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Mood Congruence or Mood Consistency? Examining Aggregated Twitter Sentiment towards Ads in 2016 Super Bowl

Tingting Nian,[†] Yuheng Hu,[‡] Cheng Chen[‡]
[†]The Paul Merage School of Business, University of California, Irvine
[‡]College of Business, University of Illinois at Chicago
{tnian@uci.edu, yuhenghu@uic.edu, cchen224@uic.edu}

Abstract

While the popularity of Social TV has recently attracted significant research efforts from various research communities, little is known about how viewers' Twitter sentiment toward TV advertising is affected by the viewers' mood state affected by the TV program. In this paper, we take a large set of tweets posted during the Super Bowl 2016 to investigate the effect of audience's mood induced by the game on their reactions the Super Bowl commercials. Our results find the support for the mood congruence theory, suggesting that game-induced mood has a positive and significant effect on the viewers' Twitter sentiment towards the commercials. We also discuss both theoretical and practical implications for our study.

Introduction

Social TV, a multiscreen activity by the joint consumption of television programming and production of social media by viewers has become increasingly popular in the past years. An estimated 36% of multi-screeners in the United States engage in social TV activity.[1] Among Twitter users active during primetime, 85% have discussed television programming on the platform. [2]

Social TV's rapid rise, however, has also created new challenges for practitioners, raising questions of how media multitasking affects viewers' responses to advertising and how advertisers and television networks and social media platforms can leverage this behavior (e.g., Hare 2012, Poggi 2012). Research in this area is in its infancy. Most previous works focused on characterizing social media responses about TV programs whiles others showed initial evidence that television advertising can influence online behaviors such as online search and shopping (Cesar and Geerts 2011; Pagani and Mirabello 2011). These works, however, have not explored the impact of television program and advertising on social media conversations.

In this paper, we aim to address the dearth of work examining the relationship between television advertising and social media posts. The central research question we focus on is: *How does TV program's context affect viewer's responses to television advertising?*In other words, *will a viewer respond to a TV ad more favorably if she or he is in a good mood induced by TV program?* To address this question, we collect over a large-scale tweets dataset contributed by the followers of Denver Broncos and Carolina Panthers during the the Super Bowl 50 – the most watched TV program in 2016, and construct measures for viewers' responses to the Super Bowl ads and viewers' mood state determined by the game context (Broncos touchdown vs. Panthers fumble, etc.) and the viewer's stance (e.g., Broncos fan vs. Panthers fan). Our results find the support for the mood congruence effect, suggesting that game-induced mood has a positive and significant effect on the viewer's sentiment responses towards the ads. That is, if the viewer is in a happy mood, no matter whether the ad is happy or sad, the viewer will write a more positive tweet about it than those in a bad mood.

This paper mainly contributes to a growing body of social computing literature (Cesar and Geerts 2011; Zhao, Wickramasuriya, and Vasudevan 2011) by providing deep insights into social TV. Besides, past literature on individuals' mood state and effectiveness of commercials mainly relied on controlled lab studies (Kamins, Marks, and Skinner 1991). Thus, we further contribute to the literature by proposing a new method to examine individual's reactions to commercials through their social media activities.

Background

Mood-Congruence Effects Theory

The mood congruency effect is a psychological phenomenon in which a person tends to remember information that is consistent with their particular mood. People also tend to recall memories that coincide with the mood they are experiencing at a certain time (Bower and Forgas 2001). Based on this, when a viewer sees a happy program, it activates and increases the accessibility of other positive material stored in the viewer's memory. Similarly, a negative mood created by a sad program would increase the likelihood that other negative material in the viewer's memory to be cued. Through the lens of mood congruency effect, researchers tried to explain how mood states of audience influence their reactions to products. In particular, through controlled lab studies, past work in consumer psychology found that the mood in-

[1]http://www.iab.com/insights/the-changing-tv-experience-attitudes-and-usage-across-multiple-screens/

[2]https://blog.twitter.com/2014/study-exposure-to-tv-tweets-drives-consumers-to-take-action-both-on-and-off-of-twitter

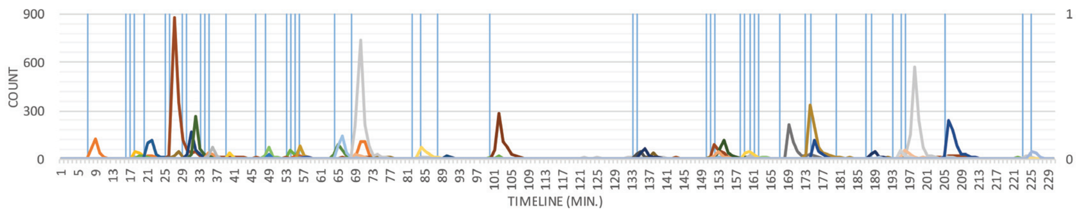

Figure 1: Volume of tweets posted by Broncos/Panthers followers regarding 52 commercials aired during the Super Bowl 50. Vertical lines indicate the airing time for each ad. All the ads were aired during commercial breaks or natural breaks.

duced by the program would carry over to the mood of the viewer when he/she evaluates a product (Singh and Hitchon 1989; Xia and Lin 2009). Following this, in the context of present research, we proposed the following:

H1: If the viewer is in a happy mood state induced by the game progress and the viewer's stance (e.g., his supporting team just had a touchdown), no matter the ad is happy or sad, the viewer will write a more positive tweet about it than when the viewer is in a negative mood state (e.g., his supporting team just had a turnover).

Mood-Consistency Effects Theory

Another related theory is rooted in the mood consistency effects in psychology, which predicts that a match between the mood states and stimuli would actually lead to a positive evaluation of the stimuli than a mismatch (Bramston 2002). While it is intuitive for the positive states, this consistency effect for negative moods has been explained by different theories. One of the explanations for why people in a negative mood may not always have a negative response to the stimuli is the negative-state relief (NSR) model (Carlson and Miller 1987). It suggests that a negative mood would facilitate prosocial behavior because people want to reduce their negative feelings through helping others (Cialdini, Kenrick, and Baumann 1982). As a result, when people watch "drama" commercials, viewers are likely to give an empathetic response to the ad. Based on this mood consistency effect, we have the following hypothesis:

H2: If the viewer's mood state (e.g., sad as his supporting team just had a turnover) is mismatched by the mood induced by an ad (e.g., a funny car ad), the viewer will write a more negative tweet about it than when the viewer's mood state is matched by the mood induced by the ad.

Examining effects of Mood Consistency and Mood Congruence

Data Collection

Super Bowl data: Super Bowl 50 is the largest televised event in 2016 with over 111.9 million viewers watched the game between Denver Broncos and Carolina Panthers. One of the most popular topics during Super Bowl is about the ads. Given Super Bowl's wide reach and impact, it often becomes a defining moment for brands. A well-executed ad can potentially boost the brand and gain exposure in front of millions of viewers whereas a poorly-designed ad can just hurt the brand as much. In Super Bowl, ads (around 30s each) are displayed in each commercial break (2 min.) as well as the natural breaks (e.g., touchdowns, injuries, reply challenges) Important to this research, we obtained the play-by-play progress transcript from the National Football League (NFL). We also obtained 52 ads aired during the game (pre-, and after-game ads were not considered). For each ad, their airing time was also recorded. Fig. 1 shows the airing time of ads and associated tweet volumes.

Variable	Mean	Std. Dev.	Min	Max
TweetSentiment	0.12	0.40	-1	1
GameSentiment	0.61	0.13	-1	1
AdSentiment	0.77	0.61	-1	1
Follower	7,424	6,9710.2	0	30,690,000
Following	1,247	6,404.1	0	518,800

Table 1: Descriptive Statistics

Twitter data: As discussed earlier, viewers' mood states can depend on the game context and their stance. For example, a viewer can be in a good mood if his supporting team has a touchdown. To determine the viewer's stance, we first collected the follower lists of both teams' official Twitter accounts and then crawled the followers' tweets during the game time and their Twitter profiles, including the number of followers, followings, and likes. Next, we used a list of keywords such as brand names and ad hashtags to filter out non-ads-related tweets. In sum, we first obtained 490K tweets during Super Bowl posted by over 110K followers (55K Broncos followers and 56K Panthers followers). From these tweets, 6.5% (32K) mentioned ads, posted by 22K followers (10K Broncos and 12K Panthers followers). To control our study, we also used Twitter API to obtain 31K tweets about the ads posted during the game by 20K individuals who did not follow any team at the time of crawling.

Variable Definitions, Measures, and Model

Since we are interested in examining whether viewers' sentiment toward ads is affected by game context and ads themselves, we use the sentiment inferred from viewers' ads-related tweets as our dependent variable. Our independent variables include viewers' Twitter profile, their game-induced mood state, and the ads sentiment. The measures for these variables are described below and the descriptive statistics are listed in Table 1.

Tweet Sentiment Towards Ads

Extracting sentiment from tweets is known to be a challenging task. Here, we used a dictionary-based approach as it can capture domain-specific contextual cues. First, we created a list of 500 most frequently used words (one and two-gram) in the tweets we obtained. We then identified the part of speech of each word, i.e. noun, verb, adjective, etc. The most frequently mentioned words are verbs and adjectives such as “go”, “win”, “good”, etc. Finally, we produced a list of sentimental words using adjectives and verbs as seed. The sentiment orientation of these words is manually labeled by the authors. We utilized WordNet to search the synonyms and antonyms of the seed words to further expand the lexicon. In all, we extract and collect 504 sentimental words (361 positive, 143 negative) as a domain-specific sentiment lexicon. Finally, we apply this lexicon to VADER (Hutto and Gilbert 2014), a rule-based sentiment tool for inferring the viewer’s sentiment from their tweets towards the ads. The performance of our approach was evaluated against two baselines: 1) a SVM-based classifier with TFIDF features, and 2) VADER-original, i.e., without using our domain-specific lexicon. Our approach can achieve 84.5% accuracy over 62.4% of SVM-based and 70.2% of VADAR-original, making the sentiment inference process satisfying.

Game-induced Sentiment

We define the mood state of the viewer when watching the game, and it is often associated with the game context/progress and the viewer’s stance. For example, when Broncos scored, their fans may have good mood while Panthers fans may have a bad mood at the same time. On the other hand, if a viewer is not a fan of two teams, he or she may view the game more objectively. In order to obtain game-induced sentiment, two coders of football fans were hired. They first watched the replay of Super Bowls 2016 and read the game progress transcript. Then, they labeled viewers’ sentiment (from -1 to 1, where -1 being very negative and 1 being very positive) towards every major event during the game (including touchdown, field goal, fumble, interception, etc.) as if they were Broncos or Panthers fans or no fans. The conflicts of labels were resolved during a discussion session. Finally, because ads can only be aired during commercial/natural breaks and the gap between these breaks tend to be short (6.7 min., see Fig. 1), we averaged the game-induced sentiment between two breaks and examined its impact.

Ads Sentiment

Ads can be very rich in emotional content, yet they oftentimes stress one type of emotion than another. Therefore, we categorized ads into one or several of the emotion categories based on its content. We follow the classic Plutchik’s wheel of categorical emotions model which describes emotions as discrete categories (Plutchik 1980). Two coders individually watched the replay of all 52 ads aired during the game and labeled them using the four pairs of primary emotions (i.e., anger–fear, anticipation–surprise, joy–sadness, and trust–disgust). After that, a discussion session was held to resolve conflicts. Finally, based on the aggregated score of these emotions (1 for positive, -1 for negative), we measure the sentiment of ad (we label an ad positive if it conveys more positive emotions; also in practice, we did not find a neutral ad).

Results and Discussion

Results

Since the dependent variable are either negative (-1) or positive (1), a natural candidate is a logistic model. However, the interaction variables in a logistic model are hard to interpret according to many statisticians (Hoetker 2007), we instead use a set of linear probability models (LPM), which typically results in qualitatively similar results as in limited dependent variables models (Aldrich and Nelson 1984). Table 2 displays the results derived from an LPM. Column 1) shows the effects of game-induced sentiment as well as the ad sentiment on the user’s sentiment towards the ad. Both coefficients are statistically significant and positive, which imply that game-induced sentiment, as well as the ads sentiment, have a positive effect on viewers’ sentiment towards ads. In addition, the coefficient on the interaction term between game-induced sentiment and ads sentiment is negative and statistically significant, contradicting to our Hypothesis 2 that the consistency between game-induced mood and ads sentiment will result in more favorability of viewers. Column 2) includes also the interaction effects between the ads sentiment and whether the viewer is a follower of Broncos or Panthers. As we can see from the results, compared with non-followers, ads sentiment has a stronger and significant effect on the viewer’s sentiment if the viewer is a follower. In summary, these results show supportive evidence for our Hypothesis 1. However, the coefficient on the interaction term between the game-induced sentiment and ads sentiment is negative which contrasts our Hypothesis 2.

Discussion and Implication

In this study, we utilized the mood induced by the Super bowl game which is exogenously determined by the progress of the game to examine the impact of program-induced mood on viewers’ processing of the ads. We found that the viewers who are exposed in positive mood environment are more likely to form a positive sentiment towards ads. In addition, the sentiment conveyed through the message of the ads is also positively associated with the viewers’ sentiment. Our results support the Mood-Congruence theory. However, we do not find evidence to empirically support the Mood-Consistency theory which suggests that the evaluations of the ads are more positive for consumers if the program-induced mood is matched by the mood the viewer experiences while watching the ads.

Our work mainly contributes to a growing body of social TV literature (Hu et al. 2012; Cesar and Geerts 2011; Zhao, Wickramasuriya, and Vasudevan 2011) by better understanding how viewers’ Twitter sentiment towards ads during a large-scale televised event can be influenced by TV program context. In addition, most past works on individuals’ mood state relied on controlled lab studies (Singh and

Variables	(1) Twitter sentiment	(2) Twitter sentiment
GameSentiment	0.030*	0.035**
	(0.018)	(0.020)
AdSentiment	0.067***	0.058***
	(0.003)	(0.003)
GameSentiment ∗ AdSentiment	-0.031*	-0.033*
	(0.018)	(0.020)
isFollower ∗ AdSentiment		0.023***
		(0.003)
isFollower		0.060***
		(0.006)
Following	0.000***	0.000***
	(0.000)	(0.000)
Followers	0.000***	0.000***
	(0.000)	(0.000)
Constant	0.200***	0.220***
Adjusted R^2	0.22	0.21
Observations	63,343	63,343

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Linear Probability Model (LPM) results

Hitchon 1989; Goldberg and Gorn 1987). Thus, we contribute to the literature by showing the effectiveness of examining psychology theories using public social media data.

More broadly, understanding how tv program viewers process TV program and how their mood state affects their behavior is fundamentally important and have implications for a wide range of areas, including journalism, e.g., event sentiment analysis (Dan, Feng, and Davison 2011; Hu, Wang, and Kambhampati 2013) and communication (Knobloch 2003). For example, in marketing, brands needs to better understand the way consumers encode information from the ad and, to what extent, their ad-viewing experience is influenced by the mood states induced by the program. Moreover, in journalism, most existing works (e.g., (Hu, Wang, and Kambhampati 2013)) focus on how the viewers' sentiment evolves over a broadcasted event's timeline. Our work here provides deeper insights into how these viewer's reactions are affected, which can enable further journalistic investigations.

Although the results of this study shed some light on the effect of mood on ad processing, our study has several limitations which may weaken our ability to causally quantify the magnitude of the effect. First, tweets are often short and noisy. Future studies could further focus on improving the accuracy in sentiment measurement. Second, we focus on the valence of the ads while there are many other dimensions in the sentiment that could be measured. Third, although we have a control group which consists of users whose rooting team is losing or behind, the effect of a sequence of positive and negative events along the course of the game is not in the scope of this study. Lastly, Super bowl is a specific event context and its viewers may be of specific characteristics. Therefore, assessing the generalizability of our findings to other contexts.

References

Aldrich, J. H., and Nelson, F. D. 1984. *Linear probability, logit, and probit models*, volume 45. Sage.

Bower, G. H., and Forgas, J. P. 2001. Mood and social memory.

Bramston, P. 2002. Subjective quality of life: the affective dimension. In *The universality of subjective wellbeing indicators*. 47–62.

Carlson, M., and Miller, N. 1987. Explanation of the relation between negative mood and helping. *Psychological bulletin* 102(1):91.

Cesar, P., and Geerts, D. 2011. Past, present, and future of social tv: A categorization. In *2011 IEEE consumer communications and networking conference (CCNC)*, 347–351. IEEE.

Cialdini, R. B.; Kenrick, D. T.; and Baumann, D. J. 1982. Effects of mood on prosocial behavior in children and adults. *The development of prosocial behavior* 339–359.

Dan, O.; Feng, J.; and Davison, B. 2011. Filtering microblogging messages for social tv. In *WWW*, 197–200.

Goldberg, M. E., and Gorn, G. J. 1987. Happy and sad tv programs: How they affect reactions to commercials. *Journal of consumer research* 14(3):387–403.

Hoetker, G. 2007. The use of logit and probit models in strategic management research: Critical issues. *Strategic Management Journal* 28(4):331–343.

Hu, Y.; John, A.; Seligmann, D. D.; and Wang, F. 2012. What were the tweets about? topical associations between public events and twitter feeds. In *ICWSM*.

Hu, Y.; Wang, F.; and Kambhampati, S. 2013. Listening to the crowd: Automated analysis of events via aggregated twitter sentiment. In *IJCAI*.

Hutto, C. J., and Gilbert, E. 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Eighth International AAAI Conference on Weblogs and Social Media*.

Kamins, M. A.; Marks, L. J.; and Skinner, D. 1991. Television commercial evaluation in the context of program induced mood: Congruency versus consistency effects. *Journal of Advertising* 20(2):1–14.

Knobloch, S. 2003. Mood adjustment via mass communication. *Journal of communication* 53(2):233–250.

Pagani, M., and Mirabello, A. 2011. The influence of personal and social-interactive engagement in social tv web sites. *International Journal of Electronic Commerce* 16(2):41–68.

Plutchik, R. 1980. *Emotion: A psychoevolutionary synthesis*. Harpercollins College Division.

Singh, S. N., and Hitchon, J. C. 1989. The intensifying effects of exciting television programs on the reception of subsequent commercials. *Psychology & Marketing* 6(1):1–31.

Xia, K.-N., and Lin, Y.-T. 2009. The effect of mood on advertisements attitude and recall–separating arousal from valence. *AP-Asia-Pacific Advances in Consumer Research Volume 8*.

Zhao, S.; Wickramasuriya, J.; and Vasudevan, V. 2011. Analyzing twitter for social tv: Sentiment extraction for sports. In *Proceedings of the 2nd International Workshop on Future of Television*, volume 2, 11–18.