Masters Program in **Geospatial Technologies**

POLITICIZATION OF NON-POLITICAL EVENTS: A Geospatial Analysis of Twitter Content During The 2014 FIFA World Cup

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POLITICIZATION OF NON-POLITICAL EVENTS:

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ABSTRACT

Spatial analysis and social network analysis typically take into consideration social processes in specific contexts of geographical or network space. The research in political science increasingly strives to model heterogeneity and spatial dependence. To better understand and geographically model the relationship between "non-political" events, streaming data from social networks, and political climate was the primary objective of the current study. Geographic information systems (GIS) are useful tools in the organization and analysis of streaming data from social networks. In this study, geographical and statistical analysis were combined in order to define the temporal and spatial nature of the data eminating from the popular social network Twitter during the 2014 FIFA World Cup. The study spans the entire globe because Twitter's geotagging function, the fundamental data that makes this study possible, is not limited to a geographic area. By examining the public reactions to an inherenlty non-political event, this study serves to illuminate broader questions about social behavior and spatial dependence. From a practical perspective, the analyses demonstrate how the discussion of political topics fluctuate according to football matches. Tableau and Rapidminer, in addition to a set basic statistical methods, were applied to find patterns in the social behavior in space and time in different geographic regions. It was found some insight into the relationship between an ostensibly non-political event – the World Cup - and public opinion transmitted by social media. The methodology could serve as a prototype for future studies and guide policy makers in governmental and non-governmental organizations in gauging the public opinion in certain geographic locations.

KEYWORDS

GIS Applications

Geographical Information Systems

Spatial Decision Support Systems

Politics

Spatial analysis

Geo-social analysis

Clustering

Distribution

PostGIS

R

Terms

English language

Spanish language

German language

Portuguese language

Russian language

Twitter

RapidMiner

Tableau

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1. INTRODUCTION

1.1. Theoretical Framework

Advances in modern science, represented by geographic information systems (GIS), can be applied as a powerful tool for performing an accurate geography-based analysis of objective data in the domain of political practice (Somers, 2004).

New technologies have created a powerful paradigm shift for new political campaigning (Spiller & Bergner, 2010). Recently, both political “technologies”, which can produce an immediate effect, and those technologies which are based on accurate scientific calculations, have been practiced. This combination allows one to actively apply the power of information systems to political life and substantiate political decisions with hard data, rather than subjective suppositions, improving decision-making efficiency.

In the modern context, geographic information systems are already widely used for the analysis of voting results and campaign planning. Governmental employees are one of the largest users of all these opportunities (Ye et al, 2014). The “visualization” of election results has been practiced for decades. GIS is also useful in the creation of election districts that give opportunities for local groups to elect preferred candidates (Clemens, 2015). In fact, an election campaign looks much like a battle map in the sense that it is important to follow all events and use it in campaigns as we can see from best practices of numerous earlier campaigns.

Any election campaign implies certain relations between ruling authorities, mass media and “non-political” events. The nature of these relations varies from country to country, depending on mass media agencies in question, the particular government in power, problems that are in the spotlight, the global and domestic situations and many other things.

Using a variety of thematic maps, business analysis software, and lifestyle mapping systems, users can quickly determine new areas for development (ESRI, 2007). As we can see from history, the influence of football world cups demonstrated a massive growth in the economic sector, at the same time bringing together different cultures and promoting trade (Li, 2013). Through such events, domestic political groups and international campaigns in other countries can easily advertise their strategy over whole world (Harris et al, 2005).

Because marketers, governmental employees, and researchers use IT systems to store and analyze large amounts of data, there is concern about the ethics of their use, especially in regard to personal privacy (Reynolds, 2007). For this purpose, a GIS must be developed long before the event or study it is intended for, rather than at the last minute. The results will make sense and be of practical use in this case only.

The World Cup has developed into one of the most significant international sporting events (Kim, W. et all, 2015). The rising number of cities bidding to host it and the rising number of investments in the event show that local leaders consider it an opportunity to improve economic and social aspects of a region or country. As a result, there has been increased interest on the impact of the World Cup on the socio-economic and political life of the host city, region, country and world.

1.2. The Intersection of Twitter and Politics in Related Literature

Some studies have implemented geospatial technologies for geo-social and political analysis while other studies have focused on detection techniques that retrieve information about specific topics and terms expressed by a community in real-time (Palacio, 2015).

As stated by Hanewicz, a great deal of convergence has occurred between wireless devices, location technologies, and spatial management and analysis tools with the outcome that many politicians can now manage information in real time in a seamless manner (2012). "Political marketing" has asserted itself across all countries, even in small municipalities. According to Wring, political marketing as “the party or candidate’s use of opinion research and environmental analysis to produce and promote a competitive offering which will help realize organizational aims and satisfy groups of electors in exchange for their votes” (1997).

Political analysis using social media is drawing the attention of many researchers to understand public opinion and social trends. With the boom of the online community, people are expressing their likes and dislikes towards different subjects in blogs, microblogs and social networking sites like Twitter and Facebook (Singhal et al, 2015).

This relatively new digital technology has made the exchange of user-generated content on the internet possible and turned the web into a very popular social medium. Facebook alone has over one billion active users and overall, people spend more than one third of their waking hours consuming social media content (Habibi, 2014).

Twitter is a microblogging website where users read and write short messages on various topics. Analyzing these expressions of short colloquial text can yield vast information about the behavior of the people, and can be helpful in many other fields of information technologies (Blenn, 2012). Twitter is currently the second most popular social media site (eBizMBA, 2015). With the torrential streams of Twitter updates (or tweets), there's an emerging demand to sieve signals from noises and harvest useful information.

It has been argued that social networks are a good resource for detecting and analyzing events (Li, Rui et al, 2012). As a tweet is often associated with spatial and temporal information, we can detect when and where an event happens. In the paper "*Tedas: A twitter-based event detection and analysis system*", a novel system was proposed. The study focused on Crime and Disaster-Related Events (CDE), such as shootings, car accidents, or tornadoes. It detects and analyzes by exploring rich information from Twitter with three functions: detecting new events, ranking them according to their importance, and generating temporal and spatial patterns for timeline of events. As the system aims to identify important CDEs for the query, those tweets are ranked according to their importance. To extract spatial and temporal patterns for the query, a clustering model groups similar tweets into different geographic regions or temporal ranges. The results are sent to the interface, where a visualization of the results is provided.

Prior to that, Cataldi et al provided a different method to extract specific topics by analyzing social networks in real-time by the terms expressed by the community (2010). They based their study on a five steps process.

First step is extraction and formalization of the user-generated content expressed by the tweets as vectors of terms with their relative frequencies. After they define a directed graph of the active authors based on their social relationships, their authority was calculated by relying on the Page Rank algorithm. The third step is modeling life cycle according to a novel aging theory that leverages the user's authority. After researcher can select a set of emerging terms by ranking the keywords depending on their life status. The last step is the creation of a navigable topic graph which link the extracted terms with their relative concurrent terms in order to obtain a set of emerging topics. This study integrates aspects of Cataldi's five-step process.

There are also many useful web applications to analyze Twitter, Facebook and other social streams for serve specific purpose. Trendistic and Twopular represent two examples from which it is possible to analyze the trends of some keywords along a timeline specified by the user (Cataldi M. et al, 2013). Users can sift through these streams, aggregate and rank data, make a decision based on extracted information and create new knowledge for future works. For the best observation of spatial components in data set, it is better to use a combination of analytic tools.

1.3. Objectives

The objective of this study is to detect changes in discussion topics during the 2014 FIFA World Cup in different regions of the world according to political terms. The impact of this event on public reactions was then interpreted based on the dynamics of terminology.

Understanding this influence and the lack of research aiming to reveal the relationship between social event and political campaign were the main motivation to do this thesis research.

The demand for such studies is going to increase, provided that timely conclusions on campaigning results are made, showing the ability of GIS to influence decision-making, which unquestionably demonstrated their effectiveness.

1.4. Research questions

The initial step in defining non-political events is to consider them within the field of all possible non-political events and to determine into which category they fall (e.g. commercial, cultural, and corporate). Therefore, the key issue to be addressed is the identification of criteria by which events are defined. In other words, the first question in our research is: "What differentiates non-political events from political events?"

Politics affecting the host country naturally play a vital role in the organization of the World Cup. Since the staging of the event usually requires large-scale construction projects of sporting facilities, infrastructure projects such as road, accommodation facilities, stadiums, and renovation of the host city buildings. Based on this information the second questions we can ask is: "How is a non-political event politicized when it is carried out?"

The last interesting part deals with huge and time-sensitive text contents and the analysis of trends across space. The real-time social content can be seen as a sensor that shows what is happening in the world. The general rule is that a topic can be analyzed only with in a specific time frame – in our case it is the duration of the main stage of the World Cup. It is important how a specific content about event behaves over time in politics. As a consequence, the last questions is: "In which locations were political topics discussed?"

1.5. Hypotheses

It is hypothesized that non-political events become politicized through social media. The second hypotheses is that social media data has certain statistical and spatial characteristics, which provide the researcher clues about public opinion in a given location within a specific time frame.

1.6. Methodology

The main steps of research were developed relying heavily on related studies, including the definition of political vs. non-political events, extraction of user-generated content, data processing, spatial and statistical analysis, and finally sentiment analysis.

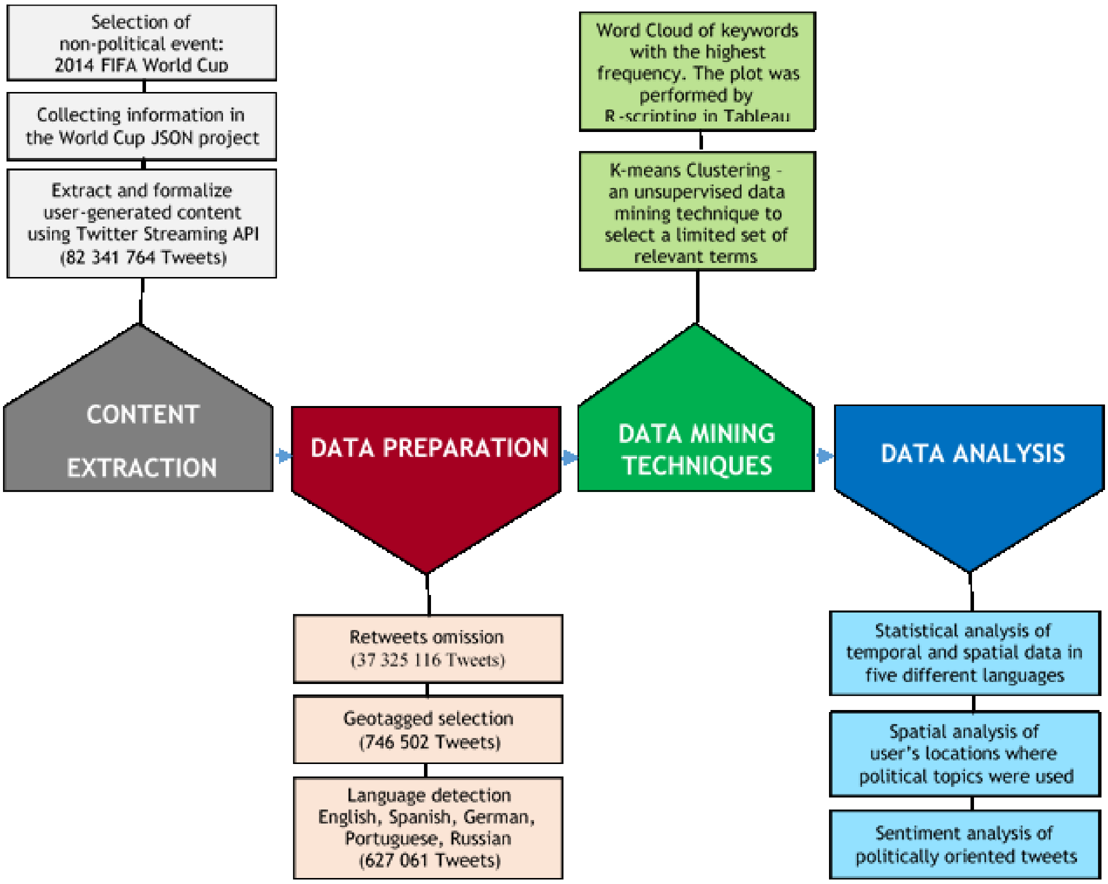

Figure 1. Thesis Workflow

First step contains analysis of term "non-political event" by the review of official definitions of political events in different regions.

The second step is extraction and formalization of the user-generated content expressed by the social posts - tweets using Twitter Streaming API. English, German, Portuguese, Spanish, Russian were chosen as the research languages.

The next step is data processing with special statistical software to select a limited set of relevant terms that exist in the considered time interval and particular location connected with political topics in Twitter.

Statistical analysis has to be done to determine the common topics, as vectors of political and event terms with their relative frequencies with information about time and location using during non-political event in different regions. Spatial analysis needs to evaluate where content related with event and politic, bring about reaction from society. Sentiment analysis determines the behavior of the politically oriented tweets. It is a field of natural language processing which focuses on extraction of objective and subjective information from a natural language sentence.

Chen C.C. et al proposed a metaphor where each term is seen as a living organism; in contrast to the approach proposed in, analyze the terms life cycles by distinguishing among different time intervals in order to highlight when a term becomes important in the community (2003). The analysis process showed on Figure 1 starts with the real-time extraction of the relevant keywords from the Twitter stream. The importance of the source, from which political topics were analyzed, is basically counting knowledge where the contents constitute the entire semantics for extraction political facts. Different classification strategies and data-mining techniques cannot be applied in our research because they usually ignore the temporal and spatial relationships of tweets related to a political event situation (Shaheen M. et al, 2013).

The first step for the selection of political terms depends on a user-specified parameter. The original assumption is based on the idea that two keywords with very high frequency values can be measured as political or not depending on the user evaluation. The second step takes into account the idea that an automatic model does not involve any user interaction. The dependence on the temporal context could be necessary to set other the threshold value.

One of the last steps, evaluate the impact of techniques in the retrieved topics by analyzing the real-time information. The main stage is analyzing the influence of events on politics, the reaction from society and how it changed trends in political topics. The results of the study could be helpful for policy makers and for government by contributing to decision-making and to visualize who is using political terms and where they are being used.

1.7. Thesis Organization

The thesis is organized according to the following methodology. In the first chapter, an overview of literature on social network analysis in geographical contexts, as well as GIS applications in politics, is presented. In the second chapter, data description, preparation, and limitations of this study are described. The third chapter is dedicated to the analysis of geotagged social data: data processing, spacial and geo-social analysis. This includes the statistical analyses of the most referenced political terms and insights about common ways political topics are used during non-political events in different regions. The fourth chapter highlights conclusions and future work expectations. There are three annexes which contain an example of a code written in R, the structure of database and keywords event's diagram.

2. RESEARCH DATA DESCRIPTION AND ORGANIZATION

2.1. Data description

The study area of the thesis comprises the main stage of the 20th FIFA World Cup, which took place in different cities across Brazil. When the decision to carry out this tournament was announced in 2003, the reactions immediately followed.

According to Barreto, the 2014 World Cup was marked by fears that the stadiums and infrastructure would not be ready in time, street protests against government expenditures to finance the event sprang up. The elections and federal budget were topics that dominated in the news through all pre-selection period (2012).

The group stage of the 2014 FIFA World Cup took place in Brazil from 12 June 2014 to 26 June 2014: each team from 32 countries played three games. Worldwide, several games have qualified as the most-watched sporting events in their country in 2014, including 42.9 million people in Brazil for the opening game between Brazil and Croatia and the 34.1 million in Japan who saw their team play against Ivory Coast (Godfrey, 2014).

The two official hashtags of the World Cup - #WorldCup and #Brasil2014 – were announced. This event broke records on Facebook and Twitter in terms of the amount of posts. For example, the game between Brazil and Chile generated 16.4 million tweets in two hours. The tournament also racked up an unprecedented 1 billion Facebook interactions by 29 June, with two weeks left to the final (Billings et al, 2014).

We aimed to detect real-world events on a global scale, in a given monitored geographic area and to conduct the experiments described in this paper with German, English, Spanish, Russian and Portuguese tweets connected with political topics from the countries all around the world. English and Spanish languages were chosen because of their popularity in Twitter. Portuguese language was selected because it is the main language of the host country. German was chosen because the

German team won the tournament. Russian was chosen because the 2018 FIFA World Cup will take place in Russia.

For all these purposes the different data sets were used. The collection of information about the 2014 FIFA World Cup began with the World Cup JSON project. JSON is a JavaScript Object Notation, in other words, it is a syntax for storing and exchanging data (Hope, 2014). World Cup in JSON is an API that gets match results for the World Cup and retrieves information on the particular soccer matches, matches for a given country, results for teams, and a list of all teams participating in the World Cup, and data for all football matches. The first database RESULTS, includes information about all matches held during this sport event. Table 1 shows an example of the final database structure with the following fields: match number, location (name of the stadium), date and time information, name of the country for the home team and for the away team, goals of both teams and the winner name with code.

№	Location	Match time	HT country	HT code	HT goals	AT country	AT code	AT goals	Winner	Winner code
1	Arena de Sao Paulo	6/12/2014 20:00	Brazil	BRA	3	Croatia	CRO	1	Brazil	BRA
2	Estadio das Dunas	6/13/2014 16:00	Mexico	MEX	1	Camero on	CMR	0	Mexico	MEX

Table 1. An example of data in the results database.

Another important step was the real-time extraction of the data from the stream of social network - Twitter. Twitter Streaming API provided opportunity to continuously listen to a stream of tweets (Chinthala S. et al, 2015).

A R Script was written to collect tweets through Twitter Search API. The data were collected between June 6th and July 14th and stored in the file DATA.csv. It includes 82 341 764 tweets. The selection was based on the official World Cup hashtags (#WorldCup and #Brasil2014). The structure of the main database represents following information about each tweet: unique ID number, creation date, text data of the tweet, user nickname, and special mark about retweet, and information about location - latitude and longitude.

2.2. Data limitations

Free, geographic and semantically rich datasets derived from the harvesting of social media sites *en masse* should continue to be of great and growing interest to all spatial analysts (Goodchild, 2007). Data quality remains a serious concern for all such research. The sheer diversity and sporadic nature of the data poses new challenges to researchers accustomed to relatively clean official datasets.

Several limitations stem from the data itself, including the limited amount of geotagged data and the high proportion of retweets which lack geographic data. Furthermore, there is uncertainty associated with the social behavior of users who did not put hashtags on their messages and it must be noted that only a small portion of World Cup spectators are Twitter users. Therefore, it is difficult to make generalizations or model future behavior based on the experimental data from this study.

When Twitter applications access GPS devices and/or cellular location info, their coordinates are broadcast as metadata attached to every tweet. These data are generated automatically, and we can be fairly confident in their accuracy. But according to Leetaru et al., only about 1.6 percent of users have this functionality turned on (2012). This presents a huge gap in the potential data to be analyzed. Due to privacy concerns, Twitter offers it on an opt-in basis, which partly explains the low level of uptake.

The broader problem of wide semantic diversity can be partially tackled by intelligent filtering, using search terms that capture only messages that can be confidently attributed to the topic of interest. Nevertheless, there will inevitably still be variations in quality and issues of self-selection even after the most stringent filtering strategies. One way of tackling this issue would be to assign a continuous weight variable to every tweet corresponding to its relevance to the research problem, although the method of assigning high and low weights would add further complexity and subjectivity to the analysis. This point is related to a more fundamental problem with social media data: the context-dependence. Tweets sent to and from individuals contain many subtleties that are useful to users who can decode them, taken out of context, data lose meaning and value. In the process of harvesting and subsequent sampling much of this context is lost: currently there is no way to consider the wider context, implicit in each tweet, over thousands and indeed millions of such data points.

2.3. Data preparation

The analysis process started with the preparation of data. To obtain clear data for geo-social analysis we needed to filter and sort the tweets in the database by some criteria.

The first step of preparation was the omission of the retweets. Retweet has abbreviation RT. It is used on the Twitter Web site, to show that users are tweeting content that has been posted by another user. The main reason was that while the original Tweet may have a location, the native Retweet does not. For example, if a tweet originates in Rio de Janeiro, and somebody given retweets in Lisbon, the retweet's location will remain to Rio. The filtering was done using R scripting by excluding the Tweets starting or comprising known abbreviation "RT". After filtering the database includes 37 325 116 rows ready for the next filtration and analyses.

According to Graham, geolocation is used by different web services and applications, which is very useful for representing a tweet's position on a world map. Unfortunately, only a small fraction of all the tweets are geotagged (2014). Users often tweet from their phones without turning on the geolocation function. The geographic features were showed by information about geo location of tweets, the latitude, the angular distance of the place relative to the earth's equator and the longitude is the angular distance of the place relative to the Greenwich meridian.

In our case only about 2% of tweets were geotagged to location, but the absolute number was still huge. After filtering tweets by non-null values in the latitude and longitude fields, we were left with 746 502 rows in the database.

The next important step in preparation was Language Detection. It was done by Text Analysis API, which uses the Language Detection endpoint to find out what human language a tweet is written in from among 76 different languages. The data set were processed one more time. Figure 2 shows the relative amount of German, English, Spanish, Russian and Portuguese tweets in the database proportionally.

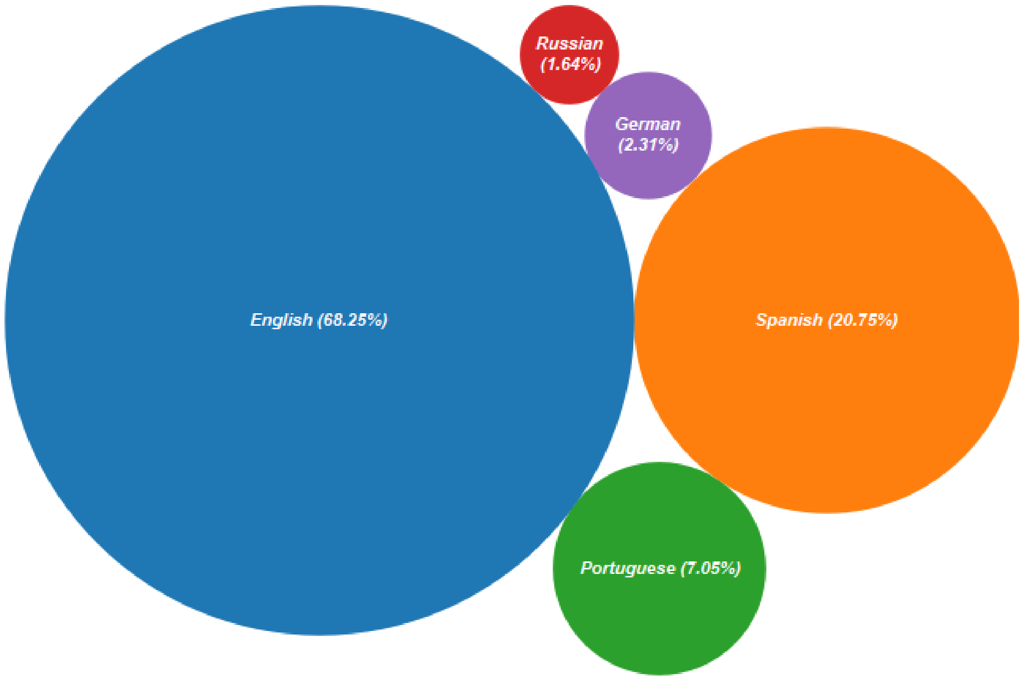

Figure 2. Language groups proportionally represented.

All tweets were grouped by language and count. The size of the circle shows percent of Total Count of Tweets in a particular language. The view is filtered by Language group, which keeps German, English, Spanish, Russian and Portuguese. These languages made up for 84% of all our posts in the database (627 061 tweets).

3. ANALYZING GEOTAGGED SOCIAL DATA

3.1. Analysis of term “non-political event”

Defining the difference between a political and non-political event is the first step of the research. According to (Westermann & Jain, 2007) an event model that aims at establishing a common foundation for a wide diversity of applications, event-centric multimedia, reusable event management infrastructure and tools, and application integration should address several elementary aspects of the event description.

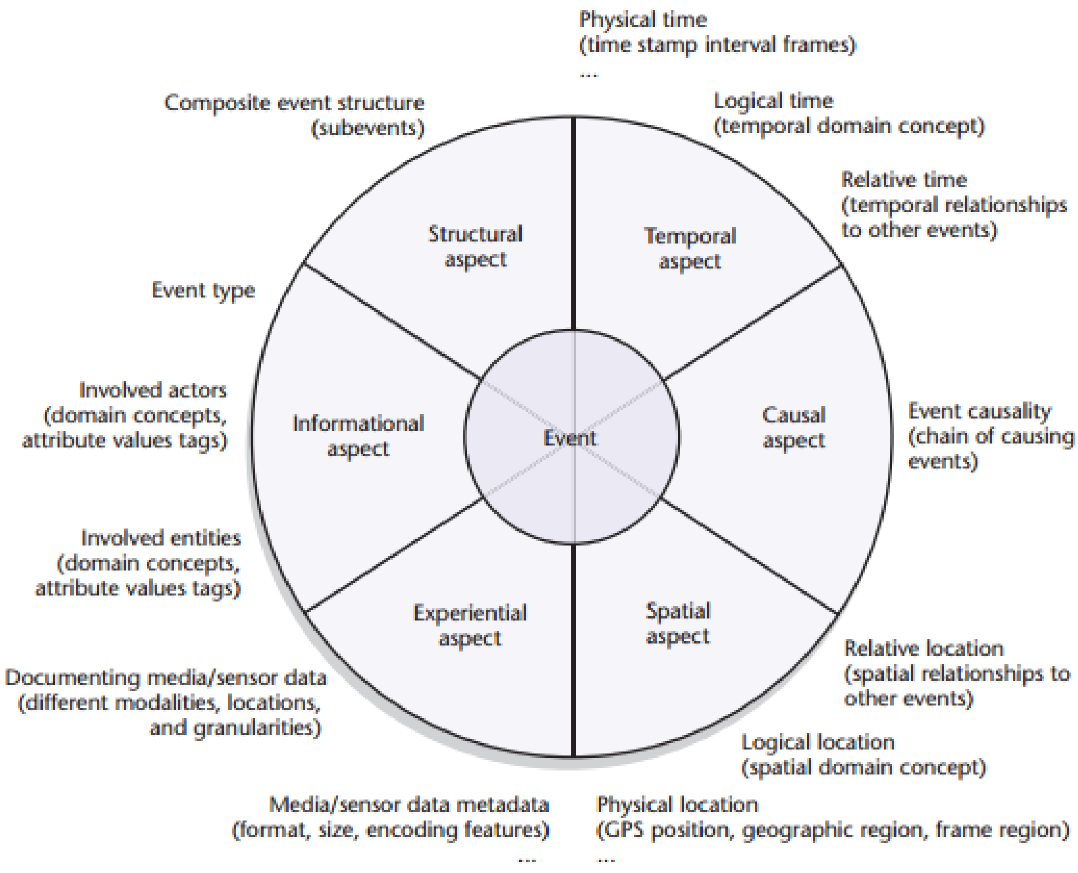

Figure 3. Basic aspects of event description (Westermann, 2007).

A "non-political" event can be viewed in two main respects: its internal characteristics (i.e. number of participants and spectators, number of sessions) and its external characteristics. Based on Figure 3 we characterized the 2014 FIFA World Cup by its basic aspects.

Temporal aspect of the 2014 FIFA World Cup inherently related to the concept of time. In this research we will take in consideration the main stage of the tournament, which took place between from 12 June to 13 July 2014.

The spatial aspect of the 2014 FIFA World Cup is our main subject of research. Brazil hosted the tournament during all stages in 2014. Twelve venues (seven new and five renovated stadiums) in twelve cities were selected for the tournament.

The informational aspect of the 2014 FIFA World Cup provides information about the individual matches that took place. In our case, information contains data about 64 small "events" that took place during the tournament, including information about teams, players, goals, coaches, stadiums, and so on.

The experiential aspect of the 2014 FIFA World Cup offers users engaging ways of exploring and experiencing a course of events to let them gain insight into how the events evolved. Usually there are different sources, ranging from streaming servers, file and content management systems, to multimedia databases. Our event will be explored through the social network Twitter.

The structural aspect of the 2014 FIFA World Cup aggregates low-level events such as person- and object- events to intermediate events such as shots, fouls, and goals.

The causal aspect of the 2014 FIFA World Cup offers a theory about how individual matches that make up the event may cause political sentiments to appear in certain geographic locations.

In 2012, Schrodt stated that a political event is anything that is initiated and organized by a political organization or political candidate exclusively to advance and promote political purposes or political candidate.

The 2014 FIFA World Cup is the biggest single-event sporting competition in the world, organized by the official sport organization FIFA (La Fédération Internationale de Football Association) and it has significant impacts on society and the environment (Butler & Aicher, 2015).

3.2. Extracting information from tweets

After filtering data we were left with 627 061 Tweets. The five languages that were chosen for analysis include German, English, Spanish, Russian and Portuguese. To do an analysis we needed to extract certain keywords for each category (political/non-political/mixed) in its native language from tweets. Figure 4 shows the predominant term used to describe football on different continents.

Figure 4. Data analysis explores how people around the world refer to “soccer” on Facebook.

Keywords were chosen by clustering - an unsupervised data mining technique. The goal of clustering is to capture natural groupings of words between different tweets represented in the data. It defines a "closeness" metric for comparing two objects and groups all objects with a similar closeness. There are two classes of clustering methods: top-down or bottom-up. In a top-down method, the user decides how many clusters the data would form. The popular k-means clustering algorithm is an example of it. In a bottom-up method, users define a distance metric. Hierarchical clustering falls into this bottom-up approach. The data mining technique such as clustering helps only if it will provide some unique ideas in the behaviour of tweets (Joshi, 2014).

For this study, RapidMiner software was chosen as a tool for data mining. It is a software platform developed by the company of the same name that provides an integrated environment for machine learning, data mining, text mining, predictive analytics and business analytics (Hofmann, 2013). RapidMiner versions of the software are available under an OSI-certified open source license. Based on Bloor Research, RapidMiner is written in the Java programming language. Alternatively, the engine can be called from other programs or used as an API. RapidMiner provides learning models and algorithms from Weka and R scripts that can be used through extensions.

The main goal of the analysis using RapidMiner was to quantify words found in tweets during the 2014 FIFA World Cup and to rank those words using clustering tools such as k-means, a commonly used clustering algorithm. The purpose of these algorithms is to divide n data points into k clusters where the distance between each data point and its cluster's center is minimized (Godfrey, 2014). Initially k-means chooses k random points from the data space, not necessarily points in the data, and assigns them as centroids. Then, each data point is assigned to the closest centroid to create k clusters. After this first step, the centroids are reassigned to minimize the distance between them and all the points in their cluster. Each data point is reassigned to the closest centroid. This process continues until convergence is reached.

First, the clustering technique was applied to the input from Tweeter streaming API, which consists of the original number of tweets. Only English tweets were considered due to the limited scope of this study and because English was the predominant language of the dataset. These tweets amounted to 480,000, or about 64% of the total number of the filtered dataset. Another filter was used to remove words words which occurred less than 5 times in tweets. Finally this cleaned output was fed into a k-means clustering operator. The plot of the word cloud was performed by R-scripting in Tableau. The clustering outputs shows the top keywords on Figure 5.

The word clouds tool was used as a visualization method for text and provided an overview by distilling text down to those keywords that appear with the highest frequency (12 words in total were chosen). It provides us a useful idea about our unstructured data from social media.

Figure 5. The result of applying k-means for the database visuliased in Tableau.

I took the most frequently tweeted words and divided them into three categories of four words each: political, non-political (purely football), and mixed.

The set of words in five different languages were chosen for the analysis of tweets. Table 2 contains four words are associated with football. Henceforth, the football topic will have a blue colors in all our graphs.

English	Soccer	Championship	Goal	Game
Spanish	Fútbol	Campeonato	Gol	Juego
Portuguese	Futeball	Mundial	Goal	Jogo
German	Fußball	Meisterschaft	Ziel	Spiel
Russian	Футбол	Чемпионат	Гол	Игра

Table 2. Set of keywords showing strong connection with topics about football.

Table 3 contains four words connected with football and political topics. This words will have green colors in all of our graphs.

English	Defeat	Victory	Profit	Budget
Spanish	Derrota	Victoria	Lucro	Presupuesto
Portuguese	Derrota	Vitoria	Lucro	Orçamento
German	Niederlage	Sieg	Gewinn	Haushalt
Russian	Поражение	Победа	Прибыль	Бюджет

Table 3. Set of keywords showing strong connection with topics about football and politics.

Table 4 contains four words connected with political topics. These words are more interesting for the purpose of our analysis and will represent by bright orange color.

English	Elections	Policy	Power	Changes
Spanish	Elecciones	Política	Energía	Cambios
Portuguese	Eleições	Política	Poder	Mudanças
German	Wahlen	Politik	Leistung	Änderungen
Russian	Выборы	Политика	Власть	Изменения

Table 4. Set of keywords showing strong connection with topics about politics.

After filtering tweets by sets of words containing political and football meanings, in Figure 6, we can see that political topics appeared during 80% of all games.

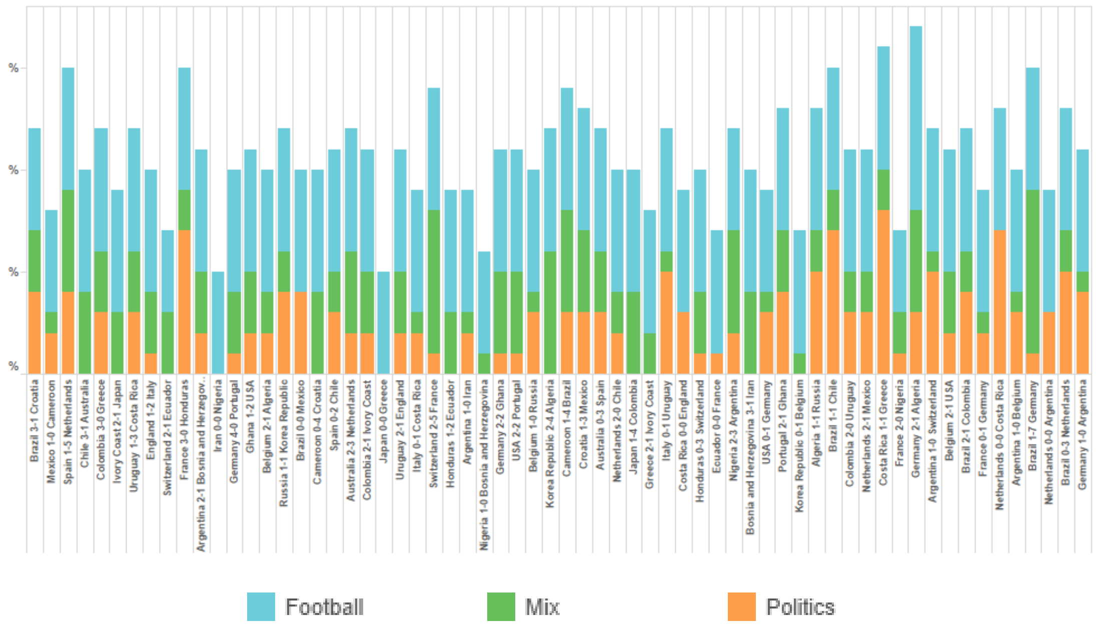

Figure 6. Different data sets of keywords in final database sort by 64 small events.

The Figure 6 allows us to visualize the percentage break down of topics by game, from the first to the 64th match. As we can see from the chart, political keywords were absent from tweets during 20 % of the games.

Only in 3% games users spoke about football topic and did not mention words from second and third data set. Teams from Japan, Australia, Nigeria, and Bosnia and Herzegovina passed games without politic discussions. Contemporaneously Brazil, Netherlands and USA showed the opposite tendency

The next Figure 7 shows the percentage of political, football and the mix of both topics by language group. The political topics were very popular in Portuguese, English and Spanish tweets, more than 53%, 46% and 33% respectively.

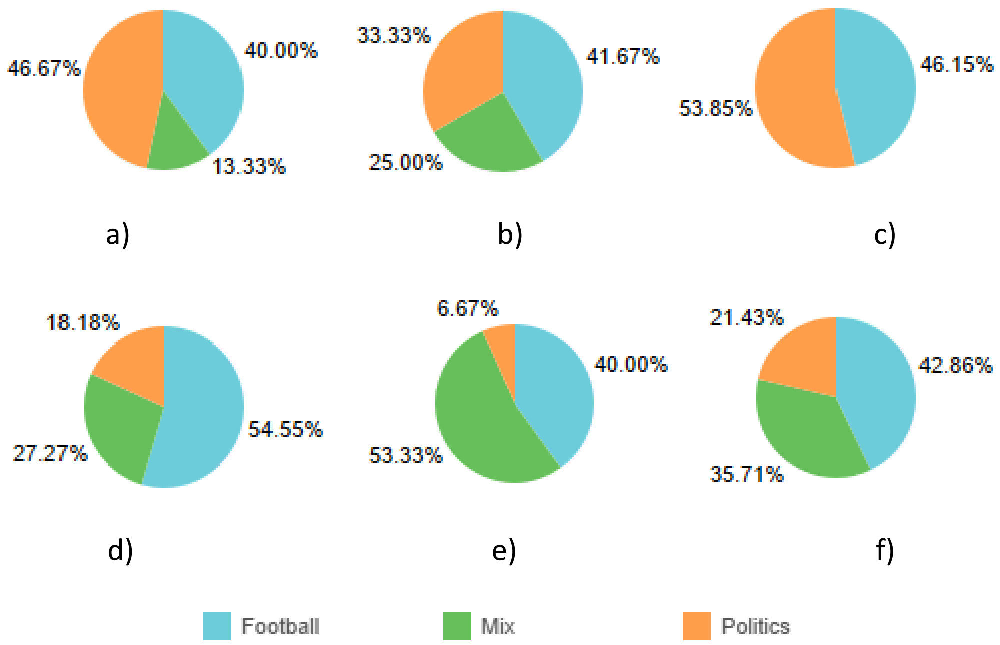

Figure 7. Different data sets of keywords represent in different language groups: a) English, b) Spanish, c) Portuguese, d) German, e) Russian, f) Total amount of geotagged tweets.

In German language users mentioned about politics in less than 20% tweets. In russian tweets people almost don't used politic keywords, only about 7% tweets contans them. However Russian tweets includes more than 53% of words from the second dataset.

German and Spanish languages showed mix of topic in 25% cases each, while the English tweets has only about 13% of mix keywords, which is still a lot comparing to Portuguese tweets, where there were not mixed topics, and more than 40% of tweets relay to football tematic, the same as in other languages. The first dataset was the most popular in German tweets.

In total our database represent 43% pure football topics, 36% of mix keywords and 21.5% of strong politic connections. The database were filtered by these set of words with politic keywords. As the result around 160 500 tweets of all geotagged tweets in our database, which means more than 21.5% of all tweets where people used keywords from the last set.

It includes 103,125 tweets in English, 38,804 tweets in Spanish, 11,802 Tweets in Portuguese, 4,207 Tweets in German and 2,560 Tweets in Russian.

The Figure 8 shows the proportion of tweets in final database count by language group. As we can see people tweet about politics in English language in more than 64% cases, about 25% of tweets were in Spanish language. Portuguese Tweets total about 7%, while the Brazil hosted this tournament.

Tweets in German and Russian languages represents only about 4% of all tweets in database, but still interesting for us to follow politic trends in this languages. The team from Germany won The FIFA World Cup 2014. And Russian Federation will host the next tournament - The FIFA World Cup 2018.

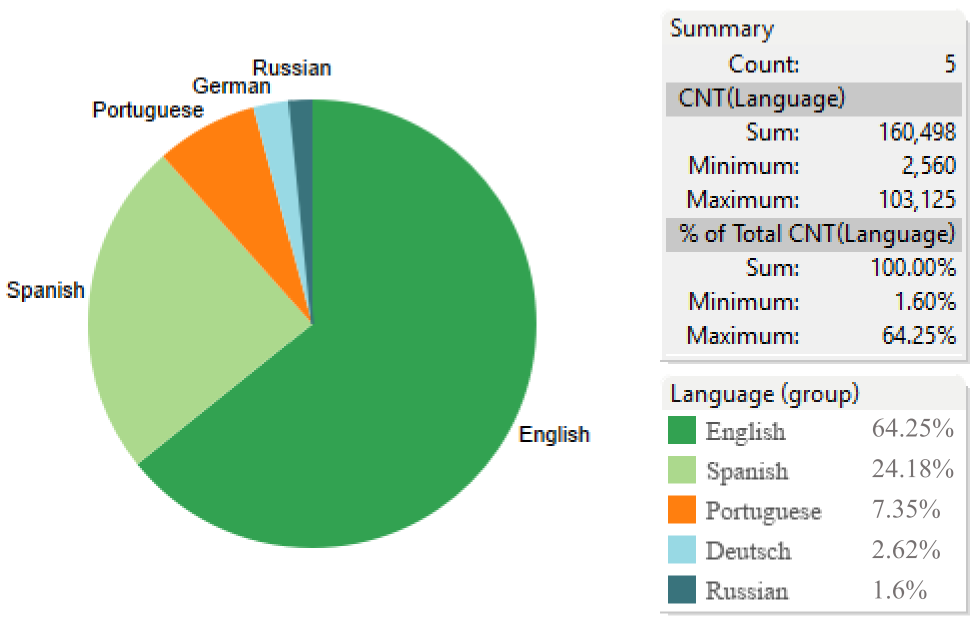

Figure 8. The proportion of total Tweets in language groups

3.3. Exploratory analysis

In order to answer the research question: "How is a non-political event politicized when it is carried out?” an exploratory statistical analysis was done.

Tweets connecting with politic topics

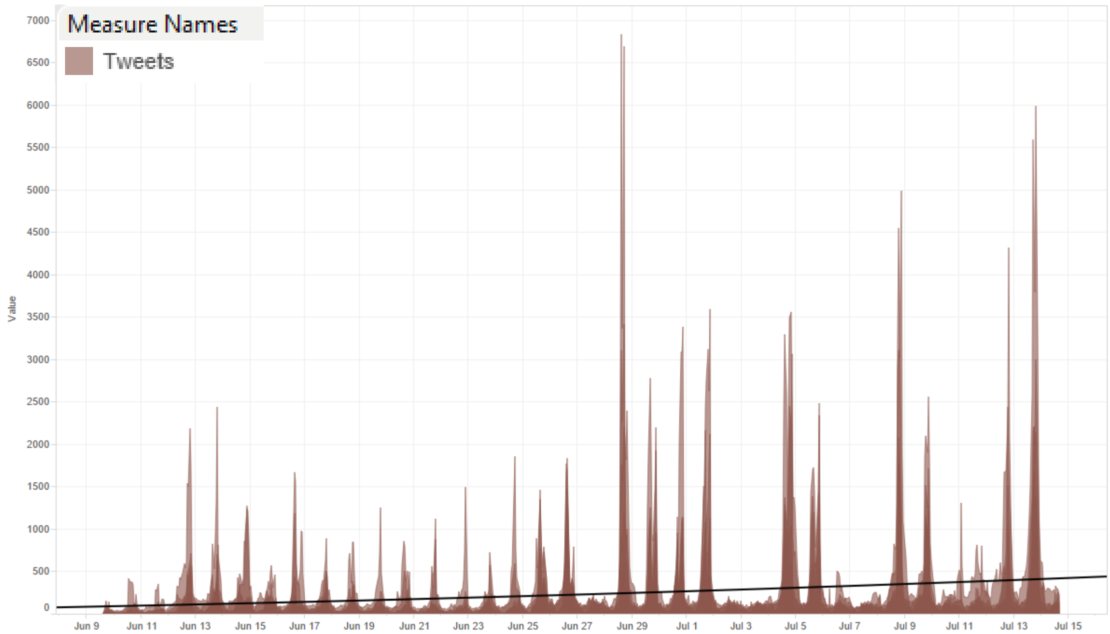

Figure 9. Plot showing the amount of Tweets contains political keywords per day

In Figure 9 one can see the plots of English, Spanish, Portuguese, German and Russian Tweets per Hour. Tweets Hour ranges from June 9, 2014 3 PM to July 14, 2014 4 PM on this plot.

The Trend Lines Model was built as a polynomial trend model. It were computed for count of Tweets given by event timeline. A polynomial trendline is a curved line that is used when data fluctuates. It is useful for analyzing gains and losses over a large data set. The order of the polynomial can be determined by the number of fluctuations in the data or by how many bends (hills and valleys) appear in the curve. For evaluation the goodness of fit of this trend line we calculate the following statistics for our model:

Sum of Squares for Error (SSE) were calculated to find the least squares line equation for a set of data. It measured the total deviation of the response values from the fit to the response values. A value closer to 0 indicates that the model has a smaller random error component, and that the fit will be more useful for prediction.

R-square is the square of the correlation between the response values and the predicted response values and measures how successful the fit is in explaining the variation of the data. R-square can take on any value between 0 and 1, a value closer to 1 indicating that a greater proportion of variance is accounted for by the model.

Mean squared error is an estimate of the standard deviation of the random component in the data and also its value closer to 0 indicates that the model has a smaller error and that the fit is more useful for prediction.

The standard deviation gives an idea of how close the entire set of data is to the average value. Data sets with a small standard deviation have tightly grouped, precise data. Data sets with large standard deviations have data spread out over a wide range of values.

In statistics, the p-value is a function of the observed sample results (a statistic) that is used for testing a statistical hypothesis. The model may be significant at $p \leq 0.05$.

SSE (Sum of Squares for Error):	8.7873e+008
MSE (mean squared error):	213180
R-Squared:	0.0413362
Standard error:	461.715
p-value (significance):	< 0.0001

Table 5. Statistical analysis on a set of Tweets.

According to our calculations in Table 5 and the plot in Figure 9, the trend in our data was found. The line of political topics trend is increasing significantly.

In Figure 10 the plot represents the number of English Tweets from June 9, 2014 3 PM to July 14, 2014 4 PM. The x-axis shows the timeline of the event, the y-axis is the Count of Tweets. Count of Tweets ranges from 10 to 2,445 on this graph. The filter associated with English tweets keeps all values.

The Trend Lines Model was built as a polynomial trend model. It were computed for count of Tweets given by event timeline.

Tweets connected with political topics in English language

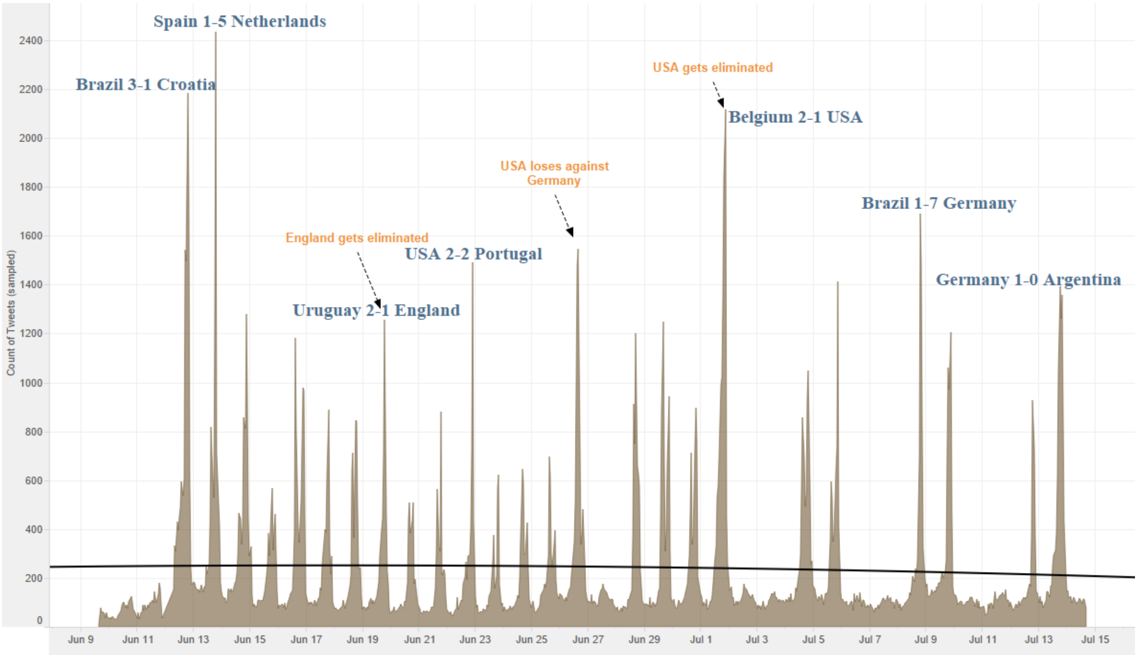

Figure 10. Plot showing the amount of Tweets contains political keywords per day (in English language).

For evaluation the goodness of fit of this trend line we calculate the following statistics for our model:

SSE (Sum of Squares for Error):	7.56349e+007
MSE (mean squared error):	91126.4
R-Squared:	0.0017212
Standard error:	301.872
p-value (significance):	0.489234

Table 6. Statistical analysis on a set of English Tweets.

According to our calculations in Table 6, any particular trend in our data was not found. However, using the 64 match results as attributes for this sheet can give us an idea of political topics. The marks are labeled by the important activity of the event.

First time the politic topic in English tweets appeared during the opening games of Brazil vs. Croatia and Spain vs. Netherlands. It can be explained by the mass media companies about the political problems in preparation these tournament and also because of the demonstrations which were carried out during the first days of the event. The next political discussions in English language appeared after England and USA were eliminated, which can be described by the unsatisfied mood of fans and their wish to make changes. The word “power” was mentioned more times on this stage. The final games of Brazil vs. Germany and Germany vs. Argentina in English tweets have a more sporty character, but still include a lot of tweets about elections and budget questions. A large amount of Tweets contains the word “changes”.

The next plot on Figure 11 shows the number of Spanish Tweets from June 9, 2014 3 PM to July 14, 2014 4 PM. The X-axis represents the timeline of the event and on the Y-axis we can see the Count of Tweets. Count of Tweets ranges from 1 to 3,060 on this graph. The filter associated with Spanish tweets keeps all values.

Tweets connecting with politic topics in Spanish language

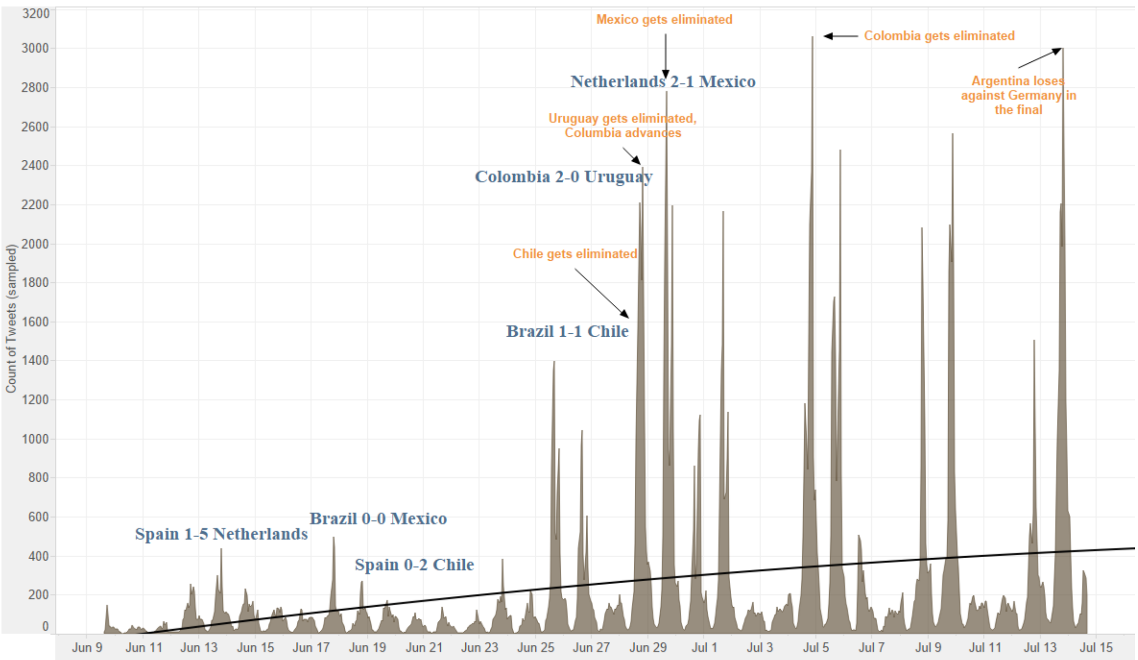

Figure 11. Plot showing the amount of Tweets contains political keywords per day (in Spanish language).

The Trend Lines Model were built as a polynomial trend model. It were computed for count of Tweets given by event timeline. For evaluation the goodness of fit of this trend line the following statistics were calculated for our model in Table 7.

SSE (sum squared error):	1.48929e+008
MSE (mean squared error):	179866
R-Squared:	0.0868349
Standard error:	424.106
p-value (significance):	< 0.0001

Table 7. Statistical analysis on a set of Spanish Tweets.

The line of political topics trend is increasing significantly. After using the 64 match results as attributes for this sheet we can have an idea of politic topics. The marks are labeled by the most important games. The event in Spanish tweets started almost without politics keywords in main topics. During the time with the elimination of main Spanish speaking teams, the political topics were started to be popular in Spanish twitter. Each day with game brought more and more discussions about changes and policy.

This behavior in Tweets once again showed us that during the unsuccessful games people starts speak about politics more and that event start to be politicized during time.

Tweets connecting with politic topics in Portuguese language

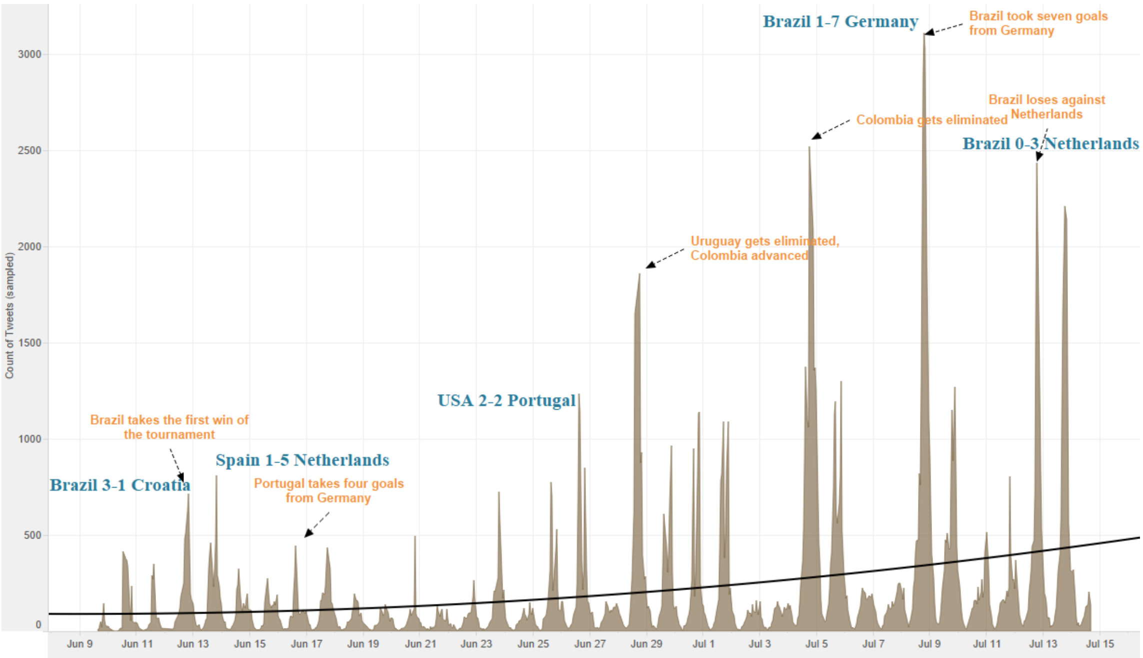

Figure 12. Plot showing the amount of Tweets contains political keywords per day (in Portuguese language).

The third plot in Figure 12 shows the count of Portuguese Tweets from June 9, 2014 3 PM to July 14, 2014 4 PM. The x-axis represents the timeline of the event and on the y-axis we can see the count of tweets, which ranges from 1 to 4,985 on this graph. The filter associated with Portuguese tweets keeps all values.

The Trend Lines Model was built as a polynomial trend model. It was computed for count of Tweets given by event timeline. To evaluate the goodness of fit of this trend line we calculated the following statistics for our model in Table 7.

SSE (sum squared error):	1.00933e+008
MSE (mean squared error):	123090
R-Squared:	0.0859428
Standard error:	350.841
p-value (significance):	< 0.0001

Table 8. Statistical analysis on a set of Portuguese Tweets.

The political topic trend line is noticeably increasing, while the range of the tweets is almost twice more than in the other languages. Politics is the main topic during almost all of the games. The use of the 64 match results as attributes for this sheet give us an idea about political topics. The marks are labeled by the most important activity during the event.

Politics was the popular topic in Portuguese tweets from the first till the last day of the event. In Portuguese tweets we could see trend of strong division on two topics football and politics. The main keywords from our data set appeared in tweets even before first game, and confirm the political problems in Brazil.

The amount of tweets increased with each game, and brought about the biggest reaction during the famous game of Brazil against Germany, where the host team lost 1-7. It was a huge disappointment for fans, at the same moment the words “Changes” and “Elections” were almost in each second tweet. During the last game of Brazil in semi-final and the final game between Argentina and Germany, users tweeted more about “Policy”.

One more plot on Figure 13 shows the counting of German Tweets from June 9, 2014 3 PM to July 14, 2014 4 PM. The x-axis represents the timeline of the event and on the axis Y we can see the Count of Tweets. Count of Tweets ranges from 1 to 5,984 on this graph. The filter associated with German tweets keeps all values.

The Trend Lines Model was built as a polynomial trend model. It was computed for count of Tweets given by event timeline. To evaluate the goodness of fit of this trend line we calculate the following statistics for our model in Table 9.

Tweets connected with political topics in German language

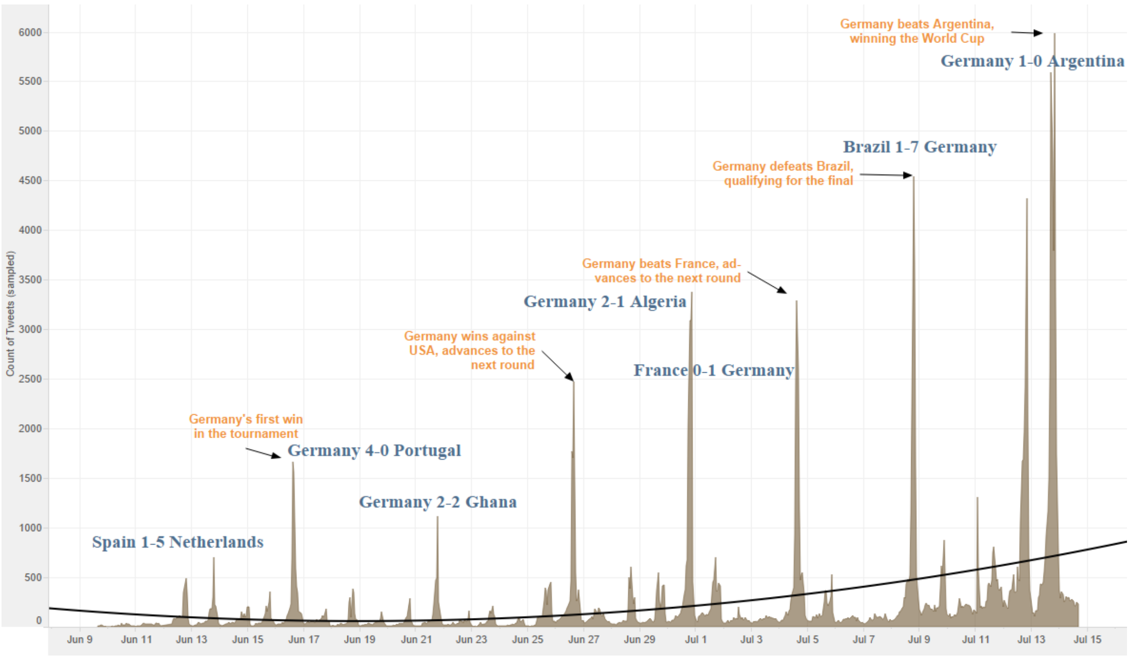

Figure 13. Plot showing the amount of Tweets contains political keywords per day (in German language).

SSE (sum squared error):	2.48712e+008
MSE (mean squared error):	299653
R-Squared:	0.120215
Standard error:	547.405
p-value (significance):	< 0.0001

Table 9. Statistical analysis on a set of German Tweets.

The trend line of political topics increased in our plot. Political topics were not so popular in German tweets, while the most used word was "Power". The results of 64 match were added to the plot and it gave us an idea of using politic topics. The marks are labeled by the most important activity during the event.

The political topics were discussed in German tweets during the main German games. The deep analyses showed that the discussion of politics were accompanied with the words "Brazil" and "Spain", which can mean that Germans discussed more the problems of other countries than the political situation in their own country.

The last plot on Figure 14 shows the counting of Russian Tweets from June 9, 2014 3 PM to July 14, 2014 4 PM. The axis X represents the timeline of the event and on the axis Y we can see the Count of Tweets. Count of Tweets ranges from 1 to 3,400 on this graph. The filter associated with Russian tweets keeps all values.

Tweets connecting with politic topics in Russian language

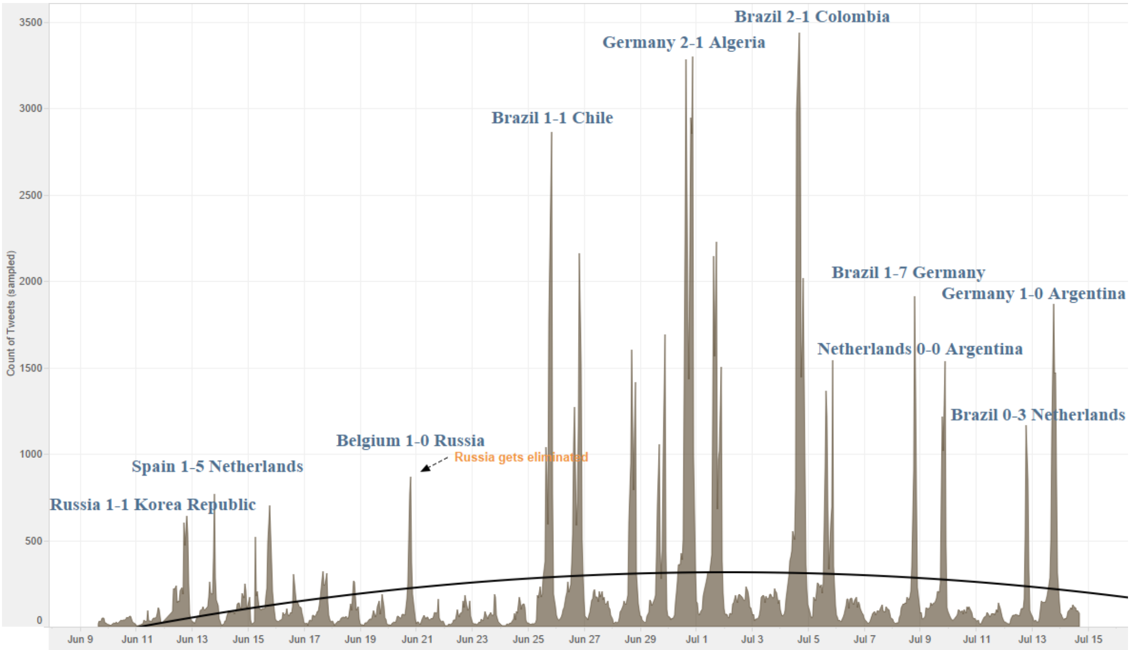

Figure 14. Plot showing the amount of Tweets contains political keywords per day (in Russian language).

The Trend Lines Model was built as a polynomial trend model. It was computed for count of Tweets given by event timeline. For evaluation the goodness of fit of this trend line we calculated the following statistics for our model in Table 10.

SSE (sum squared error):	1.49536e+008
MSE (mean squared error):	182807
R-Squared:	0.0486674
Standard error:	427.559
p-value (significance):	< 0.0001

Table 10. Statistical analysis on a set of Russian Tweets.

The line of political topics trend is increasing in the middle of our plot. The political topics was popular in Russian tweets, which was showed by big range of tweets. The results of 64 matches were added to the plot and it gave us an idea of when political topics were discussed. The peak activities are labeled by importance.

The political topics in Russian tweets are very interesting to analyze, because Russia will host the next World Cup. We can see that football was the main topic discussed in Russian tweets until the elimination of the Russian team.

During the tournament, political topics appeared during the games lost by the Russian team. The words “changes” and “policy” came up very often. Right after the elimination of the Russian team, the set of words which are mixed between politics and football started to become more popular in tweets.

The next step in the research was the analyses of trends in the tweets with particular words. The graphs represented the frequency of political terms, chosen for our purpose: “Power”, “Elections”, “Changes” and “Politic”. The tweets were written between June 9, 2014 4 PM to July 14, 2014 5 PM. The filter keeps non-null values.

Tweets connecting with politic topics filtered by words

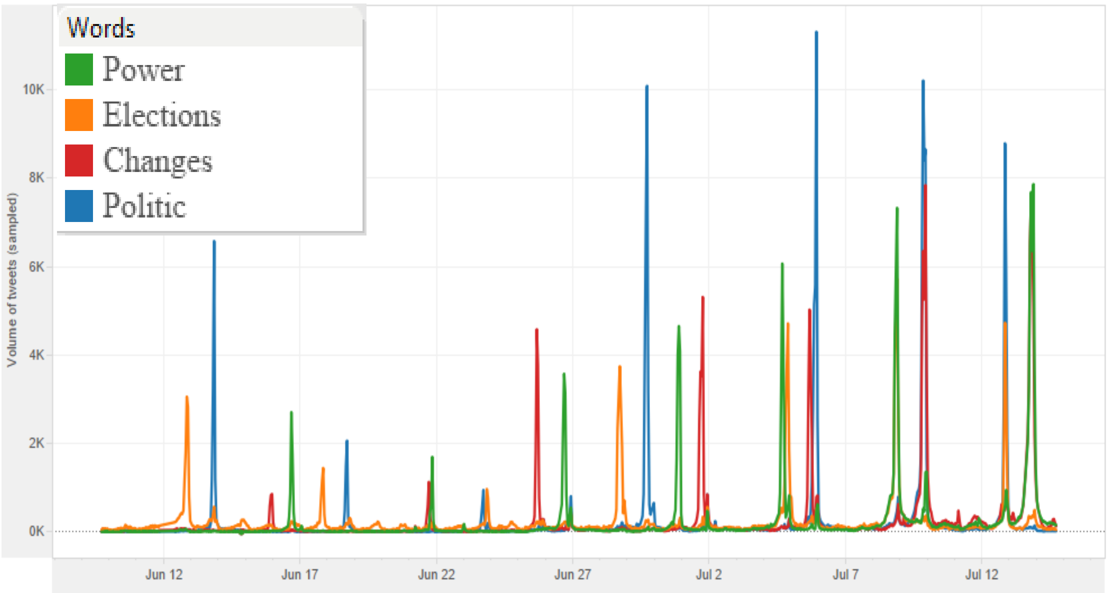

Figure 15. Plot showing the amount of Tweets contains political keywords chosen for analysis

On Figure 15, the graph contains information about several words. According to this graph, the word “Politic” had maximum references in tweets and existed throughout the whole tournament, while the word “Elections” had minimum of them and appeared more at the beginning and at the end. The use of words “Power” and

"Changes" increased every game, and in the final stage were mentioned in a lot of tweets.

The graph for the first word from our dataset - "Power" – is presented in Figure 16.

Tweets connecting with politic topics filtered by word "Power"

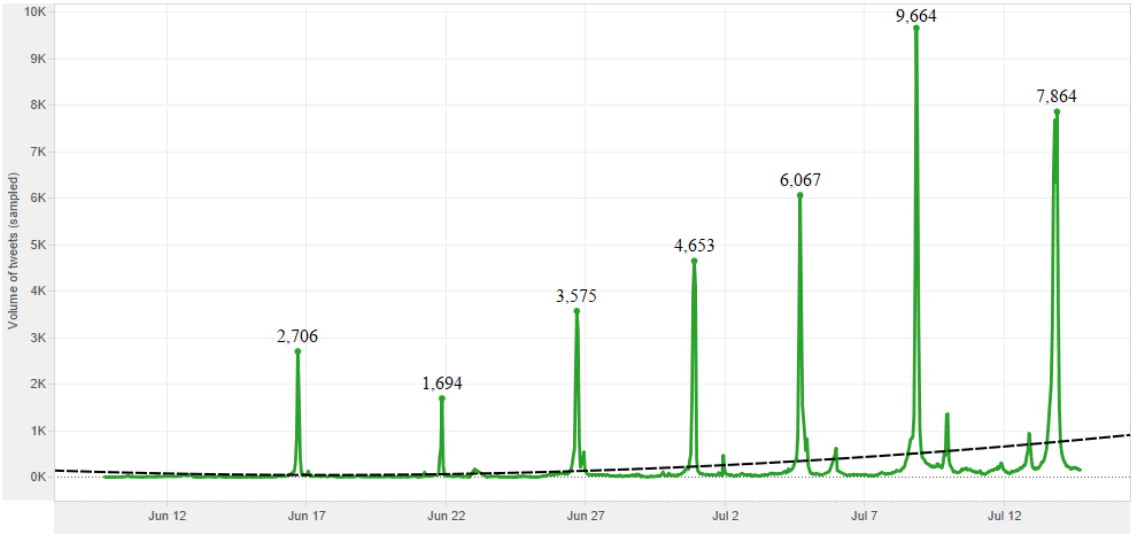

Figure 16. Plot showing the amount of Tweets, which include keyword "Power" from the third data set.

The Trend Lines Model was built as a polynomial trend model. It was computed for number of Tweets given by event timeline. For evaluation the goodness of fit of this trend line, the following statistics were calculated for our model in table 11.

SSE (sum squared error):	5.22563e+008
MSE (mean squared error):	745454
R-Squared:	0.0648028
Standard error:	863.397
p-value (significance):	< 0.0001

Table 11. Statistical analysis on a set of Tweets containing keyword "Power".

According to our calculation, use of the word "Power" significantly increased over time. It appears after the first week of the tournament (the word was mentioned in 800 tweets) and was used most (more than 9600 tweets), during the game Brazil vs. Germany. This word was used more frequently in the contexts of the word "Victory" than the context of the words "Politic" and "Power".

The graph for the second word from our dataset - "Changes" - presented in Figure 17 also shows a strong tendency to increase to almost 8000 references in Twitter at the end.

Tweets connected with political topics filtered by word "Changes"

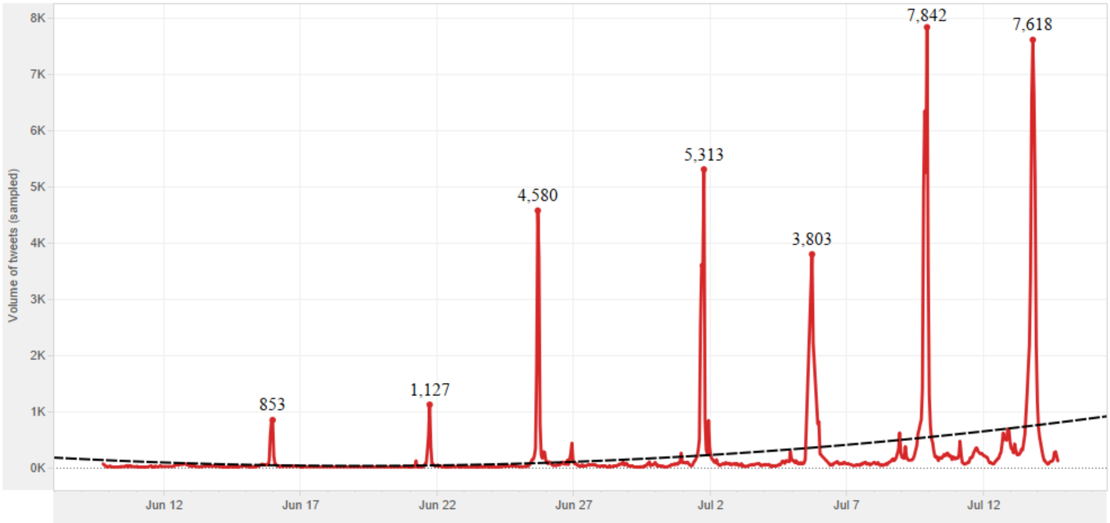

Figure 17. Plot showing the amount of Tweets, which include keyword "Changes" from the third data set.

The Trend Lines Model was built as a polynomial trend model. It was computed for count of Tweets given by event timeline. For evaluation the goodness of fit of this trend line the following statistics were calculated for our model in Table 12.

SSE (sum squared error):	4.31872e+008
MSE (mean squared error):	650409
R-Squared:	0.0736214
Standard error:	806.48
p-value (significance):	< 0.0001

Table 12. Statistical analysis on a set of Tweets with keyword "Changes".

According Figure 18, the word "Elections" was used in tweets at the beginning 3000 times and at the end it reached the absolute number of 4500 tweets.

The graph for the third word from our dataset - "Elections" - is presented in Figure 18. The Trend Lines Model was built as a polynomial trend model. It was computed for the number of Tweets given by event timeline. For evaluation the goodness of fit of this trend line, we calculated the following statistics for our model (Table 13).

SSE (sum squared error):	1.0206e+008
MSE (mean squared error):	129682
R-Squared:	0.016778
Standard error:	360.115
p-value (significance):	0.0012835

Table 13. Statistical analysis on a set of Tweets containing keyword “Elections”.

Tweets connected with political topics filtered by word “Elections”

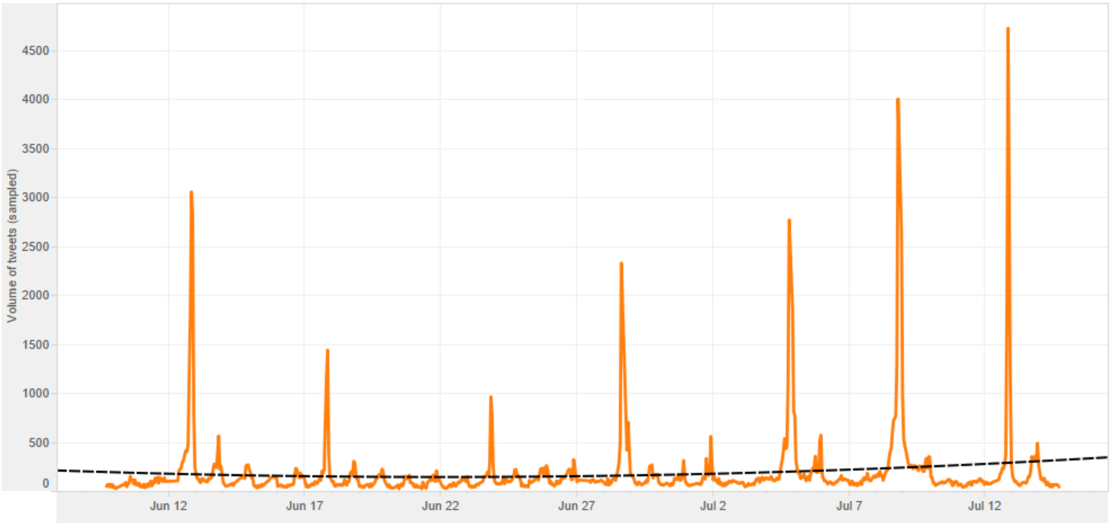

Figure 18. Plot showing the amount of Tweets, which include keyword “Elections” from the third data set.

Tweets connected with political topics filtered by keyword “Politics”

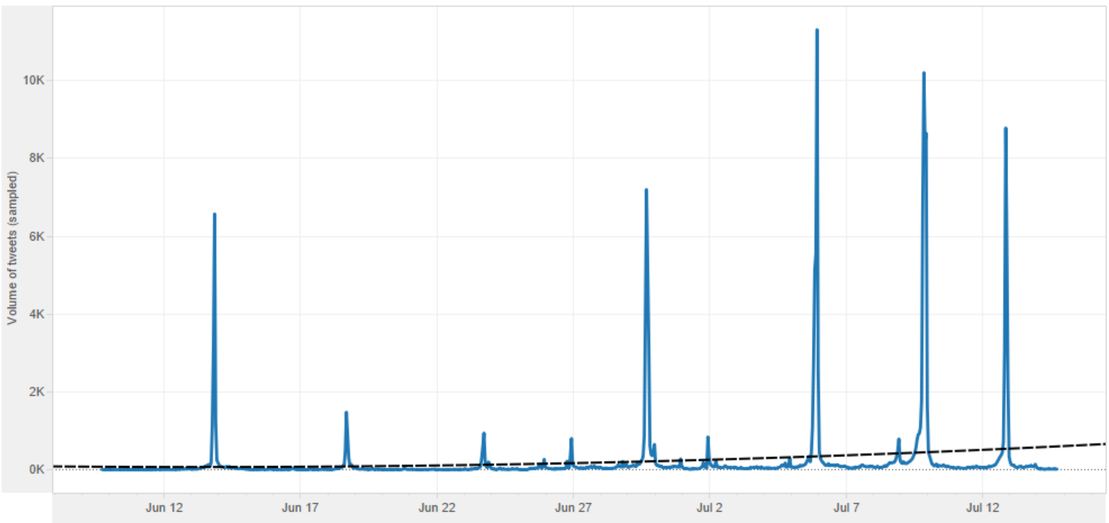

Figure 19. Plot showing the amount of Tweets, which include keyword “Politics” from the third data set.

The graph for the last word from our dataset - “Politics” – is presented in Figure 19.

The Trend Lines Model was built as a polynomial trend model. It was computed for the number of Tweets given by the event timeline. For evaluation of the goodness of fit of this trend line, the following statistics were calculated for model in Table 14.

SSE (sum squared error):	7.23969e+008
MSE (mean squared error):	902705
R-Squared:	0.0268978
Standard error:	950.108
p-value (significance):	< 0.0001

Table 14. Statistical analysis on a set of Tweets with keyword “Politic”.

According to the plot 19, the word “Politics” was tweeted 7,000 times in the middle of the tournament, and in the last stage it appeared in 10,000 tweets in every game.

After computation of the most used words and phrases in each language during the different stages of tournament, Table 15 was created.

The changes in popular words were showed in the summarize Table 14. Almost all groups of languages showed the same behavior of politicization during the “non-political” event.

Language	Stage 1	Stage 2	Stage 3
English	Political games / Profit	Power	Political changes
Spanish	Goal	Victory	Changes
Portuguese	Budget	Elections	Changes
German	Goal	Victory	Power / Policy
Russian	Game	Changes	Budget / Victory

Table 15. Main keywords for each stage of the World Cup in selected languages.

3.4. Spatial analyses

Spatial analysis was done for the purpose of answering the last research question: "In which locations were political topics discussed?" Proportional circle maps were used for this analyses. This type of map shows data that is represented by circles of varying sizes. The larger circles represent larger numbers while the smaller ones obviously represent smaller numbers. These types of maps can be considered as more simplified dot distribution maps. Dot distribution maps are a type of statistical map that show where particular data characteristics occur. They are very useful for visualizing density of the topic being studied. The first map based on longitude and latitude was extracted from each geotagged tweet represented in Figure 20. The size of one dot shows one tweet created at a particular time.

Tweets distribution during the 2014 FIFA World Cup

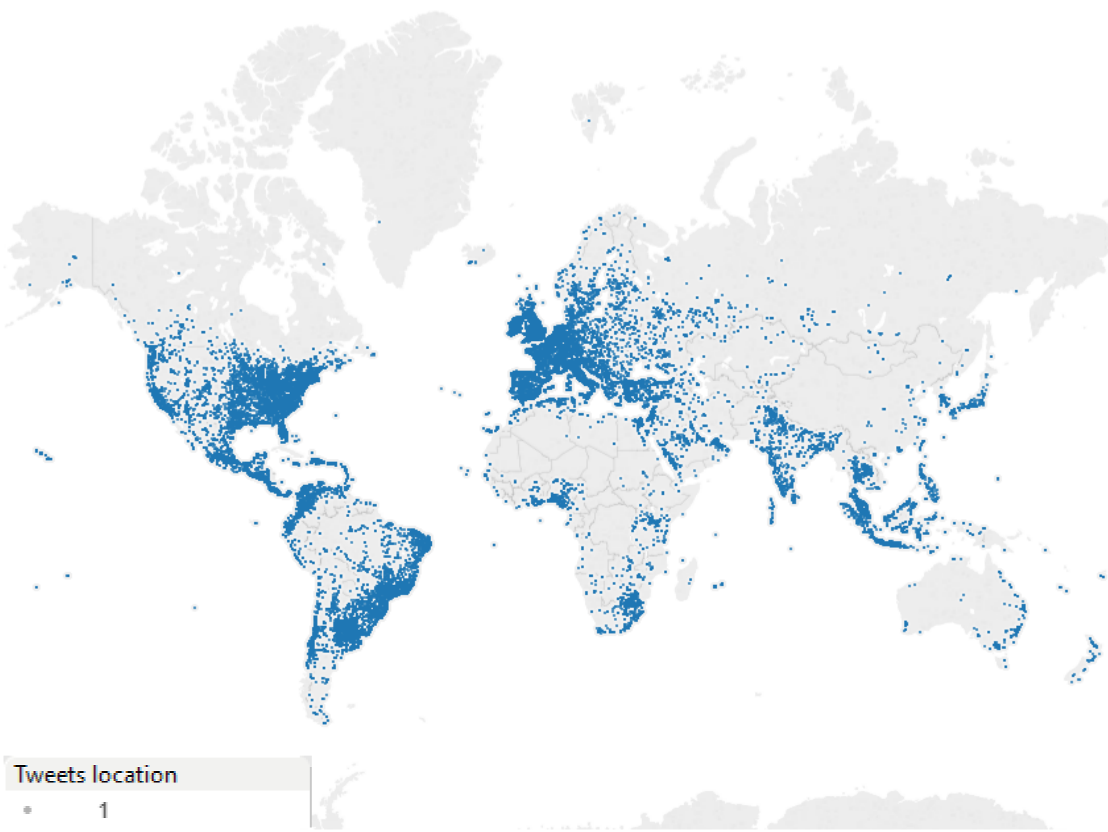

Figure 20. Dot distribution map of tweets during the 2014 FIFA World Cup.

The locations of users spans the entire world, but according to dot density map, people tweeted more from Europe, the eastern part of the USA and Brazil. The tweets were sent from more developed territories. A significant amount of users from Asia also participated in discussion about the 2014 FIFA World Cup.

The second map in Figure 21 is based on longitude (generated) and latitude (generated) of all tweets in one particular country. Size shows count of tweets. Details are shown for Country and Language. The view is filtered on Language, which keeps German, English, Spanish, Portuguese and Russian tweets. Percents are based on each column of each pane of the table.

Tweet locations during The 2014 FIFA World Cup

Figure 21. Proportional Circle Map of tweet locations during The 2014 FIFA World Cup.

Generally selected tweets in 5 languages were situated in USA, Great Britain, Brazil and Spanish speaking countries in South America. Spatial analyses of tweet distribution from particular language groups were done. To show this density of tweets, Proportional Circle Map maps were created.

The first map in Figure 22 is based on longitude and latitude of tweets broken down by language group. Size shows count of Tweets from 1 to 97 686. Details are shown for each country. The view is filtered by English language.

Location of tweets (in English language) during The 2014 FIFA World Cup

Figure 22. Proportional Circle Map of English tweets location.

According to this map, most of the posts in English language were tweeted from USA and Great Britain. It can be explain by the fact that English is the main language in both countries.

The English language was very popular for tweets in Canada, Brazil, South Africa, India, Malaysia and Indonesia, where English is also used as one of the main languages. Some of European countries tweeted in English language too. For example, Germany, Spain, France and Italy.

The next map in Figure 23 based on longitude and latitude of tweets broken down by language group. Size shows count of Tweets from 1 to 36 182. Details are shown for each country. The view is filtered based on Spanish Language.

According to this map, most of the posts in Spanish language were tweeted from South America countries, such as Columbia, Argentina, Chile and Mexico.

The Spanish language was very popular for tweets in Brazil, USA, and Spain. The Spanish tweets were not presented in other parts of the world.

Location of tweets in Spanish language during The 2014 FIFA World Cup

Figure 23. Proportional Circle Map of Spanish tweets location.

The third map in Figure 24 is based on longitude and latitude of tweets broken down by language group. Size shows count of Tweets from 1 to 10757. Details are shown for each country. The view is filtered by Portuguese language.

As we can see on the map, most of the Portuguese tweets were sent from Brazil, and only a small percentage from Portugal. It can be explained by fact that Portuguese language is the official language of these two countries. The Portuguese tweets were not presented in other parts of the world.

The fourth map in Figure 25 is based on longitude and latitude of tweets broken down by language group. Size shows count of Tweets from 1 to 3 933. Details are shown for each country. The view is filtered by German Language.

According to this map, most of the posts in German language were tweeted in Germany. The English language was very popular for tweets in USA and Spain. The Spanish tweets were presented also in USA, Brazil, Indonesia and all around Europe, but not in the other parts of the world.

Location of tweets in Portuguese language during The 2014 FIFA World Cup

Figure 24. Proportional Circle Map of Portuguese tweets location.

Location of tweets in German language during The 2014 FIFA World Cup

Figure 25. Proportional Circle Map of German tweets location.

The last map in Figure 26 is based on longitude and latitude of tweets broken down by language group. Size shows count of Tweets. Details are shown for each country. The view is filtered by Russian Language.

Figure 26. Proportional Circle Map of Russian tweets location.

According to this map, most of the posts in Russian language were tweeted from Russia. The very small percentage were also published from Brazil and Japan. The Russian tweets were not presented in the other parts of the world.

The spatial analyses of main political words from the third dataset were done.

The first map in Figure 27 was based on longitude and latitude of tweets broken down by keywords. Size shows count of Tweets from 1 to 28 081. Details are shown for each country. The view is filtered on tweets with the label “Politic”.

Figure 27 shows that word “Politic” was popular in tweets in USA. It also was tweeted from Brazil, Spain and some countries of South America.

The next map is based on Longitude (generated) and Latitude (generated). Circle size represents count of Tweets from 1 to 11 919. Details are shown by Country and the data is filtered by keywords. The view is filtered on tweets containing the word "Power".

Location of tweets contain word "Politic" during The 2014 FIFA World Cup

Figure 27. Proportional Circle Map of Location tweets contain word "Politic".

Figure 28 shows that the word "Power" was popular in tweets in USA and Great Britain. It also were tweeted from Brazil, South Africa and some countries in Asia.

One more map was created based on longitude and latitude from extracted tweets. Circle size represents the count of Tweets from 1 to 7 321 (Figure 29). Details are shown for each country. The data is filtered on keywords. The view is filtered on tweets with mark "Elections".

The word "elections" was popular in Brazil, explained by demonstrations and protests in that country. Also people spoke about elections in Germany, Russia and USA.

Location of tweets containing the word "Power" during the 2014 FIFA World Cup

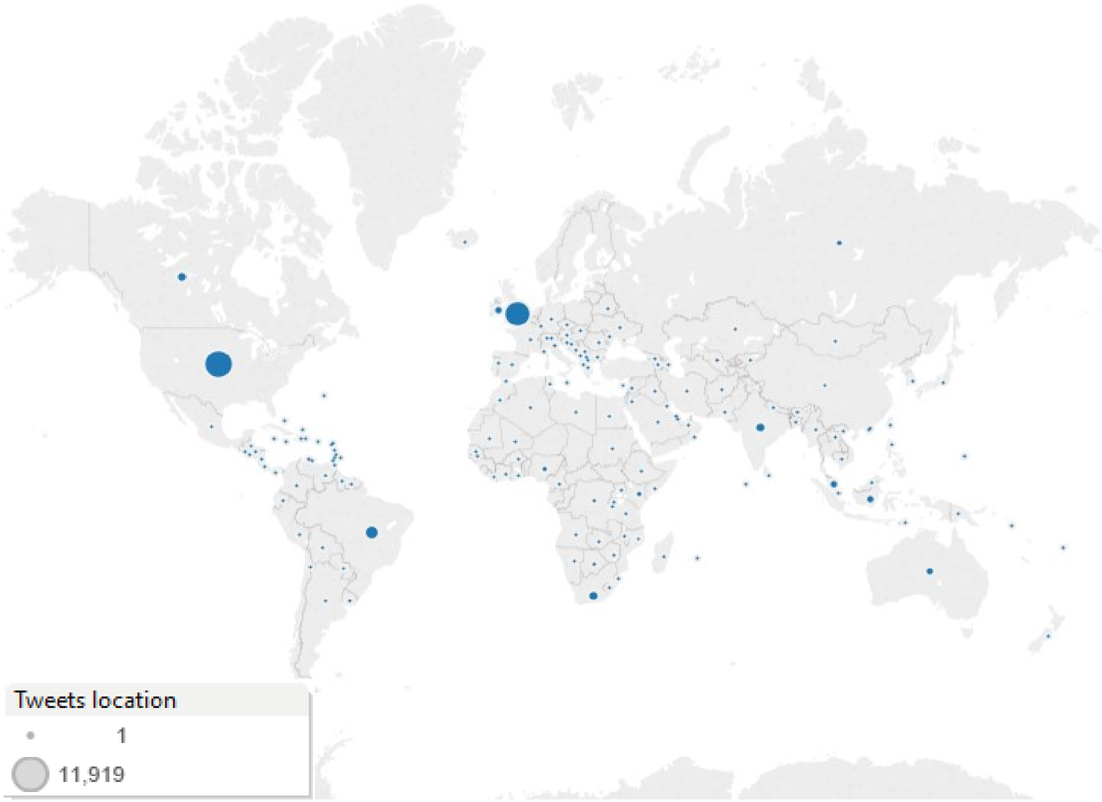

Figure 28. Proportional Circle Map of tweets containing the word "Power".

Location of tweets containing the word "Elections" during The 2014 FIFA World Cup

Figure 29. Proportional Circle Map of Location tweets contain word "Elections".

The last map were created based on longitude (generated) and latitude (generated). In Figure 30 the size shows count of Tweets from 1 to 9,942. Details are shown for Country. The data is filtered on keywords. The view is filtered on tweets with mark "Changes".

Location of tweets containing the word "Changes" during The 2014 FIFA World Cup

Figure 30. Proportional Circle Map of Location tweets contain word "Changes".

3.5. Geosocial analysis

For geo-social and sentiment analysis we integrated R with Tableau software. To execute R functions and libraries, we used R Studio Server that allows other programs to use the capabilities of R.

Sentiment analysis techniques can be classified into two high level categories: lexicon-based and learning-based techniques. Lexicon techniques rely on dictionaries of words annotated with their orientation described as polarity and strength (e.g. negative and strong, based on which a polarity score for the text is calculated.

This method gives high precision results as long as lexicon used has a good coverage of words encountered in the text being analyzed.

Learning based techniques require training a classifier with examples of known polarity presented as text classified into positive, negative and neutral classes.

There are currently two packages in R that can be used for “sentiment” purpose: sentiment and qdap. R’s sentiment package follows a lexicon based approach hence we were able to get right into the action, given it comes with a lexicon for English. When using lexicon-based systems, adding new words to the lexicon or using a completely new lexicon are potential paths to follow if you are not getting good results.

The sentiment of a piece of text is calculated using the classify polarity function in R. classify_polarity function classifies text into three classes: positive, negative and neutral. It is based on a lexicon based approach using a dictionary of words annotated with their polarity (negative or positive). This is used to calculate the over polarity of the text if it is either positive or negative.

Location of tweets containing the word “Changes” during The 2014 FIFA World Cup

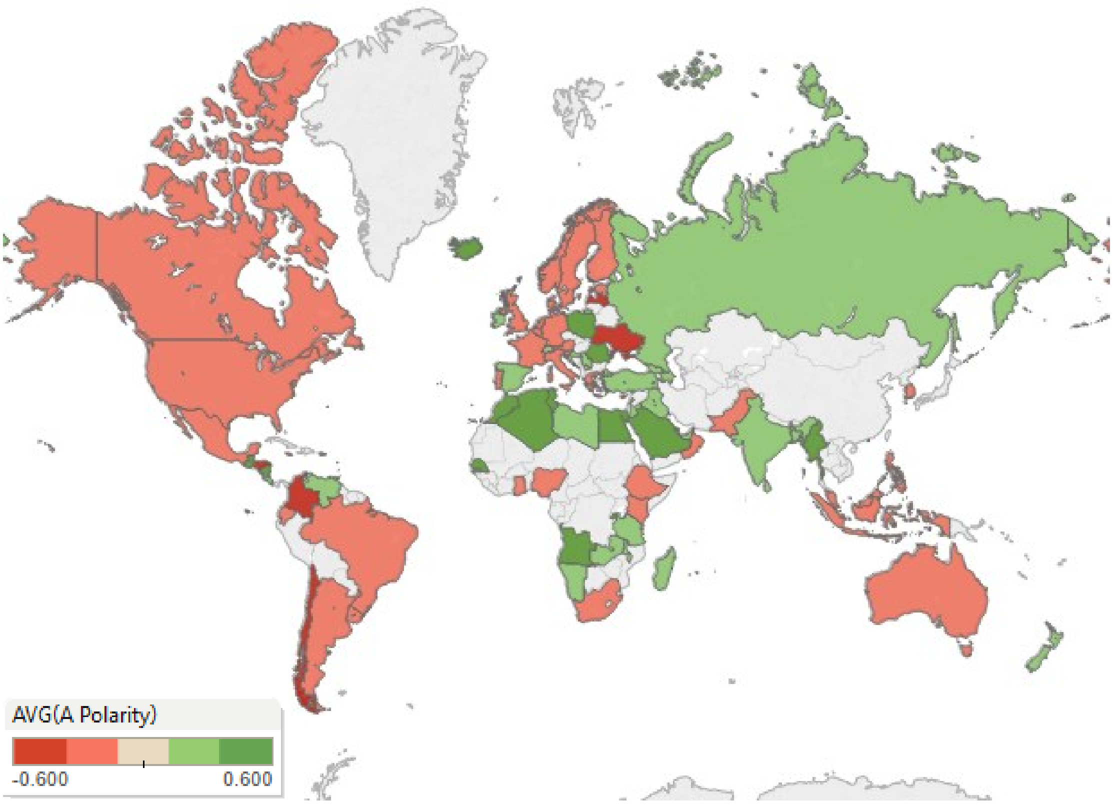

Figure 31. Map of Average of A Polarity in using political terms during The 2014 FIFA World Cup.

In Figure 31 the map based on longitude (generated) and latitude (generated) extracted from each geotagged tweet in database. Colors show average of polarity in sentimental analysis of tweets, from red (negative) to green (positive). Details are shown for each country. The average of polarity filter ranges from -0.6 to 0.6 and keeps null values. The Country filter keeps 95 of 145 members.

Based on the this map we can conclude that more negative about politics users spoke in Cyprus, Ukraine, Hong Kong, Chile, Colombia and Latvia. The positive character of tweets appeared in tweets from Iceland, Saudi Arabia, Algeria, Angola, Poland, Morocco, Senegal and Egypt.

4. CONCLUSION AND FUTURE WORK

4.1. Conclusion

In this study, we defined the 2014 FIFA World Cup as the largest single sporting competition in the world that has an inherently non-political character. Its outcome has significant impacts on society and the environment, but its intention is to serve as a venue of for a football tournament.

It was found that after the extraction of a vector with relevant terms from tweets, the most used words and phrases in each language point to a politicization of public opinion (Table 16). The event is politicized by spectators and fans who interpret the event in political terms, particularly in English, Spanish, Portuguese and German tweets. As an exception, tweets in Russian were centered more around the theme of football and budgets, which perhaps suggests preoccupation with the upcoming World Cup in 2018 which is to be hosted by the Russian Federation.

Language	Stage 1	Stage 2	Stage 3
English	Political games / Profit	Power	Political changes
Spanish	Goal	Victory	Changes
Portuguese	Budget	Elections	Changes
German	Goal	Victory	Power / Policy
Russian	Game	Changes	Budget / Victory

Table 16. Main keywords for each stage of the World Cup in selected languages

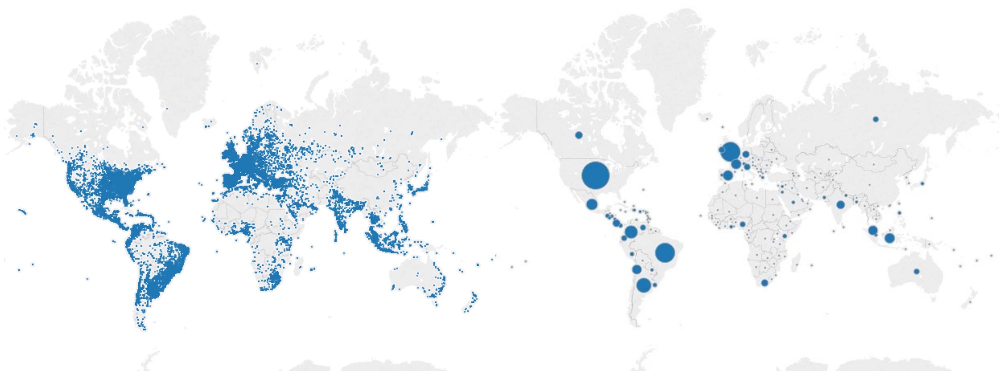

Figure 32. Location of tweets contain words from political topics.

The political keywords were used all across the world, as demonstrated by Figure 32. However, it can be observed that the highest density of political tweets occurs in the United States, Brazil, a few countries in South America and in Europe.

After applying a set of statistical techniques to answer the question about the temporal and spatial patterns of the tweets, an upward trend in the use of political terms was observed as the World Cup progressed from beginning to end. The analysis used a large sample of Tweets, and provide some insight into the relationship between an ostensibly non-political event – the World Cup - and public opinion transmitted by social media. Although the scope of this study is limited, the methodology could serve as a prototype for future studies and guide policy makers in governmental and non-governmental organizations in gauging the public opinion in certain geographic locations.

4.2. Future work

The offered methods and techniques have much room for improvement. It should be noted that a major limitation in the study was the elimination of a large number of tweets in the data processing phase due to the inability to pinpoint retweets. In addition, the given approach should include a control group. The content of tweets should be analyzed over the same time period in the absence of an event. In addition, tweets should be analyzed in languages other than English to verify the accuracy of this model and whether or not it can be generalized. In addition, other geographical analyses of tweets should be studied to improve methods. Third, the countries can be analyzed as sets of neighborhoods, which gives new aggregation levels for the study and understanding reactions as going beyond political borders of nation-states. Finally, the political sentiments of Twitter-users in different countries can be easily computed during these analyses, which gives a lot of space for new research projects. It means new data might be used as a control group. The influence of the event on politics, the reaction from society and the changes of trends in political topics can advise the decision making of leaders.

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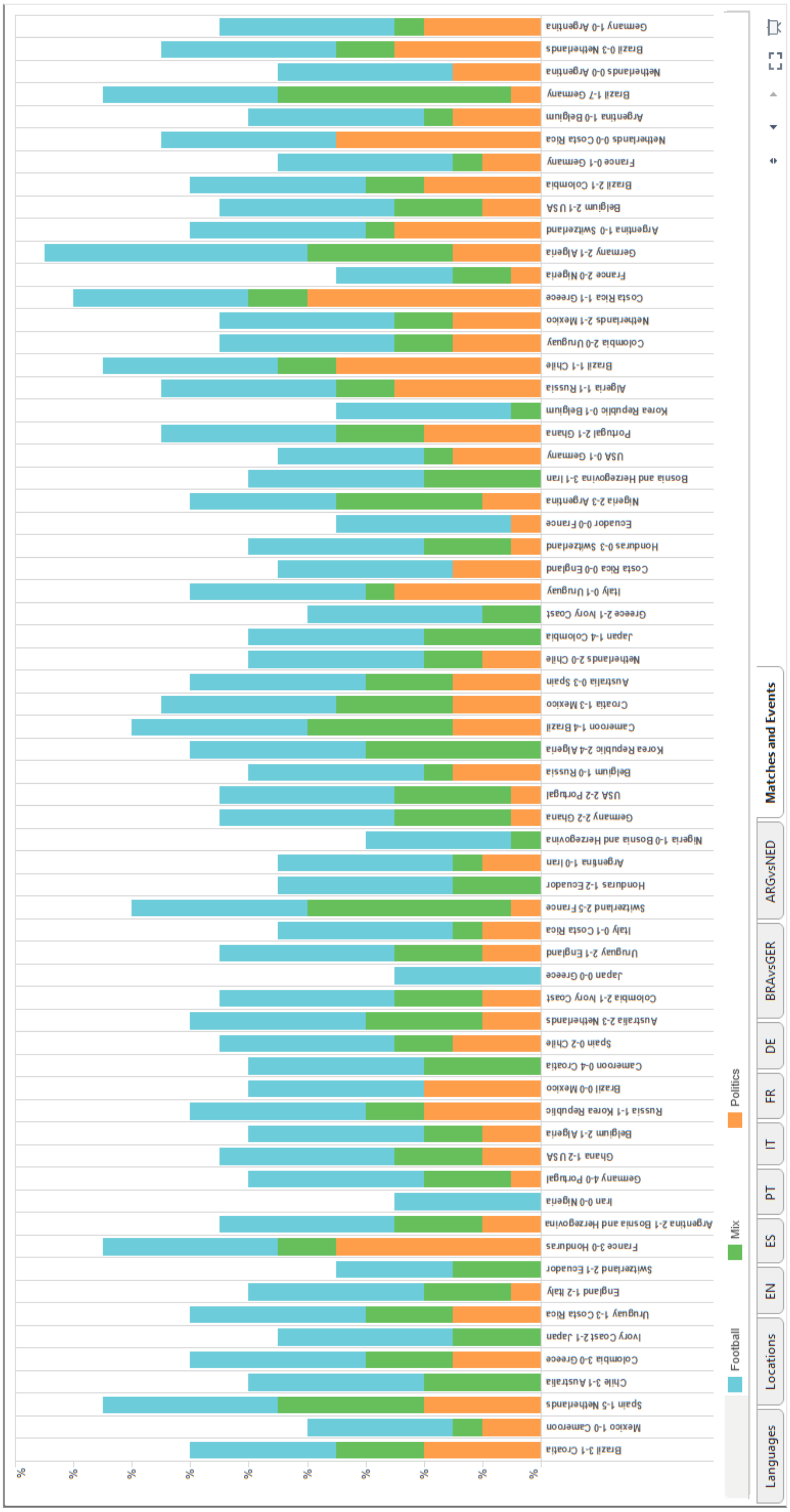
ANNEX 1: DATA STRUCTURE TABLES

№	location	Match time	HT country	HT code	HT goals	AT country	AT code	AT goals	winner	Winner _code
1	Arena de Sao Paulo	6/12/2014 20:00	Brazil	BRA	3	Croatia	CRO	1	Brazil	BRA
2	Estadio das Dunas	6/13/2014 16:00	Mexico	MEX	1	Cameroon	CMR	0	Mexico	MEX
3	Arena Fonte Nova	6/13/2014 19:00	Spain	ESP	1	Netherlands	NED	5	Netherlands	NED
4	Arena Pantanal	6/13/2014 22:00	Chile	CHI	3	Australia	AUS	1	Chile	CHI
5	Estadio Mineirao	6/14/2014 16:00	Colombia	COL	3	Greece	GRE	0	Colombia	COL
6	Arena Pernambuco	6/14/2014 19:00	Ivory Coast	CIV	2	Japan	JPN	1	Ivory Coast	CIV
7	Estadio Castelao	6/14/2014 22:00	Uruguay	URU	1	Costa Rica	CRC	3	Costa Rica	CRC
8	Arena Amazonia	6/15/2014 1:00	England	ENG	1	Italy	ITA	2	Italy	ITA
9	Estadio Nacional	6/15/2014 16:00	Switzerland	SUI	2	Ecuador	ECU	1	Switzerland	SUI
10	Estadio Beira-Rio	6/15/2014 19:00	France	FRA	3	Honduras	HON	0	France	FRA
11	Estadio do Maracana	6/15/2014 22:00	Argentina	ARG	2	Bosnia and Herzegovina	BIH	1	Argentina	ARG
12	Arena da Baixada	6/16/2014 16:00	Iran	IRN	0	Nigeria	NGA	0	Draw	Draw
13	Arena Fonte Nova	6/16/2014 19:00	Germany	GER	4	Portugal	POR	0	Germany	GER
14	Estadio das Dunas	6/16/2014 22:00	Ghana	GHA	1	USA	USA	2	USA	USA
15	Estadio Mineirao	6/17/2014 16:00	Belgium	BEL	2	Algeria	ALG	1	Belgium	BEL
16	Arena Pantanal	6/17/2014 19:00	Russia	RUS	1	Korea Republic	KOR	1	Draw	Draw
17	Estadio Castelao	6/17/2014 22:00	Brazil	BRA	0	Mexico	MEX	0	Draw	Draw
18	Arena Amazonia	6/18/2014 16:00	Cameroon	CMR	0	Croatia	CRO	4	Croatia	CRO
19	Estadio do Maracana	6/18/2014 19:00	Spain	ESP	0	Chile	CHI	2	Chile	CHI
20	Estadio Beira-Rio	6/18/2014 22:00	Australia	AUS	2	Netherlands	NED	3	Netherlands	NED
21	Estadio Nacional	6/19/2014 16:00	Colombia	COL	2	Ivory Coast	CIV	1	Colombia	COL
22	Estadio das Dunas	6/19/2014 19:00	Japan	JPN	0	Greece	GRE	0	Draw	Draw
23	Arena de Sao Paulo	6/19/2014 22:00	Uruguay	URU	2	England	ENG	1	Uruguay	URU
24	Arena Pernambuco	6/20/2014 16:00	Italy	ITA	0	Costa Rica	CRC	1	Costa Rica	CRC
25	Arena Fonte Nova	6/20/2014 19:00	Switzerland	SUI	2	France	FRA	5	France	FRA
26	Arena da Baixada	6/20/2014 22:00	Honduras	HON	1	Ecuador	ECU	2	Ecuador	ECU
27	Estadio Mineirao	6/21/2014 16:00	Argentina	ARG	1	Iran	IRN	0	Argentina	ARG
28	Arena Pantanal	6/21/2014 19:00	Nigeria	NGA	1	Bosnia and Herzegovina	BIH	0	Nigeria	NGA
29	Estadio Castelao	6/21/2014 22:00	Germany	GER	2	Ghana	GHA	2	Draw	Draw
30	Arena Amazonia	6/22/2014 16:00	USA	USA	2	Portugal	POR	2	Draw	Draw
31	Estadio do Maracana	6/22/2014 19:00	Belgium	BEL	1	Russia	RUS	0	Belgium	BEL
32	Estadio Beira-Rio	6/22/2014	Korea	KOR	2	Algeria	ALG	4	Algeria	ALG

		22:00	Republic							
33	Estadio Nacional	6/23/2014 16:00	Cameroon	CMR	1	Brazil	BRA	4	Brazil	BRA
34	Arena Pernambuco	6/23/2014 16:00	Croatia	CRO	1	Mexico	MEX	3	Mexico	MEX
35	Arena da Baixada	6/23/2014 20:00	Australia	AUS	0	Spain	ESP	3	Spain	ESP
36	Arena de Sao Paulo	6/23/2014 20:40	Netherlands	NED	2	Chile	CHI	0	Netherlands	NED
37	Arena Pantanal	6/24/2014 16:00	Japan	JPN	1	Colombia	COL	4	Colombia	COL
38	Estadio Castelao	6/24/2014 16:00	Greece	GRE	2	Ivory Coast	CIV	1	Greece	GRE
39	Estadio das Dunas	6/24/2014 20:00	Italy	ITA	0	Uruguay	URU	1	Uruguay	URU
40	Estadio Mineirao	6/24/2014 20:00	Costa Rica	CRC	0	England	ENG	0	Draw	Draw
41	Arena Amazonia	6/25/2014 16:00	Honduras	HON	0	Switzerland	SUI	3	Switzerland	SUI
42	Estadio do Maracana	6/25/2014 16:00	Ecuador	ECU	0	France	FRA	0	Draw	Draw
43	Estadio Beira-Rio	6/25/2014 20:00	Nigeria	NGA	2	Argentina	ARG	3	Argentina	ARG
44	Arena Fonte Nova	6/25/2014 20:00	Bosnia and Herzegovina	BIH	3	Iran	IRN	1	Bosnia and Herzegovina	BIH
45	Arena Pernambuco	6/26/2014 16:00	USA	USA	0	Germany	GER	1	Germany	GER
46	Estadio Nacional	6/26/2014 16:00	Portugal	POR	2	Ghana	GHA	1	Portugal	POR
47	Arena de Sao Paulo	6/26/2014 20:00	Korea Republic	KOR	0	Belgium	BEL	1	Belgium	BEL
48	Arena da Baixada	6/26/2014 20:00	Algeria	ALG	1	Russia	RUS	1	Draw	Draw
49	Estadio Mineirao	6/28/2014 16:00	Brazil	BRA	1	Chile	CHI	1	Brazil	BRA
50	Estadio do Maracana	6/28/2014 20:00	Colombia	COL	2	Uruguay	URU	0	Colombia	COL
51	Estadio Castelao	6/29/2014 16:00	Netherlands	NED	2	Mexico	MEX	1	Netherlands	NED
52	Arena Pernambuco	6/29/2014 20:00	Costa Rica	CRC	1	Greece	GRE	1	Costa Rica	CRC
53	Estadio Nacional	6/30/2014 16:00	France	FRA	2	Nigeria	NGA	0	France	FRA
54	Estadio Beira-Rio	6/30/2014 20:00	Germany	GER	2	Algeria	ALG	1	Germany	GER
55	Arena de Sao Paulo	7/1/2014 16:00	Argentina	ARG	1	Switzerland	SUI	0	Argentina	ARG
56	Arena Fonte Nova	7/1/2014 20:00	Belgium	BEL	2	USA	USA	1	Belgium	BEL
57	Estadio Castelao	7/4/2014 16:00	Brazil	BRA	2	Colombia	COL	1	Brazil	BRA
58	Estadio do Maracana	7/4/2014 20:00	France	FRA	0	Germany	GER	1	Germany	GER
59	Arena Fonte Nova	7/5/2014 16:00	Netherlands	NED	0	Costa Rica	CRC	0	Netherlands	NED
60	Estadio Nacional	7/5/2014 20:00	Argentina	ARG	1	Belgium	BEL	0	Argentina	ARG
61	Estadio Mineirao	7/8/2014 20:00	Brazil	BRA	1	Germany	GER	7	Germany	GER
62	Arena de Sao Paulo	7/9/2014 20:00	Netherlands	NED	0	Argentina	ARG	0	Argentina	ARG
63	Estadio Nacional	7/12/2014 20:00	Brazil	BRA	0	Netherlands	NED	3	Netherlands	NED
64	Estadio do Maracana	7/13/2014 19:00	Germany	GER	1	Argentina	ARG	0	Germany	GER

ANNEX 2: DIFFERENT DATA SETS OF KEYWORDS IN FINAL DATABASE SORT BY 64 SMALL EVENTS.



ANNEX 3: AN EXAMPLE OF R FUNCTION

R Script to Capture Tweets using Twitter Search API

```
# Install and Activate Packages
install.packages("twitteR", "RCurl", "RJSONIO", "stringr")
library(twitteR)
library(RCurl)
library(RJSONIO)
library(stringr)
# Declare Twitter API Credentials
api_key <- "API KEY" # From dev.twitter.com
api_secret <- "API SECRET" # From dev.twitter.com
token <- "TOKEN" # From dev.twitter.com
token_secret <- "TOKEN SECRET" # From dev.twitter.com
# Create Twitter Connection
setup_twitter_oauth(api_key, api_secret, token, token_secret)
# Run Twitter Search. Format is searchTwitter("Search Terms", n=100, lang="en",
geocode="lat,lng", also accepts since and until).
tweets <- searchTwitter("WorldCup OR Brazil2014, n=1000000000, lang="en",
since="2014-06-09")
# Transform tweets list into a data frame
tweets.df <- twListToDF(tweets)
# regular expressions to find retweets
grep("(RT|via)((?:\b\W*@\w+)+)", tweets,
ignore.case=TRUE, value=TRUE)
# which tweets are retweets
rt_patterns = grep("(RT|via)((?:\b\W*@\w+)+)",
tweet_txt, ignore.case=TRUE)
# show retweets (these are the ones we want to focus on)
tweet_txt[rt_patterns]
```