Online Dynamics of Far-Right and Far-Left Communities: The case of the September 2015 Parliamentary Elections in Greece

Lamprini Rori¹, Pantelis Agathangelou², Ioannis Katakis², Dimitrios Gunopulos³, Barry Richards¹

¹ Bournemouth University, UK,
² National and Kapodistrian University of Athens, Greece

Abstract. In the midst of a polarised campaign, on September 17th the leader of Golden Dawn Nikos Michaloliakos publicly proclaimed that Golden Dawn takes political responsibility for the murder of an antifascist rapper. As much as such a provocative statement induces rage among democratic citizens, it is certain that it was a deliberate action. Whether related or not, the party augmented its vote share from 6.3% to 7% in the September 20th election. How was this provocative statement inserted into the public agenda? What sentiments did it trigger? Did it gain any salience? This paper proposes to examine short-term dynamics in public opinion, in its social media expression. The main hypothesis is that although bigger issues covered the noise in terms of interest for the majority of the electorate, this statement fostered reactions among and between the far-right and the far-left. We will search for the reactions and interactions of candidates and cadres of those two political spaces and their interactions with Twitter users. We are particularly interested in psychosocial aspects of on-line interactive extremism. By bringing together scholars from political sociology, psychology and computer science, this paper has a threefold scope. It aspires firstly to contribute to the study of radicalism. Secondly, to fill in the literature gap regarding the use of new media to track opinion dynamics, by combining data scientists' technical skills with political scientists' concerns. Thirdly, to touch upon methodological issues related to the location of special publics in social media research. We perform a set of social network analyses and text mining techniques (sentiment analysis, graph mining) in order to analyze user content and study the social interactions. Our methodology is applied on a set of Tweets written in the Greek language during the period under study.

1 Introduction

We are interested in the on-line dynamics of radical and extremist political actors and relations between and among them. We aim to discover the on-line imprint of radical political behaviour in two different levels of research. Firstly, the discourse: which is the political vocabulary, the similarities and differences
in terms of themes, values, emotions between radicals of the far-right and the far-left? Secondly, the architecture of the discussions: are there similarities or differences between the far-right and the far-left networks on Twitter?

We consider the Greek case to provide a necessary and sufficient context for this study. As a country particularly hit by the financial crisis, having experienced international financial support followed by acute agreements on intense reforms and austerity measures, Greece has undergone deep transformations during the past six years [Dinas and Rori, 2013]. The collapse of the old two-partyism has been coupled by radicalisation of big parts of the Greek electorate which have blamed and punished old political parties, but also sought for new political shelters [Rori, 2015]. Various social movements have emerged, whilst the protest cycle, often violent and anti-systemic, has provided windows of political opportunities to new political actors.

The context of the September 2015 legislative elections was chosen not only for the general polarised climate, but because the statement of the leader of Golden Dawn (HA) has provided a trigger event which has multiplied exchanges between the extremes of the political spectrum.

The contribution of this work can be summarized in the following points:

- It compares of opinion words and opinion targets of the far-right and the far-left.
- Reveals differences in the on-line network architecture between the far-right and the far-left users.
- Indicates how communities with intense political differences and ideological conflicts interact.
- Proposes a method of identifying on-line political communities and tracing the boundaries between them.
- It provides a method for extracting opinion words from short, unstructured text (tweets) written in Greek. The method extends and optimizes previous work [Agathangelou et al., 2016] for the data and problem under study.

2 Related Work

2.1 Social media and Politics

The emergence of the “political Internet” [Sudulich et al., 2014] has had a significant effect in contemporary politics and society. Different aspects of the political landscape - everyday politics, campaigns, mobilisation and social movements, political participation - have been affected and researched.

a. Everyday politics: enhances information availability and diffusion, interaction among citizens and between citizens and politicians. Complements traditional political communication practices and enhances the tense relationship with voters [Wattenberg, 2002].

b. Campaigns: the supply-side (requires special resources, supplementary channel for broadcasting, different way of approaching citizens, visibility and personalization) and the demand (two-way communication, potential for direct
address of concerns and demands to politicians, but also opportunities for verbal aggressiveness) [Gibson, 2015], [Koc-Michalska et al., 2014]. The facility in its learning use, the capacity to by-pass mainstream media and paid visibility, the opportunity to create a personal publicity channel and to foster personalised communication important assets for politicians during elections but also in regular political life [Larsson, 2015], [Larsson and Moe, 2012]

c. Tool for mobilisation and social movements. Twitter as the social mobilization platform par excellence for political events and especially protest [Theocharis et al., 2015b][Theocharis, 2016].

d. Political participation: the open, direct and interactive character of new media platforms provides incentives for citizens participation [Vergeer et al., 2011] and a deliberative space that enhances democracy [Papacharissi, 2002].

2.2 Study of Discussions in Social Media

In [Lietz et al., 2014], the authors study on-line discussions in order to identify patterns in how German politicians acted in social media during the 2013 elections. Their main data source is the Twitter network. [dos Reis Costa et al., 2015] present a study of Twitter during the Brazilian protests of the summer of 2013. Similar to our work, sentiment analysis and user activity is the main tool for exploring the data. The authors observed that activity and sentiment peaks coincide with the days of the protests. [Gysel et al., 2015] infer the political signature of the Twitter users by applying a walking algorithm over the social graph. The output of the method is the estimated distribution of political preference over the eight Flemish political parties. A case study on the 2014 national elections is presented. [Barbera et al., 2015] discuss the way Twitter reacts on major political and non-political events. Their main conclusion is that polarization in social media is limited in comparison with what has been observed by previous work. In a similar direction, [Guerra et al., 2013] define a polarization metric that analyzes the boundaries of potentially polarized communities. They then identify polarized and non-polarized social networks according to the density of high-degree nodes in the boundary of communities.

2.3 Identifying Advocates

In [Ranganath et al., 2016] the authors build a framework for identifying advocates for political campaigns in social media. The framework models message strategies, propagation strategies and community structure. These three elements comprise the features that are utilized as input in data classification algorithms like Linear Discriminant Analysis. The authors observe that the proposed framework outperforms a set of baseline methods (random assignment, total number of tweets as a feature, bag-of-words) in identifying advocates. Experiments include two use cases utilizing Twitter data. The first regards elections in India while the second is about gun rights in the United States. [Fang et al., 2015] investigate the possibility of automatically identifying people's voting intentions for the Scottish Independence Referendum by analyzing
their Tweets. Similarly, Pla and Hurtado use sentiment analysis in order to classify political tendencies by extracting information from a corpus in Spanish [Pla and Hurtado, 2014]. [Gottipati et al., 2013] introduce a combination of collaborative filtering and text clustering in order to predict a user’s political party. This is achieved by analyzing debate.org data and identifying political stances of each user. Finally, in [Akoglu, 2014], Akoglu utilizes signed bipartite networks modeling the problem of polarity assignment as a node classification task. The effectiveness of the approach is demonstrated on real political forum and US Congress datasets.

2.4 Information, Social Networks and Polarization in Social Media

All information and communication technologies have built-in features that can both enable and constrain social relationships [Latour, 2005].

On-going debate on the double nature of Twitter: the specificity of the social media platform can fulfill or reverse democratic promises. Internet has increased the volume of information to which individuals are exposed and affected the size and density of personal communication networks. Thus, on the one hand online public sphere of deliberation, but on the other also “dark side” of Twitter: harassment, trolling, verbal aggressiveness.

Internet is said to contribute to the contemporary trend of mass political polarization [Farrell, 2012]. Empirical evidence of ideological identification of on-line communication shows that Internet use exacerbates mass political polarization [Colicoli et al., 2014].

Internet appears to create communities of like-minded individuals where exposure to political diversity is rare [Hindman, 2009].

This finding converges with classical studies of political behaviour that have shown that citizens depend on personal networks for information, construction of political identities, voting choices [Huckfeldt and Sprague, 1991], [Berelson et al., 1954].

In a comparative study which measures the ideological positions of millions of individuals in the United States, Germany and Spain over time, as well as the ideological composition of their personal networks [Barbera, 2015], most social media users are found to be embedded in ideological diverse networks, a fact which reduces political extremism. [Barbera et al., 2015] shows that social media usage reduces mass political polarization.

Through automated machine learning, [Bartlett et al., 2014] examine the volume, nature and type of ways racial and ethnic slurs are used on Twitter. They estimate approximately 10,000 uses per day of racist and ethnic slur terms in English. They are both used in an offensive and non-offensive manner. Non-offensive manners prevail, as they express in-group solidarity or non-derogatory description. Nonetheless, this research has found few cases that presented an imminent threat of violence, or individuals directly or indirectly inciting offline violent action.

Twitter facilitates the development of uncivil and anti-social behaviours. By distinguishing conceptually and empirically impolite and uncivil reactions in Twitter, [Theocharis et al., 2015a] have underlined their limiting effects on
democratic dialogue between candidates and the public. Research on the interaction between the supply and demand side in the case of the 2014 EU elections in the UK, Germany, Greece and Spain has shown that citizens impolite and/or uncivil behaviour are positively correlated with more engaged politicians with Twitter dialogue, who respond to criticism and harassment by increasing their level of engagement.

2.5 Interactive extremism

In this study we also sought to investigate a process which we term 'interactive extremism'. It is a commonplace observation that situations of political and community conflict can be exacerbated by the behaviour of the antagonistic parties, even when this behaviour does not constitute an attempt to affect the outcome of the conflict by gaining advantage in influence or material position. Expressive behaviours such as insults, threats and aggressive gestures are typical examples of such conflict-intensifiers, especially when occurring in a repeated exchange of such communications between antagonists. We suggest that in many situations this kind of toxic interaction may be an important driver of conflict, alongside obvious sources such as contestation over resources, status and values.

The term 'cumulative extremism' was used by Eatwell [Eatwell, 2006] to refer to this dimension of polarisation. We introduce the term 'interactive extremism' to focus on its psychosocial nature; the cycles of provocation and counter-provocation involved are rooted in the psychosocial dynamics of inter-group processes, which lie at the heart of many conflicts [Volkan, 2004]. Insecurities and resentments, fears and hatreds can be intensified in a spiral of words.

Whatever positive contributions it may have made to democratic politics, Twitter as a platform may lend itself to facilitating this damaging process. De-contextualised fragments of thought and feeling, impulsively translated into public speech, and easily made anonymously, as well as the platform’s week capacity to deal with harassment and trolling, are likely to bring toxicity into political debate. While the voices heard through Twitter may converge in a river of affect which drives a progressive political movement1, they may equally mingle in a lava flow of destructive antipathies. The study of Twitter content may therefore be a useful way of tracing the process of interactive extremism.

3 Background: Opinion Words and Sentiment Analysis

Sentiment analysis is the computational process that automatically analyses opinionated textual content and classifies it in two sentiment ‘classes’: positive or negative. The content may exist in various on-line sources and formats like product reviews, discussion forums or social networks. Though many approaches have been proposed and tested so far, in this paper we follow the dictionary-based sentiment analysis which is the simplest and most widely used.

---

1 See [Papacharissi, 2014]’s analysis of Twitter in Egypt in 2011.
3.1 Dictionary-Based Sentiment Analysis

A polarity dictionary is comprised of two lists of words. A positive list \(P\) and a negative list \(N\). In the literature, these words, that are used to express sentiment are called ‘opinion words’. Having this list, and given a piece of text (in our case, a tweet \(T\)) the sentiment of a tweet \(s(T)\) is calculated as the number of positive words minus the number of negative ones. Since tweets are all no more than 140 characters, we require no normalization with respect to the size of the tweet. For larger texts the ratio of positive/negative words is usually calculated. We observed that in our data \(s(t)\) ranges from -4 to +6 for the far-right party sentiment analysis and -6 to +18 for the far-left party respectively.

After calculating the sentiment of a tweet, we move onto calculating the average sentiment of a time segment (i.e. a collection of tweets posted during a certain time window). This simply is calculated by averaging the sentiment scores \(s(T)\) of all tweets in the segment.

3.2 Extracting Opinion Words

To conduct sentiment analysis, we followed two approaches:

A. Generic. We utilized a generic lexicon provided by [Hu and Liu, 2004]. The list contains approximately 6,800 words in English. In order to use this dictionary we had to automatically translate all the words in the Greek language using Google’s translate functionality.

B. Domain Specific Dictionary. In this approach we extracted the opinion words by using a tool developed by our research team (see [Agathangelou et al., 2014] and [Agathangelou et al., 2016]). More details regarding this approach are presented in the following section.

3.3 Learning Patterns for Extracting Opinion Words

Generic polarity vocabularies with words like ‘good’, ‘bad’ and ‘ugly’, are indeed useful and quite accurate in many cases. However, they are limited in including domain-specific opinion words like ‘inglorious’ or ‘prestigious’, that might be used for expressing sentiment in different cases. In our recent research, we have developed a set of tools that are able to analyze a corpus and identify domain-specific opinion words. The first one (NioeTo) [Agathangelou et al., 2014] uses a fixed set of syntactic patterns that extract opinion words given a corpus related to the domain of interest whereas the second one (DidaxTo)[Agathangelou et al., 2016] dynamically builds a set of patterns that extract opinion words from the same corpus. In this paper we utilize the method presented in [Agathangelou et al., 2016] for opinion word extraction, since it has been proved more effective than the method in [Agathangelou et al., 2014]. For more details regarding the approach the reader may refer to [Agathangelou et al., 2016]. An important feature of our tool is that it is able to extract not only opinion words but opinion targets as well. Opinion targets are the entities (words, phrases) that the opinion refers to.
(e.g. in 'such a lovely chair!', 'lovely' is the opinion word and 'chair' the opinion target). In our study, we will present results on both extracted opinion words and opinion targets.

3.4 Adapting to short, low quality text

As mentioned above DidaxTo was the method we employed in order to implement sentiment analysis of our corpus (tweets). Despite the method's ability to adapt dynamically to any opinionated content, we had to modify our algorithm by incorporating a Greek stemmer. Stemming is the process of reducing a word to its stem, base or root form. The process enables pattern's exploitation to recognise many grammatical forms of a word in a document.

Some of the challenges we encountered were that tweets were full of syntactic mistakes, the absence of sentence delimiters and clear opinion targets. These challenges were not encountered before since our tool was up until now evaluated on long, well form product reviews. Many parameters had to be adjusted in order to achieve the best performance.

4 Research design

In this section, we provide details about the data used in the analysis and the collection process. We also present an overview of our analysis.

4.1 The Data

For our analysis, we utilized Twitter messages that were posted in 2015 between Monday September 14th, 21:12 and Sunday September 20th, 21:04. The time window was selected in order to have in our pool messages before and after the statement under study, which was published at September 17th. We collected tweets written in the Greek language and we explain our methodology in the following section.

The full dataset contains 712,342 tweets. 90,230 distinct users participated in the discussions during that period. Naturally a large number of tweets were re-tweets or duplicate tweets due to the nature of the Twitter network, the API (application programming interface), and the way we collected the data (see below information about our multiple crawlers). Table 1 summarizes the data utilized in this paper. Our data is split in 15-minute segments. Note that due to an unexpected energy failures, our crawlers were not able to collect data for most of September 19th.

4.2 Crawling for tweets in Greek

In order to collect content written in the Greek language we have applied three crawlers that were running independently querying Twitter API in real time. Each crawler was tracking a list of words written in Greek. In total, our three
crawlers tracked the 1,000 most common Greek words. Three crawlers were required since the Twitter API constrains the number of keywords allowed. The assumption in this case is that in order to be considered as written in Greek, a tweet has to have at least one of those most common words in it. Figure 1 provides an overview of the data collection process.

![Data Collection Process](image)

**Fig. 1**: Data Collection Process. We consider the Twitter stream as hidden since access is possible only through the application of filters (in our case keyword filters - crawlers). Three crawlers were utilized, each one using a different list of Greek words (list A, B and C). Duplicate content was eliminated at a pre-processing level. See Figure 2 for the next steps of the analysis.

### 4.3 Overview of the Analysis

For our analysis we filtered our original dataset in two ways (see Figure 2): At first, we identified relevant users after retrieving the followers of a set of seed users (see Section 6.1). Secondly, we kept only the tweets that included words, phrase or hashtag from a list we defined (see Section 7). After this parallel filtering procedure, we forward the remaining tweets (of relevant users, or relevant content) to our analysis modules including the tools for sentiment analysis and opinion word discovery developed by our research team (see [Agathangelou et al., 2014] and [Agathangelou et al., 2016]). The outcome of the process is a set of results regarding Twitter activity in relation to time, lists of opinion words and targets,
and sentiment analysis. In the following sections, we will discuss these results individually.

![Diagram](image)

Fig. 2: Overview of the Analysis. See Figure 1 for the data collection steps.

5 Reactions of the general community

In this section we describe the analysis of our full initial dataset including all tweets and users. This analysis will aid in comparing the reactions and interactions of the general Twitter population with the reactions of the smaller groups of advocates and supporters of political parties. We analyse user activity and sentiment analysis in all those tweets and we discuss the results in the following two sub-sections.

5.1 User Activity

Figure 3 displays the activity of the whole (Greek) Twitter community in terms of published tweets. At each time step (15 minutes) we collect and count the number of tweets. As can be seen from Figure 3, the day-night patterns are evident and represent the ‘normal behaviour’ of the network. Based on that, we will identify events by identifying abnormal frequency patterns.

For example in Figure 3 we observe two peaks (unexpected high number of tweets) on September 16 and September 21. We investigated the tweets published in those segments and found out what topics were discussed then. We will refer to these abnormalities as ‘events’. As seen from Figure 3, the topics discussed during the two events were of political nature, which was to be expected since it was during an electoral campaign period for Greece. The first peak observed corresponds to comments on a televised debate between the candidates of the two bigger parties - with respect to vote share - the Coalition of the Radical Left (SYRIZA) and New Democracy (ND). Given the fact that this debate was the
first among main electoral opponents since the beginning of the financial crisis, increased interest and audience are expected. The second peak reflects the night of the election. Both events were primarily transmitted through national mass media. We, thus, observe an abnormally augmented twitter activity in events which primarily benefit from increased visibility via traditional media channels, like television and radio. With respect to political news, hence, social media follow established sources of information.

![Twitter Activity in the full dataset. Number of tweets with respect to time - 15 minutes segments.](image)

6 Tracking advocates and topic-related content

In this section we explain how we identified relevant content in the political discussions under study, and present the results of the analysis of this filtered content only. As briefly described in Section 4.3, we operate two parallel filtering procedures in order to get two sets of tweets: one coming from candidates adn users following party candidates and one set including tweets with relevant content, or, in other words, tweets that include one or more keywords or phrases that we considered relevant to the discussion. Both sets of tweets are indispensable in our analysis, as we needed to explore and be able to distinguish all the issues that those advocates bring into discussion and how the specific event under study - the statement of the leader of HA - is entering the on-line public agenda.

6.1 Identifying and Analyzing Advocates

We are searching for reactions and interactions among and between the far-right and the far-left, related to this particular statement of the leader of HA, Nikos
Michaloliakos. In order to identify the relevant users we adopted a methodology relying on three assumptions. The first is that activists and sympathizers of the extremist and radical parties would tend to follow the accounts of those parties and of their candidates. For this reason, we researched the official Twitter accounts of specific political parties and of candidates officially running with those parties. By using the official ballots of political parties in 56 electoral districts and the national list\footnote{The Greek parliament is constituted by 300 members, 288 of which are elected through the 56 constituencies, whereas 12 via a common, national list.} we identified the candidates who used a Twitter account for this specific election.

The second assumption involved identifying the political parties of the far-right and the far-left. In the elections of September 2015, the far-right political spectrum in Greece was composed by two parties: the national-populist party of Independent Greeks (ANEL) and the extremist HA\footnote{On the components of the far-right in Greece, see [Georgiadou and Rori, 2013] and [Georgiadou, 2015].}. We are investigating reactions to a declaration by the leader of HA. Activity in the space of ANEL is included in our sample, since electoral competition between the two parties dictates taking advantage of any occasion that could bring votes from neighbouring parties in adjacent political space. ANEL would therefore try to benefit from the statement of HA.

The far-left in the election under research is fragmented between four main political parties: SYRIZA, the new splinter-party Popular Unity (LAЕ), the orthodox Communist Party of Greece (KKE) and the ultra leftist party Anti-capitalist Left Cooperation for the Overthrow (ANTARSYA). The radical transformation of SYRIZA since the beginning of the financial crisis, and especially after the capitulation of the party after the signing of the third bailout agreement, substantially altered its electorate. It became less appealing to radicals and more so to moderate, ex-center left voters [Rori, 2016].

For this reason, we assumed that the users following the accounts of SYRIZA candidates would not typically endorse radical views and, thus, would distort our data with respect to our research focus. For this reason, we excluded the SYRIZA candidates from our sample. Twitter accounts of candidates of LAЕ, KKE, ANTARSYA were identified and included. Finally, we needed to capture reactions from and interactions with the anarchist milieu and individuals possibly holding more radical and extreme opinions on the far-left. Given the fact that those ideological spaces do not participate in elections and are not represented by official political actors, and also the fact that individuals from those spaces either encrypt their identity through pseudonyms or control the access to their accounts, it is difficult to locate them with certainty.

Hence our last and third assumption is that ideological one-sided news exposure may be largely confined to a small, but highly involved and influential segment of the population. In that case, the most politically sophisticated and interested seek for information by individuals who follow like-minded sources and/or sources beyond their closed circle, but which present a certain level of
ideological familiarity or proximity. For this reason, we included in our pool of data accounts of opinion leaders, journalists and media of the far-left, of political subjects and initiatives related to the antifascist movement etc.

**Twitter accounts among candidates of the far-right and the far-left** A first view at the pool of the data shows that a very small number of candidates held a Twitter account (see Table 2 for details); an observation which implies that Twitter is not considered as an important communication tool for those political actors, not even during electoral campaigns. Among the parties under research, KKE is the party least interested on communicating through Twitter, whereas the percentage of ANEL's candidates disposing an account is the highest; nonetheless, it also remains particularly low.

<table>
<thead>
<tr>
<th>Party</th>
<th>Candidates</th>
<th>Accounts</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAE</td>
<td>424</td>
<td>59</td>
<td>13.9</td>
</tr>
<tr>
<td>KKE</td>
<td>425</td>
<td>8</td>
<td>1.88</td>
</tr>
<tr>
<td>ANTARSYA</td>
<td>341</td>
<td>37</td>
<td>10.8</td>
</tr>
<tr>
<td>ANEL</td>
<td>404</td>
<td>75</td>
<td>18.56</td>
</tr>
<tr>
<td>HA</td>
<td>320</td>
<td>53</td>
<td>16.56</td>
</tr>
</tbody>
</table>

Table 2: Twitter accounts among candidates

<table>
<thead>
<tr>
<th>Table 3: Followers per party</th>
</tr>
</thead>
<tbody>
<tr>
<td>Party</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>LAE</td>
</tr>
<tr>
<td>KKE</td>
</tr>
<tr>
<td>ANTARSYA</td>
</tr>
<tr>
<td>ANEL</td>
</tr>
<tr>
<td>HA</td>
</tr>
</tbody>
</table>

**Sentiment Analysis** In order to study the sentiment expressed by both groups of users (far-right, far-left), we utilized our tool DidaxTo to extract corpus specific opinion words and opinion targets. With this process, we extract a list of Positive and Negative Opinion words as well as Opinion Targets for each space (far-right and far-left) separately. In this way we acquire knowledge regarding the terminology of each space's users while expressing opinion. We utilized these dictionaries for sentiment analysis in this section, but we discuss the extracted opinion words and opinion targets in Section 6.1.
In Figure 4 we observe the negative sentiment analysis of the tweets collected from the advocates of the far-right parties. Among 29,026 tweets exchanged attributed to far-right users, 1,883 expressed negative sentiments. Intensity of negative emotions varies across the time researched, as indicated by the density and the colours of the relevant dots. The more the ratio of negative tweets increases, the more the dots thicken and progressively turn from green to red. Among the most negative tweets, we identified two events which concentrated relative attention.

![Figure 4: Sentiment Analysis of Far-Right Users’ tweets](image)

The first is linked to the statement of Michaloliakos itself. Surprisingly enough, accepting the political responsibility for the murder of Fyssas did not generate the most negative emotion (average negative ratio on September 17th -0.08). This can be interpreted with two ways, of different nature. The first is that relative negative sentiment is distributed among various time segments, weakening the frequency of negativity at any particular time. This is possible, since evidence shows the diffusion of the sentiment triggered by the statement over time (see dashed arrow #2). The second is that the statement per se might not have provoked negative sentiments among the far-right community which is usually expressive on Twitter. This could be related either to the fact that the most publicly vocal have the biggest proximity to the party - are party activists for whom violence is part of conventional duties, a kind of party habitus, or to the fact that far-right people are used to those practices of H.A. Either by consent or because of indifference, they take it for granted. Another possible interpretation is that negative emotion is not publicly expressed, possibly because of fear of hostile reaction from like-minded users. Interestingly, the diffusion of negative sentiment related to Michaloliakos’ statement beyond the day that it was initially publicised is coupled with intense negative sentiments transmitted through abusive comments and insults against the opponents’ leaders and discussions about “the
decline of Greece". This concomitant appearance permits us to speculate on the possibility that far-right users expressed themselves aggressively in retrospect, not for the statement itself, but in order to react against negative discussions that the statement had triggered in the public agenda or among opponents of HA. Discussions hence become more negative *ex post* in order either to “cover the noise” or to answer to accusations. The higher ratio of negative tweets on September 19th (-0.17) and 20th (-0.25) relative to September 17th enhances our argumentation. That said, negative sentiments stemming from abusive comments might as well reflect the escalation of dynamics of electoral competition with respect to the election day.

In Figure 5 we observe the negative sentiment analysis of the tweets collected from the advocates of the far-left parties. Among 131,225 tweets exchanged attributed to far-left users, 10,474 expressed negative sentiment. Far-left activity is, thus, more intense and negative sentiments are slightly more present compared to the far-right. Among radical left users, the statement of the leader of HA doesn’t figure as concentrating the most negative emotions. At the relevant day and time segment the average ratio of negative tweets is -0.07, almost equal to the average ratio of negative tweets among the far-right users. Among issues fostering more negative emotions, the televised debate (-0.17, -0.18), the political situation in Greece (-0.17) and the talks on the night of the election and before transmission of electoral results (-0.15) provoked more negative emotions than the acceptance of political responsibility for the assassination of Fyssas by HA. Disapproval of the political situation in Greece reflects disappointment on the far-left for SYRIZA’s capitulation. Negative comments concerning the electoral outcomes are related to the dynamics of electoral competition targeting SYRIZA’s voters and the intra-party conflicts which led to the party split in the beginning of the campaign and ultimately the foundation of the splinter-party LAE. LAE struggled in the polls to pass the 3% threshold and achieve parliamentary representation. Users were more negatively absorbed by inter-partisan conflicts on the far-left and the eventual exclusion of LAE from parliament, than by events related to HA’s activity.

**Opinion Targets and Opinion Words** In this section we discuss the Opinion Targets and Opinion Words extracted from the tweets of the far-right and far-left users.

In Figure 6 we observe the most representative (frequent) opinion targets of the far-right (a) and far-left communities (b). Among most frequent opinion targets employed by far-right users, one can discern SYRIZA, the people, the leader of ND, Vagelis Meimarakis, Europe, the bailout and refugees. Anti-bailout and anti-immigrant discourse prevail. The first one is associated with Europe, the creditors, whilst the second with jihadism, foreigners and the borders. The pre-electoral climate is also marked by discussions about the old and the new in politics. Far-right users rank highly uncorrupted politicians and target a minister and MP of SYRIZA, Alekos Flavouraris, who was accused during the campaign by political opponents for owing shares and being on the board.
of a company performing public works. Partiality figures in discussions related to violence of the far-right and terrorism of the extreme left. The statement of Nikos Michaloliakos about the assassination of Pavlos Fyssas is mentioned by users of the far-right, who try to counter-balance it with references on murders caused by left-wing extremists and the civil war. The culture of the radical left is targeted by references on antifa activism, occupations etc. Terms related to the nation, Hellenism, the military constitute frequent opinion targets, as well as the Russians, Hitler and Zionism. Highly emotional expressions like fire, earthquake, shock, protest, hate, shame, Rubicon are used to frame the above issues.

Inter-party antagonisms among the radical left (LAE, ANTARSYA, communists) prevail in the opinion targets of the far-left and references on the anarchists are highly ranked. SYRIZA, its leader, as well as the distance between what he says and what he does are frequently discussed. Users target the prevalent electoral dilemma between Tsipras and Meimarakis, in which they juxtapose issues of militarism on the left and the governmental coalition with ANEL. Among most prominent targets figure also the middle classes, issues of partiality and corruption with references to Flabouraris and to the constructions and media businessman Yorgos Bobolas. Different terms than the ones observed in 6(a) are associated to the statement of Nikos Michaloliakos. HA is qualified as fascist, nazist, neo-nazist, racist and fanatic; the party is related to Hitler; antifascist actions are present. Immigrants, Syria and the muslim constitute another cluster of frequent opinion targets. The people are much less frequently targeted among the users of the far-left that among those of the far-right. Last but not least, discussions on Zionists, Germans, Jews and Hungary are frequent.

Figure 7 displays the opinion words of both spaces. In this case however, color represents polarity. Positive words are portrayed in green, negative in red.

Among the far-right users, positive value is attributed to power, honour, wisdom, merit, purity, morality, faith, patriotism, dignity, transparency, credibility, rebellion and the male. The society and the economy figure among the
most positively referenced issues. Numerous positive terms frame the world of labour, but one can find a few positive references on entrepreneurs. Discussions on younger generations, the youth and newness in politics are central. Among negative opinion words, problems prevail, framed with terms expressing high despair, like destruction, nightmare and dead-end. Negative connotations come up on discussions about politicians: corrupted, guilty, provocative, dirty, useless, criminal, incompetent, uncredible, stupid, liars. Inefficacy, dependence, waste, conspiracy and instability characterize politics. Strong negative emotions figure among the most frequent opinion words: creepy, disappointment, shocking, disgust, rage, pain, insecurity, opprobrious, odious. Last but not least, polarized and insulting terms are used with respect to political opponents and entities perceived as enemies: Turkish seeds, spoiled, retarded, uneducated.

Similarities and differences become evident once we observe the most frequent opinion words of radical left users. Like among far-right users, discussions on the society and the economy prevail among expressions with positive connotation. The world of labour and the production are highly ranked. Possibly linked to the capitulation, the split of SYRIZA and fragmentation on the radical left, words like end, finish, new are positively employed and give a sense of closure with the past. Terms like autonomy, progressive, responsible, original, innovative, rebels provide a positive, normative demarcation of politics on the radical left, whereas discussions on values, ideals and ideas are central. The users of the radical left refer to morality, honour, dignity, loyalty, patriotism, romanticism, fairness, meritocracy, honesty, credibility, hope and optimism. Similarly to the far-right users' preoccupations, problems prevail on the negative side of opinions, framed with terms like difficulty, disaster, destructive, tragic, deadlock, nightmare. Political discussions on the debt appear through terms introduced by prominent figures of the radical left, like odious and opprobrious; the bailout and scandals are also
frequently and negatively discussed. Prevailing emotions on the negative opinion words are disappointment, worry, rage, confusion, shock, uncertainty, depression. A plethora of negative adjectives are used, referring to political opponents and ideological enemies: wretched, ridiculous, barbarous, guilty, filthy, useless, corrupted, criminal, incompetent, provocative, cynical, unreliable, mean, immoral, spoilt, liar.

Opinion words on the far-right and the far-left have indicated similarities and differences; intense polarisation; verbal aggressiveness. [needs further systematization and development]

(a) Far Right  
(b) Far Left

Fig. 7: Opinion Words. Color indicates polarity.

**Network Analysis** Here we discuss the social network interactions within the two communities under research and between them. Figure 8a and 8b present the communications within the two communities. This visualization is based on the tweets posted by known far-right/far-left users including a ‘mention’ to another known far-right/far-left user. In other words, whenever any user A mentioned (using the ‘@’ symbol) a user B from the same political space in her tweet, we draw a line between those two users.

Data visualisation makes evident the differences in the on-line discussion mentalities between the two communities. The network of the far-left is dense, well-connected and has numerous users who appear in the periphery of Figure 8(a) as initiating discussions (thicker red dots). Interaction is intense and multi-directional. The dynamic is much less intense among the far-right users. Only 416 messages where sent in total, compared to 8,849 messages exchanged among the far-left community during the same period. Far-right users are only partially, if not exceptionally connected; any exchange seems to be initiated by specific individuals, who most possibly operate or at least try to operate as opinion
leaders; there is hardly any interaction between them. The community of the far-right is disconnected, not debating. The flow of information seems to be uni-directional and not well-diffused. One can easily infer that plurality and interaction is present among the far-left, whereas fragmentation and top-down diffusion of information is operated among the users of the far-right.

(a) Far-Left Network. 8,849 messages from 1,071 far-left senders to 1161 far-left receivers.
(b) Far-Right Network. 416 messages from 73 far-right senders to 75 far-right receivers.

Fig. 8: Intra-Community Networks

Figure 9 presents the exchanges between the two communities. This visualization is based on the tweets posted by known far-right or far-left users including a mention to another known far-left or far-right user respectively. In other words, whenever a far-left user A mentioned (using the @ symbol) a far-right user B in her tweet, we draw a line between those two users. Likewise, whenever a far-right user C mentioned (using the @ symbol) a far-left user D in her tweet, we also draw a line between those two users. The size of a bullet indicates the number of interactions related to the specific user. The more the messages, the bigger the size of a bullet. Red colored bullets represent far-left party users and dark blue far-right respectively.

Radical users of the right and the left present interaction in their on-line co-existence. Exchanges between them are numerous (10,588 messages sent in total), even if not equally distributed. Far-right users addressed slightly more messages to far-left users (1,521) than the ones the far-left users sent to those of the far-right (1,340). Inter-community exchanges stemming from users of the far-right towards users of the far-left, are stronger than the intra-community communication which far-right users maintain among themselves in Figure 8(b).

The structure of the network also reveals differences in the communication emanating from the two communities’ users. The far-right disposes three different
levels of users: those who manage most of the interaction (three thicker dark blue bullets); an intermediate level of interaction with several bullets; a lowest level of interaction which includes the majority of far-right users. The architecture of the inter-community networks reveals a one-to-many relationship between the users of the far-right and the far-left. Users of the far-right are surrounded by several users of the radical left. This observation is easily traceable for the most interactive users, but exists in all levels of interaction. On the contrary, users of the radical left present more or less the same level of involvement among themselves as when communicating with users of the radical right. Given that the same pattern of few users initiating most of the flows of communication was also observed in the intra-community network of the far-right users (Figure 8(b)), we can infer that among the on-line community of the far-right there exist a few prominent figures or opinion leaders, who manage the majority of intra and inter-community communication.

7 Relevant Content

We defined as relevant tweets, tweets that contained keywords some of which are presented in Table 4. These keywords were selected after a manual overview of relevant tweets of the period. Selection decision is based on different criteria:
1. HA's statement: on relevant words and/or phrases referring to the statement of Michaloliakos itself.

2. Political vocabulary: on meaningful words and/or phrases in the political vocabulary mainly of the far-right and the far-left, but of the general public as well that came up in the tweets referring to this particular event.

3. Names in debate: on names of figures of the two political spaces or of the terrorist 'milieu', which were mentioned in the tweets commenting on that statement.

4. Connotations: on words and/or phrases which pertain symbolic connotations, also appearing in the twitter debate.

<table>
<thead>
<tr>
<th>HA's Statement</th>
<th>Political vocabulary</th>
<th>Names in debate</th>
<th>Connotations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cynical confession</td>
<td>Gang</td>
<td>Adolph Hitler</td>
<td>Blood-Honour-HA</td>
</tr>
<tr>
<td>Assassination</td>
<td>Battalions</td>
<td>Michaloliakos</td>
<td>Only national solution</td>
</tr>
<tr>
<td>Commemoration</td>
<td>National</td>
<td>Patriotic Kasidiaris</td>
<td>EAM-ELAS-Meligalas</td>
</tr>
<tr>
<td>Front</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Political persecution</td>
<td>Neo-Nazi</td>
<td>Velopoulos</td>
<td>Katyn</td>
</tr>
<tr>
<td>Alteration</td>
<td>National-socialists</td>
<td>Stalin</td>
<td>Security Battalions</td>
</tr>
<tr>
<td>Explanatory</td>
<td>state</td>
<td>Nationalist river</td>
<td>Koufontinas</td>
</tr>
<tr>
<td>Prosecution</td>
<td>Violence</td>
<td>Xiros</td>
<td>New civil war</td>
</tr>
<tr>
<td>Investigator</td>
<td>Anti Fascism</td>
<td>Roupakias</td>
<td>National Liberating Front</td>
</tr>
<tr>
<td>Give justice</td>
<td>Antisystemic</td>
<td>Fyssas</td>
<td>Ancient greeting</td>
</tr>
<tr>
<td>Political hostage</td>
<td>Antifascist protest</td>
<td>Temponeras</td>
<td>Swastika</td>
</tr>
<tr>
<td>Fake trial</td>
<td>Activist movement</td>
<td>Kalampokas</td>
<td></td>
</tr>
</tbody>
</table>

Table 4: Sample of keywords identifying relevant content

After filtering out tweets that did not contain any of the above keyword, we end up with 6,299 tweets and 3,699 users. Different dynamics and attitudes emerge in the sphere of Twitter once the statement of the leader of HA is made.

The first reactions are shock and anger, expressed through highly emotional phrases, like 'cynical confess', 'provocative declaration'. Among those, institutional reactions figure promptly. Framing of political parties relevant statements is conditioned upon their position and strategy in electoral competition, whilst most of them use emotional expressions. The official political prosecution presented the statement as evidence that HA is a criminal organization.

A second set of reactions concentrate on interpreting strategically the choice of making this statement at this specific timing. Different groups of arguments emerge. The first can be described as 'conspiracy theories': they consist of speculations on a potential bribery or exchange that might be hidden behind the statement, given that it was deliberately made three days before the ballot.
Table 5: Sample of keywords identifying relevant content

<table>
<thead>
<tr>
<th>Keyword</th>
<th>freq</th>
<th>Keyword</th>
<th>freq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Michaloliakos</td>
<td>2110</td>
<td>Nazi voters</td>
<td>96</td>
</tr>
<tr>
<td>Kasenikas</td>
<td>998</td>
<td>Jihad</td>
<td>88</td>
</tr>
<tr>
<td>neo-Nazi</td>
<td>879</td>
<td>Nationalists</td>
<td>87</td>
</tr>
<tr>
<td>Golden Dawn</td>
<td>838</td>
<td>Nazi organisation</td>
<td>83</td>
</tr>
<tr>
<td>Nazi</td>
<td>812</td>
<td>Theory of the two extremes</td>
<td>83</td>
</tr>
<tr>
<td>Hitler</td>
<td>455</td>
<td>Cynical confess</td>
<td>82</td>
</tr>
<tr>
<td>refugees</td>
<td>338</td>
<td>German soldier</td>
<td>82</td>
</tr>
<tr>
<td>Fascist</td>
<td>286</td>
<td>Völkischer</td>
<td>74</td>
</tr>
<tr>
<td>Hatamioliakos</td>
<td>267</td>
<td>Blood-Honour</td>
<td>71</td>
</tr>
<tr>
<td>Stahn</td>
<td>260</td>
<td>RAM</td>
<td>67</td>
</tr>
<tr>
<td>Tomponeras</td>
<td>198</td>
<td>Michaloliakos' confess</td>
<td>66</td>
</tr>
<tr>
<td>Irregular immigrants</td>
<td>173</td>
<td>'serious Golden Dawn'</td>
<td>60</td>
</tr>
<tr>
<td>Leader</td>
<td>162</td>
<td>Greek nationalism</td>
<td>59</td>
</tr>
<tr>
<td>Dörl</td>
<td>158</td>
<td>Message of triumph by thousands of Greek</td>
<td>59</td>
</tr>
<tr>
<td>Political responsibility</td>
<td>157</td>
<td>nationalists</td>
<td>55</td>
</tr>
<tr>
<td>Motherland</td>
<td>154</td>
<td>Michaloliakos'</td>
<td>43</td>
</tr>
<tr>
<td>Immigrants</td>
<td>147</td>
<td>Swastika</td>
<td>41</td>
</tr>
<tr>
<td>Neopatries</td>
<td>137</td>
<td>Resistance in neighbourhood</td>
<td>31</td>
</tr>
<tr>
<td>Michaloliakos' statement</td>
<td>133</td>
<td>Polizei</td>
<td>30</td>
</tr>
<tr>
<td>Assassination</td>
<td>115</td>
<td>Michaloliakos</td>
<td>27</td>
</tr>
<tr>
<td>Koulinitis</td>
<td>115</td>
<td>Nazi killers</td>
<td>27</td>
</tr>
<tr>
<td>Lamprakis</td>
<td>96</td>
<td>German soldiers</td>
<td>24</td>
</tr>
</tbody>
</table>

Conspiracy interpretations are contextualized in different ways, being said to service the interest of political powers of the right or the left. In the first case, the statement is said to benefit ND, since ex-voters of HA citizens thinking to vote for HA are seen as being potentially shocked or insulted by the statement, and therefore thought to be likely to turn their back on the party and instead vote for ND. In the second case the argument is that the statement stemmed from an obscure agreement where a fall in HA's support would be exchanged with a pro-HA favouritism in the judicial process. Some link the timing of the statement with the need to cover the noise of an intra-governmental issue that came up in the agenda affecting a SYRIZA MP and close advisor of the Prime Minister. At last, some present Michaloliakos as a secret servant of the Greek Intelligence Service, claiming that the statement satisfies deeper systemic interests. The second consists of arguments centred on the party's objectives. According to this string, it was a vote-maximizing strategy, aspiring to cement the core of party supporters, the pure ideologues, to raise their morale, and also to re-align some floating voters. Another version related the statement to intra-party antagonisms and saw it as aimed at reminding the absolute power of the leader ('who is the boss').

A third group of reactions reflects political competition and conflict. Parallels between the judicial treatment of left-wing and right-wing extremism are drawn. Diversity of opinion reflects users' diverse political position and sensibilities: some of them accuse the political system of treating extremists inspired by an ultra-leftist ideology (e.g. members of 17 November) more severely than extremists of the far-right (HA). Others argue the opposite: that Michaloliakos will end up permanently in jail, like the leading figure of the terrorist organiza-
tion Koufontinas. Another set of reactions de-contextualize the statement and attribute a meta-utility in order to comment on other users relevant reactions. These comments identify as foes those who, by underlining the statement of Michaloliakos, are said to reveal their hidden affinity towards HA; accuse other users of showing empathy or tolerance for Michaloliakos, because of their admiration for Koufontinas; express disgust towards those - mainly identified as liberals - who do not discern differences between right-wing and left-wing extremism; accuse those who equate communism with Nazism as willing to purge Nazi crimes; comment on the low level of interest for the event in Twitter. Verbal aggressiveness is expressed towards those who compare violence of right-wing extremism to violence of the radical left; at the same time, voices raise to remind others that nobody has accepted the responsibility for the three victims who were burnt during an anti-bailout protest in May 2010. A third string emerges from those who use the statement as an opportunity to remind us of famous, old declarations of HAs leader, testimonies to the national-socialist party ideology. A fourth cluster emerges from antifascist activists who call for activism in the neighbourhood where Fyssas was murdered.

![Fig. 10: Number of topic-related tweets with respect to time.](image)

In Figure 10 we observed the number of topic-related tweets with respect to time. As expected, a peak is observed on the day of Michaloliakos’ statement. Relevant discussions rise with less intensity on the next day and the day of the election. Nonetheless, the overall distribution of those keywords shows activity on previous days as well, even if it remains lower. This means that discussions and conflicts related to the extremes of the political spectrum, political violence, conspiracy theories, systemic reactions to violent extremism are present or latent of the on-line public agenda. Interest on those issues is manifest; the statement functions as a trigger event which activates latent dynamics between and among on-line political communities.
8 Conclusions

One clear finding to emerge is the difference in Twitter strategy between the far-right and the far-left. This bears on the question of whether, in a situation where an interactive amplification of extremism is occurring, the antagonists on both extremes are likely to be equally responsible (on the principle of it takes two to tango), or whether one side may be leading in raising the temperature. Our data also suggests that underlying differences in political philosophy and in preferences for certain kinds of social relationships may shape the Twitter presence of the opposing extreme groups in different ways, with the far-left tending towards reciprocity and more dense communication, and the far-rights tweeting reflecting more of its inclination towards hierarchy and away from persistent discussion. At the very least we point to the need for, and possibility of, future empirical answers to such questions.

Acknowledgments

The authors would like to thank Mr Nikolaos Panagiotou for providing help with the data collection. Lamprini Rori is funded by a Marie Sklodowska-Curie Intra-European Fellowship.

References


