarization and early detection of contagious outbreaks that serve as foundation to this work.

2.1 Network structure and properties

Popularly, people talking about social networks refer to online social networks such as Twitter, Facebook, Linkedin or XING. Nevertheless, the concept of social network is older than the appearance of these online sites. In the field of sociology, a social network is a representation of people (also referred to as actors), represented by the vertices of the network, and their relations, represented by edges or ties.

Depending on the type of relations that are being analyzed and whether this are reciprocal by nature (eg. being family members) or not (eg. buying a present) networks can be directed or undirected. Similarly, in online social networks, relations can vary depending on the platform used or the phenomenon considered in the study. For example, friendships on Facebook are bidirectional (both users have to accept it), whereas on Twitter the concept of friendship does not exist and it is replaced by the concept of *following*, which is a unidirectional relation that a priori does not need a confirmation from the user followed. Other types of relations, such as posting into other user's wall on Facebook or mentioning somebody on Twitter have their own idiosyncrasy and can even be considered as weighted relations, in which not every link is equally strong in the network.

In our study, we analyze political behavior on Twitter considering the following concepts provided by the service:

- **Mention.** A user explicitly mentions another user by its handler (@username). Users are notified of other people's mentions when done in this way and therefore mentions pose an explicit desire of awareness of the mentioned counterpart.
- **Retweet.** A user posts other users' content in her own timeline, though keeping track of the origin of the post (RT @username). A retweet can be viewed as an interest in a particular piece of information and the desire to transmit it to ones own list of followers.

- **Hashtag.** A *hashtag* is a word prefixed by the character '#' that is used by Twitter as a direct label on the content of the message. It serves to explicitly mark a post as belonging to a particular topic.

In directed networks (in which a relation can be found from A to B but not from B to A) it is sometimes interesting to analyze the reciprocal network, that containing only those relations that are found in both directions. We will use this type of subnetwork in some studies of this work as a proxy to closer and more personal interactions filtering out, for example, mentions to newspapers that receive no response, bots and other non-human players, as well as to detect relations that play an important role in the information diffusion [Zhu et al., 2013].

Once defined the components of a network (what nodes and links represent) the analysis of its structure can reveal different properties of the system it represents. Several works focused on finding out these features or structural properties such as the small world effect [Watts and Strogatz, 1998], network transitivity or clustering [Barrat and Weigt, 2000], or omnipresent power-law degree distributions [Barabási and Albert, 1999].

The structure analysis can be used to characterize nodes or links rather than the overall system, such as defining how important is a node or a link in the network. The most relevant and well known set of measures are the centrality measures, each capturing a different flavor of what it means to be central in a network. The most important are:

- **Degree centrality**. Number of connections a node has. This is the simplest centrality measure, looking at just the most local structure by counting the number of neighbors a node has. If the graph is directed, as in the retweet network, degree centrality can be separated into in-degree and out-degree centralities. The in-degree centrality being the number of incoming edges and out-degree centrality the number of the outgoing ones.

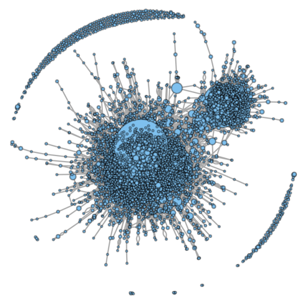

Figure 2.1: Example of network, size of node proportional to its degree.

- **Betwenness centrality**. Number of shortest paths that travel through a node. Betweennes centrality was first proposed by [Freeman, 1977], and measures the importance of a node in terms of global diffusion nodes or, in other words, how much communications in the network will suffer if a given node is removed from it. Given a node v, betweenness centrality is defined as follows:

$$g(v) = \sum_{a \neq v \neq b} = \frac{\sigma_{ab}(v)}{\sigma_{ab}}$$

- **K-coreness centrality**. Number of important connections. The k-core is a rather categorical measure of importance that focuses on the robustness of the connections of a node. The k-core 2 group (or 2-core group) is defined as the group of nodes that remain in the network after iteratively removing all nodes with less than 2 connections until all nodes in the network have at least 2 connections [Dorogovtsev et al., 2006]. The k-core of a node is defined by the highest k-core group to which it belongs.

- **Closeness**. Distance to the rest of the network. Probably the most straight forward understanding of centrality, it measures the average distance of a node to the rest of the nodes of the network. It is commonly referred to as closeness centrality or global closeness to distinguish it from other type of closeness (because of the double meaning of the word close as opposed to open and to far apart), that counts the number of connections of a node that are also connections between them or, in other words, the amount of triadic closure that can be found in the vicinity of a node.

Besides the overall structure of a network and the importance of its different nodes and links, another branch of network analysis focuses in the study of the sub structures that can be found within a network, being the most significant what is called the community structure. Defining where a sub structure ends and another begins is not trivial and many different algorithms exist to define what a community is, based on edge betweenness[Girvan and Newman, 2002], modularity optimization [Newman, 2006a], random walks, random removal of links or statistical properties among many others [Lancichinetti and Fortunato, 2009]. For our work we have used the InfoMap algorithm because is computationally faster than the rest of the algorithms. First presented by [Rosvall and Bergstrom, 2008], it uses maps to describe the dynamics between edges and nodes in a network.

One of the most important challenges for evaluating the different methods for community detection is the difficulty of finding a social network in which the ground truth of what a community is is well defined but at the same time non trivial. This is one of the main reasons for focussing the present study in the *Via Catalana*, as it provides a clear definition (concrete location at a concrete time) of a political community, against which to test our community based analysis.

2.2 Polarization, early warning and local analysis

Having defined the basic principles and measures, this work focuses on understanding political polarization through network analysis, studying its digital signature, its epidemic nature and the possibility to understand both of them through local analysis rather than through post-hoc global ones.

Regarding the digital signature of political polarization, we focus on [Conover et al., 2011], in which Conover et al. founded that, when looking at political conversations, different types of polarization arise in the retweet (information focused) and mention (person focused) networks, observing a clear divide in the former that cannot be observed in the latter. Nevertheless their network was constructed based on hashtag use and so was their definition of political groups. The particular nature of our dataset and the ground truth provided by the *Via Catalana* in terms of real communities pose a perfect opportunity to falsify this study.

In addition, political movements and demonstrations require the participation and coordination of many individuals, normally preceded by long term sharing of ideas and adoption of behaviors. This type of phenomenon can be studied as an epidemic process in which an idea, political opinion or particular behavior spreads over the network. The *Via Catalana* was planned long before the day of the demonstration but, during the actual day in which it took place, besides the final mobilization and subsequent chain formation, another interesting phenomenon was captured: the counter reaction of the non separatist group in the political arena and the counter counter reaction of the separatist group that saw the non separatist hashtag become trending topic in Twitter instead of theirs.

In [Garcia-Herranz et al., 2014], Garcia-Herranz et al. propose a method to early detect contagious outbreaks through local information. We use their findings to study the *Via Catalana* phenomenon, understand to what extent political demonstrations, reactions and counter reactions can also be detected in advance, whether or not we can distinguish between viral movements and exogenous ones and finally if such mechanism can be used to replicate Conover's finding through local analysis.

2.2.1 Political polarization

One of the most important works to the present study is [Conover et al., 2011]. In this work the authors study political polarization in the Twitter sphere during the six weeks previous to the 2010 midterm US elections with a corpus of approximately 355 millions tweets. First, they identify all the political relevant tweets in the dataset, defining the concept of politicaly relevant tweet as a tweet containing at least a political relevant *hashtag*.

To identify a list of political relevant *hashtags* they use a co-occurrence mechanism, starting with two seed *hashtags* that identify the two parties in US, #p2 ("Progressives 2.0") and #tcot ("Top Conservatives on Twitter"). They identify the *hashtags* that co-occur with these two seed *hashtags* and rank them using the Jaccard coefficient:

$$\sigma(S,T) = \frac{|S \cap T|}{|S \cup T|}$$

where S is the seed *hashtag* and T the *hashtag* analyzed. Using a minimum threshold for this coefficient to avoid unrepresentative *hashtags* and removing the ambiguous ones, they obtain 55 political *hashtags*, pruning the original corpus to a secondary corpus of 252,300 politicaly relevant tweets.

With this new corpus, they build the mention and retweet networks, applying then a community detection algorithm based on label propagation (proposed in [Newman, 2006b]), seeding it with initial node labels determined by the leading-eigenvector modularity maximization method for two clusters, for which they obtain a modularity of 0.48 for the retweets network and 0.17 for the mentions one.

The conclusion of the analysis is that, when focusing on political conversations, the retweet and mention networks display different topologies, observing a high polarization in the retweet network that do not exist in the mentions network, as we can see in the figure 2.2.

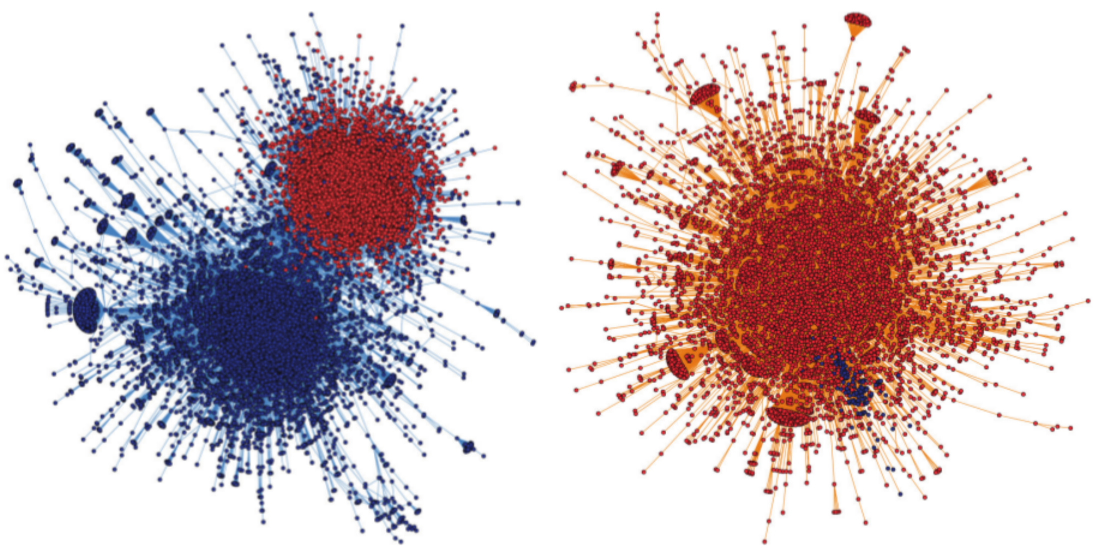

Figure 2.2: The political retweet (left) and mention (right) networks. Node colors reflect clusters assignments. [Conover et al., 2011]

2.2.2 Early warning and local analysis: Friends as sensors

A direct derivative of political polarization are escalating processes in which an action on a group leads to a reaction on the other and that into a counter reaction of the former. The study of this types of cascades, the social awareness of the counterpart's actions and the early warning signals these processes may display are of great importance to both our understanding of the political dynamics of conflict and to whatever protective measures society may take in advance to disruptive processes. From an operational point of view, rather than a purely academic, and given the sheer and increasing size of the digital exhaust, it is equally important to find mechanisms to conduct this type of analysis from local and limited information, without the computationally expensive and most times impossible need of analyzing the system as a whole.

In [Garcia-Herranz et al., 2014], Garcia-Herranz et al. propose a method based on the friendship paradox (ie. in average, your friends have more friends than you do) to early detect contagious outbreaks using friends as sensors. This method avoids the high computational cost of computing the centrality of all the nodes in a network by relying on a local method to obtain more central groups (simply choosing a random sample of the friends of a random group). Since every process traveling through the network reaches, in average, central nodes sooner than random nodes, the difference in infection time betweenn a central and a random groups serves as warning signal of a viral process traveling through the network.

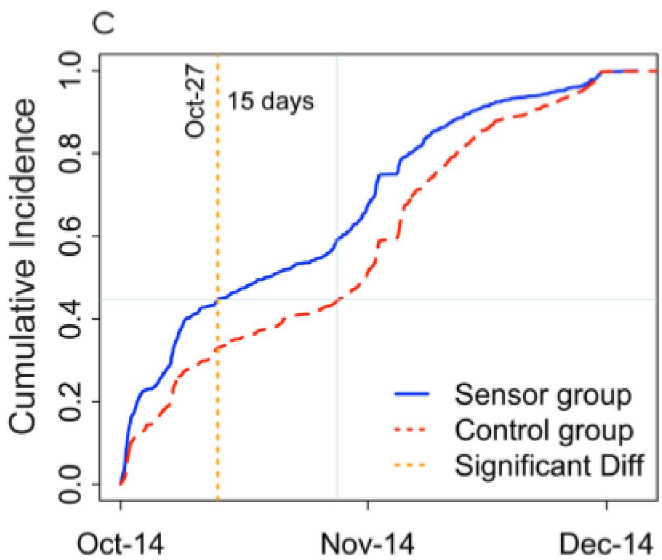

Figure 2.3: Example of contagious outbreak early warning. [Garcia-Herranz et al., 2014]

They demonstrate that the friends group is more central than the random control group (even after eliminating the mathematical trick presented by Scott Feld [Feld, 1991]. In terms of networks, if your friends have more friends than your on average, your friends are more central in the network than you are, so the authors observed that this mechanism can be used to early detect trending topics in Twitter: when there is an significant lead time in the use of a *hashtag* from the sensor group (see figure 2.3)

In the present work we will use this mechanism to study the dynamics of actions and reactions in the “war for trending”, to characterize exogenous versus endogenous processes and to find a local method to replicate Conover’s analysis.

Chapter 3

Data description

For this work we have used a dataset of all tweets published in Catalonia (100km around the coordinates 41.387956,2.169921) gathered using Twitter's REST API from November 2012 until present. This period includes the June 2013 change of Twitter's API from version REST1 to version REST1.1, (see Appendix A for more information) and includes more than 10 million tweets per month (see Figure 3.1).

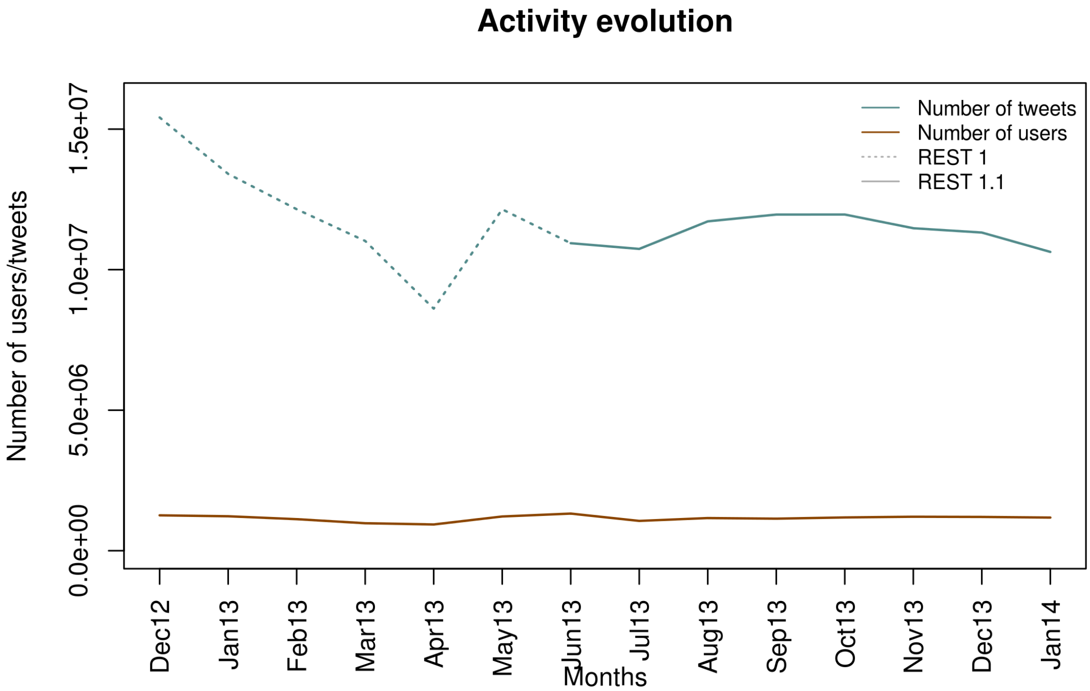

Figure 3.1: Monthly tweets and users evolution in Catalonia

Despite our best efforts, it is extremely complicated to gather a dataset of this magnitude without some inconsistencies: the change in Twitter's API and querying policies, technical problems both in our servers or in Twitter's ones or simply the access limitations imposed by Twitter (see Appendix A.2.1 for more information) combined with periods of unusual high activity (such as football events), inevitably lead to variations in the quality of the data. The REST API, as we will explain later, was precisely chosen to minimize this type of gaps but nevertheless we can still find some in our dataset such as the drop in number of tweets in April 2013 of figure 3.1, that when observed closely (see figure 3.2) corresponds to a period (March 27th to April 8th) where the number of tweets and users drops close to 0, possibly as a result of a power failure during holidays or of any other disruptive technical event.

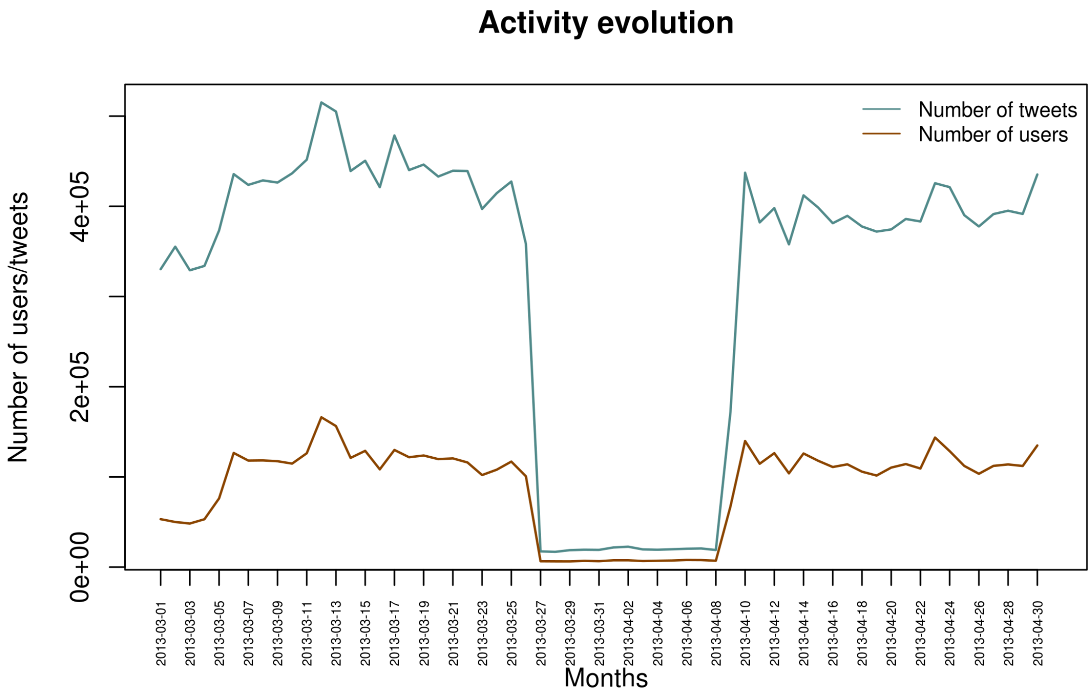

Figure 3.2: Daily tweets and users evolution in Catalonia between March 1st and April 31th 2013.

In addition, it is interesting to observe in figure figure 3.1 that the number of monthly tweets does not grow as it should be expected [Liu et al., 2014]. Explanations for this stagnation range from the hard to believe that Catalonia is stagnant and it is not following the global growth of number of Twitter users to other more plausible such that Twitter's API has been returning more and more accurate results with time, maintaining the total monthly number or that the global growth observed in Twitter is mainly due to new or developing countries joining the community and Catalonia is among the old stablished ones and had reached a more or less stable and common saturation point.

Key to this work are geolocated tweets, meaning tweets for which Twitter returns the exact coordinates of the position in which they were posted. We use this type of tweets for the most important of our users classification strategies presented in chapter 4. Geolocated tweets (geotweets) mainly correspond to tweets posted through mobile devices by users sharing their location, these type of tweets comprise approximately 3.8% of our dataset (see figure 3.3).

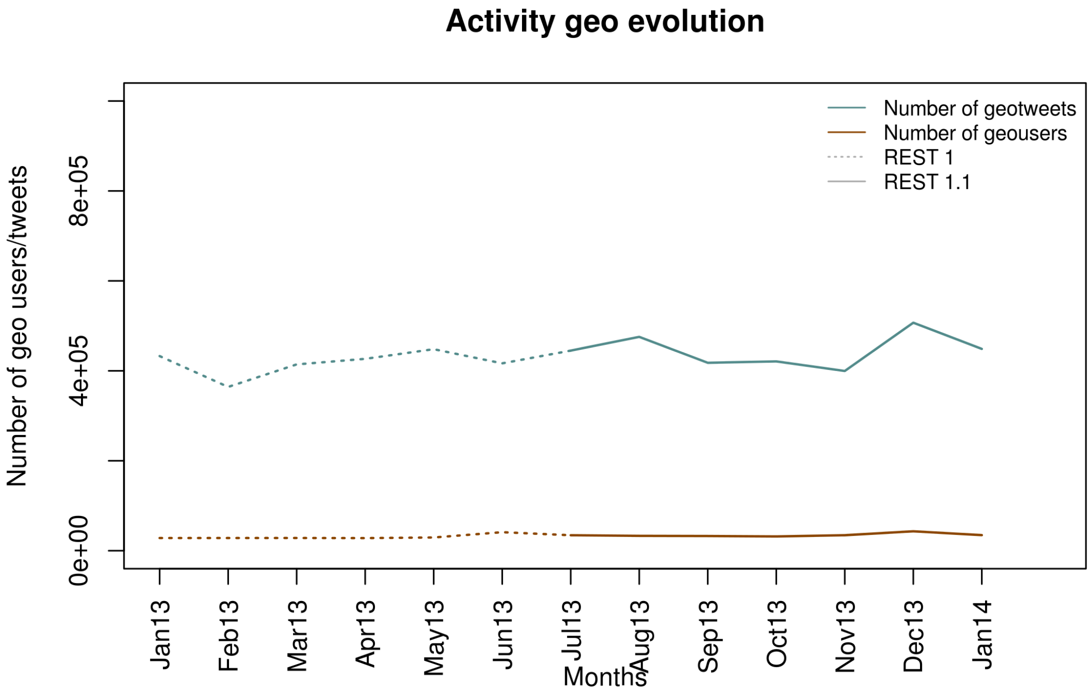

Figure 3.3: Monthly geotweets and geousers evolution in Catalonia

Chapter 4

Users classification

Political polarization states, by definition, that more than one group of political opines exist and measures the extent to which those groups tend to move apart from each other in understanding, communication or sentiment. Classifying or identifying these groups, is essential to the study of their dynamics and evolution of tensions.

Politically, our case study focuses on the social tension caused around the independence of Catalonia, also referred to as the Catalan problem. Any type of polarization has at least two sides, nevertheless in political setups in which a group challenges the status quo it is often the case to find a clearly defined social challenging group and a silent majority that can neither be classified as aligned or opposed to the challenging one. The *Via Catalana* allows us to clearly define a setup of this kind, in which the separatist group is clearly defined (as the ones forming the human chain) while the rest cannot be classified a priori by belonging to any of the in conflict groups. For a bi-polar classification we will differentiate between *separatist* (or *proindependentist*)and *constitutionalist* (or *prospanish*) groups. Being the former composed by those supporting the separation of Catalonia from Spain and the latter by those explicitly defending that Catalonia might continue to be part of Spain. Because of the nature of the conflict, and the current status quo (ie. Catalonia is part os Spain) it would be more accurate to define the latter as those actively reacting to the former's mobilizations, rather than defending a second and equally valid option as it would be the case, for example, of presidential elections.

In this section we present two strategies to detect define these groups. The first one, as mentioned before, is based on the users geolocalization during the 2013 *Diada*, taking as reference the separatist demonstration that took place that day. The second one attempts to classify users based on their use of hashtags, following a similar approach than that of Conover [Conover et al., 2011].

4.1 Geotagged based

During last years, spanish political scene has witnessed how nationalist parties and separatist groups increasingly organized public separatist demonstrations during the September 11th *Diada* (catalan national holiday). This escalation of public demonstrations peaked in 2013 where separatist organized a continuous human chain called *Via Catalana to Independence* (or simply *Via Catalana*) that crossed Catalonia from the south of France to the north of Valencia. Despite the sadly usual struggle about participation figures, sign of the tension behind the event (ranging from 400,000 people, estimated by the spanish government, about 800,000 people counted in the mega picture of the event by a non separatist organization, 1.6 million people estimated by the pro separatist catalan government or the 2.6 million people estimated by the organizers), the event was an unprecedented mobilization success in Spanish separatism.

The massive attendance, combined with the fact that the human chain passed through many low populated areas (the organization make sure that every part of the chain was covered) and the timely nature of the event (it was announced to start at 17:14) allows us to obtain an unprecedented ground truth in community classification by looking at the coordinates of geolocated tweets. Therefore with this information we categorize Twitter users as follows:

- **IsVia users:** Users who during the 2013 *Diada* tweeted at least one geolocated tweet in the coordinates of the *Via Catalana*. This group represents the ground truth for pro separatism.
- **NoVia users:** Users who during the 2013 *Diada* tweeted at least once but never in the coordinates of the *Via Catalana*. This group represents a silent majority which is not clear whether they support the *Via Catalana*, are against it or simply do not care.

While most of the human chain passed through sparsely populated areas, part of it also crossed Barcelona, the most populous city of Catalonia and therefore a noisy scenario in which demonstrators, neighbors, passbyers and tourists voices mingle in every corner. Therefore, despite the great amount of participants that were joining the chain in Barcelona, focusing in obtaining the most accurate ground truth to define the IsVia users group, we have removed the part of the human chain that pass through Barcelona from the *Via Catalana* coordinates. The final classification of tweets can be seen in figure 4.1: in blue tweets posted from the *Via Catalana* but outside Barcelona, in orange, tweets posted from the *Via Catalana* in Barcelona, and in red the geolocated tweets posted outside the *Via Catalana*.

During the 2013 *Diada*, 153,211 unique users tweeted in Catalonia, and 6,716 of them tweeted at least one geolocated tweet. The groups obtained after classifying the users attending to their geolocated tweets are the next:

- **Users isVia (with Barcelona)**: 2472 users.
- **Users isVia (after removing Barcelona as part of the *Via Catalana*)**: 1496 users.
- **Users noVia**: 4244 users.

After selecting these two groups, we can affirm with a fair degree of confidence that users who compose the isVia group are separatists, while the nature the noVia group is unclear.

Figure 4.1: Geolocated tweets during the 2013 *Diada*. IsVia users in blue (isVia in Barcelona users in orange) and noVia users in blue.

4.2 Hashtags use based

Following a similar approach to Conover et al. [Conover et al., 2011], explained in chapter 2, we have done a second group classification based on hashtag used.

For this classification we have selected the tweets of our dataset posted between the 1st of August and the 31th of December 2013, a total of 58,432,778 tweets. In the same way Conover et al. choose their categorizing hashtags to be #p2 and #tcot we have chosen #somespanya (for anti-separatist group), which was trending topic during the 2013 *Diada*, and #independencia (for pro-separatist group) which has been an historic pro-separatist slogan used on Twitter during the last years. The analyze timeframe include 5 months to categorize as many users as possible within each group and manly extends after the *Diada* because most of the anti–separatist hashtags appeared precisely in the *Diada*, as a response to the separatist movement and therefore there is no record of them after that time.

After pre-processing the hashtags to ignore case and accents we follow an iterative process to find other hashtags that might be also used to categorize the two groups. The iteration begins with #somespanya and #independencia as only seeds in the following manner:

First iteration

First step
In this step we compute the hashtags that co-occur with the seed hashtags to obtain both ideological lists. The co-occurrence happens when a tweet, containing one seed hashtag, contains also other hashtags (see figure 4.2). When this happens, we increase the count of these hashtags in the appropriate ideological list, depending on wether it is co-occurring with a separatist or non–separatist hashtag. The top 10 co-occurring hashtags for each seed are represented in the table 4.1.

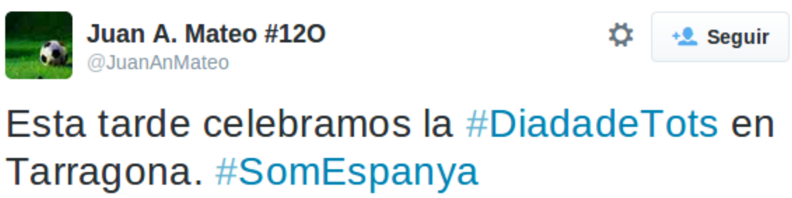

Figure 4.2: Example of a tweet where there is a co-occurrence with the seed hashtag #somespanya.

Second step
Since some hashtags co-occur with both seeds (see in the table 4.1) simply choosing

the top members of both sides is not a good option therefore, we assign a hashtag to one of the two sides according to the number of times it co-occurs with a seed and the ratio of co-occureences that also has with the other. Mathematically:

$$ideology_{hashtag} = \begin{cases} prospanish & if \ \frac{ratio_{h,prospanish}}{ratio_{h,proindependentist}} > 2 \\ proindependentist & if \ \frac{ratio_{h,proindependentist}}{ratio_{h,prospanish}} > 2 \end{cases}$$

where these ratios are computed as follows,

$$ratio_{h,proindependentist} = \frac{count_{h,proindependentist}}{max_h(count_{h,proindependentist})}$$

$$ratio_{h,prospanish} = \frac{count_{h,prospanish}}{max_h(count_{h,prospanish})}$$

On the one hand, we have discarded hashtags whose ratios for both ideologies are less than 0.05 to avoid unrepresentative hashtags. On the other hand, an ideology is assigned to a hashtag only if its co-occurs at least twice the times it co-occurs with the other, avoiding thus general hashtags. An example of this classification is the hashtag #viacatalana which appears both in the *prospanish* and *proindependentist* lists. For this hashtag we obtain the following values, which determine that the ideology for #viacatalana is *proindependentist*:

$$ratio_{viacatalana,prospanish} = 825/10089 = 0.082$$
$$ratio_{viacatalana,proindependentist} = 2022/8778 = 0.23$$
$$ideology_{viacatalana} = \frac{ratio_{viacatalana,prospanish}}{ratio_{viacatalana,proindependentist}} = 2,8 > 2$$

In figure 4.3 we can see the co-occurrence graph of hashtags with at least a ratio of 0.005 for one of the two seeds, that is, only those appearing with the seed at least 5 times of every 1,000 the seed is mentioned.

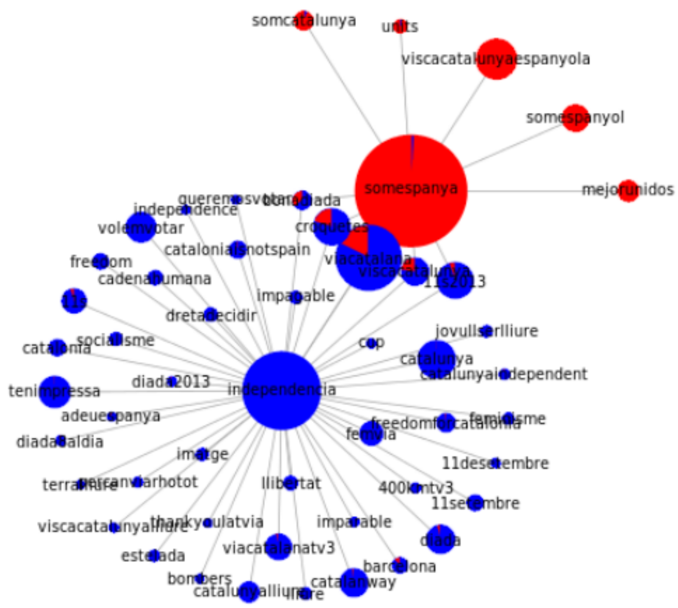

Figure 4.3: Hashtags graph. **Nodes**: HTs. **Edges**: Co-occurrence in a tweet. **Pie**: Ideology ratio. Only hashtags with ratios bigger than 0.005 are represented

Second iteration

After the first iteration we extend our seed lists with the newly found significant hashtags:

- **Prospanish hashtags**: #somespanya, #viscacatalunyaespanyola.
- **Proindependentist hashtags**: #11s2013, #catalunya, #independencia, #tenimpressa, #viacatalana, #volemvotar.

First iteration				Second iteration			
independencia	8778	somespanya	10089	viacatalana	104532	somespanya	10089
viacatalana	2022	viacatalana	825	volemvotar	64285	viscacatalunyaesp	874
catalunya	1283	viscacatalunyaesp	753	catalunya	29166	viacatalana	840
tenimpressa	710	somespanyol	271	11s2013	15586	somespanyol	271
volemvotar	694	croquetes	199	independencia	8778	croquetes	199
11s2013	602	mejorunidos	197	croquetes	8404	mejorunidos	197
croquetes	378	somcatalunya	164	tenimpressa	8054	somcatalunya	164
diada	348	viscacatalunya	126	catalonianway	6276	viscacatalunya	126
catalonianway	299	12o	122	diada	6218	12o	122
11s	266	espanyaalcor	88	queremosvotar	3856	espanyaalcor	88

Table 4.1: Co-occurrence lists for the two iterations of the analysis.

And repeat the process considering the co-occurrences with all the hashtags that appear in these new seed lists, obtain the definitive hashtags lists that we will used during the rest of our work:

- **Prospanish hashtags**: #somespanya, #viscacatalunyaespanyola.
- **Proindependentist hashtags**: #11s2013, #catalonianway, #catalunya, #croquetes, #diada, #independencia, #tenimpressa, #viacatalana, #volemvotar.

Users classification based on hashtags use

These lists are both used to identify politically relevant tweets (those containing at least one of the hahstags in the lists) and to categorize users as part of either of the two groups if they show a significant tendency to use one type of hashtags more than the other:

$$ideology_{user} = \begin{cases} proindependentist & if \quad \frac{count_{u,proindependentist}}{count_{u,proindependentist}+count_{u,prospanish}} > 0.6 \\ prospanish & if \quad \frac{count_{u,proindependentist}}{count_{u,proindependentist}+count_{u,prospanish}} < 0.4 \\ neutral & in\ other\ case \end{cases}$$

The results of the classification are two groups of users:

- **Proindependentist group:** 6,967 users.
- **Prospanish group:** 841 users.

Chapter 5

Analysis of the problem

In previous chapters, we have introduced the principal techniques to analyze and evaluate the political polarization on Twitter, providing two different user classification approaches applied to our case of study, the catalonian independence.

Given our geolocated classification (isVia vs. noVia) we analyzed the type of interactions they have with each other in order to shed some light into both the social dynamics of the isVia group and how different it is from the noVia one and from the general population.

For this analysis we considered the network of reciprocal mentions (a link exists between two users when one has mentioned the other in a tweet and also the other way around). Besides the isVia and noVia groups, described in the previous section, we define a random group. Since we found that users with geolocated tweets tend to have higher centrality than random users, we define the random group form the set of users that tweeted between 10th August and 14th August 2013 (sufficiently before the *Diada*) at least one geolocated tweet.

In the figures 5.1, 5.2 and 5.3 we show the empirical cumulative distributions (ECDF) of reciprocal mentions among groups. That is taking successive samples of each of the three groups, how many of their mentions go to members of their same group and to the other two. Figure 5.3 shows the ECDF using the network of interactions that occurred during the week of the *Diada*, figures 5.1 and 5.2 are two examples of other weeks of the year (see Appendix D for more examples).

The plots on the left represent the mentions of random users to other groups (including a second random group), showing a similar distribution of mentions to any other group.

Plots on the center represent the mentions of noVia users and though with small variations (and some weeks in which they show more mentions to noVia users than to random and less to isVia than to random), in general they behave quite similarly to the random group.

Finally, plots on the right represent the mentions of the isVia group, where we can observe a significant difference in their interactions with other isVia members than to any other type, sign of a more endogamous nature and confirmation that our ground truth correctly identifies a singular group with more cohesion to itself than to the rest of the catalan society.

In the rest of this chapter, we will take as reference the works of Conover et al. and Garcia-Herranz et al. introduced in the state of the art, replicate them in our case scenario and explore them further under the light of the ground truth provided by the geographical nature of our user classification. The main objective, as stated before, is to understand the digital signature of political polarization, its early warning signals and evolution, and the existence of local tools to identify political polarization and classify the types of events driving them.

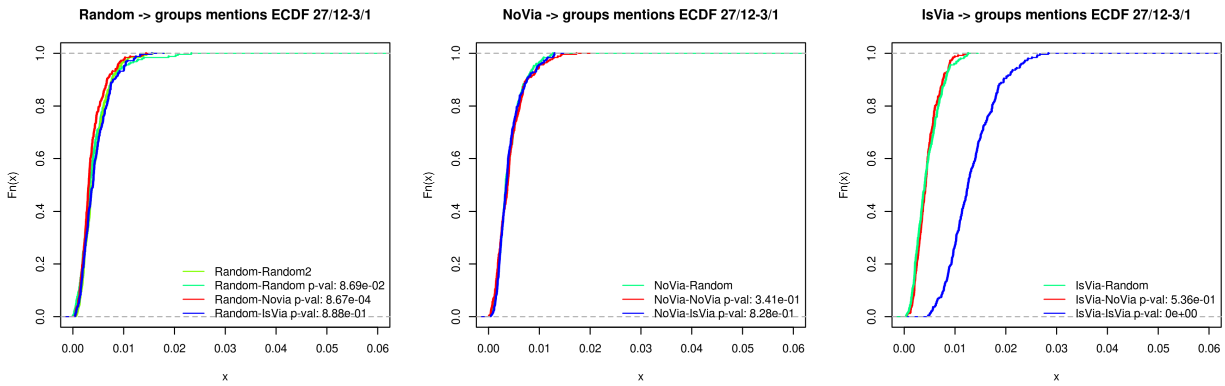

Figure 5.1: ECDF for isVia (blue), noVia (blue) and random groups (green) reciprocal mentions, from December 27th 2012 to January 3rd 2013

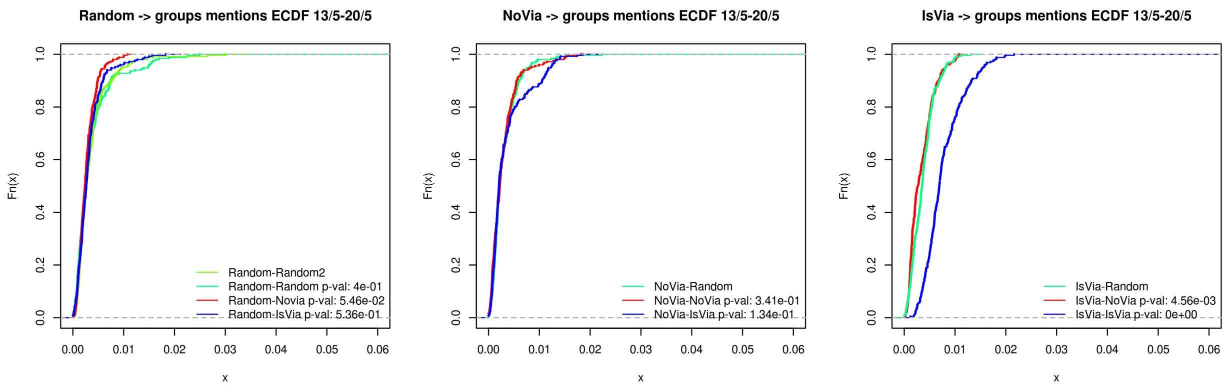

Figure 5.2: ECDF for isVia, noVia and random groups reciprocal mentions, from 15th to 20th May 2013

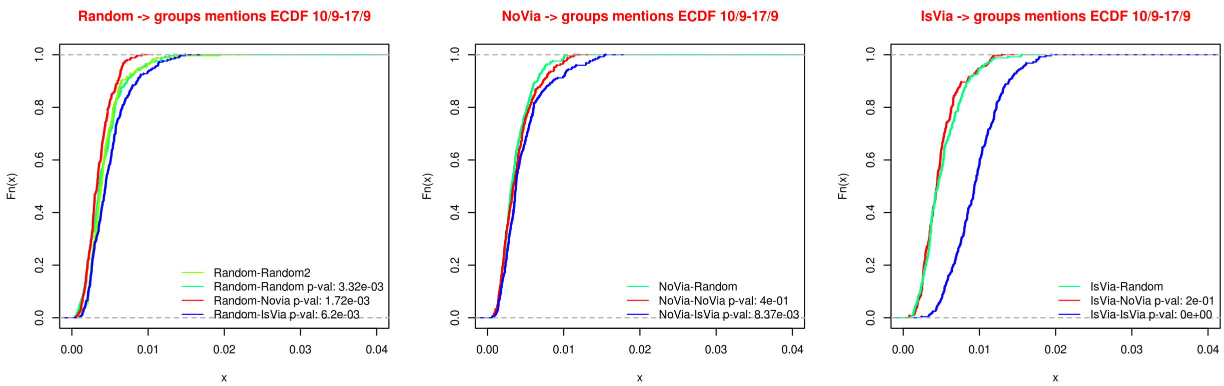

Figure 5.3: ECDF for isVia, noVia and random groups reciprocal mentions, from 10th to 17th September 2013 including the *Diada* day

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5.1 Political polarization on Twitter

As we explained in chapter 2, [Conover et al., 2011] proposed that when analyzing political conversations on Twitter there is an important difference between the community structures of the retweet and mention networks, displaying the former a polarization that cannot be observed in the latter. In other words, the modularity of the retweet network is greater than that of the mention network.

In this section we analyze their approach applied to our case of study, trying to detect if we obtain the same results. For this analysis we have used the 58,432,778 tweets published in Barcelona and 100km ratio around between the 1st of August 2013 and the 31st of December 2013.

To analyze the political conversation taking place on Twitter, and similar to [Conover et al., 2011], we use the hashtag classification (pro-separatist vs. anti-separatist) explained in chapter 4, This classification is used both to isolate the political conversation and secondly, to classify users attending to their *hashtags* use.

As a reminder, the final lists of political *hashtags* computed in chapter 4 are:

- **Prospanish *hashtags***: #somespanya, #viscacatalunyaespanyola.
- **Proindependentist *hashtags***: #11s2013, #catalonianway, #catalunya, #croquetes, #diada, #independencia, #tenimpressa, #viacataloniana, #volemvotar.

With these list of political *hashtags*, we define political tweets as the tweets that contain at least one of the *hashtag* in the list, either *prospanish* or *proindependentist*.

The corpus of political tweets consists of 82,387 tweets. In figure 5.4, we show the evolution of the ratio of political tweets respect all tweets per day. There are two days that stand out over the rest, the *Diada* (September 11th) and September 15th. Being the latter the day the President of the Spanish Government and the President of the *Generalitat de Catalunya* expressed publicly their discrepancies about the separatist mobilization. This disagreement caused an important increase in political activity on Twitter [PAIS, 2013].

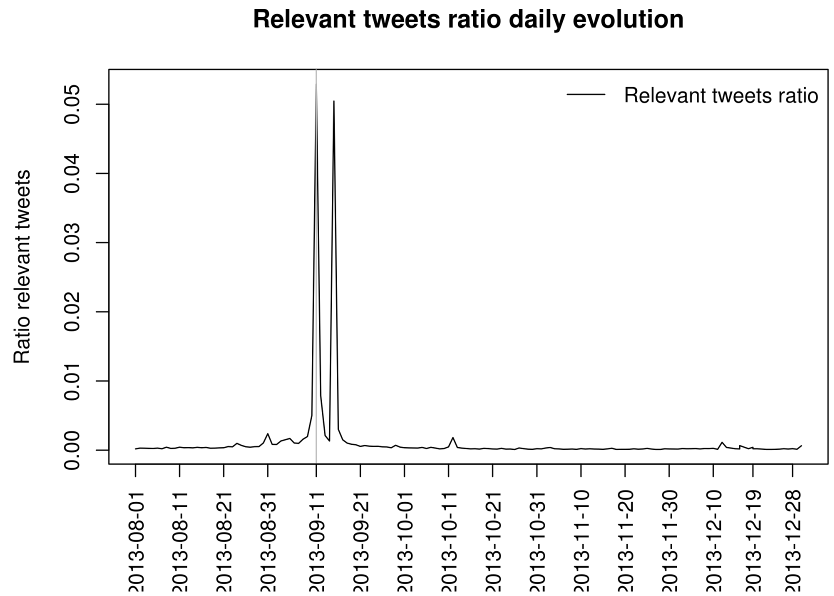


Figure 5.4: Daily ratio of relevant tweets. September 11th and 15th stand out over the rest of days.

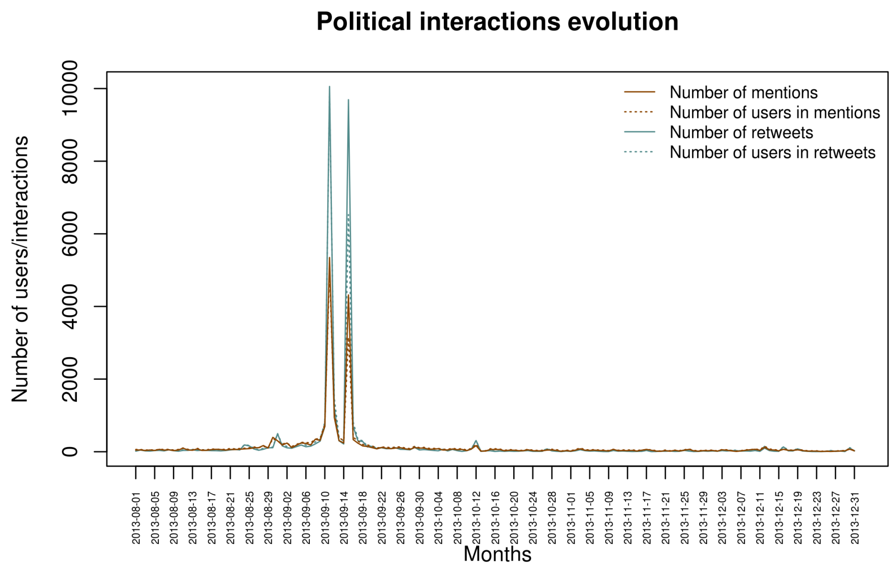


Figure 5.5: Daily evolution of political interactions. Most of the interactions gather around the day of the *Diada*

Considering our corpus of political tweets we build the mention and retweet networks. These networks, as expected, have significantly more nodes and links during the aforementioned days (see figure 5.5). We focus our analysis on the *Diada*. In figure 5.7 we can see these two networks with *proindependentist* users marked in blue, *prospanish* in red, neutral (those using political hashtgas of both lists with a ratio close to 0.5) in green, and non-political in orange. A non-political user can appear in the political mention network by being mentioned in a political tweet regardless of not having ever tweeted with a political hashtag as in figure 5.6.

Figure 5.6: Example of a tweet where the Popular Party is mentioned but it can not be classified as *proindependentist*.

We can see in figure 5.7, how in the retweet network *prospanish* users (in red) are grouped in the right part of the network forming a clearly defined cluster, and how the rest of the network is dominated by *proindependentist* users. Despite the imbalance in number of users, we obtain a similar result than that of Conover et al. in their work (see Appendix C for more examples).

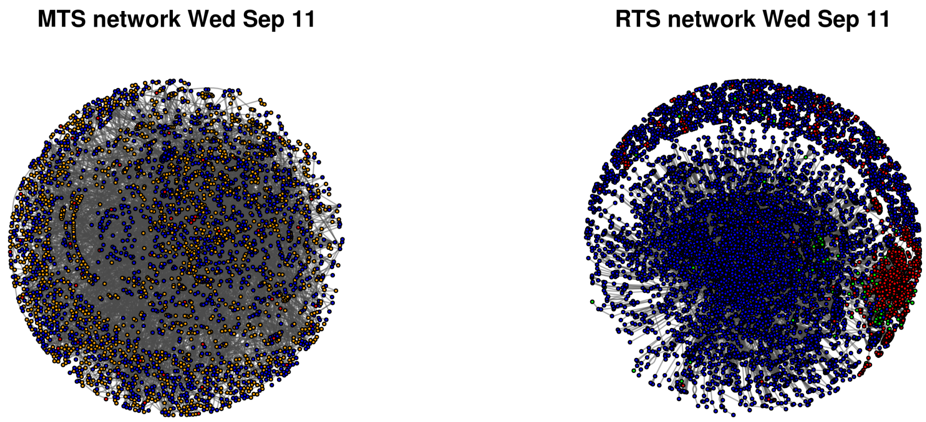


Figure 5.7: Political interactions networks 11th September. Proindependentist users in blue, *prospanish* users in red, neutral users in green and not classified users in orange. It can be seen in the retweet network the polarization between *prospanish* and *proindependentist* groups.

Similarly, we have built the mention and retweet political networks for the period of the 1st of August to 3 the 1th of December, consisting the retweet network of

20,676 nodes with a greatest connected component of 16,709 nodes and only 15 in the next-larger component. The mention network is smaller and consists of 12,968 nodes, 9,688 in its largest component and only 11 in its next-larger one. We have computed the communities of these networks using InfoMap algorithm and we have obtained a modularity of 0.58 for the retweet network and 0.49 for the mention network. Repeating the analysis of [Conover et al., 2011] for the largest components, we have obtained a modularity of 0.53 for the retweet network and 0.46 for the mention network. Conover et al. founded 0.48 and 0.17 respectively, therefore we find a similar trend but nonetheless a more fractured mention network than they did.

On the day of the *Diada*, the modularities grow even bigger being 0.90 for the retweet network (consisting of 9,811 nodes, 6,709 in the GCC and 29 in the next-larger component) and 0.78 in the mentions one (4,996 nodes, 2,315 in the GCC and 17 in the next-larger component). Analyzing only the GCCs we still obtain a high modularity for both networks: 0.82 for the retweet network and 0.65 for the mention network, but, as predicted by Conover et al., the retweet network displays a higher modularity than the mention one. Why the mentions network show such high modularity too is an unceasing finding that will need further study.

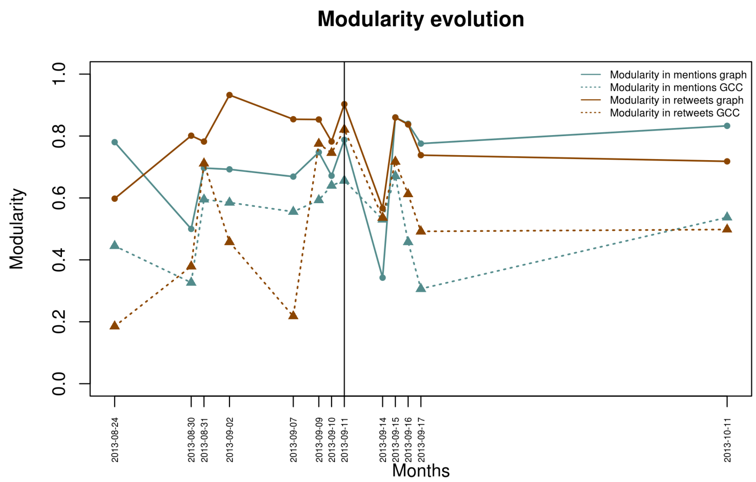


Figure 5.8: Modularity evolution for retweet and mention networks and their largest components. Only are represented days in which mention or retweet largest components networks have at least 100 nodes to avoid unrepresentative modularity values. The day with the highest political polarization, modularity induced by the RTs networks (g and gcc) are higher than the MTs networks (g and gcc).

By calculating the retweets and mentions network networks in a daily basis we are able to visualize the temporal evolution of their modularities as a proxy of political polarization. We have restricted the analysis's to only those days in which the GCC of the networks have at least 100 nodes (see figure 5.9), which leaves as with the partial but more robust image of the temporal dynamics of figure figure 5.8. In this figure, though noisy, we would like to note the inversion in trends from our first point in the graph (in which modularities are lower and the ones of the mentions networks are higher) and how this trend flips as we approach the day of the *Diada*, second, the peak in polarization in the day of the *Diada* followed by a relaxation of the polarization in the Tweetsphere that is violently broken by the event of the 15th and finally how modularizations go back to the inverse state of the initial of the graph but at slightly higher values, remanent of the added tensions.

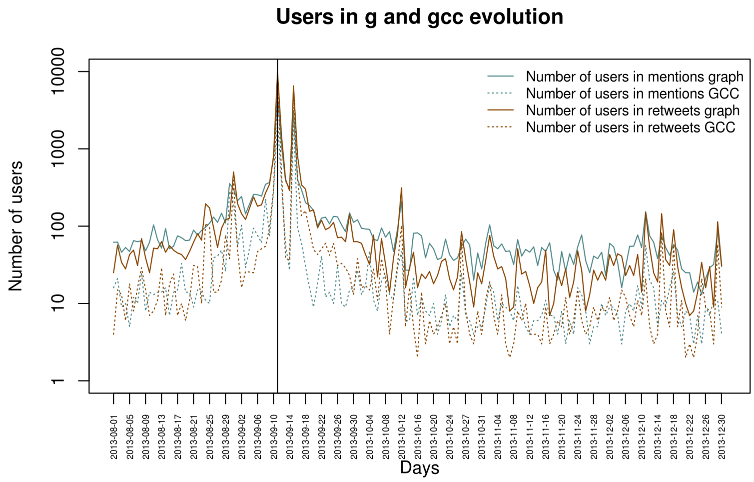


Figure 5.9: Users evolution for retweet and mention networks and their largest components.

Having followed Conover's et al. approach to this point, we focus on our geographically based classification (isVia vs. noVia, see chapter 4) to extend Conover's et al. analysis with a better nuanced ground truth and estimate to what extent it can be used to categorize the "silent majority".

First, in figure 5.10, we represent again the political networks of the figure 5.7, highlighting with a greater size the isVia (in blue) and noVia (in red) users. We can observe how isVia users are integrated into one of the clusters of the retweets network, sign that the method proposed in [Conover et al., 2011] might be used not only to measure polarization but to classify correctly the isVia users. NoVia users, on the other hand appear scattered all around the network, sign that the "silent majority" might in turn be composed of many different opinions and political trends.

As we have explained above, we obtain similar results to [Conover et al., 2011] work, but there is a difference respect the community detection algorithms used. They use an algorithm based on label propagation obtaining only two clusters for the retweet network. In our case using InfoMap algorithm, we obtain 1,051 communities in the mention network and 1,686 in the retweet network for the *Diada* day. When we compute the political networks with the interactions over all the period, we obtain 2,764 communities for the mention network and 3,394 communities for the retweet network.

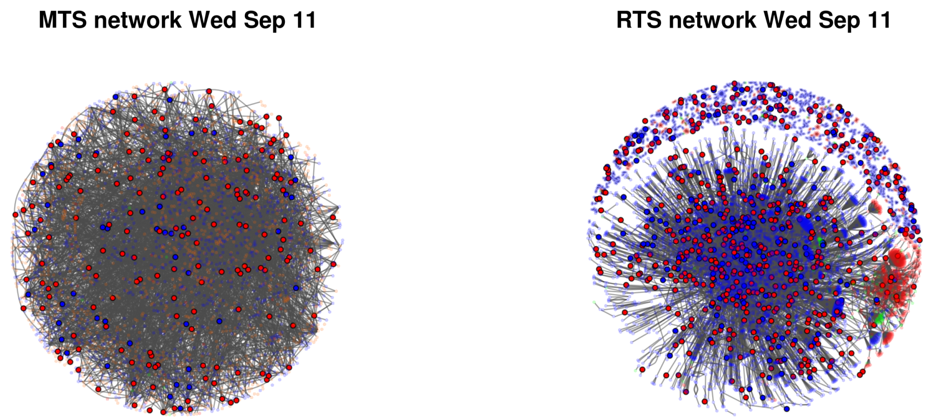


Figure 5.10: Geousers (isVia in blue, noVia in red) in the underlying political interactions networks 11th September (transparent)

In addition, while Conover et al. analyzed democratic elections our focus lies into a different realm in which a group is mobilizing to change the status quo. The different nature of the underlying process might affect the expected network structure and therefore the interpretation of the results.

For this reason and given the network structure of the retweets and mentions networks of the *Diada* day we have shuffled the users' labels (pro-separatist vs. pro-spanish) to measure the composition of communities that would be expected to be normal given the network structure and the number of people in each category. Figure 5.11 shows how users are distributed into communities. Each point represents a community and the x axis represent the *pro-separatist* ratio of the community. Considering only users in one of the two groups, *pro-separatist* and *pro-spanish*, community ratios are complementary and add up to 1 (ie. x users of group A means 1-x users of group B). Points are blue if their *pro-separatist* ratio is greater than 0.5 and red otherwise, its size is proportional to the total size of the community. On the y axis, from top to bottom we show the distribution of communities in the **political** network (ie. that in which we only consider tweets with a political hashtag) after **shuffling** the political labels of users, next the observed distribution (without shuffling), and next the same but for the complete network (i.e.. considering not only political mentions or retweets but every mention or retweet).

The difference between the shuffled and the observed distributions serves to normalize Conover's approach to uneven scenarios in which the overrepresentation of a group or tendency might obscure the underlying polarization of society.

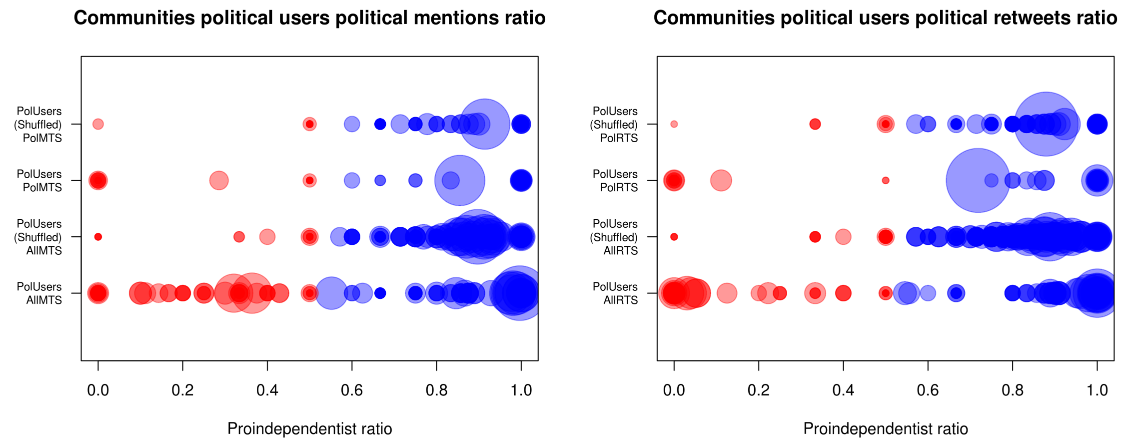


Figure 5.11: Communities *proindependentist* ratio the day of the *Diada*. Points represent communities, color represent the majoritary ideology (red for *prospanish*, blue for *proindependentist*) and in relation with the size of the communities. Polarization mainly appears in the retweet network but it can be appreciated in the mention network.

In the figure 5.11, we can appreciate how the imbalance of number of users of each group tend to skew the composition of the communities to the *proindependentist* (i.e. pro-separatist) side of the plot in the shuffled versions, stressing the importance of the observed distributions when compared to what would be expected from the pure network structure and the number of members of each group. In particular we can point out to the grouping of communities among the extremes of the plot for both political networks (retweets, as expected, but also significantly mentions), and that the apparently more even distribution found in the complete networkws (bottom plots) can be also interpreted as a shift to the left in light of the shuffled results.

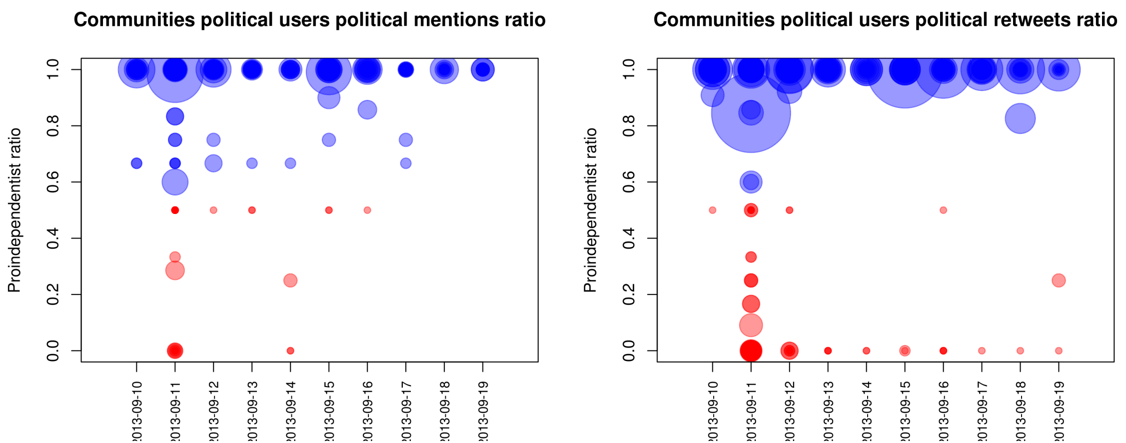


Figure 5.12: Communities *proindependentist* ratio from 10th to 19th September 2013 in political networks. Points represent communities, color represent the majoritary ideology (red for *prospanish*, blue for *proindependentist*) and in relation with the size of the communities.

This type of analysis has been conducted in a daily basis to understand the temporal dynamics of polarization. In the figure 5.12, it can be observed how in the day of the *Diada* polarization is evident in both networks. Nevertheless, polarization in the mention network tend to relax faster, with the distribution approaching that of the shuffled version of 5.11 while in the retweet network it is precisely the center space of the distribution that disappears and the community landscape gathers around the extremes of the plot as time goes by.

Both the presence of polarization in the mentions network as well as the resilience of this polarization can be used to asses the gravity of a political situation. Nevertheless further work needs to be done in this direction.

5.2 Early warning and local analysis: Friends as sensors

In the previous section, we have showed that the day of the *Diada*, political retweet network is clearly polarized. This analysis and its conclusion are based on a classification based on users' use of *hashtags*. Therefore, it is interesting to analyze when these political *hashtags* appear and how they evolve. In the figure 5.13 we show the evolution of the use of political *hashtags* that we have classified in chapter 4, during the period between 1st of August and 31th of December. In this figure we can see there are several days in which the *hashtags* activity stands out, the first one, as expected, is the day of the *Diada*, focus of the conflict. Next day is the September 15th, when presidents of Spain and Catalonia manifested their discrepances in press, and finally, the 12th of October, National Day of Spain.

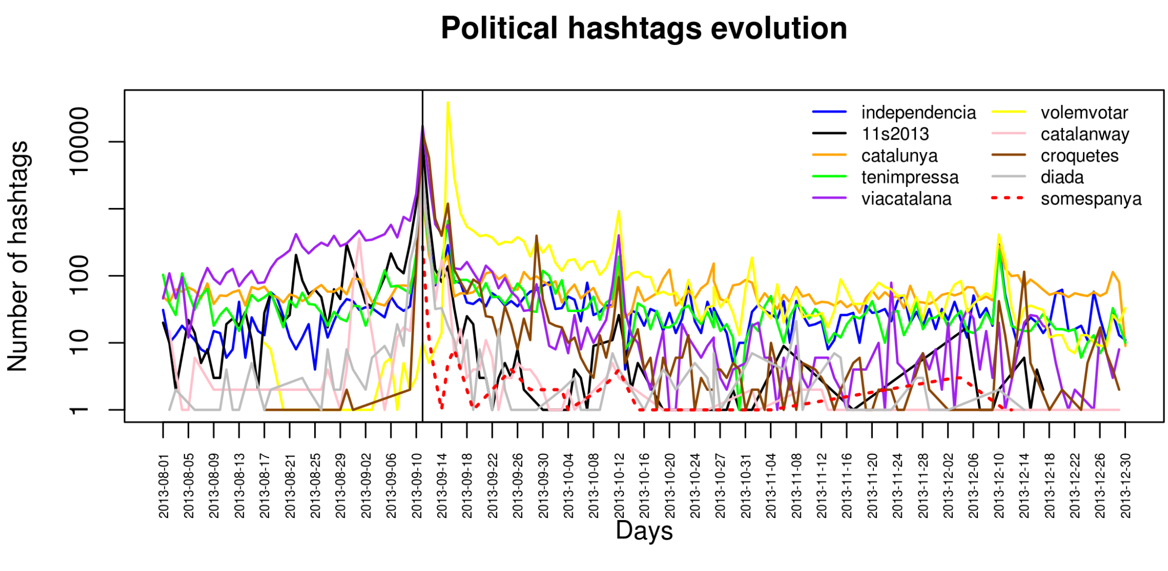


Figure 5.13: Hashtags use evolution from August 2013 to December 2013. The use of *hashtags* increases the *Diada* day (vertical grey line) and this day #croquetes and #somespanya appear.

Another interesting question is the different beginning for each *hashtag*. Taking as reference the day of the *Diada*, there are *hashtags*, as #viacatalana (in purple), #independencia (in blue) or #11s2013 (in black) all *proindependentist hashtags*, that appeared weeks before this day, so *proindependentist* supporters had structured their *hashtags* on Twitter before the day of the *Diada*. However, #somespanya (in dashed red), principal *prospanish hashtag* appear the day of the *Diada*, and #croquetes[1] (in dark orange), despite of few unrepresentative uses in previous days appears the day of the *Diada* too. Furthermore, there is an interesting question associated to #croquetes. The day of the *Diada* in 2013, the *hashtag* #somespanya became trending topic, in contrast to the *hashstag* # viacatalana, which despite the great number of uses was not since one important issue for becoming trending topic is novelty and #viacatalana had been used long before the *Diada*. For this reason, several *proindependentist* supporters, thinking that Twitter was banning their *hashtags*, called to RAC1 radio protesting for this banning. The radio speakers proposed the use of the apparently not political *hashtag*, #croquetes. The result was that, in one hour #croquetes became trending topic. Rather than being banned, #viacatalana was not considered trending topic not because it was not largely used but because it was not novel.

For these reasons, the *Diada* presents a unique scenario in which to analyze *hashtags* birth, nature and spreading. There are two interesting questions that we want to answer: first, can we early detect the trends of this new born hashtags? Second, can we distinguish the exogenous or endogenous nature of hashtags such as #croquetes or #somespanya?

To analyze all these questions, we have explained in chapter 2 how, in [Garcia-Herranz et al., 2014], Garcia-Herranz et al. propose a method to detect contagious outbreaks using friends as sensors. Authors apply this method to a wide variety of *hashtags*, mainly focusing on global trends and long early warnings. We apply their mechanism to study the fast dynamics of the *Diada* choosing for the analysis the hashtags #viacatalana and #independencia, two *hashtags* that had already appeared before the day of the *Diada* but peaked during that day, and secondly #somespanya and #croquetes, *hashtags* two new born hashtags that appeared for the first time the day of the *Diada*.

Garcia-Herranz et al. propose using friends of users as sensors to detect global contagious outbreaks. This election is due to the friendship paradox, a sociological phenomenon which enunciates that on average your friends have more friends than you do [Feld, 1991]. In terms of networks, if your friends have more friends than you on average, your friends are more central in the network than you are and therefore they will be reached sooner by viral processes traveling through the network, hence serving as a good proxy of forthcoming epidemics. In their work they propose to use two groups for monitoring: a random control group and a sensor group composed of random friends of the first one. Being the sensor more central than the control, divergences in their

[1] Croquetes is the catalan word for croquets, a typical spanish (as well as catalan) dish.

"time of infection" can be used as early warning signs of epidemic processes (or trends in Twitter jargon).

For choosing the friends groups, Garcia-Herranz et al. rely on the follower network. In our case, our dataset does not include such network and therefore we first need to demonstrate that the friendship paradox also holds for the mention and retweet networks. In other words, do people who I mention or retweet have more mentions and retweets than I do?,

To answer these questions we have computed the control and sensor groups for each *hashtag* using the mentions and retweets networks to represent their degree distributions. The selection of the control and sensor groups consist on the next steps:

1. **Selection of the control group.** From all users that have used a particular *hashtag* we choose a random sample with a size of 5% of all users.
2. **Selection of the sensor group.** We take a sample of its neighbors (mentioned or retweeted, depending on the network) of the same size than the control group. This sample is the sensor group.

Once we have the different control and sensor groups we compute their degree distributions. In figure5.16 we can observe how the sensor groups degree distributions are above the control groups degree distributions and their tails are also heavier, meaning that the friendship paradox, as described by Garcia-Herranz et al. also works in retweet and mention networks in Twitter.

Finally, the authors propose an outbreak alarm that is triggered when there is a significant difference between the sensor and control groups 'infection rates". In our case we have imposed a minimum difference of the 25% between the control and the sensor groups cumulative use. When there is a difference greater than this minimum the model triggers the alarm.

With this alarm model, we analyze the *hashtags* evolution during the day of the *Diada*, with particular attention to the *hashtags* #somespanya and #croquetes that appear during this day and particularly to the latter, which was caused by the exogenous intervention of RAC1 radio.

In the figure 5.14, we have represented the cumulative density functions of the *hashtags* use during the 24 hours of this day, in addition we have represent *hashtags* uses evolution every 2 minutes. In the figure we can observe how *hashtags* that have been used weeks before the *Diada*, start earlier in the morning but they grow more slowly than the #croquetes and #somespanya, most possibly because in the morning political activity was still low. For #somespanya our alarm triggers at 11:30, 6 hours before the outbreak. In the figure 5.15c we show in more detail this spreading in which the sensor group cumulative incidence is shifted forward in time with respect to the control's one, showing that the sensor model works and that this is a typical example of viral spreading occuring within the network.

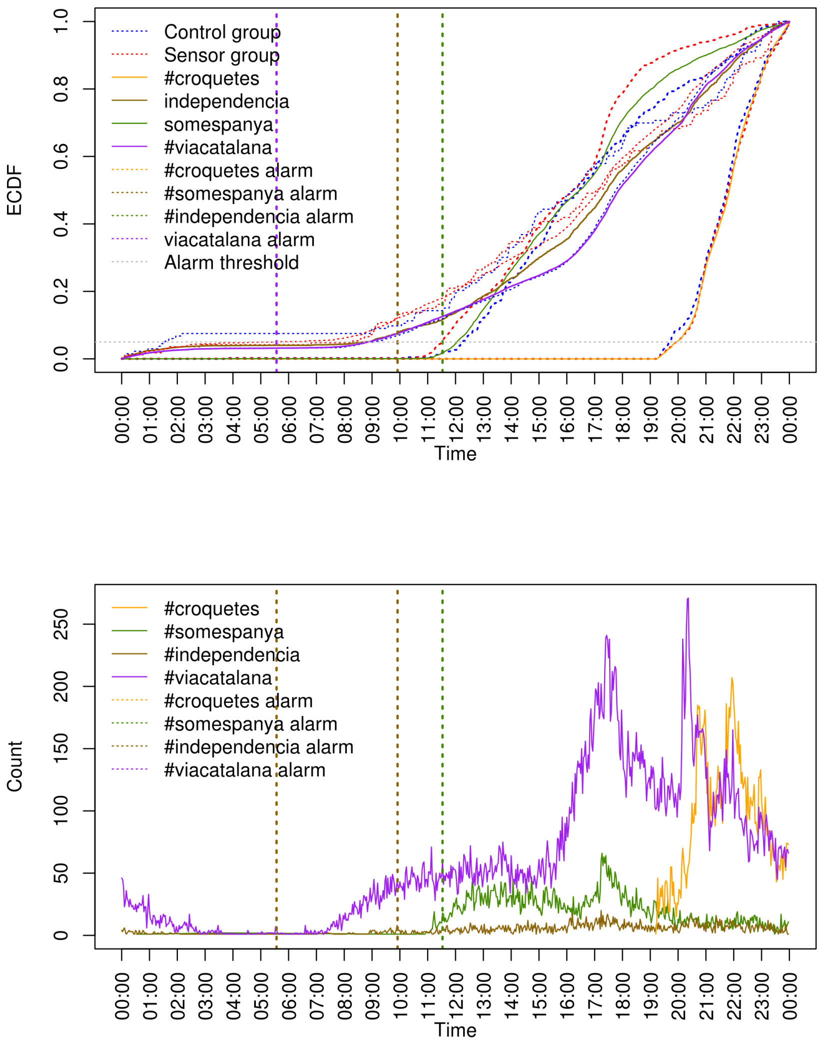
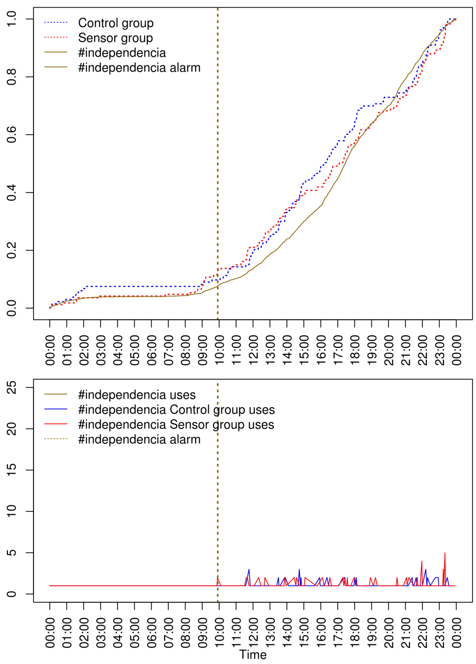
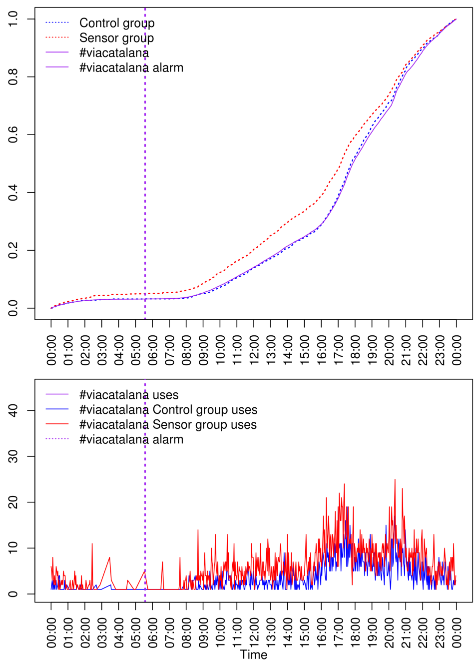


Figure 5.14: Cumulative incidence during the day of the *Diada* for *hashtags* #viacatalana in purple, #independencia in brown, #somspanya in green and #croquetes in orange. There are three alarms: #viacatalana around 5:30, #independencia just before 10:00 and #somespanya around 11:30.

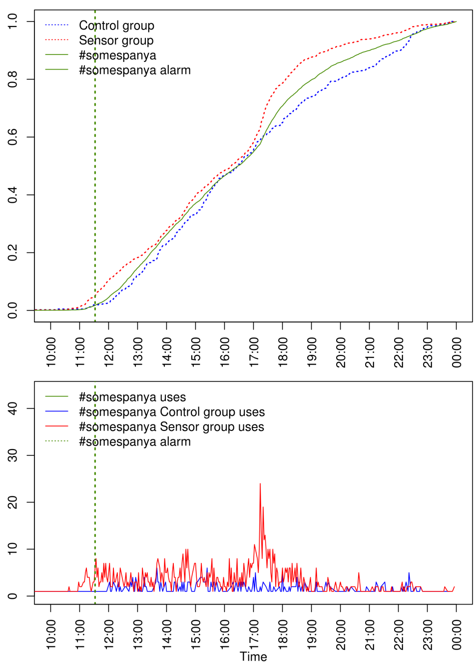
The other example is #croquetes, this *hashtag* displays the fastest growth of the analyzed ones, beginning at 19:00 and peaking in few hours. Nevertheless, it can be observed in the figure that the model does not trigger an alarm and that the control group is actually behind the sensor group in "time of infection" therefore showing that the sensor mechanism can be used to distinguish endogenous events from exogenous ones.



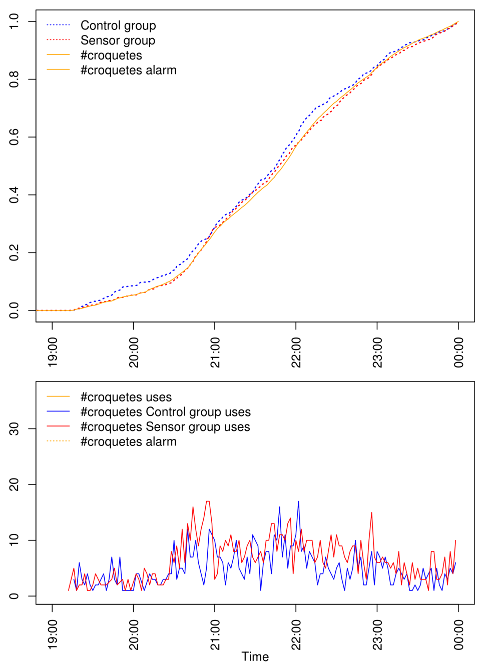
(a) Cumulative incidence during the day of the *Diada* for the hashtag #independencia



(b) Cumulative incidence during the day of the *Diada* for the hashtag #viacatalana



(c) Cumulative incidence during the day of the *Diada* for the hashtag #somespanya



(d) Cumulative incidence during the day of the *Diada* for the hashtag #croquetes

Figure 5.15: The average and standard deviation of critical parameters: Region R4

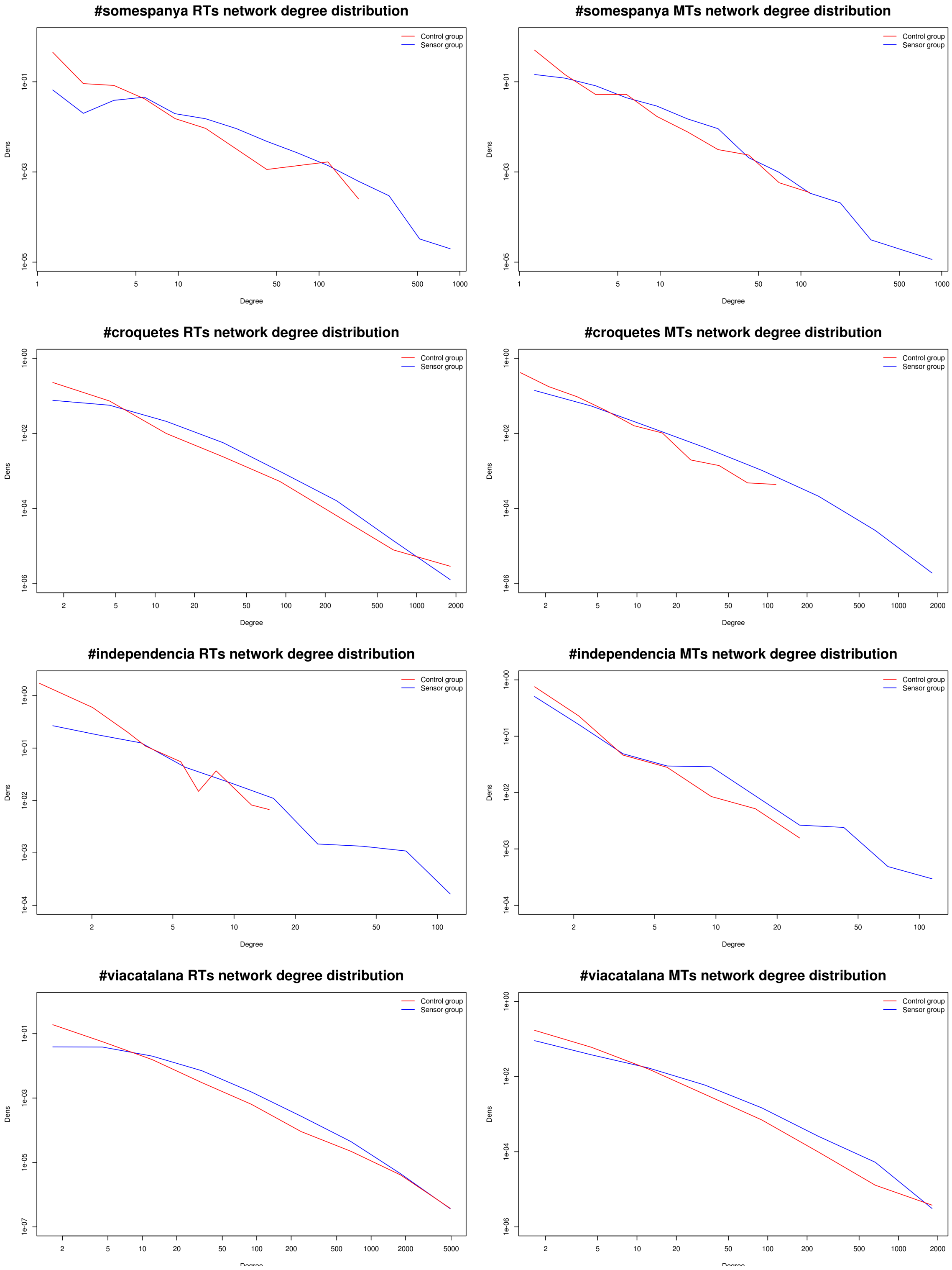


Figure 5.16: Degree centrality distributions of the *hashtags* #somespanya, #croquetes, #independencia and #viacataloniana for the mention and retweet networks. The sensor groups have a higher centrality. Group samples 5% of total users.

Sensors as polarization detector

After showing that the friendship paradox holds in Twitter's mentions and retweets networks and that the sensor mechanism can be used both to early warn of viral outbreaks and to distinguish endogenous from exogenous events, could we apply it to detect political polarization too? The strength of the sensor mechanism lies in its ability to perform global analysis from local information, allowing to perform fast and inexpensive analysis that can be exported to realtime scenarios.

Attending to our two different users classifications (isVia vs. noVia and pro-separatist vs. pro-spanish):

1. For each ideology, we select a sample of 100 users (similar to the control groups).
2. For every user in these groups we calculate the ratio of *proindependentist*/*prospanish* (and isVia/noVia) ratios of their friends.
3. We compute the mean and standard deviation of the ratios of each sample.

This analysis, as in the previous section has been done both with the retweets and mentions network in their real and shuffled variatiations (ie. the user classification is shuffled while preserving the structure of the network and the number of users in each group).

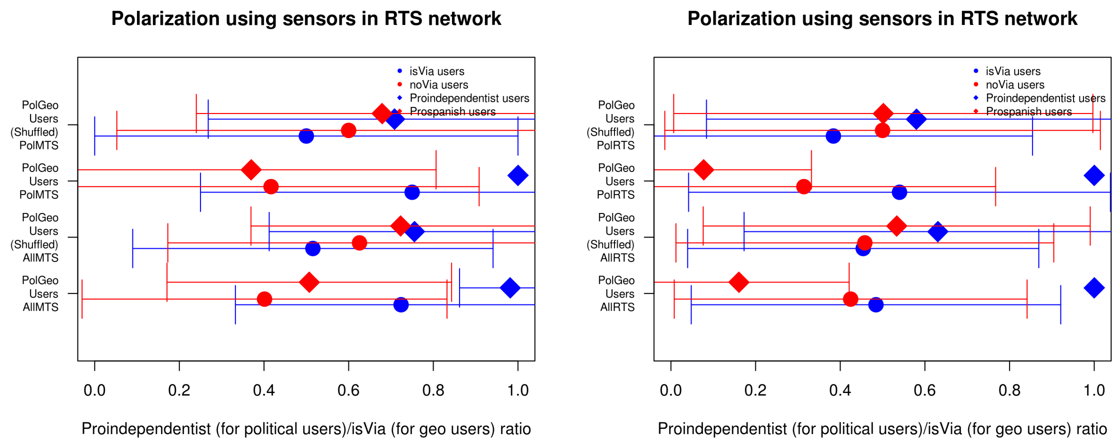


Figure 5.17: Proindenpendentist and isVia mean friend ratios for the random samples. IsVia users (blue circles), noVia users (red circles), *proindependentist* users (red triangles) and *prospanish* users (blue triangles). Political samples are polarized for the mention and retweet networks, however geousers are not.

Figure 5.17 shows a similar finding than the one observed in the replication of Conover et al. analysis, though this time without the need to analyze the whole network. In the figure we can clearly see how the pro-separatist and pro-spanish communities fall apart compared to their shuffled versions, showing a clear polarization in which birds of a feather flock together, both in the network composed by only politically relevant tweets and in the overall network of tweets.

For the isVia vs. noVia classification, while the means show exactly the opposite to what we should expect (that retweet networks are more polarized than mention networks), the standard deviation is so big that nothing can be said that is statistically significant. This variation is due to the smaller number of isVia-noVia users (captured only in the *Diada* day) in contrast to the *proindependentist-prospanish* users captured during several days.

The scarcity of data can be fully appreciated in figure 5.18 in which we present the same data but not aggregated (each dot represents a single user, the vertical axis represents the number of politically relevant users among his/her friends). Triangles correspond to the political users (*proindependentist* in dark blue, *prospanish* in dark brown) and the circles to the geousers (isVia in red, noVia in blue). The problem is clear, the number of geousers friends that are also geousers is very small.

Besides the statistical problems associated with the scarcity of data in the isVia-noVia case, we have shown that the sensor mechanism can serve as a proxy to replicate Conover's et al. analysis relying only in local information, key point to rapidly asses and evaluate situations and first step towards realtime analysis.

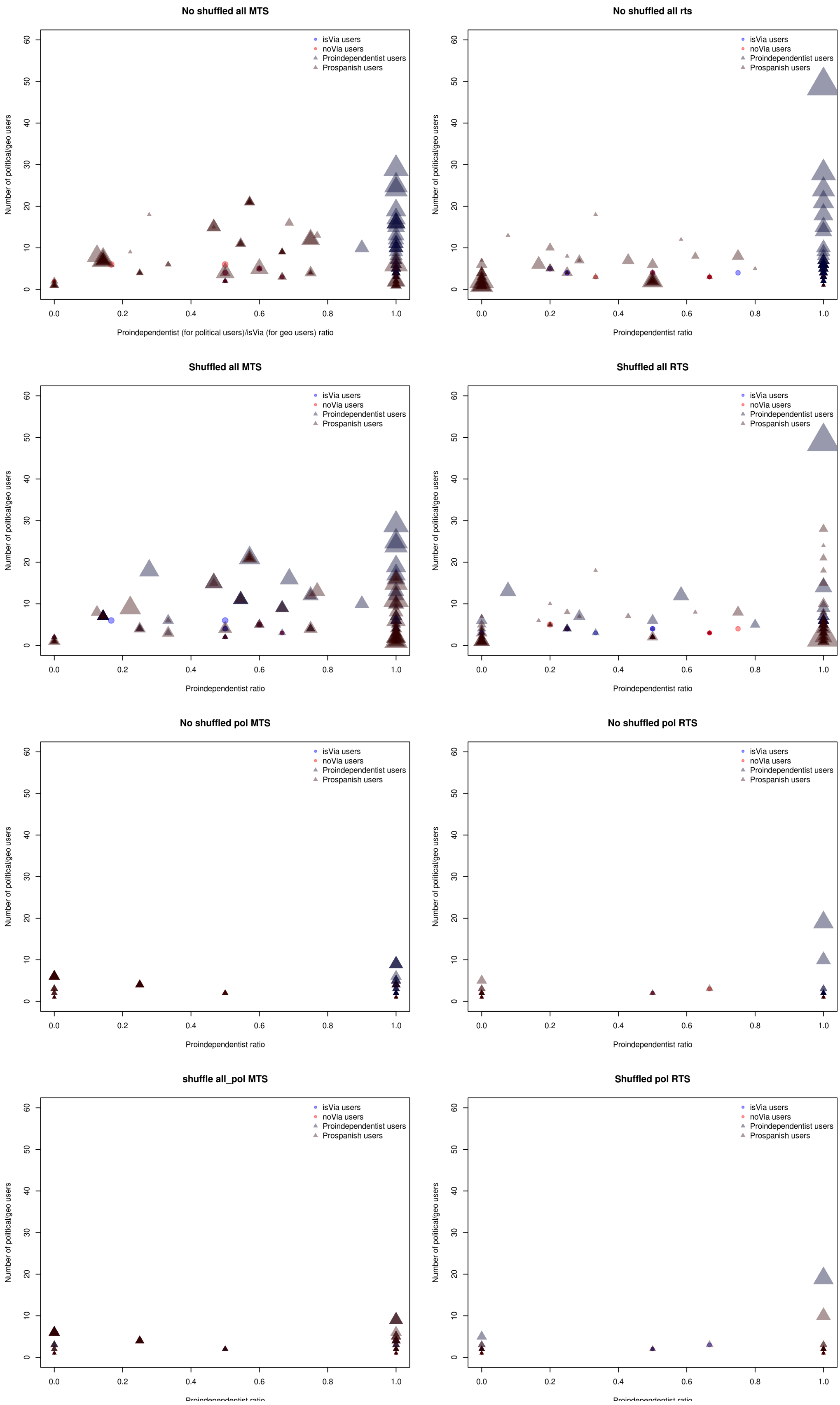


Figure 5.18: Proindependentist/isVia ratio (x axis) and number of friends for each user of the random sample for isVia users (blue circles), noVia users (red circles), *proindependentist* users (brown triangles) and *prospanish* users (dark blue triangles). It can be observed that the number of geousers is not relevant.

Chapter 6

Conclusions and further work

6.1 Conclusions

The principal objective of this work has been to analyze the digital data exhaust that people generate on Twitter, to evaluate and predict social polarization in political scenarios. The case of study that we have analyzed has been the catalan independence conflict which, because of the *Via Catalana*, provides a ground truth for the identification of separatist supporters.

The work focus on studying network analysis tools for analyzing political polarization. For this purpose, this work starts by introducing the most relevant theoretical concepts of social networks as well as two works in political polarization and early detection of outbreaks that we apply and extend during the study.

Besides this theoretical introduction, we propose two strategies for user political classification. The most novel one is based on the geolocalization of users during the 2013 *Diada* obtaining two groups, the isVia group which is composed by separatist supporters that attended the human chained demonstration and the noVia group (those who does not). The second classification is inspired in Conover et al. [Conover et al., 2011], labeling users according to their use of political *hashtags*.

Once defined our groups of study, we presented the results on the network based analysis of political polarization based on two lines of work:

Political polarization on Twitter. In [Conover et al., 2011] authors propose that in political stress situations, polarization appears in the retweet network but not in the mention network, as a higher modularity of the former than in the later. After applying their techniques and proposals we obtain the following conclusions.

- The users classification that the authors proposed based on *hashtag* co-occurrence with an ideological seed *hashtags* also works for our problem, obtaining consistent results. In addition we have used these *hashtag* selection to classify users.

- When we consider all the political interactions of the period studied our results are similar to the results that the authors proposed, we can observe clearly polarization in the retweet network and this polarization is not that strong in the mention network. Nevertheless the modularity of our mention network is higher than the one observed by Conover et al. suggesting that it might be an additional symptom of political polarization. Repeating the analysis, the *Diada day* we also obtain consistent results.

- Repeating the analysis with our geolocation based user classification we also observe a great polarization in the retweet political network, however this polarization, although with a lesser importance, also appear in the complete networks, and surprisingly in the mention networks, both complete and political.

- Furthermore, we propose the use of shuffled versions of the networks to establish an expected polarization. This approach may serve to extend Conover's et al. work to unbalanced political scenarios.

- Finally we show that the polarization of the mention network fades faster in time, and conjecture that it can be a more sensitive measure of high political scenarios. Polarization in the retweet network is, on the other hand, more resilient and can be used as a long term measure of accumulated social stress.

Early detection and local analysis In [Garcia-Herranz et al., 2014], authors propose a method based on the friendship paradox to early detect contagious outbreaks using friends as sensors. Furthermore, this method uses limited information to detect global outbreaks reducing the computational cost of the analysis. Focusing on the day of the *Diada* we apply the mechanisms proposed to our problem finding the following conclusions:

- The friendship paradox, as proposed in [Garcia-Herranz et al., 2014], works for Twitters mentions and retweets networks.

- The sensor mechanism can be used to detect fast occurring events (under one day) with up to 6 hours of early warning, and possibly to analyze the awareness of political factions of the other's actions and campaigns.

- The sensor mechanism can be used to distinguish exogenous from endogenous events. This has been done using the #croquetes hashtag, promoted by RAC1 radio in response to #somespanya becoming trending topic while #independencia did not.
- Finally, we have extended the possibilities of the method to replicate Conover's et al. analysis by using only local information, showing that the polarization of the retweets and mentions networks can be obtained by using the sensor mechanism rather than by computing the modularity of the overall network.

In summary, studying previous works, we have performed a series of classifications and analysis that not only work in our case of study, but also looking at how they can be applied in future scenarios of diverse nature.

6.2 Further work

The study of political polarization through network structure and local analysis is still a new born field and therefore many improvements are needed to fully understand the potential and limitations of this type of studies. Nevertheless we will name a few lines of research that follow directly the work presented in here:

1. Long term analysis of temporal dynamics: The Catalan separatist movement, besides its inner importance to the Catalan and Spanish societies (and to a significant extent to the European society) presents an interesting case of political polarization escalation in a democratic developed country. This means that most actions have been long termed thought and prepared and normally have moved within soft paths. In the last years we have witnessed a change in the pace of the separatist movement looking forward to more direct confrontation. This has in turn led to the recent appearance of civil groups responding to the separatist actions. This long term action reaction dynamic with focal points of tension such as the Diada requires further research into how political tension is stored in the social fabric, how it can be measured through the digital exhaust and whether or not state transitions can be predicted that may led to unwanted scenarios on every part.
2. The present analysis has focused solely on network structure, nevertheless this approach can easily be enriched by adding Opinion Mining and Sentiment Analysis techniques despite the loss of language generality they might bring. In fact, combining network analysis with data mining might bring to this type of studies the best of both worlds.

3. Finally, within the realm of local techniques to global analysis, we have extended the sensor mechanism with new test studies. Nevertheless this have been conducted with post-hoc information, relying in the knowledge of who end up using a particular study. Further work is needed in determining what are the real time limitations of this type of analysis when such information is not known a priori.

Appendix A

Twitter data

In this section, we briefly introduce how we have obtained the data for our analysis. We have collected the data using the public Twitter's REST API. This tool allow us to select tweets posted in an specific zone or region. As our case of study is the catalan independece, we need to analyze tweets posted in Catalonia, therefore we select the tweets 100 kilometers around Barcelona (with coordinates 41.387956,2.169921)

Figure A.1: In grey, the area where we have selected the tweets for our study, 100 kilometers around Barcelona (with coordinates 41.387956,2.169921)

The Twitter REST API (Representational State Transfer), currently at the version 1.1, allows us to obtain the information needed for the study. During the period of this work, in June of 2013, Twitter changed from the version 1 to the version 1.1. In this last version, Twitter provides more information for each query, in particular, it includes for each interaction the information corresponding to all users involved in this interaction. Previous version did not provides this information explicitly, so the works started with a pre-processing, in which after detecting the interactions, you could select users wo interact analyzing ther screen name, but this was not a totally reliable system because the screen name can be changed by the user, so it is not unique. This is why some of our analyses start in June of 2013 with the REST 1.1. In the following sections we explain the data included in both versions and their differences, and a brief section about the limitations that Twitter imposes for its API.

A.1 REST 1

Name ▲	Value
created_at	"Fri, 01 Mar 2013 00:00:37 +0000"
from_user	"Sempiternat"
from_user_id	898730262
from_user_id_str	"898730262"
from_user_name	"Sleepwalking"
geo	null
id	"307279168574464002"
id_str	"307279168574464002"
in_reply_to_status_id	307262712000430100
in_reply_to_status_id_str	"307262712000430080"
iso_language_code	"in"
location	"Barcelona"
metadata	...
profile_image_url	"http://a0.twimg.com/profile_images/3316961414/7...
profile_image_url_https	"https://si0.twimg.com/profile_images/3316961414/...
source	"<a href="http://twitter.com/download/iphon...
text	"@Octa_e si :3"
to_user	"Octa_e"
to_user_id	588381241
to_user_id_str	"588381241"
to_user_name	"."

Figure A.2: Tweet object representation in the REST 1

The variables that we use in this version are the next:

- **created_at**: Tweet timestamp.
- **from_user_id**: User who post the tweet.
- **geo**: Coordinates where the tweet has been posted. This field is very important, we will use to classify the users who posted from the *Vía Catalana*.

- **id**: ID of the tweet.
- **in_reply_to_status_id**: ID of the tweet which reply the tweet.
- **text**: Content of the tweet.
- **to_user_id**: User which posted the tweet replied.

A.2 REST 1.1

Name ▲	Value
contributors	null
coordinates	null
created_at	"Wed Sep 11 00:00:12 +0000 2013"
entities	...
favorited	false
favorite_count	0
geo	null
id	"377582310427992064"
id_str	"377582310427992064"
in_reply_to_screen_name	null
in_reply_to_status_id	null
in_reply_to_status_id_str	null
in_reply_to_user_id	null
in_reply_to_user_id_str	null
lang	"es"
metadata	...
place	null
retweeted	false
retweet_count	0
source	"<a href="http://twitter.com/download/android" r...
text	"En la final de la Copa del Rey en Madrid 2012 ...
truncated	false
user	...

Figure A.3: Tweet object representation in the REST 1.1

The most important variables that the API added in this version are *retweeted_status*, *entities* and *user*. This data in the tweet object provides more information in the same object without having to do more requests. Below we explicit what information include these objects.

- **retweeted_status**: If the tweet is a retweet, this field contains all the information related to the original tweet. (tweet id, users who posted id...)
- **entities**: Information about the entities included in the tweet including: user_mentions, hashtags, symbols and URLs.

- **user**: Information about the user which post the tweet in which the most relevant information included is the unique identificator of the user which is very useful to consider the activity of the interaction networks.

A.2.1 Limitations of the API

Twitter API is a public tool, but Twitter imposes some limitations to avoid a bad use of its API. These limitations based on 15 minutes windows in which the number of queries allowed is delimited. The most usual limitation is the code 88, "Rate limit exceeded", that implies that the window in use has exceeded the number of interactions, furthermore if these limitation and its warnings are ignored and the application continues querying the API, Twitter includes the application in a blacklist and all the IPs in your range are not allowed to query the API.

Appendix B

Users classification algorithms

Data: Prospanish and proindependentist hashtags use
Result: Hashtags classified

```
hashtagProindependentist.ratioProindependentist = hashtagProindependentist.uses /
  max(proindependentistSeed.uses);
hashtagProspanish.ratioProspanish = hashtagProspanish.uses / max(prospanishSeed.uses);
hashtags = merge(hashtagProindependentist,hashtagProspanish);
hashtags = hashtags[hashtags.ratioProspanish > 0.05 — hashtags.ratioProindependentist > 0.05];
hashtags.Proindependentist = hashtags.ratioProindependentist / hashtags.ratioProspanish;
hashtags.Prospanish = hashtags.ratioProspanish / hashtags.ratioProindependentist;
newHashtagsProspanish = hashtags[hashtags.Prospanish > 2]
newHashtagsProindependentist = hashtags[hashtags.Proindependentist > 2]
```

Algorithm 1: Hashtags classification algorithm

Data: JSON tweets
Result: List of users hashtags use

```
for tweet in Tweets do
    tweetHashtags = getHashtags;
    user.prospanish = tweetHashtags ∩ prospanishHashtags;
    user.proindependentist = tweetHashtags ∩ proindependentistHashtags;
end for
for user in Users do
    user.ratioProindependentist = user.proindependentist / sum(user.proindependentist,user.prospanish);
    if user.ratioProindependentist > 0.6 then
        user.ideology = ‘proindependentist‘;
    else {user.ratioProindependentist < 0.4}
        user.ideology = ‘prospanish‘;
    else
        user.ideology = ‘neutral‘;
    end if
end for
```

Algorithm 2: Users classification algorithm

Appendix C

Political graphs evolution

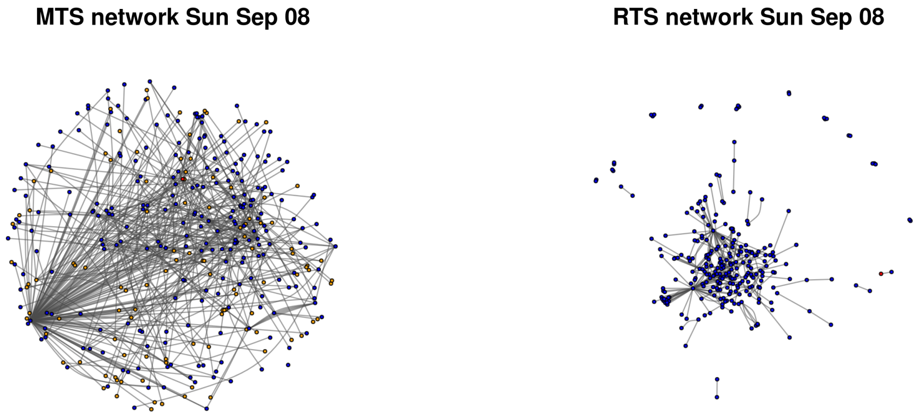


Figure C.1: Political interactions networks September 8th. Proindependentist users in blue, prospanish users in red, neutral users in green and not classified users in orange.

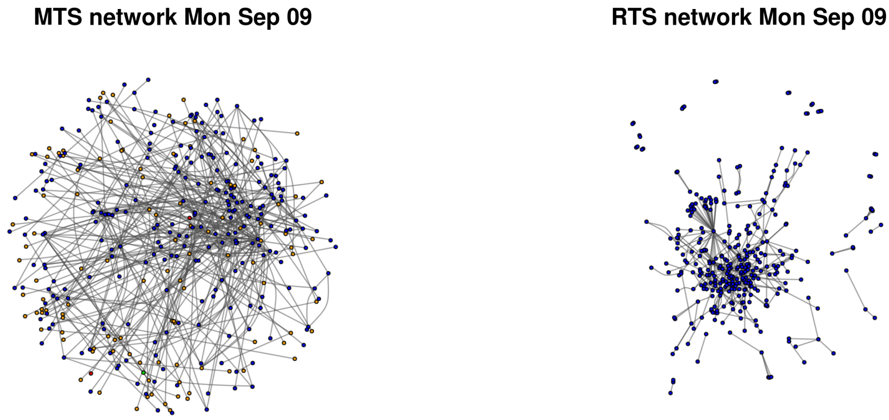


Figure C.2: Political interactions networks September 9th. Proindependentist users in blue, prospanish users in red, neutral users in green and not classified users in orange.

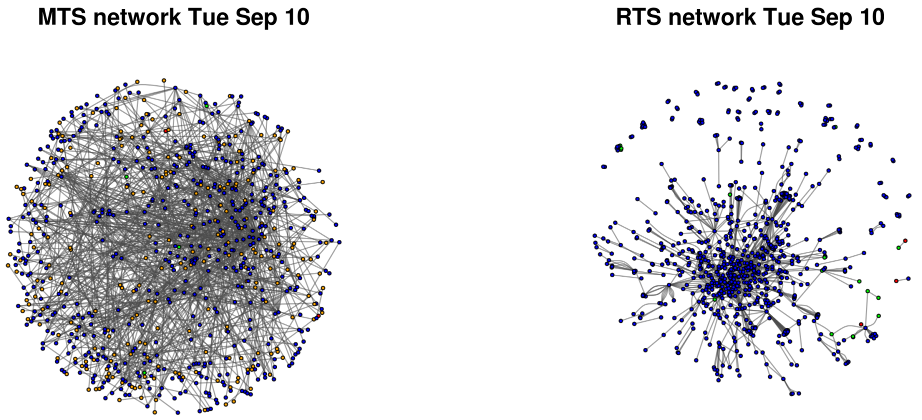


Figure C.3: Political interactions networks September 10th. Proindependentist users in blue, prospanish users in red, neutral users in green and not classified users in orange.

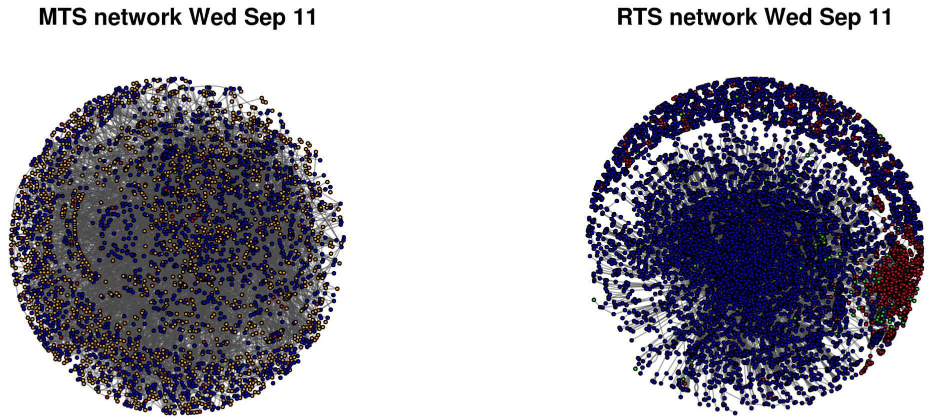


Figure C.4: Political interactions networks September 11th (*Diada* day). Proindependentist users in blue, prospanish users in red, neutral users in green and not classified users in orange.

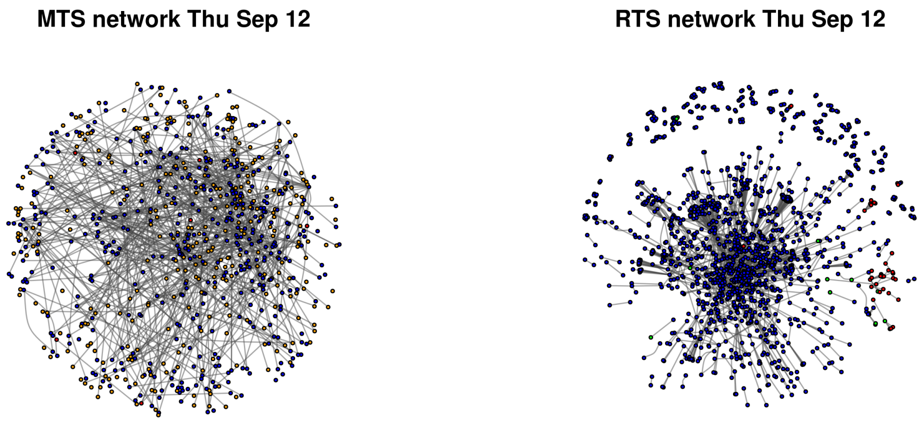


Figure C.5: Political interactions networks September 12th. Proindependentist users in blue, prospanish users in red, neutral users in green and not classified users in orange.

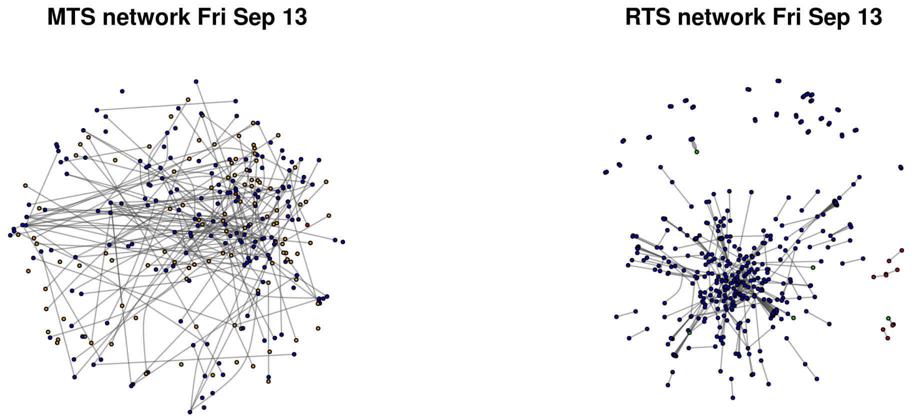


Figure C.6: Political interactions networks September 13th. Proindependentist users in blue, prospanish users in red, neutral users in green and not classified users in orange.

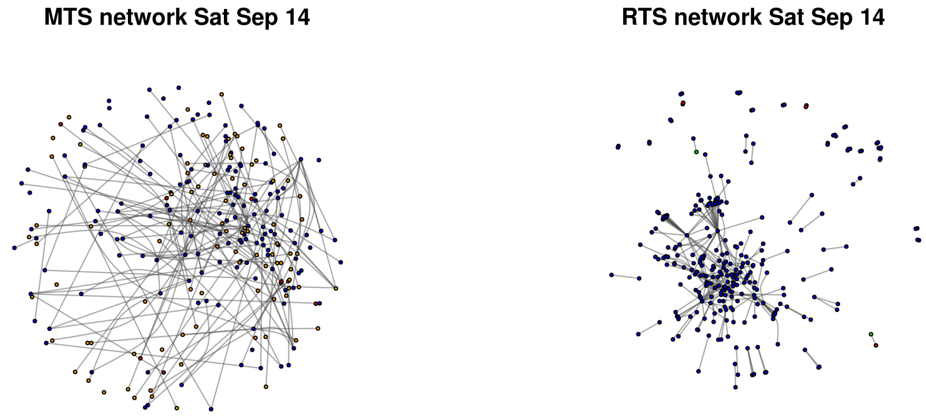


Figure C.7: Political interactions networks September 14th. Proindependentist users in blue, prospanish users in red, neutral users in green and not classified users in orange.

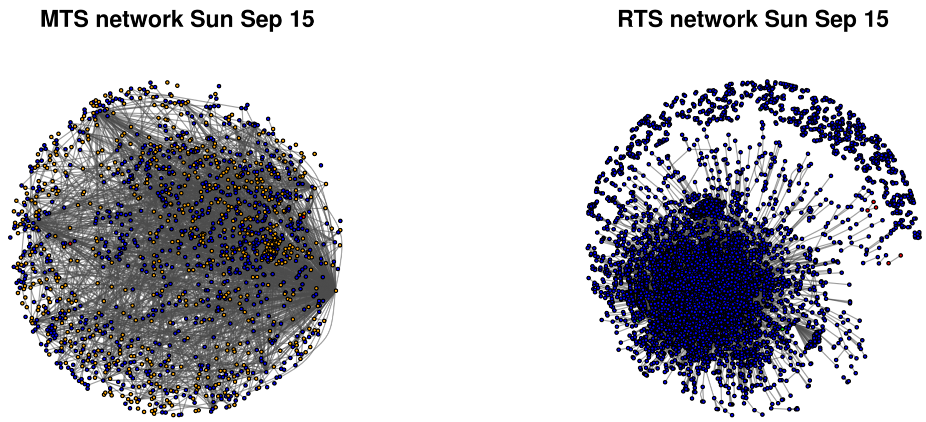


Figure C.8: Political interactions networks September 15th. Proindependentist users in blue, prospanish users in red, neutral users in green and not classified users in orange.

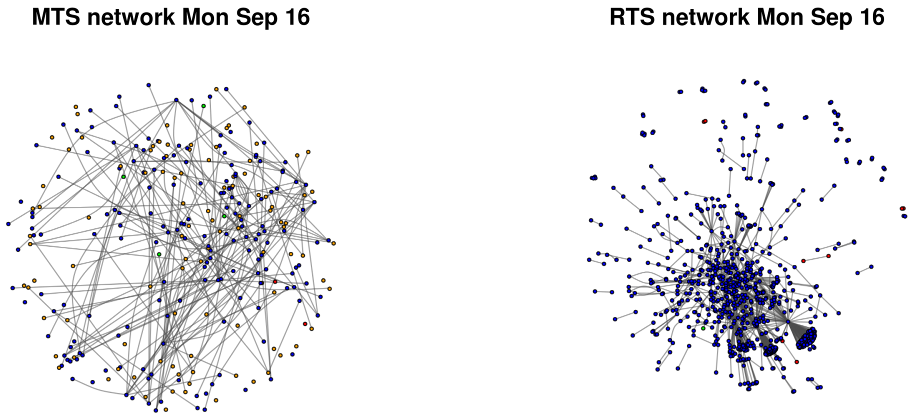


Figure C.9: Political interactions networks September 16th. Proindependentist users in blue, prospanish users in red, neutral users in green and not classified users in orange.

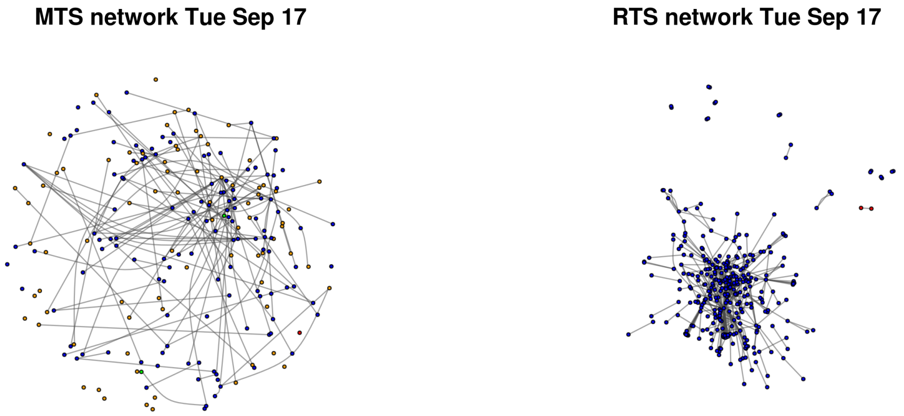


Figure C.10: Political interactions networks September 17th. Proindependentist users in blue, prospanish users in red, neutral users in green and not classified users in orange.

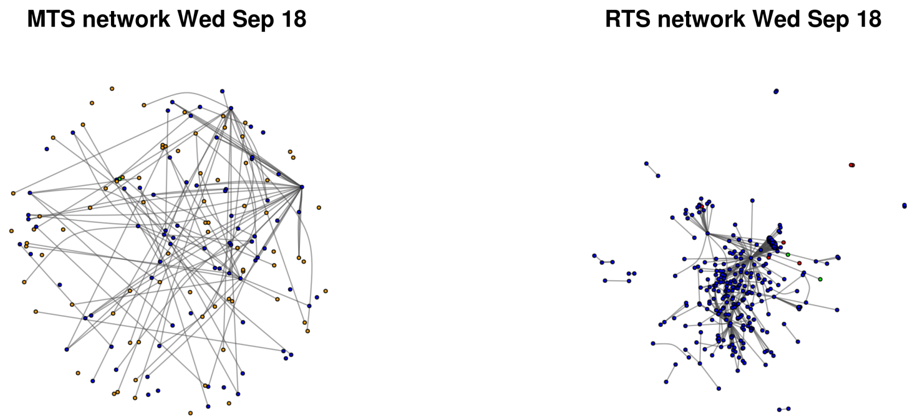


Figure C.11: Political interactions networks September 18th. Proindependentist users in blue, prospanish users in red, neutral users in green and not classified users in orange.

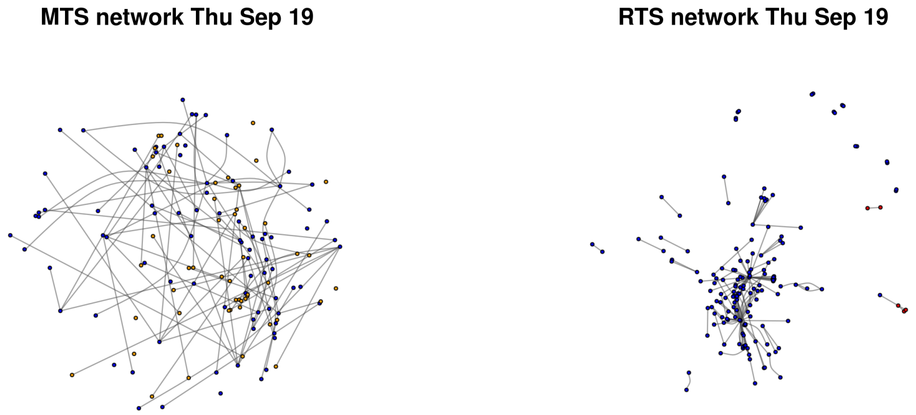


Figure C.12: Political interactions networks September 19th. Proindependentist users in blue, prospanish users in red, neutral users in green and not classified users in orange.

Appendix D

ECDF reciprocal mentions evolution

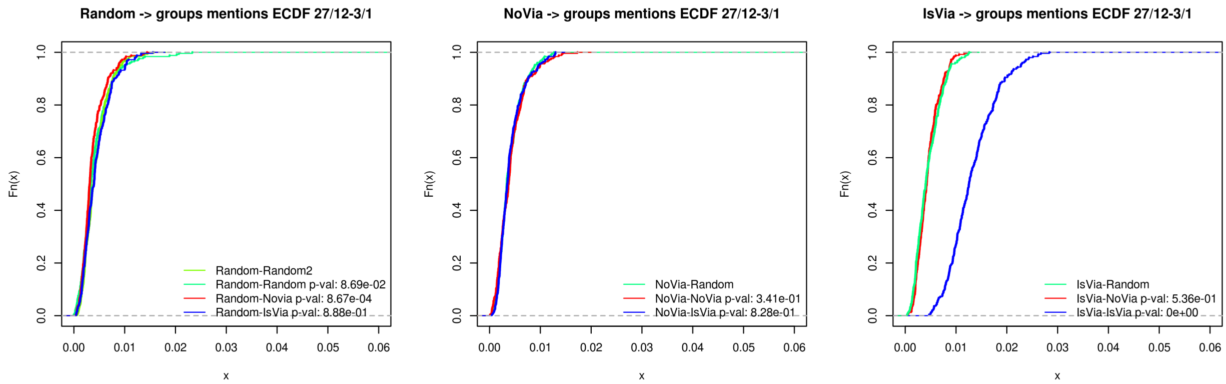


Figure D.1: ECDF for isVia (blue), noVia (blue) and random groups (green) reciprocal mentions, from December 27th 2012 to January 3rd 2013

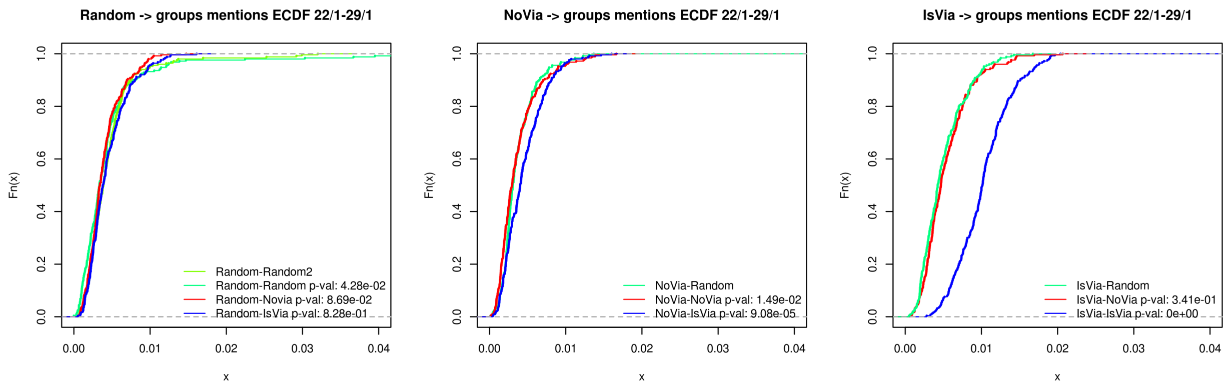


Figure D.2: ECDF for isVia (blue), noVia (blue) and random groups (green) reciprocal mentions, from January 22th to 29th 2013

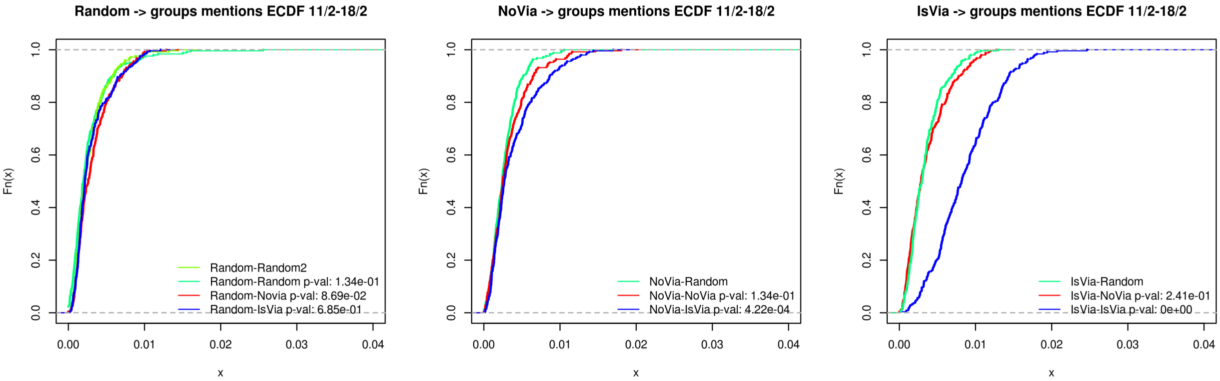


Figure D.3: ECDF for isVia (blue), noVia (blue) and random groups (green) reciprocal mentions, from February 11th to 18th 2013

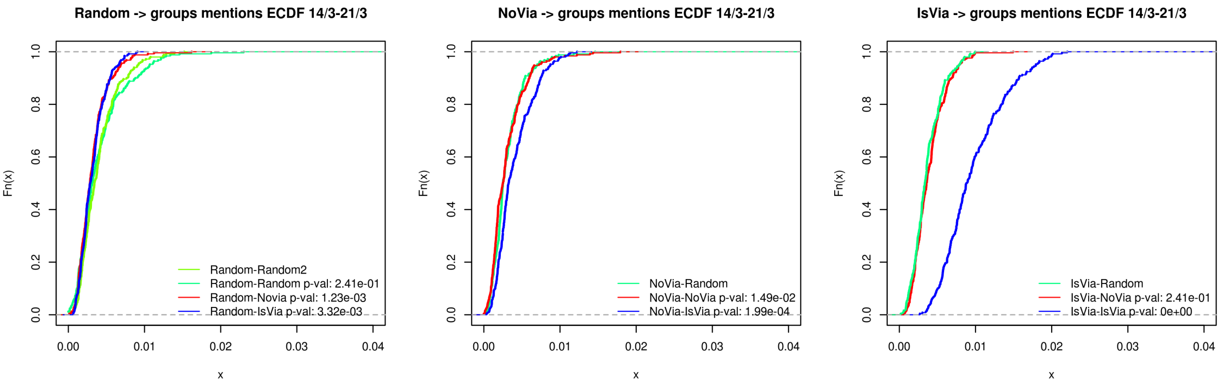


Figure D.4: ECDF for isVia (blue), noVia (blue) and random groups (green) reciprocal mentions, from March 14th to 21th 2013

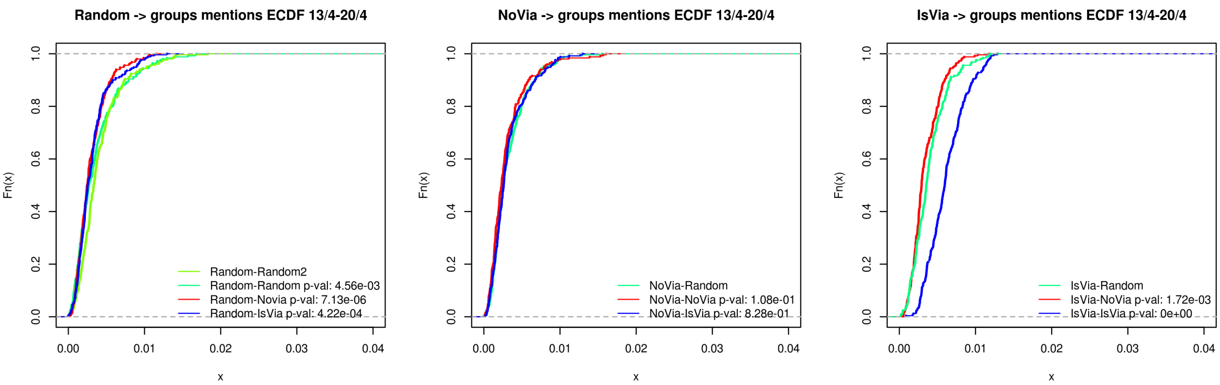


Figure D.5: ECDF for isVia (blue), noVia (blue) and random groups (green) reciprocal mentions, from April 13th to 20th 2013

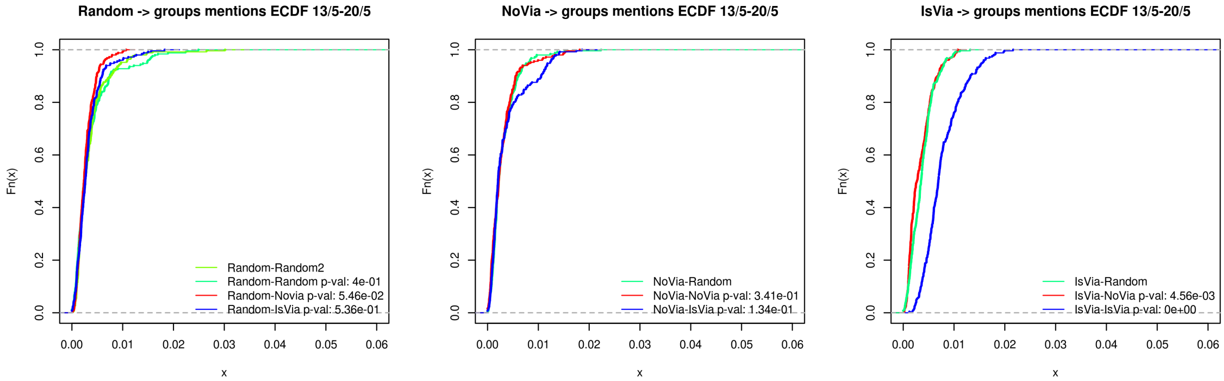


Figure D.6: ECDF for isVia (blue), noVia (blue) and random groups (green) reciprocal mentions, from May 13th to 20th 2013

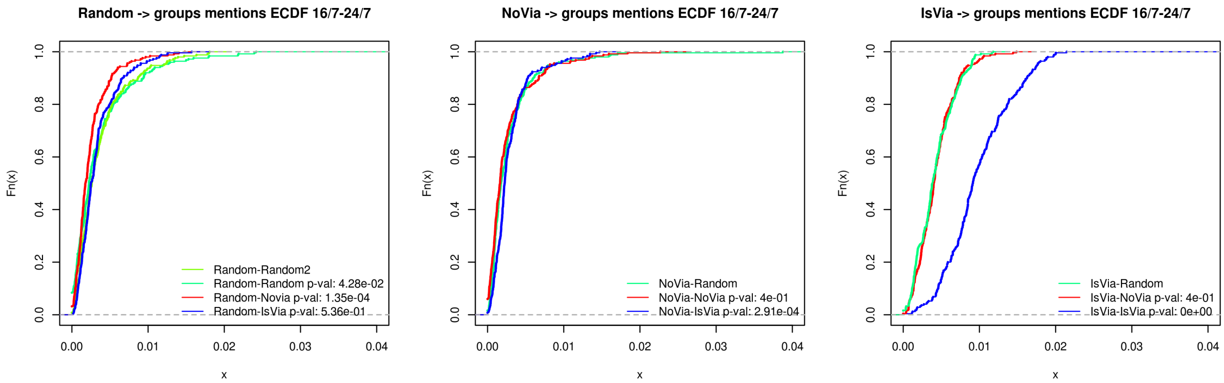


Figure D.7: ECDF for isVia (blue), noVia (blue) and random groups (green) reciprocal mentions, from July 16th to 24th 2013

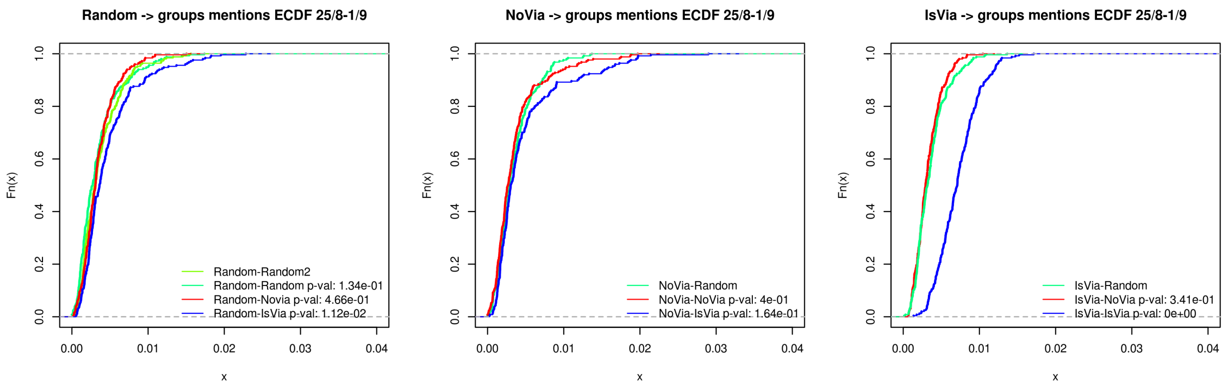


Figure D.8: ECDF for isVia (blue), noVia (blue) and random groups (green) reciprocal mentions, from August 25th to August 1st 2013

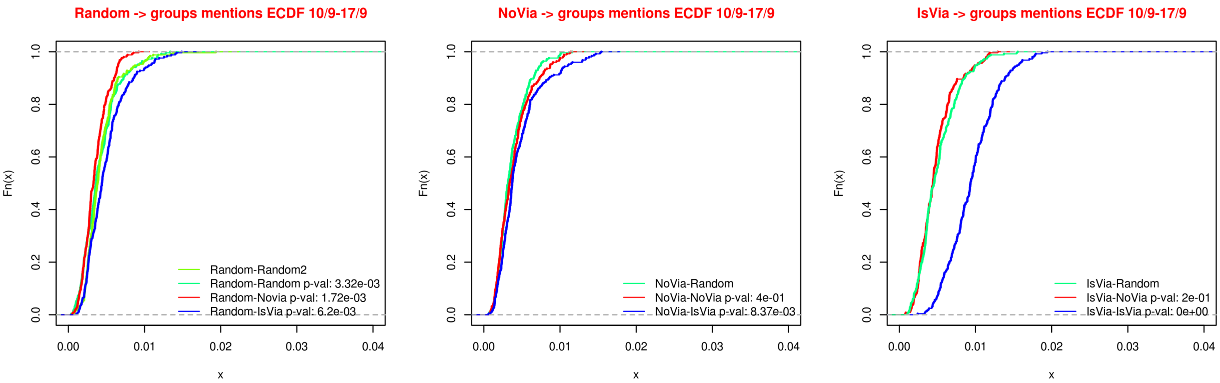


Figure D.9: ECDF for isVia (blue), noVia (blue) and random groups (green) reciprocal mentions, from September 10th to 17th 2013

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