Revolution, religiosity, and social change during the Arab Spring as viewed by the news and Twitter

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Abstract

1 Introduction

Much has been made of the use of social media during the Arab Spring. At this point, it is almost common knowledge that the emphasis on social media as a *cause* of the revolutions is overblown (Bruns, Highfield, & Burgess, 2013). However, many scholars have pointed to the fact that the use of social media may have aided certain aspects of the revolutions in important ways for different people (Gallé, Renders, & Karstens, 2013; Papacharissi & de Fatima Oliveira, 2012; Starbird & Palen, 2012; **?**) and that data from social media may help to understand how the revolutions grew and spread (Bruns et al., 2013; Lotan et al., 2011). By the same token, recent work has suggested

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that data from news media during the time of the Arab Spring may have itself been indicative of important developments during that time period Joseph, Carley, Filonuk, Morgan, and Pfeffer (2014); Pfeffer and Carley (2012).

In the present work we investigate the extent to which news media and social media data, specifically from Twitter, correlate with publically avaialable indicators of political stability, religiosity and social change during the Arab Spring. Our work provides a significantly more detailed view of the conclusions that can be reached via the analysis of both social media and newspaper data, and the relation of these indicators to what actually occurred on the ground during the Arab Spring and the underlying social and political climates of the region.

We consider the relationship between social media indicators, news media indicators and publically available, expert-driven indicators at three different "levels" of analysis. These three levels are increasingly detailed in their consideration of the variety of geotemporal, social and political covariates across which one can consider the data. As we will show, we find that only particularly nuanced considerations of these covariates leave an informative picture of the underlying variables we treat as ground truth. This finding suggests that high-level analyses of things like the number of tweets from a given country and tweets relevant to a particular word are only useful after careful consideration of the variety of biases inherent in this sort of data and of other important covariates.

2 Related work

Also this special issue: `http://onlinelibrary.wiley.com/doi/10.1111/jcom.2012.62.issue-2/issuetoc`

(Mishra et al., 2014)

3 (Expected) Results

We are considering the following three things for three "levels":

1. How do the following correlate with any of the religiosity or instability indicators?

    (a) religious terms

    (b) revolution/insurgent/violence or adaptation terms

    (c) network graph level metrics

    (d) mentions of terror groups

    (e) mentions of ethnic groups

    (f) size metrics - number of actors, number of posts, number of words, number of ties

    (g) mentions of sports

    (h) mentions of disease

2. Overall- is there a stronger signal in news or twitter?

3. Are news and twitter at all correlated with each other?

3.1 General Covariates- the "strong obvious signal"

We study these things in general (not worrying about over time)

I (KC) expect most of this will say - NO CORRELATION

3.2 Country differences by time - the "somewhat hidden signal"

We study these things using the images for country only data where the boxes are normalized by number of articles.

I (KC) expect here that most of this will show - a) twitter and news have similar signals, and most things are across most countries

3.3 Temporal differences - the "subtle" signal

Here we pick the indicators - general instability (low high), level of terrorism, and for each indicator we take the set of countries that are in some level - e.g. low on general instability, then for each value on the indicator we take the variable (e.g. number of articles using a term related to violence) that has been normalized and find the average across the countries for that month. Then we plot the over time images (so there is one line per level of the variable) and talk about the trends - and put a verticle bar where the revolutions began

Here we are therefore analyzing change by time by level of indicator

I (KC) expect here that most of this will show - a) twitter and news have similar signals, and the average for some indicators will be very different

4 Our To-dos

1. Change/iterate this document to something we actually think we can do
2. Figure out what is up with that jump in the Twitter data
3. Motivation for the article
4. Related Work
5. Method for correlation analysis for each of the three levels
6. Run Netmapper, etc

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