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Multilevel Exploration in Twitter Social Stream

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***Abstract*—This paper describes a methodology approach and a tool dedicated to the exploration of the twitter social stream by combining different contextual parameters such as time, keywords, gender or the opinion. The exploration can be made in two main modes depending on the fact that the phenomenon is either known or not. The first mode, similar to the use of *Googlefight* search engine, allows to compare the stream feedback for several groups of words. A typical example, that we will discuss, consists in evaluating trends in the domains of fashions or politic. The second mode consists in exploring the timeline of the social stream looking for unknown emerging events. This mode can be used to explore the past or to identify, in near real time, an event that will probably make the buzz.**

Keywords— opinion, poll, visualization, politic, fashion

I. INTRODUCTION

The Social networking platforms are becoming more and more central in our society. In fact, the increasing number of users and the democratization of mobile technologies make, that social networks data are a true mirror of society. Indeed, interactions in text mode, image or video show the tastes or the concerns of individuals as well as their social, political or economic preferences. This is particularly visible in the case of Twitter that produces an, almost immediate echo of all important events from anywhere in the world. This reactivity appears to be higher than that of the press even if it is less structured. As an example, Paul S. Earle and his colleagues have shown that, Twitter allows about 75% of earthquakes detection within two minutes following the origin time. [11]. This is considerably faster than seismograph detections in poorly instrumented regions of the world. It is also interesting to see that in parallel, the use of social networks by end users have also evolved. A 2015 report from Pew Research Center finds, for example, that a clear majority of Twitter (63%) and Facebook users (63%) says that each platform serves as a source for news about events and issues outside the realm of friends and family. [20] Many other studies, in the domain of public health, security, economy, etc. show that social networks can be useful, not only to be informed rapidly but also in order to provide many details for the diagnosis of the events and to forecast their evolution.

One of the most interesting feature of Twitter is its relation with time, allowing users' spontaneity and reactivity. All these characteristics make that Twitter provides a very good time resolution for the analyze of phenomena. The problem is that time analysis of human interactions is not easy due to the multiple influence parameters. In order to investigate these temporal aspects we describe a set of tools and a methodology of analysis including visualization of results. The goal is to have a better view of low signals and trends' evolutions. In this paper, we investigate the relations between the temporal resolution and various parameters (semantic, sentiment, sociodemographic). We suggest two ways to explore the social stream. The first one consists in looking for unknown item or event that make the buzz at present or in a particular period in the past. Once this event has been discovered, it can be analyzed more precisely (opinion per gender, etc) in different periods of time. In the second mode, the user knows the topic for which he seeks details. For example, let us imagine that he want to study the evolution of the Twitosphere feeling about the latest fashionable smartphone. Instead of measuring the opinion on one device alone, we will see that the comparative strategy (e.g between 2 smartphones) is a method to reduce the uncertainty in the opinion evaluation.

This paper is structured around five other sections. The two next ones provide several examples showing how to explore the Twitter social stream under the two modes we evoked. First, we discuss the formation of the buzz linked to the recent death of the artist Prince. Then, we apply the comparative methodology as a survey tool in the fashion domain and in the context of the present US presidential campaign. In the section four, we describe our computer architecture and its performances. Finally, in the section five, we present a state of the art of comparable works before to conclude in the last section.

II. BUZZ FINDER WITH MULTI-SCALE TIME PERIOD ANALYSIS

In the following, we give an example of this exploration strategy with a tool that allows to zoom in the timeline of the social stream. Here, the user looks for an unknown event generating emerging buzz. The web interface includes 4 parameters: a starting date, a period of analyze, a gender and a language selection. The starting date is always updated at the most recent date but the user can modify it in order to explore the past. The period of analyze, from 15 min to 72 h, allows to select all the corresponding tweets in database. The gender selector allows either to display separately a word cloud for men and another for women or alternatively, to display a cumulative view. Finally, the language lets to filter the tweets in English or in French (other languages can be added easily).

The figure 1 shows the corresponding word clouds for women (left) and men. Each cloud displays the most frequent words tweeted by each gender during a 48h period before the 22 April 12:00 a.m. We can see that one of the most evoked event is related to Prince, which was only reported by men at that moment.

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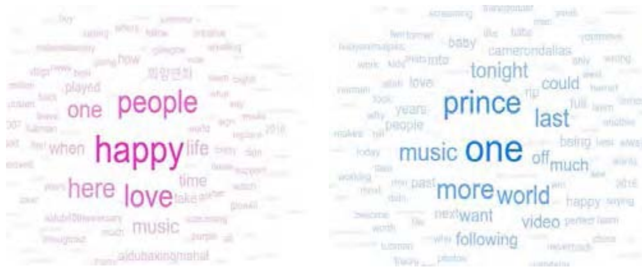

Fig. 1. Most frequent words tweeted by women (left) and men

These word clouds show a frozen picture of the overall activity during a 2 days period. It provides a clue that something happened in relation with Prince but, it doesn't give chronological details. In order to explore the event, we can represent the most frequent words in the timeline stream as shown in the figure 2 where time is decomposed in consecutive sequences. Here, a 4 hours period has been chosen but interactively, the user can change this period from 15 min to 72h in order to zoom-in or zoom-out in the timeline. In our case, we can see that the news regarding the death of Prince start to make the buzz the 21 Avril between 5:00 p.m and 9:00 p.m. This means that, less than 2 hours after the event, the information was already largely broadcasted in the Tweetosphere (Prince is dead the 21 Avril at 15:00 GMT).

In the figure 2, the colors help to identify most frequent words. At starting, they range between dark blue (>600 tweets) and light gray (<100 tweets). But, a slider allows to modify these limits in order to change the contrast between words' colors when they are too similar.

Fig. 2. Timeline exploration with sequential words lists

This timeline zooming functionality is useful to identify the semantic and chronological context of an event. Once this event is identified, it is possible to click on one or several words of this sequential word list in order to obtain the status of the most retweeted messages containing the selected words. The user interface also allows to directly obtain the news, if available, (via Google News API) linked to these keywords. This exploration mode is interesting if we do not know what happened and if we want to explore what is going on at present or at a particular period in the past. But, if we know the event, we can analyze its features from different points-of-view. If we take again our example, a quantitative view provides complementary informations. The figure 3 shows that the event start to be discussed at 6 p.m and peaked (30 000 tweets in English) around 7 p.m before to slow down within a period of one day.

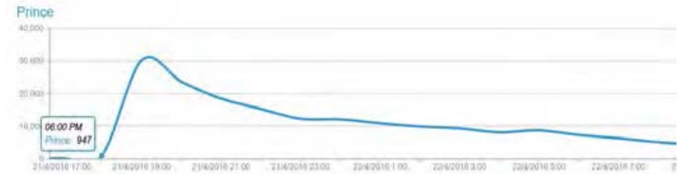

Fig. 3. Quantity of tweets dedicated to Prince around April, 21

The overall recorded tweets by our system in this period was sent with a little majority by men (53%). This probably explains why men broadcasted the information before women (see figure 1). Also and logically, this event was perceived, in majority, as negative (53%) with no significant difference between men and women (2%). But, if we examine this situation before the 21 April (4 months period), when Prince was still alive the feeling was clearly positive (76% women, 71% men). During this period, the tweets were broadcasted mostly by men but with a larger majority compared to the moment when the death was known (58% vs 53%).

This strategy of contextual exploration of a particular event can also be done at a lower or a larger time scale compared to that related to Prince (2 days). For example, around a football match or a TV show, the period can last 2 hours or less. Conversely, some phenomena, such as fashions, can last several months. The social stream exploration tools can provide precious insights on the opinions during these periods. Sometimes, these findings are counterintuitive. During a soccer match, for example, it seems logical to think that the majority of tweets are broadcasted during a major action such as a goal or a refereeing error. Actually, if these actions tend, indeed, to induce a high level of tweets, it is far to be as higher than the one occurring within the 5 minutes before the start of the match, when people are waiting and are available to discuss with their friends. This appears to be slightly different with sports having more timeout period (American football, basketball, etc).

Outside of academic applications, Twitter is already largely used in talkshows as online survey or for measuring the audience. That said, the use of Twitter as measuring tool remains, still, basic but it allows real time interactivity with the audience. At the other end, Twitter is also used to manage influences in a context of viral marketing in order to promote a product, a company or even a politician as we will see in the next section. In this field, also, except for academics, the measure or the exploration functionalities still remain a marginal use.

III. Comparative Analysis

The analysis or the forecast of a long-term phenomenon, such as a fashion is commonly made by online or face-to-face surveys. This needs a lot of resources and time with results that lack in precision. Indeed, surveys are often only made episodically with less than 2000 persons most of the time. A social stream analyzer can provide insights at low price and at any time by measuring feelings of millions of people. As an example, let us imagine that we want to explore and compare the opinions' trend on colors in order to target the design of pants. We select a period of time and a group of words representing our requests. We start 4 research processes where each one can be formed with AND/OR operators. For example, the first process selects all tweets in database containing the words “red” AND "pants". In the same way, the three other request processes relate with blue, yellow and pink pants.

The results web page is difficult to be represented here since it is four A4 pages long with several types of graphics (temporal quantitative and opinion, word cloud, pie chart, etc) as well as a list of tweets. In order to evaluate the trend over the time, we reported the opinions per gender for two consecutive periods of 15 weeks each. We synthesize these results on the two following tables.

Looking at these tables, the first remark we can make is that there is a hierarchy of colors' taste. Some are more evoked than other and some are preferred to other. But, this hierarchy is not the same on all periods. If blue is always the most evoked color, it is not always the preferred one. In period 1 (table 1) we see that pink has 85% of positive feelings whereas it falls to 67/68% on period 2 where blue is the preferred color. Most of the time, the difference of feelings between genders is low (less than 5%) except for yellow where the difference is very high as shows the table 2 (73 % of positive opinions for men, 49 % for women). Also, if blue is mostly evoked by men, the positive opinions of women are slightly higher to those of men, differing from what show regular surveys. Actually, when people are interviewed in face-to-face for their preferences, blue appears always in first position, both for men and women. But, the difference between each gender can largely vary from one survey to another (sometimes from single to twice). Other large differences also appear, between surveys, regarding less popular colors [22][23].

TABLE I. OPINION ON COLOR FROM OCT. 2015 TO JAN. 2016

Color	Red		Blue		Pink		Yellow	
Gender	M	W	M	W	M	W	M	W
Total Tweets	590		1397		788		231	
% Tweets	65	34	67	32	39	60	50	49
% Opinion +	78	80	61	66	85	85	70	57
% Opinion -	17	13	30	26	11	9	16	25
% Opinion =	4	6	8	7	2	5	12	17

TABLE II. OPINION ON COLOR FROM JAN. 2016 TO MAY. 2016

Period 2	Red		Blue		Pink		Yellow	
Gender	M	W	M	W	M	W	M	W
Total Tweets	1451		3042		1391		502	
% Tweets	56	43	64	35	61	38	58	41
% Opinion +	72	76	59	71	67	68	73	49
% Opinion -	21	17	30	17	17	19	23	37
% Opinion =	5	5	10	10	15	12	3	12

Another example of comparative analysis is that of political polls. We may wonder to which extent a candidate is preferred versus an other. We benefit from the 2016 US campaign to discuss the feeling of the Twitosphere on the four major candidates to the White House. In addition, we also compare this feeling in two linguistic communities (English vs French speaking people). As in the previous example, with colors, the research was done with the first name and the family name of candidates (Donald Trump, Hillary Clinton, Bernie Sanders and Ted Cruz). This may seem to limit the quantity of collected tweets because supporters often use only diminutives (Hillary,..) but in the other hand, this avoid to consider off-topic tweets. Furthermore, we will see that, finally, the amount of tweets remains very high compared to face-to-face surveys. The comparison takes into account the tweets collected during nearly 3 months (from 1/1/16 to 21/3/16). The table 3, presents the difference of perception for both speaking communities. We observe that neutral position is nearly two times more higher for French than for English, probably because these are less directly concerned. We see also that democrat candidates are largely preferred by francophones. This is not surprising since the political trend in France (for example) is mainly on left wing.

TABLE III. POLITICAL SURVEY FROM JAN. 2016 TO MARCH. 2016

	Trump		Clinton		Sanders		Cruz	
Language	En	Fr	En	Fr	En	Fr	En	Fr
Total Tweets	14 282 800		4 655 700		5 969 200		4 841 700	
% Opinion +	75	39	54	49	58	46	48	35
% Opinion -	6	21	33	14	27	18	34	21
% Opinion =	17	38	11	35	13	35	16	42

At the end of march, The table 3 shows that D. Trump is largely preferred by the English speaking Twitosphere. This is also confirmed by a longitudinal view of the opinions as presented in figures 4 and 5. In these two figures, the black, white an gray areas respectively represent negative, positive and neutral opinions, in a scale from 0 to 100%.

Fig. 4. Evolution of political opinions over the time (D.Trump)

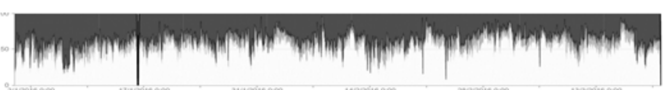

Fig. 5. Evolution of political opinions over the time (H.Clinton)

Of course, it is important to remember that surveys are only a picture of the opinion at a given time. The history, especially in the politic domain, has proven that predictive use of surveys needs a lot of precautions. Moreover, Twitter is also largely spammed or manipulated. Depending on one study to another, the amount of spams or malicious tweets are evaluated to 5% to 8% of the total Twitter stream [31]. Merchants also use this media to promote their products or to make special offers. In the context of an election campaign, the politicians' staffs are omnipresent on Twitter. All these uses added to the natural noise generated by the 140 sign written style tend to pull down the reliability of tweets in a way that is difficult to evaluate.

Thus, the comparative strategy is conceived as a way to reduce this uncertainty. It is based on the point of view that all these errors are quite equally distributed on all topics and tend to compensate each other where seen comparatively.

IV. Design and performance of the Computer Architecture

In order to propose these exploration functionalities, we designed a partially distributed architecture based on the Twitter public Streaming API around a software-as-service (SaaS) model. This service, dedicated to scientists and policymakers, allows longitudinal studies of various phenomena, linked to human behavior, in near real time.

One of the major component of this architecture is the open source search engine ElasticSearch, based on Apache Lucene Core. The research of data is done (Json format over HTTP) in a database where documents are saved in indexes, possibly with several independent tokenization methods. This choice of technology has several advantages in the case of twitter, especially when the number of tweets received increases sharply. In this case, it is crucial to have a system that is very quick to perform database inserts and avoid a timeout disconnection by Twitter. ElasticSearch shows, up to two times faster than MySQL for data insertion [20]. Second, the tweets are partially processed for insertion ("tokenization"). Thus, it is possible to make queries on the freshly inserted tweets and observe trends in near real time in the user interface.

For the moment, 5 computers (Intel Xeon) operate our architecture from a local network having a firewall. We currently have a storage capacity of 12 TB disk and 100 GB RAM. Our architecture has the advantage of being scalable simply by adding one or more machines in our cluster.

The first service added to our system ensures that the capture of tweets is not faulty. If this is the case, it tries to revive, in autonomous way, the capture service and warns administrators by mail with the nature of the problem, if it is identified. Having a reliable capture is necessary to obtain, as possible, accurate results for data mining. The tweets capture is based on anticipated steps where users have to identify a set of words that describe their topics of interest. These words are submitted to twitter through the API as long as they are not deleted by the users. This makes that some topics can be monitored (Tweets stored in the local Elasticsearch database) during several months. The only constraint is the storage size.

Then, we have different search and data analysis services written in Python in connection with a couple of applications that consist in a server part (back-end) in Node.js and a client part (front end) written mostly using Angular.JS and jQuery. The server side is primarily a secure link between the ElasticSearch cluster and connections from the Internet. The client side provides several tools to end users. When the front end wants to view or update a directive, the request is transmitted to the server side that, then, queries the ElasticSearch cluster. During this time, it performs other requests from other users until it finds no other task to do. There is no blocking process.

As an example of performances, the political survey described above (processing around of 30 millions tweets resulting in equivalent to 4 A4 pages) takes 1 min 50 sec in our 5 computers platform.

V. State of the art

This section focuses on works in relation with two main topics. First, we describe different kind of graphical representations for semantic and chronological analysis of social networks. Then, we present works that deal with sociodemographic comparisons and sentiment analysis on twitter.

A. *Word Cloud and semantic representation*

The purpose of a word cloud is usually to present a visual overview of a collection of text. Fernanda B. Viégas and Martin Wattenberg, describe in their paper the history of word cloud [2]. In short, the first example may have been the outcome of an experiment carried out by the social psychologist Stanley Milgram in 1976 who asked people to name points of interest in Paris. Then, he created a collective “mental map” of the city using the font size to show how often each place was mentioned. In 1997, Jim Flanagan wanted a way to show which search terms had led people to his website. For that, he has make to vary the type sizes in the HTML page with a Perl script that produce a graphic word cloud. However Flanagan’s script remained a curiosity until the years 2000. At this period, this representation began to be used in the press and in innovative web sites. For example, in 2002, Flickr needed a way to show how users had classified, or “tagged,” their images. Borrowing Flanagan’s idea, Flickr added a “tag cloud” that showed the popularity of various tags using font size variations. Two years after, the MIT Media Lab declared this type of graphic “The Greatest Diagram of 2004”

The design of a words cloud can take several aspects. Outside the basic one-word-tag with the size depending on words frequency, we can also find two-words-tag repartition [2]. But, some works show that word cloud is not always the best design. In one experiment, this representation performed worse in word recognition and overall sense making compared with a simple vertical list of words ranked in alphabetical order [3][4].

B. *Timeline representation in Twitter*

The analysis of millions of Tweets and web search queries have found that, unlike web search which is more fact-based, people use Twitter to look for temporally relevant information, such as breaking news, popular trends, and information about people [6]. In this domain several works deal with social networks but also on the analyze of documents' sequentiality [1].

For example, Lee et al proposed a solution (KeySee) that groups the posts into events. Then, it tracks the evolution patterns of events as new posts stream in and old posts fade out. Keyword query can be made on evolving events by allowing users to specify the time span and designated evolution pattern. [5] Other works aim at detecting and visualizing bursty and viral events. This is, for example, done with a three-stages system: First, with a real-time bursty event detection module. The detected event is summarized by clustering related topics detected in successive time periods. Third, by visualizing the event evolution both along timeline and across other news media to offer an easier understanding of the events.[12].

A other way to represent a social stream is the streamgraph proposed by L.Byron in 2008 [14]. This tool can be used, for example, to display the variation of a graph of connections. For instance, let us imagine that a graph displays connections between Twitter users based on who is “talking” to who. This graph can be partitioned into subgroups of users that tend to intercommunicate. One limitation of this representation is the inability to track the change of content within a graph over time. In his paper Stojanovski et al. give an example of use of streamgraph to analyze temporal variation on Twiter [13]. The link between the timeline and communities has also been made by Lim et al who use word cloud to explore sequential evolution of Twitter data stream in relation with communities of interest. Their tool named Palanteer enables searching microblog data by focusing on harvesting community relevant contents. Next, Palanteer uses a timeline-based interface and a word cloud visualization to allow the searchers to explore and make sense of temporally-relevant information [7]. The timeline can also be represented in association with the location [8].

C. *Extraction of sociodemographic parameters from Twitter*

Accurate identification of demographic attributes from social media and other informal online content is valuable for marketing, personalization, and legal investigation. But, Twitter does not provide many details regarding the users. On one side, this is quite logical for ethical and legal reasons but the situation differs from one social network to another. For example, if the language or contacts relations are available, the location of the user is not always usable. Sometimes it is not present or not significant. The age and the gender are not available and, of course even less, the level of education and the socioeconomic position.

Several researchers have tackled these problems from a datamining perspective. The idea is to use the content of the tweet or the contextual informations to extract non explicitly present knowledge. Most of the works dedicated to gender identification of the tweets' author are extracted from firstname, written style or used vocabulary [15,16,17,18]. For example, Burger et al. describe the construction of a large, multilingual dataset labeled with gender, and investigates statistical models. They explore several different classifier types on this dataset and show that best classifiers performed at 92% accuracy, and the classifier relying only on tweet texts performed at 76% accuracy [15].

Existing researchs did not provide a unified framework on how men and women use microbloging plateforms, with gender insights scattered across multiple studies. Baumann et al. conduct a meta-review of existing research. They find differences in adoption, shared content, stylistic presentation, and interaction [19].

D. *Sentiment analysis in Twitter*

In the last decade there has been an increasing effort in the linguistic and datamining communities to address the question of the computation of the opinion from a textual content. Opinion mining is often viewed as a sub-field of sentiment analysis that, as the discourse analysis or the linguistic psychology, seek to evaluate affective state through the analyze of natural language. Nevertheless, many researchers define sentiment, loosely, as a negative or a positive opinion. The results of these works is pretty good but it largely depends on the quality and the length of the text [25]. Indeed, we can notice that in the 29 studies from 1997 to 2009, reported by Mejova, 19 reveal more than 80 % of accuracy and 6 of them more than 90 % [24]. But, measuring the opinion of tweets that are short and noisy is far to provide such results. Abassi and his colleagues have tested 20 sentiment analysis tools on a collections of annotated tweets corresponding with 5 thematic domains (retail, telco, etc.). They found an average accuracy near 50% [21]. Despite these limits, several works turned their attention to the issue of public mood, or sentiment analysis in Twitter. For example, in ther paper "The mood of the nation", Lansdall Welfare et al have used tweets sampled from the 54 largest cities in the UK over a period of 30 months [9] (see also [10]). But, this loss of efficiency is expected to be, at least partially, compensated with the high number of tweets.

E. *Twitter as a polls resource for predictive analysis*

The use of twitter for polls was one of the first topic of study with, most of the time, the ulterior motive of predicting the future. If the predictive efficiency can vary from one study to another, some of them present impressive results.

In the domain of stock exchange forecasting, Bollen et al show that the inclusion of some specific public mood dimensions allows an accuracy of 87.6% in predicting the daily up and down changes in the closing values of the Dow Jones Index [30]. In the same spirit, O'Connor and his colleagues analyze several surveys on consumer confidence and political opinion, and find they correlate to sentiment words frequencies in contemporaneous Twitter messages. While the results vary across datasets, in several cases the correlations reaches 80%.[26] (see also [29]).

Other studies point out the biases of using social networks data as poll source. In his paper, Gayo-Avello study the 2008 US campaign and shows why the results could not have been predicted from twitter by applying commons methods. He develops 5 biases as, for example, the non representativity of Twitter users compared to the real population or the lack of precision in opinion measure [27]. Other even more negative studies have shown that methods for predicting election results based on tweets words polarity alone are no better than random classifiers [28].

VI. CONCLUSIVE REMARKS

This work shows the potential of the social stream exploration but also its limits. The huge quantity of tweets broadcasted each second allows a potentially good statistical representativity at any moment. The results can be obtained quickly at low price compared to face-to-face surveys. The drawback is that tweets are noisy and difficult to analyze from a natural language processing perspective. The opinion analysis is little accurate, the subject or the target of the expression is also difficult to identify. We also discussed the influence of other kinds of errors coming from spams or opinion influencers. In one word, it is necessary to find an equilibrium between the benefit of the high quantity of data as well as the good time granularity and the drawbacks of the lack of precision at the tweet scale.

We put forward, from a methodological point of view, that an adequate analysis strategy can make that this kind of tool become very profitable despite these limits. First, when it allows to find information impossible to obtain by other means. This is the case, for example, for a near real-time exploration. Even with errors, the results can provide interesting clues that can be compared with other information feeds (press, etc.). Second, the comparative strategy can reduce the effect of errors that probably equally affect in the same way the different items to compare.

While most of the researches linked to Twitter deal with datamining and natural language processing, we think that there is a substantial margin of progress from the side of new usages of such tools. Many questions should, still, be deepen. For example: What methodology of investigation for a Twitter data analysis? How to evaluate the uncertainty of the results? What display form for the graphical data representation?

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