Alternative Narratives of Crisis Events: Communities and Social Botnets Engaged on Social Media

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Abstract
This paper presents an early stage exploratory analysis of communities engaging in alternative narratives about crisis events on social media. Over 11,000 user accounts on Twitter engaged in conversations questioning the mainstream narrative of the Paris Attacks and Umpqua Community College Shootings in Autumn 2015. We analyze the social network of communication, examining the composition of clusters of accounts with shared audiences. We describe some of the common traits within communities and note the prevalence of automated accounts. Our results shed light on the nature of the communities espousing alternative narratives and factors in the spread of the content.

Author Keywords
Alternative Narratives; Rumoring; Twitter; Communities; Social Botnets

ACM Classification Keywords
[Human-centered computing]: Empirical studies in collaborative and social computing

Introduction
Alternative narratives of crisis events, such as the "truther" notion of the September 11 attacks being an "insight job", are a common feature of man-made disaster events. In an ongoing research project focused on examining online

	Tweets	
	Pro-AN	Con-AN
Paris	24,272	965
UCC	6,412	539
Total	30,785	1,504

Table 1: Number of tweets promoting and countering the alternative narrative (AN).

	Users	
	Pro-AN	Con-AN
Paris	7,953	899
UCC	2,779	470
In Both	916	10
Total	9,816	1,359

Table 2: Number of users promoting and countering the alternative narrative (AN) by event

rumors during disaster events, we have repeatedly identified rumors that question the predominant narrative of the event. In the Autumn 2015 two very real, very tragic events happened: the Paris Attacks and Umpqua Community College Shooting. Following both events, some users of Twitter turned to the platform to debate the mainstream narratives of the attacks. Our research seeks to better understand the dynamics of these rumors, specifically asking here *Who are the people discussing these alternative narratives and how do these ideas spread across different communities of users on Twitter?*

Alternative Narratives

Though the term "conspiracy theory" is often used to talk about the phenomena we investigate here, we use the term "alternative narrative", both to be more inclusive of similar rumor that may not imply large-scale conspiracies and to avoid a negative predefined value judgment to people and their motivation. An alternative narrative of a crisis event is therefore an explanation of events that rejects the predominant narrative – for example, the narrative supported by mainstream media and/or government sources. Describing a related phenomenon, Best describes urban legends as "products of social tension or strain. They express fears that the complexities of modern society threaten the traditional social order" [1]. Provided a list of accepted and contested facts (both of which are readily available online), people are inclined to even include the contested facts in their reconstruction of events [4]. Following the Boston Marathon Bombing of 2013, claims of the event being a "false flag" appeared online within minutes of the blasts and kept spreading for months after the event [5].

Events and Rumors

On October 1, 2015, a student of Umpqua Community College (UCC) brought a gun to his college and started shooting, killing 10 people and injuring 9 others. On November 13, 2015, a group of French citizens and foreign nationals perpetrated a large scale attack on the city of Paris and its neighborhoods. At the conclusion, 130 people had died and 368 people were injured. In the aftermath of each event, an alternative narrative began to spread online that the event was not perpetrated by the individual(s) that were currently identified as the suspects, but was instead staged by the government.

After the UCC Shooting, the most prominent alternative narrative centered around the perception that the government was staging shootings to encourage gun legislation. One of the most widespread posts was an image meme of four pictures of people from different crisis events who look similar, asserting that they are the same person, a "crisis actor" hired by the government to stage the event. The most visible alternative narrative regarding the Paris Attacks was that the French government was staging false evidence to blame Syrian refugees. A frequently tweeted URL in the Paris Attack data links to an article on the website therealstrategy.com that refers to the passport found near the epicenter of a suicide bombing attack and alleges that it was planted there to make the public think it was a ISIL militant, when "in fact", government agents were the real perpetrators of the attacks.

Methodology

In this study, we collected event-related tweets from Twitter, using the Streaming API, and filtered the tweets we collected about each event to focus on discussions about alternative narratives, using common terms like "false flag" and "crisis actor". We combined the tweets from both events into a single dataset because these rumors were very similar in content and many of the accounts participating shared alternative narrative tweets related to both events. With

$$\frac{|\text{Followers}(A) \cap \text{Followers}(B)|}{|\text{Followers}(A) \cup \text{Followers}(B)|}$$

Equation 1: Pairwise Shared Audience Computation

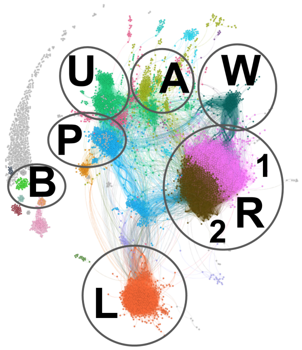

Figure 1: Graph of Twitter Users engaged in Alternative Narratives connected by Pairwise Shared Audience. Nodes are colored by Louvain Clustering groups, general clusters are labeled, explained in the text

Cluster	Users	Tweets Pro-AN
B	188	100.0%
A	297	99.1%
P	357	98.6%
W	128	98.3%
R_1	425	98.3%
U	487	97.7%
R_2	365	97.3%
L	402	64.3%

Table 3: Summaries of different clusters

a team of undergraduate and graduate researchers, we manually coded each tweet as to whether it was actually related to the alternative narrative rumor, yielding 30,684 total tweets in the Alternative Narrative (AN) discussion –79% of the tweets were about Paris Attacks, the rest from the UCC discussion.

For each account that sent an alternative narrative rumor, we gathered their Twitter following relationships. We measured connections between users by examining their Shared Audience – a pairwise metric, the number of users following both accounts A and B divided by the number of users following either A or B. We thresholded the metric to only count edges with at least 5% shared followers.

Figure 1 shows the users that were connected with other users. We clustered the users using Louvain Clustering [2], visualized the graph using a graph layout, coloring the groups based on the Louvain clusters. The community graph contains one large component of 14 Louvain clusters consisting of 26.0% of the Twitter accounts in the alternative narratives discussion, 8.4% of users were in smaller clusters, 6.9% were protected so we could not gather user follower relations and 58.7% of users did not share a significant audience with any other user in this dataset.

Through mixed-method analysis, we built descriptive labels of users and groups of users for each cluster and subcluster shown in the graph layout using n-gram calculations and by manually visiting at least 15% of the users in each group (at least 15 users for the smaller groups). After noticing many suspicious accounts, we also iterated over these users, labeling them as bot, human or unclear.

Observations

Each cluster identified has a strong geographic and/or ideological characteristic. The largest communities represented mainstream ideologies. The **R** area contains two clusters of right-leaning individuals in the U.S., broken in two groups by the Louvain clustering: one half of which strongly supported Donald Trump's 2016 campaign for president ($\mathbf{R}_1$) and the other group which posted less about politics and did not align to a specific candidate ($\mathbf{R}_2$). While not as large as the right, the left-leaning community from the U.S. was quite sizable (**L**), but also contained the most cross-talk, it had the smaller majority of users affirming the alternative narrative (See Table 3). The cluster **U** consists of people from the United Kingdom, generally members of the UK Liberal Party. Interest based clusters include people aligned with different contemporary movements: supporting Palestine (**P**), anonymous (**A**), and white nationalism (**W**). The intermediate component connecting the Right, Left, and Pro-Palestinian communities did not have a robust identity shared between the people in the cluster.

Many of the clusters detached from the central component were small, special-interest communities, and investigating them we noticed that three of these groups were made entirely of bot accounts, labeled in region **B**. The botnet for therealstrategy.com (TRS) consisted of about 150 accounts, all repeatedly tweeting the same tweet with minor tweaks in order to evade most spam filters. In all, one quarter of the alternative narrative tweets were generated by this botnet. This led us to manually investigate other accounts with suspicious temporal signatures, leading us to estimate over 10% of accounts for this conversation were bots, and one third of these tweets were generated by them. The only group of bot accounts in the central component identified as part of the Trutherbot community within the Anonymous affiliated cluster (**A**). The Trutherbots consists of many accounts, some purely human, some purely bot, some with identifiable mixed streams of automated and human tweets.

Follow Relation	Mentions Count	Percent
$A \Leftrightarrow B$	3,094	16.34%
$A \Leftarrow B$	3,768	19.90%
$A \Rightarrow B$	341	1.80%
$A \not\Leftrightarrow B$	11,736	61.97%

Table 4: Number of mentions between users (A mentioning B, information going from B to A) given their following relationship. $A \Leftarrow B$ means A follows B, information should go from B to A.

Considering the way that users interact with each other, we count the total retweets, replies, and @mentions between users graphed. Unexpectedly, 62% of all mentions were between users of which neither followed the other, as shown in Table 4. Of the top 20 mentioned users across all tweets in both rumors, 10 were accounts of alternative-media websites and 6 were completely automated.

Discussion and Conclusion

These observations show a complex and varied network of users and kinds of actors spreading alternative narratives. Most saliently, rather than the singular, centralized group of conspirators that might be expected, we found a wide network of groups of individuals that were not defined by a single ideology, rather spanning across both many different mainstream ideologies and single-issue politics. The left-leaning cluster **L** shows relevance of alternative narratives regardless of side of the aisle. This is unlike the 9/11 rumors which were largely circulated by the political-left [6]. Rather, the size of these clusters and relative amount of alternative narrative discussion may be directly related to which party is in control of the government, further supported by the most prominent European cluster being of people in the UK Liberal Party (**U**), a former majority party in the UK that has spent the last century as a minority.

This work sheds light on the way alternative narratives propagate on Twitter. One established idea to stop the spread of misinformation involves using the a-priori social graph and inoculating nodes, preventing the spread of bad information [3]. In this network though, mentions transcended a-priori following connections and communities derived from them. These mentions were driven by alternative-media blogs and while some of the automated accounts turned out to have a very small audience, some affected much more users outside of their direct Twitter-audience. Thereby, to construct a conversation graph we would need to look across many forms of online media and user patterns to generate a proper information network – using Twitter's graph alone will not be sufficient.

This analysis shows promising work elucidating the varied types of users engaged in discussions contrary to the mainstream narratives. It shows a larger variance in users, and the role of outside actors in transmitting information about these narratives through Twitter. It challenges assumptions about containing rumors and presents novel measures like Shared Audience to evaluate groups of users.

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