Revolution 2.0 in Tunisia and Egypt: Reactions and sentiments in the online world

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Introduction

Since the beginning of 2011, social unrest has cascaded across the urban centers of North Africa and the Middle East. In this paper, we analyzed over 3 million web documents to understand the scale of reactions and sentiments in the Internet on the 2011 Tunisian and Egyptian revolutions.

Many researchers are interested in knowing the role of the Web 2.0, in particular social media, in these revolutions (AFP 2011). Traditionally, journalists and mass media were considered a key player of social movements (Howard 2011) and the sentiments of international audience were not considered important. While debates are on-going, it is hard to deny that social media sites like Facebook spawned wide international support (M. M. Skoric and N. D. Poor and Y. Liao and S. W. H. Tang 2011).

In order to understand the intricate interplay between news and social media, we investigated the timing, the scale, and the sentiments of reactions from the two groups. Descriptive statistics of words in the media display the volume was changing in accordance with the gravity of the event. Given the popular conventions of cross-citations, it is not surprising the news and social media exhibited a common fluctuation in volume across pivotal events. However, an inferential statistics shows a different picture about the changes in sentiments over time. We conducted an analysis of log-odds ratio of positive vs. negative sentiments identified by LIWC. While the individual bloggers and social media users were more prone to be positive about the regime change, the formal news media were consistently negative about the process. We discuss the theoretical implications of our observations.

Data Methodology

The dataset provided by the Spinn3r web service company (K. Burton, N. Kasch and I. Soboroff 2011), consists of various types of content including weblogs, mainstream news, forums. Among them, we used three largest datasets: weblog, social media, mainstream news. Mainstream news contained updates from popular news outlets such as BBC and NYTimes. Weblogs include blog post updates from sites like blogger.com, and social media contained updates from sites like Facebook and Reddit. While weblog is conceptually a subset of social media, Spinn3r classified them in different categories and we follow this convention.

We limited our focus to English articles, which comprise an overwhelming portion (74%) of the entire dataset. Therefore, our analysis provides a view from *outside*, as opposed to inside from the Arab world. The Spinn3r dataset contained meta information about the articles such as the publish date and source, as well as the article body itself such as news content and blog updates.

We first extracted articles relevant to the Egyptian and Tunisian revolutions by using 83 English keywords. We obtained these keywords by consulting various news sources. Most keywords included proper nouns of the relevant places, persons, organizations of the two revolutions (e.g. Mohamed Bouazizi, RCD and Tahrir). Once we obtained a target subset of the data, we indexed the data by several attributes including date, source, and keywords. Indexing creates a hashtable, which enables us to rapidly search for the articles containing specific keywords or features.

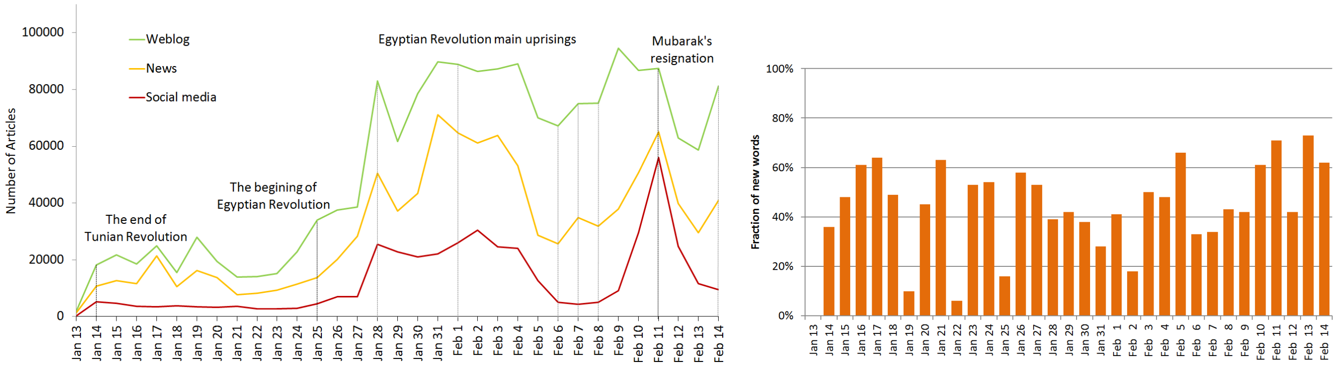
Sources	Egypt	Tunisia	Total (Intersection)
Weblog	1,590,698	493,625	1,747,874 (19.2%)
News	930,339	272,009	1,027,104 (17.1%)
Social media	393,342	49,972	422,102 (5.0%)

Table 1: Number of articles on the two revolutions

In total, we identified 3,197,080 articles on the two revolutions (Table 1). Weblogs, news, and social media each comprised 55%, 32%, and 13% of the parsed data, respectively, although we mention that the ratio might be specific to the Spinn3r dataset. Many articles included both keywords on Egypt and Tunisia, indicating that the two revolutions were frequently compared.

The Scale and Dynamics of Reactions

We first begin by examining the timeline of daily volume of articles spanning four weeks of data, for each of the three types of media sources in Figure 1(a). We marked notable events as vertical lines. We make several observations. First, the volume of articles vary largely throughout the period. Some peaks coincide with the key events, indicating that nature of reaction on the two revolutions is event-driven. Second, weblogs and news show a similar trend in their slopes,



(a) Overall trend for each media source (b) Daily refresh rate of top-100 keywords

Figure 1: Time evolution of the Egypt revolution

although weblogs exhibit more consistent interest (i.e., persistent volume). The reactions in social media, however, are skewed towards February 11th, the day Mubarak resigned. Furthermore, certain peaks in weblogs and news do not necessarily appear in social media (see January 31st).

Similar to the varying volume of articles over time, the three media sources exhibited rapid change in topics covered. For each media source, we identified the set of 100 keywords that were most frequently mentioned each day. In order to capture only meaningful keywords, we ignored pronouns, articles and conjunctions in the set. We then checked the rate at which the top keywords changed over every two consecutive days of the trace period. Figure 1(b) shows the refresh rate for social media. On average 45.2% of the top keywords are refreshed from one day to another, while certain days exhibit over 60% of change, indicating that the frequently mentioned topics were changing rapidly.

While the volume of articles showed varying trends for the three media sources in Figure 1(a), the three media sources surprisingly showed remarkable similarity in the refresh rate of their top keywords. The average refresh rate for weblogs and news were slightly higher than that of social media, 61.4% and 54.6%, respectively. However, the Pearson's chi-squared test indicated that the tree had no statistical difference in their distributions (p-value$\approx$1), indicating that the refresh rates were identical.

In order to investigate why the three media sources show simultaneous changes, we compared the frequency of the individual top keywords over the month period across the three media sources. Figure 2 shows the resemblance of word frequency on 10 example keywords for social media and news. The x-axis, in log scale, represents the total occurrence of the keyword in social media and news, and the y-axis shows the Pearson's correlation coefficient in the daily frequency of that word in social media and news. When the correlation value is close to 1.0, it means that the usage pattern of that particular word is similar in news and social media. Value of 0.0 indicates no correlation.

We find that general terms like Egypt, bomb, and problem have low correlation, which means their usage patterns in social media are not related to those in news. While the use of certain proper nouns like Bouzid, Mohamed, Ben Ali (president of Tunisia), and Tahrir in social media and news

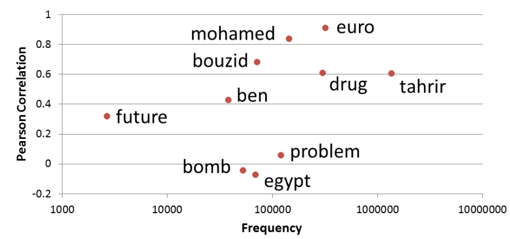


Figure 2: Frequency correlation in news and social media

increased and decreased similarly over time. We discuss the implications of these findings later.

Changes in Sentiments

Having examined the volume and dynamics of reactions, we now investigate the tone in which the online articles are written. The Egyptian revolution had a series of major turning points including hundreds of deaths, small scale protests, march of millions, and the sudden resignation of President Mubarak. Hence, we hypothesized that the sentiments online would change rapidly along these events, for instance, from anger and anxiety to joy. We also hypothesized that news media sources would remain objective as opposed to blog and social media articles.

For analyzing the sentiments in articles, we used Linguistic Inquiry and Word Count (LIWC) (J.W. Pennbaker, R. J. Booth and M. E. Fancis 2007), which is a computational text analysis program. This dictionary consists of almost 4,500 English words, where each word could be part of several sentiment categories. For instance, the word *cried* is part of sadness and negative emotion sentiments.

Among the sentiment categories of LIWC, we considered the following major categories: positive emotion, anxiety, anger, sadness, and the other negative emotion. For every single article in our dataset, we examined the appearance of the sentiment words and classified each article accordingly. We normalize the weight of each article, so that if an article contains one positive emotion word and three sadness words, the article was scored to have positive emotion of 0.25 and sadness of 0.75. For those articles that we could not find any of the relevant sentiment words in LIWC, we do not judge their sentiment and ignore in this section.[1]

The temporal evolution of sentiments for social media is depicted in Figure 3. We normalized the sentiment scales by the total volume of articles, so that the total sentiments add up to 100% each day. Regardless the number of published articles, the overall sentiments remain rather steady over time. Throughout the month, half of the articles (42–61%) had positive sentiments for the three media sources. More surprisingly, the trend is similar for the days with notable events. Even towards the final days of the revolution, the same amounts of angry and anxiety sentiments persist.

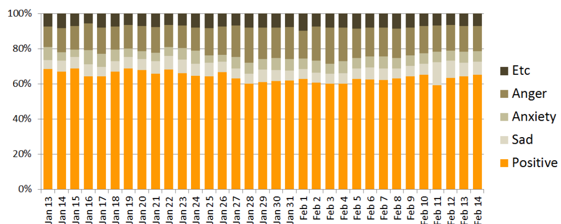


Figure 3: Overall changes in sentiment of social media

In order to verify whether there really does not exist any variations in sentiments, we use a more sophisticated statistical tool for validation, the log-odds ratio. We first divide the trace period into four time segments based on emotionally important events: (T1, Jan13–Jan27) beginning of the revolution, (T2, Jan28–Jan31) Mubarak refuses to resign, (T3, Feb1–Feb10) Mubarak pledges not to run for another term and political reform but staying for current term, and (T4, Feb11–Feb14) resignation of Mubarak, the Friday of departure. For these four time segments, we retrieved the fraction of positive and negative (sadness, anger, anxiety, and the remaining negative emotions) articles. While T1 contains periods before the start of Egyptian revolution, the volume affected by Tunisia is minimal.

In the log-odds ratio analysis, the odds for each time segment is calculated as the number of positive words against that of negative words. For two consecutive time segments, we then calculated the ratio of 'odds at T_i/odds at T_{i+1}', then finally took the log value of the ratio. Hence, a positive log-odds ratio means that the ratio of positive words against that of negative is larger at T_i than T_{i+1}, indicating that the use of negative words increased relatively over time. On the other hand, log-odds ratio of zero means that the numbers of positive and negative words changed independently over time. We can test the null hypothesis (H0: log-odds ratio=0) using z-statistic of the log-odds ratio.

The set of z-statistic, which shows the significance and direction of sentiment changes though the time periods is displayed in Table 2. Above all, the z scores in absolute value are all larger than 1.96, so the H0 is rejected for all the log odds-ratio. Namely, through each time period, all media shows significant emotional changes. However, all media went through different emotional changes from one another. On social media, people became negative after the president refused to resign. However, as the revolution headed towards success, their sentiments changed positively. On the other hand, the tone of news media is quite different. Regardless of the revolution's progress, more and more they became negative even after the success. Bloggers expressed dramatic emotional changes during the month period. Until the success of the revolution, they strictly adhered to be negative position and Mubarak's negotiation made them strongly negative.

Z score	Social	News	Weblog
T1 vs T2	5.7672	2.9837	5.7809
T2 vs T3	-2.3959	3.0634	13.2788
T3 vs T4	-2.6644	2.5640	-2.4436

Table 2: Analysis of the log-odds ratio on sentiment changes

Discussion and Conclusion

In this paper, we examined the volume and sentiments of online articles related to the 2011 Arabic revolution. We found that while people's reactions based on the number of produced articles varied largely according to the size and frequency of the offline events, the overall sentiments of the produced articles remained largely the same. Given the dynamic nature of the revolution, it is surprising that the sentiments had minimal variability over time.

In understanding this discrepancy, we may consider the following reasons. First is due to redundant information. Revolution is event-driven and the news articles must be produced in a timely fashion. Hence breaking news will likely carry fewer vocabularies with strong sentiments. This ensures that many of the articles produced by mainstream media sources are breaking news, which are less prone to media bias. Second, online users who talk about Egypt frequently reuse and discuss media updates, which cause circulation of redundant information. Through manual validation, we have found that many social media articles were indeed referring to news media articles.

It as also interesting to confirm a continued positive sentiments from the online part, given hundreds of deaths and massive injuries among protesters. The following might explain the positive sentiment: The online articles we studied are mostly from outside the Egypt regime, which allow people to emotionally detach themselves from the event. This hypothesis is in contrast to existing work on dominant negative feedback on (internal) political events (Lau 1982).

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[1] Objective articles might belong to this category. It may be also due to LIWC dictionary being an incomplete set, containing no more than 4,500 words. The non-classified articles were 4%, 3%, and 70% for weblogs, news, and social media, respectively.