

Twitter and the European Hyperagora: What can the Twittersphere Tell us about Political Deliberation and Opinions in Europe?

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Introduction

Twitter is an online social network that allows users to broadcast short posts known as Tweets. Since its launch in 2006, the platform has increasingly been used for everyday communication as well as for political debates, crisis communication, marketing, and cultural participation (Weller et al. 2013). The public-debt crisis in Europe is widely discussed across Europe and presents an interesting point in time to investigate whether European issues are discussed in a common European public sphere. This project looks at data from the communication platform Twitter. It specifically looks at the reaction in the Twittersphere to the negotiation between the Troika and Greece leading up to the signing of the three memorandums.

Research Question

The following questions were investigated:

What can twitter tell us about pan-European reactions to the European governance of the public-debt crisis in Greece?

- What can variation across time and space in the volume of Tweets regarding the euro crisis tell us about popular engagement with the issues?
- What can the content of Tweets related to the crisis tell us about the spread of public opinion on the handling of the crisis in Greece between and within countries?

The answer to these questions could potentially add to the literature on the emergence of a European public sphere.

Literature Review

On Twitter Research

The body of twitter research has grown steadily in recent years (for a comprehensive analysis and typology of twitter research up to 2013, see Zimmer and Proferes 2014). Some of the findings relevant to our research design are discussed below.

Twitter is a source of meaningful information about engagement with and opinions about political topics. Twitter is also used as a platform for political deliberation. In a recent study on Tweets mentioning parties or politicians before the 2009 German federal election, Tumasjan et al. found that "Twitter is not just used to spread political opinions, but also to discuss these opinions with other users" (Tumasjan et al. 2010, 183). Furthermore, specific patterns of twitter usage have been identified that correspond with high-profile political events. Hughes and Palen found that, compared to general Twitter usage, more broadcast-based information sharing activities take place (Hughes and Palen 2009, 259) during events. Moreover, Tumasjan et al. found that it was possible to extract meaningful information about political opinions from both the volumes and the content of these Tweets: "the mere number of Tweets reflects voter preferences and came close to traditional election polls" (Tumasjan et al. 2010, 183).

Twitter gives information on the location of Tweets and users, which must be carefully interpreted. Devin Gaffney points out methodological problems with using the given location of twitter users - "in many cases user-entered profile locations differ from the physical locations users are actually Tweeting from" (Graham, Hale, and Gaffney, Devin 2014, 1) which must be considered when interpreting results.

Though the field of Sentiment Analysis (SA) is perhaps most developed in the business world (Zimmer and Proferes 2014, 250), an increasing body of literature has developed, focused on retrieving information about

political opinions from the Twittersphere. Though Tumasjan's results have come under scrutiny (see Jungherr, Jürgens, and Schoen 2012), the authors found that "the sentiment of Twitter messages closely corresponded to political programs, candidate profiles, and evidence from the media coverage of the campaign trail" (Tumasjan et al. 2010, 183).

Grimmer provides an overview of recent developments in SA in political science, noting how "automated content methods can make possible the previously impossible in political science: the systematic analysis of large-scale text collections without massive funding support" (Grimmer and Stewart 2013, 2). He advises caution, however, about the utility of SA in predictive models: "The goal of building text models is therefore different than model building to make causal inferences. [...] Emphasis in evaluations should be placed on helping researchers to assign documents into predetermined categories, discover new and useful categorization schemes for texts, or in measuring theoretically relevant quantities from large collections of text." (Grimmer and Stewart 2013, 4).

Due to the enormous amount of text available, Pak and Paroubek identify that "microblogging web-sites are rich sources of data for opinion mining and sentiment analysis" (Pak and Paroubek 2010, 1320). The multilingual nature of Tweets across Europe presents some difficulties, but is the subject of a growing body of research: "Noisy social media, such as Twitter, are especially interesting for sentiment analysis (SA) [...] given the amount of data and their popularity in different countries, where users simultaneously publish opinions about the same topic in different languages" (Vilares, Alonso, and Gómez-Rodríguez 2015, 2). Balahur and Turchi are confident about the ability of Statistical Machine Translation (SMT) to provide a basis for consistently applied SA across languages (Balahur and Turchi 2012, 58). Other approaches include using emoticons to train models that assign sentiment to a multilingual text corpus (Narr, Hulphenhaus, and Albayrak 2012).

Finally, some studies discuss ethical aspects of twitter research. For example, concerns about creating a permanent archive of Tweets have been voiced. These concerns included whether "such archive was aligned with users' privacy expectations" (Zimmer and Proferes 2014, 258; Zimmer 2010).

On Awareness and Public Opinion across Europe on the Governance of the Public-Debt Crisis in Greece

Academic research on the emergence of a European public sphere is not a recent phenomenon (Risse 2003, 1). Hitherto, however, research has been characterized as rather normative, as the "research community has been [...] interested in producing policy recommendations for public sphere-building" (Trenz 2015, 234). Recent studies, on the other hand, seem to put emphasis on an empirical grounding of the debate (Trenz 2015; Drewski, Gerhards, and others 2015). This development is being mirrored in research on the public debate across Europe on the euro crisis. It has been suggested that "there is an emerging demos in the European polity and it has been strengthened during the euro crisis" (Risse 2014, 1213). When testing this hypothesis empirically, though, by looking at newspaper editorials in Spain and Germany, Drewski found that there were significant differences along national instead of ideological lines in the discussion of the Euro crisis (Drewski, Gerhards, and others 2015, 5).

Max Hänska and Stefan Bauchowitz in a recent LSE blog entry track twitter activity during the negotiations leading up to the third Greek bailout agreement. (Haenska and Bauchowitz 2015) According to their findings, Tweets synchronised around key mini-events throughout the negotiations, with peaks and troughs mirrored across national twitter-spheres. These results suggest that popular engagement with the issue converges across Europe.

They further looked at instances of Tweets containing #ThisIsACoup, representing a particular opinion on the agreement. They then showed that the spread of #ThisIsACoup was not reflected in the studied countries equally. This indicated a divergence of public opinion along national lines.

Data Sources

For our investigation in the European public discourse on the Euro crisis, two datasets were required. The first was the corpus of Tweets relating to the Greek debt crisis and the measures taken to manage the crisis by

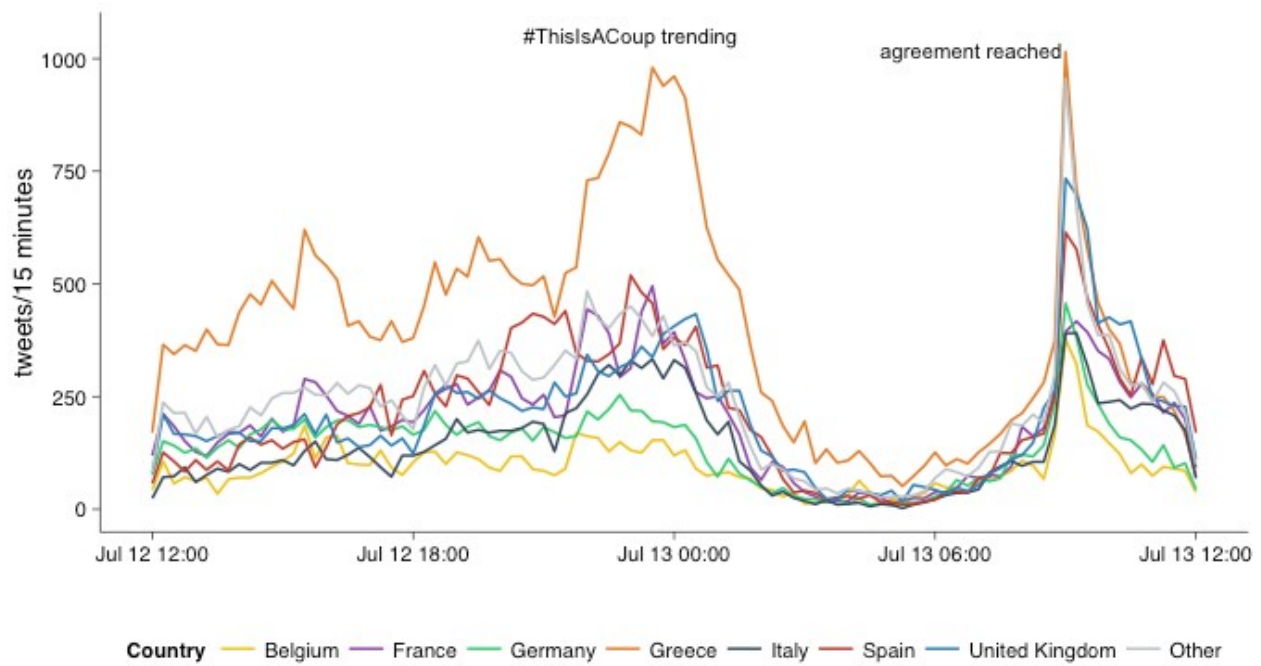


Figure 1: Tweet volumes by country on 12-13 July 2015 in European countries (source Haenska and Bauchowitz 2015)

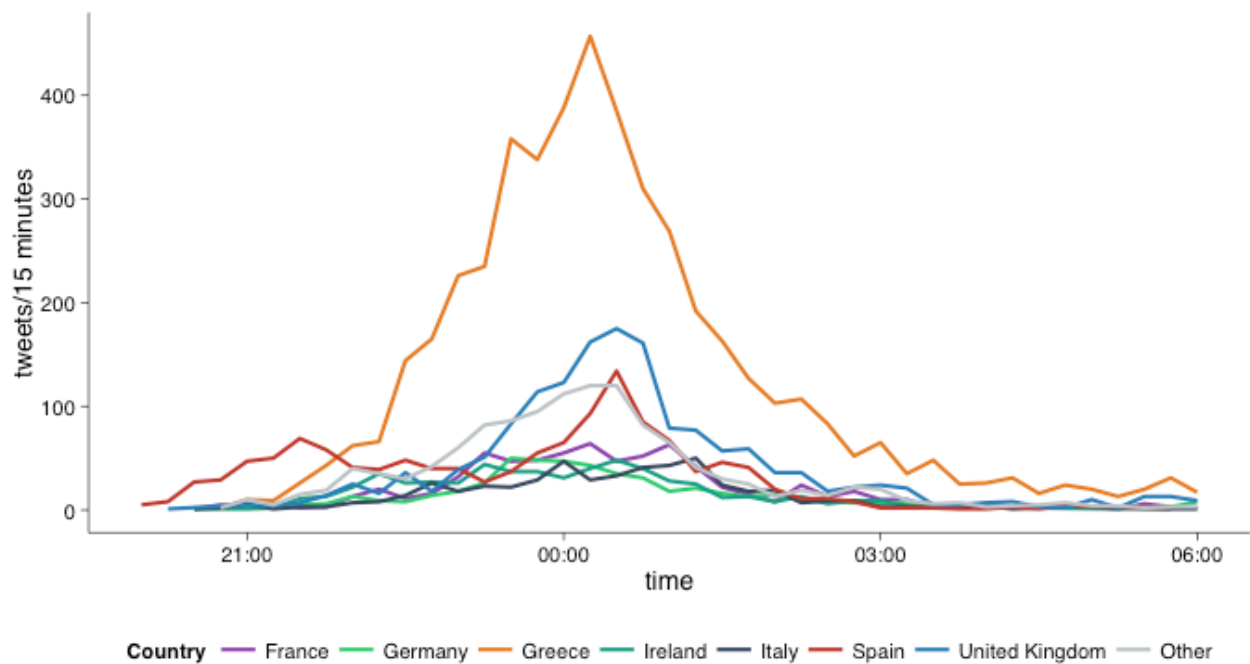


Figure 2: Number of Tweets containing the #thisisacoup hashtag on 12-13 July 2015 (source Haenska and Bauchowitz 2015)

European institutions. The second was information about the users whose Tweets form the body of that corpus. Zimmer and Proferes identify the Library of Congress' decision to place every Tweet since Twitter's inception in 2006 into an archive as validating "the research importance of twitter" (Zimmer and Proferes 2014, 251). Despite this announcement occurring in 2010, five years later, the archive is still not open to researchers (Scola 2015). Since late 2014, the whole corpus of twitter data has been searchable online (Metz 2015). Programmatic access to this archive is, however, more restricted. Twitter's public search API "is not complete index of all Tweets, but instead an index of recent Tweets. At the moment that index includes between 6-9 days of Tweets." ("The Search API" 2015). Twitter sells access to historical Tweets through an API provided by its "enterprise API platform" GNIP (Tornes 2015). This paper adapts a publicly available program written in Java which scrapes results from Twitter's online search page (Henrique 2015).

Data Gathering

Due to the large amount of data we process, we ran the data gathering and cleaning in the background on a server using the prefix `setsid`.

Tweets

We used a modified version of `GetOldTweets` (Henrique 2015), a Java program that scrapes data from twitter search. The file `getting_tweets/input.txt` contains a list of search terms related to the Greek crisis in three periods, each comprising some weeks before and after the negotiation and signing of the memoranda. The search terms were collected using an adapted form of snowball sampling (Biernacki and Waldorf 1981), searching an initial list and recursively adding related terms found in the results. By running

```
sudo setsid ./compile_run.sh ../getting_tweets/input.txt
```

from the `GetOldTweets` folder, we ran through each search term and each period, searched twitter, and saved the results as a txt file in the data folder. After an initial assessment of the results, we refined our search terms and ran `GetOldTweets` again with `/getting_tweets/input2.txt`. A third file (`getting_tweets/input3.txt`) aims to return a time-inpedependent list of tweets in order to control for the growth of Twitter over time.

We end up with a long list of files in the `data/GOToutput` folder, which in the data cleaning process will be merged into one corpus file.

Users

We found the unique users in our corpus of tweets and used the `Twitter` package (Gentry 2015) to gather richer data about each user. `Twitter` uses the twitter API and gives the opportunity to collect all information twitter has about the user. Where a users's last tweet was geocoded, we took the latitude and longitude. We end up with the file `data/user_info.csv`

Many users do not geotag their tweets, instead stating their location, and we used APIs from MapQuest and Google to geocode user-reported location, giving us the file `places.csv`.

Merging & Cleaning

The txt files containing the tweets for each query and period are merged into a corpus file. This corpus file was merged with the `user_info` file, which in turn was merged with the `places` file. We end up with a large file containing tweets for our queries in each period with elaborate user information.

Some of the queries we defined returned irrelevant data, due to their ambiguity. We identified these by selecting random tweets from the search queries, reading the tweets, and checking for relevance to the topic. For example,

the query “bailout”, although certainly relevant for our topic, was insufficiently precise and returned a lot of data about the banking bailouts, especially in the 2010 period. The following list summarizes the queries which we excluded.

- athens
- bailout
- 2-pac
- 3-pac

Translation

In a next step we identified the language of every tweet (Hornik et al. 2015) and translated those tweets written in European languages other than English into English (Lucas and Tingley 2014). Danish and Romanian were excluded from the list because these languages were not adequately identified by the program.

Final Dataset

A dataframe ‘merged_corpus’ containing all of the above information was pulled together. We filtered all tweets from Europe.

Methodology

Volumes of topic-relevant Tweets were mapped across space and time, to analyse the distribution of topic-awareness and its relation to political developments in responses to the crisis. The distribution of hashtags that clearly represent an opinion on the response to the crisis (e.g. ‘#ThisIsaCoup’, ‘#ThisIsNotaCoup’ *inter alia*) were similarly mapped in order to approximate the distribution of opinion within and between countries over time. The paper attempts a sentiment analysis of Tweets expressing opinions about the agreed bailout deals using machine translation to translate all texts into English before performing sentiment analysis. Analysis was then carried out using unigrams to indicate polarity through comparison with a lexicon. Following Grimmer, we assumed “documents are a *bag of words*, where order does not inform our analyses” as “In practice, for common tasks like measuring sentiment, topic modeling, or search, *n-grams* (combinations of words rather than individual words) do little to enhance performance” (Grimmer and Stewart 2013, 6).

To carry out the sentiment analysis process, we use the R package `tm.plugin.sentiment` (Annau 2014) to compare the words in our translated corpus of tweets with the General Enquirer lexicon (Theussl, Hofmarcher, and Hornik 2015). Each tweets is given a positive score and a negative score according to the number of positive and negative words found in the tweet. We calculate an overall sentiment score by subtracting the negative score from the positive score. Low scores therefore indicate negative sentiment; high scores indicate positive sentiment.

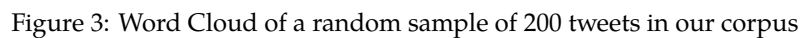
Based on the results of sentiment analysis carried out and analysis of volumes of tweets and users using opinion-signifying keywords, the paper gives an indication of the scale of dialogue, consensus and disagreement across and within countries in the European Twittersphere.

Analysis

Descriptive Statistics

The word cloud gives us an overall picture of the words used in the collected tweets connected to the European public-debt crisis.¹

¹to a certain degree in this case a word cloud is redundant, because it mainly returns our query turns. However, it also indicates the prevalence of specific terms, and further, which other terms are mentioned regularly in those tweets.



Variation Across Space

Variation Across Time

Variation Across Space and Time

The following table summarizes the collected data by queries. It shows absolute numbers and relative distributions of specific query returns.

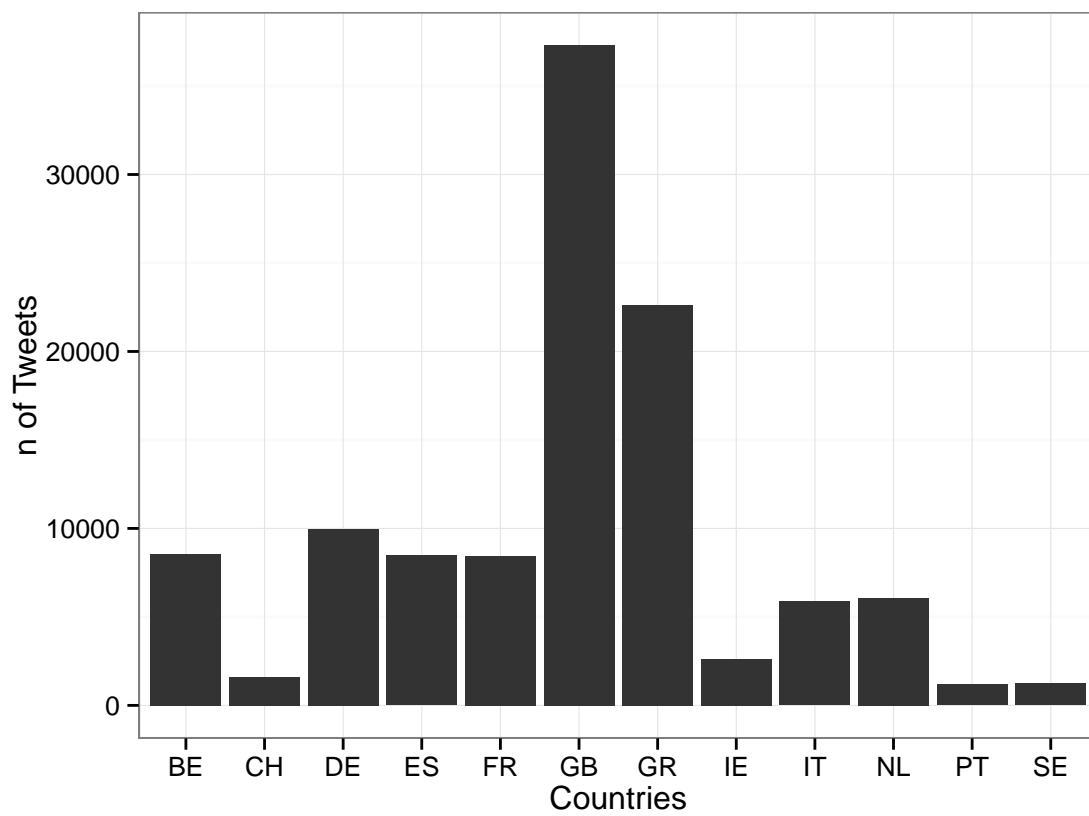


Figure 4: Geographical Distribution of Tweets

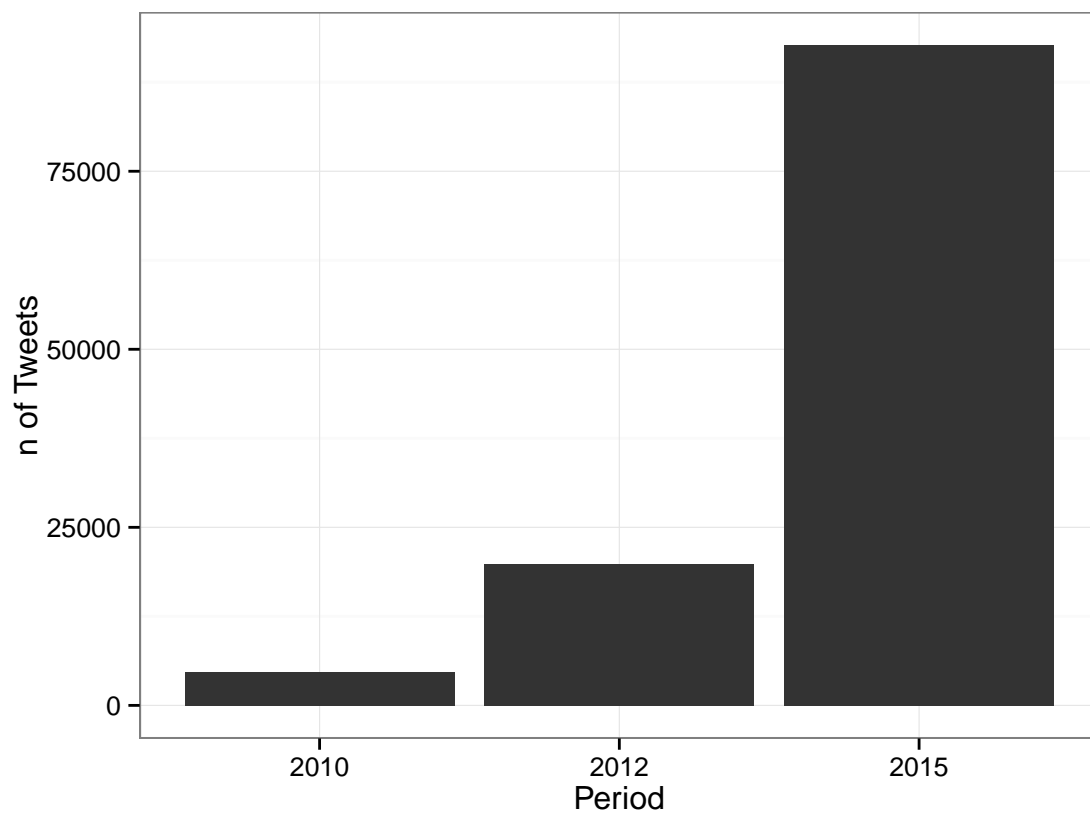


Figure 5: Tweets matching our queries by year

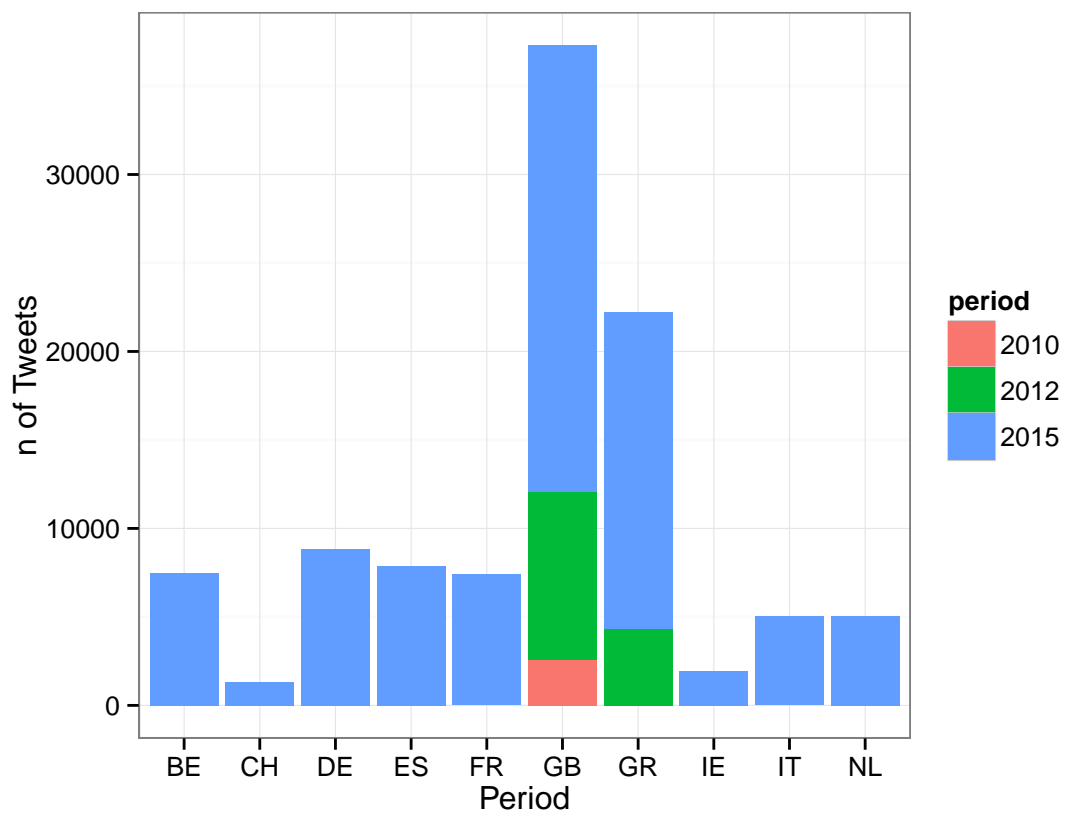


Figure 6: Spatio-Temporal distribution of total tweets in corpus

query	n	percent
#aGreekment	2761	2.36
athens+berlin	372	0.32
austerity+greece	2277	1.94
economic+adjustment	42	0.04
eucrisis	93	0.08
eurocrisis	1964	1.68
eurogroup	1255	1.07
eurogroup+agreement	272	0.23
eurosummit	7226	6.16
euro+summit	8277	7.06
germany+greece	3285	2.80
greece+crisis	2996	2.56
greece+reforms	3603	3.07
grexit	4591	3.92
imf+greece	2087	1.78
memorandum+greece	419	0.36
merkel+greece	4618	3.94
mou+greece	383	0.33
#nai	3079	2.63
#nai+greece	115	0.10
notmyeuropa	217	0.19
#oxi	1484	1.27
rescue packages	32	0.03
schäuble+greece	2114	1.80
syria	2318	1.98
tax+evasion+greece	259	0.22
#thisisacoup	5448	4.65
#thisisnotacoup	244	0.21
tsipras	5313	4.53
varoufakis	10940	9.33
bailout+eurozone	3759	3.21
bailout+greece	5290	4.51
bailout+greek	1425	1.22
efsm+greece	352	0.30
efsm+greek	66	0.06
ems+greece	14	0.01
esm+greek	298	0.25
greece+debt	4137	3.53
greek+crisis	17351	14.80
greek+debt	3977	3.39
greek+reforms	2333	1.99
memorandum+greek	148	0.13
six-pack+greek	2	0.00

The results that our queries returned differ substantially in size. While some queries (e.g. greek+crisis) return over 16000 tweets, others (e.g. economic+adjustment, rescue+packages) return only around 30 tweets in the specified time periods. We therefore think it is for analytical reasons useful to differentiate between high-return and low-return queries. The following charts report the developments over time for the high return rates as this group creates more intelligible results.

In the 2010 period, “greek+crisis” and “bailout+greece” are the most frequently used query. “Bailout” usage in tweets peaks around April 23rd when Greek prime minister Papandreu formally requested an international

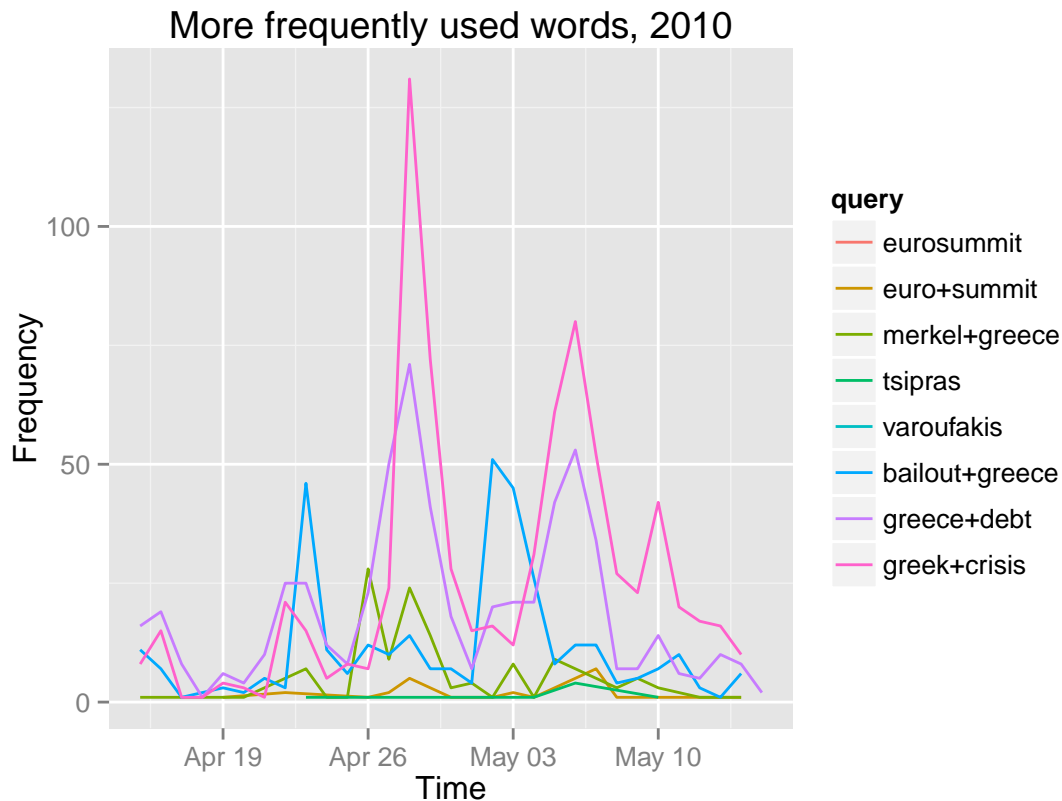


Figure 7: Most common search queries, 2010

bailout for Greece. In the following day, “greek+crisis” is used at its highest level, with nearly 125 occurrences on April 28th. However, the use of “greek+crisis” in tweets dropped dramatically for a short period of around 6 days, before it peaked again, however somewhat less pronounced. The drop in usage of “greek+crisis” was accompanied by an increase in usage of “greek+bailout”, which peaked around May 2nd before it subsided. On May 2nd, the agreement on the First bailout package was reached (Goncalves 2015). During this short phase, “greek+bailout” was the most prominently used word combination (from our sample). Only after “greek+crisis” became most frequently used words.

In the 2012 period, there was a discourse on the greek crisis weeks before the agreement. “greek+crisis” was used from the beginning of February until February 21st when the agreement between the Greek government and the Troika was reached (Economist 2015) constantly in between around 40 to 75 tweets. The usage of “greek+crisis” peaked at the date when the agreement was reached (in contrast to 2010 when it dropped around this phase). However, just like in 2010, “bailout+greece” became the most frequently used phrase in all tweets (of our sample) at the time when agreement was reached. After that, twitter users tweeted less about “bailout+greece” and “greek+crisis”. However, it took nearly a month for those words being used only ten times a day. Notably, “grexit” which had not been used in 2010 was used frequently in the negotiation phase.

In the 2015 period, “greek crisis” was still amongst the most commonly used words in the corpus of tweets we collected. While at its highest peaks in 2010 and 2012 it was used around 120 times daily, we found around 1500 occurrences of “greek+crisis” in one day in the 2015 period. Equally popular were “#ThisIsACoup” and “Varoufakis”, and “Tsipras”. The most frequently used word in the 2015 period was “eurosummit” which was used a lot in the time running up to the summit and during the summit. During the summit, “greek+crisis” also peaked. In the aftermath of the announcement that an agreement had been reached, there is much less tweets. The Hashtag “This is a Coup” emerged on July 14th, peaked in July 15th - equally prominent as “greek+crisis”. “Varoufakis” becomes frequently used in tweets in late July, which may have been caused by the release of an interview with revelations about a previously secret “plan B”. (Kitsantonis 2015) “bailout+greece”

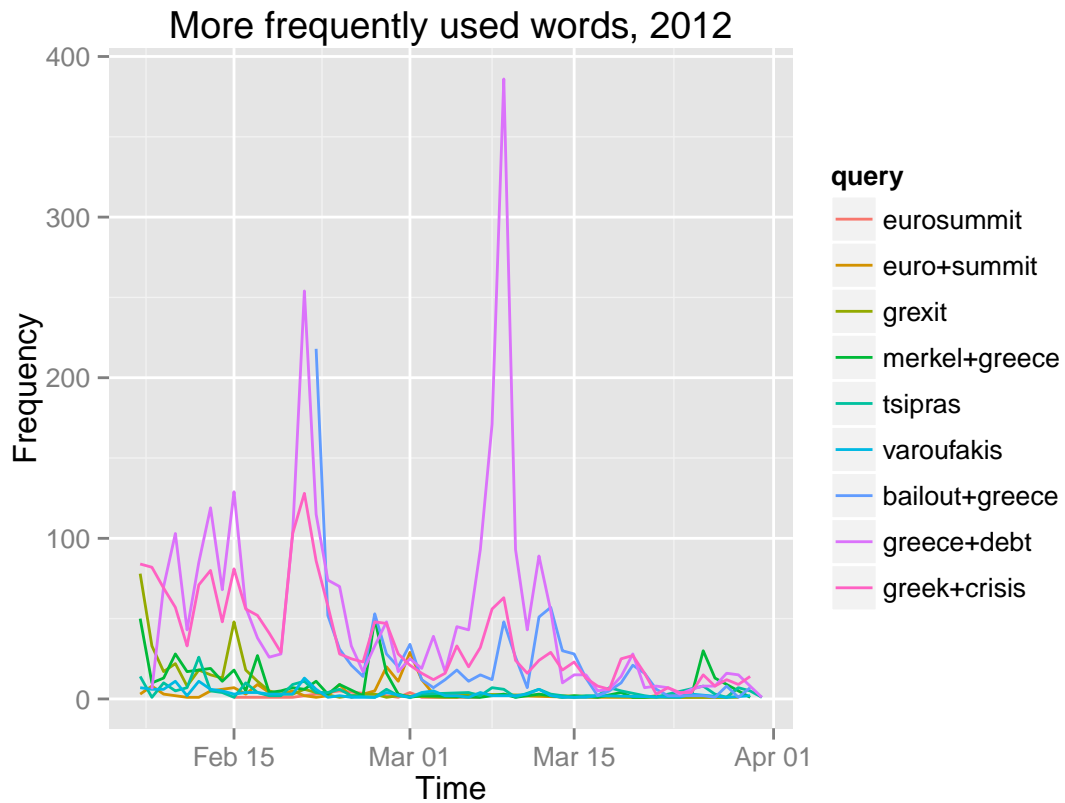


Figure 8: Most common search queries, 2010

peaked around the 14th of August, when the Greek parliament approved the third bailout package. Towards the end of the period, “varoufakis” and “tsipras” become frequently used. “varoufakis” has a second peak when he resigns (on August 20th).

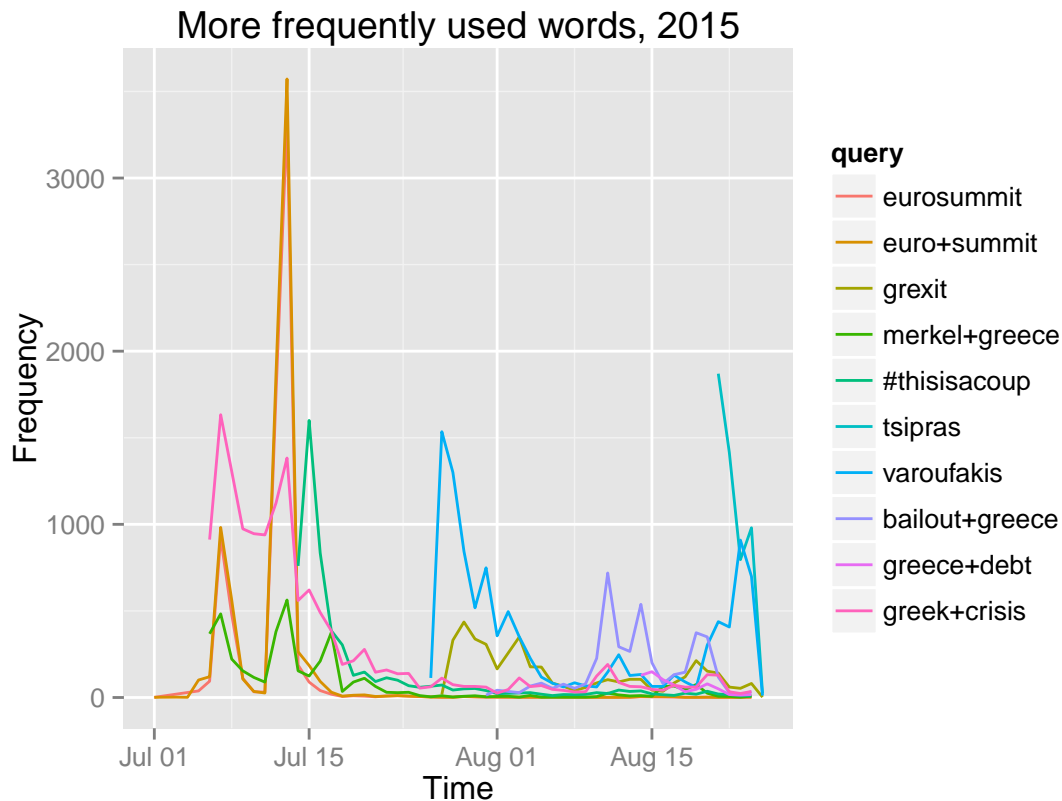


Figure 9: Most common search queries, 2010

Inferential Statistics: Sentiment Analysis

We summarised sentiment over time and across countries. Figures 10-12 show total sentiment scores (across all queries) and sentiment variance for all of the European countries in our dataset in each of the three time periods. We can visually identify variation in the overall score and in the variance between countries and across the three time periods.

To test whether the spatio-temporal distribution of sentiment in tweets is significant, we regress sentiment score on country and time dummies.

An F-test on the joint significance of country and time finds that we can reject at the 1% significance level ($p = 0$) the null hypothesis that time-period and country have no effect on sentiment. Interpreting the variation between countries and time periods at this aggregated level, as it is hard to make assumptions about how positive or negative sentiment expressed in tweets relates to opinions about political events or persons.

We focus in this paper on some specific search queries, though we also release our dataset aggregated at the country level in [interactive form](#).

Here we can see differences between these countries in this period. For a more detailed picture, we show daily averages and variance for two countries.

The two lines tend to follow each other. This may suggest that twitter users in both countries both respond to the evolution of events in the news cycle. We can identify correspondences between particular peaks and troughs and actual events. e.g. Further to the finding by (Haenska and Bauchowitz 2015) that tweet volumes respond to political events, we find evidence to suggest that the sentiment of those tweets' content also responds to political events.

Despite this, the countries' lines do sometimes diverge. This is particularly apparent here. This shows a difference in the average sentiment between the two countries at the same point in time. To establish that this difference

is not due to random noise, we once again regress total sentiment score on country and time dummies, this time limiting the analysis to the two countries in question and to the selected query.

We looked at individual tweets and compared the results to our perception of sentiment of the tweet. While there seemed to be some problems, the sentiment analysis scores did seem reasonable.

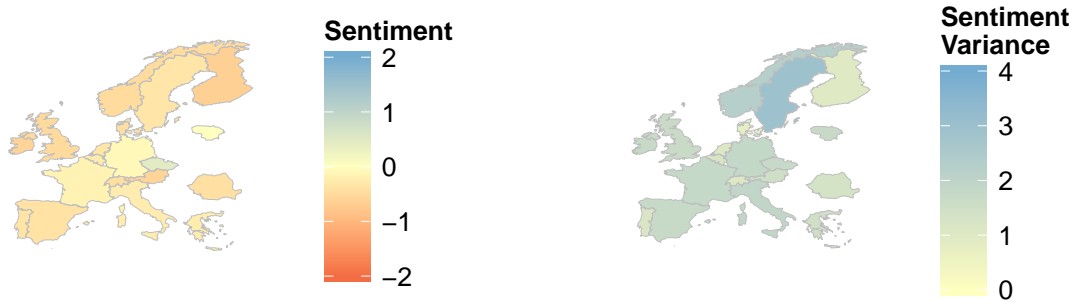


Figure 10: Sentiment scores and variance across all search queries (2010)

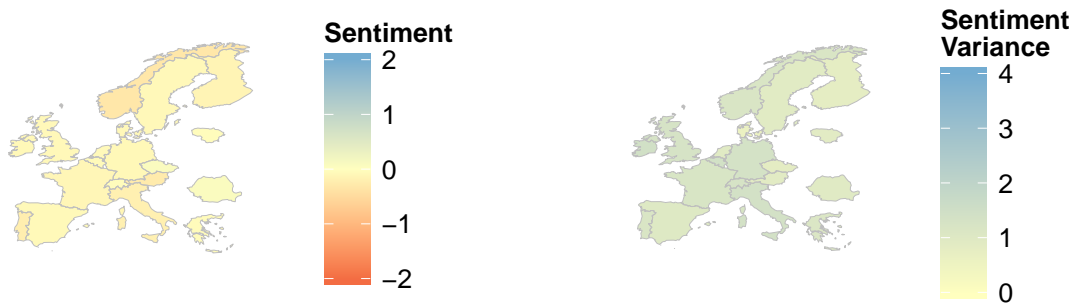


Figure 11: Sentiment scores and variance across all search queries (2012)

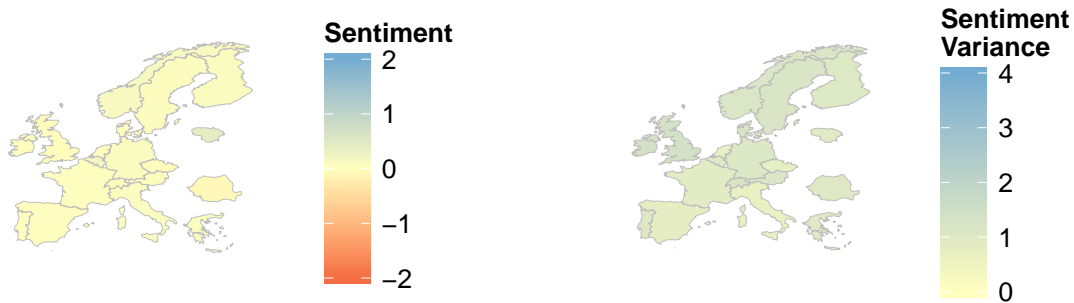


Figure 12: Sentiment scores and variance across all search queries (2015)

However, when calculating the sentiments for queries, the returned results did not match our expectations. Below we report the resulted for the query “merkel+greece”. We report the sum of the positive scores divided by the number of tweets. The figures indicate that the sentiments were very positive in most of the European countries and very similar.

We conclude from this that our current sentiment analysis does not return reasonable results. We will in the next stage of the project try to create a model that returns more accurate results.

Caveats

- Location
- translation: danish, romanian,
- “normalizaion” of values not conducted for some, because of huge data amounts
- SA: caution, however, about the utility of SA in predictive models (Grimmer and Stewart 2013, 4). “For shorter texts, accompanying information (or an extremely large volume of texts) is often necessary for classification or scaling methods to perform reliably” (Grimmer and Stewart 2013, 6)
- research design: case selection ambiguous - for research on a common european sphere, choosing a case that by definition deviates along national lines

Conclusions

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