Vaccination (Anti-) Campaigns in Social Media

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Recent years have witnessed explosive growth of online social media sites such as Facebook and Twitter, discussion forums and message boards, chat-rooms, and inter-linked blogs. While social networks greatly facilitate information exchange and dissemination, they can also be vulnerable to exploitation and manipulation. Most online activity is organic information dissemination, i.e., people innocently or unwittingly sharing information they find interesting with their followers, friends and social contacts. However, a significant portion of online activity is composed of deliberate attempts to manipulate how many people will see the information and how it will spread. Such campaigns seek to manipulate public opinion, disseminate rumors and misinformation. Insidious special interest campaigns try to mimic the appearance of genuine grassroots campaigns with broad support in a process sometimes called "astroturfing" (Ratkiewicz et al. 2011).

It is well known that social networks of interconnected individuals also have mediating effects on health (Smith and Christakis 2008). Positive and accurate information obtained by social means can help individuals make better health care decisions. However, unhealthy practices and incorrect beliefs can also spread through social networks, and these are reinforced by shortcomings in health literacy. These social processes include, for example, propagation of influential memes such as medical myths (Vreeman and Carroll 2007; Goldberg 2010), and transmission of powerful norms affecting such choices as nutrition and smoking (Christakis and Fowler 2007; 2008).

Exposure to such harmful beliefs and practices can have stark direct effects: delays in work-up for cancer symptoms (Rauscher et al. 2010), overconfidence in care (Van den Bulck and Custers 2010), failure to comply with medications for chronic illnesses (Mann et al. 2009), and even suicide among the vulnerable (Luxton, June, and Fairall 2012). Repercussions may also extend to close others: getting friends addicted to drugs and alcohol (Valente 2003) or denying the connection between HIV and AIDS (Kalichman, Eaton, and Cherry 2010).

One of the most important harmful practices that can spread through social networks is failing to vaccinate family members due to incorrect beliefs about vaccine safety (Diekema 2012; Hinman et al. 2011). The successful spread of such beliefs goes beyond merely small fringe groups. Community vaccination rates are below critical levels for measles and whooping cough in several states (Centers for Disease Control and Prevention 2013), while unfounded concerns are particularly widespread among parents in California (Mascarelli 2011).

Analogous to the science of real viral infections, population health would benefit if the mechanics of social network processes were understood better. Robust knowledge about social networks and the transmission of health-related norms would improve the design and implementation of future interventions to inoculate and treat such virtual contagion. Yet very little is known about why and what types of information flow as memes in social networks, how such flows happen, how contagious they are, who is susceptible, and what ensues.

In this preliminary study we explored two approaches to understanding anti-vaccination related social media activity. Vaccine skepticism, we conjectured, is transmitted both through genuine interest and non-correlated views as well as deliberately through active dissemination of anti-vaccine propaganda. First, we investigated posts in Twitter and the corresponding user network. Second, we used a commercial off-the-shelf media access platform, Sysomos Marketwire, to investigate blogs, forum comments and other social media disclosures related to a new vaccine for HPV virus.

Case Studies

AVN study Our preliminary analysis of large-scale Twitter social networks dealt with vaccine safety. One of the primary voices in this arena is the Twitter account of the Australian Vaccination Network (AVN) @nocompulsoryvac, which is a well-known advocate of non-compulsory vaccination. The primary pro-vaccination voice that opposes AVN is another Australian-based user/account, @stopavn. In our preliminary data collection process, we used snowball sampling to grow a graph of users that either responded to or retweeted messages from these accounts. This resulted in a network of 1,064 Twitter users (nodes) linked via 1,270 *respond* or *retweet* relationships. Note that this network is based on activity rather than the friendship and follower links that are typically studied (Romero et al. 2011). In Figure 1(a) we show only a sub-network of nodes that re-

sponded or re-tweeted to the seed accounts more than eight times. Only a small number of users account for most of the activity, while the bulk of the users have very low levels of activity.

(a)

(b)

Figure 1: (a) Respond-retweet and (b) transfer entropy networks for the AVN example.

Next, we constructed a directed graph between the users using an information-theoretic notion of transfer entropy, or information transfer (Ver Steeg and Galstyan 2012). Essentially, we consider each ordered pair of nodes in the network and consider their temporal pattern of activity. Information transfer, represented as a directed link from user A to user B, measures a predictable influence of user A's activity on user B. In Figure 1(b) we show a graph induced by information transfer between the nodes. In this graph, we can see a bidirectional link between the 2 key players (bolded connecting arrow). However, note that in the retweet-response graph of Figure 1(a), @nocompulsoryvac never directly responds or retweets to the others posts, while the reverse responses do occur. Information transfer reveals that @nocompulsoryvac is strongly influenced by @stopavn's activity, even if no explicit responses occur.

Gardasil In our second exploratory analysis of vaccine skepticism, we considered public disclosures of opinions about HPV vaccination with Merck's Gardasil vaccine. We purchased access to Marketwire/Sysomos, a software-as-a-service media access platform. Using this commercial-off-the-shelf tool we found, over the one year period Feb. 26, 2012 through Feb. 25, 2013, a total of 54,207 mentions of Gardasil through searches in hundreds of millions of data sources in blogs (e.g. Blogger), wikis (e.g. Wetpaint), citizen journalism portals (e.g. Digg), sharing tools for consumer reviews (e.g. Crowdstorm) and feedback (Feedback 2.0, Quora), discussion forum tools (e.g. Phorum), social neworks (e.g. Facebook [limited to only 6 weeks recent status updates] and Orkut) and related tools (e.g. Ning, GroupOn, Livingsocial), microbloggers (e.g. Twitter) and social aggregation tools (e.g. FriendFeed). Using the proprietary natural language processing algorithms of the Sysomos tool, we also analyzed sentiment of the expressed opinions and comments.

The harvested mentions were broadly distributed across different media platforms, with Twitter being the most common medium (62%). The most common terms adjacent to Gardasil in social media were medical or public health in nature, reflecting virus, vaccination, cervix, cancer, HPV, papillomavirus, and agencies such as the Center for Disease Control (CDC). We found no highlighted specific mentions of anal or oral cancers linked to HPV virus infection, nor of vaccination of boys. This was unexpected, given the known and approved indications of Gardasil for young male vaccination.

(a)

Figure 2: Sampled mentions of Gardasil in blogs.

Despite only representing 10% of all mentions of Gardasil, blog activity was rich. Conversations in blogs related to Gardasil tend overwhelmingly to focus on alleged harms and risks associated with Gardasil vaccination. Apart from helping to isolate the level of sentiment and provide examples of the most common beliefs, this high-prevalence content also indicates sources of such beliefs. In the example conversation text extracted (Figure 2(a)), it is clear that "sane vax" and "truth about Gardasil" are two internet sources for such inaccurate and harmful beliefs.

We analyzed the most common terms generated by the vaccine skeptic site truthaboutGardasil.org and generated a site-specific "buzz graph" (Figure 3(a)). These graphs are constructed using a proprietary tool on the Sysomos platform that attempt to measure important word relationships in text.

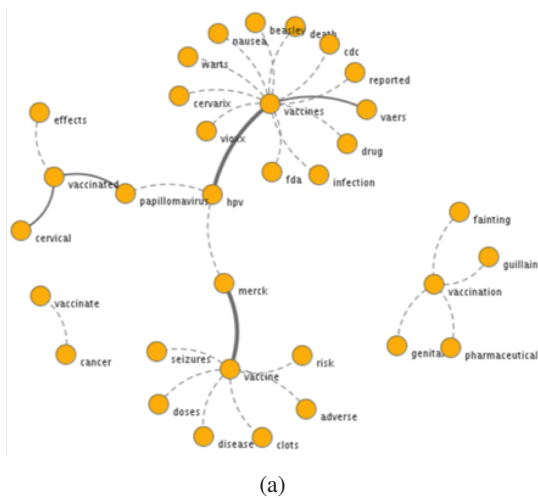Intriguing features of the content here were the preponder-

Figure 3: Buzz graph around truthaboutGardasil.org.

ance of negative terms (e.g. clots, adverse, faint, risk, nausea, death, seizures) but also the inclusion of terms that represent respected entities (e.g. CDC, Merck, the government's VAERS reporting system) in associations that call into question the motivations and trustworthiness of these entities. We found that truthaboutGardasil.org is one of the most prolific US-based producers about vaccine skepticism related specifically to Gardasil and HPV vaccination. This website is linked to 49 others, and produces approximately 2 posts each month relating to alleged harms and risks of Gardasil (Figure 4(a)). Related US-based websites that seem to mirror, or cross-promote, such beliefs are therefusers.com and sanevax.org (also listed in the key conversations extracted above).
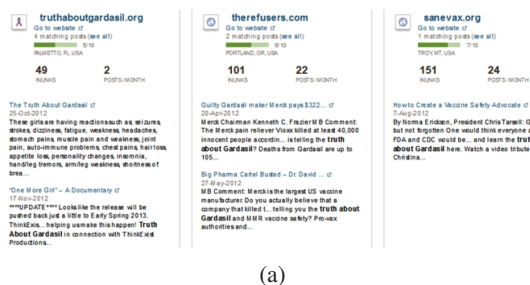

Figure 4: Cross-blog mirroring of vaccine skepticism by leading blogs.

Of note, much of the content of blog posts originating from these websites appears to use similar phrases as truthaboutGardasil.org's blog posts. This phenomenon may be a case of astroturfing, or false grassroots approaches that seek to build buzz and momentum by fabricating related websites that serve merely to amplify these inaccurate and harmful messages (Ratkiewicz et al. 2011).

While these websites are clearly US-domestic based organizations, we found that many websites hosting blogs re-

lating to vaccine skepticism were linked internationally as well as locally. We surfaced ten other sites (Figure 5(a)) related to truthaboutGardasil.org that produced closely related content, including from three European countries. Whether the central website of interest deliberately uses international sites to add credibility to its offering, or whether this is done to prevent easy checking of sources is not clear at this stage.
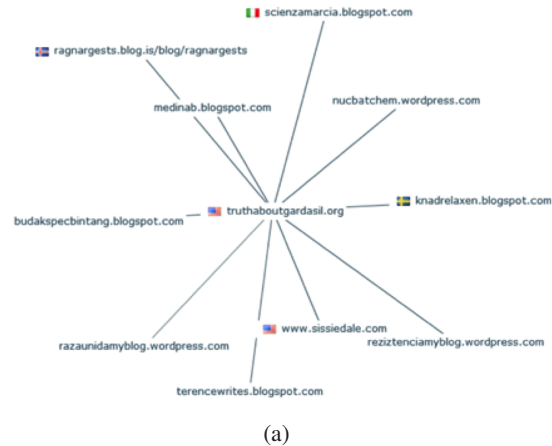

Figure 5: Cross-country mirroring of vaccine skepticism by leading blogs.

Discussion

In conclusion, our brief and superficial use of social media monitoring tools suggest that research activity can profit from extending focus beyond just Twitter. Blogs can be used to identify beliefs and opinions, and their origination in websites, in forum postings, in other social media postings and most importantly among networks of individuals, networks of sites, and networks of disclosures.

Use of such tools can complement Twitter natural language processing and information entropy approaches by extending the range of platforms spanned. The evidence base for how and why, and what sort of information flows as memes in social networks, is currently under-developed. We are currently proposing to measure and infer cross-platform individual beliefs and collective norms on harmful health-related propositions, construct and validate reliable predictive models of harmful belief flows on identified networks, and define complex links between beliefs and norms, and downstream behavior.

Consumers need to know about, be interested in, have access to and understand accurate, helpful, objective and complete information that guides their health-related behavior and actions (Kolstad and Chernew 2009). On a system-wide level, consumers acting on such information would help achieve the triple aim of higher care quality, enhanced service experience and lower costs (Berwick, Nolan, and Whittington 2008). For individuals, autonomy and empowerment would be increased. Between these two levels, social networks would allow informed and empowered consumers to confidently share key health information with their friends, relatives, and contact network.

Even among highly educated individuals such as clinicians in the health care industry, information is not homogenously distributed (Phelps 1992; Berwick 2003). Individuals with common conditions such as the chronic illnesses of obesity, diabetes and asthma, as well as individuals and families with less common conditions such as behavioral illnesses or autism spectrum disorders are faced with inaccurate information on causes and available treatments. Some of this information is well-intentioned, but subjective and poorly validated. Other information is ill-intentioned and non-objective, such as that spread by vaccine skeptics with an anti-vaccine agenda. Apart from specific information on conditions, causes and treatments, other health-related information may be more generically wrong. For example, erroneous and distorted beliefs may be spread regarding the safety, efficacy and effectiveness of generic and biosimilar pharmaceuticals, or the healthcare system in general.

Social networks are vulnerable to exploitation and manipulation. While most social media users are benevolent in nature, they coexist with more insidious organizations. Such campaigns seek to manipulate public opinion, disseminate rumors and misinformation (Conover et al. 2011). For example, astroturf campaigns try to mimic large, well-grounded grassroots efforts.

We believe that understanding better how harmful health-related information spreads in communities of socially connected individuals will positively impact population health by providing much-needed information for developing optimal clinical, social and public health strategies for reducing, repudiating and controlling such flows in social networks.

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