
Munmun De Choudhury
munmund@gatech.edu
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The Revolutions Were Tweeted: Information Flows during the 2011 Tunisian and Egyptian Revolutions
Summary

• Analysis of Twitter information flows during the 2011 Tunisian and Egyptian uprisings
  • Tunisian demonstrations from January 12–19, 2011
  • Egyptian demonstrations from January 24–29, 2011
• Identify “key actor types,” e.g., MSM organizations, individual journalists, influential regional and global actors, and other participants who actively posted to Twitter on these two revolutions
• Study contagion of information by each actor type
• Examine relationship between traditional news media and social media in the two revolutions
We assumed that an organization’s Twitter account plays a different role than an individual account, often serving as the official voice of a group, company, or organization. We define organization accounts as the following: MSM, non-media org, Web news org, and bots (which, in many cases, are controlled by automated programs representing no individual interests). All other actor types are considered individual accounts. In comparing organization accounts to individual accounts in our datasets (see Figure 2), we found that roughly 70% of the actors in each dataset are individuals.

Table 1. Twitter User Behavior: Number of Followers and Level of Activity per Type.

To understand further how different actor types behaved, we looked at their tweet to retweet ratio (see Tables 2 and 3). This is an indication of how often different actors’ tweets are retweeted by their followers. We take this to be a measure of how well actors engage their audiences. At the low end of this metric are “other” users, who are able to elicit retweets approximately 30% of the time, compared to 88% for MSM accounts. Additionally, Twitter accounts of organizations (MSM, Web news org, and non-media org) have substantially higher retweet rates (i.e., flow sizes) than do individual accounts.
To understand the impact of actor types on the information flows, we look at two important attributes: source and size. An information flow's source refers to the user who first posted the content. If we look at the distribution of information flows across source types, the differences in dynamics between the Tunisia and Egypt datasets are prominent (see Figure 3).

Figure 3. Distribution of Information flows by Source Type for Tunisia and Egypt.

Note: Bars represent the number of threads (as a % of total threads) in each dataset that were seeded by an actor of the given type.

We define an information flow's size as the total number of participatory tweets, namely, tweets that are close copies or retweets of the information flow source (see Figure 4).

Figure 4. Information Flow Sizes for Tunisia and Egypt.

Note: Bars represent the median number of tweets in threads that were originated by an actor of the given type.

When considering the Tunisia dataset, Figures 3 and 4 suggest that, while more journalists than bloggers served as sources for information flows in Tunisia, those flows started by bloggers were substantially larger in size. This suggests that bloggers played an important role in surfacing and disseminating news from Tunisia, as they had a substantially higher likelihood to engage their audience to participate, compared with any other actor type. Additionally, the Tunisia dataset showed less engagement from MSM, journalists, or activists, compared to Egypt.

When looking at the Egypt data, there are very clear distinctions: MSM, journalists, and activists were much more engaged in information flows, serving as the main sources of flows much more than in the Tunisia dataset. Additionally, they drew larger participation from their audience, as measured through flow size. Meanwhile, although non-media orgs account for being the source of 5% of all flows (26 out of 500), they had the largest average size, most notably a flow started by the official WikiLeaks account, which read: “WikiLeaks did more for Arab democracy than decades of backstage U.S. diplomacy.”

In order to gain another dimension of understanding of the flow of information on Twitter and the relationship between actor types in our data, we examined what we call sub-flows. Each information flow is made up of multiple sub-flows. A sub-flow between user A and B (A → B) exists if user B retweeted text that user A had previously posted.

By collapsing every sub-flow within all chosen information flows, we see recurring patterns of retweet behavior among actor types. In the ten most common sub-flow paths between coded actors across both datasets, journalists, activists, bloggers, and “other” actor types are the most prominent (see Table 4). This reinforces the claim that, while organizational actors have larger followings on average, individual actors are much more likely to play an active role in information dissemination.

Table 4. Ten most common sub-flows for each Dataset (Tunisia left, Egypt right).

<table>
<thead>
<tr>
<th>Sub-flows (Tunisia)</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activist → Activist</td>
<td>49</td>
</tr>
<tr>
<td>Journalist → Other</td>
<td>48</td>
</tr>
<tr>
<td>Journalist → Blogger</td>
<td>41</td>
</tr>
<tr>
<td>Activist → Blogger</td>
<td>38</td>
</tr>
<tr>
<td>Other → Blogger</td>
<td>37</td>
</tr>
<tr>
<td>Journalist → Activist</td>
<td>34</td>
</tr>
<tr>
<td>Blogger → Blogger</td>
<td>31</td>
</tr>
<tr>
<td>Blogger → Other</td>
<td>31</td>
</tr>
<tr>
<td>Journalist → Journalist</td>
<td>30</td>
</tr>
<tr>
<td>Activist → Journalist</td>
<td>29</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sub-flows (Egypt)</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Journalist → Activist</td>
<td>111</td>
</tr>
<tr>
<td>Journalist → Other</td>
<td>109</td>
</tr>
<tr>
<td>Journalist → Blogger</td>
<td>102</td>
</tr>
<tr>
<td>Activist → Other</td>
<td>102</td>
</tr>
<tr>
<td>Activist → Activist</td>
<td>100</td>
</tr>
<tr>
<td>Other → Other</td>
<td>97</td>
</tr>
<tr>
<td>Activist → Blogger</td>
<td>85</td>
</tr>
<tr>
<td>Blogger → Blogger</td>
<td>78</td>
</tr>
<tr>
<td>Journalist → Journalist</td>
<td>70</td>
</tr>
<tr>
<td>Blogger → Activist</td>
<td>69</td>
</tr>
</tbody>
</table>
The dynamics of protest recruitment through an online network
Summary

- Basic premise: not much evidence on how exactly SNSs encourage recruitment during protests and movements
  - Limited research on protest growth
  - Research has shown that information cascades in online networks occur only rarely, with the implication that even online it is difficult to reach and mobilize a high number of people

- Analysis of the growth of protests in Spain in May 2011

- Findings:
  - Most early participants – i.e. users who sent a message prior to the first mass mobilizations and to the news media coverage of the events – needed, on average, less local pressure to join, which is consistent with their role as leaders of the movement
  - While being central in the network is crucial to be influential in the diffusion process, there is no topological position that characterizes the early participants that trigger recruitment. This suggests that whatever exogenous factors motivate early participants to start sending messages, the consequence is that they create random seeding in the online network
Summary

• Findings
  • Horizontal organizations are successful at mobilizing people through SNSs because their decentralized structure, based on coalitions of smaller organizations, plant activation seeds randomly at the start of the recruitment process, which maximizes the chances of reaching a percolating core; users at this network core, in turn, contribute to the growth of the movement by generating cascades of messages that trigger new activations, and so forth.

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![Graph showing the proportion of recruited users over time. The vertical axis is normalized by the total number of users (87,569), and the horizontal axis tracks the number of activated users accumulated by hours. At the end of our time window the proportion of activated users is 98.03%, which means that the vast majority of users sent at least one protest message during this month. Vertical labels flag some of the events that took place during the period.](image)
Your reflections...
Class Exercise

- Go to search.twitter.com
- Each of you pick one of the hashtags:
  - #FreddieGray
  - #BlackLivesMatter
  - #NoJusticeNoPeace
  - #BaltimoreUprising

- Look at the first six returned tweets.
- What kind of an actor is the author of the tweet?
- How many followers and followees do they have?
- How many tweets?
- Is the tweet retweeted by others?
- Post your results on Piazza (under “discussion”)

Traditional news organizations are often not the main actors in the revolutions that were examined. Why is this the case?
Lotan et al quote Shirky “Given that Twitter and other social media tools can be leveraged to spread information, Shirky (2009) has argued that social media may have the potential to provoke and sustain political uprisings by amplifying particular news and information”

How much of an important role did Twitter play in the Tunisian and Egyptian revolutions?
Relatedly, it is important to tease out whether Twitter helped bring interested parties together, or allowed interest to grow in a community. What are the methodological challenges in trying to investigate this question?
The outstanding question remains, what is the role of the average Twitter user? How can such an ecosystem that allows users with more authority to drive conversations, what kind of provisions need to be made to have the voice of the average user heard?
Lotan et al used the shingling method for string comparison to identify information flow patterns. What other alternative mechanisms could be adopted to detect flow of information?
Lotan et al also identified many diverse actor categories ranging from mainstream/non mainstream media, bloggers, activists, celebrities, political actors, researchers, bots, digerati etc. Are these roles context dependent? If so how and what implications does it have in studies of Twitter?
Does the structural position of a user matter in what role emerges out of their activity? Discuss in the light of strong and weak ties.
Other than hand-coding, what could be alternative ways of identifying actor roles on Twitter?
Lotan et al. also noted that different actors engaged differently with their audiences. MSMs and journalists commanded high response rates. Do you expect this to be consistent across events?