How TV Advertising and Social Network Help Tobacco Control Campaigns Influence More

Qianyi Zhan  
National Laboratory for Novel Software Technology, Nanjing University, Nanjing, China  
zhanqianyi@gmail.com

Sherry Emery  
University of Illinois at Chicago, Chicago, IL, USA  
slemery@uic.edu

Philip S. Yu  
University of Illinois at Chicago, Chicago, IL, USA  
Institute for Data Science, Tsinghua University, China  
psyu@uic.edu

Abstract

The influence of new social media on health behaviors has been well established. In this paper, we focus on social network activities related to tobacco control advertisement campaigns. We aim to find out how advertising is related to the social media conversation, and to what extent the social conversation stimulates further engagement with the campaign. Three methods of measurement are used to solve this problem. Among them a novel inference model: SII model is proposed, which can predict whether user will attend the conversation. The results of all methods shows TV exposures information launches the social conversation and the diffusion process inside the social network further stimulates the engagement with the campaign.

The media landscape has been changing rapidly and dramatically over the past 10 years. Whether it takes the form of social marketing or traditional advertising, the influence of media on health behaviors has been well established. For example, anti-tobacco mass media campaigns have been found to be associated with reductions in tobacco use, while drug prevention campaigns were related to decreased risk perceptions and increased likelihood of substance use (Daubresse et al., 2015; Emery et al., 2005, 2012). Further, our research has shown that health-related advertising generally works: televised ads for products ranging from electronic cigarettes, to prescription drugs for cessation, asthma and arthritis are associated with greater sales volume and use of these products (Kim, 2015; Pagani and Mirabello, 2011). In the new media environment, social media platforms play two roles: they can provide initial exposure to the message via a tweet or Facebook message that mentions the campaign and may provide a link to the online version of an ad; in this role, social media messages can amplify the effect of exposure to advertising, to gain a larger audience. Second, social media can provide a forum for commentary, interpretation, and/or expression of behavioral intentions related to the message of the ad; in this role, social media users can provide campaigns with important feedback on perceived effectiveness of an ad.

Little is known however, about how advertising is related to the social media conversation, and to what extent the social conversation stimulates further engagement with the campaign. In this paper, we examine the propagation, or diffusion, of information about two different health campaigns, focusing on understanding how much messaging is generated from traditional (TV advertising) versus social conversation (Tweets) about each campaign. We propose three methods to measure the influence of TV advertising and all results illustrate TV advertising makes a great impact on activities in social networks.

This paper is organized as follows: a description of measurement and analytic methods; an outline of analytic framework; presentation of two case studies, using television ratings and twitter data from two different anti-smoking campaigns; summary of results.

Methods of Measurement

In this section, to identity what launchs social conversation about a specific topic, we introduce three methods of measurement: statistics measurement, source measurement and the inference model.

Statistics measurement

In statistics, Pearson Correlation Coefficient (PPMC) is a measure of the linear correlation between two variables and Spearman rank correlation coefficient assesses how well the relationship between two variables can be described using a monotonic function. We conduct both Pearson and Spearman correlation tests to measure the relationship between the number of related tweets and TV rating, an index indicating how many people have watched this advertising.

Source measurement

This measure can tell us how quickly and from where users are influenced. We define a time window which represents a time duration before user being activated. For example user $u$ posted a tweet $t$ at 3pm and if the length of time window is 2 hours, time window of $b$ is 1pm to 3pm. TV set $S^t_u$ collects TV advertising in this time window. Similarly, tweets set $S^n_u$ gathers tweets from $u$’s friend. Exposure set $S_u = S^t_u \cup S^n_u$ contains all exposures related to the campaign. We change the length of time window and examine whether users can get information from TV, tweets and either way during this time window, i.e., whether $S^t_u$, $S^n_u$ and $S_u$ is not empty.
Inference model

We also develop a novel model: Social Influence Inference (SII) Model, which is proposed to predict users who will get infected to join the social conversation related to a specific ad. We estimate TV advertising’s social influence by incorporating the public media effect created by TV broadcasting and social media effect from user to user through social links.

The existing information diffusion models which take external events into consideration are proposed for news and popular social trends (Lin et al., 2013; Myers, Zhu, and Leskovec, 2012). However these models cannot be applied directly on TV advertising, because the aim of advertising is different and user feelings evoked by advertising is more complicated. Since the consumer attitude has been extensively researched in psychology and marketing area, our SII model is designed based on classical model mentioned in both social psychology and marketing theories. (Fiske and Gilbert, 2010) The theory defines that user attitude has three stages: Cognitive, Affective and Conative. We modify these stages to fit our case and explain them in detail as following.

- **Cognitive**: At first audiences become product aware. In the SII model, this stage represents that users gather knowledge from TV and tweet.
- **Affective**: This stage ensures target consumers liking the product or audiences having strong feelings on the advertising. In the SII model, affective means that users are deeply touched by TV and SN appearances.
- **Conative**: On this stage, audiences have tendency to take action toward the campaign. In the viral marketing, the action is defined as posting tweets related to this campaign.

The advertising information spread through TV exposures and tweet exposures and each exposure influence audience according to the above three stages. At last impressive exposures are aggregated to activate users taking social actions.

We learn the parameters from training data and predict whether a user will be influenced. Mean squared error (MSE) which reports the average of the squares deviation of predictions to the ground truth data, is used to measure the correctness of the prediction.

Case Study

In this section, we describe two real-world TV advertising campaigns of tobacco control in detail. Health Media Collaboratory of UIC\(^1\) is funded to conduct evaluations of these campaigns and the evaluations are designed to draw upon data from Twitter network to characterize the social conversation about the campaign.

The first campaign is “Tips from Former Smokers 2013”, hereinafter to be referred as “CDC Tips”, launched by Centers for Disease Control and Prevention (CDC). The other campaign is “Truth” launched by American Legacy Foundation (Legacy), which is a Washington, D.C.-based national public health organization devoted to tobacco-use prevention and education. We call this campaign “Legacy Truth” for short in the following parts.

\(^1\)http://www.healthmediacollaboratory.org/

### CDC Tips

“CDC Tips” was the federal government’s first nationwide effort to use paid advertising to prevent smoking and encourage quitting. The Tips 2013 campaign began at March 4 and ended at June 23 and contained 10 stories from the former smokers. Besides the main placement strategy: TV advertising, the CDC also placed ads in print publications, outdoor venues and radio.

Overall, the “CDC Tips” campaign generated a total of 146,759 tweets related to the televised advertisements, an average of 1,277 tweets per day. The statistics summary of tweets collected over the duration of the campaign (Mar. 1-Jun. 23) is listed in the “CDC Tips” column of Table 1. We use the three measurements mentioned above to check the influence from TV advertising and social links.

#### Statistics Results

The total number of tweets (146,759) was summed daily over the duration of the “CDC Tips” campaign from March 1 to June 23 (115 days). Fig. 1(a) and 1(b) shows the results of both correlation tests for the entire campaign and creative themes. Both the Pearson correlation coefficient (0.64) and Spearman rank correlation (0.83) report a strong positive relationship between ratings and tweets. Among all the topics of “CDC Tips”, Terrie exhibited the strongest correlation in both the Pearson correlation coefficient (0.64) and Spearman rank correlation (0.80). Jessica and Suzy had lesser correlations but still had very strong relationships.

#### Source Results

We calculate the proportion of users can get information from TV, tweets and either way. The statistic results with different time windows are shown in Fig. 1(c), which counters the intuition that people will tweet as soon as they see these exposures. When the length of time window is 1 hour, more than 70% of users cannot receive any kind of exposure. Therefore the probability of tweeting behavior happens immediately (less than 1 hour) is much below 0.3. Until extending the time window to 12 hours, most (93.2%) of users can get campaign message. While even forward tracing 3 days, only quarter (25.4%) users can see tweets from their friends, which indicates the social network constructed by tweeting users’ is very sparse. This may because “CDC Tips” did not do much online marketing in Twitter network.

#### Inference Results

The prediction results are shown in Fig. 1(d), which with the training ratio increasing, the accuracy of prediction im-
proves. The proposed SII model consistently outperforms other methods which indicates the advertising campaign’s social conversation is launched by both TV and social links. The prediction based on only TV outperforms the result of only tweets greatly demonstrates that TV broadcasting plays a significant role in ads information propagation.

**Legacy Truth**

“Legacy Truth” provides young people with facts and information about the health and social consequences of tobacco, and empowers the teens generation to finish smoking. As “Legacy Truth” advertises all year around, we intercepted the record during Aug. 11 to Oct. 28, 2013. “Legacy Truth” payed much attention on TV advertising and televised their ads during the 2013 MTV Video Music Awards. At the same time it adopted a social media strategy that cultivates and encourages engagement. It promoted some specific hashtags, encouraged social conversation, and required some celebrities to join the social activities.

“Legacy Truth” column in Table 1 lists this campaign generated a total of 59,605 related tweets during three months, an average of 647.88 tweets per day. Significantly, 76.6% tweets are generated by retweeting, which is a proof that users’ network is less sparser. Like “CDC Tips”, we find the answers to the same two questions.

**Statistics Results**

Like the analysis of “CDC Tips”, we also measure the Pearson and Spearman correlation between TV rating and tweets amount of “Legacy Truth”. The result is shown in Fig. 2(a) and 2(b), where TV rating reached a high peak on Aug. 24 since “Legacy Truth” ads were aired during 2013 MTV Video Music Awards. Moreover tweets amount also rose dramatically and peaked at 28,958 on Aug. 25 because of much more viewers and some music stars started discussing “#Truth” in Twitter at the same time. The Pearson correlation coefficient (0.48) and Spearman rank correlation (0.79) demonstrate that the TV rating and tweets amount have strong co-relation. Since there is an extreme situation in this data, which makes the relation in other normal days not obvious, we move out the 10 days data (Aug. 24–Sept. 2). The even higher correlation Pearson correlation coefficient (0.62) proves the strong relation still exists and Fig. 2(b) also illustrates it.

**Source Results**

We analyze “Legacy Truth” with the same analysis setting to observe user twitter behavior. Fig. 2(c) shows the proportion of tweets’ authors can be influenced by TV and social media exposures with different time windows. Unlike “CDC Tips”, most users (75.1%) can receive campaign message in 1 hour, because of intense TV advertising. “Legacy Truth” also enjoys high probability of users influenced by social friends which is the result that campaign made an effort on viral marketing. However, it is interesting that even for 3 day time window, two ways of spreading information still cannot cover all users, which means a small part of users (2.5%) are activated through other channels.

**Inference Results**

Fig. 2(d) shows the prediction results, which the proposed SII model predict better than one resource model. This result supports the conclusion of “CDC Tips”: Both TV advertising and social media influence the social conversations. But the better prediction result based on only TV demonstrates that more tweeting users are influenced by TV ads than social diffusion. This conclusion is in agreement with Fig. 2(a), in which twitter amount is highly correlated with TV rating.

**Conclusion**

In this paper, we aim to identify the role of TV advertising and social media in launching social conversation about tobacco control. We proposed a novel inference model: SII model, which can predict whether user will attend the conversation. With other two methods of measurement, we check the interaction of TV advertising and social networks activities. The results of all methods shows both the external TV exposures information and the diffusion process inside the social network stimulates the engagement with the campaign, and TV advertising plays a more important role.

**References**


Figure 1: Measure results of “CDC Tips”

Figure 2: Measure results of “Legacy Truth”