Coordination on Twitter: far-right reaction to Colombian protests[1]

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Abstract

This project aims to analyze the impact of non-virtual political events on the online behavior of a political community, specifically how the Colombian far-right on Twitter coordinates in the context of an extended social protest. Social media presents the possibility to communicate with large communities in real-time, therefore it has become a tool for politically coordinated people to react to an event with low costs. We will answer a crucial question to understand the dynamics of politics in social media: how do non-virtual events impact the ability to disseminate information of a political community? This question allows us to understand a political community as a dynamic network, which changes its structure depending on its priorities. This paper analyzes a set of tweets using a novel method of social network analysis (SNA) to understand how a community becomes more efficient in the dissemination of information when an important event is occurring for them. We found that on the most important days of the selected period the far-right community communicated more efficiently, this means that the information flowed easier. This result reflects a coordinated set of users which, on important days, not only increased the volume of their tweets but also tweeted more at the same time and interacted more with one another

1. Introduction

Political behavior research on social media has grown steadily in the last decades. There has been a special interest in both academic and non-academic circles in the impact of social media on non-virtual political events and the other way around, the impact of these events in social media, such as in elections (Pedro-Carañana, 2020; Panizo-LLedot et al., 2020), protests (Zervopoulos et al., 2020; Neogi et al., 2020; Tremayne, 2013), debates (Zheng, 2020), etc. As a result, new ways of obtaining data, and methods for online behavior analysis have evolved (Jemielniak, 2020): social network analysis, natural language processing, and more have risen to be new ways of understanding large sets of data. However, a rather underexplored dimension of this political data is time, and subsequently, the flow of information accounting for it. This happens although it is one of the most important characteristics of social media: fast live reacting and communicating.

Previous research has monitored real-time conversation while important political events elapse and has tried to understand the evolving characteristics of the data (Mora-Cantallops, 2021; Bermudez, 2019; de Val, 2015). Our research belongs to this set of literature, specifically in the field of dynamic social network analysis, which allows us to explore the characteristics of users' interactions in time,

1 Code repository: https://github.com/jjcorredor99/far-right-coordination

and therefore how information flows in their interaction network. Even though this type of analysis is predominant in other fields, there has been some social research that focuses on the dynamics of a social network. Literature has studied how influencers emerge or change in a social network (Bermudez, 2019), how the sentiment of the posts evolves (Scrivens, 2020), and how the structure and the communities change after an important event (Fani, 2020). Our research studies how non-virtual political events affect the information dissemination efficiency of a community, under the assumption that the most important days for the community need more information to travel faster and further away. To our knowledge, this is a novel approach in the literature of dynamic social networks and social research.

In this article, we undertake the question: how do non-virtual events impact the ability to disseminate information of a political community? For this purpose, we created a temporal graph with various important non-virtual political events over a two-month span. To measure the ability to disseminate information we used a metric developed by Tang (2009): temporal efficiency, which accounts for the order of contacts to model the transmission of information from one user to another. In the next section, we show the research that led us to this question and supports some of our assumptions. Afterward, we developed our theory on why a temporal graph can show the dissemination of information in social media and how this reflects the coordination of users. In the fourth section, we showed how we collect our data, select the far-right accounts and important events, and how the metrics were constructed. Finally, our fifth section shows our main results, while the sixth concludes and suggests future research strategies to tackle our question.

2. Background

2.1 Study of politics in social media

Social media encompasses a significant share of the public discourse about politics nowadays, therefore making research on public opinion in these platforms indispensable. Literature that centers on the digital conversation have grown steadily using innovative methods and huge sets of information, to the extent that some argue a change of paradigm (Jemielniak, 2020; Chang, 2014). Twitter, a popular microblogging platform, seems to be of preference for this kind of research. The reason is twofold: first, Twitter seems to be of preference to communicate short ideas about ongoing political events (resulting in various research such as Tien et al., 2020; Mora-Cantallops, 2021; Darwish, 2019), and this platform gives researchers good quality data through its API.

Broadly we could say that literature has used two methods to understand the use of this platform: content-based analysis and social network analysis (SNA) (Karami, 2020; Anber, 2016). The content-based analysis uses the text of the tweet to explain its meaning and SNA constructs a social network with users’ interactions (retweets, comments, and mentions), and explains its structure. Furthermore, the first describes the content of messages users produce, for example explaining the topics of different communities (Panizo-LLedot et al., 2020, Kaiser, 2019), the sentiment of the posts (Neogi et al., 2019; Manguri, 2021), and the predominant words when referring to something or someone (Wu, 2018). On the other hand, the second one has centered on what factors make a user popular (Casero-Ripolles, 2020) or in understanding social networks structures that arise from interactions (Guerrero-Solé et al, 2015; Zinoviev, 2020). This last set of research, SNA, understands social media as a complex system that looks for explanations in users' behavior highlighting the connections with others in the system (Newman, 2010). Understanding how people interact in social media can help us find communities that were not visible to us in plain sight (Panizo-LLedot et al., 2020), as well as understand the dynamics of a community (Mora-Cantallops, 2021; Fan et al., 2020). Part of our research stands in this last methodology.

The access to data also has opened the possibility to understand real-time reactions to ongoing political events which are producing a constant stream of information. Hence, literature has monitored the discussion on Twitter while presidential debates (Zheng, 2020) or rallies (Tien et al., 2020), elections (Pedro-Carañana, 2020; Panizo-LLedot et al., 2020), and social protests (Zervopoulos et al., 2020; Neogi et al., 2020; Tremayne, 2013) elapse. Our research is a part of the last one: analysis of real-time reactions to social protest. Researchers have looked at these phenomena from multiple perspectives: it has been studied activists' coordination (Bastos, 2015), where are people that talk about the protest tweeting from (Karduni, 2020; Bastos, 2014), and what sentiment do they post (Neogi, 2021). When combining these analyses with an ongoing event, a new dimension emerges as crucial; time arises as a dimension that cannot be ignored. This is why most of them try to understand this phenomenon as evolving (eg. Fani 2020, 2016, 2015; Loia, 2019; Mora-Cantallops, 2021), not only describing what users do as an aggregate but also understanding how the behavior can change depending on external events (Mora-Constallops, 2021). Our research is circumscribed within these two types of literature, research on evolving, dynamic phenomena, and social network analysis. In the next section, we will explain the background of this type of analysis.

2.2 Dynamic networks and political events

Static social networks are defined as a graph *G* with a set of nodes *V* = {n_j...n_i} and a set of edges *E* such as $i, j \in E$, if and only if, there is at least one contact between $n_j$andn_i (Tang, 2009). The study of dynamic social networks or temporal graphs adds the time dimension accounting for when the connection was made (for a formal definition see Tang, 2009). Although the study of dynamic social networks in SNA is not new in fields like physics or computer science, its application in characteristic problems of the social sciences is certainly recent. Most of this research seems to extract the logic of static networks and apply it with more complex algorithms to dynamic ones. For example, instead of detecting communities in a static network, researchers try to add the time dimension, trying to be more accurate, therefore detecting temporal communities (Fani 2020, 2016, 2015). With this logic researchers have seen evolving centralities (de Val, 2015), describing how leaders emerge in a political community (Bermudez, 2019), an abnormal number of interactions (Mora-Cantallops, 2021), and evolving communities (Fani 2020, 2016, 2015; Loia, 2019).

Although the most common analysis in dynamic networks is developed using the same logic as static ones but with the time dimension, there are also new kinds of analyses. The most prominent is the understanding of dynamic networks as an information dissemination structure (Li et al., 2017). Some researchers have modeled this as an infection system (Dinh, 2021; Khandelwal, 2021; Lerman, 2010), or as a contact chain (Yang, 2010), others have focused their efforts on identifying the source of the information and most influential spreaders (or super-spreaders) (Fan et al., 2020; Cha et al., 2012). Moreover, most of these research models the information spread in a social network, under the assumption that the structure of a network benefits or detriments the flow of information. Mora-Campbell (2021) relates this change in the social network structure to non-virtual political events, arguing that the importance of the event impacts the structure and generates abnormal behavior within the community. We share our hypothesis with them, though we use what we think is a better metric to capture the dynamic of the network and the flow of information. In the next section, we show the theoretical argument behind our hypothesis, arguing that there is an information diffusion structure that can change in time.

3. Theoretical argument: Information dissemination as coordination

As aforementioned, an information system can be modeled as a social network: nodes transmitting information and paths or edges in which this information flows. This model can be seen as a static graph (illustration 1) or as a temporal graph (illustration 2), which accounts for the time in which the contact was made. In some cases, the static graph model may be better, though in a transmission system time is crucial to understand the contact order. This is to say that if any transmission system ignores the time dimension it would fail to predict the flow of the thing that is being transmitted. A sadly close example nowadays would be a virus transmission. If we assume that node *A* is contagious and we model the contacts as illustration 1, we will say that all the nodes would be infected. On the other hand, if we account for the time windows in which the contacts occur, such as in illustration 2, we will conclude that nodes E and F could not be infected.

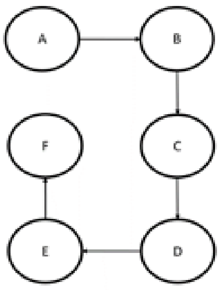


Illustration 1

In our case, we wanted to model information diffusion in a social media context, specifically in Twitter. This has some differences with normal epidemiological models. First and foremost, information has no rate of recovery, it is too big of an assumption that after some time the node stops transmitting information (Li et al., 2012). Also, we do not have certainty of the "infected" nodes on social media, because we cannot access the data that shows that an account has read any information, nor know which are the "infectious" nodes. After all, they decide to transmit or retain the information as a rational decision (Li et al., 2012). To solve this, we could try to look at the content of their posts, though it is too difficult to isolate a piece of information because of its changing form. To face these problems there are multiple solutions, some of which will be addressed in the methodological section. But the biggest problem of trying to make an epidemiological model to understand the flow of information is to isolate which is the information that is being transmitted.

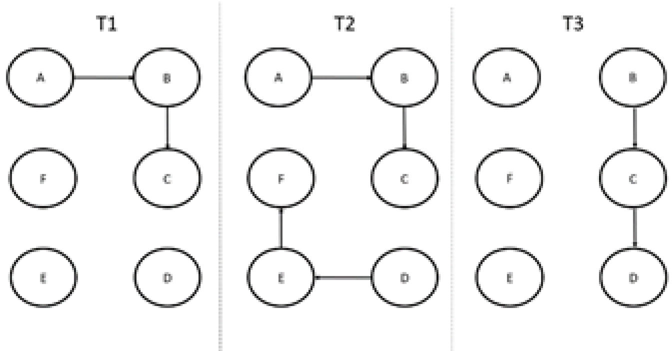


Illustration 2

For this, we propose not to look at what nodes are or are not "infected" or "infectious", but to center in the network structure. If we know that a network can be efficient or inefficient in transmitting information, we can better understand its flow in a community. As Kossinets (2008) argues, and Mora-Cantallops (2021) reiterates, information diffusion is a result of discrete contacts of communication, therefore making the flow of information dependent on the number and order of communication in time. Thus, if we have a finite community of nodes, we can deduce how easily information flows through its members. This is because we are not interested in specific information, but in any information that any node transmits and how it is disseminated through the whole community.

Coming back to the social science lens, this allows researchers to understand how well connected and how coordinated a political community is on social media. The varying efficiency shows coordination because it depends on when and how much members of a community interact with each other. This means that if many nodes (or accounts in our case) are communicating with one another at the same time, the efficiency of transmitting information rises. In these moments where the efficiency is at its peak, it would be easier for any message to travel. Our hypothesis, drawing on past research on the impact of non-virtual political events (Mora-Cantallops, 2021) and information dissemination, is that: *important political events increase the efficiency of a community structure to disseminate information.*

4 Data and methods

4.1 Case study

Our case study needed two big decisions: a time period and a political community. For this research, we selected an extended social protest in Colombia: 2019, November 21st national strike: *"Paro Nacional 21N"* and, for the political community, we selected the antagonist of this protest, the far-right Colombian movement. We selected a two-month span with the 21st of November right in the middle to see the variation of the metric on different days. This means the period begins on the 21st of October and ends on the 21st of December[2]. The national strike was a major event for Colombia and has been labeled by the media as one of the biggest strikes in national history, with hundreds of thousands of Colombians protesting (Pardo, 2019; Vanguardia, 2020; Prensa Latina, 2020). Although it started as a strike announced for the 21st of November, the protests continued throughout the following weeks resulting in multiple and discontinuous important days.

Equally important, the reasoning behind selecting the far-right is twofold. First, presumably, the Colombian far right was live reacting to the social movement. This is because the message of the protestants was anti-Duque's government (Pardo, 2019), the Colombian far-right president. Therefore, the government sympathizers wanted to control the narrative of the protest, they needed to communicate effective messages against the social unrest. Second, the online far-right movement has been studied internationally, and in social media literature has been flagged with radicalized behavior (Crosset et al., 2019; Scrivens, 2020). Although our study does not address this problem, we want to open the discussion about the online far-right movement in Latin America.

The identifiable breaking points of the protest allow us to understand the reaction of the community to the major events. We identify four relevant events following three criteria shown by Mora-Castallops (2021). The criteria are that the event must have a political meaning, broad attention of the media, and different paths to reach the public. This led us to find three major events that related to the protests, and we noticed that, within the selected time frame, there was a 4th political event that was not part of the strike: the local authorities, mayors, and governors' election on October the 27th. We included this relevant event, because, although it was not part of the national strike, it followed the three criteria argued before. The events are:

1. 27th of October: local authorities' election
2. 21st of November: national protest
3. 25th of November: activist Dylan Cruz is pronounced dead
4. 4th of December: national protest

[2] After adjusting to Colombian Time, the period started on October the 20th.

4.2 Selecting far-right accounts

To create a set of Twitter accounts owned by far-right Colombian sympathizers we started by selecting a set of Twitter accounts from known far-right politicians (Appendix A: describing the set). This strategy follows Thorburn (2018) by starting the dataset with preidentified far-right users, in our case: politicians. We downloaded the list of followers of the 102 politician accounts for 7,152,304 unique identification numbers. Operating under the assumption that far-right accounts are more likely to follow more far-right politicians (Crosset, 2019), we filtered out all accounts that followed less than 5.5 far-right politicians, this threshold comes from the mean of followed (2.04) plus one standard deviation (3.49). 389,683 accounts that meet this criterion were selected. We downloaded their overall Twitter account information: name, username, description, and other variables.

Although with the threshold of following some politicians the probability of being part of the movement increases, we needed the accounts to meet other criteria to ensure it. Therefore, to select the accounts we created a list of keywords characteristic of Colombian and international far-right movements and a list of keywords used to antagonize the far-right movement (Appendix B: keywords). If the description, name, or username contained at least one of the characteristic words and did not have any of the words from the latter list we selected the account as a far-right user, we used these criteria following Crosset's et al. (2019) argument. Finally, we filtered out the accounts that were part of our original politician database and the accounts that have low activity or reach[3]. This left us with a total of 10,633 users (Table 1: Data filtering). We used the Academic Twitter API, using the R package *academictwitteR* (Barrie, 2021), to access the historic Twitter database and to extract tweets from the 10,633 accounts from 21/10/2019 to 21/12/2019, one month before and one month after *Paro Nacional 21N*. More than 5 million tweets from this period were found.

Stage	**# of accounts**
Followers download	7,152,304
Filtering by politicians followed (>5.5)	389,683
Filtering by keywords, followers, and tweets	10,633
Filtering by interactions (at least 1)	5,699

Table 1

[3] Less or equal than the first quartile of followers or statuses

4.3 Temporal network construction

To analyze the efficiency of the information transmission we needed to construct a dynamic network. As in previous papers, we used interactions between two accounts as an edge and each account as a node. This means that if an account *A* mentioned or retweeted an account *B* there is a directed edge from *A* to *B*. Considering the time, as Tang (2009), discrete, every edge is active the hour in which it is made. In other words, if user *A* mentioned *B* on the 23rd of November at 2:34 pm, the edge was considered active from 2 pm to 3 pm on the same day. This hour time span will be referred to in what follows as a time window, expressed by *w*. Also, we selected an hour window because the accuracy of the metric would not increase as much given the number of interactions per day and the computational demand would increase exponentially. This structure allows an edge to be active in multiple time frames in the network; as seen in illustration 2, edge *AC* is active in T1 and T3. To create an object with these characteristics, we used the *network* (Butts, 2015), *networkDynamic* (Butts, 2015), and *tsna* (Bender-deMoll, 2021) packages from R.

To be precise there was not a single network constructed but one per day. This is to analyze the network structure as evolving. This approach is a common trait of the literature (Mora-Cantallops, 2021; de Val, 2015), normally looking at static metrics divided into time frames. Though, our methodology differs from them by accounting for time in two ways. As most research we compute a per day metric, but also our metric, efficiency accounts for the order of the edges within the day (an in-depth description of this metric is in the following section). Also, it is worth noting that although the network is dynamic the set of nodes is constant at 5,699, excluding all nodes without interactions within our timeframe.

4.4. Metrics

To measure the flow of information on a social network we used a metric developed by Tang (2009): global temporal efficiency. This metric is defined by formula 2: where N is the number of nodes in the network and $E^h_{T_{ij}}$ is the temporal efficiency of each possible ordered pair of nodes. The temporal efficiency ($E^h_{T_{ij}}$) (formula 1) of each pair of nodes is calculated dividing one in the length of the shortest temporal path ($d^{\,h}_{ij}$) between the nodes, sometimes referred to as the journey, which in turn is computed with a search algorithm. The length of the shortest temporal path between two nodes might be infinite, therefore this metric accounts for disconnected nodes, being the temporal efficiency $1/\infty$, which equals 0.

$$E_{T_{ij}}(t_{min}, t_{max}) = \frac{1}{d^h_{ij}}$$

Equation 1

As we said before, the number of nodes in each day remains constant, which makes the metric for each day comparable and allows us to understand whether the efficiency increments or not per day. In this sense, we have a couple of more set variables, for these formulas $t_{min}$is the start of each day, and t_{max}

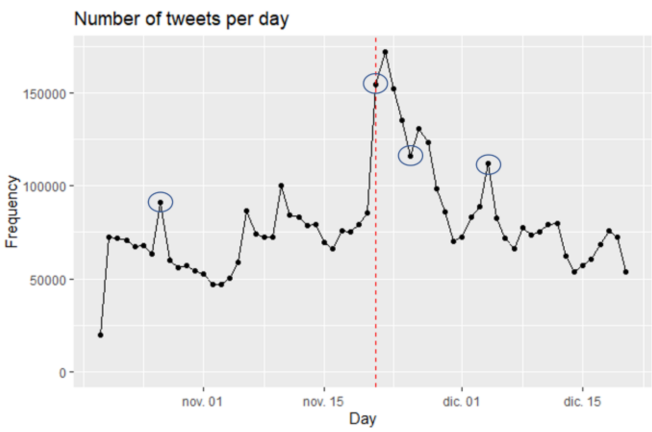
the end of the day. Another interesting variable that we set constant is *h* which Tang (2009) defines as the number of hops that information can travel within the same time window (*w*). In our case we set this parameter to infinite because we wanted to describe the flow of information and, being Twitter a fast-paced platform, seems likely that information can travel long distances within an hour window span.

$$E_{glob}(t_{min}, t_{max}) = \frac{1}{N(N-1)} \sum_{ij} E_{T_{ij}}$$

Equation 2

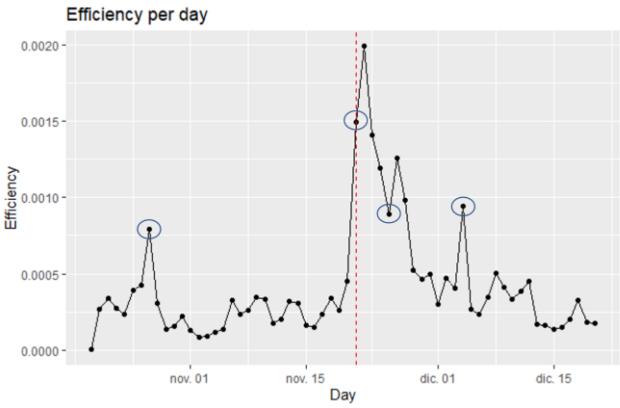
5. Results

To test our hypothesis, we needed to understand the frequency of tweets from the far-right users (Graph 1). We can see that frequency varies over time, and its peak is November the 22nd (the 21st being the dotted red line). It is worth noting that this frequency represents the population of tweets of the identified far-right users. Therefore, unlike other papers, we are not working with a sample selected by the Twitter API. This is to say that we are observing real changes in frequency which means that our first result is that the volume of tweets depends on time. On the other hand, we can preliminarily observe that the peaks in frequency match or follow the important events mentioned above (highlighted by circles).



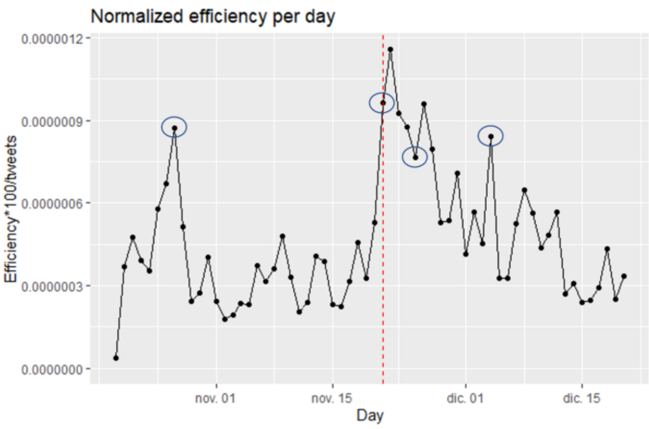
Graph 1

After observing a variation in the frequency, we can proceed to discern if these events impacted the efficiency of the flow of information in the network structure. In graph 2 we calculated the efficiency of the interactions network. We can draw two results with this: first that the efficiency, although it is low overall, varies; and second, that the important events are matched or followed by the peaks of efficiency. Furthermore, although we are working with the population of tweets of the selected users, the efficiency may only be reflecting the change of volume. If there are more contacts it is more probable that more paths are created through which the information flows, as Kossinets (2008) shows. Thus, we wanted to see what happens to the efficiency if we normalized it by the total number of tweets per day (graph 3). We can observe that part of the variation of the efficiency is given by the number of tweets collected, though the efficiency spikes seem to remain constant from one graph to another, which means that volume is not the only factor changing behind this metric.



Graph 2

Preliminarily, we could hypothesize why some events are followed and not matched by the spike in efficiency; it may be because of the spontaneity of the events. If we classify our 4 events as spontaneous or not, the pronouncement of Cruz dead was unplanned, the election day and the 4th of December protest were planned, and the 21st of November protest, although it was planned by the left, it was inadvertently big for everyone else. Following this argument, we could see that for the planned non-virtual events, the spike in efficiency matched, while for the death of Cruz the spike followed the pronouncement. This difference may also occur because of the time windows we compared. As was noted in the methods section, we are comparing the efficiency of the network day by day. Although this is not a random time window, because our communication patterns follow this time frame, with an event that occurs late at night, such as the death of Cruz, the response on social media may transcend the limitations of the day.



Graph 3

6. Discussion and future research

Our study shed light on how non-virtual events impact the ability to disseminate information of a political community on Twitter. This was seen by exploring the efficiency in which their network structure disseminates information. We can conclude that during or following these important events there was a spike in the efficiency of the structure, which resulted in information traveling faster from node to node. This reflects a characteristic of the structure of the network day by day and is an indication of coordination on the platform. This means that the spikes of efficiency reflect not only the volume of tweets of the users, but also that they were tweeting at the same hour and interacting more with one another on the most important days of the two months. We preliminarily showed that, whether the events are spontaneous or not, may affect how the efficiency of the network structure varies, and that, even though day windows are an accepted convention, this can change the interpretation of the results when an event occurs late at night.

These are promising results on political behavior in social media during important political events, though we can advance this study through two research lines. First, we want to compare these results with a random sample of Twitter users to understand if this is a characteristic of the far-right community or if any set of users will share this characteristic. This research line would need to address how this randomization works. This means it would need to choose between a random set of Colombian users or a random political community, both can raise problems to the comparison. Furthermore, the second research line to advance can use event analysis like Mora-Cantallops (2021) to understand if the observed efficiency is significantly abnormal when the events occurred.

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8. Appendixes

Appendix A: Criteria for selecting the set of far-right politicians

Criteria	# of accounts
Centro Democrático congresspeople who were elected for 2014-2018 legislature or 2018-2022	59
Politicians who have served as ministers or in high-level offices of the current far-right Colombian government	33
Candidates or pre-candidates that have been supported by the government's party in the last two presidential elections	2
Politicians who served during Uribe´s governments (2002-2004, 2004-2008) and have shown support to the current government	7
Members of *Centro Democrático* with directive jobs at the party.	1

Appendix B: Keywords for selecting far-right accounts

	words
Pro far-right	["uribista", "uribismo", "#uribistasigueauribista", "catolico", "catolica", "cristiano", "cristiana", "evangelico", "evangelica", "patria", "antimamerto", "anticomunista", "anti-mamerto", "anti-comunista", "antisocialista","anti-socialista", " maga ", "mano firme", "mano fuerte", "mano dura", "centro democratico", "antipetrista", "anti-petrista", "derecha", "provida", "pro-vida", "libertario", "conservador", "FFMM", "qanon", "qwarrior", "q-anon", "q-warrior]
Anti far-right	["antiuribista", "anti-uribista", "anti uribista", "petrista", "antiuribismo","anti-uribismo", “"ant uribismo"]