THÈSE POUR OBTENIR LE GRADE DE DOCTEUR DE L'UNIVERSITÉ DE MONTPELLIER

En Science politique

École doctorale

Unité de recherche - Droit et Science politique Et du Centre d'Études Politiques de l'Europe Latine

POLITICAL HOMOPHILY AND THE ROLE OF RETWEETERS IN FRENCH TWITTER NETWORK

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Le 29 Septembre 2021

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Introduction

Efforts to understand the political implications of Twitter discourse started as soon as this platform started to gain popularity. Researchers in computational social sciences were quick to realize the potential of multiple forms of data that Twitter presented and started to explore the possibility of testing multiple hypotheses using large data sets from Twitter. In the early 2000s, there were very high expectations from the internet 2.0, in general, to help increase the political engagement of ordinary citizens to create something akin to an ideal public sphere in Habermasian sense (Dahlberg 2001). But within the initial few years, it was clear that such expectations were to be met with doubt (if not disappointment). Even cursory exploration of Twitter data showed that there were very visible signs of the unequal distribution of influence and high levels of homophily in the network (Conover, Ratkiewicz and Francisco 2011). A small minority of elites managed to dominate the network to a large extent and effectively used it to directly communicate with their 'followers' (Avin, et al. 2012). However, initial studies in Twitter were mostly done using data only from the United States (as Twitter gained most of its initial users from the US) and that set the tone for future studies. Network homophily, political polarization, and election predictions were the general themes of most research papers published between 2008 and 2012 using Twitter data. Interestingly enough the first two of these themes were prevalent in American political science studies even before Twitter became a popular network (DiMaggio 1996) (Evans 2003). This points to the fact that observations made about American Twitter may be a reflection of particularities of American politics rather than a being a feature of Twitter as a medium of communication. Initial observations of high levels of homophily in Twitter data were met with suspicion once the Twitter network started to gain popularity in other countries and there was more data available for researchers to observe the levels of homophily in multiple countries. It was clear that context mattered a lot in measurements of political homophily and that the two-party system, in general, showed higher levels of polarization on Twitter1 (Urman 2019). Contextualization of claims based on Twitter data has thus become very important in political science literature in recent years. It is for this reason that in this research I will focus on French Twitter.

1 This can potentially explain why we observed such high levels of homophily in initial studies of Twitter.

In appearance, Twitter's role in political debates can be considered as that of a facilitator of communication. It has certainly made it easy for its users to maintain direct contact with each other and also with the political and non-political elite. This 'facilitation' has raised some very important questions with regards to Twitter's ability to challenge the agenda-setting power of traditional media. It has been found that traditional media still holds a considerable amount of agenda-setting power over Twitter discussions especially in "non-breaking-news" times but, Twitter discussions have become primary drivers of agenda in "breaking news" times (Su and Borah 2019). This may be interpreted as if Twitter encourages the democratization of public debate to some extent by giving voice to common people (Jackson 2019). While it is true that Twitter has decreased the cost of public debate, but it is far from being well-established that Twitter has 'democratized the public debate'. Access to public debate forums is only one part of the process of deliberation. For the public to reach a meaningful consensus through deliberation, other pre-requisites have been discussed in detail in the works of Jurgen Habermas. His vision for communicative rationality puts forth a vision where 'force of better argument alone' allows the public to reach a consensus through deliberation. Such a vision assumes unidirectionality of public debate and an environment of deliberation where discussants can 'set aside' their social status.

In addition to the above, post-modernists have also raised some serious questions on the viability of a Habermasian public sphere in a post-modern world of the internet where the 'definition of self is fundamentally fragmented':

"*In the first, oral, stage the self is constituted as a position of enunciation through its embeddedness in a totality of face-to-face relations. In the second, print, stage the self is constructed as an agent-centered in rational/imaginary autonomy. In the third, electronic, stage the self is decentred, dispersed and multiplied in continuous instability*" (Poster 1990)

As pointed out above, data collected from some deliberation platforms on internet 2.0 also point to a largely divided set of groups. This may look as if the easier it becomes to engage in public debate (with new technological tools) the more fragmentation we will see in the public sphere.

This does not however mean that Habermas's conception of communicative rationality has to be abandoned in favor of a new framework before investigating the reasons behind public fragmentation in a more thorough manner. Also, the Post-modern conception of 'decentered self'

and its explanatory power in terms of levels of fragmentation in social networks has to be put to test.

1.1 Research Questions

There are means through which the concept of political fragmentation can be operationalized using Twitter data. In the Twitter literature, one of the most popular mediums through which levels of political fragmentation are judged in social networks is the level of 'political homophily'. As mentioned above the initial studies with Twitter data were mostly done with American data and the levels of homophily that were observed through these studies provided credibility to the hypothesis that internet 2.0 may contribute to an increase in the level of group polarization. The root of the hypothesis that internet 2.0 may cause an increase in political homophily and also increase group polarization levels can be traced back to cass sunstein's work in Republic.com (Sunstein 2001). Twitter was one of the first venues where observations regarding this hypothesis were made, but most of these studies treated Twitter as an observatory reflective of the real world and not a venue in itself only accessible to (and interesting for) certain kinds of people. Twitter users and their activity was thought to be an effect of them being on the Twitter platform and not a function of them being fundamentally different from the population in other important demographic ways. It was a later stage in research on this question that demographics of Twitter users were found to differ from the rest of the population (Mellon and Prosser 2017) and it was also found that political involvement in Twitter is a function of many demographic features absent from data provided by official Twitter API (Boyadjian and Marie 2014). Twitter studies on homophily showed that Twitter users were divided on issues, they ignored the fact that this did not necessarily imply that being on Twitter is the reason for this division in opinion.

Following is the list of research questions I will try to answer in this thesis.

1. Is the Twitter network in France fragmented into communities with similar political and social interests?
2. If they are divided then does this fragmentation affects all political groups in a uniform way?
3. What does fragmentation mean in terms of the identity of groups and deliberation between the groups?

4. If communities in Twitter are formed based on the social and political interests of the users, are these communities internally hierarchical or more egalitarian?

Political homophily is still a popular theme in Twitter studies and it is an open question if ease of communication that came with social media platforms like Twitter allowed users to have a serious selection bias in finding people to connect with or if this bias already existed and Twitter just provided a way for social scientists to measure it. In this thesis, I will make the case that if the level of homophily in French Twitter is measured over time using the follow-network, we will notice that not all clusters formulate echo chambers. I will test the hypothesis that level homophily in a Twitter community is dependent on the type of ideology modulated by the level of motivation from the community's opinion leaders. The argument is structured in two parts, In the first part, I aim to study the levels of political homophily in the context of French Twitter. I will focus on strategies used in previous works to measure the levels of homophily in the Twitter network and present a novel method of collecting and validating country-level follow networks on Twitter. This network graph will then be used for extrapolating political affiliations, community structure, and the level of embeddedness for a large database of French users on Twitter. Once the above community structure has been established, I will then study the evolution of political clusters over time to see If the 'increase in political homophily' is a phenomenon orthogonal to the type of ideological inclinations.

In the second part of this thesis, I will make the case that high-frequency political retweeters act as intermediaries between the political elites and common users in Twitter. While political retweeters are generally more elitist than non-political retweeters but retweeters of more isolated political clusters (such as nationalist right-wing) are highly motivated individuals who act as ideological reinforcers in the network and thus prove instrumental in maintaining the hierarchical structure of the network.

Overall this study will show that the group polarization phenomenon in Twitter is inherently top-down, where political elites can use intermediaries such as retweeters to exercise political

influence2. I will argue that Twitter's failure to create a rational debate in the Habermasian sense was due to factors external to Twitter and had to do with the hierarchical nature of the society rather than the conception of the 'decentralized self'.

2 Much as it was observed in erie county study of paul lazarsfeld.

Chapter 1: Keeping the expectations realistic

There is an ever-increasing amount of literature about Twitter that tries to judge the platform through the lens of Habermass' ideal of the public sphere (Bruns, et al. 2015) (Yang, Quan-Haase and Rannenberg 2016). In this chapter, I will describe the socio-economic origins of the Habermassian public sphere and argue that Twitter and other social media platforms do not change the fundamental nature of socio-economic relationships among classes which were a pre-requisite for the Habermassian public sphere of the 17th century. Therefore, it is futile to judge twitter's conversations on the criterion set forth by Habermas. What twitter essentially does is reduce the cost of many-to-many communication, which in itself is not sufficient for triggering a rational debate but can lead to long term effects on the ability of masses to argue rationally after hearing debates of active political agents, provided that it does not end up creating isolated communities or filter bubbles. In this chapter, I will also make a case that a more interesting question that Twitter can answer is:

> **Does reducing the cost of creating a weak one-sided relationship (such as a 'follow relationship' on Twitter) encourage people to access information equally?**

Answering the above question will require an insight into the literature related to political homophily and polarization (their connection will be discussed in detail in the following chapter). Most of the literature with regards to the question of Twitter's connection with political polarization makes use of theoretical frameworks of Jurgen Habermas or Paul-Lazarsfeld. Although these two frameworks appear to be addressing different questions, they have underlying similarities which can be useful for understanding political polarization. Habermas tried to understand the communal reasoning that allows groups to reach political consensus through deliberation, while Paul Lazarsfeld was concerned with the flow of 'influence' during events of political significance such as elections. Lazarsfeld's work is immensely popular among marketing practitioners, one example of this being how his idea of 'opinion leadership' has led to a focus on personalization in the advertisement industry. In this chapter, I will claim that while Lazarsfeld's theory is observational and not explanatory, but when combined with the concept of 'feudalization of public sphere' by Habermas it can be particularly useful for understanding the reasons behind political polarization in a social network like Twitter.

1.2 Opinion Leadership in Paul Lazarsfeld

In 1948, Paul Lazarsfeld, Bernard Berelson, and Hazel Gaudet published their ground-breaking work in the study named *The People's Choice*. The most novel idea presented in the book was concerning the flow of political influence. It had been previously thought that Political influence flows directly from the media to the general public. A theoretical basis for the idea of media's direct influence on the public came from hypodermic needle theory which is sometimes referred to as magic bullet theory as well. According to this theory, the public was only passive receivers in the flow of communication and is also likely to be influenced by whatever is said in the media (Lasswell 1936) . Lazarsfeld and his co-authors challenged this idea with a two-step flow hypothesis, which traces the trajectory of political influence from media to a group of people who are comparatively more active in seeking political news and then to ordinary people through these 'more interested' individuals. These individuals who were more interested in political issues were called 'Opinion Leaders'. In the original study of 1948, Lazarsfeld found these opinion leaders only through their testimonies. During the interviews, the following questions were asked from the people:

- "Have you recently tried to convince anyone of your political ideas?"
- "Has anyone recently asked you for your advice on a political question?"

This method of detection of opinion leaders was problematic as pointed out by authors themselves that a better method would've been "asking people to whom they turn for advice on the issue at hand and then investigating the interaction between the advisers and advisees (Lazarsfeld, Berelson and Gaudet 1968). It was not done by authors because in their study they had taken a sample of a much larger population of a county, and it would've been unlikely that both advisers and advisee would fall in the sample. Katz stated this design issue in the following words.

"The data, in other words, consist only of two statistical groupings: people who said they were advise-givers and those who did not. Therefore, the fact that leaders were more interested in the election than non-leaders cannot be taken to mean that influence flows from more interested persons to less interested ones. To state the problem drastically it may even be that the leaders influence each other, while the uninterested non-leaders stand outside the influence market altogether." (KATZ 1957)

The subsequent contributors to the theory improved on the original hypothesis considerably. An improvement on the above-mentioned study was done in the Rovere study published in 1948 by Robert Merton. The design for this study was looked for Opinion leaders by asking people the following question:

‘Who influences you?’

The answers to this question were compiled and then if an influencer was mentioned more than 4 times, he was considered an opinion leader and interviewed. The conception of opinion leaders also changed in this study. An opinion leader was thought to be a person who has a broader influence, which is opposite to what Lazarsfeld originally proposed where his idea of opinion leader was limited to being able to influence even a single person would designate one as an opinion leader. (Lazarsfeld and Merton 1948)

The findings of 'the people's choice' about the spread of personal influence were once again put to test in *“decature study”* to know more about the diffusion of fashion trends among women. This study not only found the opinion leaders who were designated by advisees but also verified the self-designation method by asking the self-designated opinion leaders as to who they had advised on a certain issue and then the researcher also interviewed the person who was advised by the opinion leader. The findings of this study made clear that Opinion leadership is not a quality that people possess or not, but it is dependent on the topic of interest and the dynamics of the society for a particular time. It was also concluded that it would be profitable to trace 'a specific item's diffusion over time, through the social structure of the entire community (Katz and Lazarsfeld 1955)

The tracing of specific items was done in a later study on opinion leadership among doctors of the specific area using an audit of prescriptions in local pharmacies. This study also investigated the diffusion pattern of a new drug among doctors. It was found that the doctors who were strongly integrated into the community and had higher connections with doctors of other counties were more likely to be opinion leaders when it came to the diffusion of a new drug (MENZEL and KATZ 1955).

Using the above studies as a reference point, Katz reached the following 7 point conclusions:

1) The effectiveness of inter-personal influence is reflected in the homogeneity of opinions and actions in primary groups.

2) Mass media often plays a reinforcing role in strengthening predispositions and of decisions already taken.

3) Media can be divided into two parts, one part acts as 'information' media, and the second part acts as 'Legitimizer' of decisions already taken.

4) It was found that there are two sets of opinion leaders, one that deals with 'local affairs' and another that deals with 'cosmopolitan affairs.

5) Personal influence is dependent on the following factors:

a. The personification of values (Who one is)

b. Competence (What one knows)

c. Strategic and social location (whom one knows)

6) The reason that personal influence flows in this direction is that influence wants to be as much like influential as possible.

7) Men are more likely to be opinion leaders in public affairs than women.

1.3 Moving from Opinion Leadership to Habermas's notion of 'Public Sphere'

To understand the reasons as to why 'opinion leaders' gained importance in communication that Lazarsfeld observed in his study, I will now describe the framework proposed by Jurgen Habermas in his popular book titled "The Structural Transformation of the Public Sphere" (Habermas 1962). Although the book was originally published in 1962 it remains very relevant in the literature that explores the concept of 'Public Sphere' with the evolution of internet-based social platforms and media such as Twitter and Facebook. The larger question that most of the researchers are trying to explore is to find out if platforms such as Twitter and Facebook are a step towards the formation of a Public Sphere in a normative sense as Habermas described it in his book (Colleoni, Rozza and Arvidsson 2014) (Yang, Quan-Haase and Rannenberg 2016) Although this thesis will not attempt to directly answer this question It will explore one of the main reasons proposed by many

researchers for the failure of internet 2.0 to live up to the optimistic expectation of acting as a platform of open, rational and inclusive political debate which are fundamental to the concept of 'Public Sphere' as proposed by Jurgen Habermas. "Polarization", "Filter-Bubbles" and "Echo-Chamber" are terminologies used to describe the phenomenon that prevents platforms such as Twitter to act as a Public Sphere. Although all of these terminologies have particular connotations attached to them but one concept that underlies all of them is the idea of the formation of isolated communities based on common believes of individuals that are common among the members but lacking among the non-members. This thesis aims to explore the methods used to measure the level of this isolation on Twitter and to find out the reasons why this type of isolation happens and what kind of effects it can have on participatory democracy.

To understand Habermas's framework, it is important to know that his derivation of the idea of the 'public sphere' is deeply rooted in historical developments and structural changes that happened in western Europe as a result of enlightenment and a shift towards the capitalist mode of production.

1.4 Birth of Public Sphere in Habermas's conception

Looking into socio-economic conditions of multiple eras, Jurgen Habermas draws on the history of separation between the 'public' and 'private' realm which according to him existed as early as Greek and early Roman times. However, this notion of differentiation between what is 'public' and what is 'private' disappeared during medieval times as feudalism reached its more advanced form. With the development of the characteristic hierarchy of feudalism, peasantry became more and more involved with the lord's household which was the center of social and economic power at that time. This paved the way for the dissolution of concepts of 'private' and 'public'

"During the Middle Ages in Europe …. the opposition between the public and private sphere on ancient (or the modern) model did not exist. Here too, the economic organization of social labor caused all relations of domination to be centered in the Lord's household. " (Habermas 1962)

Habermas's analysis takes the form of a linear understanding of history and explains the formation of the participatory ability of common people in political affairs with changes in modes of production and relationships formed as a result of that. The genesis of one of the most important institutions of public sphere newspapers was a gradual result of the appearance of a new merchant class in Medieval Europe (Bourgeoise) that were interested in access to faraway markets to

maintain the comparative advantage over their opponent. These businessmen needed market and political information that could benefit them which in turn gave rise to a market for information which was at first privately exchanged in form of newsletters and then later evolved into public newspapers with bourgeoise as its primary producer as well its primary consumer. Initially, due to their locally depoliticized nature, these newspapers were often used by states for the dissemination of important information which was beneficial for both state and newspapers. However, with a gradual shift from a feudal mode of production to a capitalistic one, the power of the feudal state came in direct opposition with newspapers who were, by that time under complete control of commercial classes and had developed a considerable interest among the bourgeoise reading public.

For Habermas, the first cracks in the older state started to appear when the dichotomy between the public and private property for monarchy appeared. Although the causes of this break were the socio-economic but spill-over effect of this change was also felt in social life and differentiation between private and public realm started to reappear as they existed before the feudal mode of production. 'Public Sphere' evolved out of the private realm of exchange of newsletters rather than the Public realm. This new public sphere soon directed its guns towards public authorities using unconventional tools such as 'public reasoning'.

"The bourgeois public sphere may be conceived above all as the sphere of private people come together as a public; they soon claimed the public sphere regulated from above against the public authorities themselves, to engage them in a debate over the general rules governing relations in the basically privatized but publicly relevant sphere of commodity exchange and social labor. The medium of this political confrontation was peculiar and without historical precedent: people's public use of their reason"

While the emergence of the public sphere in so much as modern newspapers can be understood as an evolutionary product of the exchange of newsletters in the private sphere and increasing need for information in expanded markets, but that was not the only ingredient needed for a complete transformation of the structure of the state so as it could better serve the interests of the new dominant commercial class. Newspapers emerged as a source of opinion formation for the public but without the ability to take action these opinions would have been inconsequential. There was a need to recognize 'public opinion' as something of importance in so far as the governance was

concerned. Although in England, the house of commons managed to assert its supremacy over the king by the late 17th century, the lack of universal suffrage disconnected it from people and the political process of election scarcely involved public deliberation. With the rise of demand and supply of Newspapers in the 17th century, the bourgeoise reading public started to frequent coffee houses in London and Paris. Among the institutions of the public sphere, public discourse played an important role and most of these discussions took place in these popular coffee houses or reading societies (German case) where there was a relative 'semblance of equality (although still limited to bourgeoise). Habermas proposes that these coffee house discussions had three common qualities in them.

1. There was relative equality of opportunity to participate in discussions and 'better argument' was what prevailed in discourse and due to their informal nature, there was a relative disregard for the status.

2. Discussions among people 'presupposed the problematization of areas that until then had not been questioned'. This made way for the loss of aura of extra-ordinariness of church and court and even cultural products such as arts came under the scrutiny of public reason.

3. Generalizability of discussions coffee houses to a broader public. Although, there was a scarcity of people who could read among rural masses and even 'court aristocracy of the seventeenth century was not a reading public' yet among the bourgeoise visiting these coffee houses there was a general desire to reach consensus on issues.

Although Nancy Frazer contests Habermas's assertion that within these coffee houses there was a relative 'disregard for status' which allowed for an equal opportunity discussion among people, yet it can be plausible to think that within the 'property holding men' of educated classes there was a possibility of such disregard in ranks (Fraser 1990).

1.5 Political Implications of newly emerging Public Sphere in 17th Century

A natural incompatibility that occurred between the monarch's discretionary powers and commercial interests of the bourgeoisie, was the inherent unreliability of the rules. As Max Weber

talks about how ‘guarantees of calculability’ were important to the development of industrial capitalism, codification of laws was thus a matter of interest for commercial classes (Weber 1905). It was thus necessary to increase the power of parliament as opposed to the King as the parliament, in theory, would be under the yoke of ‘public opinion. Although it has to be noted that the term ‘public’ was a universal term at that time but in practice, there was a qualification criterion that needed to be fulfilled to enter ‘public’ which favored the bourgeoisie more than any other group. 'The *bourgeois idea of the law-based state, namely, the binding of all state activity to a system of norms legitimated by public opinion (a system that had no gaps, if possible), already aimed at abolishing the state as an instrument of domination altogether’.*

Implications of the development of the bourgeoise public sphere and the change in the dominant mode of production ultimately lead to a significant political shift in all major European powers. While the process of bringing both the monarchy and parliament under the check of public opinion was a gradual process in England that extended for the whole 17th century but it was the act of appealing to public opinion by parliamentary opposition after failing in parliament that leads to an increase in opposition’s power temporarily but brought the whole of parliament under the influence of public opinion.

1.6 Redefining Reason

Frankfurt school on instrumental reasoning and weaknesses on enlightenment

While enlightenment provided ample ground for questioning the authority and use for the reason for determining individual pathways, the meaning of reason itself kept getting redefined. Adorno and Horkheimer's critique of instrumental reasoning and its classification as ‘subjective reasoning’ and ‘means to an end’ lead to a bleak view of the political future as rationality was reduced to its practical use and ultimately a tool for domination of nature. Political implications of this thought process lead to seeing politics as a competition among ‘rackets’ for power and foreign to the general public. This view of reason however did not view ‘public’ as a unified entity in an abstract way that could reach a meaningful consensus of political significance. Collective political action was thus a doomed cause in early Frankfurt school scholars.

Habermas on the other hand traces a particular period during the enlightenment when a sub-section of a society created an ideal space for a limited-scale public deliberation. Habermas described enlightenment with the lens of a new type of rationality that he called ‘communitive rationality’

where public discourse under some rules could lead to consensus on an issue which was enough to grant legitimacy to an opinion. Reasoning itself was thus subjected to public opinion. His view on this period is not idealistic and he is careful in pointing out that the 17th-century public sphere was an exclusive bourgeoise public sphere.

'*The cliches of "equality" and "liberty," not yet ossified into revolutionary bourgeois propaganda formulae, were still imbued with life...the results that under these conditions issued from the public process of the critical debate lay claim to being in accord with reason; intrinsic to the idea of a public opinion born of ' the power of the better argument was the claim to that morally pretentious rationality that strove to discover what was at once just and right'*

Nevertheless, the existence of such space despite its limitations provides a future for deliberative democracies provided the socio-economic conditions for the formation of such sphere could be achieved in so much as it provides equal access to all and helps reach actionable consensus over major issues from the public.

1.7 Transformation of Public Sphere according to Habermas

The structural basis for the public sphere lay in its separation from the realm of political power. According to Habermas, the bourgeoise public sphere of the 17th century essentially existed in the private realm away from the state which guaranteed its ability to criticize the agents of the state. The participant of this public sphere maintained their status as property owners and 'Homme' which directed their debates in directions that favored these statuses. These two roles gave a human character to debate within the public sphere and since initially there was a barrier of entry (education and property), it was possible to have a rational debate about the matters of civil concern. In the post mercantilist, free-market phase of least government intervention, the public sphere played a positive role in directing the pathways of state to some extent. However, this balance did not last very long as it was realized that the balance between the statuses of 'Homme' and 'bourgeoise' came in direct conflict with each other. Due to the universality of the idea of the public sphere, it was impossible to keep it limited to the bourgeoise public for long and there was a fast expansion in the sphere and soon property and education did not remain a necessary part of entry requirement. This was disadvantageous to the bourgeoisie as Coffee house debates allowed the usage of political power against those who could not be defeated in commercial ventures.

Human rights also became a mobilizing factor so much so that in Germany Bismark was forced to give concessions such as social security Insurance.

'The concentration of power in the private sphere of commodity exchange on the one hand, and in the public sphere with its institutionalized promise of universal accessibility (established as an organ of the state) on the other, strengthened the propensity of the economically weaker parties to use political means against those who were stronger by reason of their position in the market. In Great Britain there were electoral reforms in 1867 and 1883; in France, Napoleon I11 had introduced universal suffrage

Realizing the direction where the public sphere was going, private interests took it upon themselves to change the nature of their relationship with the state and allow state policies to reintroduce government interventions in so much that they would not affect the 'private character of their commerce with each other. This merger of private interests with the state power reintroduced the feudal hierarchies and paved the way for what Habermas called 'refeudalization of public'. This loss in equality within the public sphere lead to its ultimate transformation into a less egalitarian space, where commercial success could buy political influence.

1.8 The separation between the intimate sphere of family and the social sphere of work-life

As mentioned above Habermas's public sphere existed in the private realm as opposed to public realm. Within the private realm, the public sphere cohabited with the intimate sphere of family and the social sphere of commodity exchange. It was due to the closeness of the intimate sphere of family and social sphere of commodity exchange that bourgeoise members of the public sphere of 17th century could act in the capacity of 'Homme' and property owner. With the entry of people with no property into the public sphere, the singular status of 'homme' and property owner broke down and the intimate sphere of family and social sphere of work and property polarized and came in conflict with each other. The institution of family was further affected by the demands of newcomers in the public sphere. With Social security nets gained under the pressure of evolved public sphere, the state assumed economic responsibilities of individuals that were traditionally taken by the family. This weakened the family institution, which was the basis of the development of the literary sphere in the bourgeoise public. In absence of a mechanism for the evolution of the literary sphere within the intimate sphere of family, individual capacity to reason deteriorated, and

the movement towards cultural consumption rather than production became a priority. An increase in cultural consumption and search for leisure was the need of the new inductees in the public sphere as most of their energies were dedicated to making a living as opposed to the bourgeoise public sphere where members enjoyed considerable freedom from their work-life to dedicate to public discourse. This deteriorated the rational critical thinking process among those involved in the public sphere. Bourgeoise who took charge of once relatively free institutions of a public sphere such as press and other mediums of broadcasting took advantage of the cultural consumption trend and capitalized on the development of the advertisement industry. The commercialization of press itself played a major role in the transformation of the public sphere into its new form. Initially, these newspapers were managed under an armature business category but soon their potential as an advertisement medium was realized which transformed their character from an instrument of politicization of the public to a medium of cultural consumption.

'Marx shared the perspective of the propertyless and uneducated masses who, without fulfilling the conditions for admission to the bourgeois public sphere, nonetheless made their way into it to translate economic conflicts into the only form holding any promise of success-that is, into political conflict. In Marx's opinion the masses would employ the platform of the public sphere, institutionalized in the constitutional state, not to destroy it but to make it into what, according to liberal pretense, it had always claimed to be. In reality, however, the occupation of the political public sphere by the unpropertied masses led to an interlocking of state and society which removed from the public sphere its former basis without supplying a new one. For the integration of the public and private realms entailed the corresponding disorganization of the public sphere that once was the go-between linking state and society' (Habermas 1962)

The private sphere which previously consisted of the sphere of commodity exchange and family thus broke in the social sphere of work and intimate sphere of the family. A mark of this separation is still seen in the separation of social media for work such as LinkedIn from social media for family and friends such as Facebook. However, this separation between social media can best be interpreted as symptomatic of larger polarization that has been happening between the intimate family sphere and the social sphere of work since the evolution of the first public sphere in the 17th century.

1.9 Connecting work of Lazarsfeld with Habermas

Most of the existing literature in Twitter investigations takes their theoretical frameworks from the works of Paul Lazarsfeld or Habermas. However, little effort has been done in forming the connections between the two authors and their findings. In the following paragraphs, I will try to bridge the two kinds of literature and explain how political homophily can affect twitter's potential to act as a public sphere. As mentioned above, Habermas talks about a brief period when social hierarchy within bourgeoise social circles was put on hold, and public discourse took a more horizontal form where the power of argument was the sole determinant of deliberation. He then explained how hierarchies reappeared after socio-economic conditions of a horizontal public sphere no longer favored the interests of the bourgeoise. He goes on to call this change 'refeudalization' of the public sphere and the nature of these relationships to be vertical. Habermas mentioned Lazarsfeld and Katz in his work to justify this point:

"Such characteristics of a liberal public sphere preserved in the voting behavior of the population can also be demonstrated in the flow of political communication investigated by Katz and Lazarsfeld. In contradistinction to a more horizontal, social stratum-specific spread of fashions and consumption habits in general, the stream of political opinion flows in a vertical direction, from the higher status groups down to the ones just below the "opinion leader(s) in public affairs" are usually wealthier, better educated, and have a better social position than the groups influenced by them.87 On the other hand, it has been observed that these politically interested, informed, and active core strata of the public are themselves the least inclined to seriously submit their views to the discussion. Precisely among the carriers of this two-tiered process of communication, mediated by these opinion leaders, an opinion once assumed often becomes fixed as a rigid habit.88 Even those opinions that do not have to bear public exposure do not evolve into a public opinion without the communication flow of a rationally debating public."

In the conception of Katz and Paul Lazarsfeld political homophily was a result of the formation of such a hierarchy as Habermas pointed out in his work. According to Lazarsfeld, opinion leaders happened to be ones who shaped opinions of people lesser interested in Politics due to their knowledge on the field and the position they enjoyed in social circles and due to the interpersonal nature of the connection between local level opinion leaders and public, it was more likely that

people who would consult the same opinion leader would end up forming same kinds of opinions which could be seen as an indication of hierarchical homophilic society.

This chain of the flow of political influence is contrary to the idealistic nature of the horizontal public sphere which Habermas envisioned and political homophily can be an indicator of such hierarchy.

Modern communication technologies in the context of 'Public Sphere'

1.10 Technological transformations and evolution of public sphere

It is interesting to look at the nature of technological developments that moved hand in hand with the developments that happened in public spheres and the impact they had over these spheres. Habermas talks about the emergence of coffee houses in 17th century London and Paris which severed the purpose of facilitating public discourse (limited the access to only bourgeoise). Here are notable features that existed in these coffee houses but missing in media and printing press

1. The possibility to have back and forth conversations allowed the natural flow of conversations.
2. These platforms could only be monetized at a very small scale. Even so, the content of conversations was not a monetizable product but the coffee itself. Thus, they allowed for a freer conversation for people devoid of political or otherwise cultural advertisement.

For Habermas the transformation of the public sphere occurred not because of changes in mediums such as television or radio but mainly due to changes like the relationship between bourgeoise and State. However, it is hard to ignore the scalability of these new instruments of expressions and their fundamental nature, and how it affects the formation of public opinion. Although coffee house conversations did get affected by agenda-setting power of media such as TV and newspapers as mentioned above commercial monetization of coffee house conversations themselves was never a practical possibility. Here is a list of communication modes and their primary features which can affect their ability to serve as an aid in the public sphere.

Table 0: Comparison of capabilities of multiple media technologies

Tech	Source of information	Target of Information	Speed of Information	Advertising Capability
Coffee House	Many	Many	Slow	Low
News Papers	One	Many	Slow	High
Telephone	One	One	Fast	Low
Radio/TV	One	Many	Fast	High
Internet 1.0	Few	Few	Fast	High
Internet 2.0	Many	Many	Fast	Very High

Internet 2.0 presents a potential to be close to coffee houses of the 17th century to serve as a template of the public sphere but in recent years we have seen break down of internet 2.0 into specialized platforms each of which, although based on commercial interests of newly emerging tech-bourgeoise, serves a specialized purpose in the realm of social life. Facebook is one major platform that evolved out of the desire to scale personal-social life. Although Facebook pages allow users to gain access to follow general trends the users on the network generally treat it as a social network using it for staying in constant contact with people they know in real life. Twitter is another platform that allows users to connect and converse on topics they are interested in. These conversations are generally two-way conversations allowing all users to participate almost simultaneously. That makes it ideal for public deliberation on large scale and in theory, it should act as a sound platform for rational political deliberation.

1.11 Why is Polarization Problematic for an ideal Public Sphere?

While historical tracing of the public sphere in the 17th century carries a great value in itself but his framework has been deemed as idealistic (yet useful) by people such as Nancy Frazer (Fraser 1990). Habermas's notion of ideal public deliberation includes the following characteristics

(1) inclusion in Deliberation;

(2) equality of participants in the discussion;

(3) the degree of justification of arguments;

(4) respecting and listening to other points of view;

(5) the ability to take the position of its interlocutors;

(6) the sincerity of the arguments put forward.

As Julien Boyadijan has shown in his thesis that online political exchanges barely qualify as 'discussions' and it is futile to judge the quality of deliberation on that scale (Boyadjian 2014). But this does not diminish twitter's potential to provide a platform that is more vertical as it allows combined opinions of millions of users to contest powerful actors and makes space for communicative action. Habermas's notions of the ideal public sphere included two broader aspects:

1) Equality of status, access among the participants.

2) Rationality of participants.

Most of the studies on Twitter that employ Habermas's framework try to judge twitter for the 'rationality' of arguments presented. However, I will use this framework to judge twitter's ability to provide equality and inclusivity. I will thus built on the dichotomy drawn by Ellanor Colleoni between the public sphere and echo chamber to understand if Twitter provides equality of opportunity to participate in public debate (Colleoni, Rozza and Arvidsson 2014).

As pointed above, common ground can be built on frameworks of Lazarsfeld and Habermas by looking into the relations between users in Twitter and trying to judge if the level of homophily is consistently increasing over time and for what kind of users it is increasing or decreasing. Using this longitudinal analysis, it is then possible to judge what kind of impact this new technology is having on public debate.

1.12 Can Twitter "defeudalize" the public?

Twitter's ability to act as a new public sphere in Habermasian sense is a topic of interest among Political scientists since the last decade. As described above the bourgeoise public sphere of the 17th century was transformed due to the entry of people with conflicting political interests

particularly propertyless people entering the public sphere and using political means to fight battles that they could not win in the economic sphere. For this kind of change state's intervention in the public sphere was necessary and thus the neutral character of the public sphere was compromised as power balance was lost and society in Habermasian terms 'refeudalised' due to new hierarchies.

Optimistic proponents of social media think that platforms like Twitter provide a side-track where power balance could be restored and relative equal access to all can be guaranteed. So far the actual measurement of influence of users suggests otherwise. Most popular online personalities and bloggers are generally the people who would be popular in offline platforms such as journalists and traditional media personalities (Dubois and Gaffney 2014) (Neihouser 2015). Others doubt the ability of online spaces, in general, to cater as a public sphere.

In addition, the status of these web spaces may be ambiguous as their "political" character is difficult to establish and many of them are very far removed from the notion of "public sphere", characterized by Habermas (Greffet 2012).

This should not be surprising as traditionally popular journalists gain reinforcement publicity from still popular media houses, TV, and radio. Expecting an abrupt revolutionary break from tradition with the arrival of Internet 2.0 is perhaps asking too much from it but It is still an interesting question to ask if platforms like Twitter are gradually changing the paradigm towards creating a 'horizontal' public sphere.

Here are some ways in which Twitter can provide a better medium for the exchange of ideas than traditional newspapers, Television, and Radio.

1.13 Two-way conversations

As opposite to media such as television, newspapers, and radio twitter provides a two-way conversation option, although on a limited scale (texts have to be limited to 140 characters). This puts twitter closer to coffee houses of the 17th century in its ability to generate a conversation. Not only does it allow a conversation, but it also gives a chance to participate in it without using one's own words, through options such as retweet and Likes.

Separation from the social realm of work (LinkedIn) and the intimate realm of family and friends (Facebook)

Habermas talks about the separation of the intimate sphere of family and close relations from the social sphere of work as a factor that leads to change in the basis of the public sphere. This fragmentation deprived the ability of a person to be a 'homme' and 'bourgeoise' at the same time and lead to his being a citizen only (a label that gives him power only under the umbrella of state).

Today's online platforms create a new kind of fragmentation in social life, where the social sphere of work exists in a different platform (LinkedIn) than the intimate sphere of family and friendship (Facebook), and participation in tasks related to publicity are performed in a socio-political platform like Twitter. It must be noted however that Twitter is not solely dedicated to political discourse but also includes a strong cultural element to it as the entertainment industry and sports industry has a major presence in the same platform. While it does not get us back to the situation of the bourgeoise public sphere but this fragmentation has the potential to take away the social pressure from political opinions and agents can potentially act free from the pressure of conformity from friends and family and co-workers. I will discuss in the next chapter in light of previous research if individuals avail this freedom and create diverse new relationships that they would otherwise not have created in real-life. In other words, Does Twitter acts as a social network or not?

1.14 Anonymity and VPN allows separation of state and the public sphere

For Habermas, public sphere needed to be separate from the influence of the state. In such a sphere no topic of conversation can be considered taboo or forbidden and the presence of powerful state and interest groups within this sphere can lead to the formation of hierarchies which can hinder the free flow of ideas. Collective reasoning of the public can only achieve consensus on the issue of public concern without nudges from any of the interest groups as such.

Twitter allows a unique opportunity of anonymity which can allow users to keep a check on the advances of the state without overtly confronting it in real life. Twitter's capacity in this regard was tested during the Arab Spring where it was effectively used against aggressive states.

1.15 Relevance of traditional media theories to Twitter

As mentioned before, the fundamental question of the field of political communication has been to find out how media influences the public's political opinion. With the arrival of web 2.0 the need to rethink the traditional theories in political communication was felt. web 2.0 provided the opportunity to record the interactions of people in a more comprehensive way to study the process of diffusion more effectively (Domingos and Richardson 2001) It has evolved since then and adopted many facets. In the micro-blogging space, Twitter became a prominent player and started to attract major political and non-political personalities on its platform. There has also been a major surge in the academic literature on Twitter. Many scholars have used Twitter data to find justification for hypotheses from traditional media theories like agenda-setting theory (Conway, Kenski and Di 2015) Two-step flow hypothesis (M. Cha, H. Haddadi and F. Benevenuto, et al. 2010) and one step flow theory (Hilbert, Vásquez and Halpern 2016). Following are the reasons why Twitter acts as a reasonable platform for these studies:

1. A large number of important personalities on the platform.
2. Ease of getting data.
3. A large presence of endorsers and audience.

Here it is important to demonstrate what tools these scholars used to support their claims and how Twitter was used in their analysis, so the following paragraphs will provide these descriptions.

Starting with the description of the paper written by Sujin Choi in 2014 (Choi 2014), to track the flow of information on Twitter among two South Korean political groups in Twitter. Using the description of Opinion leaders from the work of Katz and Lazarsfeld he assigned the role of Opinion-Leaders to people most central in the network using betweenness centrality (As demonstrated in the following works (Lee, Cotte and Noseworthy 2010)). Using this definition of Opinion leadership, the most important profiles were identified, and following conversations direction counts were observed from the data:

1. (Non-opinion Leaders × Non-opinion Leaders)
2. (Opinion Leaders × Non-opinion Leaders)
3. (Non-opinion Leaders × Opinion Leaders)

4. (Opinion Leaders × Opinion Leaders)

"If the two-step flow of communication exists in online group discussions, the size of block density would increase in the ascending order of (Non-opinion Leaders × Non-opinion Leaders), (Opinion Leaders × Non-opinion Leaders), and (Non-opinion Leaders × Opinion Leaders). This implies that non-opinion leaders—that is, general participants—communicate more frequently with opinion leaders than they communicate with other non-opinion leaders and refer to opinion leaders more frequently than opinion leaders refer to them." (Choi, 2014)

Choi's conclusions supported the two-step flow hypothesis and he also found evidence that opinion leaders identified on Twitter using the above-mentioned method generally get retweeted significantly more often than non-retweeters.

In addition to this many scholars used Twitter data to verify the one-step flow model as well. The work of Vásquez Hilbert showed us that while the Two-step flow hypothesis is still relevant on a platform like Twitter, and yet 90 percent of mentions of large media outlets come directly from the participants. It is therefore impossible to separate Twitter from the one-step flow hypothesis (Hilbert, Vásquez, Halpern, Valenzuela, & Arriagada, 2016).

There has also been a growing body of literature that explores the agenda-setting power of Twitter and its relation to traditional media in that context. It has been found that Twitter can be used as a tool by politicians and the public to communicate an agenda that, in turn, shapes the media agenda (Neuman, et al. 2014)

While Twitter provides a large record of conversations and it is possible to track the flow of information, but it must not be forgotten that Twitter users are not representative of the population in general. They are usually younger, well-educated, and more interested in politics (Mellon and Prosser 2017). It must therefore be noted that any conclusions drawn about the relevance of a communication theory to Twitter may not apply to the population outside of Twitter. An area for future researchers to explore might be if the people on Twitter (being well educated and more interested in politics) act as opinion leaders for the general population who are not on Twitter?

1.16 How is the Twitter network different from traditional social networks?

To understand Twitter better, it will be a good starting point to draw comparisons of its fundamental characteristics with the world outside of Twitter. This comparison can be adequately expressed in form of the question, 'Is Twitter a social network or news media?". In terms of the basic structure of networks within Twitter, the factors that make Twitter different from other human social networks are non-reciprocity of relationships, higher levels of homophily and a shorter degree of separation (Kwak, et al. 2010). Knowing that Twitter is different from the human social network in the above-mentioned ways, one can ask about the possibility of categorizing Twitter into news media and ask how its reliability perception compares with other more traditional media and how can the information flow be described among these two media. At least, until 2011 Twitter users were more likely to share entity-oriented news which is unlikely to be shared on the traditional media (ZHAO, et al. 2011). It was also perceived by some scholars as a news-breaking media which could at times be considered faster than traditional media. (Castillo, Mendoza and Poblete 2011).

In terms of reliability, the rise of news from social media has given rise to questions on the reliability of the information it spreads. While it is of great importance to explore the question of actual coherence between factual news and news spread through social media, this thesis will not deal with that question. For this thesis, it is important to know the reliability perception of news coming from Twitter is constantly increasing as compared to traditional media (Morris, 2017).

A major difference between traditional news media such as newspapers and Televisions is the user's ability to filter his/her own news. While it was also possible in the pre-twitter age to read a certain kind of newspaper or watch a certain Television channel but they both came as a ready package chosen by the editors. Whereas Twitter provides an individual user the power to narrow down to exactly who he/she wants to get his news from. This increase in freedom to choose the sources of news has also cast doubt on Twitter's ability to improve the deliberative space on the internet. In the next chapter, I will discuss details of Literature produced on Twitter's role in increasing political homophily.

Chapter 2: Does Twitter increase political homophily? Review of Literature

While some literature suggests that social media sites can play a role in increasing political homophily through different means such as "algorithmic suggestions" on what video to watch on YouTube and which profiles to follow on Twitter but there has been some evidence against these possible roles that social media can play in pushing individuals towards `filter bubbles` (Roth, Mazières et Menezes 2020)

To present the state of art on the question, whether Twitter plays a role in increasing political homophily and subsequently in group polarization or not, the following pieces of the puzzle need to be understood.

1. How can we model political alignments on Twitter? And what format should the result be in to be useful for measuring political polarization?
2. Is there a systematic way to decide which profiles should be included in the analysis? How does the context matter?
3. What is the connection between political homophily and group polarization?
4. How is the polarization variable defined in the literature and how is it quantified?
5. What do we know about the possible causes of increasing political polarization?

Due to the unstructured nature of textual data, it is difficult to analyze the quality of deliberations in online discourse especially in the case of political discussions. Many attempts have been made to develop a normative template to judge the quality of debates in online forums, but the operationalization of such concepts poses some serious challenges (Greffet and Wojcik 2008).

These challenges get magnified in the case of Twitter's textual data as texts written on Twitter are short and highly informal. Thus there is a need to look for another form of data that can be useful in analyzing concepts such as political homophily and group polarization. I propose that network data from Twitter has the potential to fill this gap. It cannot be ignored that a strong connection

has been observed between political alignments expressed through textual means and the position in the Twitter network (Barbera 2015). It is an important development in this field as the structured nature of network position in the Twitter network can supplement the text and provide additional information regarding the quality of debates in multiple clusters. Network position also allows for finding common grounds between concepts of ’homophily', 'echo-chambers and ’political polarization. Network position can, not only tell about the political alignment of a user but also the intensity of the alignment.

1.17 Differentiating between two different types of Political Polarization

To judge the relationship of events with levels of political polarization, it is necessary to clarify that the term ‘political polarization has been interchangeably used in two different senses in literature. Liliana Mason describes this inter-change of terms in her essay “***Issue*** *versus* ***behavioral polarization*** *in the American electorate*" where issue-based polarization is defined as a temporary disagreement among people over issues that are considered important at a time. (Mason 2012). However, behavioral polarization refers to "increasing partisan strength, partisan bias, activism, and anger. In a population undergoing behavioral polarization, citizens will report stronger affiliations with their chosen political party”.

In the case of Twitter, issue-based polarization can be visible using methodological tools such as hash-tag, mention, and retweet networks. There is overwhelming evidence that suggests that the active Twitter population tends to be polarized on issues (identified by the use of hash-tags during events) such as elections or different political movements. However, in this thesis, I am interested in looking for evidence of behavioral polarization and its likelihood of increase due to Twitter usage. It is therefore necessary to see if there is a relationship between issue-based polarization and behavioral polarization.

1.18 The connection between the two polarizations

A standard method for collecting data from Twitter to measure issue-based polarization is to use hash-tags based on the events that occur during the time of the data collection. For example, to evaluate the polarization levels in the 2010 midterm elections, Conover used hash-tags such as #whyimvotingdemocrat and #glennbeck as seeds for collecting tweeters who were actively debating each other before the elections. He concluded from the results he got that the Twitter

network is highly polarized. While it is true, but this type of polarization can only be characterized as issue-based polarization as it does not provide any evidence that the same profiles keep sharing partisan hashtags in the long run or not. While it's highly valuable to know that opinions on certain issues are divided but more importantly it is necessary to find out if this disagreement leads to a more permanent form of polarization, 'behavioral polarization'.

In this thesis, I proceed by equating political homophily as evidence of issue attitude polarization by relying on literature from researchers in political science, social psychology, and computer science. Once I can establish a link between political homophily and attitude polarization, it will be possible to measure and quantify polarization in a better way.

1.19 The connection between Homophily and Polarization

As mentioned before the primary objective of this thesis is to study attitude-based polarization among Twitter users. At this stage, it may be helpful to clarify the relationship between political homophily and attitude polarization on Twitter. As it has been discussed from the studies done by social psychologists such as Myers that homogeneity in a group over a subject matter can lead to a stronger opinion over that subject after the exchange of ideas takes place within the group. Twitter allows users to follow people from diverse backgrounds and offers a very proximate platform for the exchange of ideas in today's world. From Sunstein's work, we know that online communities are likely to follow the same polarization patterns as real-world and if that is highly likely that homophily in Twitter will lead to attitude political polarization (Cass R 1999). While it is very hard to quantify the strength of conviction over an idea using Twitter's textual data, yet the level of political homophily is something measurable as shown by other researchers in the field and discussed extensively in the literature. Using the bridge between political homophily and political polarization, I will follow the footsteps of researchers such as Pablo Barbera and Kiran Garimella to use levels of political homophily over time to judge the level of political polarization in Twitter (Barbera 2015) (Garimella and Weber 2017). In this way, a community of users that are extensively creating inter-connections with each other more so than with other communities will be assumed to increase the level of attitude polarization over time. Isolation of a community from other groups will be considered to be a reflection of the attitude of the community towards ideas based on which it is united. There is considerable literature in social psychology which

experimented with multiple compositions of smaller groups to analyze the effects of deliberation on homogenous or heterogeneous groups. To establish a connection between homophily and attitude-polarization, I will rely on this literature.

1.20 How was group polarization explained by Social Psychology?

Before the arrival of Twitter, Social psychologists had long been working on the following questions,

> what is the most likely result of discussions among groups that have members with opposing viewpoints discussions? or in a homogenous group? (Myers and Lamm 1976)

In 1961 James stoner in his Master's thesis did an important study with help of 101 research subjects. He wanted to know if individuals are more prone to risk-taking behavior than groups or vice-versa. The study revealed that groups tend to acquire the ability to take much more risky decisions than what an individual is willing to take (Stoner 1961). This phenomenon was deemed as 'Risky Shift Phenomenon'. As it gained considerable interest among scholars of social psychology, later researchers found evidence for a more generic group behavior which suggested that certain groups can become more 'cautious' than individuals after having a discussion, whereas other groups can become more risk-taking than individuals in the group after talking to each other. In any case, groups with uniform initial opinions tend to move towards extreme individual opinions (Friedkin 1999). In general, social psychologists such as David G. Myers were interested in finding the factors that can lead to "group polarization". The term 'group polarization refers to the idea that an individual's attitude towards an issue becomes more extreme if he/she involves in discussion with people having similar ideas towards that issue (Myers and Lamm 1976). There were a variety of settings that were checked in over 200 studies that asked the above question (Brauer and Judd 2011). Following are a few key variations that were made in most of the experimental studies.

1. The initial similarity in opinions of the discussion group.
2. External stimulus (News)
3. Competitive situations among groups

4. Frequency of repetition of same ideas by same people
5. Frequency of repetition of same ideas by different people

A general trend in social psychology is to look into inter-personal factors for knowing more about attitude extremities.

In the following paragraphs, I will explain the two competing ideas that try to explain the emergence of group polarization. In both of these explanations, the primary assumption is that the initial state of opinion for all members of the group was similar before the group started having discussions.

First explanation as to why people tend to get polarized after group discussions are the idea of *social comparison*. In this framework, each member is considered to have a high desire to be seen in a favorable light by other members of the group. Members of a group tend to become more confident about their opinions and adopt a harder line when they realize that other members of the group agreed with them to a greater extent than they had initially thought (D. Myers 1978). To fall in favor with the group, members choose to increase the intensity of their attitude. Considering that this happens with most of the members of the group, the cumulative effect of this phenomenon results in a shift of attitude on the group level towards more extreme.

"To be virtuous … is to be different from the mean_ in the right direction and to the right degree." (Isenberg 1986)

Some other researchers have shown that group discussions are the only means to reveal the average position of the group on an issue. Once the group members know the average position of the group, they readjust their opinion to be more extreme than the average. If a researcher eliminates the group discussion at all and simply informs the member about the average opinion of the group, it will have the same polarization effect as the group discussion does (Vinokur and Burnstein 1977) (Friedkin 1999) . This shift is explained by *social comparison* whereby the knowledge of others' opinions is enough to readjust one's own opinion to the extreme.

The second explanation that is presented as the reason for political polarization is popularly known as the '*persuasive argument'.* According to this idea, an individual forms his/her opinion on an issue based on the limited information that they have. This information includes a small set of

arguments that favor the position and an even smaller set of information that does not. In a group discussion with people having similar opinions, these arguments about the issue are shared and since the group is of uniform initial opinion, every member of the discussion gets to hear more arguments that favor his/her initial position. This leads to a higher level of polarization among the group members after the discussion (Vinokur and Burnstein 1977).

Comparison of frequency of both of these phenomena suggests that both of them occur among groups with initially similar opinions. However, 'persuasive arguments' tends to occur at a higher frequency than 'social comparison' (Ziegler and Sieber 2019).

1.21 Factors that lead to political polarization

In 1972 Brickman, Harrison and Redfield showed through a series of psychological experiments that no external stimulus will be needed to strengthen the ideological convictions inside a group with similar ideological inclination, if there is simple repetitive exposure to the same idea repeatedly (Brickman, et al. 1972). This is an interesting idea as it would characterize the diffusion of political ideas as a social phenomenon independent of external events as such. If a small population has a slight political inclination towards a certain political idea, there is only a need to repeat the idea within the group to strengthen the conviction over time.

Twitter groups at ideological extremes fulfill the basic criteria of being ideologically uniform and having little exposure to opposing political ideas. It is thus natural to assume that they are likely to behave in as group describes in Brickman's study.

Sunstein's Hypothesis on Internet

Cass Sunstein extensively used the literature in the above paragraphs from social psychology in developing a hypothesis that internet 2.0 may cause an increase in levels of group polarization due to selective exposure to people from one's political camp (Cass R 1999) . His hypothesis has been extensively discussed among the scholars of internet 2.0 and Twitter is a popular venue for testing this hypothesis. The challenges in this regard have been methodological as polarization or adoption of extreme attitude is difficult to measure from Textual data. From this point onwards I will discuss these challenges and propose why levels of homophily can serve as a proxy for group polarization as well.

Literature on Measurement of Polarization on Twitter

In Twitter, there are two ways in which political alignments can be known. The first one is the automated method, which takes advantage of the information that has been already shared by the user, or his/her placement in the network of connections. The second one utilizes manual observation by annotators who go through a profile and decide about the political alignment based on the combination of multiple features seen in the profile. In most modern-day political alignment detectors, both of these methods go hand in hand and I will be following the same path in this thesis but for the sake of clarity, I will explain the techniques separately in this part.

1.22 Automated extrapolation of Political Alignments in Twitter

Extrapolation of political opinions based on Twitter data has been a topic of interest in academia for about 10 years now and it has had considerable literature dedicated to it from researchers in political sciences, artificial intelligence, and network studies. The main ambition behind this momentous task is the realization that despite having access to larger data sets from social media platforms such as Twitter and Facebook, the power of modern analytical tools will not be leveraged unless we find the right features with which political opinion and the intensity of it could be measured. As for Twitter, the following are the features that can be potentially used for predicting the political opinions of Twitter users active in the Twitter political network.

1. Textual features such as words used in Tweets posted by a user.
2. Retweet or Like frequency of Politicians in a particular group.
3. Network position where the user is embedded.
4. Self-descriptions through profile details

It was the initial interest of computer scientists in making election predictions that gave a consistent push to find an acceptable answer to this question. Most of the research in the initial days was directed towards this end and there were some positive developments in detecting the political affiliations of tweeters. Andranik Tumasjan was the first one to push the field in this direction by pointing out the possibility of using texts tweeted by Twitter users for predicting elections in Germany (Tumasjan, et al. 2010). They found that the mere number of messages mentioning a party reflects the election result'. This paper gained a lot of attention in academic circles and soon

other possible variables in Twitter were also tested for making political predictions even though some researchers contested the possibility of using Social Media to make political predictions rights after Tumasjan ‘s paper and these (Gayo-Avello 2012). Their primary concern was that by that time it was known that social media users do not accurately represent the demographic composition of voters, therefore, the correlation of Twitter mentions with election results is not strong and reliable evidence in itself that could be depended on for future research. Some researchers tried to replicate the same method to test the validity of Tumasjan’s claims and found evidence against the predictive power of Twitter (Metaxas and Mustafaraj 2011). According to critics of these initial techniques, “correctly identifying likely voters and getting an unbiased representative sample of them” (something that this thesis intends to do). Despite these criticisms, there were continued efforts to predict election results of different countries using some combination of above mentioned 4 variables. This line of research continues to this day and there are still claims coming from new researchers (especially in computer science) about the predictive power of Twitter (Grover, et al. 2019). While the judgment of the predictive power of Twitter for election results is an interesting question in itself but it brings very little advance to social sciences without any theoretical explanation for the contradiction between demographics of Twitter and actual voter demographics (Mellon and Prosser 2017). Given these differences in demographics few critics went on to say, "electoral predictions using the published research methods on Twitter data are not better than chance” (Gayo-Avello 2012). This lack of explanation and limitations of Twitter did not mean that Twitter data could not be used for studying questions of political nature.

An interesting direction that some other researchers took was not to use Twitter data to claim the election results but to study individuals on the platform and their behavior including their political affiliation. This type of research was interesting for both social scientists and marketers as it allowed testing some important questions related to individuals' and groups' behavior in these fields. As for political sciences, it reduced the cost of studying both individuals and groups, provided that the researcher acknowledged the limits of the platform. One such important question in Political science and Sociology was if Internet-based Social Media such as Twitter and Facebook cause Political Polarization to increase. One major pre-requisite for answering this question was to know the opinion of the users in social media and to be able to have it on a continuous scale rather than a binary scale which is very important for quantifying political polarization. Most of the users in Twitter do not expose their political alignment explicitly so much

of the research in this domain had to infer this information from the variables that are available on Twitter. In this part, I will explain the developments in the literature on the detection of Political alignments and will deal with the methodologies to measure political polarization in a later section of this part.

The first significant paper which worked on political opinion mining in Twitter was written by Michael Conover in 2011 which explored multiple possibilities in opinion detection. Using the power of Machine Learning they were able to leverage text and network features of manually annotated 1000 users to gain very high accuracy (91 percent) in predicting political alignments before the 2010 mid-term US elections (Conover, Ratkiewicz and Francisco 2011). They used support vector machines (SVM) classifier on text and hash-tags as it has been reported that SVMs perform very well in text-based classification tasks. While they managed to get high accuracy in detection of political opinions, applying classical machine learning methods, they reported even higher accuracy (95 percent) using retweet-network based features and application of clustering algorithms (which is a similar method used in this thesis except that I will use friendship-follow relationship instead of retweet). While this was an important study and showed the potential of text and network-related features in predicting political alignments on Twitter, but the scale of the study was very limited (1000 people) and these 1000 users were not selected through random sampling which was criticized by *Panagiotis T. Metaxas* (Metaxas and Mustafaraj 2011). These users were chosen because they had tweeted one of the hash-tags chosen by the author and these hash-tags represented either the Democratic or Republican Party in the US.

Given the success of the network-based approach in Conover's work and the discovery of high levels of homophily among Twitter connections (friendship and follow) in previous works. Zamal leveraged the Twitter network 'neighborhoods' to infer latent attributes such as political affiliation. (Al Zamal, Liu and Ruths 2012) He found out that "inferences using only the features of a user's neighbors outperformed those based on the user's features alone".

While most of the above studies were done by computer scientists, political scientists quickly realized the potential in the usage of network proximity-based data in Twitter and the need for methods to infer political ideologies for multiple research purposes. New methods were proposed by political scientists such as Pablo Barbera who used Bayesian ideal point estimation in the Twitter network to infer political alignments of a very large set of people (from a small number of

manually annotated profiles) and since these estimated political alignments were on a continuous scale, it was possible to use them to measure levels of political homophily (Barbera 2015). The key assumption behind this paper was that Twitter is highly homophilic in following relationships. In this work, each user's probability of being democrat or republican (in American case only) was corrected as they kept on following more and more politicians from one party or another. This readjustment of probability ultimately leads to a person's final probability of being either republican or democrat. In essence, it gave weight to how many of the politicians from one party or another that you follow. Barbera's work is highly sophisticated and does address that criticism raised against the non-representativeness of samples on Twitter by involving the majority of followers of famous political figures in each of the countries. However, one possible objection that can be raised on the data collection method in this study is that while the majority of followers are included but we do not know about mutual relationships among all these users. From the study, we know that they follow a certain number of politicians from a political party but to correctly quantify homophily we need to also account for the mutual relationships among the users themselves. This information can be a significant factor in the calculation of political polarization as there is a chance that people who are deemed republican through Barbera's method follow lesser-known profiles from the democratic party. These inter-relationships of the two sides have to be accounted for as they can have a significant impact on the polarization score that we get for each country's Twitter (this thesis intends to solve this problem).

Other Social scientists such as Elanor Colleoni also developed the work done by computer scientists and used machine learning-based text classifiers to determine the political orientation of Twitter users in the USA (Colleoni, Rozza and Arvidsson 2014). Although text-based classification can offer much more clarity and reliability with regards to political alignment if the researcher only includes users who explicitly expressed their political orientation and ignores the users who do not, then in measuring political polarization it will be exceedingly difficult to control for the amount of activity as we will only have active users in the population.

Another technique that was proposed by social scientists working on the question of inferring political affiliation was to get network on friends and followers on Twitter and then determine their political affiliation by plotting this graph in multi-dimensional space and finding Euclidean space between users whose political affiliation we are aware of and the user in question [53]. This

technique of finding political affiliation is not very far from machine learning-based classifiers such as support vector machine (SVM) which finds a boundary line that maximized the Euclidean distance between multiple classes by optimizing the importance of different features. While with machine learning the process of finding optimized weights for each of the features is achieved iteratively, but with the above method an extra step of dimensionality reduction is required.

Beyond finding political affiliations through text and networks, some sociological and linguistic researchers looked into linguistic behavioral tendencies in democrats and republicans on Twitter and tried to model political affiliation predictors based on sub-lexical features such as punctuation usage and capitalization and combination of retweet frequencies (Prime and Pinandito 2018). They also used machine learning classifiers such as SVM but unsurprisingly their accuracy rate (67 percent) was much lower than the state of the art predictors at the time (87 percent) but this accuracy score was higher than the mere chance which is enough to establish that there are repetitive behavioral patterns in textual content written by Twitter users and it has a correlation with political affiliation which is not strong enough in itself to be an indicator of political affiliation buy that it can be leveraged in political affiliation prediction in conjunction with network and explicit textual features.

1.23 Complications with Automated Political Alignment Classifiers

Like all healthy academic debates, the claims of authors who performed automated political affiliation detection tests did not go without criticism (apart from criticisms mentioned above about Twitter's inability to predict elections). Cohen & Ruths have pointed out some serious problems with the data-sets that have achieved the highest accuracy (Cohen and Ruths 2013). For example, "Conover's dataset falls somewhere between the Political Figures and Politically Active Datasets". When the same model that Conover had used for predicting political affiliation was applied to 'normal individuals who do not tweet as frequently about politics as politically active users do, it was found that the accuracy of the model dropped from 95 percent to 65 percent. Although Cohen and ruth give credence to this finding to assert that finding political affiliations on Twitter is not an easy task but I will use this issue to question Conover's assumptions about political homophily. In his paper Conover says,

“Many social networks exhibit homophilic properties — that is, users prefer to connect to those more like themselves — and as a consequence structural information can be leveraged to infer properties about nodes that tend to associate with one another” (Conover, Ratkiewicz and Francisco 2011).

Combining this to Cohen's findings that Conover's database was biased towards more active users and only found high accuracy for his models among active users and for politically. A possible explanation for this failure on inactive users can be that highly active political users are more polarized than less active users. As pointed out in the latter part of this section, I will show that most of the calculations of homophily on Twitter are also based on users from stream API which only gives users who are active and active Tweet about issues. Therefore, polarization calculations that are using stream API may be overestimating its levels. I will assert in this thesis that to get true levels of polarization, we will have to map an entire political context that includes both active and inactive users and then make the calculation that also accounts for people who are mere observers and not active participators.

Literature on the question of inferring political affiliations is extensive and over the years there are common lessons that can be learned from previous works.

1. Network position and textual features on Twitter are the most important feature in detecting political alignment
2. Political affiliation prediction of Twitter users is not the same task as election predictions. Demographic differences between Twitter and the population of potential voters do not allow researchers to find the results of elections in advance.
3. To correctly model a user’s political affiliation, so that It can be useful for measuring political polarization, it needs to be in continuous scale rather than binary scale.
4. Calculations about political polarization are based on most active users and passive recipients of political information are generally ignored in the analysis.

1.24 Manual Annotation of Political affiliations

Almost all machine learning tasks start with manual annotations of training data. In the case of Twitter as well, each of the automated political affiliation predictors based on machine learning used a manual annotator for training their models. There are some worth mentioning databases that have been produced over time that are manually annotated.

The largest manually annotated database of political affiliations was created on the binary scale in the French Presidential elections of 2017 by Ophelie fraisier. As the database is large enough (more than 22000 profiles) and is based on people who described themselves as belonging to a party in their official profile description, it can be a reliable indicator of political affiliation. The only downside to this database is the absence of other variables such as age, education level, and income group (Fraisier, et al. 2018).

Panel Method is another creative option that has been used for research on Twitter. Julien Boyadijan used the panel method in his doctorate thesis to gain access to unknown features of active profiles in Twitter to know about variables such as Income group, education level, age, and gender, and using that data he was able to determine the non-accidental nature of relationships in Twitter. While it is an extremely powerful method and can result in detailed information about the individual profiles being studied, but a possible issue that I might encounter with this method is that since one of the goals of the thesis is to account for inactive profiles while calculating political polarization and it is unlikely that inactive or passive users in Twitter will reply to a survey like that. Therefore, that method was not employed for this thesis and I chose to employ automated data collection and analysis.

1.25 Two different types of data and Two different results

Much as literature on other social media platforms, the literature on the links between Twitter and political polarization is not uniform both in terms of methodology and results. Before moving any further, I would like to put forth two definitions:

> **Twitter Stream API:** Stream API is a way to get live data from Twitter as it happens. A researcher can request Twitter to provide access to all Live Tweets that include a hast-tag or a Keyword. This request is usually responded to with details of texts/pictures and profile details of accounts that used that hashtag.

Twitter Rest API: Another possible way to get data from Twitter is REST API which returns all the information on Twitter that a researcher asks for. Through these requests, a researcher can ask for follow-graphs, friend-graphs, tweets of a profile, or tweets including a hashtag or a keyword (from the past)

In this part of my review of Literature, I will try to establish that using STREAM API can lead to over-estimation in the calculation of political polarization.

1.26 Literature that estimates Political Polarization:

One of the advantages of Twitter as a platform is that it allowed researchers to measure political fragmentation on party lines and ideological lines much more conveniently than surveys. It depends on the researcher to choose the data to use from Twitter as the quantity of data on Twitter is constantly going up. It is proposed here that this choice of data is what determined the outcome of many of these inquiries, and in some cases, it may have resulted in over-estimation of political polarization.

1.26.1 Literature that Uses Stream API:

One of the first studies to measure the political polarization on Twitter was conducted by *Michael D. Conover* and his colleagues. This work was presented at AAAI's ICWSM conference and was highly appreciated. Conover analyzed 250000 tweets from the 2010 U.S. congressional midterm elections and gathered the Twitter profile details of the users who were included in these conversations. The method for data gathering that they primarily used was Twitter Stream API. Their results indicated a high level of polarization among retweet networks for users who were included in the study, however, they noticed the relatively lower level of partisanship in the mentioned network (a topic I will address in this thesis) (Conover, Ratkiewicz and Francisco 2011). Conover used the cluster detection algorithm approach to find polarization levels in both retweet and mention networks (on a much smaller level than this research). As a result, he got a modularity score of 0.48 for retweet network and 0.17 for mention network. From this result, the team was able to deduce that there is a high level of homophily among the right and left-leaning users in Twitter in the USA and that politically motivated individual provoke interaction by injecting partisan content into information streams.

Another Important paper coming from the same conference (AAAI-ICWSM) used a similar method of collecting data using stream API in the German Twitter-sphere and found evidence in favor of political homophily on Twitter (Tumasjan, et al. 2010). To quantify the homophily, the method that was adopted was to use the percentage of internal connections in the party in comparison to external connections with other political parties.

Among the much-quoted studies with extensive coverage in the field was conducted by *Itai Himelboim* in 2014 using the stream API as a collection method but a much catchier title, "Birds of a feather tweet together ...". The study also gathered data of users that tweeted about important political issues in the US at that time and applied a clustering algorithm (Caluset Newman Moore algorithm) to find out major clusters and communities. The results for this study aligned with other studies done using the same methods and showed a very high level of homophily among the users who talked about chosen issues (Himelboim, Sweetser and Tinkham 2014).

Among the researchers who have repeatedly attempted to answer the question of political polarization on Twitter in recent times, Kiran Garimella is a prominent name who found evidence not just of the existence of a high level of political polarization in Twitter but also its persistent increase (Garimella and Weber 2017). He extrapolated timing of the formation of relationships on Twitter and based on that calculated the scores of political polarizations to make a longitudinal study. Despite the sophistication of his innovative method, his results can be questioned based on the fact that he did not account for the growth in the size of the website itself with time. He might be right in pointing out that Twitter communities are constantly polarizing but establishing a causal link between being on Twitter for a long period and getting polarized is hard to establish without normalizing for the growth in the number of people who joined the people in recent years.

In recent years the usage of stream API of Twitter to quantify political polarization has increased manyfold. Most of these works are focused on important issues at that time such as Kareem Darwish gathered the data on users who were talking about Brett Kavanagh's nomination in the USA on Twitter which in July 2018's major topic of discussion (Darwish 2019). He limited his analysis to users who posted or retweeted a hash-tag related to the event. Using supervised and semi-classification methods, he was able to say conclusively that the debate was highly polarized on Twitter. Although an important finding in itself it does not tell if this polarization is temporary

and based on the issue at hand, or if it is a mark of long-term effects to the usage of social media websites such as Twitter.

1.26.2 Literature that used complete Graphs:

I would like to index the literature based on complete graphs of Twitter in a separate section because it is proposed in this thesis that a complete graph of the whole network with all users included from a political context provided a more robust and thorough method to measure political polarization. The database that gained the most popularity among the researchers who wished to inquire about the state of homophily in Twitter was first produced in 2009 for inquiry into the question if Twitter acts as a news network or a social network by Kwak and his research team. Although it was a giant task to create this database, it was still possible as the number of subscriptions on Twitter were not very high and were based mostly in United Stated (single political context). When looking at the complete network it was seen there was a low level of homophily, but it was not quantified in a way that comparison could be drawn with other measurements (Kwak, et al. 2010). Kwak and his team reached the conclusion that Twitter acts more as a news network and deviates from known characteristics of human social networks (homophilic). To prove this, they used network qualities such as reciprocity, degrees of separation, and difference in the level of homophily to quantify the difference in the network structures.

On the same database as above, *Elanor Colleoni* and her team used machine learning in conjunction with network analysis techniques to show that the homophily in non-reciprocated relationships is lower than in reciprocated relationships. This can be interpreted as a piece of evidence that elite profiles (famous political figures, party heads, and media) exhibit low levels of homophily whereas homophily tends to increase as a user tends to build mutual ties (as opposed to one-sided) (Colleoni, Rozza and Arvidsson 2014). They were also able to show Twitter is more likely to act as a social network in the later period of usage. It must however be noted that Colleoni and her team only chose the nodes from the graph that had Tweeted at least once (since their opinion classifier was based on the text) .

Another parallel database that was created on all of Twitter was done by cha and fellow researchers for measuring the power of indegree as an influence metric (M. Cha, H. Haddadi and F. Benevenuto, et al. 2010). The same database was later used by the same team to measure the

levels of homophily based on mainstream media accounts in the Twitter network. It was discovered that homophily levels based on large media in the complete Twitter graph of 2010 (mostly comprising American users) were relatively low and Twitter provided a diverse environment for cross-exposure to opposite media (An, et al. 2011).

1.27 Are these results compatible?

As we can see from the above summary of literature based on complete Twitter graph and Twitter graph based on active users (stream API) tend to give different results. Stream API-based results show high-level homophily whereas the complete graph-based results show a relatively low level of homophily. There are three ways in which this split of opinion can be informative in understanding the nature of Twitter as a political platform.

First, it can be claimed that since the context of these inquiries has been different (geographically and in terms of timespan) therefore, we see different results. This is a plausible way to explain the above dichotomy and as Alexandra Urman points out that political context matters a lot when it comes to calculating the effects of platforms like Twitter on political polarization (Urman 2019). Her explorative analysis of the Twitter-sphere of 16 different democratic countries shows that ‘polarization is the highest in two-party systems with plurality electoral rules and the lowest in multi-party systems with proportional voting’. While that may be true but it does not explain why researchers who used a full graph of the US found different results on the level of polarization from those who used active users only. The second quandary in that regard is that her study is meant to be reflective of the polarization situation and only uses Twitter data as means to show that levels of polarization for different countries vary. It does not help establish whether Twitter as a platform causes this polarization or if its impact varies in multiple political contexts. To help answer this question, it is necessary to correlate the level of activity on Twitter and the length of the active period with the level of political polarization.

The second way to synthesize the literature divide is to claim that more politically active users on Twitter tend to be more homophilic than less active users. This claim can bring together the two kinds of literature because the users that researchers tend to get from STREAM-API are politically active users (which is exactly why they shared some hashtag or keyword) and the users that researchers would get from complete graph would include both active and inactive users or

semi-active users (those who follow just large media and famous politicians but do not tweet, retweet or actively involved in political activity on Twitter). With the data that includes the level of activity for multiple users, it is possible to ascertain whether active users tend to be highly polarized or not.

Third, this dichotomy in literature can also be explained with the dual nature of Twitter as news and social network as mentioned by Kwak and later by *Colleoni*. If Twitter acts as a news network at first and a social network at a later stage as claimed by Colleoni, then it would make sense that level of homophily would be high for people who use Twitter extensively as after a certain period of time, Twitter for them will start to act as a social network and their relationships will have higher reciprocity (which is one indicator of social network) and more homophily. However, for users who are not very active, the network will continue to act as a news network for a long period of time. Their relationship formation would not reach a level where Twitter can act as a social network. For them, Twitter will remain a news network with a large number of non-reciprocal relationships. For politically active profiles, the network would turn into a social network as they would form more connections as time passes and eventually end up being in a politically homogenous community. As mentioned above, Stream-API from Twitter provides data on active participants on Twitter.

1.28 Literature on crawling Twitter network:

Twitter until 2010 and 2011 was a relatively smaller platform with less than 60 million profiles and most of these profiles were based in the United States. Due to its relatively smaller size and uniform political context (American Politics), it made practical sense for researchers to crawl all of the Twitter networks to study political homophily. The last known crawls of all of Twitter network was done in 2010 by Jisun An and his team. This resulted in 54 million (active and inactive) Twitter profiles and 1.9 billion mutual relationships, which would be a gigantic task to handle for research analysis. Ever since that time, Twitter has grown enormously whereas in the first quarter of 2019 there are 330 million profiles that log in at least once a month from all over the world. In addition to the high computing costs that would incur due to the very large number of profiles a major problem with crawling all of Twitter will be that the researcher would end up with a diverse set of profiles acting in completely different political contexts and nationalities. To calculate Political Polarization is not suitable as communities are more likely to be found based on

factors other than political homophily such as geographic or cultural proximity. it is due to this reason that a new approach is needed to solve this problem.

1.29 Importance of crawling complete networks within a political context.

As noticed in the literature, the measured value of homophily can get affected by the fact if you include all the users in a political context or if you choose to include only the users that are politically most active users (from stream API). For the purpose of this thesis, I will attempt both these approaches to see if the measurement of homophily gets affected by these different approaches. As I have described above, crawling all of Twitter is no longer a viable option that will give accurate results, it is therefore proposed to use 'community search' approach using the knowledge that we have about the Twitter network and how it behaves to separate a single country's profiles and extract a community structure within a singular political context and then make the comparison between highly political and active profiles within that context vs complete graph of the Twitter users in a single country.

Although it is problem that would interest many fields as of now the only serious effort in this regard has come from computer science where it is known as a 'community search' problem as opposite the popular 'community detection' problem since it was well-defined by *Mauro Sozio, Aristides Gionis* (Sozio and Gionis 2010).

In this thesis, I will be using this state-of-the-art approach in computer science to suggest a way to separate the political contexts of a particular country from a global Twitter network and study it individually to find community structures. For demonstration, I will do so with Political Sphere in French Twitter and use that the network graph that I obtain to Judge the validity of the hypotheses presented above.

Chapter 3: Crawling political communities in Twitter and extracting political affiliations

1.30 Abstract:

In theory, a major advantage to the big data approach in studying online communities is that it should be possible to collect a representative random sample from a broadly defined population. However, in practice, data collection processes are not formalized, even for famous social media platforms such as Twitter and Facebook. As a result, there is ambiguity left on questions like 'how much data is enough?' and how representative are the samples of the broader population being studied in online social networks.

In this chapter, I propose a focused back-and-forth crawl approach and a validated seed choice method for collecting network-level data from Twitter. The proposed crawl method can extract community structures without needing a complete network graph for the Twitter network and validate its size using 'reference score' (Blenn, et al. 2012). It also takes care of the sampling size problem in Twitter by tracking the percentage of known nodes that have been included in the data. Thus, solving most major problems in Twitter data collection procedures and moving a step further to formalizing data collection methods for the platform.

Once the communities are crawled, and the network graph is clean and complete; it is then possible to train Machine Learning classifiers using communities as features to predict the political affiliations of users on a larger scale. As a case, I used the proposed method for separating French political communities on Twitter from the global Twitter community and knowing the political affiliations of users on a continuous scale.

1.31 Introduction

While attempts to link social and semantic aspect of epistemic communities has been an active area of research since the early days of internet 2.0 (Roth et Bourgine, Epistemic communities: description and hierarchic categorization 2005) , As the popularity of Twitter is growing, it is becoming increasingly hard for social scientists to gather profile samples that represent the target

population in a study. The standard method of gathering samples3 for research on questions such as ‘Is Twitter Polarizing its user?’, includes arbitrary cut-off points which make the data collection process more convenient but less representative (Blenn, et al. 2012). As there are more and more researchers using Twitter for studying questions in social sciences, there is a need to formalize the data gathering process while keeping in mind that Twitter’s network data comes in graph format which has its additional traversal and sampling complications that need to be addressed (Wang, et al. 2011).

One of the major problems of using the network topology of social networks for answering sociological questions is that sampling methods for large network graphs is still an open question (Krishnamurthy, et al. 2007) and any sort of missing data can have a serious effect on results (Smith, Moody et Morgan 2017) (Zhang et Patone 2017) (Zhang, et al. 2015). The Network-graph sampling problem is different from traditional sampling problems where snow-ball sampling (or other forms of convenient sampling) is used. Where snow-ball sampling can help know characteristics of nodes, it tells nothing about the characteristics of the overall network such as degree distribution (Ribeiro et Towsley 2012), betweenness centrality distribution, average path length, assortativity, and clustering coefficient (Wu, et al. s.d.) and modularity, which are important measures for investigations on questions on network homophily and polarization. For such questions, it is important to devise sampling methods that reflect the characteristics of the network (Lee, Kim et Jeong 2006).

The minimum sample size of a network that could preserve its topological properties is also an important and relevant debate when it comes to studying a large social network. To the best of my knowledge, even the smallest proposed sample size that accurately represents the characteristics of the full graph constitutes at least 15 percent of the original population size (Leskovec et Faloutsos 2006). Jure Leskovec’s method does well for finding the sample of a known graph but in most real-world scenarios larger network graphs are unavailable and their sizes are unknown. For example, if a researcher is trying to answer a sociological question using Twitter’s network data from a particular country, it Is difficult to know if the sample of profiles he/she is using

3 By ‘Standard method’, I mean methods that use stream-api to collect live tweets and process them to get users.

represents the rest of the community since Twitter does not tell us how many profiles of a particular community there are in total. Most studies in political science and sociology that use data from social media, tend to ignore this problem and use an 'arbitrary' number of profiles who tweeted a particular hashtag to reach conclusions on questions such as the extent of political polarization and homophily (for which graph modularity is an important measure). While such inquiries can help establish the extent of polarization on an issue (being discussed through hashtag), long-term network-based polarization which is known to be caused by higher levels of homophily requires that we investigate network graphs and relationships as well (Cass R 1999). Thus, the graph sampling problem requires more attention and inquiries from social scientists.

In this chapter, I argue that the graph-sampling problem becomes more complicated when the population Graph is unknown (which is usually the case in Twitter investigations). I then suggest a comprehensive method for seed selection and community crawl that ensures that at least 50 percent (in the worst-case scenario) of the target community is included in the study which is enough to act as a target population. Only then, it becomes possible to collect a representative sample of the target population and study the community structure and try to answer sociological questions that require network topology. I go further by extracting information about features such as political affiliations from the crawled network graph and show that a high level of accuracy can be reached with machine learning models when predicting political affiliation using relationships in Twitter.

Most of the work concerned with political polarization in Twitter has been using data from stream API which only provides information on nodes that are active on a particular political issue (represented by a hashtag). While this type of study can accurately estimate issue-based polarization, but they fail to capture the long-term picture of the Twitter network. Due to the close relationship between political homophily and polarization, it is possible to treat polarization as a latent variable dependent on levels of homophily which have been studied using 'graph modularity' in Twitter. Although It is not unprecedented to study political polarization and homophily in this manner but in recent years, it has become less common to use modularity as an indicator of homophily Twitter as it has grown into a highly diverse network in many countries and contains a lot of different type of communities that range from science, fashion, sports, and politics. With such diversity in location and interests among users, modularity does not make sense

as an indicator of homophily as people can be in the same community due to shared interests or location. To use the modularity score as an indicator of pollical homophily, it is important to separate a political network belonging to a single political context from the global network. It is thus high time to formalize crawling mechanisms in Twitter so that it is possible to validate the representativeness of the data collected through crawls. Since the crawls are highly targeted, we will only get users from a single political context, it will be meaningful to use modularity score as an indicator of political homophily. In the case of this chapter, it is assumed that French National politics falls in a single political context, and methods used for studying homophily in French network can be replicated for other national political contexts in Twitter

1.32 Review of Graph Traversal Methods:

1.32.1 Breadth-First Crawl:

Breadth-First is the most widely used crawl mechanism in network graphs. BFS starts with a list of seed nodes and crawls all the neighbors of each node included in the list while creating a new list of found nodes. Once all the neighbors of each seed node have been explored, it moves to the newly found nodes and repeats the same process. The time complexity of BFS is O(|V|+|E|). The selection of seeds is of paramount importance in BFS if crawling a subgraph is an objective (which is the case in this research).

1.32.2 Depth-First Crawl:

“Depth-First algorithm starts at the root node (selecting some arbitrary node as the root node in the case of a graph) and explores as far as possible along each branch before backtracking.”. For problems like crawling of Twitter, DF is highly impractical as many nodes are connected to people outside of the target community and it will be very easy to lead the crawler out of the target nodes.

1.32.3 Random-Walk:

Random walks are by far the most widely used method for both traversing and sampling network graphs. It starts with a randomly selected node and ‘selects the next node at random from the neighbors’. While Random walks can represent the graph properties very well but they can not be used on Twitter for inquiries on questions of homophily unless one has access to the target population. Since questions about homophily are usually focused on a political context (like French Politics or American Politics) and the size of the community that Is part of that context is unknown in Twitter, it will be impossible to know when to stop the crawl and what percentage of

target community has been crawled (I will solve this problem using a variation of BFS in this Chapter)

1.33 Review on Graph Sampling:

Over the last few years, there have been developments in graph sampling problems in general but not a lot of attention has been given specifically to Twitter's network sampling issues (Ahmad, et al. 2010). Here are a few sampling methods generally used for sampling large graphs.

1.33.1 Random Node Sampling:

Random Node Sampling is a highly used technique that works well to represent topological properties of a network graph only if, the larger graph is known, and samples are at least 15 percent of the complete network (Leskovec et Faloutsos 2006). Due to its large size and unavailability of complete data, the Twitter network graph can not be represented using Random-Node Sampling.

1.33.2 Random Degree Node Sampling:

Random Degree node sampling is a variant of random node selection but only adjusts the probability of being selected in the sample using degrees of nodes.

1.33.3 Random-Edge Sampling:

Random-Edge sampling is another technique used for sampling relationships. It randomly selects the edges in a graph and represents them as a sample. Its ability to represent properties of the network has been tested in different studies and this method has proved ineffective as a sampling method for questions where network properties are needed (Wu, et al. s.d.).

1.34 Problem description

In a well-connected global social network like Twitter, it is now more likely than ever for a national politician to be globally popular. This global Twitter network can be formally interpreted as a graph with nodes acting as users and edges acting as relationships. We can call this graph, $G(V, E)$, where V is a set of vertices (profiles of individuals) and E is a set of V's edges (follow the relationship between individuals). Within this graph, we know that there exist several sub-graphs where nodes are highly connected but less connected to other sub-graphs. Since our goal is to

measure group polarization in the French context, we are looking to capture only one sub-graph (French Political Community) and separate it from other sub-graphs in the global network so that we can measure political polarization within it. This French graph is entrenched in the global network and overlaps many other sub-graphs of the global network for example many French users tend to follow American, British and German politicians and celebrities with millions of followers. If we do not separate the French subgraph, then our automated crawler will end up crawling millions of International users who will have very little interest in French politics and will act as noise in the measurement of group polarization phenomena.

For clarity, we will call the French political subgraph f(v,e). To get a rough idea of the audience I will use statistics published for marketing purposes by multiple advertisers[3]. According to these numbers, the number of profiles V in G(V, E) stands at about 330 million whereas the number of 'v' in f(v,e) stands around 2.5 million. Our objective here is to come up with a crawling strategy that only crawls f(v,e) users.

1.35 Selecting Seed Profiles:

The goal of the crawl is especially important when It comes to choosing the best seed profiles, as they determine the starting point of the crawl. In our case, it is equally important to know the distribution of kinds of users in the community structure that we end up detecting. I will be looking at the following qualities in the seed profiles.

1. Their political affiliation must be known.
2. Seed profiles should be diverse enough to cover the political spectrum.
3. Political affiliation in profiles should be evenly distributed (There should be the same number of profiles for each of the parties or political groups)

For France, I will be using Twitter data from the French Presidential elections of 2017 and will be using data of supporters of the top 5 presidential candidates this election to create a seed profile dataset.

1. Emmanuel Macron
2. Marine Le Pen

3. Jean Luc Melenchon
4. Francois Fillon
5. Benoit Hammon

During the first round of presidential elections, these candidates managed to gain over 91 percent of the total voter turn-out which testifies to the fact that taking data of their supporters is likely to cover a large majority of French Political context in Twitter. In addition to that diversity of opinions of these candidates (Extreme Left to Extreme Right) also provides enough reason to believe that taking data of their supporters will serve as a good starting point to crawl.

A popular strategy for seed selection in Twitter research is to manually compile a list of profiles that are most popular in multiple communities. While such a strategy can be effective, but it is difficult to test its validity. As mentioned above, in BFS based crawling algorithms seed selection is of paramount importance. Keeping in mind that the goal of the crawl is to maximize the number of profiles from the French Political context in Twitter, it is important to formalize the problem and come up with rules that can help with seed selection for Twitter in future research. In the case of seed selection following questions are the most important ones to address.

1. How big should the seed database be?
2. What type of profiles should be included in the seed database?

To answer the above questions, I started by gaining the last 3200 Tweets of the party leaders mentioned above (as this is the maximum number of tweets allowed through Twitter API). These Tweets were then used to create a database of high-frequency retweeters (who are most likely to be supporters of the leaders). These retweeters can be a key to creating an effective database of seed profiles.

The first step towards the process of seed selection was that I collected all the accounts followed by high-frequency retweeters (‘Friends’ in Twitter’s official language). Rate-limit in Twitter made it exceedingly difficult to collect this data but parallel crawling using multiple API increase the speed of this process to some extent. This data can be expressed in form of sets.

Set U represents the accounts in a manually annotated database.

$$U = \{u_1, u_2, u_3 \cdots u_{22853}\}$$

Set $U_{friends}$ contains five different sets where sub-text indicate the party to which the set belongs. F_{fn} which is one of the members of $U_{friends}$, contains sets of 'friends' of accounts from U who support *Front National*

$$U_{friends} = \{F_{fn}, F_{ps}, F_{em}, F_{fi}, F_{lr}\}$$

Expressing the database in the above two formats, I am now in a better position to formalize the seed selection problem. Since the goal of the crawl is to separate the profiles that are included in the French Political context from the global Twitter graph, seed profiles should be the most popular exclusive profiles within the target community. This problem can be mathematically expressed as:

From $\cup F_{fn}$ *select the minimum number of elements to form a set* S_{fn} *(seed profiles for FN) such that set* S_{fn} *meets the following conditions:*

$\boldsymbol{Condition 1}$: $|S_{fn} \cap (\cup F_{fn})|$ *is maximized*

$\boldsymbol{Condition\ 2}$: $|S_{fn} \cap \left(\cup\left(U_{friends} - \cup F_{fn}\right)\right)|$ *is minimized*

This is a multi-objective optimization problem with no exact solution, and I will now try to assess its difficulty and propose the best course of action for our case. The first condition of the above problem (as stated) is a classical problem in combinatorics, 'set hitting problem', and has been categorized as an NP-complete problem which makes it computationally expensive to come up with the best possible solution (Fijany et Vatan 2004). The approximation is the usual course in set-hitting problems if we are dealing with large datasets.

The second condition was added after testing the first one as the resulting profiles were out of contexts such as those of famous footballers, Actors, and American celebrities. By minimizing $|S \cap \left(\cup\left(U_{friends} - \cup F_{fn}\right)\right)|$ it is ensured that we will only get profiles that are exclusively popular in one political party. At the seed stage, it will suffice to get exclusive profiles. Choosing universally popular profiles is not an optimum approach as they are bound to be part of the graph in the third step of this crawl and including them at this stage will only diverge the crawl outside of the target population (French political context).

I approached this problem by solving it in two steps to find a final approximate solution. In the first step, I will use the following greedy algorithm to fulfill the first condition. Once I have enough profiles to cover data that meets the first condition, I will then take profiles from that set which will also meet the second criteria.

Fig 1: This is the plot of the most popular accounts in France Insoumis according to the manually annotated database.

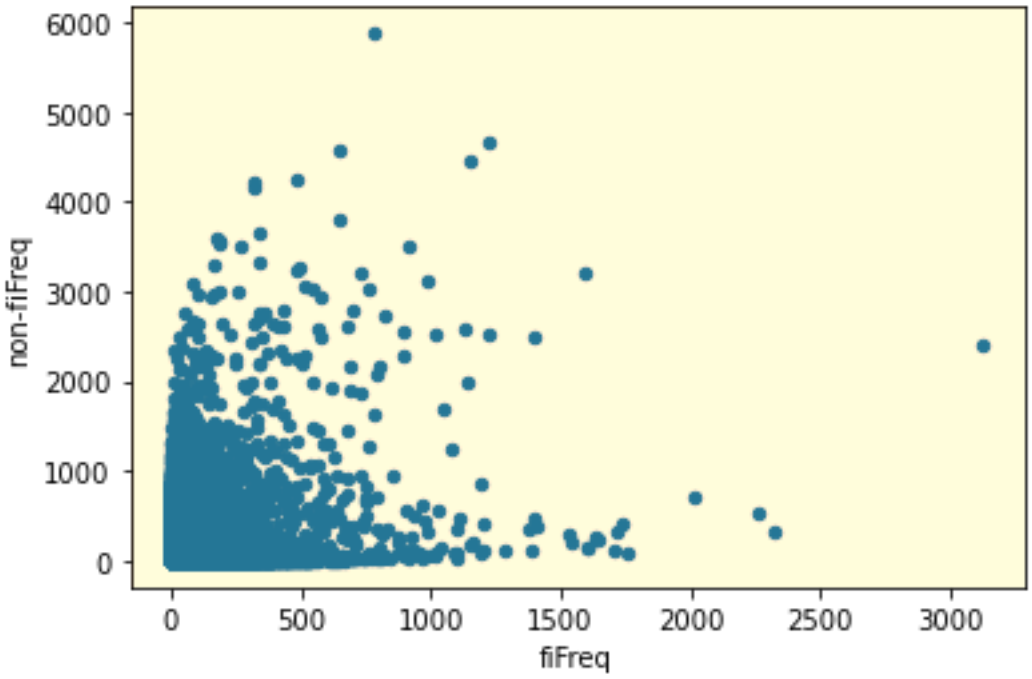


Figure 1: This is the plot of the most popular accounts in France Insoumis according to the manually annotated database.

On the x-axis, we have their frequency of being followed by France Insoumis and on the y-axis by other parties combined. The best seed profiles for France Insoumis lie in the bottom right corner.

It was observed that just to get all over 5000 *France Insoumis* profiles from the manually annotated database, I will need at least 502 seed profiles. By that observation, it was inferred that if cost and time of crawling were not a factor, over 2500 seed profiles, would be needed to get a comprehensive database of French profiles on Twitter for all major political parties. To reduce the time of crawl, a compromise was reached using the observation that 84.5 percent of the profiles in

the manually annotated database that support FI could be covered using under 30 seed profiles. Similar compromises were made for all parties and it was ensured that seed profiles are selected that would cover at least over 80 percent of the manually annotated database. Using the above method, a final dataset of 122 seed profiles was compiled.

To make sure that seed profiles are exclusively popular in only one of the political parties, profiles that returned a value of less than 0.8 for the ratio $\frac{\#\ of\ Followers\ from\ one\ party}{\#\ Total\ Followers\ in\ Database}$ were taken out of the seed database.

1.36 Resulting Seed Profiles

Table 1: Seed profiles for each political party in France

Party	**Number of Seed Profiles**	**Percentage of manual database profiles covered4**	**Types of Seed Profiles found**
France Insoumise	**25**	**85.16**	Second tier party leadership, Allies in 2017, party activists, Official and unofficial party accounts
En Marche	**33**	**86.6**	Second tier party leadership, Former *Parti Socialiste* and EM activists
Front National	16	84.5 %	Second-tier party leadership, party accounts, Anonymous Accounts, party activists
Parti Socialiste	**55**	**68.4 %**	Former and current party leader, Official and unofficial party accounts

4 Represents the percentage of profiles from manually annotated database that have been labelled as supporters of the same party

Les Republicains	26	91.226 %	Party Leadership, Official and unofficial party accounts

Table 1 Seed profiles for each political party in France

1.37 Crawl Algorithm

Knowing the trade-offs from each of the directions, I propose the following back and forth scheme between elites and ordinary users for crawling a complete political context in Twitter

1. Start with a database of known profiles with known political affiliation
2. Select the best seed profiles that fit best with known data
3. Towards Ordinary + shortlist
4. Towards Elite + shortlist
5. Move to step 3, unless the average Reference score is close to 50 percent (Justify).

1.37.1 Advantages of the above crawling:

The main advantage of the above crawling mechanism is that it will move from a targeted community (People embedded in French Political Context) and crawl that community first before moving to the next one (at which point I stopped the algorithm). In this case, once we have enough French profiles to get a reference score of over 0.5 it will be possible to stop the crawl and process the network graph.

1.37.2 Limitations of above crawling

Although the above-proposed crawling mechanism will be effective in terms of its ability to crawl through political context and profiles involved in the political discussion but the downside of this method is the run-time it might take to finish the crawl. Twitter API does not allow crawling without the application of a rate limit which can prove to be a serious bottleneck for the time required for such crawls to finish. To overcome this limitation, parallel crawling on a limited scale was applied which solved the problem to some extent but it remains a significant issue that can limit future studies.

Another limitation of the crawling mechanism proposed above is that many profiles are highly embedded in many different political contexts (such as both France and Algeria) but here we will work under the assumption that once the crawl is complete and we can run a community detection

algorithm on the detected profiles, we will be able to find the profiles that are from a completely different political context as they will be clustered together and manual analysis will eliminate that possibility.

1.37.3 Reference Score

To the best of my knowledge, the first paper that has tried to crawl communities in social media without using the complete graph came from *Blenn, Doerr, Kester, and Piet Van Mieghem*[5] in their seminal work published in 2012 which allowed for faster crawling of communities without knowing the full graph. They called their method "*Mutual Friend Crawling"* which was based on a strategy of crawling nodes that the highest "reference score" which they defined as following:

$$S_R = \frac{Found\ Referances\ of\ Each\ Node}{Degree\ of\ Each\ Node}$$

The major benefit of crawling with the *Mutual Friend crawling* method was that it allowed to crawl densely connected communities first and then move to the next community that would be most connected to the first community. MFC approaches the question by crawling from a community towards the broader graph but fails to explain when to stop the crawl and does not clarify the different results that one might (or may not) obtain by choosing a different starting point for the crawl. In this chapter, I will address this question and try to define a well-targeted community to crawl in a social network and suggest how Mutual friend crawling can be customized to crawl a political community on Twitter. I will also analyze the role seeds can play in crawling with the community first approach.

1.38 Setting a Target Reference Score:

To make sure that the crawler has been successful in getting a large portion of the targeted graph, it is important to set a goal reference score. This goal reference score can be known from the profiles that we know already (I.e: manually annotated profiles). Setting a concrete value for reference score requires that we manually look into the friends of a sample of these profiles and for each profile, we find out the ratio of his/her friends who belong to the political context we are targeting to the total number of Friends that they have. Once we know the target score of all the

profiles in a sample, we can take an average of this score and set it as our crawl's target reference score. (50 percent)

1.39 Crawl Direction for efficient implementation of MFC

When crawling a social network like Twitter from any set of profiles A, there will always be two directions a crawler can take.

1. Towards Followers (Profiles who follow A)
2. Towards Friends (Profiles which A follows)

Each of these directions has unique features, which must be accounted for before devising the direction in which a crawler should move.

1.39.1 Towards Followers (Ordinary)

Starting with a set of Twitter profiles A, crawling towards the followers will provide the following:

a. Edges (connections) between profiles included in A.

b. The larger set of profiles which are likely to be more 'ordinary' than profiles in set A5

1.39.2 Towards Friends (Elite)

Starting with a set of Twitter profiles A, crawling towards Friends will provide the following:

a. Edges (connections) between profiles included in A.

b. A larger set of profiles which are likely to be less 'ordinary' than profiles in set A

1.40 Shortlisting Thresholds

After each crawl, there will be a need to clean the results as each crawl from ordinary users towards their friends will give global celebrities (which are not specific to French context) such as Barack

5 Twitter is a highly stratified network which act like a news media and reciprocity of connections is rare compared to social networks like Facebook (*https://dl.acm.org/doi/abs/10.1145/1772690.1772751*) .

Obama who has to this date 126 million followers. If the result of this crawl are not cleaned and profiles such as Barack Obama are kept in the index then the next crawl (which will be finding followers of this index) will become extremely costly and ineffective as it will spend most of its time in populating the network of these large profiles (which are very important globally but not specific to French context). To keep the crawl manageable a small trade-off is needed here in favor of efficacy as opposite to accuracy. To materialize this trade-off a metric is suggested called **Shortlisting Threshold.** To make it inside the index, a Friend profile has to meet the following criterion:

1) Be followed by at least (seed ordinary /number of targeted politicians)

When crawling from the elite profiles to the ordinary profiles, the same problem can occur as there will be many foreign profiles that follow French celebrity politicians or large media and for these profiles to not be part of the index following **Shortlisting Threshold** will be applied:

2) Be a follower of at least (seed elite/number of targeted politicians)

1.41 Judging the distribution of cluster among political parties

Once the context has been crawled, the next step will be to estimate the political affiliation of the large number of users from the seed profiles whose political affiliations are already known. To perform this step, it is important to know that Twitter is known to have highly homophilic connections between users which can be used for determining political affiliations of users on a large scale using an affiliation of a smaller number of known users.

Using the network graph gained from the step above, I will run a modularity-based community detection algorithm to find out the community structure. For a graph of this size, using Louvain's algorithm was the most feasible step forward considering that it has a linear run-time (time complexity) and maximizes the modularity. This algorithm was run 50 times to ensure the consistency of the results and the resulting average modularity score of was found to be 0.40 with 12 communities.

Once the community structure has been determined, the distribution of political affiliations in each cluster was initially estimated using the location of each of the seed profiles that were self-declared

and manually annotated. To cross-validate the predicted community structure, and to eliminate irrelevant clusters, random samples were extracted from each of the clusters and studied manually.

In addition to the cluster's distribution of political affiliations, the embeddedness score of each individual in the network of a particular kind of politician was calculated using the following function.

E (Support candidate 1) = (Reference score) * (1/avg path-length to known support candidate 1)

"Embeddedness" in the network of a political party or a political personality is not a guarantee that the individual is supporting that candidate, but it can serve as a measurement tool on a continuous scale to judge the level of political homophily in a network.

1.42 Crawl Results

Using candidates of the 2017 presidential elections, three crawls proved to be sufficient to achieve a reference score close to 0.5. The first crawl was from seed profiles towards the elite and resulted in more than 3 million elite profiles but managed to achieve a poor reference score of 0.03 which is understandable considering that I had only explored one side of a bidirectional graph.

The second crawl from the selected features towards their followers fared much better in terms of reference score (0.17) which can be explained by the fact that most of the elite profiles do not have as many 'friends' as 'followers' in Twitter.

The third crawl was from ordinary profiles discovered in the second crawl towards the people who they follow. During this crawl, the numbers of input nodes were significantly larger than the previous two crawls, and in total, 1.7 million calls were made using parallel crawling techniques which resulted in million profiles. To reduce the graph to a manageable level only the edges within the input graphs were kept and others were discarded. I also added profiles of elites discovered in the third crawl if they had a significant following within the seed profiles (being followed by at least 10 people). This resulted in a complete network graph of 2.2 million profiles with 35 million edges.

Fig 2: Reference scores of all three crawls.

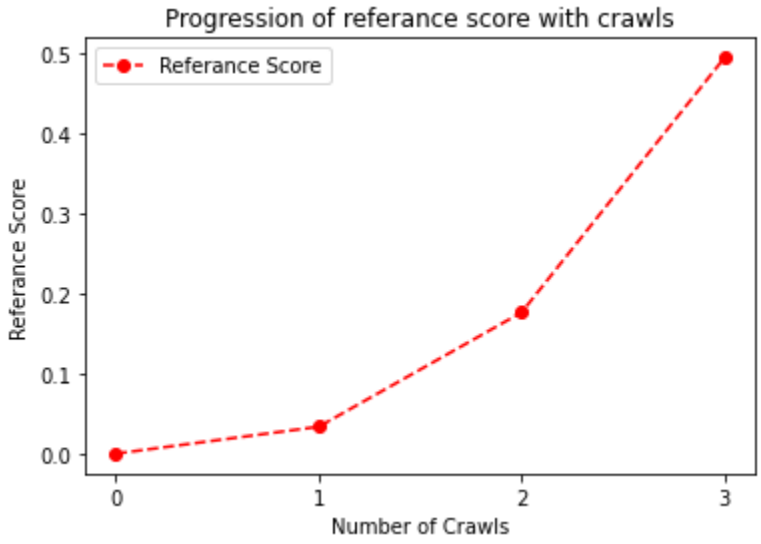


Figure 2 : Reference scores of all three crawls.

Fig 3: Number of nodes found in each crawl

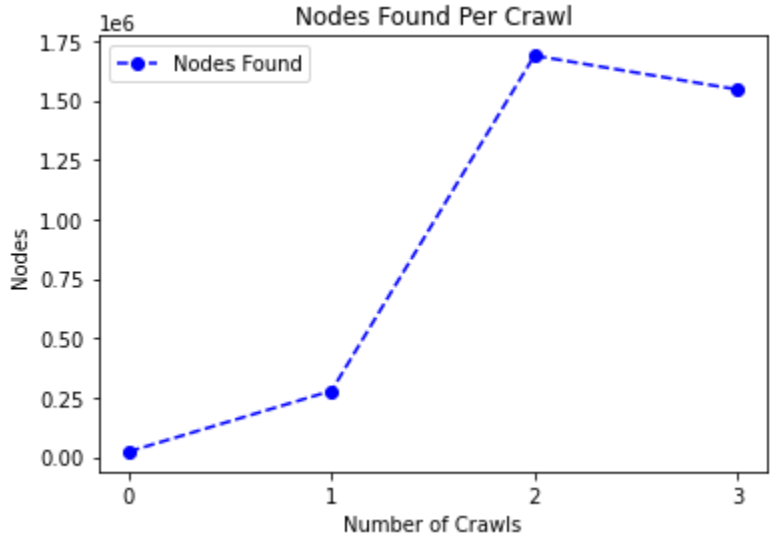


Figure 3: Number of nodes found in each crawl

1.43 Cluster Distribution Results:

Once the crawls were complete and I had access to a decent proportion of the graph which is highly likely to retain the qualities of the complete graph (which can be double in size in a worst-case scenario as we are sure to have 50 percent of the data), it was ready to study for running a modularity-based clustering algorithm. Louvain's algorithm was chosen for the task due to its run-time in large network graphs. Running it on the complete graphs returned 12 communities which were studied in both manual and automated manner.

1.44 Manual Analysis of the communities:

Small samples were taken from each of the communities and found profiles were then studied individually for characteristics that clarified if they could be members of the community or not?.

For finding out the distributions of political affiliations in different clusters, I looped through each of the clustered and looked for the location of 22000 profiles whose political affiliations are known through manual annotations done in previous literature (Fraisier, et al. 2018).

Table2: Number of manually annotated profiles discovered in all clusters

Community Number	**PS**	**LR**	**FI**	**EM**	**FN**
Community 0	17	64	63	155	12
Community 1	20	10	45	25	1
Community 2	808	1200	130	2182	19
Community 3	44	33	124	85	18
Community 4	15	1943	83	79	1600
Community 5	9	26	26	50	17

Community 6	130	32	2023	108	26

Table 2 : Number of manually annotated profiles discovered in all clusters

1.45 Discussion:

It has been found through repeated crawls and validation by 'reference score' of nodes Twitter network that at least 3 crawls are needed to make sure that found graph will represent the network qualities of the broader graph. if seed profiles are manually annotated and large enough, it will be possible to infer political affiliations of broader networks based on the known patterns of homophily in the Twitter network.

Although Twitter API provides data for free since the primary method of the crawl is breadth-first approach, therefore, each new crawl requires exponentially more time than the previous one. To perform a large crawling exercise in Twitter, it is useful to have parallel crawlers going through nodes at the same time.

Knowing the community structure in large social networks can be useful for quantifying political polarization but one needs to make sure that there is a systematic way to factor in the margin of error that can arise from the missing nodes6. Data gained from conversations on Twitter can indeed provide ample proof that the communities are polarized based on the issue being discussed but the bigger question that we need to answer is that if this polarization leads to network-level homophily in Twitter. This can only be done through large-scale studies of the evolution of a political network.

1.46 Conclusion:

In this Chapter, I have proposed a new data gathering method on Twitter keeping in mind the complications of gathering graph data, and used the example of French Political community structure to demonstrate the validity of the proposed method. Speed bottle-neck in the proposed method exists in so far Twitter restricts the amount of data that could be gathered in a specific time window but using parallel crawling this speed can be increased considerably. The main advantage of this crawling method is that it can detect community structure in a country. Such a structure

6 (Smith, Moody et Morgan 2017)

allows us to make apples-to-apples comparisons between communities as they all come from a singular political context.

Chapter 4: Network Structure in French Twitter

1.47 Abstract:

While there is an enormous amount of literature that focuses on understanding the network structure in Twitter, but most of this work does not connect the 'network structure' (follow-network structure) with the 'conversational structure' of Twitter debates. It is thus still unclear, what it means to 'follow' a group of profiles on Twitter and what could be possible consequences of that on political discourse. This chapter is an attempt to fill this gap and to study the effects of being in the 'follow-cluster' on the frequency of conversations, topics of conversation, target profiles of conversation, and the sentiments of conversations that go on between the clusters and within the clusters. I will start by identifying the self-descriptions of clusters found in the last chapter and to get an overall picture of the qualities of the cluster, I will be using word-cloud strategies.

As the body of political science literature based on Twitter data is increasing, it is clear that there are two main information sources used for modeling the behavior of Twitter profiles. A large set of articles in political science focus on the conversational aspect of Twitter and reach conclusions based on observations about the profiles that make active contributions to the debate, whereas there is also a rising body of literature that uses the network structure as the basis for hypothesis testing. It is high time to connect the two approaches by studying the associations between the network structure and variables concerning discourse.

This chapter has two-fold aims. The first goal is to solidify our understanding of the network structure in the context of French Twitter and to know in detail about the identity and hierarchy of these clusters. Once we have a satisfactory understanding of the identities of these clusters, I will proceed with an attempt to decipher the meaning of being in the cluster by answering the following questions.

1. What is the strength of association between the *follow* clusters and identities of the profiles in it?

2. Does being in a Twitter cluster affect the frequency or sentiments of conversation between individuals and between the clusters?

1.48 'Follow clusters' and identities of the profiles:

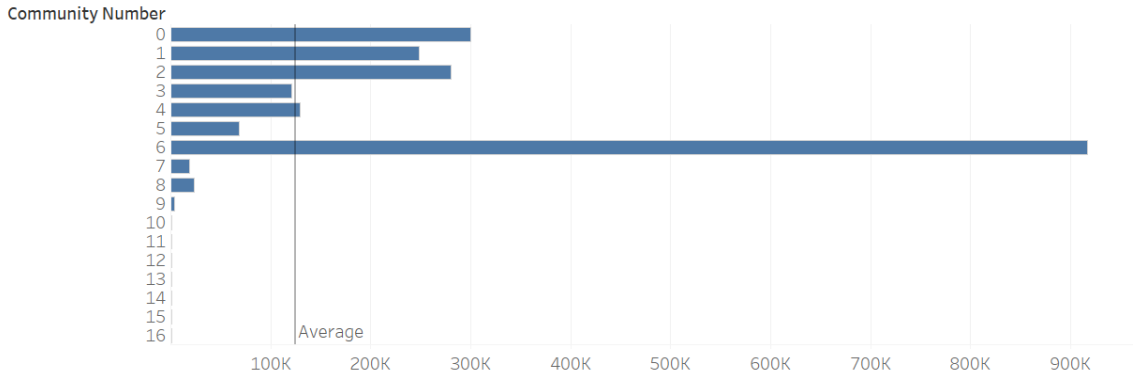
As mentioned before, this thesis aims to extract information based on the evolution of network structure on Twitter. It is thus imperative to think of what other variables are associated with network structure on Twitter for which network structure can be considered a latent variable. Thus, if there is a satisfactory association between the network structure and identity of the profiles or conversational structure then changes and network structure over time can be interpreted as changes in the 'cumulative identity' of the group and possibly like conversation within these clusters.

From here on the chapter is organized in the following manner. In the first part, I will explore the identity of multiple clusters in the French Twitter network on two levels. First, I will study the identities of the important profiles in each of the clusters, using manual analysis and explaining the distribution of political affiliations and within the manual analysis, I will try to judge the profession and status of these profiles. Secondly, I will try to synthesize the self-descriptions of the profiles in these clusters by running correspondence analysis on the word-frequency data of the self-descriptions to try to understand the terms in which these profiles describe themselves. In the second part of this chapter, I will explore the meaning of the term, 'network cluster' in terms of its effects on the conversation structure. Thus, trying to answer if being in a cluster means that you are more likely to have conversations with positive or neutral sentiments compared to cross-cluster conversations. The goal of this inquiry is to establish that Twitter clusters are mostly based on 'topic-based interests' rather than ideological inclinations or party affiliations. This understanding of Twitter allows us to see political polarization (the focus of this thesis) from a different perspective. For the most part, political polarization on Twitter has been understood in terms of surface-level contact which is top-down in nature, where influencers play a major role in forming people's opinions.

1.49 General Properties of French Twitter Network:

The first observation from the data collected in the previous chapter is that not all communities have a similar size.

Fig 3a: Number of nodes in a community



As seen from the above graphs there are only 7 large communities from the network that. Since the other detected communities are of very small size compared to these communities, from this point onwards in this thesis, only these communities will be considered for further studies.

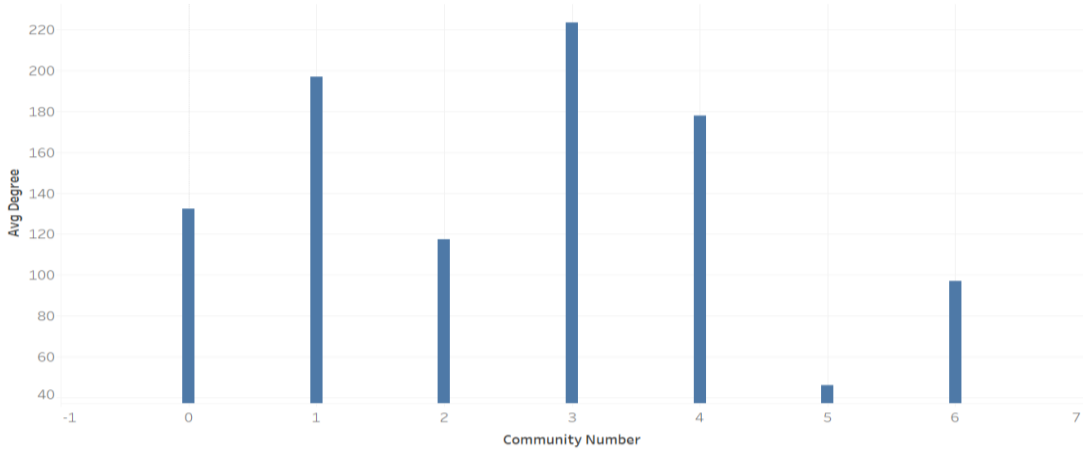
1.50 Degree distributions within communities:

The average degree in a network graph represents the average number of nodes that are connected with each node. In other words, it is an indicator of the density of connections within a community. However average degree in community-based network graph does not tell about cross-connections between the communities. For that information, I will do further inquiries in the next sections of this chapter.

From the above graph Community Number 3 is the most highly connected community in the network followed by community 1 and 4. As we will see in the latter part of this chapter all these communities are political, whereas other communities are non-political. This can be taken as an indicator that political communities are much more densely connected in the French Political context than non-political communities. However, without knowing how these communities

connect, it is not clear if it is the general interest in politics that makes these people connect or is it an indicator of ideology-based partisanship.

Fig 3b: Average Degree of each community



1.51 Why are elite Media and Famous Politicians have shown as a separate cluster?

One of the features of the data collection methods that I proposed in the last chapter is that exceptionally large profiles such as internationally famous politicians and International Media tend to fall in the same community despite having different support bases and viewership. In our case, the elite profiles have clustered together in community number 6 because they get followed by a large number of international users who do not follow anyone in the rest of the network. Since international users are more likely to follow only this group of people based on their size, due to which these profiles are shown to cluster together. For my analysis, this formation has an added advantage as it clarifies which of the clusters (left, right, or center) tend to gravitate towards elites when it comes to conversation and creating connections.

1.52 Political Properties of French Twitter Network:

1. **Communities are not created based on political parties but rather on Interests.**

The presence of political parties across all the communities shows that communities are not primarily created based on political parties, but rather on a combination of multiple social factors. The primary visible factor on which these groups are created is a combination of interests and the

view of oneself. While the Right-wing community sees itself as ‘patriotic’ and ‘nationalist’ and includes a large chunk of center-right party activists *Les Republicain* as well.

From Paul Lazarsfeld’s work, we know that opinion leaders can have a major impact on people’s voting behavior. While Lazarsfeld defined the term ‘opinion leader’ in a very local sense in his Erie county study, its implications in the world connected by the internet beg the question if the political elite on the national scale can play the same role as opinion leaders did in Lazarsfeld's study.

Early research in Twitter has shown that the Twitter network is highly centralized and favors the traditional elites in establishing and maintaining constant contact with their ‘followers’ (Kwak, et al. 2010). It is therefore not surprising that we see the emergence of clusters around elites of similar type. Manual analysis of top elites in each cluster will be the easiest way to recognize the clusters and provide them identity and also to find the interests of people who are a part of these clusters.

1.53 Elite Identification:

As described in the network topology sections, almost all the clustered discovered through network analysis are highly hierarchical in terms of the distribution of connections. There is a small percentage of users who attract the majority of the connections within the clusters. Such a structure allowed me to ask the question, ‘who leads each cluster?’. The answer to this question will reveal important details about these clusters that can be useful in the latter part of this thesis. To perform this task, I separated the top 100 most popular profiles from each cluster and hand-coded general qualities of these individuals (or organizations), and investigated the following criteria to know them better.

1. Vocation (What makes them popular)
2. Political Affiliation (If any)

For the sake of simplification in analysis at this stage, I will use the general left-center-right spectrum to categorize the leaders of these clusters (and not the political parties) as some of the leaders have switched political parties many times and these switches will complicate the analysis if party names are considered to be the unit of analysis. Although the general left-right spectrum is not universally understood in the same way as economic left can sometimes be different from value-left in many countries. As shown in the last chapter, the crawl of Twitter communities using

major political parties as a seed will also gather information on smaller political parties as they tend to be a part of a greater political network where taking only large party candidates would be sufficient to crawl network of smaller parties. While manually inspecting the leaders in these clusters, I will also categorize the leaders of smaller parties that are popular in one cluster or the other. For categorization according to the traditional political axis, I will rely on the political-axis opinions regarding these parties as revealed by voters from the 2012 presidential elections (For those who participated in that election) (Lebon, et al. 2017). For some of the political parties that did not contest the election of 2012 and did participate in the 2017 presidential election, such as Emanuel Macron's EM I used the self-declaration in public addresses as criteria for placing the party on the traditional political axis. The following table will be used as a guide in left-right spectrum affiliations from here on, in this thesis.

Table 4: Ideological categories and respective parties

Political Axis	**Political Parties**
Left	La France Insoumise, *Lutte Ouvrière* , *Nouveau Parti anticapitaliste* , *Solidarité et progrès*
Centre-Left	*Parti socialiste*,
Centre	*En marche* , Francois Bayrou (did not participante in 2017)
Center-right	*Les Républicains*,
Right	*Front national, Union populaire républicaine, Debout la France , Résistons*

The above table was used in the manual annotation of the 100 most popular profiles in each cluster to judge the 'political affiliation' and their profession. In the section on vocation, I also simplified the analysis by using the term 'politician' for the major political figures even if they have some secondary profession.

During the process of manual annotation, the political affiliation of a user is only mentioned if he/she explicitly supports a political party. The annotation process found that many journalist profiles in the database have tacitly supported one political party or ideology but maintain an officially neutral position. The political affiliation of these journalists was labeled as 'unclear'.

1.53.1 Cluster 0

After looking at the top 100 most connected users in cluster 0 which comprises over 200k nodes, I concluded that this cluster is based on Business and technology-related profiles. While there are some minor variations, but these profiles contained three broader categories of elites:

1. Entrepreneurs
2. Business facilitators or helpers (start-up hubs)
3. Business Journalists

Fig 4: Vocation of sample from Community 0

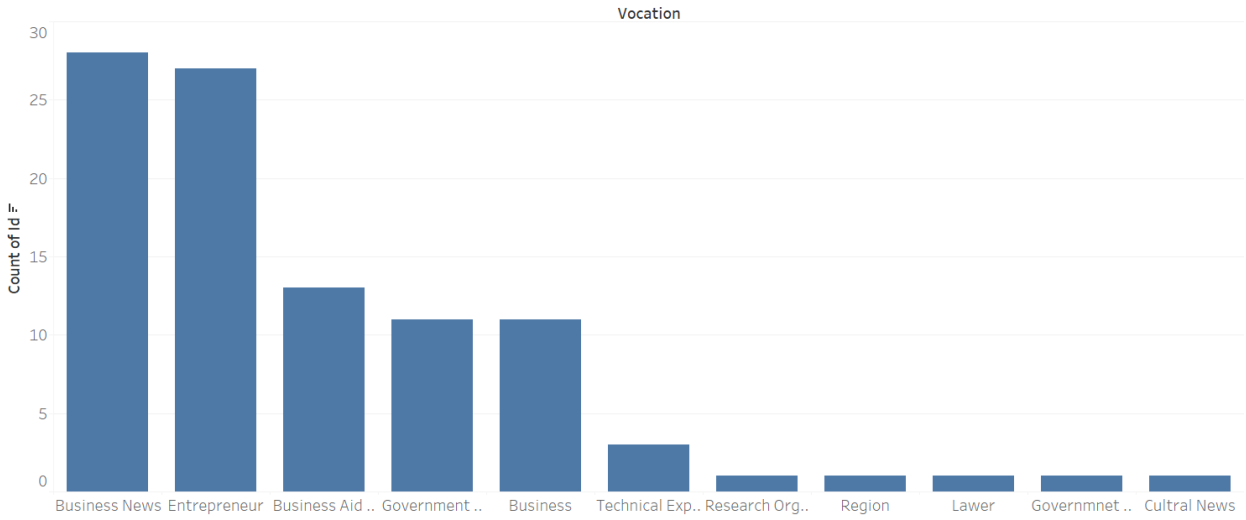


Figure 4 : Vocation of sample from Community 0

In terms of political affiliation, it was discovered that none of the top 100 elites in this cluster declared an explicit political affiliation which is not surprising considering that this cluster is not based on political affiliation.

1.53.2 Cluster 1:

Cluster 1 in the French network is a highly politicized cluster with a large number of political journalists and politicians from the ‘left’.

Fig 5: Political affiliations of a sample of profiles from Cluster 1

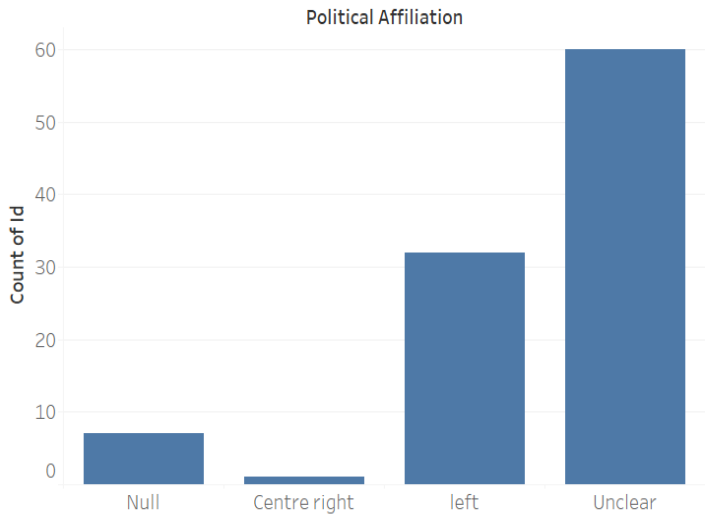


Figure 5: Political affiliations of a sample of profiles from Cluster 1

Fig 6: Vocation of individuals in cluster 1

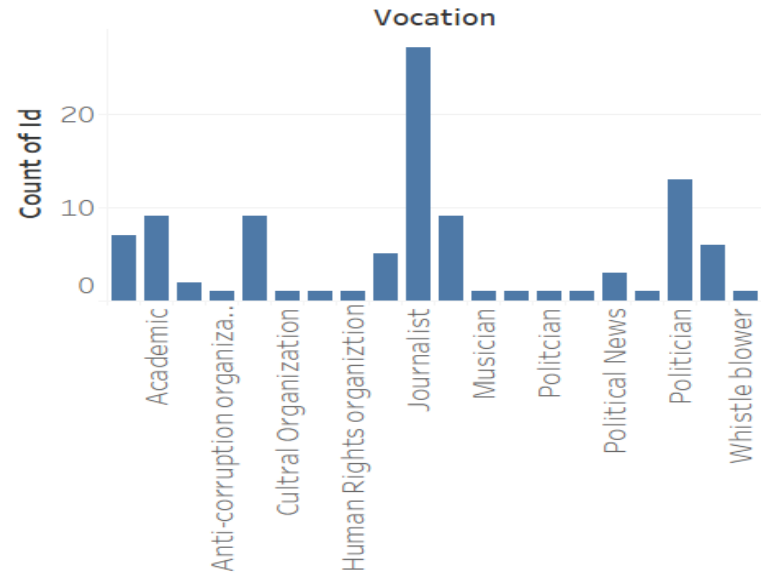


Figure 6: Vocation of individuals in cluster 1

As seen from the figures above, many profiles have ‘unclear’ marked as their political affiliation. It is because even though journalists in this cluster tacitly support the left but since they do not explicitly declare their support for it, I marked these profiles to have ‘unclear’ political affiliation. From the second graph which reveals the vocation of these profiles, we can see that a major chunk of these profiles has a journalistic background. It can also be seen that in terms of vocation this cluster has many academic and cultural profiles in it is elites. As we will discover in the latter part of this chapter, cultural and academic interests are uniquely popular in the leftist cluster in the French network.

1.53.3 Cluster 2:

This cluster is highly dominated by TV entertainment and sports accounts. These profiles do not give any explicit political affiliation; therefore, it is not surprising that almost all users have their political affiliation marked as ‘unclear’.

Fig 7: Vocations of Individuals in Cluster 2

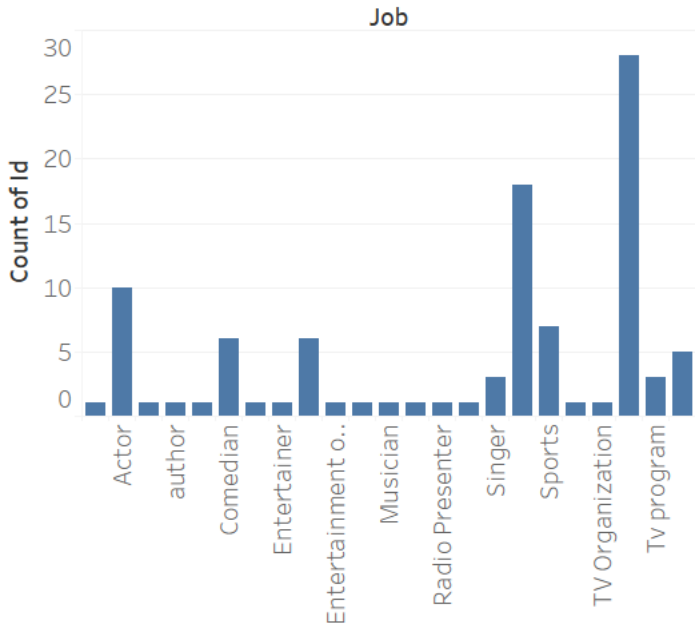


Figure 7: Vocations of Individuals in Cluster 2

1.53.4 Cluster 3:

Cluster 3 is an interesting political cluster with a major right-wing nationalist figure from FN in their elites. Out of all clusters in the French network, this cluster is most politicized and almost fully dedicates itself to political discussions.

Fig 8: Political Affiliations of sample users in cluster 3

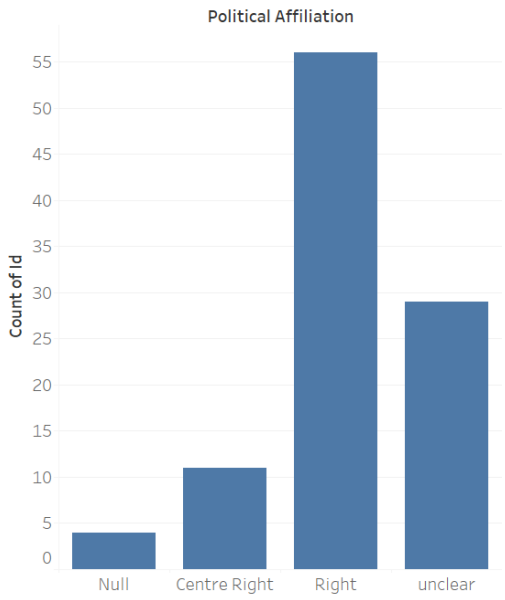


Figure 8: Political Affiliations of sample users in cluster 3

Fig 9: Vocation of Individuals in cluster 3

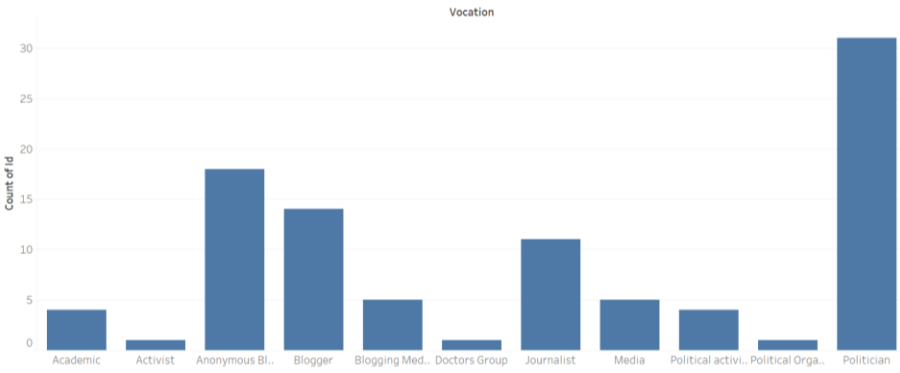


Figure 9 : Vocation of Individuals in cluster 3

The first thing to notice in the right-wing political community is that as opposed to the left-wing cluster, the right-wing cluster is dominated by political figures and anonymous bloggers. One hypothesis that can explain the popularity of anonymous bloggers in this cluster is the global mistrust in the populist-nationalist right-wing towards the traditional media (Schroeder 2018).

Here it should be noted that in the political identity, it is not solely Front Nationale and other 'extreme' right parties that occupy this cluster but also a large portion of center-right parties such as Les Republicain. The center-right party is divided into two major clusters, cluster 3 and cluster 4, where cluster 3 represents the nationalist elements in the party and cluster 4 represents the traditional economic right-wing political players.

As pointed out before, another noticeable difference between the vocations in this cluster and the left-wing is almost a complete absence of cultural interests such as music or literature and more focus on the political usage of the Twitter network.

1.53.5 Cluster 4

Cluster 4 comprises centrist parties, such as En Marche (party in power at this moment) and Les Republican (center-right) but also contains some portion of center-left party 'Partie Socialist' (which has lost a lot of political support since its defeat in presidential elections of 2017).

Fig 10: Political affiliations of users in cluster 4

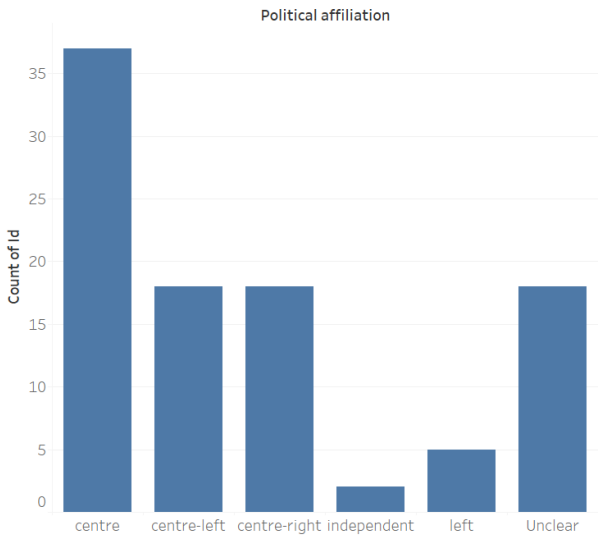


Figure 10: Political affiliations of users in cluster 4

Fig 11: Vocations of Individuals in cluster 4

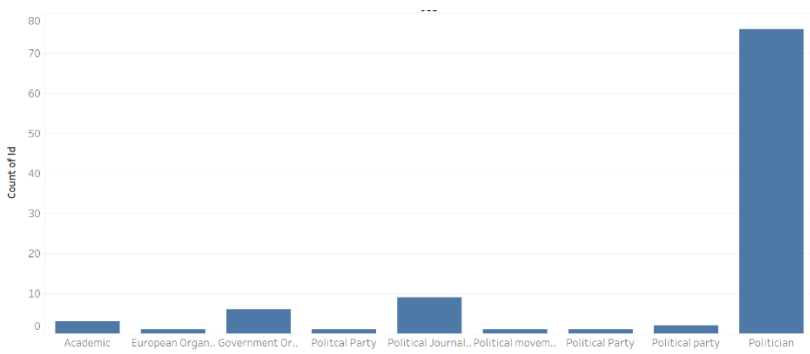


Figure 11: Vocations of Individuals in cluster 4

As seen from the above diagrams, cluster 4 is also highly politicized and comprises mostly of politicians, political parties, and political journalists. Most of these politicians belong to the centrist party of President Emmanuel Macron who won over a lot of support from people who previously voted for traditional centrist parties such as Les Republicain and Partie Socialist. Although most of the elite accounts in this cluster are centrist politicians as seen from the Figure some traditional media political journalists are very popular in this cluster.

1.53.6 Cluster 5

In terms of elites, cluster 5 is mostly comprised of political journalists from multiple newspapers, internet media, and Television. Since these journalists have not explicitly declared their political affiliations, therefore their affiliations are marked unclear. However, when combined with the politicians in the same cluster, it can be seen that these journalists cater to news requirements of the audience from the center-left such as members of Party-Socialist and break-offs from the center-left such 2017 presidential candidate of PS Benoit Hamon, who has created a new political party.

Fig 12: Vocations of individuals in cluster 5

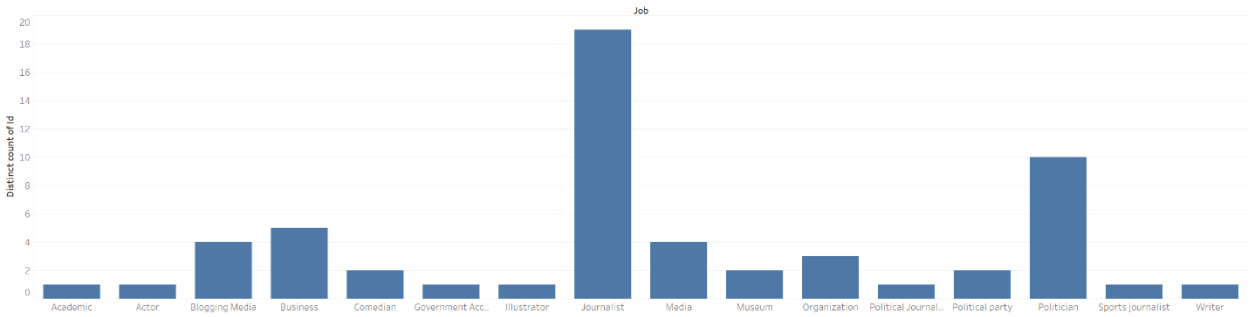


Figure 12: Vocations of individuals in cluster 5

Fig 13: Political affiliations of individuals in cluster 5

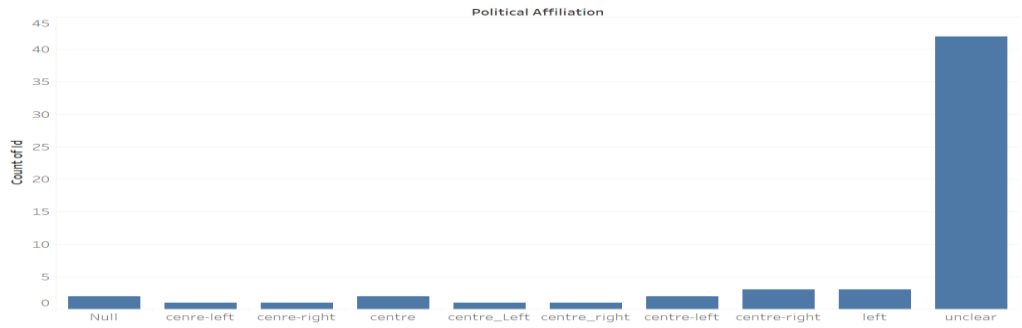


Figure 13: Political affiliations of individuals in cluster 5

1.54 Analyzing Twitter self-descriptions

When an individual joins Twitter, he/she gets an opportunity to write a noticeably short (160 characters maximum) 'bio' or 'self-description' which is visible on their profile. Since there is a strong character limitation, many people use just keywords in this section. These self-descriptions have the potential to provide insight into the collective identities of the clusters identified in the previous chapter (if such a thing as collective identity exists in these clusters). In this section, using the precedence from Eszter Bokanyi (Eszter Bokányi 2016) , I will use the word-frequency approach to analyze Twitter descriptions of multiple clusters and run correspondence analysis on the data to see if some patterns emerge which can help in deciphering more details on identities of the clusters.

1.55 Pre-Processing of self-descriptions.

After collecting the self-descriptions of profiles in each group, they were stored in ‘list’ data structure. Multiple python scripts were written to perform text-mining tasks on these descriptions. Since most of these descriptions were in French, therefore relevant French database from nltk library was used. Looping through each of the self-descriptions, following text cleaning steps were taken.

1. Non-descriptive singular words (Stop-words) such as ‘bon’, ‘ceci’, ‘est’, ‘qui’ were removed from each description
2. To reduce the number of words and make the results visual, only Nouns were kept from descriptions.
3. To further simplify the analysis, all the words were passed through a “French Stemmer” which reduced each word to it is the essential stem. This was done so that multiple variations of the singular word could be grouped and analyzed as a single stem. After this step, words such as ‘culturel’, ‘culturelle’, ‘culture’ and ‘des cultures’ were reduced to ‘cultur’ and treated as the same word.
4. Each self-description was then broken down into a collection of single keywords.

Once the text in self-descriptions was cleaned. The frequency of each keyword was calculated for each of the communities separately. These frequency lists for each community were then combined to create 2-dimensional tables where rows represented the keywords and columns represented community.

To normalize the data, and make sure that the result does not get affected by the number of people within each community who decided to write their descriptions, respective columns of the frequency table was divided by the number of people who wrote their description. These frequency tables were then passed through correspondence analysis to visualize the association of different keywords with communities.

Fig 14: Correspondence Analysis on word frequency of self-descriptions for all Twitter communities

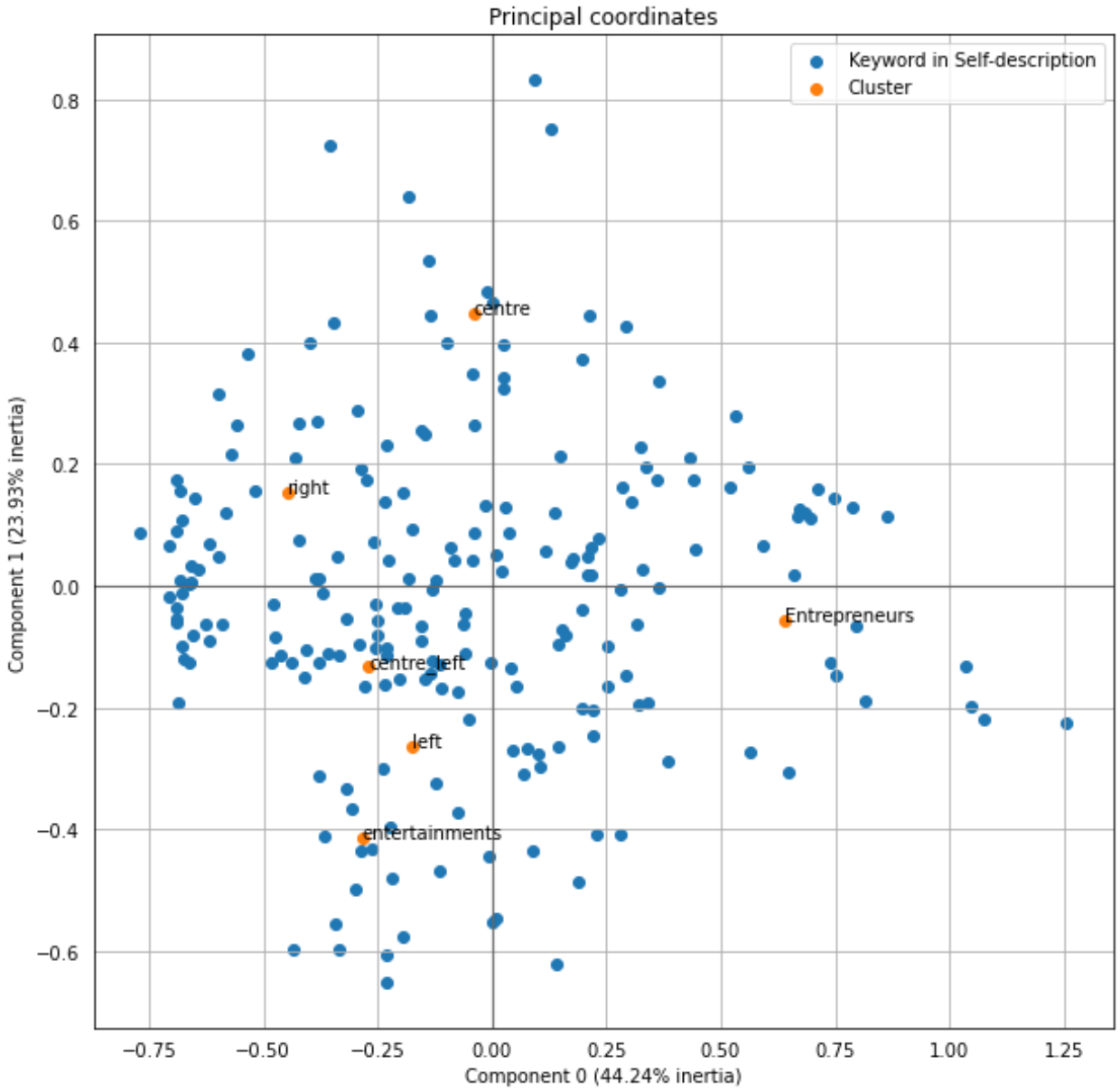


Figure 14:Correspondence Analysis on word frequency of self-descriptions for all Twitter communities

Fig 15: Result of Correspondence Analysis on Self-description keywords and political affiliation Community (just for political communities).

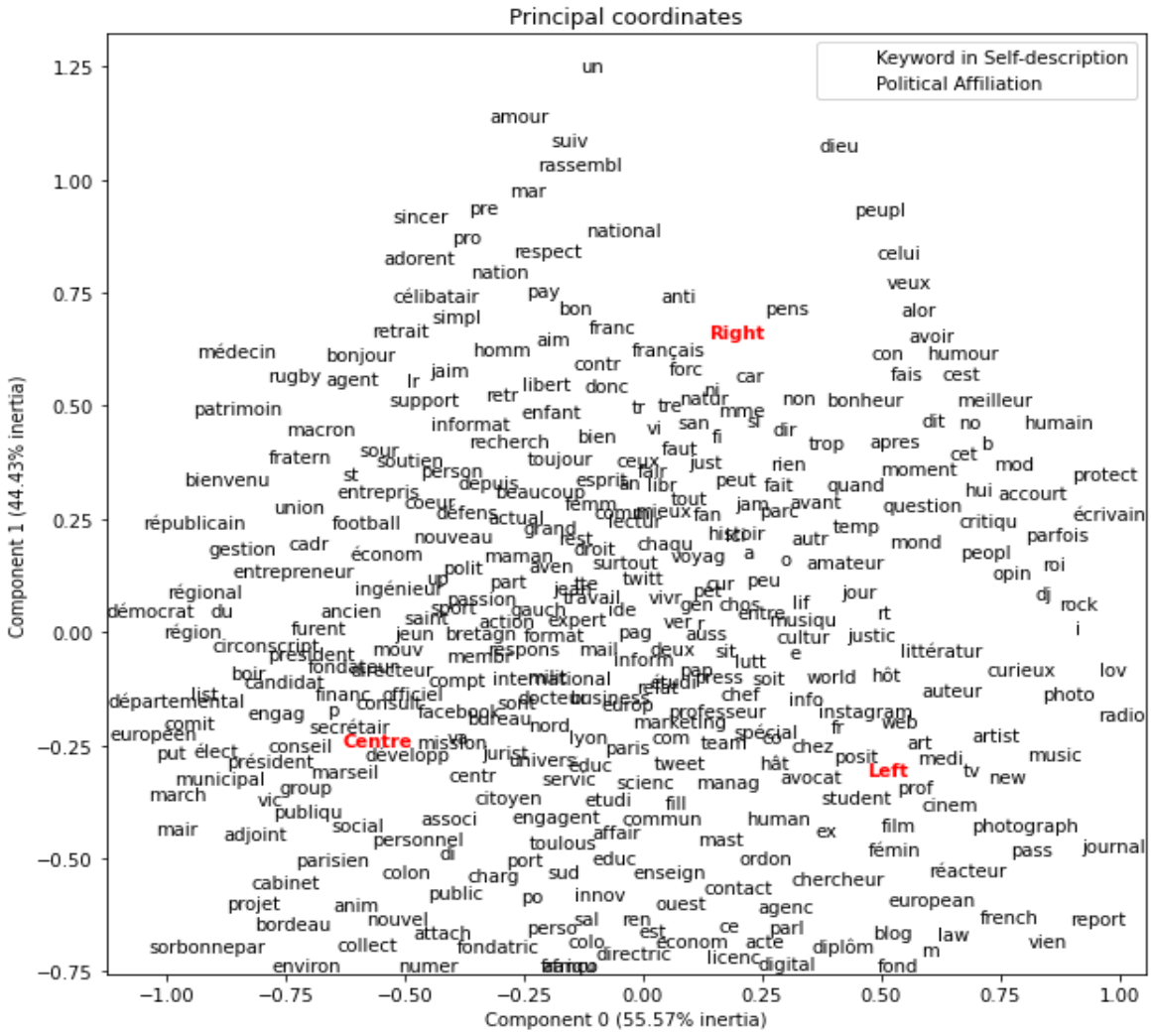


Figure 15: Result of Correspondence Analysis on Self-description keywords and political affiliation Community (just for political communities).

Results of Correspondence Analysis:

Total Intertia = 0.2951088491664543

Eigenvalues = [0.16399756121470774, 0.1311112879517468]

Explained Intertia for Component 1 = 0.5557188870409167

Explained Intertia for Component 2 = 0.4442811129590842

Total inertia of 0.29 is a high value which indicates there are clear terminology differences betwe en all three communities.

1.55.1 Interpreting Correspondence Analysis:

In the previous chapter I had discovered that when the community-detection algorithm was used on graph relations, it yielded a modularity value of 0.40 which is not a high value and indicates that even though there is a community structure, but the divisions are not strong. Comparing that to results of correspondence analysis indicate a clear difference between the three communities in terms of self-descriptions. It can be an indication that Twitter acts as a bridge between users of completely different political/social interests. This however is not compelling enough evidence to reject the null hypothesis and there is a need to further investigate the role of Twitter in socio-political space.

1.56 What can I say about these Communities using results of Correspondence Analysis?

Although the association between political values and non-political interests is not the main topic of this thesis but the correspondence analysis above does provide a much clearer picture of these political communities and how they see themselves. These associations have been discovered and talked about in detail by scholars such as Pierre Bourdieu.

The above picture only depicts the top 330 words with at least 2 non-zero values in three columns of the frequency table. The keyword associations found through correspondence analysis elaborate on the multiple interests that these political communities have. As seen from the graph, ‘left’ (Community 1) is highly associated with cultural keywords such as ‘photograph’, ‘art’, ‘auteur’, ‘cinema’, and ‘music’. On the other hand, we can see that Community 4 (Centre) which contains both EM and Les Republicain contains keywords that are associated with administration such as ‘conseil’, ‘secretair’, ‘comit’, ‘officiel’.

Unsurprisingly, the right cluster includes the most keywords that are associated with political values or clear ideological political motivations. Keywords such as ‘anti’, ‘national’, ‘france’,

'paye', and 'nation' are highly popular among the Twitter descriptions of this community. It does not come as a surprise, but It is pertinent to note that all these keywords point to in-group tendencies of these profiles.

In terms of party distributions, these clusters are not monoliths. Within the left, France Insoumise is highly popular but center-left party such as Parti Socialist has a very minimal presence7. The center cluster includes *En Marche*, which is the party of French President Emmanuel Macron, but it also includes many supporters of *Les Respublicain (Centre Right)* and a large group from Parti Socialist (Centre Left). The 'right' has also had an interesting composition that includes both supporters of *Les Republicain* and *Front National*. The distribution of supporters of Les Republicain between the 'centre' cluster and the 'right' cluster points to the divide in values among these people. As noted from the keywords, the republicans who are more inclined towards 'right' cluster might be interested in nationalistic ideas. Whereas there are also a significant number of Republicans who are attracted by similar centrist ideas as *En Marche* and Parti Socialist and are placed in community 4.

One thing to note here is that communities discovered in the data collection chapter are more consistent in terms of their interests expressed through keywords than in terms of their political affiliation of parties.

1.57 Characteristics of the left-wing cluster in Twitter

Cultural and entertainment interests

As noticed in the section on the cluster elites, there is a significant presence of profiles in the left-cluster elites who are associated with cultural activities. Based on correspondence analysis on word-frequencies it is observed that this finding gets replicated. There are significantly more leftist individuals who identified themselves in terms of keywords such as 'music', 'art' and 'film' then in any other cluster. The exclusivity of the political left in cultural activities can be explained by concepts from field theory such as 'habitus' (boyadjian 2014) .

7 PS did not have a lot of support during the 2017 elections

High concentration of 'Journalists'

Another observation that matches the results between correspondence analysis and manual annotation of elites is the prominence of journalists in this cluster. As seen from the notes on elites, these journalists work for traditional media outlets such as newspapers, news television and cultural media. In addition to these elite journalists, some prominent bloggers identify as 'journalists' in this cluster.

1.58 Characteristics of Centre-cluster in French Twitter

'Centre' cluster in the French Twitter occupies a unique position and is not proximate to any other clusters. In terms of characteristics in the self-descriptions the only notable thing about this cluster is the repetition of word's associated with party positions such as 'secratair' and 'president'.

1.59 Characteristics of the right-wing cluster in Twitter

In-group Tendencies of Right-wing cluster

Front National in France has been a significant nationalist-populist party in France since it's surprising first-round performance in the presidential elections of 2002. Among its popular agenda items are nationalism, anti-immigration rhetoric, and anti-Europe rhetoric. In terms of its ideology, it has a classic in-group attitude which reflects clearly from the Twitter descriptions of the group members. A study done in 2014 showed that a significant portion of FN activists was previously part of center-right political party *Les Republicain* and got disgruntled from the party due to multiple reasons. This fact has the potential to explain the inclusion of many Les Republicans in the right-wing community from the network discovered on French Twitter. To further clarify the terminologies used in Twitter descriptions of this community, I also created word clouds from keywords extracted from the descriptions of this community based on their frequency within the group.

Fig 16: Word-Cloud of Unprocessed Keywords used in Right-wing Community, Size of each keyword in this diagram is proportional to it frequency in Community's self-descriptions



Figure 16: Word-Cloud of Unprocessed Keywords used in Right-wing Community, Size of each keyword in this diagram is proportional to it frequency in Community's self-descriptions

This word cloud represents the unprocessed keywords in the right-wing cluster. Although the general theme of these keywords is like keywords shown in correspondence analysis, there are some new words in this interpretation. Since word-cloud was being created for a single community in this case, therefore there was no need to stem and merge the keywords. The results again highlight the terms 'patriot' , 'France' and 'politique' which clarifies the ideological inclinations of the people in these clusters.

So far in this thesis, I have elaborated on the structure of the communities in French Twitter's follow network. It is now time to look into the implications of being in a cluster. In particular, I would like to see if being a community hinders people's inclination to communicate with other users outside their community. In other words, how does the topology of the Twitter network affect the conversational structure? I would like to see, how much cross-communication goes on between the clusters and what is the sentiment of these conversations and then I would like to compare these results with results of in-group conversations.

Finding the structure of in-group and cross-group conversations on Twitter has been a topic of interest since the 2012 paper of Shaomei Wu (Shaomei Wu 2012) which emphasized that most of the conversations are highly elite centered and within the elites the network was highly homophilic,

" We find that attention is highly homophilous, with celebrities following celebrities, media following media, and bloggers following bloggers" (Shaomei Wu 2012)

Since 2012 we have also found out that the Twitter network is highly homophilous in terms of political affiliations in the context of several countries (Himelboim, Sweetser and Tinkham 2014). There is however a dearth of literature on what it means in terms of conversations. Does the homophily in the follow network imply that the conversations within the clusters would be more positive (thus reinforcing and solidifying the identity of the cluster), compared to conversations between the cluster? Or does being in a follow cluster mean that the frequency of your conversations with other clusters will drop significantly? Either of the above two scenarios has serious consequences for the echo-chamber hypothesis in Twitter. Finding an answer to the above question would render meaning to longitudinal studies for the identification of changes in the network structure over time.

1.60 How are communities connected to each other?

As seen in the section on correspondence analysis of the self-descriptions in the French Twitter clusters we can see proximity between left-cluster and entertainment cluster which is mostly concerned with cultural debates (or cultural consumption) and similarly we can also view self-description proximities between multiple other clusters. It will be interesting to see if these self-description proximities are associated with the inter-connectivity of clusters. If such associations exist, then we will have convincing evidence that longitudinal studies of network evolution will have ramifications in terms of how people define themselves on Twitter. Thus, it will provide the sociological basis for a longitudinal study of the evolution of the Twitter network in France.

In-group and cross-group follow connections:

1.61 In-group and cross-group follow the connection

To evaluate in-group and cross-group follow connections between the communities I generated two different tables. Table 1 is normalized concerning the number of followers whereas Table 2 is normalized based on the number of users that are followed in the group.

Table 5a : Cross-connections between the communities

	Entrepreneurs	Left	Journalists	Right	Centre	Elite Media & Politicians
Entrepreneurs	0.55	0.14	0.07	0.03	0.09	0.02
Left	0.11	0.55	0.08	0.04	0.09	0.03
Journalists	0.08	0.11	0.49	0.03	0.04	0.03
Right	0.06	0.12	0.05	0.59	0.10	0.01
Centre	0.12	0.17	0.05	0.07	0.46	0.02
Elite Media & Politicians	0.04	0.06	0.10	0.03	0.05	0.41

Vertical Axis on the left represent the community of follower. Horizontal axis on the top represents the communities of users being followed. This table has been normalized for the size of followers

Table 5b:

	Entrepreneurs	Left	Journalists	Right	Centre	Elite Media & Politicians
Entrepreneurs	0.55	0.11	0.07	0.04	0.12	0.17
Left	0.14	0.55	0.11	0.08	0.16	0.29
Journalists	0.07	0.08	0.49	0.04	0.05	0.22
Right	0.04	0.06	0.04	0.59	0.09	0.08
Centre	0.09	0.10	0.04	0.07	0.46	0.16
Elite Media & Politicians	0.00	0.01	0.01	0.00	0.01	0.41

Vertical Axis on the left represent the community of follower. Horizontal axis on the top represents the communities of users being followed. This table has been normalized for the size of communities of users being followed.

Table 5b is a better indicator of proximity between the communities as it has been normalized for the size of receivers. As seen from the values in column 'Elite Media & Politicians' there is a striking contrast between the 'right' community and the left-wing community. It indicates quite clearly here that all the communities except 'right-wing' are interested in following elite group to users who are mainly accounts belonging to mainstream media, elite politicians such as contestants of the presidential election of 2017 in France. Following results were obtained after running a T-test on these relations from multiple clusters towards elites and traditional media.

Table 6: T-Test results of connections from multiple clusters towards traditional elites.

Variable 1	**Variable 2**	F-Statistics	P-Value
Number of connections from left to Elites	Number of connections from right to Elites	99.0	Less than 0.001
Number of connections from left to Elites	Number of connections from center to Elites	0.7423338677734459	0.4578861083908222

As confirmed from the t-test above there is a significant difference between right-wing and other communities when it comes to creating relationships with traditional elites. Within the right-wing, this lack of interest in following the large profiles can be an indicator of a lack of trust for mainstream media and internationally popular French political figures (except for Marine le Pen). This phenomenon is not a novel observation as in recent years as the United States has also seen a rise in the popularity of political figures such as Donald Trump that have explicitly announced their mistrust for mainstream media and traditional political elites. As described in the last chapter the type of profiles that are clustered together in this group are highly interested in politics and usually describe themselves in terms of their political and nationalistic values, which is significantly different from the self-descriptions of other clusters that have been found in this thesis. We will see in the next chapters that right-wing cluster's lack of interest in elite profiles and traditional media while active interest in politics, pushes these profiles to seek new sources of information and ideological reinforcement from a large number of value-based anonymous Twitter accounts that play a crucial role in the socialization of this cluster.

Chapter 5: Not all Birds of feather Tweet together

Abstract:

A popular hypothesis to explain the rise of political polarization on the Internet is that the internet provides freedom to choose one's connections which leads to the creation of echo chambers or groups that are similar in their way of thinking because people choose to follow the people who they already like (Boyd and Yardi 2010). Such echo chambers can then lead to the adoption of extreme versions of initial ideas because of the group-polarization phenomenon. To establish a link between the usage of Twitter and an increase in the extremity of ideas, the first necessary step would be to show that homophily in Twitter progressively increases for all groups. In this chapter, I will show that the only significant increase in homophily is observed in right-wing communities, which at best shows that Twitter-based group polarization only impacts people with certain kinds of ideas (in-group or nationalistic).

I will show that this hypothesis ignores that homophily-based polarization or group polarization is independent of the size of the audience, but rather depend on the proportion of the audience. To analyze the impact of Twitter It is thus necessary to check if the proportion of the audience of certain groups alters over time and then propose a hypothesis as to why it happens in that manner.

1.62 Absence of Causal connection

Although the rise of political polarization is a much-discussed global phenomenon there is no consensus in the literature on the reasons behind it. Incidentally, this increase in polarization coincided with a paradigm-shifting change in communication technologies and an increase in popularity of internet-based many-to-many communication platforms such as Twitter and Facebook. While there is an association between the two, it is still not clear if there is any causal link. There have been many studies that associate usage of Twitter (or the internet in general) to the rise of political polarization (Bail, et al. 2018). Most of these studies are influenced by (or at least refer to) work done by Cass Sunstein, who originally applied the idea of group polarization to the internet and proposed that the internet, in general, will increase political polarization (Cass R 1999). His work generally refers to over 200 experiments done in social psychology, which established that interaction with people who hold a similar belief as oneself on a certain matter

will end up polarizing the individual (Myers and Lamm 1976). According to Sunstein, since individuals using the internet will end up interacting with people like himself/themselves and land in a state of a social bubble where only people of the same polarity will be present. It has been known from experiments in social psychology that socialization with the same people as oneself increases the intensity of opinion. For example, if people who are against abortions socialize with other people as themselves, they will likely become more anti-abortion (If it is possible). It is therefore plausible that the internet will polarize the individual. Using these projections from Sunstein, many researchers measured the level of polarization in Twitter based on a conversation about certain topics and found out the evidence for a high level of polarization. Most of the later studies are observational and found evidence that the population on Twitter and other social media platforms was indeed polarized with some exceptions (Urman 2019). Although there are no clear causal studies done to measure the impact of Twitter (to the best of my knowledge), it was implied in most of these studies that Twitter raised the level of homophily in the political sphere, which increased political polarization. In this chapter, I will use data from the French Twitter network to show that there are some strong exceptions to this explanation of the rise in political polarization and establish the need for an alternative way to think about the rise in political polarization.

1.63 Does group size matter?

The experiments that Sunstein referred to, were constructed such that social conditions were artificially modified for the experimental process to check If socializing with similar people as oneself has any compact effect in on opinions. In most such experiments, social settings were organized in a way that proportions of people favoring a certain idea (or the opposite) were increased in an individual's immediate social circle. The impacts of these changes in proportions were then measured in terms of how extreme the individual became after interacting with his social circle. Although a change in the proportion of people with a similar idea as individual itself, was found to impact the opinion by making the individual more extreme, it must be kept in mind that the size of the social group in social psychology experiments was found to not affect the extremity of individual's opinion (Knippenberg, Vries and Knippenberg 1990). In real life, it is plausible to imagine a change in proportions of people in an individual's social circle favoring a certain idea, but it remains a question whether the arrival of web 2.0 allowed individuals to alter their pre-

internet social opinion balance altogether in favor of opinions they preferred. The fact that the internet allows an individual to choose his/her social circle does not necessarily mean that he/she will choose a path completely disconnected from their real-life in favor of their preferred social group. It is plausible to think that the internet will make an individual to move on the same social trajectory as before but much faster. In practice, (on Twitter for example) it will mean that individuals will just increase the size of their social group but not alter the balance of opinions in their social circle. To investigate the role that Twitter plays in forming an individual's socio-political opinion it is necessary to measure the change in the socio-political balance of opinion from the start of their account till a certain period (which in our case is August 2018).

Before presenting the alternative hypothesis, I would like to investigate the nature of change in socialization that technology like the internet is likely to bring. As discussed before internet 2.0 is a 'many-to-many' communication tool that can increase the size of the social circles. A casual observation can inform us that the internet has indeed increased the size of our social circles. In social spaces like Twitter and Facebook, we can interact with many more people than before. While its impact on the size of social circles is clear but an interesting question to ask is whether it affects the balance of social circle we had before the internet by disproportionally increasing people of certain opinions in our social space and is it even possible to establish a concrete causal inference that this imbalance (if it exists) in social space is caused by the internet and not some other external factor.

1.64 Why is the French presidential election of 2017 an interesting case to study polarization?

As discussed before, the socio-political space on Twitter is not based on political parties but the interests of people. These interests can sometimes be shaped by political parties and political actors. French Presidential election of the year 2017 is an interesting case to study political homophily on Twitter. In terms of appearance, Emmanuel Macron was a new political actor, and it is interesting to see how his party carved a new socio-political space for itself on Twitter. This allows for the opportunity to study the impact of his rise to prominence on Twitter's socio-political space. Macron cannot be denoted as a new entry into politics of France altogether as he had a

substantial political and public profile before running for the president but a sudden increase in his popularity after Francois Fillon who was the favorite to win the election found himself involved in a financial scandal allows an opportunity to see if major shifts in Twitter's socio-political space occurred during this scandal.

The Presidential Election of 2017 in France saw a big rise in votes gained by both right-wing (Marine Le Pen) and left-wing compared to the 2012 presidential election8. In the first round of elections, right-wing candidate Marine Le Pen gained 21.3 percent of total votes cast, and left-wing candidate Jean Luc Melenchon managed to get 19.58 % votes as opposite to 2012 when Marine had gained 17.90 % votes and Melenchon had received a little over 11 percent of votes. There are many ways to explain the rise in the percentage of votes in extreme polarities but a strong argument in favor of the rise in on-ground political polarization can be made. Although it is subject to multiple variations there are strong center-left and center-right parties in the French Political context which has traditionally dominated the French Presidential races.

As shown from the previous chapter, in essence, France's socio-political Twitter space is divided into three major communities at the time of the last measurement in this study (December 2018). This divide maps very well with the on-ground political space in France. The divide between these communities in Twitter is very low, (modularity score of 0.40) but this score does not indicate the effect internet is having on the state of political polarization. To get a better estimate of the effect brought in by Twitter in socio-political space, it will be better to compare polarities (or direction of socio-political space) over the period that a particular user has been on Twitter.

1.65 Methodology:

The methodology for this chapter has been divided into two parts. In the first part, I will work on proposing methods to identify the communities discovered through graph crawls of the French Political Network using seed selection methods proposed in the previous chapter. I will start by looking at the political party support in each cluster by analyzing the distribution of manually annotated profiles (whose political affiliations are known) in each cluster. To know more about the properties of the communities, I will extract keywords from self-descriptions posted by

8 In a survey done by IPSOS, 80 % of Marine Le Pen's supporters described themselves as 'Very Right Wing' whereas as 74% of Jean Luc Melenchon's supporters labelled themselves as 'very left wing'.

individuals in these groups on their Twitter biography section and use correspondence analysis to get a clear sense of the identity and values of major communities. In the second section of the methodology, I will explain how I measured the direction of polarity in party space for individuals in these communities and how a change in polarity was measured.

1.66 Methodological Literature:

Ideological estimations based on social space in Twitter have been an important part of political literature on Twitter. Pablo Barbera used bayesian ideal-point estimates to assess political affiliations of millions of users using the follow relationship as data-source and was able to validate his results using 'Ohio voter registration file' which showed that such measures result in highly accurate models (Barbera 2015). While the prediction power of his methodology was highly valuable but his method does not shed light on how Twitter affects the levels of political polarization due to the cross-sectional nature of this data. To estimate the effect of Twitter on polarization, it is necessary to judge the change in social space over time. With Twitter, it is possible to judge these changes.

1.67 Exclusivity & Popularity of elite profiles on Twitter

As mentioned before, there is a strong link between group polarization and homophily and in the interest of establishing causal links, it is necessary to state that the role of the Internet in creating polarization is not conceived to be a direct one. Internet is thought to have a major role in increasing homophily (due to choices it allows), which in turn would increase the level polarization as well. Since establishing or denying causality between internet-based social platforms such as Twitter and the rise in group polarization is a highly non-trivial task, I will try to approach this research problem by checking if the criteria for group polarization i.e. homophily gets increased due to Twitter.

Sunstein's hypothesis proposes that the 'law of group polarization' will be dependent on the strength of initial inclinations. Although the strength of inclinations can be measured on the Likert scale an individual's perception of the strength of his ideas can be dependent on his knowledge of his surroundings and the type of ideas. This is different in highly controlled settings such as experiments in social psychology where the individual is aware of his/her position relative to other participants and might adjust accordingly. On the other hand in real life the

To measure what it means to follow a particular elite profile on Twitter I came up with two measures that can be used to operationalize the 'meaning' of following that elite user9. While following a famous political actor like, 'Marine Le Pen' or 'Jean Luc Melanchon' on Twitter does not say much about the political affiliation of a user but following overall less popular political accounts who are only exclusively popular in '*Front Nationale'* such as *'@GNation_off'* can say much more about the political affiliation of that Twitter user. To take advantage of this observation, I used a manually annotated database created from the 2017 elections which included political affiliations of 22000 users (Ophelies). First, I gathered all 'friend10s' of these users through a python script which resulted in over 3 million profiles. I then score each of these 'friends' according to the following two factors.

$$Popularity\ of\ user\ i\ within\ party\ j\ \ = \ P_j^i$$

The following equation demonstrates how P_{party1} was calculated. This process was done for all 5 major political parties in the presidential election of 2017

$$\boldsymbol{P_j^i = \frac{Annotated\ user\ from\ party\ j\ who\ follow\ user\ i}{Numer\ of\ Annotate\ Users\ from\ party\ j\ in\ the\ database}}$$

Through the above calculation, it was clear which elite users had reasonable popularity within a party, but as mentioned above if an elite user has an extremely high P_{party} score, it does not mean that following them indicates that an ordinary user supports that party. It is necessary to capture the exclusivity factor elite user:

$$How\ exclusivly\ popular\ is\ user\ i\ among\ \ \boldsymbol{annotated\ profiles\ from\ party\ j\ =\ E_j^i}$$

9 By 'meaning', I mean only that from the eye of an observer, a Twitter user following a particular elite can clarify his/her political affiliation.

10 A 'friend' in Twitter is a an account a user's follows. This is opposite to 'followers'

$$E_j^i = \frac{\boldsymbol{Annotated\ user\ from\ party\ j\ who\ follow\ user\ i}}{\boldsymbol{Number\ of\ All\ annotated\ users\ who\ follow\ user\ i}}$$

The score for each user i can be written in the following manner:

$$Score_j^i = \boldsymbol{P_j^i} \times \boldsymbol{E_j^i}$$

Scores were then normalized in the following manner

$$Score_j^i = \frac{Score_j^i}{\sum Scores^i}$$

The objective of this process is to capture the exclusive popularity of certain users in Twitter. I calculated these exclusivity scores for 3 million 'friends' of a manually annotated database.

1.68 What is 'socio-political space'?

The term 'political space' in this context is used to describe an imaginary multi-dimensional space where each party represents an axis. A vector in this multi-dimensional space can represent the balance of socio-political opinion. To explain this construct, I will use a two-party system example, since it is easy to visualize the methodology through it. In such, a system a vector can be placed to represent an individual's politico-social space. The direction of this vector will represent the ratio of socialization for that individual between multiple parties and the length of this vector can represent how embedded an individual is in a certain socio-political space and the direction of the vector would represent his/her inclinations.

French political context in the 2017 presidential elections was such that five major parties received over 90 percent of the votes that were cast. For a Twitter user in the French context, I imagined a five-dimensional party space where that individual's socio-political preferences were taken as a 5-dimensional vector. If over time, only the size of that vector increases, and the direction stays the same we can say that individual has surrounded himself/herself with more people of the same kind as his previous socio-political space. Since the size of the community has been seen to not affect the intensity of opinions (Knippenberg, Vries and Knippenberg 1990), then it can be claimed that attitude-based polarization is not an effect of political homophily or echo chambers.

If the direction of these socio-political vectors changes for a significant number of people in all communities over time, it will be necessary to see if the new direction of these vectors is more inclined towards initial party biases. If that is also the case, then it will be a strong indicator to not reject the null hypothesis11. Whereas if the direction of this vector changes for a statistically significant number of people in a community (and not for any other community) then it can be taken as a sign that the socio-political space of certain communities is changing, and it will be necessary to reject the null hypothesis since this effect will be noticed on a particular kind of group and not all groups on Twitter.

1.69 Operationalizing the variable 'Change in Political Polarity':

To conceptualize the change in polarity (on Twitter), it is necessary to quantify who a Twitter user follows and what does it mean in terms of the information he/she will end up consuming. From previous works we know that Twitter users prefer to consume data from political actors who they support to some extent in real life. Once a user starts a Twitter account, he/she is asked to follow some actors in Twitter. Since non-accidental nature of choices to follow political accounts has been demonstrated in the thesis of Julien Boyadjian (boyadjian 2014) . It is a reasonable assumption that this choice of 'who to follow' at the very start of a user's account is driven by pre-inclinations or pre-twitter biases and not from biases developed by using Twitter itself. To operationalize this 'Pre-Twitter inclination', I used the first 10 accounts a user followed and quantified what it means in terms of user's placements in 'socio-political space'. To get access to these first ten accounts that a user followed when he started using Twitter, I took advantage of the fact that when Twitter API returns 'friends' they are ordered chronologically. At the time of data collection, I marked this sequence using table indexes. For this part of the analysis, the first 10 accounts were separated from the list of complete 'friends' for each user.

1.70 Initial polarity

There are only a few traces of pre-Twitter inclinations a Twitter user leaves on the site. Measuring this inclination requires using one of these available resources to approximate this value. One

11 Sunstein's hypothesis is null hypothesis in this case where he predicted that internet based social media will result in increase in political polarization.

possible way would have been to investigate the Tweets of the individuals right after they joined Twitter. Although this approach has the advantage of providing qualitative details about the individual from the start after several attempts at this approach it was found that very few Twitter users Tweet right after they join the platform and even if they do, it is usually an ideologically uninformative Tweet. An alternative approach that was used was to investigate the network, which in some ways can be more informative than ideological inclinations. The choice of who to connect with when the cost of connection has been considerably lowered is shown to be a non-accidental one (boyadjian 2014). It is reasonable to assume that Ideological and interest-based similarities at that time are an important factor in this choice since these choices will lead an individual into a socio-political space where they will experience Twitter-based socialization.

The initial direction in socio-political space was measured through the first 10 accounts a user followed in Twitter. For each of these 10 accounts the 'exclusivity score' P (calculated above) was obtained from the exclusivity score database mentioned in section (tell the section). An individual's initial polarity score was calculated by taking the average of polarities of these 10 accounts that the individual followed when he created his Twitter account. These averages were then normalized to obtain an initial socio-political vector for that individual. As described above this vector would represent the biases the individual had before he/she joined Twitter12. Following is an example of this polarity vector

1.71 Final Polarity

Like the initial polarity of everyone, final polarity was calculated for each account in all 3 major political clusters. This final polarity was based on all the accounts individuals ended up following until (November-December of 2018). For the final polarity of everyone as well, the exclusivity score of all 'friends' of each individual was obtained from the above-mentioned exclusivity table. The average of these scores was then obtained for everyone. Since I am only interested in the directional change of these vectors, I will normalize the mean vector to obtain the sum of scores on each axis to be 1.

12 Even though it is a major assumption that initial socio-political vector on Twitter would represent the pre-Twitter biases but it is the best possible approximation of initial Twitter socio-political life of an individual. Comparing this with the direction of later socio-political vectors will provide information about the change in socio-political space.

1.72 How different are the initial Polarities of all the political clusters?

To inspect the change in polarity of the profiles, it is necessary to measure the difference between them in terms of their initial polarities. In simple terms, I would like to inspect if a user who ended up being in Community 3 (Right-wing) followed a different set of profiles when he joined Twitter than users who ended up being in Community 4(center) or Community 1(left-wing). To answer this question, I calculated the average initial polarity of each of the communities and found a cosine difference between each of them. Here are the results of this calculation.

Calculate the differences between initial polarizations and explain the results.

1.73 Measuring the change in Polarity:

'Cosine similarity' between two vectors measures how close two vectors are to each other using the angles between them. The cosine similarity value of 1 indicates that vectors are similar. It is often used in modern word2vector applications for translation purposes or to check the similarity of documents. In our case, it can be particularly useful to measure the similarity between the initial and final polarity of everyone. If initial and final vectors are highly similar then it will indicate that Twitter does not change the balance of opinions that individuals have. On the other hand, if there are significant changes in polarity direction, then it can warrant further investigation if these changes in polarity can be attributed to Twitter or not.

I measured cosine similarity between initial polarity vector and final polarity vector for one percent random sample from each of the 3 major political clusters (3120 profiles) and obtained the following results.

1.74 Results of change in polarity:

If using Twitter increases homophily as it allows users to follow more of the same type of profiles that they are initially inclined towards and less of the profiles that they dislike, then this phenomenon should impact all three major political communities in the French political context and their final polarity value should be significantly different from their initial polarization values and be directed more towards their initial inclinations. Whereas if only a subset of communities is getting more and more embedded in their socio-political direction, then it must be further

investigated as to why a certain community is getting more and more homophilic over time and others are not.

Using Python's SciPy library, I passed all three of these samples through One way ANOVA to check to see if there is any statistically significant difference between these communities when it comes to changes in direction of their initial polarity. In other words, do any of these three political communities significantly diverge from their initial social-political space.

$$F - statistic = 33.184873143492794$$

$$P = 6.138888273809066 \times 10^{-15}$$

While it is still unclear from the above results, where the difference lies but with such a small P-value, there must be a significant difference between the initial and the final polarity of at least one of these three groups.

After getting significant ANOVA it was necessary to distinguish the group that is making the above difference. Using the same python Library SciPy, I performed a post-hoc test to identify the different communities. During this test, a T-test was applied on all combination three communities. Following are the results that were received from this test.

Table 7: Initial and Final polarities of Communities

First Community	2nd Community	P-Value	F-Statistic
Left Community	Right Community	$1.29003100 \times 10^{-13}$	7.46722824561249
Left Community	Centre Community	0.6396053701922808	0.4683308695834476
Right Community	Centre Community	$4.873417194 \times 10^{-9}$	5.895481500781321

The above table indicates the results of post hoc test between two communities at a time to identify the Community that is causing the difference in ANOVA. It shows that except for right the other two communities are relatively similar to each-other when

From the above results, there is only one community (Right-wing Community) that significantly changed the direction of their political socialization. Whereas both other communities do not show any significant change in their initial and final direction. it is surprising to see that even though President Macron's political party carved a significant political space for itself in Twitter and yet the socio-political direction of his community has not shifted its direction at all. This can be explained by the fact that Macron had previously been working with Parti Socialist and his increase in popularity coincided with the decline of the other two major parties in the center. It is no surprise that supporters of Emmanuel Macron have the same socio-political space as the other two center parties and that it did not shift its direction although a new political party emerged victorious in the presidential elections.

Another important observation is about the socio-political direction of the 'Left' community. If Sunstein's hypothesis is correct and Twitter causes homophily which in turn causes group polarization, this effect should have been visible in the case of the French Left to some extent. However, the F value between left community and center community is 0.46 with a p-value of 0.639 which shows that there is no significant change socio-political direction of these clusters and this raises a reasonable doubt about the causal connection between Twitter and the rise of political polarization.

Although this evidence does put the null hypothesis in serious doubt, it is still not enough to completely reject it. At this point, the need for the alternative hypothesis is abundantly clear. The strength of this new hypothesis will be checked by how well it can explain the primary observation in the data which shows that only a certain cluster (rightist community) changed the direction of its socialization and as we will see in the next section, it is the only cluster which is becoming increasingly homophilic.

1.75 Changing direction from where to where?

A natural question to ask about this directional change is, 'what was 'Right-wing' community's initial direction and what is their final direction in the 5-dimensional political space of France?

The following table represents the averages of initial and final polarity values of members in group 3.

Table 8: Party-wise polarity changes

	PS Polarity	Lr Polarity	Fi Polarity	Fn Polarity	Em Polarity
Initial Polarity	0.06814312778883326	0.3396674591289328	0.11754338021465527	0.26000488224936064	0.2146411506182176
Final Polarity	0.05591287699541845656	0.34853936650062023	0.09782693173099562	0.3424965653348322	0.15522425943813348

Polarity change in Community 3, (Right-wing). 'Ps = Party Socialist , Lr = Les Republicain, Fi = France insoumise, Em = En March'

From this table, that the major difference between initial and final polarity is coming from a significant increase in FN polarity and a big decrease in EM polarity. It shows that over time this group's initial inclinations which were more biased towards Les Republicain (and to some extent towards FN) have moved significantly in favor of FN. An interesting observation is that LR polarity for this group has not changed significantly in this table. Since there are many LR members in the center community, it will be interesting to see if the same trend has been observed for them.

Table 9 : Party-wise polarity changes in community 1 (Left-wing)

	PS Polarity	Lr Polarity	Fi Polarity	Fn Polarity	Em Polarity
Initial Polarity	0.15575992857215654	0.22439346189009954	0.25433962189575265	0.0576678260293054	0.3078391616126851

Final Polarity	0.1619885143827934	0.21128745996500634	0.28357406505816873	0.052112618339835694	0.2910373422541959

Polarity change in Community 1, (Left-wing). 'Ps = Party Socialist , Lr = Les Republicain, Fi = France insoumise, Em = En March'

As seen from the figures in the above table, within the left cluster, the popularity of FI increases to some extent over time but overall, the balance in socio-political space remains consistently in the same direction.

Table 10: Party-wise polarity changes in community 4 (Centre-wing)

	PS Polarity	**Lr Polarity**	**Fi Polarity**	**Fn Polarity**	**Em Polarity**
Initial Polarity	0.16625223684414078	0.3369860173717593	0.11447950130684373	0.05119861965343448	0.33108362482382225
Final Polarity	0.17167763731925195	0.32985631375012814	0.09555719027577768	0.04340052075825093	0.3595083378965914

Polarity change in Community 4, (Centre-wing). 'Ps = Party Socialist , Lr = Les Republicain, Fi = France insoumise, Em = En March'

The table above indicates the changes in polarity in the center cluster from the start of profiles to till December 2018. It can be seen the balance of socialization remains consistently in the same direction for the account in this cluster.

1.76 The difference in initial and Final Socio-Political:

To assess which of political clusters are diverging over time and which clusters are converging over time, I compared the cosine-similarity of each community's initial and final cluster.

Table 11: Comparison of the initial and final polarity of each category.

	The difference in initial Socio-Political Space	**The difference in final Socio-Political Space**	**Interpretation**
Left and Right	0.8022670161882175	0.6844825249190307	Diverging strongly over time
Left and Centre	0.9362215582117713	0.8977512982593128	Diverging weakly over time.
Right and Centre	0.8571248895639666	0.7428557856877809	Diverging strongly over time.

It can be seen in the above cluster that while all the clusters are diverging over time but the effect on the left and center is very weak compared to the right-wing cluster. This comparison also makes it clear that while left and center clusters had a relatively similar socio-political space from the beginning but the direction of socialization pattern for users in right-wing clusters is unique as soon as they join Twitter and continues to diverge over time.

1.77 How does this result question the role of Twitter in Polarization?

From the above result, it is deduced that the socio-political space of 2 of the three major clusters in France has remained uniform from the time these users start their Twitter account till the time

of observation in December 2018. It is only the right-wing cluster that progressively diverges from the other two clusters. Right-wing clusters composed of both Les Republican and Front National have strong nationalistic ideas as visible from correspondence analysis in the last chapter. Interestingly a major part of Les Republicain who a part of center clusters have stayed on the same social track as they start with and do not diverge in any new direction.

From this analysis study, it is visible that if there is a real polarization effect of Twitter then it can only be visible in right-wing clusters in France and does not impact other major clusters in the political sphere.

1.78 Implications for Sunstein's Hypothesis:

As mentioned before, the above evidence is not enough to reject that Twitter increases the level of homophily which in turn could increase the level of political polarization. It is however clear that Twitter does not affect each political community uniformly and it is not that the whole network is getting polarized but only one major community is getting more and more detached from the general network over time.

A wide range of alternative hypotheses can be presented to explain why only the right-wing Twitter community polarizes and not others. One of these hypotheses can connect the increasing homophily of the right-wing community to major terrorist attacks in France. (I will present the findings of manual analysis and time-series data in the next chapter).

1.79 Strengths and weaknesses of the above approach:

The above approach has two major advantages in clarifying the historical development of polarization in a Twitter network. First and foremost is that it identifies the clusters or community that gets most isolated over time. Although modularity score (which is generally used for measuring polarization) does indicate how divided the overall network is, it does not point to the community that changed the most in terms of it being placed in the network.

The second advantage is that this approach also tells us the new socio-political direction of the group, which can be highly informative in the investigation as to why certain groups are more homophilic than others?

The weakness of this approach is the absence of a concrete way to determine the number of initial users to measure initial polarity. Although it is unlikely to affect the result in a major way for this study, this parameter was taken to be 10 but further investigations are needed to determine the approximate number of users a Twitter user follows as soon as he/she joins Twitter.

1.80 Conclusion

From the above test, Sunstein's hypothesis does not have the explanatory power for an increase in political polarization. At best it can be said that this phenomenon only occurs in right-wing clusters with nationalistic inclinations whereas Sunstein's hypothesis would have predicted it to occur at least to some extent in all clusters. There must be an alternative explanation for this result, and in the next chapters, I will look into the frequent retweeters of the extreme right cluster to establish that there exists a hierarchical structure in the flow of communication in Twitter. This hierarchical structure is similar to what Habermas called ‘refeudalization’ of the public sphere and paul Lazarsfeld observed in his eerie county studies.

Chapter 6: Who are Political Retweeters?,

1.81 Abstract

In this chapter, I will be studying the phenomena of information diffusion, and focus on nodes that are responsible for spreading political information everywhere on the Twitter network. This chapter attempts to fill gaps in the literature regarding the demographics of political retweeters using various techniques on the name and location-related data from the most active French political retweeters. Here I will try to state the breakdown of these accounts in categories based on gender, language, location, education level, and self-descriptions.

1.82 Introduction

In the recent decade, retweeting has become one of the most important information diffusion mechanisms for politicians. Many major political figures in the world tweet frequently to stay in touch with their followers and try to engage with them on a regular basis. Some of these tweets get retweeted more often than others. In order to understand why people, retweet and how the retweeted information defuses in a network it is important that we first investigate who retweeters are, and group them into meaningful demographic categories that can be studied to conclude spread of political information on Twitter. The main objective of this chapter is to put retweeting behavior in context by knowing more about the people behind the accounts who retweet major French politicians. From this inquiry, it has been found that although high-frequency political retweeters have a significant number of party-dedicated political participants but overall demography of this group is very similar to randomly selected Twitter followers of politicians but very different from accounts that are active retweeters of non-political content, which helps establish that the act of retweeting itself cannot be associated with Twitter accounts of particular demographics. Establishing this will provide ample justification for looking into the community dynamics of a group on Twitter, and the content of original tweets to decipher the motivations behind retweeting.

1.83 Review of Literature

1.84 Why is this question important?

Researchers on political polarization patterns have found that political debate on Twitter is largely dominated by a small group of people who are highly interested in politics (Bekafigo and McBride

2013) (Tumasjan, et al. 2010). It has also been proposed that the people that are politically active on the internet, in general, tend to be the ones that are also actively participating in political activity in real-life (Bekafigo and McBride 2013) and that amount of free time available plays an important role in determining the amount of online political participation. Retirees, unemployed, and students tend to participate more so than other professions but the nature of their participation can be different. While students are more interested in information consumption, retirees are more prominent in active engagement with other users (Greffet, Wojcik and Blanchard 2014).

From Political science and communication studies perspective, some important questions can be asked about the nature of groups in which political information spreads quickly and where political argumentation and debates happen. Are there any demographic differences in these groups? Is there any hierarchy in these groups through which political information trickles down? Are these groups representative of any real-world groups? While these questions have not been directly addressed in the literature to the best of my knowledge, but researchers have tried to check if the Twitter population, in general, is representative of the real-world population. The answer to this question has been found to be largely negative (Mellon and Prosser 2017). It has been found that Twitter users are largely male and highly concentrated in rich urban areas with a younger population (Barbera and Rivero 2014) (Mislove, et al. 2011). While this is an important result and has serious implications for scholars trying to make real-world predictions based on Twitter data (Tumasjan, et al. 2010). However, this result also raises questions about subgroups in Twitter and if these sub-groups are reflective of the same trend and what kind of effect would the basis of the group have on the demographics of profiles present in it. For example, one can ask how different the demographics of a group of political retweeters are compared to groups that retweet non-political personalities like sportsmen or actors. It is hypothesized here that the general demographic trend of Twitter will be more magnified in the community of political retweeters as compared to other non-political groups. In this chapter, I will try to investigate into demographics of political retweeters and compare the results with other most popular groups of non-political retweeters.

Demographics of users on Twitter have been an important topic in the literature surrounding Twitter. As Twitter does not provide clear demographic information about its users except the name, location, and language, it becomes harder to look at the demographic divisions of the users.

In literature, there have been a few attempts to determine more knowledge about the users from the information that Twitter provides. I will list these strategies here and then use them to determine the demographics of the target population.

The ways in which, gender and location of a Twitter user can be determined have been discussed by various scholars. As per Sloan (Sloan, et al. 2013), the most reliable way to get the gender of Twitter users is to make use of first names and as far as location is concerned the location provided voluntarily by the users, can be considered a reliable measure when used in conjunction with yahoo place finder. For the sake of this chapter, we will not be using yahoo place finder, but Google's geocoder service will be used to determine the region, department, and commune, which has a higher accuracy rate due to the ubiquity of android systems and higher usage of Google maps around the world.

Another methodology that will be used to determine the demographic features of retweeters in France is the usage of department-level (County Level) official data from insee (Institut national de la Statistique et des etudes économiques) for inferring information about Twitter profiles. Mohammady originally proposed this method and yielded valid results and we will use it to aggregate the education level of political retweeters (Mohammady and Culotta 2014). However, since we will be detecting associations on a population level for this part of the study. Therefore, it would be not accurate to assume that our conclusions will apply to individual retweeters. Otherwise, we will be at the risk of committing an ecological fallacy.

1.85 Compared to what?

In order to explain the findings, there is a need to put the found knowledge in context. There are two basic features in accounts that we want to study

1) They are very interested in politics.

2) They retweet politicians frequently.

Following (Yellow boxes) are the possible groups one can study in order to draw meaningful conclusions about the variables, ‘political interest’ and ‘retweet frequency’.

Fig 17: The figure shows the 3 groups we will study to draw conclusions about political retweeters.

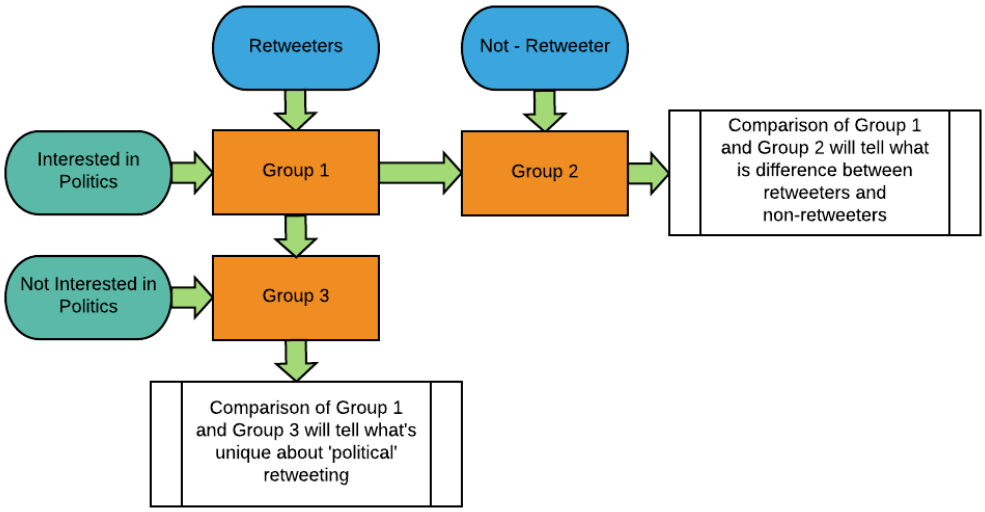


Figure 17: The figure shows the 3 groups we will study to draw conclusions about political retweeters.

1.85.1 Group 1

The first group that we need to study is the people who are active retweeters of politicians. From the French political context, I selected the top 5 contestants of the French presidential election of 2017. I then found out their official Twitter accounts and collected their most frequent retweeters using Twitter API. The first step towards the process of selecting group 1 will be to sort the retweeters of each of the 5 French politicians based on the frequency of their retweeting. Here the frequency means how often they retweet a politician. The accounts that retweet a politician more frequently were placed on top, followed by others who retweeted less frequently for the same politician. Among these retweeters, I selected only the top 10000 most frequent retweeters of each of the politicians and created 5 tables containing profiles of each of the top 10000 retweeters of politicians. These 5 tables were then merged to create a combined table of 44779 rows containing at least 10000 retweeters of each of the politicians. The reason that there are less than 50000 profiles in this merged database is that many of the top retweeters of one politician were also top retweeters of another politician; therefore, the repeated rows were eliminated in the data cleaning

process. In this database of 44779 unique twitter profiles, the following is the count of profiles of retweeters who have been retweeting these politicians.

Table 12: List of Politicians we will study

Politician	Number of Retweeters in the Database
Francois Fillon	14408
Jean Luc Melenchon	13048
Marine Le Pen	11914
Emmanuel Macron	13826
Benoit Hamon	13914

As it can be observed from the table there are considerably more than 10000 values for each of the politicians which shows that retweeting is not an exclusive behavior and an account that frequently retweets one politician can also retweet many other politicians at the same time.

1.85.2 Group 2:

The second group will constitute people who are not active retweeters of politicians, but they follow these politicians, which are assumed as an indicator of their interest in politics. For this group, we selected random 50000 profiles from the list of followers of five major French politicians, repeated the same process for them as for group 1, and collected their profile information. There is a need for this group because using this group, we can observe if some property is specific to retweeters of politicians or is it a general trend among the accounts that are interested in following politicians on Twitter.

1.85.3 Group 3

The third group will constitute profiles that are active retweeters but not of politicians. Since the non-political group can be a very large group with multiple subgroups. It was concluded that it would be better to study two non-political subgroups so that found variables can be compared between these sub-groups and then also compared with political retweeters. If there is uniformity

in non-political groups and differences with the political group, then it can be concluded that the concerned property is specific to the political retweeters group. For this purpose, I selected the most popular personalities in France on Twitter with no explicit political affiliation. Two options were considered, the first one was to use Twitter accounts of soccer players as they are among the most popular Twitter handles in France. The second option was to consider entertainment personalities. It was decided to select both of these groups and study them simultaneously to make meaningful conclusions about non-political retweeters.

Table 13: Non-Political Twitter accounts whose retweeters, I will study

Sub-Group 1	**Sub-Group 2**
Jamel Debbouze (*@debbouzejamel*)	Antoine Griezmann *(@antogriezmann*)
Gad Elmaleh (*@gadelmaleh*)	karim benzema *(@benzema*)
Cyprien (*@monsieurdream*)	matuidi blaise *(@matuidiblaise*)
Kev Adams (*@kevadamsss*)	Paul Pogba (*@paulpogba*)
Norman Thavaud (*@normandesvideos*)	raphael varane *(@raphaelvarane*)

A similar database of retweeters was created from these accounts like that of politicians and similarly, detailed information was also collected from these profiles.

1.86 Found Attributes

The following information was then gathered about the retweeters from the Twitter API, multiple attributes were collected about these retweeters from Twitter API. These attributes include,

id, name, screen_name, location, description, protected, verified, followers_count, friends_count, listed_count, favourites_count, statuses_count, created_at, time_zone, geo_enabled, lang

Knowing this information allows us to move toward the analysis of this data set to figure out information that can be useful in studying the general features of political retweeters.

1.87 Language breakdown

We will start this analysis with the 'lang' attribute which represents the primary language in which a user uses his/her Twitter interface. The language attribute is important as it provides an idea of the national background of the users and helps us determine if there is linguistic uniformity or diversity among the groups. Here is the percentage breakdown of all the groups in terms of language.

Fig 18: Language breakdown of Group 1 (Political Retweeters)

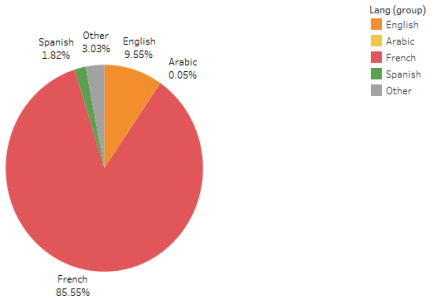


Figure 18: Language breakdown of Group 1 (Political Retweeters)

Fig 19: Language breakdown of Group 2 (Political non-retweeters)

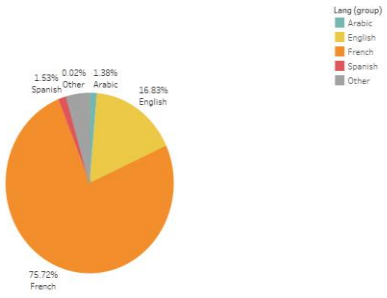


Figure 19: Language breakdown of Group 2 (Political non-retweeters)

Fig 20: Language Breakdown of Group 3 (Entertainers)

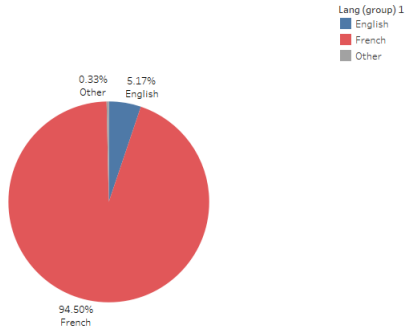


Figure 20: Language Breakdown of Group 3 (Entertainers)

Fig 21: The image below represents the language breakdown of retweeters of footballers

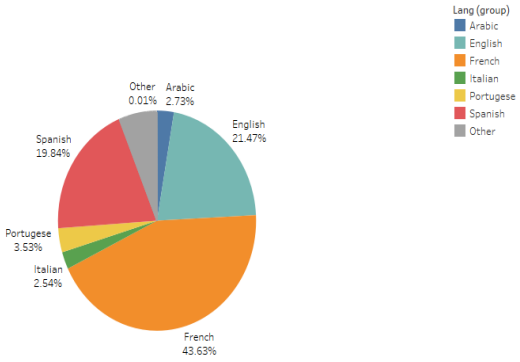


Figure 21: The image below represents the language breakdown of retweeters of footballers

1.88 Discussion about Language break-down of multiple groups

As seen from the comparison of graphs about the language, the diversity among the language groups is consistent among group 1 and group 2 whereas it is very different from group 3 which has huge variation among the sub-groups as well. This shows that the distribution of languages that we see in group 1 and group 2 is particular to both political retweeters and political non-retweeters and not present in non-political retweeters. This compels to infer that this division is specific to people who are interested in politics.

If we inspect deeper into the division of political retweeters we will see that almost 86 percent of retweeters use the French Language as their interface language in using Twitter. While the second most used language is English, which can be explained by the fact that many French people are

bilingual. What is noteworthy here is the number of people who have chosen to use Twitter in Arabic. According to data collected from Adult Education Survey in 2007 by European Union, Arabic is the second most common maternal language in France with 3.6 percent of the French population speaking it as their mother tongue (European Union Adult Education Survey 2016). Whereas in the representation of political retweeters, it represents as little as 0.05 percent of the population. There may be several explanations behind this. One possible reason is that although Arabic is a mother tongue for 3.6 percent of people, yet they use French on daily basis and have become fluent enough in French to use websites like Twitter in French rather than their native tongue (Myers, et al. 2014). Another explanation for the lack of Arabic speakers among the retweeters will be the underrepresentation of this ethnic group among the retweeting population of France. There is a need to investigate this further and we will do this in the next section of this chapter where we will break down the first and second names of retweeters to create a classifier to see if there is indeed an under-representation of people of Arabic origin in among the retweeters.

Following is the breakdown of languages for each of the politicians separately:

Table: Percentage of each language for each politician among his/her retweeters

Lang (group)	Le Pen	Macron	Melenchon	Hammon	Fillon
French	78.76%	81.14%	91.33%	92.24%	91.22%
English	11.97%	13.56%	7.02%	7.05%	7.76%
Italian	4.54%	0.68%	0.33%	0.20%	0.20%
Other	1.69%	1.24%	0.85%	0.27%	0.30%
Russian	1.68%	0.27%	0.05%	0.00%	0.08%
German	0.88%	0.58%	0.33%	0.16%	0.15%
Japanese	0.31%	0.25%	0.06%	0.01%	0.04%
Spanish	0.12%	2.13%	0.04%	0.07%	0.19%
Arabic	0.04%	0.15%	0.00%	0.00%	0.05%
Total	100 %	100 %	100 %	100 %	100 %

If we look at the table closely, we can see that there are many observations, which require an explanation. The first observation is a follow-up on the lack of Arabic-speaking retweeters. Here we can note that the small number of Arabic retweeters that do retweet French politicians prefer to avoid leftist candidates such as Melenchon (0.0 %) and Hammon (0.0 %). This phenomenon needs to be explored further to see the reasons why it is happening.

The second observation is the international appeal of both macron and marine le-pen in contrast to their popularity among French-speaking retweeters. This can be explained by the fact that they reached the second round of the French presidential elections of 2017 which had more international media coverage than the first round which included the other 3 candidates too.

The third observation is that non-French speaker appeal of le-pen and macron comes from completely different language groups. While Macron has managed to get retweeted significantly more by Spanish-speaking profiles, Marine Le-pen has attracted significantly more Italian and Russian speakers which can be explained by her general popularity in those countries. (Batchelor 2017)

Section 2 (Location Data):

In this section, we will investigate the location data of retweeters and try to see what kind of areas they come from. We will start with the country-level analysis and then concentrate on France, its regional data, and data of its departments. We will then use multiple educational and social indicators from the official on-ground surveys done by French government organizations to try to see what kind of areas retweeters come from.

1.89 Where does the location data come from?

The location data of retweeters is taken from the location tab in their profile. This location is self-reported and serves as the best option to approximate the location of these users. The cleaning of this data is much more complicated as location data is not reported in a uniform format. Some profiles just add country names, whereas there are other profiles that have reported their full location. There is also a problem of obviously misreported locations as there are many users who

have reported their location to be something like ‘dans la lune'13, ‘Narnia’ or ‘dans la l’espace’14. These profiles had to be discarded during this analysis as it was not possible to determine their location. Another problem in the database is that although the majority (approximately 60 percent) of the retweeters have mentioned their location yet there is a significant portion of retweeters who have not revealed their location and it is difficult to ascertain where they are from.

The reported locations were then further broken down in the following columns:

Pays/Country

Region/State

Département/County

Arrondissement /Locality

Code Postal/ Postal Code

As twitter only provides a single column for location and this location needed to be cleaned and distributed in above-mentioned columns where possible. This was done with the help of Google's geocoding API as it provides the most reliable results in terms of location. Once this data was cleaned, it was then put in tableau software to provide visualizations. In terms of country following is the mapped graph that can provide a clear picture of the location of the retweeters.

Fig 22: Countries where retweeters are located



Figure 22: Countries where retweeters are located

13 Translation: On the Moon

14 Translation: In Space

Table 14: Top 10 locations of retweeters. (Percentages have been calculated from the total of the population who reported their location)

Country	Percentage of Retweeters
France	76.71%
United States	7.87%
Canada	1.98%
Spain	1.26%
Belgium	1.22%
United Kingdom	1.15%
Italy	0.90%
Switzerland	0.71%
Germany	0.56%
Morocco	0.28%

More than 75 percent of retweeters reported their location to be France, which is very consistent with the language data analysis. After that, the united states is the second most popular place among the retweeters. Surprisingly, the contribution of European countries toward the retweeters is lower than the US and Canada. Just to confirm that it is not due to the smaller size of European countries as compared to states, I grouped European countries to create a block (excluding France). In that case, the result came out to be that the Percentage of retweeters living in European countries outside of France is 7.3 percent of total retweeters who have given their location, as opposed to 7.87 percent retweeters from the USA. This means that there is a definite interest in retweeting French politicians from the United States. Not necessarily by American Population but this could be due to large French diasporas in these countries.

Looking into the distribution of multiple politicians among countries can perhaps provide a clearer picture of where are the foreign retweeters located. Here are the retweeters of each of the politicians according to their location.

Table 15: Percentage of retweeters concerning countries using the 'location' tab in the Twitter profile.

Country	Fillon	Hamon	LePen	Macron	Melenchon
France	82.18%	81.23%	69.20%	76.61%	74.53%
United States	6.60%	6.97%	11.19%	6.82%	8.48%
Canada	1.92%	1.95%	2.67%	1.77%	2.84%s
Belgium	0.97%	1.09%	1.01%	1.30%	1.78%
United Kingdom	0.70%	0.86%	1.72%	1.27%	0.94%
Switzerland	0.64%	0.57%	1.04%	0.62%	0.86%
Spain	0.54%	0.68%	1.20%	0.84%	2.30%
Italy	0.38%	0.31%	2.44%	0.52%	0.42%
Côte d'Ivoire	0.32%	0.12%	0.29%	0.40%	0.17%
Lebanon	0.27%	0.09%	0.31%	0.18%	0.09%
The Democratic Republic of the Congo	0.26%	0.15%	0.26%	0.35%	0.13%
Germany	0.26%	0.40%	0.86%	0.71%	0.44%
Réunion	0.22%	0.17%	0.17%	0.22%	0.25%
Morocco	0.20%	0.27%	0.18%	0.32%	0.56%

Cameroon	0.18%	0.07%	0.18%	0.20%	0.13%

As it can be seen from table 15 that Marine Le Pen has the highest rate of retweets from the United States and she also has a very significant retweet rate from Italy (2.44 percent) as compared to other politicians, which confirms the findings from the language section of the retweeters analysis. However, here we can see that the percentages of Russian retweeters for Marine Le Pen are although the highest compared to other politicians (0.81 %), yet not very significant in numbers. It

Department Analysis of France

Looking into the county-level data in France, we will treat the county (*Département)* as the unit of analysis. To have a cursory look at the data, I will first put map out the retweeters

Fig 23: Number of retweets located in each of the counties in France (Darker blue indicates more retweeters)

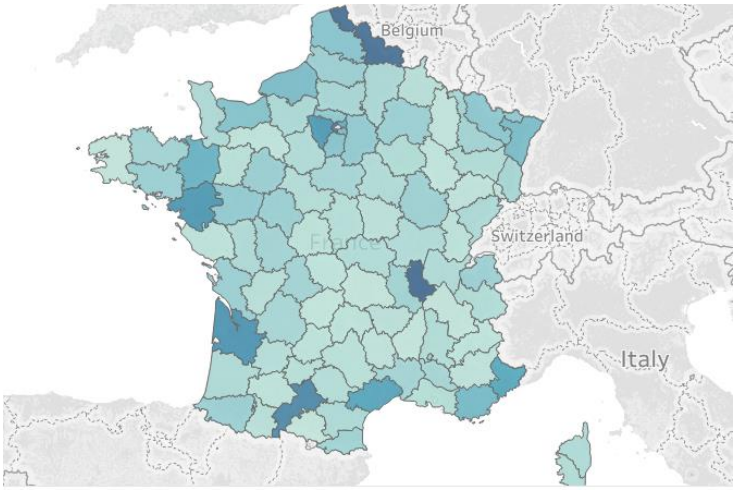


Figure 23: Number of retweets located in each of the counties in France (Darker blue indicates more retweeters)

Figure 23 shows the number of retweeters located in each of the counties (*Département)* in France. After looking at the map, it is clear that the retweeters are concentrated in counties with bigger cities likes Marseilles, Lyon, Toulouse, Lille, Montpellier, and other major French cities with large population concentrations. Although it is not very surprising, it will still be interesting to plot each

of the (department) county's number of retweeters against its population to try to see if there is a strong linear correlation.

Fig 24: Number of Retweeters concerning population



Figure 24: Number of Retweeters concerning population

As expected, there is indeed a strong correlation between the population of each of the counties and the number of retweeters it produces. The R-Square value of this regression is 0.79 which indicates a strong correlation. There is however an exception of Paris city, which holds disproportionally more retweeters than its population, therefore Paris city was excluded from the above two graphs and needs to be treated separately. From this analysis, it seems like most of the retweeters come from large cities in France, it will, therefore, make sense to find out the percentage of retweeters that come from the top 10 major cities in France concerning population.

Grouping the top 10 cities of France, it seems that 41 percent of retweeters come from these metropoles with a population larger than 200000 people. Combining this with the regression results that we have above, it will be reasonable to think that a large proportion of French retweeters live in large cities. The same experiment was replicated for each o\f the politicians separately and it was found that the results were very similar to the combined results presented above.

1.90 Education in the Areas where retweeters are located.

Linear correlation between population and retweeters count has some implications that we need to be careful about while analyzing the data in the next step. As the size of the population can affect the number of retweeters in the county, therefore when we are looking at the kind of areas where these retweeters come from it will make sense to take the percentage of the demographic measure rather than the actual number from the demographic surveys. For example, the population has a high correlation with both numbers of retweeters and other measures like the number of people with higher education. To reduce the bias in the data, we should take the percentage of highly educated people from the total population and find its correlation with the retweeted count in that area.

An important question that one can ask about the areas where the retweeters come from is the education level and try to see if there is any relation between the education level in a department and the number of retweeters that come from that area. Data for education level in each county was collected from Insee (Insee 2015). In each department, we looked at the level of education in terms of the percentage of the total population and then saw how it relates to the number of retweeters.

First, I compared the level of the number of retweeters in each department with the percentage of people with no diploma or a technical studies diploma. Here are the results for this:

Fig 25: Correlation between number of retweeters and percentage of people with diploma

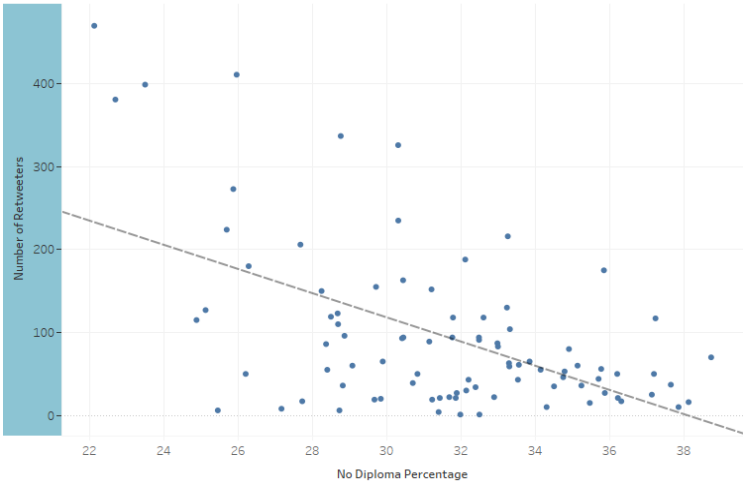


Figure 25: Correlation between number of retweeters and percentage of people with diploma

Fig 26: Correlation of number of retweeters Percentage of Technical Diploma

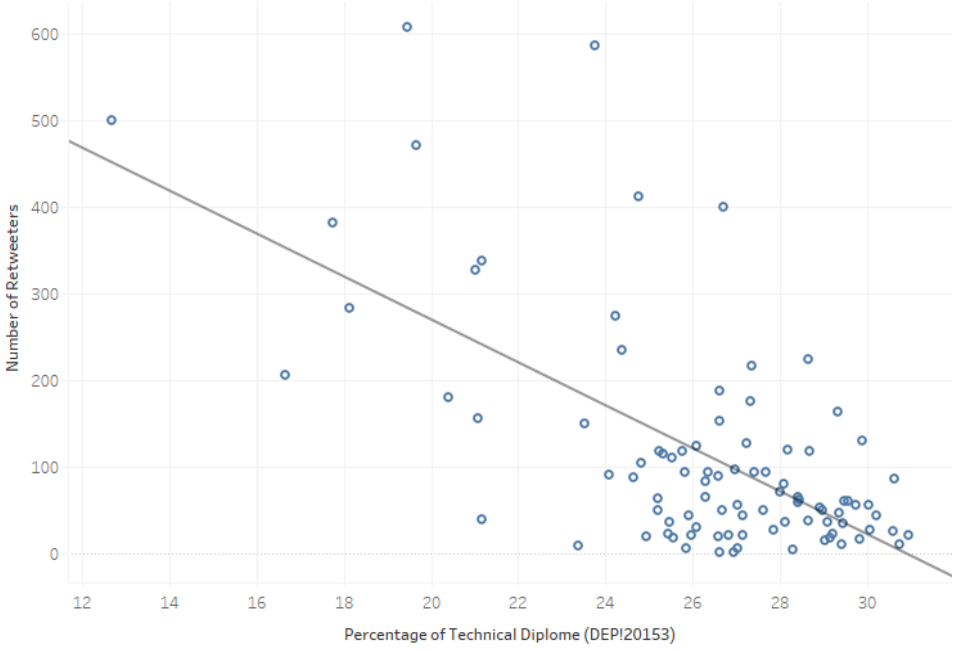


Figure 26: Correlation of number of retweeters Percentage of Technical Diploma

As visible from the above two graphs the relationship between the two variables seems to be negative. R-squared value for the no-diploma graph is 0.29 whereas it is 0.41 for the second graph with both p-values being less than 0.0001 which indicated that there is a good chance that there is a negative relationship between these variables.

Fig 27: Relation between the percentage of bachelor's degree holders and retweet count of each department

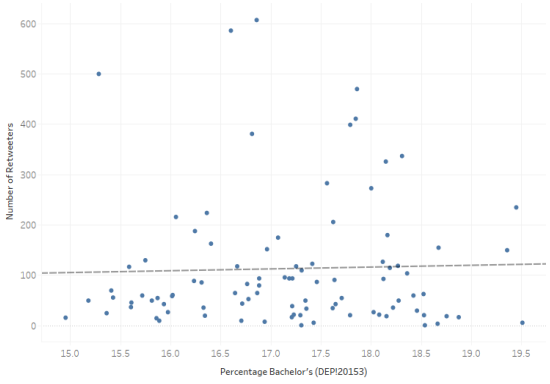


Figure 27: Relation between the percentage of bachelor's degree holders and retweet count of each department

Figure 27 represents the graph between the percentage of bachelor's degree holders and its relationship with the number of retweeters living in a department. The R-squared value of this graph is 0.0009 and the p-value is about 0.77 which is enough to confirm that no statistically significant correlation between the two variables is found. Although, it is observed here that the trend is moving towards positive as compared to the trend from the no-diploma regression.

Fig 28: Here I show the relationship between retweeters and the percentage of masters or higher-level diploma holders in each department.

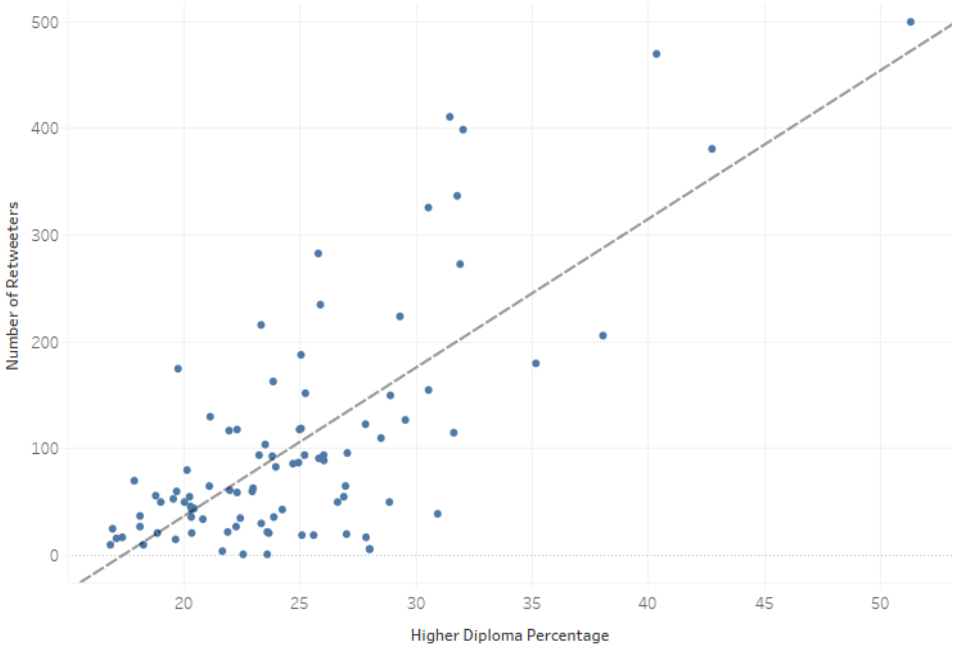


Figure 28: Here I show the relationship between retweeters and the percentage of masters or higher-level diploma holders in each department.

In figure 28 we can see that there seems to be a positive correlation between the percentage of graduate or post-graduate degree holders and the number of retweeters. Here the R-squared value is 0.51, which indicates that the possibility of correlation is very high as 51 percent of data points can be explained with the correlation. P-value is less than 0.0001 here which means that there is very little chance that this happened by coincidence.

As mentioned above, before drawing any conclusions about political retweeting and its connection with population and education, we need to study these trends in non-political groups to see if this is a general trend among all Twitter users or specific to political retweeters.

1.91 Education in Group 2 (Political non-Retweeters)

To find out the relationship between education and Twitter accounts that are interested in politics but not active retweeters, the details on location were converted to the department level data using Google geocoder API from group 2. This data was then mapped in contrast to the education data from the insee concerning each department.

Fig 29: Correlations of Political non-Retweeters

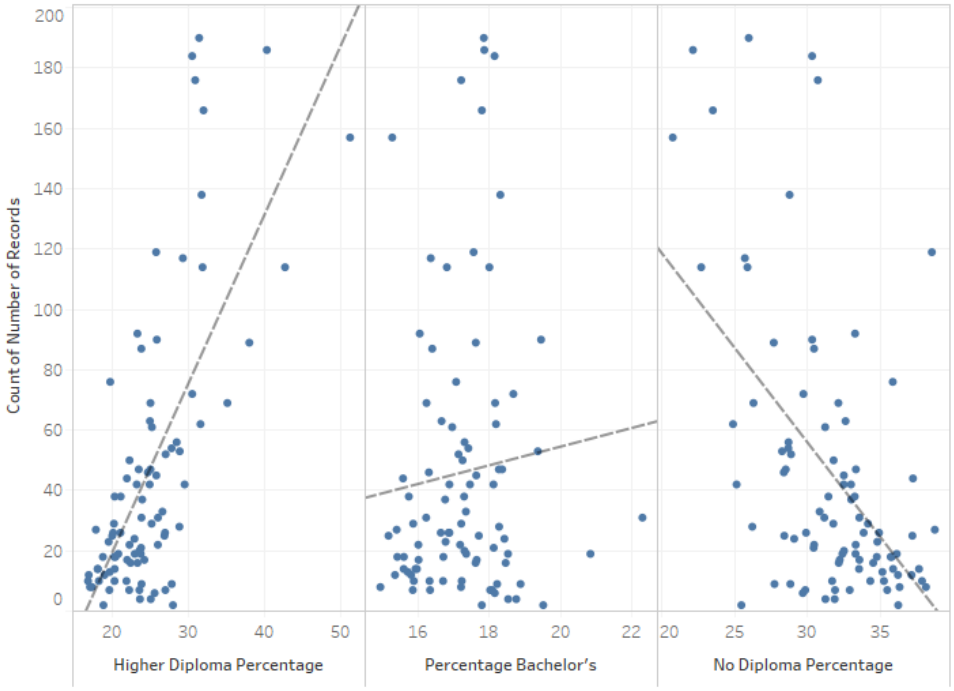


Figure 29: Correlations of Political non-Retweeters

	R-Squared	P-Value
Percentage Bachelor's	0.007	0.4
Higher Diploma Percentage	0.48	<0.0001
No Diploma Percentage	0.28	<0.0001

It can be seen here that the trends are very similar to those of political retweeters. Although the R-values are lesser but still very close to the original number. The evidence points to the similarity

between the areas where political retweeters originate from and where followers of politicians come from in terms of education.

1.92 Education in Group 3 (Non-Political Retweeters)

As mentioned above there are two subgroups in non-political retweeters (Footballers and Comedians). We will look at each of these groups and try to determine if the retweeters of this group are also coming from departments where the education level is higher. If that is the case then we can conclude that there is a high chance that this is the case of Twitter users in general and has no statistically significant relation with political retweeting.

Following are the graphs for the entertainment industry retweeters with respect to higher education percentage in a Département in contrast to the number of retweets coming from that Département.

Fig 30: Correlations of Non-Political Retweeters

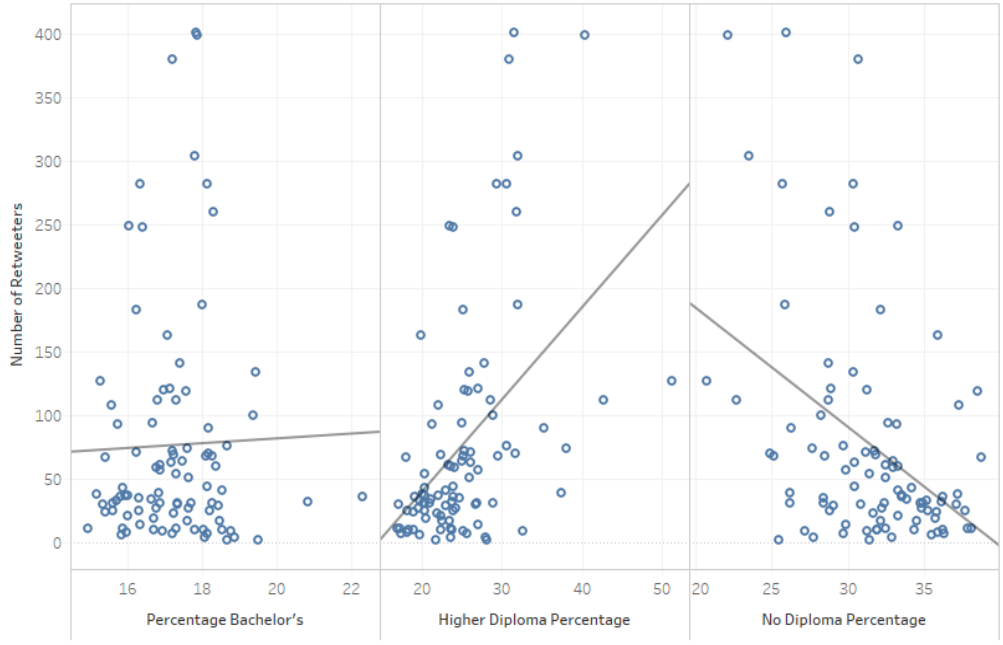


Figure 30: Correlations of Non-Political Retweeters

	R-Squared	P-Value
Percentage Bachelor's	0.00069	0.8
Higher Diploma Percentage	0.22	<0.0001

No Diploma Percentage	0.17	<0.0001

From this graph above it is visible that the general trend looks very similar to the political retweeters. As we can see that in the departments with a higher level of education contain more retweeters from the entertainment industry than the departments with a lower level of education. But if we look at the R-squared values for each of these graphs. These values are much lower than group 1. For example, the R-squared values for group 1 in Higher Diploma Percentage is above 0.5, whereas it is 0.22 here. This difference is enough to consider the possibility although entertainment group retweeters come from the more educated areas in France political retweeters have a comparably higher correlation with a high-level diploma than entertainment group retweeters.

Checking the retweeters of footballers concerning education yield the following results.

	R-Squared	P-Value
Percentage Bachelor's	0.001	0.7
Higher Diploma Percentage	0.33	<0.0001
No Diploma Percentage	0.18	<0.0001

The trend in retweeters of footballers is also very similar to the retweeters of entertainers. All the graphs look very similar to those of graph 1 and general trends are in a similar direction. But the R-squared value from political retweeters is considerably higher than both retweeters of entertainers and soccer players. It can, therefore, be seen that political retweeters are coming from areas with higher levels of education than retweeters of most popular non-political groups like the entertainment industry and sports.

As it can be seen from the above-mentioned observations, that there is a positive correlation between the percentage of educated people in a department and the number of Twitter profiles that come from there for each Group 1, Group 2, and Group 3. Although it is seen that this correlation becomes stronger for both political retweeters and political non-retweeters as compared to Group

3 which constitutes retweeters of non-political personalities. This leads me to conclude that, twitter population, in general, comes from areas that have a higher level of education, but this becomes particularly true for Twitter users (Both retweeters and non-retweeters) who are interested in politicians. About political retweeters, we can say that they come from areas that are well educated, but this is not specific to just this group and we cannot conclude that they are exceptional in terms of education when compared to political non-retweeters.

1.93 What can we know from names?

An important and very useful piece of data that we can gather from the profiles of retweeters is the name. Names can be used as a reasonable indication of the gender and ethnicity of retweeters.

How was the name data collected and cleaned?

Although twitter API does provide names of the users as entered in their profiles but a similar problem as the location was encountered, where names were either meaningless or incomplete for a large portion of the population. All the given names of the retweeters profiles were collected in a single database and then these names were partitioned into first names and last names. The first names were used for the classification of gender and ethnicity and last names were used only for the classification of ethnic background. To make this classification into subcategories based on gender and ethnic background, I needed a reference database to make comparisons with the retweeters database. This reference database was separately created using the most frequently used baby names in the world from multiple online sources that listed baby names. All together a database of 75 thousand names database was created where each name was assigned a gender and ethnicity in which that name is most popular. This name table was then cross-matched with the retweeters database first-names to determine the gender of the profile and then with last names to determine the ethnic background of a profile. Out of a retweeted database of 44,536 profiles, I was able to classify 23775 based on ethnic background and about 20855 retweeters profiles based on their gender using their first names.

1.94 Gender Results for Group 1

From the retweeters first names. The most important information I was able to retrieve was the gender of the users. As mentioned above, it was not possible to determine the gender for all the users as many of the names were not real and it was not possible to classify them. Here is the basic gender division of the total population of retweeters.

Fig 31: Gender division of the total population of retweeters.

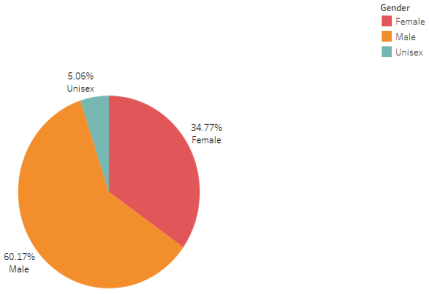
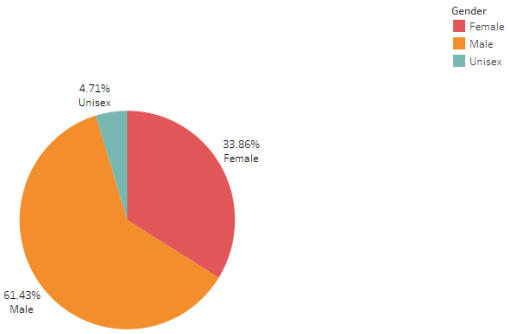


Figure 31: Gender division of the total population of retweeters.

One thing that needs explanation in this graph is the 'Unisex' label. These labels were given to the names that are usually given to both boys and girls. Therefore, it was difficult to classify them. As seen from the graph, a large portion of retweeters is male (60 percent) and the female population represents only 34 percent of the retweeters. It will, however, be interesting to see if this male-female ratio is maintained when we separate the French retweeters from the foreign retweeters. This separation will be done using the country tag which we have found out in the location section of this chapter. Here is the result for retweeters from France.



As seen from the above figure the division of gender for French retweeters is roughly the same as all retweeters. The percentage of male retweeters has only increased 1.43 percent at the expense of female retweeters and unisex names. However, the general trend is the same as above. It is, therefore, possible to infer that French Political retweeting is generally male-dominated. The analysis of gender will, however, be incomplete without looking into the candidate individually to see if there is a different picture on that level.

1.95 Gender Bias on individual Candidate Level

Here is a table describing the gender distribution of each of the individual politicians in France.

Table 16: Individual gender distributions for each of the politicians

	Hamon	Melenchon	Le Pen	Macron	Fillon
Female	35.87%	35.36%	35.02%	33.66%	31.52%
Male	59.22%	57.66%	60.64%	61.98%	63.61%
Unisex	4.92%	6.98%	4.35%	4.37%	4.87%

In general, it can be observed that the gender distribution for each of the politicians is very close to the collective gender distribution. Although, some deviations can be observed here. For example, Francois Fillon has considerably larger male retweeters when compared to the total male retweeters percentage (60 Percent), He also has a smaller percentage of female retweeters compared to other politicians and collective gender distribution from table 16.

Another anomaly that is boggling me, is that Melancon has a much lower percentage of male retweeters than others which becomes puzzling as the percentage of his female retweeters is the same and yet the percentage of unisex retweeters names are much higher for him. It was therefore manually checked to see if this was through an error in processing and it was discovered that this reflects the data correctly and no processing error has been made at this stage.

1.96 Ethnic Background and political retweeting

Because of the prohibition in France to collect ethnicity-related data, it is very difficult to find data on this matter. Here the context of this data processing is that we discovered in the language exploration of the retweeters data above that Arabic represented a small portion of retweeters as opposite to a significant presence in the French population according to data from OECD. It is, therefore, necessary to countercheck if this is indeed the case or some error has been made in the data processing. This was done by finding out the origin of the Twitter names. It is reasonable to assume that name can be used as a good measure to assess the presence of ethnic diversity among

the retweeters. Simons has shown that in the absence of ethnic data, the next best thing to use is the name (Simon 2010).

1.97 Results for the ethnic inquiry

It is found that the Arabic names represent only 3.05 percent of the total population and this result is very far from the result we got for the Arabic language 0.05 percent and much closer to OECD data which showed that people who speak Arabic in France represent roughly 3 percent of the population. It was found that most of the people with names of Arabic origin live in France and tweet in French. This confirms my first explanation from the language inquiry that Arabic-speaking people in France are more likely to tweet in French instead of using Arabic as their interface language for Twitter. So, we can conclude that the idea of the underrepresentation of Arabic people in political retweeting is not based on facts.

1.98 Gender Results for Group 2

The same process as above was repeated for the non-retweeters who are interested in politics. This was done to put the above findings in perspective. Following results were found from this inquiry.

Fig 32: Gender breakdown of Group 2

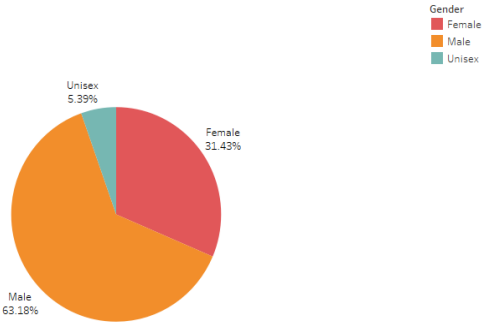


Figure 32: Gender breakdown of Group 2

1.99 Gender Results for Group 3

The same process as above was repeated for the non-political retweeters. Following results were found from the inquiry of entertainer retweeters group.

Fig 33: Gender breakdown of entertainment personality retweeters

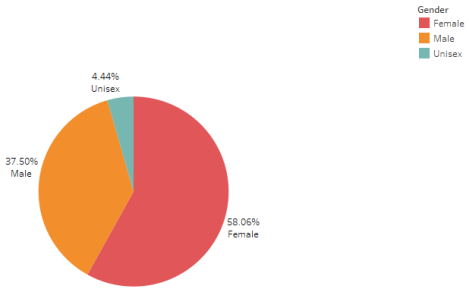


Figure 33: Gender breakdown of entertainment personality retweeters

The footballer retweeters yielded the following result with respect to gender.

Fig 34: Gender breakdown of football retweeters

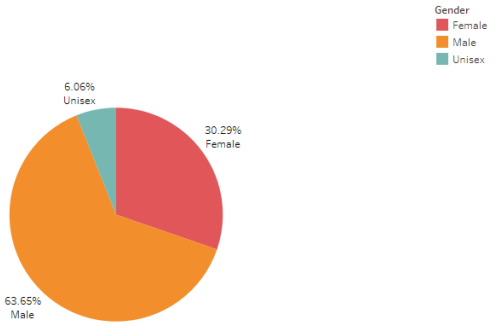


Figure 34: Gender breakdown of football retweeters

1.100 Conclusions about political retweeters from gender-related category

It can be seen from the graphs above that the gender division is very uniform between (Group 1) political retweeters and (Group 2) political non-retweeters. However, when we look at the non-political retweeters we can see from the difference between the gender divisions of retweeters of footballers and retweeters of entertainers that gender division is something very particular to each group and not a general trend among all groups on Twitter.

1.101 Self-Description of Retweeters

This analysis will not be complete without coming up with a generic picture representing the self-description and professions of political retweeters. It is an important factor in this analysis as a

cursory look in the data reveals that many of the retweeters have a professional interest in retweeting the politicians. They are either politicians themselves or then involved in political journalism of some sort, it will, therefore, be interesting to verify this from the data. For the purpose of this inquiry, I will divide the data into 8 broad categories.

Politicians

Official Political Party Accounts

Political Party titleholders

Government Officials or Government Offices

Political Journalists and Bloggers

Academic personals, (Students, Researcher, Teachers)

Generic Description profiles

Unidentifiable

1.102 Categorization of Retweeters according to the self-description

Professional identification using Twitter is an extremely difficult task as there is no profession-related section in Twitter API that will reveal that information about an account. Two approaches were explored to detect this kind of information. The first approach included the cross-matching of Twitter profiles with LinkedIn profiles as LinkedIn is a more professional platform where one is more likely to find professional information. This approach turned out to be unsuccessful as only 10 percent of retweeters profiles could be found on LinkedIn and this ratio was not good enough to detect the general trend. The second approach that was tried was the usage of Twitter description to identify the professions, which turned out to be relatively more successful. In our case, 72 percent of the retweeters have written something in their description while others have left that section blank. For each of the above-mentioned categories, certain keywords were selected that can be used to describe that category of individuals. A generic search for these keywords in the self-description database revealed the professional inclinations of retweeters. Following is the list of keywords searched for each of the categories.

Profession	Keywords Searched	Verified	Profiles Found	Percentage
Politicians	Ministre, Député, Dpute, Politician, senateur, Snateur, Maire, Prsident, Commissaire,	no	878	1.9%
Political Party title holders			1455	3.25%
Government Offices	Compte officiel , Ambassade,	Yes	68	0.15%
Political Journalists and Bloggers	Blog, Journal, Tele , auteur, écrivain, rédacteur , commentateur , critique, éditorialiste	No	1158	2.5%
Academic personals	Etudiant, prof, professeur, chercheur, ecole, linguist, science po, universit , scien, phd , docto , Diplôme , License, lyce, student	No	2085	4.66%

Political Party and group Accounts	Fillon, officiel, macron, republicains, Jeunes Républicains, en marche, em , ump, jeunes avec, parti socialiste, socialiste, hamon, ps, Fn, Front National, marine, pen, mlp, melechon, insoumis	No	523	1.1%
Dedicated Supporter Accounts		No	4684	10.47%
Generic self-description with no explicit political adherence		No	24021	53.7 %
No Description		No	11915	25.03%

Since the data about education and salary is not directly reported by the retweeters and is based on secondary information collected from their profile, we must be very careful in drawing conclusions from this information. Correlation cannot certainly be considered the same thing as causation and even if there is a healthy correlation between the retweeters count, what can conclude from this correlation is that people living in departments with higher education levels are more likely to retweet French politicians than the people who live in areas with lesser number of highly educated people.

1.103 Conclusions

Exploring the demographics of political retweeters has made it clear that demographics of political retweeters are generally close to demographics of general participation in online social platforms of political participation found through survey distributions (Greffet, Wojcik and Blanchard 2014). The space of political retweeting is male-dominated and concentrated in urban areas with relatively higher education levels. It has also been revealed that a very significant percentage of political retweeting happens on accounts of dedicated political workers and party accounts, which corroborates with the literature whereas the presence of international population among both political and non-political retweeters is highly representative of real-world international popularity.

Chapter 7 : Role of Retweeters in solidification of identity

1.104 Abstract

It is hard to ignore the role of retweeters in Twitter discourse as retweeting feature initially made Twitter different from other social media platforms. The role of retweeters can be thought of as rebroadcasters of the messages which is generally thought to be a part diffusion mechanism in both online and offline social networks. In the previous chapter about retweeters, I was able to show that the space of political retweeting is male-dominated and concentrated in urban areas with relatively higher education levels and quite possibly with higher income levels. In this chapter, I will further develop this point and try to argue that high-frequency retweeters in a divided network such as Twitter play the role of identity reinforcement in a top-down manner and can act as an important bridge in the implementation of what Habermass called 'refeudalization of the public sphere'.

To test the hypothesis that high-frequency retweeters play the role of ideology reinforcercement in the network, I will check the effect of external events15 on the subscription of large elites, compared to the effect of events on subscription of a smaller network of high-frequency retweeters. I will show that significant mobilization events such as elections or even unexpected events such as terrorist attacks have a large effect on the subscriptions of party heads and other such elite accounts (depending on the nature of events) whereas it has little to no effect on the subscription of smaller retweeters who grow gradually but in much more steady manner. This demonstrates the difference between the nature of elite networks and retweeter networks where elite subscriptions fulfill the subscriber's news consumption needs and retweeter subscriptions serve as a network of trust where opinion formation and reinforcement takes place.

1.105 Introduction

Habermas's framework on the public sphere has been extensively used in attempts to understand Twitter debates and also to make judgments on Twitter's role in the potential 'enrichment' or decline of the public sphere (Liu and Weber 2014) (S Bodrunova, Litvinenko and Blekanov 2016)

15 Such as elections, multiple terrorist attacks in France and other such events.

(Soares, Recuero and Zago 2018) (Dagoula 2019). The potential for Twitter to act as a public sphere in a normative sense as Habermas had envisioned it has been questioned in literature (Colleoni, Rozza and Arvidsson, Echo Chamber or Public Sphere? Predicting Political Orientation and Measuring Political Homophily in Twitter Using Big Data 2014). Despite its extensive usage in understanding the roles of Twitter, Habermas's tools have not been previously used to inspect detailed features in Twitter to inquire as to why Twitter does not act as a public sphere?. Retweeting is a prominent feature in Twitter that has the potential to allow individuals to rebroadcast any message on their network. On the surface, this feature has the potential to allow public debate to break the agenda-setting power of traditional media and allow for comments from the general public to gain popularity which has been observed to be the case with 'Viral Tweets'. But to generally understand the practical role of retweeting in Public debate, it is necessary to look at the possible functions that it can perform in establishing or distorting consensus. Retweets (without comment) can be imagined to perform two primary functions when it comes to political debates.

1. Diffusion of ideas
2. Reinforcement of identity

Diffusion mechanisms in Twitter are well defined and operationalized (Bastos, Raimundo and Travitzki 2013) (NgocHoang and Mothe 2018) but in addition to the diffusion, the role of retweeting has to be understood in terms of ideological reinforcement tool for the political elite. When it comes to the features of Twitter one obvious consequence of the increase in political homophily on Twitter and the division of Twitter communities into smaller clusters that are highly interconnected within themselves but not very well connected between themselves is the dearth of the path-ways for the spread of messages between the groups. As we discovered in the previous chapters that the only community that has been gradually becoming isolated from the main network are the communities that identify with nationalistic 'right-wing' populist values such as Front-National and some users from Les Republicain (who also have nationalistic ideas) and also some other nationalistic parties. This chapter is divided into two parts. In the first part, I will show in this chapter that the direct consequence of this isolation of one community from the global cluster is the formation of an isolated bubble with a high level of reinforcement of top-down messages through retweeting and a very low level of diffusion of messages and this process

reiterates and solidifies the identity of the community based on top-down social structure and prevents the open and rational public discourse on Twitter. As we saw in our data collection chapter, most of the very large profiles clustered in community 5 because a very large number of their followers came from a non-French context and followed only the very famous national figures from France. By looking at the retweeters of Marine Le-Pen I will show how high-frequency retweeters create an ideological reinforcement bridge between the leader and the community on Twitter and play more of a role of ideological reinforcer rather than information diffusers. The first part of this chapter will also provide support to the two-step flow hypothesis in the context of Twitter and make the case for high-frequency retweeters with medium to low indegree to be treated as 'influencers' in the flow of information rather than very large profiles.

In the second part of this chapter, I will try to further test the claim made about retweeters in the first part by checking the effect of external events on the growth rate of the elite subscriptions and comparing it with that of subscriptions in retweeters network. If we can consider the retweeter network to be a 'trust network' rather than a news network, its growth should be slow, consistent, organic, and not dramatically affected by external events.

1.106 Review of Literature

The committed agent hypothesis states that in a highly clustered network, a small set of committed agents have the power to reverse a majority-held opinion (Xie, et al. 2011) (Centola, Willer and W. Macy 2005). As we saw in the previous chapters of this thesis, Twitter has an increasingly divided follow network in France where high-frequency retweeters can be considered highly committed individuals. These individuals can be instrumental in spreading the 'influence' either through diffusion or reinforcement. While common users can connect to the top leadership directly through Twitter, it has been shown through previous studies that the level of trust between the individual user and 'opinion leaders' (in Lazerfeld's words) is much higher compared to the common user and top party leaders (Jain and Katarya 2018). If one considers high-frequency retweeters to be opinions leaders not in the sense that they diffuse messages to their large number of followers, who would've otherwise not found the message, but in the sense that they put their own stamp of approval of the message from the top hierarchies of the political party to common

users (no matter how many they are) who trust them16, it can refine the concept of opinion leadership in the context of Twitter and also help us understand that Twitter is a further continuation of the previous known structure of the hierarchical structure of political communication.

Part 1

To measure the effectiveness of the high-frequency retweeters on their receivers, I created two constructs 'diffusion effect' and 'reinforcement effect' and I will measure both of these effects on the audience of high-frequency retweeters and low-frequency retweeters to test the following hypothesis:

High-Frequency retweeters act as ideological reinforcers more so than low-frequency retweeters who act as diffusers of information to new users.

1.107 Diffusion effect

The diffusion effect in case of Twitter is defined as getting a Tweet to a user who is unlikely to see it if it had not been diffused by a retweet. Diffusion of both political and non-political messages is a topic of great interest in computational social sciences where much of the literature is dedicated to predicting the reach of a particular message based on network characteristics and text content of the Tweet (Meng, Peng and Tan 2018) (Kawamoto 2013).

1.108 Reinforcement effect

The reinforcement effect in the case of Twitter is defined as a phenomenon where a user who is already well embedded in a particular political cluster gets reinforcement of his already well-established political beliefs by seeing a tweet from someone he follows. (very close to echo chamber phenomena) . The reinforcement effect of Tweets is something that has not been studied extensively with respect to the retweeting activity. While diffusion is about knowing the content

16 This is the closest sense to Lazarsfeld's sense of opinion leadership from erie county study

of a message from another cluster, reinforcement can be an indicator of a having a long-term effect on a user where it becomes increasingly difficult for the user to change his initially held believes.

Fig 35: Visualization of Diffusion Paths and Reinforcement Paths

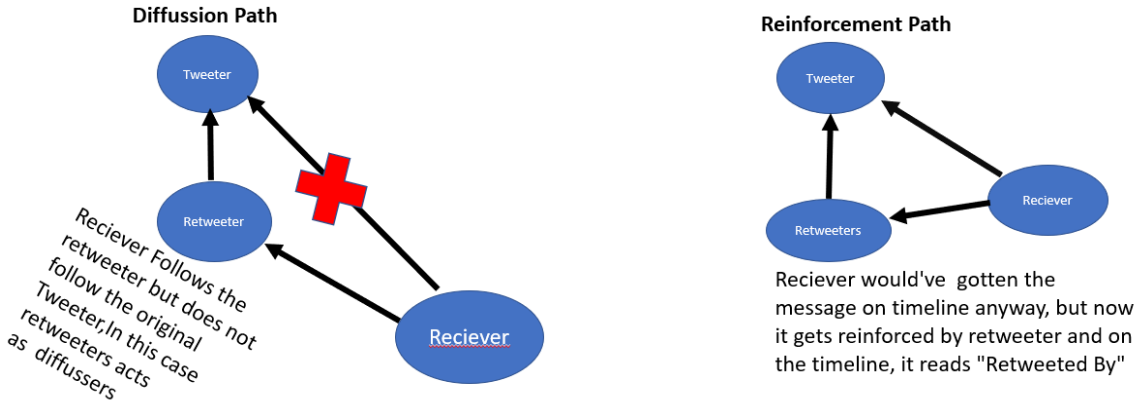


Figure 35: Visualization of Diffusion Paths and Reinforcement Paths

To isolate the effect of frequency of retweeting from other confounding variables, I only took retweeters from the 'right-wing' cluster in Twitter detected in the previous chapter and collected the following data from the Twitter account of Marine le Pen.

To test the difference between diffusion and reinforcement paths of the extreme right. The following information was gathered through Twitter API.

1. Tweets of mlp_officiel
2. Retweeters for each of the Tweets
3. Followers of each of the retweeters

Using this data another database was created that categorized the retweeter and their follower relationship into either a diffusion path or reinforcement path based on the criteria if they follow the original politician or not. These paths will then be regressed against each-other using retweet frequency as the third dimension. Hypotheses will be given credit if the positive relationship holds between frequency of retweeting and reinforcement paths and a negative relation holds between frequency and diffusion paths.

Figure 36: Paths found in all retweeters (both high-frequency and low-frequency)

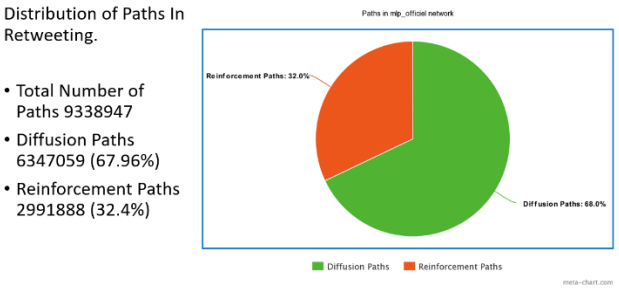


Figure 36: Paths found in all retweeters (both high-frequency and low-frequency)

Fig 37: Diffussion counts vs reinforcement counts among the retweeters of Marine Le Pen.

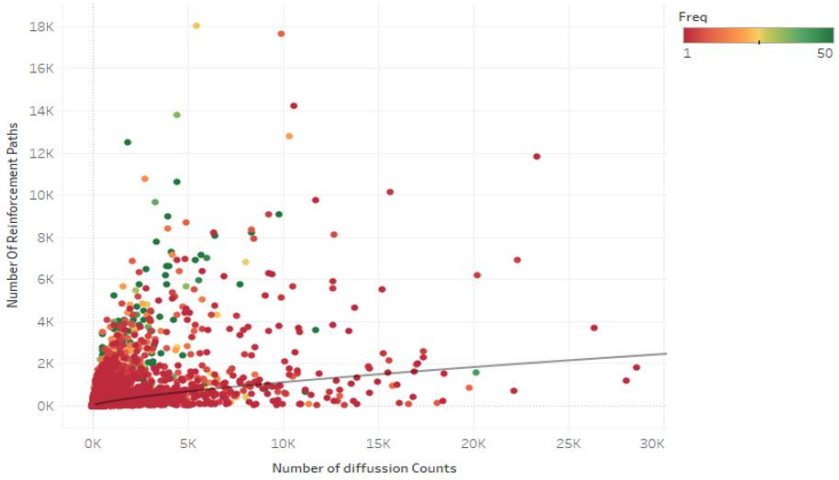


Figure 37: Diffussion counts vs reinforcement counts among the retweeters of Marine Le Pen

Here the Color indicates the frequency of retweeting mlp-official

From figure 37 It can be seen that high-frequency retweeters tend to have more reinforcement paths than diffusion paths, whereas low-frequency retweeters tend to have more diffusion paths as compared to reinforcement paths. This meaning of figure 37 can be interpreted in two ways. Either the people who follow high-frequency retweeters become influenced by the ideological reinforcement of high-frequency retweeters or the people who are already interested in the ideology follow the high-frequency retweeters because they want to consume the ideas presented

by these retweeters. In both cases, retweeters set themselves up as intermediaries of the flow of trust in a social network much like what opinion leaders of Paul Lazarsfeld's study.

1.109 How much of retweeting is diffusion phenomena and how much is reinforcement phenomena

As seen from the above graph, elite Tweets are used for both diffusion and ideological reinforcement and we also saw in the previous chapter that over time, the followers of the nationalist right-wing cluster are getting more and more isolated from other political groups. It will be interesting to see if this isolation has had any effect on the ratio of Marine-le-pen's diffusers and reinforcers. I will look into this using the following approach:

- For each of the retweeters of her tweet, I will loop through his/her followers.
- Assuming that each of the followers of the retweeter was able to see the tweet, I will then cross-match that follower with the database of reinforcement paths and diffusion-paths.
- If the follower is following at least one of the frequent retweeter who retweeted the same tweet before the retweeter that we are considering now, then the act will be considered reinforcement
- It will also be considered reinforcement if the recipient already follows the original politician and is likely to see the tweet on his time-line even if it was not retweeted
- The act will be considered diffusion if a follower of the retweeter does not subscribe to any of the previous retweeters of the same tweet and has no connection with the original politician.
- Once the above steps are done, I ran a time-series analysis of the ratio of diffusers and reinforcers of each of her tweets in the first 3 years of her Twitter account (Results are visible in figure 4)

Fig 38: Ratio between reinforcement and diffussion of Tweets of Marine Le Pen during first 3 years of her Twitter account

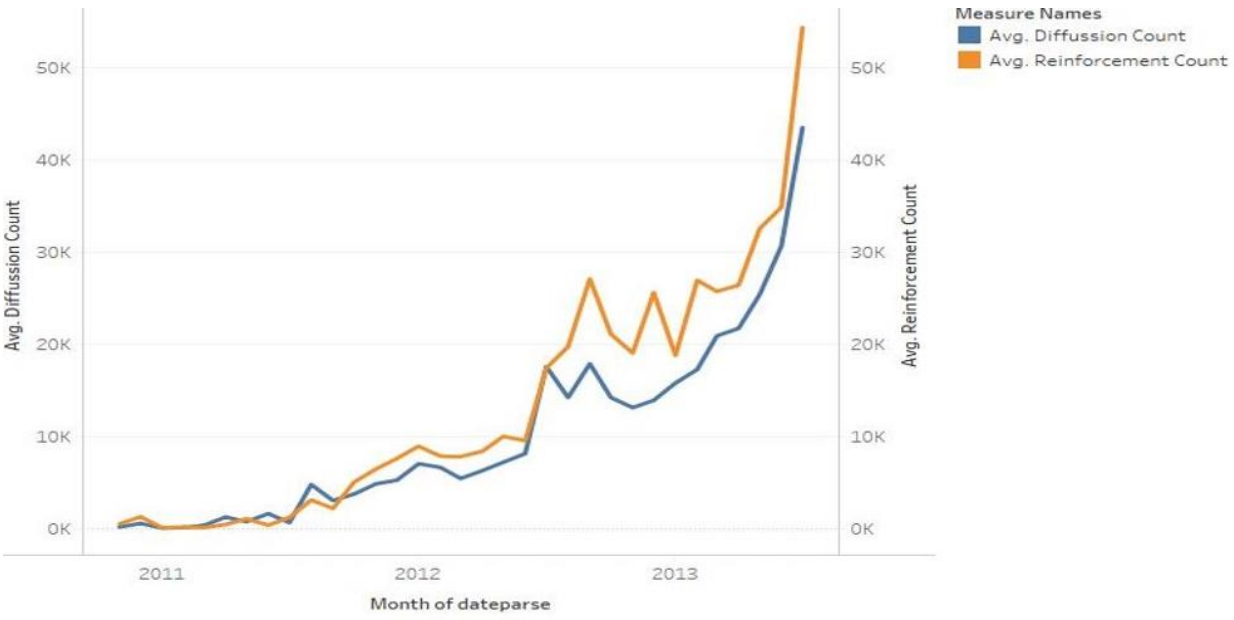


Figure 38: Ratio between reinforcement and diffussion of Tweets of Marine Le Pen during first 3 years of her Twitter account

From figure 38 we can see that Marine le pen's initial tweets were generally about the diffusion of her messages. One can argue that from 2011 and a few months before 2012 her account was mostly about direct communication with the followers as interpreters of Twitter as the one-step flow of communication would predict (Hilbert, Vasquez, et al. 2016). During the 2012 elections as well, it can be seen that the amount of diffusion and reinforcement was almost equal and it's not surprising that both of them had an upward trend. However, after that period, a larger number of her tweets were received by people who were already embedded in the reinforcement network of right-wing retweeters. This shows that there is a gradual increase in the ratio of reinforcement effect of her Tweets which increases our understanding of the role that amplification by retweeters plays in the spread of messages in a top-down communication network.

I will now manually look into the profiles of the retweeters to see who plays the role of reinforcer and who plays the role of diffuser in Marine le Pen's Twitter network. The following categories in table 1 were created for this manual analysis.

Table18: List of categories for manual annotation of retweeters

Category	Description
Dedicated Supporters	These are individuals who have overtly described themselves as party Supporters through their Photos, names or description.
Highly Politicized Sympathizers	These are individuals who are sharing a lot of political content that aligns with the party ideology but they do not explicitly declare themselves as party supporters.
Mildly Political Bloggers	These are individuals who do not post explicitly political content and do not have any overtly political affiliations.
High Ranking Party Leader	Any Member of Party ranked on a regional or higher level.
Low Ranking Party Leaders	Any members of the party that are ranked lower than the regional level
Common Sympathizers	People who are not highly active on Twitter and appeared to have put their genuine pictures and generally tweet about the mixture of political and non-political content

Sympathetic Media	Retweeter account that calls themselves media or alternative media and posts content that aligns with party idealogy
Non-dedicated Political Individual	People who are tweeting political content but without any political affiliation and they also retweet rival politicians

Once these categories were created, I took a random sample of 100 retweeters of Marine le Pen from the database of top 10k retweeters and placed them in one of the above categories by looking a the profile manually. To make a comparison between the two groups, I used the following formula

$$\text{Comparison matrix} = \frac{\text{Average Number of Reinfocement Paths}}{\text{Average Diffusion Path}}$$

Fig 39: Longer bars are an indicator that you are a reinforcer whereas shorter bars indicted that you are a diffuser

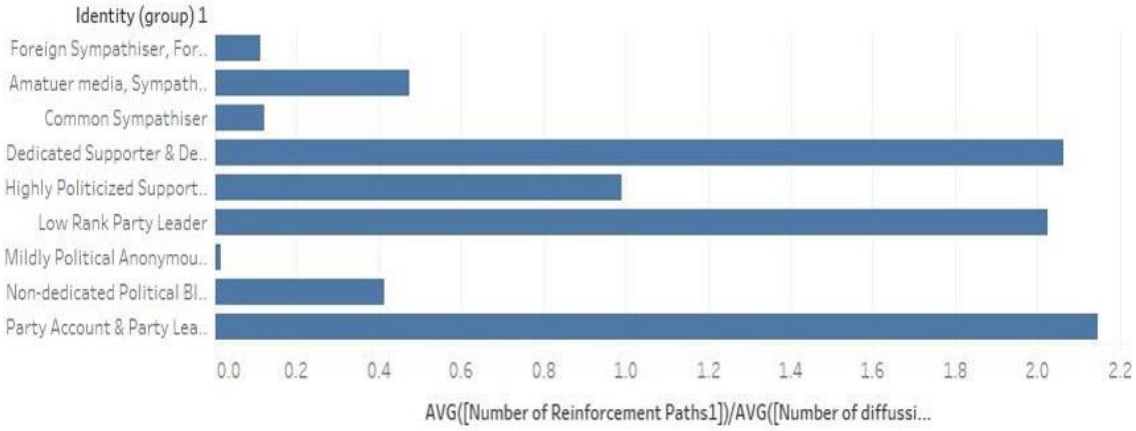


Figure 39: Longer bars are an indicator that you are a reinforcer whereas shorter bars indicted that you are a diffuser

From figure 39 we can notice that mildly political users, common sympathizers, and foreign sympathizers act as diffusers which means that they create a bridge between the political group and non-political groups. It is there possible to reject the null hypothesis in the favor of idea that mildly political entities are more responsible for diffusion and dedicated supported are responsible for reinforcement.

Part 2:

In this part of the chapter, I will trace back the history of the formation of follow relationships in both elites(party leaders) and opinion leaders (i.e high-frequency retweeters) and compare their growth rates with respect to multiple national events that transpired in France. The goal is to show that the growth pattern of large elites such as party leaders is highly associated with the nature of events whereas the cumulative effect of small and medium opinion leaders grows gradually but steadily over time which is similar to a 'trust network' (Wu, et al. 2019).

1.110 Methodology

Although there are a lot of examples of time-series analysis studies with Twitter data most of these studies are done using Twitter time-stamps in Tweets data (Michael and Paxson 2011) (Tinati, et al. 2012). An area that largely remains unexplored is the tracking of the history of the formation of follow relationships in Twitter concerning time. One of the reasons that time-based analysis of the formation of relationships is a difficult task to accomplish is because Twitter does not provide the time and date of formation of follow relationships through it's API. The challenge here is to infer this timing as accurately as possible. Here I overcame this obstacle using long-term time-based analysis methodology provided by using a time extraction algorithm originally proposed by Brandon Meeder (Meeder, et al. 2011) and later on used by Kiran Garimella for longitudinal studies of the Polarization question in question (Garimella and Weber 2017). The algorithm primarily works as follows; since Twitter provides the relationship data in chronological order as they were formed. I used the creation dates of follow profiles (provided by Twitter) to set lower bounds on time when the relationship started. While going through all the relationships in chronological order I change the lower bound value if the creation date of the encountered profile

occurs later than the previous one. As analyzed in the original paper, this method provides accurate results for profiles with a large number of followers or friends.

Fig 40: Number of new edges gained concerning time for all party leaders

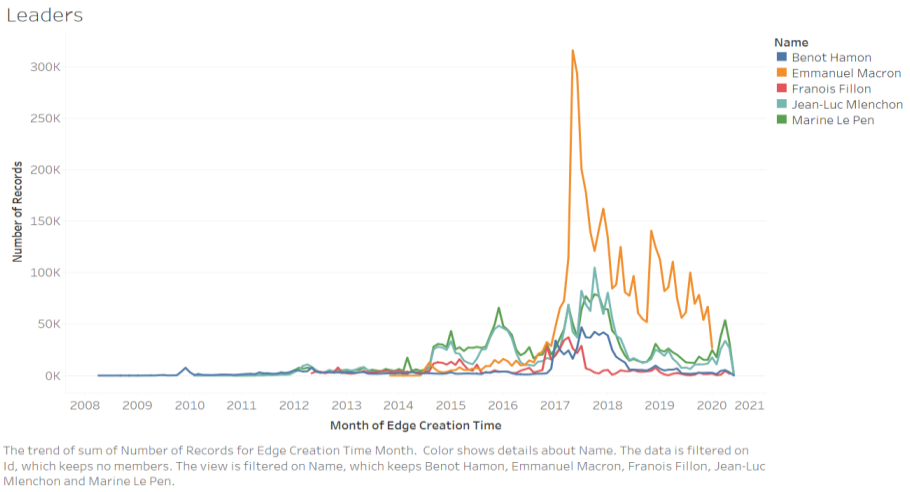


Figure 40: Number of new edges gained concerning time for all party leaders

From figure 40 we can see major spikes during election periods and in January 2015 and December 2015. This indicates that a lot of people started to subscribe to these elite profiles. Part of the reason for this growth in popularity of these profiles could be that traditional media gives serious coverage to these events and especially to certain elite political figures, therefore their popularity graph increases. If we compare the 2015 Terrorist attacks with elections of 2012 and 2017 we notice that both the center-left and center-right and even Emanual Macron did not get major spikes during the terror attacks of November 2015. However, populist charismatic leaders such as marine le pen and jean luc melenchon attracted a lot of attention and were able to build new relationships during these times which confirms our proposition that the nature of events determines who will gain most followers during a certain event.

Contrary to what we see in elites, I found a different type of graph in the growth of connections in the top 10k retweeters of Marine le Pen. They do grow over time, but the growth is not sudden and less dependent on the events compared to large elites.

Fig 41: Number of edges gained by top retweeters of Marine Le Pen

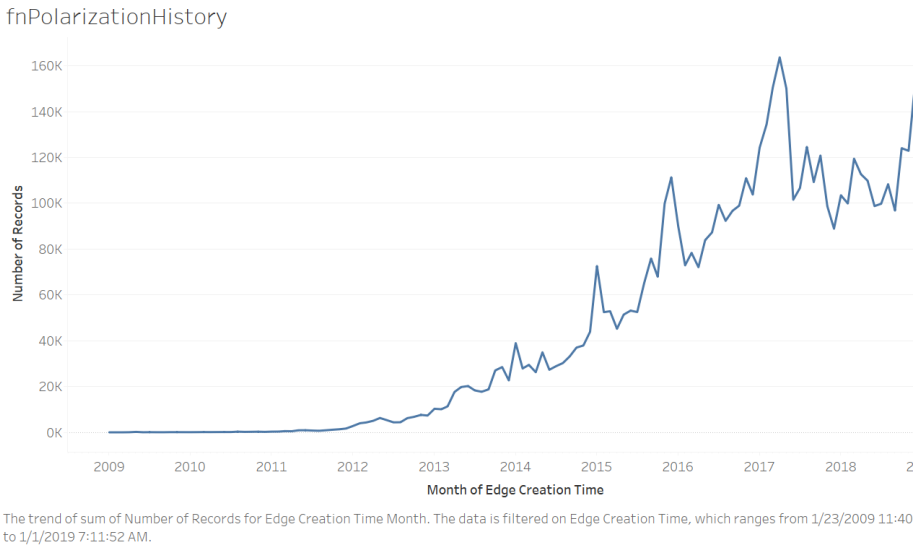


Figure 41: Number of edges gained by top retweeters of Marine Le Pen

We can notice, there is a gradual upward trend in the number of subscriptions that keeps on accelerating over time, as opposed to elite networks where they only get major spikes during the large events which die down later on. Given the sudden spikes in elites during the same periods as large events happened and small spikes among the followers of retweeters it can be inferred that retweeters are possibly playing a different role in the flow of communication than elite profiles and it is highly likely that this role akin to 'idealogy reinforcement' rather diffusion of news.

This result also has important implications for the debate of whether Twitter is a news network or a social network. We know from a study conducted on a complete Twitter network in 2010 that Twitter acts as a news network in the beginning and acts as a social network in later stages and the above result fall coherent with it and show that trend has continued ever since even though Twitter has grown immensely in size (Kwak, et al. 2010).

1.111 Conclusion

From the above chapter, it was possible to see that political retweeting plays a crucial role in the flow of communication and allows for the solidification of identities in the political clusters of Twitter. However, for that to happen a necessary condition is the dedication of a small number of devoted workers of a political party. The frequency of retweeting is one way in which this dedication can be judged. It can be seen here that recipients of high-frequency retweeters gradually increase over time largely independent of events in the real world (at least in the short term) which

points to their status as a network similar to a ‘trust network’ or a network of influence in terms such as that of the ‘opinion leaders’ from Erie County study of Paul Lazarsfeld. Even in cases where large events such as terrorist attacks transpire in a country, it is not the event itself that formulates the opinions of users but the deliberation that takes place afterward. In this deliberation, retweeters have the power to amplify or not amplify certain messages from the party leadership. It is through this mechanism that retweeters possess a limited amount of power like that of a gatekeeper.

Concluding Remarks

In this Thesis, I have made the case that although Twitter data in France may show moderate levels of homophily[17], this effect may have more to do with the type of beliefs and levels of motivation of the individuals reinforcing (retweeters in our case) these beliefs in a community rather than the nature of the technology itself. The uniqueness of Twitter lies in the fact that it has reduced the cost of many to many conversations, but the ease and accessibility of conversations is only one factor that could have possibly aided in scaling of public discourse without any regard for the quality of the conversations. This mere increase in the number of conversations can lead to the formation of political clusters as individuals are more likely to connect with other individuals, based on pre-existing affinity and alignment of interests. I demonstrated using data from French Twitter that, although there is visible fragmentation in the political sphere in France but over-time this fragmentation increases only for one group with extreme nationalistic and ethnocentric tendencies whereas for other groups the level of fragmentation remains relatively stable. This points to the non-uniformity of the impact of Twitter on the levels of political fragmentation which is enough to reject the hypothesis linking the use of the internet 2.0 to a general increase in levels of political homophily and consequent group political polarization (Cass R 1999).

As an alternative perspective, I proposed that Habermas's notion of transformation of public-sphere due to structural 'refeudalization' and top-down flow of communication can provide a better way to understand the increase in political homophily in Twitter. To demonstrate the hierarchical structure in the flow of communication in Twitter I showed that high-frequency political retweeters in the French network are elitist and can serve as a bridge between the political leaders and their followers. Whether we can call these retweeters 'opinion leaders' in Lazarsfeld's sense is highly debatable but their presence in the flow of communication is enough to point to the fact that ideological reinforcement is a top-down phenomenon with intermediaries playing the role of reinforcers.

A major methodological contribution of this thesis to Political Science literature is the proposition of a way to separate a country's Twitter network structure from the global Twitter network

[17] Modularity levels in American Twitter were found to be 0.48, whereas this level in the French case is 0.40

structure [18]. Future researchers can use this crawl method for taking representative country-level samples for further research.

[18] Python code for this tool is available in the Gurchani/crawl-Code: Crawling ssn (github.com)

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Detailed Summary of Thesis in English

Political Homophily in French Twitter

In the early 2000s, there were remarkably high expectations from the internet 2.0, to help increase the political engagement of ordinary citizens to create something akin to an ideal public sphere in Habermasian sense (Dahlberg 2001). But within a few years, it was clear that such expectations were to be met with doubt, if not a disappointment. Even cursory exploration of the Twitter data showed that there were very visible signs of the unequal distribution of influence and high levels of homophily in the network (Conover, Ratkiewicz and Francisco 2011). A small number of elite Twitter users managed to dominate the network to a large extent and effectively used it to communicate with their 'followers' (Avin, et al. 2012). However, initial studies on Twitter were mostly done using data only from the United States (as Twitter gained most of its initial users from the US) and that set the tone for future studies. Network homophily, political polarization, and election predictions were the general themes of most research papers published between 2008 and 2012 using Twitter data. Interestingly enough the first two of these themes were prevalent in American political science studies even before Twitter became a popular network (DiMaggio 1996) (Evans 2003). This points to the fact that observations made about American Twitter may be a reflection of particularities of American politics rather than a being a feature of Twitter as a medium of communication. Contextualization of claims based on Twitter data has thus become very important in political science literature in recent years. Initial observations of high levels of homophily in Twitter data were met with suspicion once the Twitter network started to gain popularity in other countries and there was more data available for researchers to observe the levels of homophily in multiple countries. It was clear that context mattered a lot in measurements of political homophily and that the two-party system, in general, showed higher levels of polarization in Twitter[19] (Urman 2019).

In appearance, Twitter's role in political debates can be considered as that of a facilitator of communication. It has certainly made it easy for its users to maintain direct contact with each other and also with the political and non-political elites. This 'facilitation' has raised some very important questions with regards to Twitter's ability to challenge the agenda-setting power of

[19] This can potentially explain why we observed such high levels of homophily in initial studies of Twitter.

traditional media. It has been found that traditional media still holds a considerable amount of agenda-setting power over Twitter discussions especially in "non-breaking-news" times but, Twitter discussions have become primary drivers of agenda in "breaking news" times (Su and Borah 2019). This may be interpreted as if Twitter encourages the democratization of public debate to some extent by giving voice to common people (Jackson 2019). While it is true that Twitter has decreased the cost of public debate, it is far from being well-established that Twitter has 'democratized the public debate'. Access to public debate forums is only one part of the process of deliberation. For the public to reach a meaningful consensus through deliberation, other pre-requisites have been discussed in detail in the works of Jurgen Habermas. His vision for communicative rationality puts forth a vision where 'force of better argument alone' allows the public to reach a consensus through deliberation. Such a vision assumes unidirectionality of public debate and an environment of deliberation where discussants can 'set aside' their social status[20]. However, in the 'real world', political debates in informal settings do not always meet these criteria. In theory, Twitter is a venue where anonymity can be used to 'set aside' the social status of participants in a debate but in practice, Twitter has failed to act as a venue for a rational socio-political debate.

Post-modernists have also raised some serious questions on the viability of a Habermasian public sphere in a post-modern world of the internet where the 'definition of self is fundamentally fragmented':

"*In the first, oral, stage the self is constituted as a position of enunciation through its embeddedness in a totality of face-to-face relations. In the second, print, stage the self is constructed as an agent-centered in rational/imaginary autonomy. In the third, electronic, stage the self is decentered, dispersed and multiplied in continuous instability*" (Poster 1990)

As pointed out above, data collected from some deliberation platforms on internet 2.0 also point to a largely divided set of groups. This may look as if the easier it becomes to engage in public debate (with new technological tools) the more fragmentation we will see in the public sphere.

[20] Habermas claims in 'Structural Transformation of public sphere' that discussants could 'set aside' their social status when having political discussions in cafes in Paris and London during the enlightenment period

However, this does not mean that Habermas's conception of communicative rationality has to be abandoned in favor of a new framework before investigating the reasons behind public fragmentation in a more thorough manner. Also, the Post-modern conception of 'decentered self' and its explanatory power in terms of levels of fragmentation in social networks has to be put to test.

To understand political fragmentation from the angle of 'political homophily', I define homophily as preferring to interact with someone similar to oneself in any way as opposed to interacting with people who are different. In the context of Twitter, it is taken to be an act of 'following' or interacting exclusively with people who are similar to oneself. When homophily is replicated on a larger scale in a social network, it can lead to the formation of clusters of users who are similar to each other. Skeptics of internet 2.0's ability to create a meaningful public sphere point to this phenomenon as a primary effect of political debates in social media (Sunstein 2001). Websites like Twitter are presented as platforms where individuals only connect with people like themselves and end up adopting an extreme version of one's initial political beliefs. As pointed out above, most of the evidence presented for high levels of homophily observed in Twitter comes from American data. In recent years, there has been a lot of interest in this question in France but there is still room for improvement of methods. It is for this reason that in this research I focus on French Twitter to see if the levels of homophily in French Twitter can be explained by the echo-chamber hypothesis.

Research Questions

There are means through which the concept of political fragmentation can be operationalized using Twitter data. In the Twitter literature, one of the most popular mediums through which levels of political fragmentation are judged in social networks is the level of 'political homophily'. As mentioned above the initial studies with Twitter data were mostly done with American data and the levels of homophily that were observed through these studies provided credibility to the hypothesis that internet 2.0 may contribute to an increase in the level of group polarization. The root of the hypothesis that internet 2.0 may cause an increase in political homophily and also increase group polarization levels can be traced back to cass sunstein's work in Republic.com (Sunstein 2001). Twitter was one of the first venues where observations regarding this hypothesis were made, but most of these studies treated Twitter as an observatory reflective of the real world

and not a venue in itself only accessible to (and interesting for) certain kinds of people. Twitter users and their activity was thought to be an effect of them being on the Twitter platform and not a function of them being fundamentally different from the population in other important demographic ways. It was a later stage in research on this question that demographics of Twitter users were found to differ from the rest of the population (Mellon and Prosser 2017) and it was also found that political involvement in Twitter is a function of many demographic features absent from data provided by official Twitter API (Boyadjian and Marie 2014). Twitter studies on homophily showed that Twitter users were divided on issues, they ignored the fact that this did not necessarily imply that being on Twitter is the reason for this division in opinion.

Following is the list of research questions I will try to answer in this thesis.

5. Is the Twitter network in France fragmented into communities with similar political and social interests?
6. If they are divided does this fragmentation affect to all political groups in a uniform way?
7. What does fragmentation mean in terms of the identity of groups and deliberation between the groups?
8. If communities in Twitter are formed based on the social and political interests of the users, are these communities internally hierarchical or more egalitarian?

Political homophily is still a popular theme in Twitter studies and it is an open question if ease of communication that came with social media platforms like Twitter allowed users to have a serious selection bias in finding people to connect with or if this bias already existed and Twitter just provided a way for social scientists to measure it. In this thesis, I make the case that if the level of homophily in French Twitter is measured over time using the follow-network, we will notice that not all clusters formulate echo chambers. I will test the hypothesis that level of homophily in a Twitter community is dependent on the type of ideology modulated by the level of motivation from the community's opinion leaders.

The argument is structured in two parts. In the first part, I aim to study the levels of political homophily in the context of French Twitter. I will focus on the strategies used in previous works to measure the levels of homophily in the Twitter network and present a novel method of collecting and validating country-level follow networks on Twitter. This network graph will then be used for

extrapolating political affiliations, community structure, and the level of embeddedness for a large database of French users on Twitter. Once the above community structure has been established, I will then study the evolution of political clusters over time to see if the 'increase in political homophily' is a phenomenon orthogonal to the type of ideological inclinations.

In the second part of this thesis, I will make the case that high-frequency political retweeters act as intermediaries between the political elites and common users in Twitter. While political retweeters are generally more elitist than non-political retweeters but retweeters of more isolated political clusters (such as nationalist right-wing) are highly motivated individuals who act as ideological reinforcers in the network and thus prove instrumental in maintaining the hierarchical structure of the network.

Overall this study will show that the group polarization phenomenon in Twitter is inherently top-down, where political elites can use intermediaries such as retweeters to exercise political influence[21]. I will argue that Twitter's failure to create a rational debate in the Habermasian sense was due to the factors external to Twitter and had to do with the hierarchical nature of the society rather than the conception of the 'decentralized self'.

The theoretical framework that I use for this study comes from Jurgen Habermas's conception of the Public sphere presented in his book 'The Structural Transformation of the Public Sphere' and his conception of 'consensus through communicative rationality. I will not argue that Twitter has the potential to act as a public sphere but I investigate political homophily as a possible cause for Twitter's failure to act as a venue for rational public debate. I argue that Habermas's public sphere can only exist when the pre-assumption of rationality (communitive) aligns. Without this necessary condition, communal fragmentation will continue to increase as individuals will move to social circles where such alignment is possible. In parallel to such clusterization, there is also a visible increase in hierarchies in these social networks where only a few nodes attract or spread most of the content on the whole network. Haberman's notion of feudalization of socio-political space and increase in hierarchies can better explain the polarization phenomenon on Twitter as, within this framework, it is possible to account for the fact that the 'nature' of ideas matter and that political

[21] Much as it was observed in erie county study of Paul Lazarsfeld.

polarization is not a mechanized phenomenon immune to identity and hierarchical dynamics of a group.

Theoretical Contributions:

Following is the list of theoretical contributions from my thesis:

- This thesis brings together two theoretical frameworks largely used for understanding political homophily in Twitter data. I argue that Habermas's notion of 'refeudalization of public sphere' points to the same hierarchical structure of communication with intermediaries that Paul Lazersfeld had previously observed in his studies of political influence.

- I show that political fragmentation of multiple ideological clusters in Twitter can be better explained by the type of ideological inclinations of clusters and by the dedication level of smaller intermediaries(retweeters) between the leadership and the common users who play a role of ideological reinforcer in the network.

- I show that Habermas's normative concept of the 'public sphere' has value in understanding the failure of Twitter to turn out to be a more democratizing social space. In his work, Habermas pointed out to reintroduction of hierarchies in the public sphere as one of the main reasons for the quality of deliberations to decline in the public sphere. I show that in the Twitter network, it is not only the small number of the political elite that influence the opinions but also that there is large number of smaller nodes similar to 'opinion leaders' who act as intermediaries between leaders and the general public and act as ideological reinforcers in the network.

Methodological Contributions:

Following is the list of methodological contributions from my thesis:

- The main methodological contribution of this thesis is that I propose a method to crawl and validate country-level follow networks from Twitter and developed a python tool for such a crawl. This crawl is an important step in measuring the level of political fragmentation

in multiple communities on Twitter as it can separate a country's networks on Twitter from a global network graph.

- Ideal point estimation using Twitter data is an area of interest in Twitter-based political studies. By running community detection algorithms on the network graph of French Twitter, I was able to extrapolate the political affiliation of users on a very large scale.

- I also developed a method for vectorization profiles in Twitter such that initial ideological inclinations could be compared with their final ideological inclination. This comparison allows me to claim that not all profiles will experience significant changes in their level of homophily and only nationalist right-wing profiles in France show signs of significant homophily after being on Twitter for a long time.

- To the best of my knowledge, this thesis is the first one to run a correspondence analysis on Twitter self-descriptions. Using this method, it is possible to see the way Twitter clusters see themselves. This is done to know more about the ideological inclinations of clusters in Twitter.

Discussion:

From the results of this thesis, we can observe that homophily on Twitter is not a phenomenon that affects all political clusters in the same way. If political polarization is also a function of the level of homophily as put forth in the social psychology literature (Myers and Lamm 1976) , it is then possible to treat levels of homophily as a latent variable for levels of polarization. Using this approach it is possible to question the hypothesis put forth by Cass Sunstein regarding the polarizing impacts of internet 2.0. Sunstein assumes that websites like Twitter will allow individuals to selectively follow the people that they already support. Thus it will create groups of people who will be similar to each other in their political convictions who will reinforce each other in ideological issues. Sunstein proposed that this will increase levels of homophily and also augment the levels of political polarization.

In this thesis, I demonstrate that this model does not take into account the types of ideologies and that while we see the formation of isolated groups in Twitter but this effect is not uniform and does not impact all groups in the same way as Sunstein predicted. Another factor that affects the level of homophily in a group is the level of conviction from dedicated users in a cluster. Ideological reinforcement in Twitter clusters happens through intermediaries who belong to demographics that are not randomly distributed. These are highly committed men, living in urban areas and are more likely to be well-educated. In this way, the adoption of ideological convictions in Twitter is not a result of rational debate but still relies on hierarchical structures of communication as Paul Lazarzfeld has observed in his studies. The failure of Twitter to encourage rational political debate is attributed to what Habermas called ‘refeudalization of public sphere’. In other words, Twitter could not have functioned as a public sphere because of the hierarchical structure of society, external to any communication network.

Detailed Summary of Thesis in French

Au début des années 2000, on attendait de l'internet 2.0 qu'il permette d'accroître l'engagement politique des citoyens ordinaires et qu'il créé un espace qui s'apparente à une sphère publique idéale au sens habermassien. (Dahlberg 2001). Mais dès les premières années, il est apparu clairement que ces attentes allaient se heurter à des doutes, et être source de déception. Même une exploration superficielle des données Twitter a montré qu'il y avait des signes très visibles de la distribution inégale de l'influence et des niveaux élevés d'homophilie dans le réseau. (Conover, Ratkiewicz and Francisco 2011). Une petite minorité d'élites est parvenue, dans une large mesure, à dominer le réseau et à l'utiliser efficacement pour communiquer avec ses « followers » (Avin, et al. 2012). Cependant, les premières études sur Twitter ont été réalisées en utilisant des données provenant uniquement des États-Unis (puisque la plupart des premiers utilisateurs de Twitter étaient américains), ce qui a donné le ton aux études futures. L'homophilie de réseau, la polarisation politique et les prédictions électorales étaient les thèmes généraux de la plupart des articles de recherche publiés entre 2008 et 2012 à partir de données Twitter. Il est intéressant de noter que les deux premiers de ces thèmes étaient prédominants dans les études de sciences politiques américaines avant même que Twitter ne devienne un réseau populaire... (DiMaggio 1996) (Evans 2003). Cela montre que les observations faites sur Twitter aux États-Unis peuvent être le reflet des particularités de la politique américaine plutôt qu'une caractéristique de Twitter en tant que moyen de communication. La contextualisation des affirmations basées sur les données de Twitter est donc devenue très importante dans la littérature de science politique ces dernières années. Les observations initiales de niveaux élevés d'homophilie dans les données Twitter ont été accueillies avec suspicion lorsque le réseau Twitter a commencé à gagner en popularité dans d'autres pays et que les chercheurs disposaient de davantage de données pour observer les niveaux d'homophilie dans plusieurs pays. Il est apparu, de manière évidente, que le contexte importait beaucoup dans les mesures de l'homophilie politique et que le système bipartisan, en général, présentait des niveaux plus élevés de polarisation sur Twitter. [22] (Urman 2019).

[22] Cela peut potentiellement expliquer pourquoi nous avons observé des niveaux d'homophilie aussi élevés dans les premières études sur Twitter.

En apparence, le rôle de Twitter dans les débats politiques peut être considéré comme celui d'un facilitateur de communication. Il a certainement permis à ses utilisateurs de maintenir aisément un contact direct entre eux, mais aussi avec l'élite politique et non politique. Cette "facilitation" a soulevé des questions très importantes quant à la capacité de Twitter à remettre en question le pouvoir de fixation de l'agenda des médias traditionnels. Il s'est avéré que les médias traditionnels détiennent toujours un pouvoir considérable sur les discussions de Twitter, surtout en dehors des périodes de "nouvelles de dernière minute", mais que les discussions de Twitter sont devenues les principaux moteurs de l'agenda en période de "nouvelles de dernière minute". (Su and Borah 2019). Cela peut être interprété comme si Twitter encourageait, dans une certaine mesure, la démocratisation du débat public en donnant la parole aux gens ordinaires. (Jackson 2019). S'il est vrai que Twitter a réduit le coût du débat public, il est loin d'être établi que Twitter a « démocratisé le débat public ». L'accès aux forums de débat public n'est qu'une partie du processus de délibération. Pour que le public parvienne à un consensus significatif par le biais de la délibération, d'autres prérequis ont été discutés en détail dans les travaux de Jurgen Habermas. Sa vision de la rationalité communicative propose une vision où "la seule force du meilleur argument" permet au public de parvenir à un consensus par la délibération. Une telle vision suppose l'unidirectionnalité du débat public et un environnement de délibération où les participants peuvent "mettre de côté" leur statut social[23]. Cependant, dans le "monde réel", les débats politiques dans des cadres informels ne répondent pas toujours à ces critères. En théorie, Twitter est un lieu où l'anonymat peut être utilisé pour "mettre de côté" le statut social des participants à un débat, mais dans la pratique, Twitter n'a pas réussi à servir de lieu pour un débat sociopolitique rationnel.

Les post-modernistes ont également soulevé d'importantes questions sur la viabilité d'une sphère publique habermassienne dans un monde post-moderne d'Internet où la "définition du soi est fondamentalement fragmentée" :

"Dans la première étape, orale, le soi est constitué comme une position d'énonciation à travers son encastrement dans une totalité de relations de face-à-face. Dans la deuxième étape, celle de l'impression, le soi est construit comme un agent centré sur l'autonomie rationnelle/imaginaire.

[23] Habermas affirme dans *Transformation structurelle de la sphère publique* que les discutant pouvaient " mettre de côté " leur statut social lors des discussions politiques dans les cafés de Paris et de Londres à l'époque des Lumières.

Dans la troisième étape, électronique, le soi est décentré, dispersé et multiplié dans une instabilité continue" (Poster 1990).

Comme nous l'avons souligné plus haut, les données recueillies auprès de certaines plateformes de délibération sur l'internet 2.0 font également apparaître un ensemble de groupes largement divisés. On pourrait croire que plus il devient facile de s'engager dans un débat public (grâce aux nouveaux outils technologiques), plus la fragmentation de la sphère publique s'accentue.

Cela ne signifie pas pour autant que la conception de la rationalité communicative de Habermas doive être abandonnée en faveur d'un nouveau cadre avant d'étudier les raisons de la fragmentation publique de manière plus approfondie. En outre, la conception post-moderne du "moi décentré" et son pouvoir explicatif en termes de niveaux de fragmentation dans les réseaux sociaux doivent être mis à l'épreuve.

Pour comprendre la fragmentation politique sous l'angle de l'" homophilie politique ", je définirai l'homophilie comme le fait de préférer interagir avec une personne similaire à soi, de quelque manière que ce soit, plutôt qu'avec des personnes différentes. Dans le contexte de Twitter, il s'agit de l'acte de "suivre" ou d'interagir exclusivement avec des personnes qui sont similaires à soi. Lorsque l'homophilie est reproduite à plus grande échelle dans un réseau social, elle peut conduire à la formation de groupes d'utilisateurs qui sont similaires les uns aux autres. Les sceptiques quant à la capacité d'Internet 2.0 à créer une sphère publique significative soulignent que ce phénomène est l'un des principaux effets des débats politiques dans les médias sociaux (Sunstein 2001). Les sites web comme Twitter sont présentés comme des plateformes où les individus n'interagissent qu'avec des personnes comme eux et finissent par adopter une version extrême de leurs convictions politiques initiales. Comme indiqué ci-dessus, la plupart des preuves présentées pour les niveaux élevés d'homophilie observés sur Twitter proviennent de données américaines. Ces dernières années, cette question a suscité un grand intérêt en France, mais les méthodes peuvent encore être améliorées. C'est pour cette raison que dans ce travail de recherche, je me concentrerai sur le Twitter français pour voir si les niveaux d'homophilie dans celui peuvent être expliqués par l'hypothèse de la chambre d'écho.

Questions de recherche

Il existe des moyens par lesquels le concept de fragmentation politique peut être opérationnalisé à l'aide des données Twitter. Dans la littérature sur Twitter, l'un des moyens les plus populaires par lequel les niveaux de fragmentation politique sont jugés dans les réseaux sociaux est le niveau d'" homophilie politique ". Comme nous l'avons mentionné plus haut, les premières études sur les données Twitter ont été réalisées principalement sur des données américaines et les niveaux d'homophilie observés dans le cadre de ces études ont apporté de la crédibilité à l'hypothèse selon laquelle l'Internet 2.0 peut contribuer à une augmentation du niveau de polarisation des groupes. L'origine de l'hypothèse selon laquelle l'Internet 2.0 peut entraîner une augmentation de l'homophilie politique et également une augmentation des niveaux de polarisation de groupe remonte au travail de Cass Sunstein dans Republic.com. (Sunstein 2001). Twitter a été l'un des premiers sites où des observations concernant cette hypothèse ont été faites, mais la plupart de ces études ont traité Twitter comme un lieu d'observation reflétant le monde réel et non comme un site ~~en soi~~ uniquement accessible à (et intéressant pour) certains types de personnes. Les utilisateurs de Twitter et leur activité étaient considérés comme un effet de leur présence sur la plate-forme Twitter et non comme une fonction qui les différencie fondamentalement de la population par d'autres aspects démographiques importants. C'est à un stade ultérieur de la recherche sur cette question que l'on a constaté que les caractéristiques démographiques des utilisateurs de Twitter différaient du reste de la population. (Mellon and Prosser 2017) et que l'engagement politique sur Twitter est fonction de nombreuses caractéristiques démographiques absentes des données fournies par l'API officielle de Twitter. (Boyadjian and Marie 2014). Les études portant sur l'homophilie sur Twitter ont montré que les utilisateurs de Twitter étaient divisés sur des questions, mais elles ont ignoré le fait que cela n'impliquait pas nécessairement que le fait d'être sur Twitter soit la raison de cette division de l'opinion.

Voici la liste des questions de recherche auxquelles je vais tenter de répondre dans cette thèse.

1. Le réseau Twitter en France est-il fragmenté en communautés ayant des intérêts politiques et sociaux similaires ?
2. S'ils sont divisés, cette fragmentation affecte-t-elle tous les groupes politiques de manière uniforme ?

3. Que signifie la fragmentation en termes d'identité des groupes et de délibération entre les groupes ?
4. Si les communautés sur Twitter se forment en fonction des intérêts sociaux et politiques des utilisateurs, ces communautés sont-elles hiérarchisées en interne ou plus égalitaires ?

L'homophilie politique est toujours un thème populaire dans les études sur Twitter et la question reste ouverte de savoir si la facilité de communication qui accompagne les plateformes de médias sociaux comme Twitter a permis aux utilisateurs d'avoir un important biais de sélection dans la recherche de personnes avec lesquelles interagir ou si ce biais existait déjà et que Twitter a simplement fourni un moyen pour les chercheurs en sciences sociales de le mesurer. Dans cette thèse, je vais démontrer que si le niveau d'homophilie dans le Twitter français est mesuré dans le temps en utilisant le réseau de followers, nous remarquons que tous les clusters ne forment pas des chambres d'écho. Je testerai l'hypothèse selon laquelle le niveau d'homophilie dans une communauté Twitter dépend du type d'idéologie modulée par le niveau de motivation des leaders d'opinion de la communauté. L'argumentaire est structuré en deux parties. Dans la première partie, je vise à étudier les niveaux d'homophilie politique dans le contexte du Twitter français. Je me concentrerai sur les stratégies utilisées dans les travaux précédents pour mesurer les niveaux d'homophilie dans le réseau Twitter et je présenterai une nouvelle méthode de collecte et de validation des réseaux de follow au niveau national sur Twitter. Ce graphe de réseau sera ensuite utilisé pour extrapoler les affiliations politiques, la structure communautaire et le niveau d'encastrement pour une large base de données d'utilisateurs français sur Twitter. Une fois la structure communautaire établie, j'étudierai l'évolution des clusters politiques dans le temps pour voir si l'augmentation de l'homophilie politique est un phénomène orthogonal au type d'inclinations idéologiques.

Dans la deuxième partie de cette thèse, je soutiendrai que les retweeters politiques à haute fréquence agissent comme des intermédiaires entre les élites politiques et les utilisateurs ordinaires de Twitter. Alors que les retweeters politiques sont généralement plus élitistes que les retweeteurs non politiques, les retweeteurs de groupes politiques plus isolés (tels que la droite nationaliste)

sont des individus très motivés qui agissent comme des catalyseurs idéologiques dans le réseau et s'avèrent ainsi instrumentaux dans le maintien de la structure hiérarchique du réseau.

Dans l'ensemble, cette étude montrera que le phénomène de polarisation des groupes sur Twitter est intrinsèquement descendant, les élites politiques pouvant utiliser des intermédiaires tels que les retweeters pour exercer une influence politique[24]. Je soutiendrai que l'incapacité de Twitter à créer un débat rationnel au sens habermassien est due à des facteurs externes à Twitter et est liée à la nature hiérarchique de la société plutôt qu'à la conception du "soi décentralisé".

Le cadre théorique que j'utiliserai pour cette étude provient de la conception de la sphère publique présentée par Jurgen Habermas dans son livre *The Structural Transformation of the Public Sphere* et de sa conception du " consensus par la rationalité communicative ". Je ne soutiendrai pas que Twitter a le potentiel d'agir comme une sphère publique mais j'étudierai l'homophilie politique comme une cause possible de l'échec de Twitter à agir comme un lieu de débat public rationnel. Je soutiendrai que la sphère publique de Habermas ne peut exister que lorsque la présomption de rationalité (communitive) s'aligne. Sans cette condition nécessaire, la fragmentation communautaire continuera à s'accroître, les individus se déplaçant vers des cercles sociaux où un tel alignement est possible. Parallèlement à cette clusterisation, on observe également une augmentation visible des hiérarchies dans ces réseaux sociaux où seuls quelques nœuds attirent ou diffusent la majorité du contenu sur l'ensemble du réseau. La notion de féodalisation de l'espace socio-politique et d'augmentation des hiérarchies proposée par Haberman peut mieux expliquer le phénomène de polarisation sur Twitter car, dans ce cadre, il est possible de rendre compte du fait que la "nature" des idées compte et que la polarisation politique n'est pas un phénomène mécanisé qui échappe aux dynamiques identitaires et hiérarchiques d'un groupe.

Contributions théoriques :

Voici la liste des contributions théoriques de ma thèse :

- Cette thèse réunit deux cadres théoriques largement utilisés pour comprendre l'homophilie politique dans les données Twitter. Je soutiens que la notion de " reféodalisation de la sphère publique " de Habermas indique la même structure hiérarchique de communication

[24] Comme cela a été observé dans l'étude du comté d'Erie de Paul Lazersfeld.

avec des intermédiaires que Paul Lazersfeld avait précédemment observés dans ses études sur l'influence politique.

- Je montre que la fragmentation politique de multiples clusters idéologiques sur Twitter peut être mieux expliquée par le type d'inclinations idéologiques des clusters et par le niveau de dévouement des petits intermédiaires (retweeters) entre les dirigeants et les utilisateurs ordinaires qui jouent un rôle de catalyseur idéologique dans le réseau.

- Je montre que le concept normatif de Habermas de la " sphère publique " est utile pour comprendre l'échec de Twitter à devenir un espace social plus démocratisant. Dans son travail, Habermas a souligné la réintroduction des hiérarchies dans la sphère publique comme l'une des principales raisons du déclin de la qualité des délibérations dans la sphère publique. Je montre que, dans le réseau Twitter, ce n'est pas seulement un nombre réduit d'élites politiques qui influence les opinions, mais aussi qu'un grand nombre de nœuds plus petits, semblables aux "leaders d'opinion", agissent comme des intermédiaires entre les leaders et le grand public et comme des catalyseurs idéologiques dans le réseau.

Contributions méthodologiques :

Voici la liste des contributions méthodologiques de ma thèse :

- La principale contribution méthodologique de cette thèse est une méthode pour « crawler » et valider les réseaux de follow au niveau national à partir de Twitter ainsi qu'un outil python dévéloppé pour un tel crawl. Ce crawl est une étape importante pour mesurer le niveau de fragmentation politique dans de multiples communautés sur Twitter car il permet de séparer les réseaux d'un pays sur Twitter d'un graphe de réseau global.

- L'estimation du point idéal à l'aide de données Twitter est un domaine d'intérêt pour les études politiques basées sur Twitter. En exécutant des algorithmes de détection de communauté sur le graphe du réseau Twitter français, j'ai pu extrapoler l'affiliation politique des utilisateurs à une très grande échelle.

- J'ai également développé une méthode de vectorisation des profils dans Twitter afin de pouvoir comparer les inclinations idéologiques initiales avec leur inclination idéologique finale. Cette comparaison me permet d'affirmer que tous les profils ne connaissent pas de changements significatifs dans leur niveau d'homophilie et que seuls les profils de droite nationaliste en France montrent des signes d'homophilie significative après avoir été sur Twitter pendant une longue période.

- À ma connaissance, cette thèse est la première à effectuer une analyse des correspondances sur les auto-descriptions de Twitter. Grâce à cette méthode, il est possible de voir comment les clusters Twitter se perçoivent eux-mêmes. Ceci afin d'en savoir plus sur les inclinations idéologiques des clusters dans Twitter.

Discussion :

D'après les résultats de cette thèse, nous pouvons observer que l'homophilie sur Twitter n'est pas un phénomène qui affecte tous les clusters politiques de la même manière. Si la polarisation politique est également fonction du niveau d'homophilie, comme l'indique la littérature en psychologie sociale, il est alors possible de traiter les niveaux d'homophilie comme une variable latente pour les niveaux d'homophilie. (Myers and Lamm 1976) Il est alors possible de traiter les niveaux d'homophilie comme une variable latente pour les niveaux de polarisation. En utilisant cette approche, il est possible de remettre en question l'hypothèse avancée par Cass Sunstein concernant les impacts polarisants de l'Internet 2.0. Sunstein part du principe que des sites web comme Twitter permettront aux individus de suivre sélectivement les personnes qu'ils soutiennent déjà. Cela créera donc des groupes de personnes similaires dans leurs convictions politiques, qui se renforceront mutuellement sur des questions idéologiques. Selon Sunstein, cela augmentera les niveaux d'homophilie ainsi que les niveaux de polarisation politique.

Dans cette thèse, je démontre que ce modèle ne prend pas en compte les types d'idéologies et que si nous voyons la formation de groupes isolés sur Twitter, cet effet n'est pas uniforme et n'affecte pas tous les groupes de la même manière que Sunstein l'avait prédit. Un autre facteur qui affecte le niveau d'homophilie dans un groupe est le niveau de conviction des utilisateurs dévoués dans

un cluster. Le renforcement idéologique dans les clusters Twitter se fait par le biais d'intermédiaires qui appartiennent à des catégories démographiques qui ne sont pas distribuées au hasard. Il s'agit d'hommes très engagés, qui vivent dans des zones urbaines et sont plus susceptibles d'être bien éduqués. Ainsi, l'adoption de convictions idéologiques sur Twitter n'est pas le résultat d'un débat rationnel, mais repose toujours sur des structures hiérarchiques de communication, comme l'a observé Paul Lazarsfeld dans ses études. L'incapacité de Twitter à encourager un débat politique rationnel est attribuée à ce que Habermas appelle la "refeodalisation de la sphère publique". En d'autres termes, Twitter n'aurait pas pu fonctionner comme une sphère publique en raison de la structure hiérarchique de la société, extérieure à tout réseau de communication.

Short Summary of Thesis in English

In this thesis, I separated the French Twitter network from the global Twitter network and detected community structure within this network intending to measure the evolution of levels of homophily concerning the identities of the communities. I wanted to find out if being on Twitter and being a part of a political community on Twitter encourages all types of communities to be increasingly isolated from other communities and thus making it difficult for the Twitter network to act as a 'public sphere' in the Habermasian sense. Secondly, I wanted to check the unique feature of 'Retweeting' on Twitter to investigate who these retweeters are and if political retweeting can be seen as a bridge between elites and masses, which will confirm the deeply hierarchical nature of the Twitter network and thus confirming to Habermas's notion of 'refeudalization of the public sphere'.

In this research, I found out that the only cluster that has been progressively diverging over time from the rest of the public sphere belongs to users with extreme nationalistic values and generally belongs to political parties such as Rassemblement National and (some groups in) Les Républicains. The effect of being on Twitter is thus not uniform on all political groups.

In the second part of the thesis, I looked closely at the role of political retweeting and I found out that retweeting in the case of Twitter users from Rassemblement National is generally used for ideological reinforcement in a top-down manner rather than for diffusion of ideas to the general public. This observation allows us to see that isolation of one community from the global network can lead to the formation of clusters with high levels of ideological reinforcement, which is also done in a top-down hierarchical manner.

Short Summary of Thesis in French

Dans cette thèse, j'ai séparé le réseau Twitter français du réseau Twitter mondial et j'ai détecté la structure communautaire au sein de ce réseau dans le but de mesurer l'évolution des niveaux d'homophilie concernant les identités des communautés. Je voulais savoir si le fait d'être sur Twitter et de faire partie d'une communauté politique sur Twitter encourage tous les types de communautés à s'isoler de plus en plus des autres communautés, rendant ainsi difficile pour le réseau Twitter d'agir comme une " sphère publique " au sens habermassien. Deuxièmement, j'ai voulu vérifier la caractéristique unique du " retweet " sur Twitter afin d'enquêter sur l'identité de ces retweeters et si le retweet politique peut être considéré comme un pont entre les élites et les masses, ce qui confirmera la nature profondément hiérarchique du réseau Twitter et donc la notion de Habermas de " refeudalisation de la sphère publique ".

Dans cette recherche, j'ai découvert que le seul groupe qui s'est progressivement écarté au fil du temps du reste de la sphère publique appartient aux utilisateurs ayant des valeurs nationalistes extrêmes et appartient généralement à des partis politiques tels que le Rassemblement National et (certains groupes de) Les Républicains. L'effet de la présence sur Twitter n'est donc pas uniforme sur tous les groupes politiques.

Dans la deuxième partie de la thèse, j'ai examiné de près le rôle du retweet politique et j'ai découvert que le retweet dans le cas des utilisateurs de Twitter du Rassemblement National est généralement utilisé pour le renforcement idéologique de manière descendante plutôt que pour la diffusion d'idées au grand public. Cette observation nous permet de voir que l'isolement d'une communauté par rapport au réseau global peut conduire à la formation de clusters avec des niveaux élevés de renforcement idéologique, qui se fait également de manière hiérarchique descendante.