Media and Communication
Mediji i komunikacije

UDK 3316.774:070]:303.442.3
Originalni naučni rad/Original scientific article

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Social Sentiment Analysis and its use in the Context of Journalism[2]

Abstract: When looking for an opinion of specific groups, journalists can find an unlimited number of discussions containing users' opinions and emotions on social media. Automatic sentiment analysis tools use mathematical algorithms and computational linguistics that can determine authors' opinions and emotions. This gives journalists the opportunity to introduce a voice of multitude directly and at first hand, instead of focusing solely on pundits' claims.

This paper examines the concept of data-driven journalism with the focus on social sentiment analysis and how it can be used to support journalists' coverage of various news events. In order to demonstrate the use of social sentiment analysis tools, the sentiment analysis of messages related to Super Bowl 2015 was conducted using free online tools for sentiment analysis (Topsy, Sentiment140 and Social Mention), which revealed that selected tools can produce consistent and compatible results that affirm them as a valid research method for journalists.

Key words: *sentiment analysis, data journalism, social media, opinion mining, research method*

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2 This paper was developed as term paper for course "Media and Intelligent Text Retrieval" led by Nives Mikelić Preradović PhD, associate professor at Faculty of Humanities and Social Sciences, University of Zagreb, Croatia and author would like to thank her for valuable support and feedback on various drafts of this paper. A shorter version of the paper was presented at the conference on 8th Central and Eastern European Media and Communication Conference on "The Digital Media Challenge" organized by the University of Zagreb in cooperation with the ECREA CEE Network and co – sponsored by ICA.

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Analiza društvenih osjećanja i njihova upotreba u kontekstu novinarstva[3]

Apstrakt: Kada istražuju mišljenje određenih grupa, novinari mogu naći neograničen broj rasprava koje sadrže mišljenja i osjećanja korisnika na društvenim medijima. Automatski alati za analizu osjećanja koriste matematičke algoritme i računarsku lingvistiku koja može odrediti mišljenja i osjećanja autora. To daje novinarima priliku da uvedu glas mnoštva direktno i iz prve ruke, umjesto da se usredsređuju samo na stručna mišljenja i tvrdnje.

U radu se razmatra koncept *data-driven* novinarstva s naglaskom na analizu društvenih osjećanja i kako ona mogu biti korišćena kao podrška novinarima u praćenju raznih događaja. Kako bi se pokazalo korištenje alata analize društvenih osjećanja, sprovedena je analiza osjećanja poruka vezanih za Super Bowl 2015 koristeći besplatne internet alate za analizu raspoloženja (Topsy, Sentiment140 i Social Mention), koja je otkrila da odabrani alat može proizvesti dosljedne i kompatibilne rezultate koje ih afirmišu kao valjanu istraživačku metodu za novinare.

Ključne riječi: *analiza osjećanja, data novinarstvo, društveni mediji, istraživanje mišljenja, istraživački metod*

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3 Ovaj rad je nastao kao semestarski rad kursa „Mediji i inteligentan povraćaj teksta" na čelu s dr Nives Mikelić Preradović, vanrednim profesorom na Filozofskom fakultetu u Zagrebu, Hrvatska, i autor želi da joj zahvali na dragocjenoj podršci i povratnim informacijama na različitim radnim verzijama ovog rada. Kraća verzija rada predstavljena je na Osmoj konferenciji Medija i komunikacije Srednje i Istočne Evrope o „Izazovima digitalnih medija" u organizaciji Univerziteta u Zagrebu u saradnji s ECREA CEE Network and co – pod pokroviteljstvom ICA.

1. Introduction

Since 2000, sentiment analysis has developed into one of the most active areas of research in natural language processing due to the development of the Internet and social media that allow access to a large amount of data in digital form that contain the opinions and emotions of the authors (Liu, 2012). This paper was developed as part of the term paper for the course "Media and Intelligent Text Retrieval" where application of sentiment analyses through different fields were analysed, from marketing and advertising to journalism (Vladović, 2015).

Recent researches of journalists' practices (Willnat & Weaver, 2014; Zateva, 2014) suggest that journalists frequently use social media in their daily work. Among other uses, journalist use social media to find potential leads for their news story. Social networks are abundant with discussions that contain opinions, subjective statements and emotions of users. The focus of this paper is on how automatic social sentiment analysis of social media conversations can support journalists' coverage of various news events.

The paper brings the definitions and the characteristics of the social sentiment analysis and evaluates three free online sentiment analysis tools: Topsy, Sentiment140 and Social Mention.

In order to demonstrate the use of social sentiment analysis tools, a sentiment analysis was conducted on messages related to the Super Bowl game 2015, as well as an evaluation of how effective selected tools are when it comes to tracking and analysing the number of published messages and the prevailing sentiment.

An evaluation of these free tools revealed that selected tools, despite all the challenges that measuring the social media possess to research, can produce consistent and compatible results regarding the number of published messages and the prevailing sentiment, which affirm them as a valid research method for journalist. (Vladović, 2015)

2. Social Media As A Source Of Information

Before the emergence of the Internet, if journalist wanted to investigate the opinion of certain group, he/she had to rely on research, focus groups, surveys, experts, pundit and other persons who represent the opinion of the group. The development of the Internet and social media opens up the possibility of finding any number of discussions on almost any topic and thus get the statements directly from the public, as well as their attitudes and emotions on a topic. Sentiment analysis gives opportunity to news organizations and journalist to bring a crowd's views instead of punditry (Petulla, 2013).

Recent researches confirm that social media has changed how people find, share and talk about news. According to the research conducted by the Media Insight Project, social media is becoming an important tool for people to discover news. 40% of Americans across all generations stated that they got news from social media, through platforms such as Twitter or Facebook (The Personal News Cycle: How Americans choose to get their news, 2014).

At the same time, Pew Research found that in 2014, 50% of social network site users have shared news stories, images or videos, and nearly as many (46%) have discussed a news issue or event, while 14% of social network site users have posted their own photos of news events to a social networking site, and 12% had posted videos (Anderson & Caumont, 2014).

Keeping up with what is going on social media opens great opportunities for journalist to discover leads or trends and to develop them into news stories. Researches of journalists' practices suggest that journalists frequently use social media to receive, gather and distribute news. In the study in which they conducted online interviews with 1,080 U.S. journalists, authors Willnat and Weaver find that most journalist use social media to check for breaking news and to monitor what other news organizations are doing (Willnat & Weaver, 2014).

Authors Žlof, Herljevic and Hadžić conducted a research about the perception journalists have of the importance of social networks in the production of media contents using the focus-group method, with participation of 13 Croatian journalists. The authors concluded that social networks do have an important influence in the production of media contents but the impact of users on creating media content passes through the additional filters of media professionals and in that way media professionals are taking over the role of gatekeepers (Žlof, Herljević, & Hadžić, 2014).

Analysis of data from social media can help in detecting trending topics and identifying influential individuals or groups, but discovering useful information from social media proved to be very challenging. Separate report by the Pew Research Center on Twitter news consumers notices that majority of posts on Twitter involves sharing breaking news; sentiments of the conversations shift considerably over time; and the conversations do not necessarily correspond with public opinion (Guskin, 2013). Authors Oh, Sasser and Almahmoud describe data obtained from social networks as "large, noisy and dynamic" (Oh, Sasser, Almahmoud, 2015).

In order to research, collect and process large amounts of data generated on social networks automatic sentiment analysis software can be used to follow online conversations in real-time, to search and process relevant communication and to analyse prevailing sentiments. Many news organizations have developed such tools like Politico, Pew, NBC, CNN, Twitter, Facebook (Petulla, 2013).

In their paper "Diamonds in the Rough: Social Media Visual Analytics for Journalistic Inquiry" authors Nicholas Diakopoulos, Mor Naaman, and Funda Kivran-Swaine presented a visual analytic tool, Vox Civitas, designed to help journalists and media professionals extract news value from largescale aggregations of social media content around broadcast events. Authors have shown that journalists effectively use the tool to generate insight about the social media response to the event, and about the event itself (Diakopoulos, Naaman, & Kivran-Swaine, 2007).

The article "How Journalists are Using Social Media for Real Results" by Brenna Ehrlich brings several examples of stories picked up by the journalist on social media, such as how Aaron Lazenby, DJ for Pirate Cat Radio, discovered the story about "stolen elections" in Iran by noticing the trending hashtag #iranelection which, in that moment, still had not reached the mainstream news media. The article also brings the story about journalist Kitty Bean Yancey who wrote a story about hotel price extortion conducted using Twitter. After a huge snow storm in 2008, journalist searched the terms "snow" and "hotel" and discovered tweets in which people were complaining about hotels doubling their prices for snowbound guests who had to stay another night (Ehrlich, 2010).

Two articles about the Twitter reaction to Lady Thatcher's death provide an interesting example of using sentiment analyses to find and develop new news angles. While Vanessa Barford in her article "Margaret Thatcher and the taboo of speaking ill of the dead" at the BBC cites several tweets to illustrate different opinions about the subject (Barford, 2013), Campaign's Wall Blog brings Twitter sentiment analysis infographics demonstrating that "social media remained negative during Thatcher's funeral" (Macmillan, 2013).

3. Data Journalism

There is no single definition for data journalism, but in his article "5 tips for getting started in data journalism" Troy Thibodeaux (Thibodeaux, 2014) defines data journalism as s a "tendency to look for what is categorisable, quantifiable and comparable in any news topic and a conviction that technology, properly applied to these aspects, can tell us something about the story that is both worth knowing and unknowable in any other way."

Until recently not many journalists had the skills and knowledge needed for using large data sets in reporting nor did journalist have simple access to data for research. Journalist had to rely on data provided by other sources, such as organizations, governments, research companies, etc. (Aitamurto, Sirkkunen, & Lehtonen, 2011).

The progress of technology and Internet has changed this drastically and today there is an abundance of data that is freely available online as well as the tools that can help gather, analyse and publish not only by experts and journalist but by average citizens as well. This creates certain competition between journalist and average citizens, but at the same time this can provide a great benefit for journalists and enable them to find hidden stories and individuals who might have first-hand information or experience about a certain event (Zateva, 2014).

Considering the vast amount of data available on social media, the "journalistic sense of what is relevant and interesting, and of what questions need to be asked" is becoming more and more important (Aitamurto, Sirkkunen, & Lehtonen, 2011:18).

4. Automatic sentiment analysis

The automated sentiment analysis developed from the need for a system that will automate the detection and processing of opinions and views. Due to the complexity and ambiguity of natural language, text analysis is a complex task that relies on natural language processing, computational linguistics and machine learning. (Vladović, 2015)

In his book "Sentiment Analysis and Opinion Mining", author Bing Liu gives a comprehensive introduction to the sentiment analysis and asserts that "the inception and rapid growth of sentiment analysis coincide with those of the social media." (Liu, 2010: xiii).

Internet and social media enable access to a large amount of texts that contain the opinions and emotions of the authors. This content is in digital format suitable for further processing, but to find relevant content on the Internet is a major challenge given the large number of different sources and posts that contain opinions and views. Often the opinions and views are hidden inside long posts on forums or blogs with a form that makes recognition and retrieval very difficult, while the amount of posts in the form suitable for further use makes non-automatic searches, analysis, summarizing and organization of posts extremely difficult (Liu, 2010).

Bing Liu highlights several challenges associated with the automatic sentiment analysis:

- different levels of analysis, i.e., whether the whole to be analysed is a document, sentence, word, aspect;
- different types of opinions: conventional opinion and comparative opinion;
- different word sentiments: depending on the domain of use the same word can have two different polarities; a sentence does not have to express feelings even though it contains words with that sentiment; a sentence can express a view or opinion even though it does not contain words with that sentiment; it is difficult to distinguish sarcasm with or without an expressed sentiment; understanding slang, etc.
- problems of natural language processing where one should pay attention to the fact that the automatic sentiment analysis uses limited functionality of natural language processing because it is not necessary to fully understand the semantics of each sentence, just to recognize positive and negative sentiments of related terms and sentence conditionalities;
- detection of false reviews (Liu, 2012)

As automatic sentiment analysis starts to be used more frequently, the question of its accuracy is becoming more intriguing. In his article about sentiment analysis, author Sam Petulla raises this question and brings the claim of the Crimson Hexagon - big data company that provides social media analytics to CNN, NBC, Pew, and Current TV) that its technology produces 97% accuracy and that there is no statistically significant difference between analysis done by human coders and automatic analysis. However, Petulla cites Philip Resnik, professor at the Department of Linguistics at the University of Maryland who claims that "the humans sucked at annotating sentiment just about as much as the algorithms" (Petulla, 2013).

4.1. Tools For Automatic Sentiment Search

Tools for automatic monitoring and analysis of posts on the Internet and social networks allow us to search and process relevant communication with the aim of obtaining data suitable for further use.

As the interest of scientific and professional community for sentiment analysis grew, so did the interest in developing tools that allow automatic analysis. The market has a large number of tools developed by small start-ups, while lots of large companies are developing their own internal solutions as well (SAP, IBM, Adobe, Crimson Hexagon) or have taken over the existing solution (e.g., in December 2013 Apple bought TopsyLab that develops a social network search engine Topsy) (Wakabayashi,MacMillan, 2013).

In this study, we used three freely available tools for analysing sentiment: Topsy.com; Sentiment140; Social Mentioning

4.1.1. Short overview of the Topsy.com

Topsy.com[4] is a search engine for social networks and socially shared content in real-time and it stands out because of the possibility to search all posts on Twitter in the time span from 2006 to today. Topsy.com provides quantitative and qualitative analysis of posts. Analyses can be done in real-time while Topsy.com offers the possibility of searching in a certain period of time as well as comparing the number of posts for up to three different terms.

Topsy.com gives insight into the number of posts, sentiment analysis, identification of influential authors and a comparison of the number of posts for longer terms.

Topsy.com analyses trends and allows identification of authors with an extensive online influence on Twitter and other networks. The influence is determined by measuring the number of responses and sharings of certain posts. The sentiment is determined on a scale of 1 to 100, but Topsy.com does not give insight into sentiment classification of individual posts so we have no way of checking how accurate the classification is. Also, we could not find information on the methodology used to determine sentiment. Topsy.com supports searches in 10 languages. The professional version Topsy Pro offers advanced analyses with additional payment, at the time of writing this paper there was no the possibility of using the demo version.

4.1.2. Short overview of the Sentiment 140

Sentiment140[5] is a free tool to analyse sentiment posts on a specific topic on Twitter in real-time.

It has a very simple foundation and functionality. It is possible to search and analyse in English and Spanish. It shows the general sentiment as a percentage and

4 http://about.topsy.com/support/search/

5 http://help.sentiment140.com/

the number of positive and negative posts for the searched term.

Posts are classified into three possible sentiments and are marked in appropriate colour: positive - green, negative - red, neutral - white. Sentiment140 gives insight into the classification of sentiment which allows you to check how accurate the sentiment analysis is.

Sentiment140 only gives the results for the latest posts in a range of one hour and there is no possibility to view the results in another period or to identify influential authors.

4.1.3. Short overview of Social Mention

Social Mention[6] is defined as a platform for searching and analysing social media that collects content created by users on the Internet and combines them into a single sequence of information. It is a tool for monitoring and collecting relevant results on social networks, blogs, microblogs, forums, news, networks for video and audio content. It allows you to search by date and source.

After the analysis, Social Mention delivers measurable results for the following characteristics:

1. Strength: the likelihood of mentioning a searched term. It is calculated by dividing the number of mentions of a specific term by the number of all possible mentions;
2. Sentiment: the relationship between generally positive mentions and mostly negative mentions;
3. Passion: the likelihood that those who mention the searched term will mention it several times;
4. Reach: the reach of the impact is calculated by dividing the number of unique posts that mention the searched term by the total number of posts.

In addition to the above features, Social Mention allows filtering by the following characteristics:

1. classification of posts by sentiment in three categories: positive, negative, neutral. Marking each category with a certain colour allows easy detection of the post with a certain sentiment as well as the accuracy analysis and classification of sentiment for each post. It also allows analysis by sentiment, and thus only filtering the posts with predominantly negative sentiments offers insight into potential sources of customer dissatisfaction;
2. a list of the most frequently used keywords with the number of mentioning. This list gives a very useful insight into the associated search which facilitates the planning and implementation of further, more detailed analyses;

6 http://socialmention.com/about/

3. top users, i.e., authors that most commonly use the searched term. Identifying influential authors is very useful for businesses, but the author makes it easy to analyse and identify the so-called “opinion spammers” or authors who publish commercial posts shaped like user posts (equivalent to covert advertising).
4. top hashtags i.e., most used hashtags and the number of uses thereof.
5. sources included in the search and the number of results per each source.

The last two filters provide marketing experts with insight into the sources and content which are worth investing into so that their campaigns are more successful.

5. Sentiment analysis - super bowl 2015

In order to test the selected tools for analysing sentiment, we have conducted an analysis of messages on social media related to the Super Bowl game in 2015. The effectiveness of the selected tools in finding and collecting the published posts and the prevailing sentiment analysis was tested. The reports provide information on the number of posts and the prevailing sentiments in the period during and after the event.

5.1 Super Bowl

The Super Bowl, the NFL playoffs final football game, traditionally has been among the most popular TV programmes in the U.S. and the world. In 2015, Super Bowl XLIX became the most watched TV programme in the history of U.S. television with an average number of viewers of 114.4 million (NFL Communications, 2015).

Authors Shin, Byun and Lee, while examining Twitter usage during Super Bowl XLVIII in 2014 concluded that “users of Twitter post tweets about current active topics or events, as well as they tend to reflect their opinion on the subject” (Shin, Byun, & Lee, 2015).

5.2 Results of Analyses with Selected Tools

The analyses were conducted by using the keyword “super bowl”. The searches were conducted during the entire duration of the game, with more frequent searched during the half show. We decided to use the keyword “super bowl” over the hashtags that were in use, such as #superbowl and #sb49. We based this decision on results obtained from the trend analyses of the three keywords on Topsy.com which reviled the strongest usage of the keyword “super bowl”.

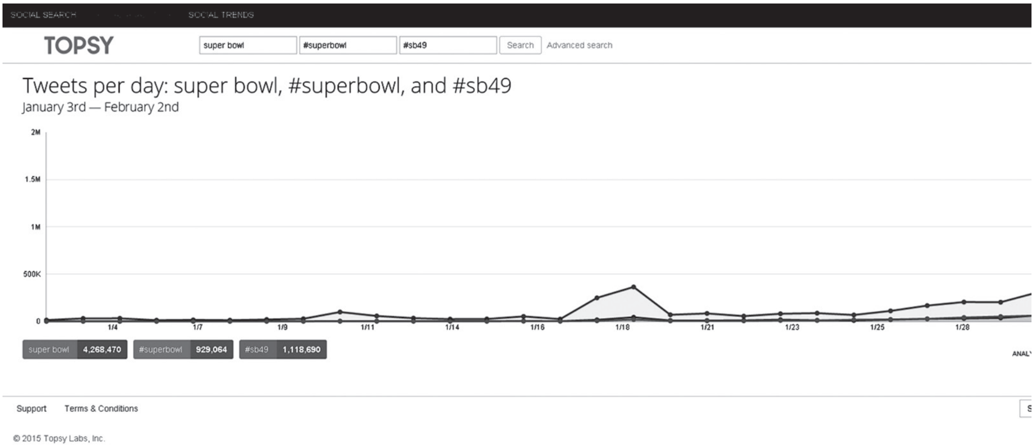

Figure 1: comparison of the number of tweets for keywords: "super bowl", #superbowl and #sb49

5.2.1. Analysis with Topsy.com

The analysis conducted on Topsy.com showed that the keyword "super bowl" generated high number of tweets and in general really high sentiment confirming high and positive audience engagement that is to be expected considering the popularity and the high viewership of the Super Bowl. The number of tweets gradually rises and the highest growth was achieved in the period after the halftime show, while just before the end of the game there was a slight drop prior the peak that was reached at the very end of the game. The sentiment score follows the same trend, generating the highest sentiment score after the halftime show and at the end of the game.

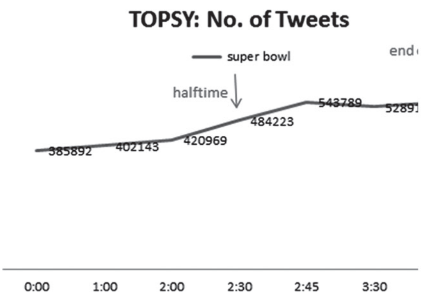

Figure 2: number of tweets reported by Topsy.com on February 2nd (CET)

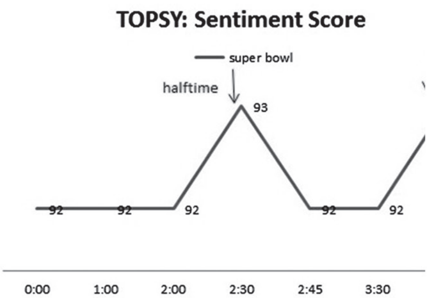

Figure 3: Sentiment score reported by Topsy.com on February 2nd (CET)

Topsy.com allowed us to identify authors with the most influence for the keyword “super bowl”. Among top five influencers, four of them were sport media, while only one, ranked on the second place, was an individual, Darren Rovell who is a sports business analyst (engaged by ESPN, but tweeting on his personal account).

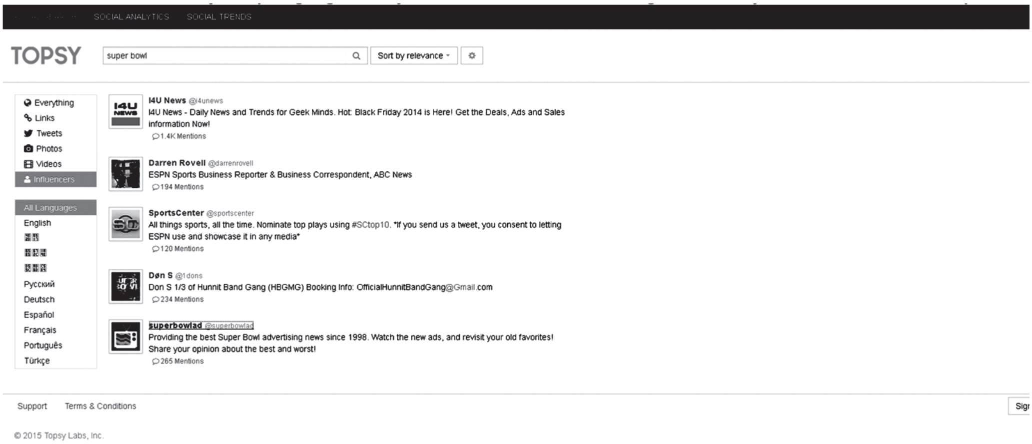

Figure 4: top five influencers for keyword “super bowl” on Topsy.com

While analysing the results, it was impossible to check the accuracy of the sentiment classification or more detailed analyses, because Topsy.com does not provide information on sentiment classification methodology (such as offered by Sentiment140 and Social Mention) or on the associated most commonly used terms (as in Social Mention).

5.2.2. Analysis with Sentiment140

Just as the results obtained on Topsy.com, the results from Sentimen140 confirm the gradual rise of the number of tweets during the game as well as the slight drop prior the peak reached at the end of the game, but the high rise after the halftime show is not visible. This can be due to the fact that Sentiment140 does not have the possibility of precisely defining the search period, therefore all results are real-time, while Topsy.com enables setting the search period (we selected a search period of 1 hour). Concerning the percentage of tweets classified as positive, Sentiment140 confirms Topsy’s results regarding the positive sentiment after halftime show, but brings lower results for the end of the game.

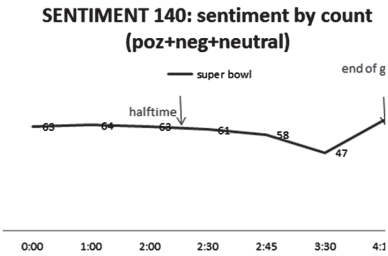

Figure 5: sentiment by count reported by Sentiment140

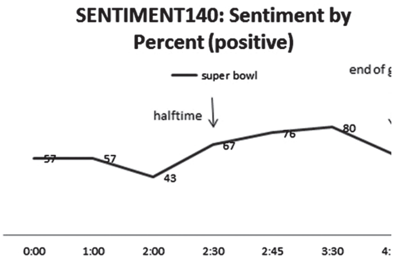

Figure 6: positive sentiment percentage reported by Sentiment140

Sentiment140 gives insight into the classification of the sentiment for a particular tweet that allows us to check how precise the analysis of sentiment is, and we noticed a few posts with mistakes in sentiment classification:

5.2.3. not recognizing sentiment due to the negation: tweet classified as negative sentiment, but is actually positive

> jennyramirezzz: didn't know i could get so emotional over these **super bowl** commercials.
> Posted: 22 seconds ago

5.2.4. not recognizing positive sentiment due to words with negative meaning: tweet classified as negative sentiment, but is actually positive

> Hanguyening16x: Crap... I fell asleep and didn't wake up on time for the **super bowl**.
> Posted: 25 seconds ago

5.2.5. not recognizing sarcasm: tweet classified as neutral sentiment, but is actually negative

> WinstonS6079W: RT @PolitiBunny: Dear Men, On behalf of women who aren't sensitive little flowers I apologize for the dumbass tampon **#LikeAGirl** commercial.?
> Posted: 24 seconds ago

5.2.6. not recognizing sarcasm: tweet classified as positive sentiment, but is actually negative

> Syeeed13: RT @WayneRooney: Trying to watch **super bowl** final. How do they call this football. Like watching paint dry. Looking forward to adverts and ?
> Posted: 22 seconds ago

5.2.7. not recognizing positive sentiment

> katygirldreamin: Liam Neeson's Clash of Clans commercial & **#LikeAGirl** are best Super Bowl ads so far. #superbowlcommercials
> Posted: 28 seconds ago

5.2.3. Analysis with Social Mention

The results obtained from the search conducted with Social Mention cannot be completely comparable with those gained through Topsy.com and Sentiment140 because Social Mention monitors and collects relevant results not only from Twitter, but also from other social networks, blogs, microblogs, forums, news, networks for video and audio content.

The analysis shows that during airtime, the highest percent of strength, the likelihood of mentioning a searched term, confirm the results of the analyses on Topsy.com with the highest percent of strength after the halftime show.

As for the sentiment, the results clearly confirm the results from Topsy.com and Sentiment 140 - the sentiment was highest just after the halftime show and at the end of the game.

The results for passion, a measure of the likelihood that those who mention the searched term will mention it several times, show a lower percent just after the beginning of the game, during the halftime show and at the end of the game, while the highest percent was reached almost an hour after the halftime show.

As for the reach which measures the influence; that is, the number of individuals who are mentioning the keyword, “super bowl” generated highest reach just after the halftime show.

By cross-analysing this results we can notice the difference of the results during the game and during the half time show, showing that during the game conversations are conducted by a smaller number of people but with greater passion, while conversations related to the halftime show attract more people, but with lower passion, although with higher ratio of positive sentiment.

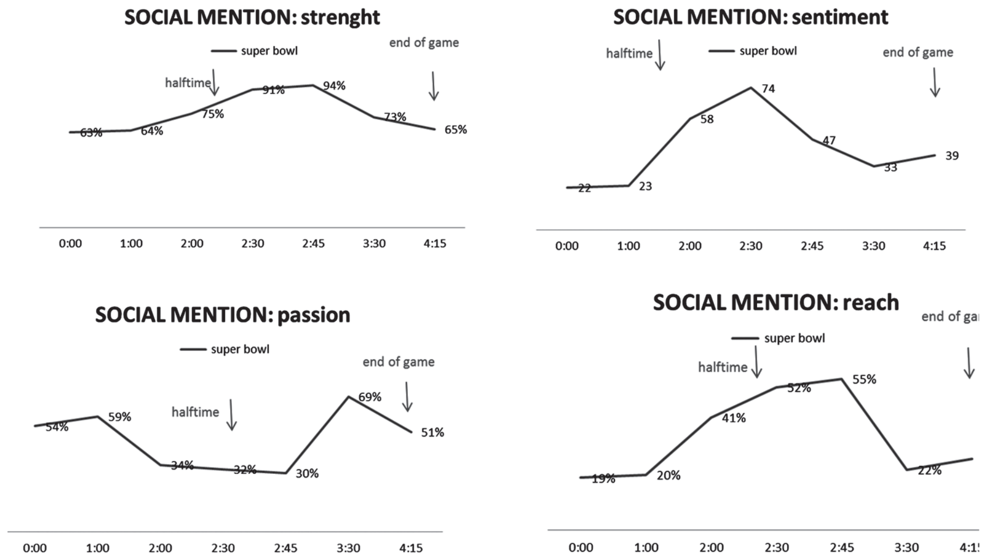

Figure 7: strength, sentiment, passion and reach reported by Social Mention

Social Mention has filters that allow deepening analysis, which proved to be very useful in detecting trending keywords that could be starting point for more detailed research for that particular keyword.

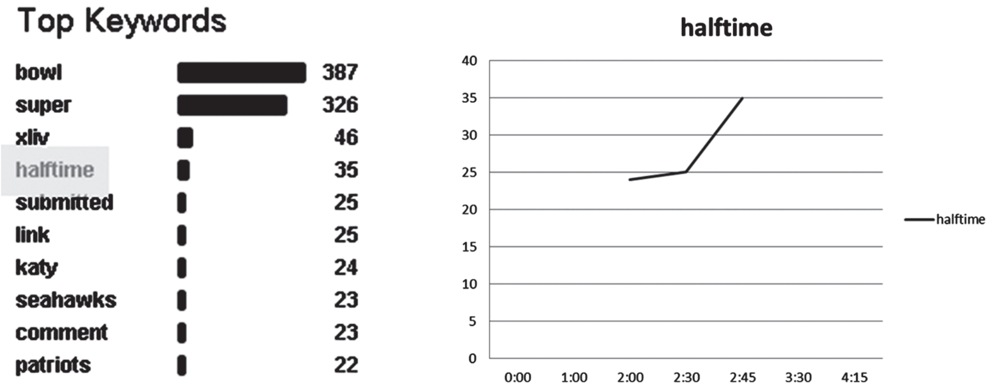

Figure 8: filters by top keywords indicating rise of mentioning for keyword "halftime" just after the Halftime show

Additionally, filters by Top Users and Sources did reveal some influencers and that Twitter is the most active social media for Super Bowl.

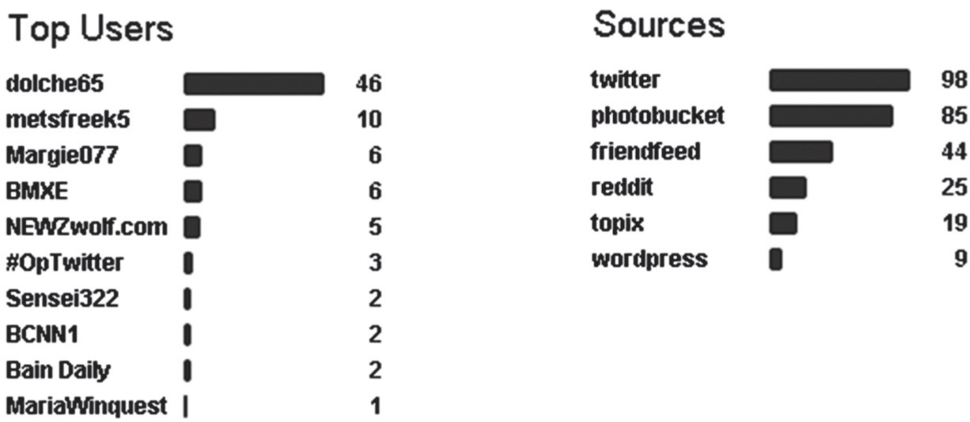

Figure 9: filters by Top Users and Sources

6. Conclusion

None of the tools used managed to give a detailed analysis, and we needed to use additional tools like Excel in order to conduct analysis, but considering that these are freely available tools we believe that we managed to acquire some useful data, as we did in our previous test of selected tools (Vladović, 2015). Even if the tools do not show completely comparable results on the number of posts and the prevailing sentiment, they still confirm the gradual rise of the number of posts during the game as well as the slight drop prior the peak reached at the end of the game. In addition, all confirmed the high rise of the positive sentiment just after the halftime show.

We confirm that the possibility of viewing sentiment classification is crucially important because the automatic classification still has many weaknesses, therefore a check is necessary in order to gain insight into the accuracy of the classification, and therefore into the credibility of the obtained data.

Sentiment analysis on social networks is than just a supplement to traditional forms of journalistic research since it enables to monitor and analyse the audience's sentiments and opinions in real-time and at first hand.

This paper did not have the ambition to provide a detailed analysis of the conversations related to Super Bowl or a comprehensive insight into the area of sentiment analysis; what we have been shown by this exercise is that the skilful use of free tools can help journalist to filter interesting conversation, detect influencers and provide insights that would not be possible without automatic sentiment analysis.

This research confirm the findings from our earlier research that each of the selected tools has its advantages and disadvantages, so it is crucial to know the functionalities and limitations of each tool and to select the tool depending on the research objective. Using multiple tools at the same time can also improve the end result, but one must be aware of the differences in the methodology of each tool in order to be able to read and compare the results.

From our research, we are inclined to conclude that we were given the most beneficial results by the Social Mention browser. Even if Topsy.com gave some very useful functionalities as comparative search of more keywords and identification of influencers, Social Mention despite some flaws (such as the lack of a historical presentation of the results), and due to its other functionalities (such as insight into post classification and filters for various criteria), allowed further analyses that provided us with a detailed understanding of the basic results obtained through sentiment analysis.

Tables of figures

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