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SOCIAL MEDIA ANALYTICS FRAMEWORK: THE CASE OF TWITTER AND SUPER BOWL ADS

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ABSTRACT

Social media (e.g. Twitter and Facebook) present a nascent channel of communication that is real-time, high volume and socially interactive and may provide timely feedback on performance of brand advertising. While advertisers continuously seek better monitoring of their return on investment, they face immense challenges in measuring social media initiatives owing to a paucity of research in the area of social media analytics. The present study implemented a social media analytics (SMA) methodological framework in the context of brand TV advertising. We examined social media word-of-mouth (WOM) surrounding 2014 Super Bowl TV advertisements (ads) in relation to performance as measured by the *USA Today* Ad Meter ad likeability ratings. Over 660,000 Twitter messages for fifty-one ads pertaining to forty-two brands were downloaded via automated scripts and then processed and analyzed. We tested the framework by providing evidence that social media measures of Twitter message volume and sentiment pertaining to Super Bowl ads positively correlated with ad likeability ratings. Thus our framework fills the research gap in offering a nascent approach for monitoring ad performance for improved decision making in the context of brand TV advertising.

Keywords: social media, social media analytics, Twitter, microblogging, Super Bowl advertisement, Ad Meter, Word-of-Mouth (WOM), sentiment

INTRODUCTION

Social Media

Social media (Sasser, Kilgour & Hollebeek [37]) are a conglomerate of Internet communication technologies that transform web-based communication into interactive social platforms (e.g. Twitter and Facebook). These channels came into existence due to the second evolution of the World Wide Web or Web 2.0 (Kaplan & Haenlein [20]) which collaboratively harnessed the collective intelligence of the masses involving content co-creation that increases content value via increased usage. Unmistakably, the business model is rapidly changing from B2C (business-to-consumer) to

C2B2C (consumer-to-business-to-consumer) where firms' and brands' goals are now increasingly focused on driving customer conversations (Prahalad & Ramaswamy [34]) resulting in consumers' contributing to brand communication in the form of new ideas and opinions. One example is the PC company Dell which engaged its customers via 'storm' sessions to obtain over 17,000 ideas for new and improved products (Mullaney [30]). Not surprisingly, scholars have also concluded that highly engaged consumers lead to greater brand equity, share of wallet, retention, return on investment (ROI) and proactive word-of-mouth (WOM) (Vivek, Beatty & Morgan [42]). Some scholars have even argued that social media provide information that is inaccessible through traditional channels (Kozinets [23]). The presence of 1 billion Facebook users, 700 million QQ China users, 4 billion YouTube views, and 500 million Twitter users are testaments of the popularity of social media (Schultz & Peltier [38]). This is further evidenced by the $5.1 billion spent on social media advertising by US companies in 2013 alone (Elder [12]).

Social Media Analytics

Along with opportunities, social media present many challenges. Social media technology is disruptive and shifts brand control away from the organization into the hands of consumers, consequently placing businesses in a conundrum. Due to the lack of best practices, most current social media marketing initiatives fixate on marketing traditional sales promotions to existing consumers instead of establishing long-term relationships via consumer-brand engagement (Schultz & Peltier [38]). Practitioners have alluded to such as causes of social media failures to live up to earlier expectations (Elder [12]). Clearly, businesses are content to focus mainly on short-term gains from sales promotions instead of long-term benefits from customer engagement and relationship building probably due to obstacles to the measurement of these benefits (LaPointe [25]). These obstacles include challenges in understanding how co-creation of brand content and brand experience relates to consumer engagement using digital social footprints (Bruce & Solomon [3]). Voice of Customer (VOC) research has shown that firms are having a difficult time collecting, analyzing, and integrating social media data into their operations (Fowler & Pitta [16]). Such impediments underscore the critical need for Social Media Analytics (SMA), defined as the concern over the development and evaluation of informatics tools and frameworks to collect, monitor, analyze, summarize and visualize social media data (Zeng, Chen, Lusch & Li [47]). SMA differs from traditional data analytics particularly due to the nature of its unstructured data formats (text, pictures, video, etc.) which are characterized by heterogeneous and natural human language that is heavily context dependent (Kurniawati, Shanks & Bekmamedova [24]). Researchers have pointed out that SMA is a vital tool in today's competitive business environment and is increasingly transforming marketing from an art to a science (Davenport & Harris [7]). In short, SMA presents a competitive advantage to those who have the knowledge and capacity to implement it well (Baltzan, [2]). Despite the demand and need for SMA, scholars Schultz and Peltier [38] and Bruce & Solomon [3] succinctly point to the paucity of scholarly research in examining SMA. As in the words of Zeng et al. [47] "From a research perspective, there have been discussions about various conceptual dimensions of social media intelligence, related technical challenges, and reference disciplines that could potentially bring about useful tools… However, systematic research and concrete, well-evaluated results are still lacking".

We seek to fill this research gap by implementing a SMA methodological framework based on the CUP SMA process framework (Fan & Gordon [14]) for the benefit of both scholars and practitioners in the social media advertising context. Specifically this study contributes to the intersection of information systems, computer science and marketing in presenting a systematic approach in measuring ad performance. The objective is to extract and analyze social media WOM, specifically Twitter messages surrounding fifty one 2014 Super Bowl ads with the *USA Today* Ad Meter ad likeability ratings. We employed web mining[1] (Liu [27]), text mining (Witten [45]) and sentiment analysis (Pang & Lee [33]) approaches in downloading and extracting measures of Twitter message volume and sentiment from over 660,000 Twitter messages. Using Bootstrap linear regression models (Efron & Tibshirani [10]) we tested the relevant social media measures, specifically measures of tweet volume and sentiment for each ad, and found them to be significant and positively correlated with ad performance. We contribute a systematically-researched and well-evaluated methodological framework to the SMA research stream and by so doing encourage brand managers and scholars to consider the use of social media

[1] Bing Liu (Liu [27]), a prominent researcher described web mining as "a data mining approach to discover useful information or knowledge from the Web hyperlink structure, page content, and usage data. Although Web mining uses many data mining techniques, it is not purely an application of traditional data mining due to the heterogeneity and semi-structured or unstructured nature of the Web data."

as a set of reliable supplementary performance measure in addition to traditional marketing metrics in practice and research.

The Research Context

The present study has two research contexts: The Super Bowl and Twitter contexts.

The Super Bowl Context

The Super Bowl is the premiere live event for television advertising in the U.S. With over 90 million viewers, the Super Bowl is the most-watched TV broadcast (Kim, Cheong & Kim [22]; Tomkovick, Yelkur & Christians [41]) reaching over 40% of the U.S. population. It also permeates across various demographic groups making it the most attractive channel for advertisers to promote their brands. At the same time, Super Bowl advertisements (ads) have become a cultural phenomenon of their own with many viewers more interested in the ads than the game itself (Freeman [17]). As a result of so much attention on Super Bowl ads, national surveys to judge these ads (particularly their effectiveness) have also become popular. One such is the *USA Today* Super Bowl Ad Meter (Lawrence, Fournier & Brunel [26]), which is discussed under "Methodology."

Not surprisingly, the cost of Super Bowl advertising is exorbitant. For example, a 30-second Super Bowl commercial spot in 2014 was an extravagant $4 million. Additionally the cost of producing the commercial itself could swell to $1 million or above (*Forbes* [15]). Even with such significant investment, brands still find Super Bowl advertising to be a cost-effective venture due to its extensive market reach and widespread demographics (Kim et al. [22]; Elliot [13]). As a case in point, the 2014 Super Bowl attracted 111.5 million viewers (CBS News [4]) with 15.3 million people on Twitter generating 1.8 billion Twitter impressions (Nielsen [31]). As such, some have argued for the need for credible ROI measures with this investment (Eastman, Iyer & Wiggenhorn [9]). Astonishingly, even though the Super Bowl broadcast has a wide viewership of over 100 million, it has yet to receive the respected attention from the academic community (Kim et al. [22]).

Despite the hype, some brands failed miserably in the Super Bowl. For instance the ad in the 2006 Super Bowl for the movie *World's Fastest Indian* generated only a mere $5.13M at the U.S. movie box office while the ad air time cost alone was already $2.5 million (Monica [29]). One cause of such missteps could be due to marketers' reliance on feedback from focus groups during the creation of their ads, a practice which is not only costly but may not represent public opinions. As stated by Fowler and Pitta [16], traditional methods such as surveys and focus groups are becoming more difficult to use. In recent years, with the advent of social media, more and more marketers are realizing the power of co-creation with consumers through social media (Schultz & Peltier [38]) and the mechanisms available to measure their ad investment.

The Twitter Context

As of January 2011, nearly 200 million registered users were on Twitter posting 110 million Twitter messages per day (Chiang [5]). Tweets or microblogs are limited to 140 characters long, thus ensuring each message's succinctness. The act of tweeting or microblogging has resulted in the generation of rapid, high volume and real-time tweets on many topics including politics, socio-economics, sports, and technology, to name a few. For these reasons, the Twitter community is a rich and appropriate source of data for the present study. In fact, scholars have concluded that such conventional online behavioral metrics as Google searches and web traffic are less significant to firm value when compared to social media metrics (Luo, Zhang, & Duan [28]).

Those who are active on Twitter generally invite their friends and family members to participate, a practice that has led to individuals and their groups of followers intertwining into many overlapping personal networks (Oh [32]). In addition, within Twitter itself, individuals may choose to follow those they deem interesting. In the presence of these social networks individuals naturally tend to perpetuate their preferences for a particular product or service upon consumption and to share that preference. Such word-of-mouth (WOM) in relation to ads is well observed in Twitter. Table 1 shows examples of three Super Bowl Twitter messages with respective keywords. It is noted that keywords or hashtags are used to tag or categorize each message to enhance search-ability and to include the tweet in the wider conversations about a particular ad or brand.

Two anecdotal examples from the 2014 Super Bowl ads show the strong influence of Twitter. The first ad is the 'BestBud' ad from Budweiser, a company which, incidentally, has been sponsoring successful Super Bowl ads since 1986. This particular ad, based on the heart-warming friendship between a puppy and its horse pal, is built upon the theme of past award-winning ads using Clydesdale horses. This 'feel good' ad was voted top commercial by *USA Today* (Ad Meter score 8.29) and received a high volume of 17,317 Twitter messages and a high positive sentiment score (sentiment index of 1.708) in our dataset. The second ad is from the US telecommunication company Sprint, and was ranked among the bottom five in the *USA Today* (Ad Meter score 3.96) with only 124 Twitter messages, and was deemed highly negative (sentiment index of -0.532) in our dataset. The details of measuring Ad Meter, tweet volume and sentiment index are discussed under "Methodology".

Table 1: Example Twitter Messages with Respective Keywords and Hashtags

	Tweet Message	Keywords/Hashtags
1	Those Budweiser commercials had me balling my eyes out!! #Budweiser #SuperBowl #horsepuppy #tearjerker	#horsepuppy, #Budweiser, #SuperBowl, #tearjerker, commercials
2	Thanks #CocaCola & #Cheerios for showing U.S. multicultural families and successfully including diverse markets #adbowl #AmericaIsBeautiful	#AmericaIsBeautiful, #CocaCola, #Cheerios, #adbowl
3	Scarlett Johansson should realize that the only real flavor of #SodaStream is oppression http://t.co/QLpDD7vkXA #superbowl	#SodaStream, #superbowl

SOCIAL MEDIA ANALYTICS METHODOLOGICAL FRAMEWORK

This section describes the SMA methodological framework which is adapted from the CUP SMA framework, a three-stage process that was introduced by Fan and Gordon [14]. The abbreviation of CUP involves the processes of *capture*, *understand* and *present* (Figure 1). *Capture* is the process of obtaining relevant social media data by monitoring various social media sources, archiving relevant data and extracting pertinent information (Fan & Gordon [14]). *Understand* is the process of assessing the meaning from collected social media data and generating metrics useful for decision making. This is the core of the entire SMA process. Assessing meaning may involve statistical methods, text and data mining, natural language processing, machine translation and network analysis. The *present* stage is when the results of different analytics are summarized, evaluated and shown to users in an easy-to-understand format including visualization techniques. We selected this framework because it is sound and able to cater for common SMA implementations.

In the process of implementing our system we discovered the need to modify the CUP framework to include the *identify* stage to allow for the identification of tweets prior to the *capture* stage. This identification is done using keywords which are determined by experts viewing Super Bowl ads. These keywords are then used in the automated scripts query requests to Twitter API in collecting tweets containing those keywords.

Thus the four stages of the modified CUP framework is as follows: 1) *identify*, 2) *capture*, 3) *understand* and 4) *present* and illustrated in Figure 1 outlining descriptions for both the framework and our implementation. The *identify* stage is in dotted line in Figure 1 representing a modification to the original CUP framework. This system follows the approach of identifying keywords pertaining to respective Super Bowl ads (*identify*), thereafter collects the tweets that contained those keywords and pre-processed (*capture*). Relevant metrics or measures are extracted collectively for each ad and subsequently linear regression models are created and analyzed (*understand*). And finally the findings are summarized and presented (*present*). The details of each stage are described hereafter.

Identify

The first stage is to identify tweets about each Super Bowl ad by determining associated keywords. Four student teams from both the information systems and the marketing departments in a mid-western US university volunteered to identify keywords while watching the 2014 Super Bowl ads. Whereas some keywords are specific to the ad or are explicitly displayed by the advertiser at the end of the ad (e.g. #bestbuds from the Budweiser ad) (Figure 2), other keywords are implicitly gathered from cues such as brand name, ad title, celebrities, related objects and events. We classified these keywords into one of four types: 1) ad-specific keywords, 2) ad-generic keywords, 3) brand keywords and 4) event keywords. Each type has a specific function and is described in Table 2. Table 3 displays examples of keywords for selected ads in our dataset.

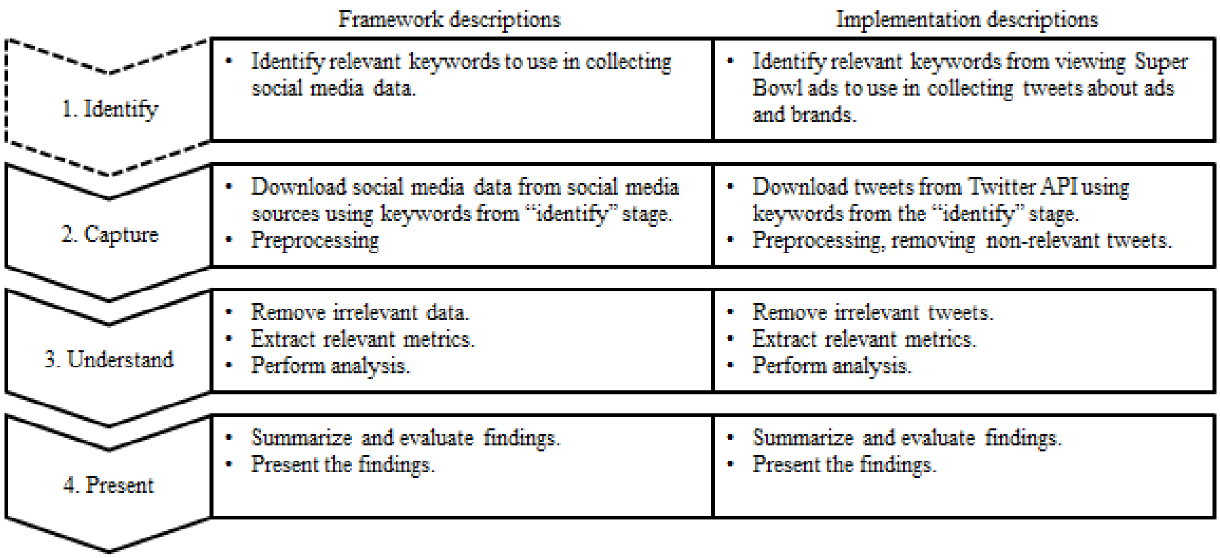

Figure 1: The Modified CUP SMA Methodological Framework

Notes: The CUP framework (Fan & Gordon [14]) has only 3 stages (Steps 2, 3 & 4). An additional stage *identify* (Step 1) is added to enhance the process in our implementation which resulted in the modified CUP SMA framework.

Figure 2: Example of a specific ad keyword (#BestBuds) displayed at the end of the Budweiser 'bestbud' Super Bowl ad.

Table 2: Keyword type and function

	Keyword Type	Function
1	Ad-specific keyword	These keywords are identified directly from the advertiser (e.g. hashtags) or specific to the ad such as ad title.
2	Ad-generic keyword	These keywords are identified from related objects associated with the ad.
3	Brand keyword	These keywords relate to the brands of the ads.
4	Event keyword	These keywords relate to the event which in this case is the Super Bowl.

Table 3: Keywords for Selected Ads

	Ad Title	Brand	Keywords			
			Ad-specific	Ad-generic	Brand	Event
1	BestBud	Budweiser	bestbuds	Horse, puppy	Bud, Budweiser	Superbowl, adbowl
2	America is Beautiful	Coca Cola	americaisbeautiful	openhappiness	coca cola, coke	Superbowl, adbowl
3	S. Johansson: Viral Video	Sodastream	NA	sorrycoke	sodastream	Superbowl, adbowl
4	D. Beckham: Naked Photo Shoot	H & M	beckhamforHM	underwear, soccergod, uncovered	H&M	Superbowl, adbowl
5	Make Love not War	Axe	Kissforpeace, makelovenotwar	vietnam, love, bodyspray	Axe	Superbowl, adbowl

Capture

The second stage in the modified CUP framework involves two tasks: 1) download and 2) preprocessing -- filtering relevant tweets. Using the web-mining approach (Liu [27]), keywords identified in the *identify* stage were used to search for relevant tweet messages via Twitter API (application programming interface). Multiple variations of each keyword were also generated to capture all tweets related to that keyword (e.g. bud, budweiser, #bud, #budweiser). PHP scripts were programmed to broadcast search query requests every 30 seconds to Twitter API (http://api.twitter.com). The 30-seconds time limit is a constraint of Twitter API rate limit. These scripts collect samples of Twitter messages containing previously identified keywords. Due to the high volume of tweets generated during the Super Bowl -- 24.9 million according to Gross [18] -- we were only able to collect a subset of all possible messages for each keyword. The result is a collection of 660,000 tweets for 2014 Super Bowl made during the game between 6-11 pm. Additionally, we collected Super Bowl ads data from Business Insider.

The second task in this stage involves text mining[2] (Witten [45]) in filtering downloaded Twitter messages. This is needed to remove irrelevant tweets or to assign tweets such as in case of tweets belonging to more than one ad or brand. Due to the unpredictable nature of human language, some Twitter messages may contain multiple keywords and thus be tied to more than one ad or brand (e.g. “Oh I so love those *budweiser* and *coke* ads!”).

We filtered Twitter messages in three levels (Figure 3). The first level (1) used ad-specific keywords such as “bestbuds” or “americaisbeautiful”. The second level (2) used ad-generic keywords such as “puppy” or “horse” together with brand keywords such as “budweiser”. The third level (3) filtered brand messages by using brand keywords such as “coke” or “budweiser” along with Super Bowl event keywords such as “superbowl”. Some brands may decide to advertise in two or more ads as in the case of Budweiser with two ads: ‘Hero’s welcome’ and ‘BestBud’. In such a situation, tweets mentioning the brand may be for one ad or another or both, but are not easily determined from the text (example: “These Budweiser ads are so emotional”). Such a tweet is assigned to both ads. The process of filtering ad and brand tweet messages are outlined below.

[2] “Text mining is a burgeoning new field that attempts to glean meaningful information from natural language text. It may be loosely characterized as the process of analyzing text to extract information that is useful for particular purposes. Compared with the kind of data stored in databases, natural language text is unstructured, amorphous, and difficult to deal with algorithmically” (Witten [45]).

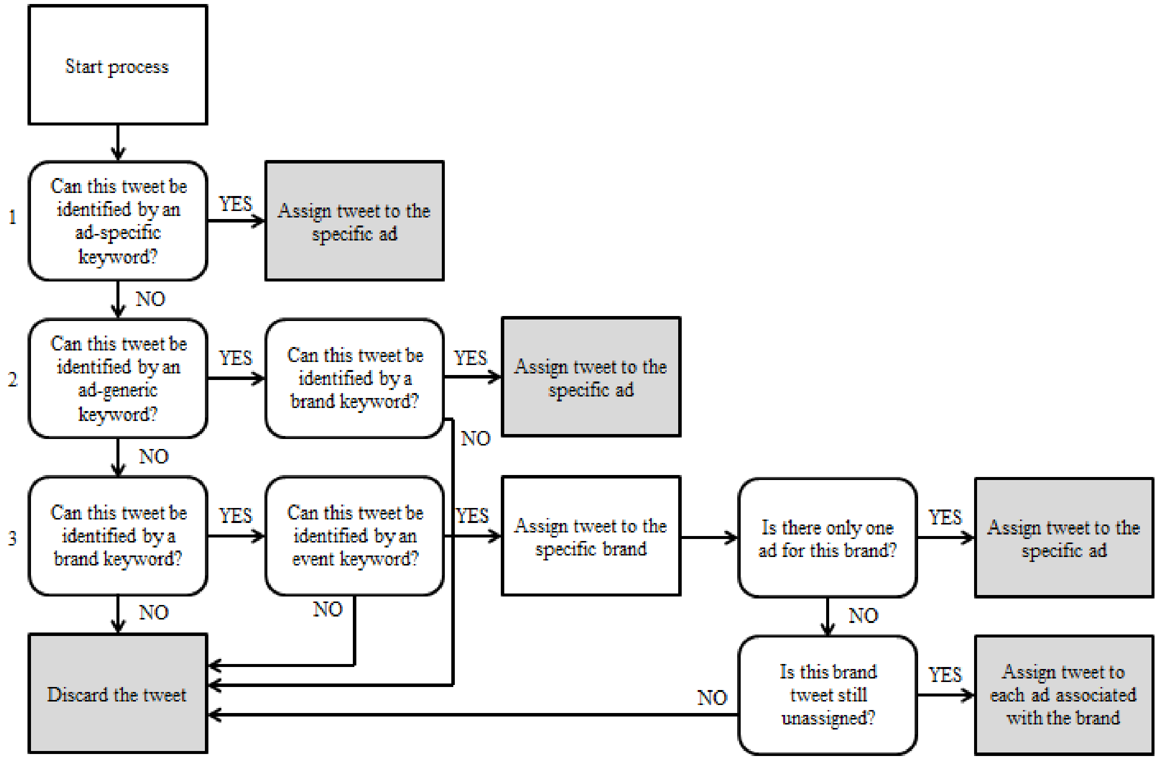

Figure 3: Process flow for filtering ad and brand tweets by three levels

Understand

The *understand* stage involved two tasks: 1) extracting of relevant measures for each Super Bowl ad and 2) data analysis. First we discuss the extraction of relevant measures. These measures consist of both ad likeability characteristics and social media measures. We determined two measures of ad likeability characteristics: humor (*HUMOR*) and length of air-time (*AD-LENGTH*). Both characteristics have been shown in past literature to be relevant predictors for Super Bowl ads (Yelkur, Tomkovick, Hofer & Rozumalski [46]) (More discussion on both variables are available in the Methodology section). Social media measures of volume of messages for each brand (*TWEET-VOL*) and sentiment index for each ad (*SENT-INDEX*) were also extracted. While most of these involved simple counting processes, the generation of *SENT-INDEX* was more complex and is explained in detail in the next section.

Sentiment Extraction

Extraction of sentiment (i.e. positive, negative or neutral emotion) from text is a process known as sentiment analysis[3] (Pang & Lee [33]). We employed the LIWC2007 - Linguistic Inquiry and Word Count Dictionary (Pennebaker, Francis & Booth [35]) - software to extract each message's sentiment. LIWC is a popular text and sentiment analysis program (Tausczik & Pennebaker [40]) that scores words in psychologically meaningful categories. The program determines the linguistic expression of emotions in a section of text by drawing on a wide range of genres of psychologically validated internal dictionaries.

For the present study, we were particularly interested in two emotional categories: positive and

[3] "Sentiment analysis and opinion mining is the field of study that analyzes people's opinions, sentiments, evaluations, attitudes, and emotions from written language. It is one of the most active research areas in natural language processing and is also widely studied in data mining, web mining, and text mining. The growing importance of sentiment analysis coincides with the growth of social media such as reviews, forum discussions, blogs, micro-blogs, Twitter, and social networks" (Liu [27]).

negative emotions, whose scores (LIWC *POS or NEG),* were used to determine the sentiment of each tweet. The algorithm to determine sentiment is as follows: If *POS* > *NEG*, sentiment = 1; if *NEG* > *POS*, sentiment = -1; otherwise, sentiment = 0. Table 4 shows three examples of Twitter messages about Coke with LIWC scores and respective sentiment indicators. For example, the first message commenting on Coke's ad 'America is beautiful' obtained a LIWC *POS* value of 14.29 and a LIWC *NEG* value of 0, which resulted in a positive sentiment (1). The second message had a LIWC *NEG* value of 11.11 and a LIWC *POS* value of 0 thus a negative sentiment (-1), while the last message had a value of 0 for both LIWC *POS* and LIWC *NEG* thus resulted in a neutral sentiment.

Table 4: Sample Twitter messages with LIWC index and sentiment

	Message Content	LIWC index	Sentiment
1	That coca-cola commercial was beautiful! #AmericaIsBeautiful	14.29 (*POS*) 0 (*NEG*)	1 (positive)
2	RT @alexhammay: Coke you liberal <EXPLETIVE> <EXPLETIVE > @cocacola #americaISbeautiful	0 (*POS*) 11.11 (*NEG*)	-1 (negative)
3	@CocaCola: The people are why #AmericaIsBeautiful. Send a selfie & maybe well see you in Times Square!	0 (*POS*) 0 (*NEG*)	0 (neutral)

We then counted the total positive and negative Twitter messages for each ad (*i*) and generated a sentiment index (*SENT-INDEX*) for *i*. Neutral messages were discarded. *SENT-INDEX* score was adopted from the work of Antweiler and Frank [1] in the finance literature where the authors used this measure to determine the bullishness index of a stock ticker for each trading day. They found this measure to be robust in accounting for large numbers of messages expressing a particular sentiment. A *SENT-INDEX* measure that is more than 0 is positive (bullish), while 0 is neutral and less than 0 is negative (bearish). We adopted this measure and assigned positive as bullish and negative as bearish. Eq. 1 shows the equation for $SENT\text{-}INDEX_i$ where *i* is the ad and $TOTAL_i^{POSITIVE}$ and $TOTAL_i^{NEGATIVE}$ are the total count of positive and negative messages for that ad. Table 5 lists top and bottom five ads with respective $TOTAL_i^{POSITIVE}$, $TOTAL_i^{NEGATIVE}$ and *SENT-INDEX* scores.

$$SENT\text{-}INDEX_i = \ln\left[\frac{1 + TOTAL_i^{POSITIVE}}{1 + TOTAL_i^{NEGATIVE}}\right] \quad (1)$$

The second task in the *understand* stage is to analyze the extracted features in testing four Bootstrapping Regression Models (for further details on this model, see Efron & Tibshirani [10]) with 1000 replications. The Methodology Section provides the details for this task.

Present

The *present* stage involved the process of summarization and reporting of the findings in the SMA framework. This stage is outlined in the Discussion Section.

Table 5: Measures for Top and Bottom Five Ads ranked by Ad Meter Ratings

	Rank	Ad	Brand	*ADMETER*	*AVG-LENGTH (seconds)*	*HUMOR*	*TWEET-VOL*	*TOTAL$_i^{POSITIVE}$*	*TOTAL$_i^{NEGATIVE}$*	*SENT-INDEX*
TOP	1	BestBud	Budweiser	8.29	60	0	17317	7788	1410	1.708
	2	Cowboy Kid	Doritos	7.58	30	1	12892	5734	1274	1.503
	3	Hero's Welcome	Budweiser	7.21	60	0	21091	9782	1635	1.788
	4	Time Machine	Doritos	7.13	30	1	15256	6371	1402	1.513
	5	80's celebrities	Radio Shack	7	30	1	5316	2418	337	1.968
BOTTOM	47	Need for Speed	Walt Disney	4.34	30	0	2364	487	262	0.618
	48	Bodybuilders	GoDaddy	4.04	30	0	7519	2691	811	1.198
	49	Family	Sprint	3.96	30	0	124	26	45	-0.532
	50	Celebrities love the crunch	Subway	3.91	30	0	739	137	96	0.352
	51	Cooltwist	Budlight	3.89	30	0	6035	2059	470	1.475

METHODOLOGY

Data & Variables

Data for this study were drawn from Twitter (http://twitter.com), *USA Today* (http://admeter.usatoday.com) and *Business Insider* (http://businessinsider.com). From 6-11 pm EST on Feb 2, 2014 during the 2014 Super Bowl game, the SMA framework collected over 660,000 tweets published by 525,000 unique individuals were collected covering fifty-one Super Bowl ads relating to forty-two brands. The *USA Today* Ad Meter rankings representing ratings for these ads were obtained from *USA Today*. Other information pertaining to each ad was collected from *Business Insider*. Table 5 shows top five and bottom five ads sorted by Ad meter rating with Twitter volume of messages (WOM). Figure 4 shows a chart of total tweet volume while Figure 5 shows a close association between volumes of ad tweets with time of ad broadcasts for every five minutes interval from 6 to 11 pm.

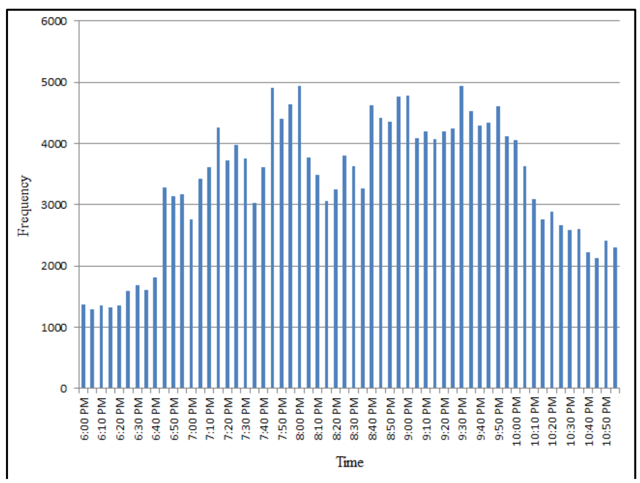

Figure 4: Tweet volume every 5-minute interval during the game between 6pm to 11 pm.

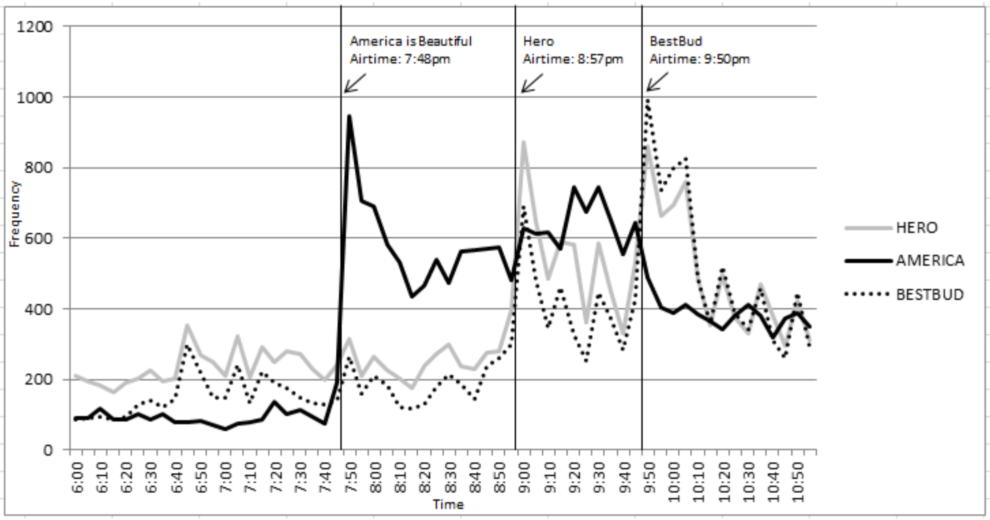

Figure 5: Volume of Twitter messages with Time of Ad broadcast

Note: This chart shows a close association between volumes of ad tweets with time of ad broadcasts. For example the Budweiser's 'BestBud' ad was aired at 9:50 pm which corresponded with the ad's peak of tweet volume. A similar corollary was found for Budweiser's 'Hero Welcome' and Coke's 'America is Beautiful' ads. Data for this chart were aggregated from the dataset collected in this study.

Dependent variable

The dependent variable in this study is the *USA Today* Ad Meter ad likeability measure (*AD-METER*). Ad Meter is an annual survey by *USA Today* of television ads aired during the Super Bowl game telecast. Ad Meter is the most widely recognized measure of Super Bowl ad popularity and performance (Kanner [19]). The survey, which started in 1989, uses a live response from focus groups based in McLean, Virginia, the newspaper headquarters and other site(s) around the country. In addition to focus groups, starting in 2013 *USA Today* recruited thousands of panelists across the U.S. to participate in Ad Meter (*Wall Street Journal* [43]). The 2014 Super Bowl used over 6000 panelists. This ad likeability measure was used by Yelkur et al. [46] to explore Super Bowl ad likeability, and by Lawrence et al. [26] to examine consumer-generated advertising. For more details on Ad Meter, please refer to Yelkur et al. [46].

Control variables

The control variables in this study are the Super Bowl ad characteristic measures: AD-LENGTH and *HUMOR*.

AD-LENGTH$_i$ – This is the length in seconds of the ad's air time, another significant element of ad likeability based on past literature (Yelkur et al.[46]). Longer ads were found to generate greater recall, better sponsor identification and greater consumer desire for the products (Wheatley [44]; Yelkur et al.[46]). This information was obtained from *Business Insider*.

HUMOR$_i$ -- For years, the attribute of humor (*HUMOR*) has been labeled as a valuable advertising element directly affecting ad likeability (Yelkur et al.[46]). Humor has been shown to gain viewer attention (e.g., Eisend [11]), improve viewer recall (e.g., Chung & Zhao [6]) and positively influence viewer attitude towards the ad (e.g., De Pelsmacker & Geuens [8]). A panel of marketing faculty and students volunteered to label this variable while watching each Super Bowl ad. *HUMOR* is a binary measure: If the ad contained humor (*HUMOR*=1), otherwise (*HUMOR*=0).

Independent variables

The social media variables of *TWEET-VOL* and *SENT-INDEX* are the independent variables of interest in this study.

TWEET-VOL$_i$ -- the ad volume of Twitter messages -- represents the number of messages about a particular ad (*i*). Past literature has shown this measure accurately gauges WOM (Oh [32]; Rui et al. [36]). This measure was generated by the analytics framework by aggregating all Twitter messages belonging to each ad (*i*).

SENT-INDEX$_i$ -- is an index measure of the polarity of the number of positive over negative messages for each ad (*i*) as discussed in the previous section. It shows the viewers' aggregated sentiment on any particular ad via their Twitter messages.

The following charts and statistics present a clearer understanding of the dataset. Table 6 outlines the descriptive statistics, while Table 7 shows the correlation matrix for all variables. Figure 6 shows the scatter plots, and Figure 7 shows the histograms of key variables.

Table 6: Descriptive Statistics of Key Variables

Variable	Data Type	Description	Mean	SD	Min	Max
$AD\text{-}METER_i$	Numeric	*USA Today* ad likeability rating for an ad (*i*).	5.588	.952	3.89	8.29
$AD\text{-}LENGTH_i$	Numeric	Ad (*i*) air time in seconds.	43.269	20.070	15.00	120.00
$HUMOR_i$	Binary	Whether an ad (*i*) contains humor element.	.24	.432	0	1
$TWEET\text{-}VOL_i$	Numeric	Volume of messages about a particular ad (*i*).	4967.903	5791.856	111.00	22501.00
$SENT\text{-}INDEX_i$	Numeric	Sentiment index generated from all tweets collected for a particular ad (*i*).	1.477	.668	.168	3.795

Table 7: Correlation Matrix of Key Variables

		1	2	3	4	5
1	$AD\text{-}METER_i$	1.000				
2	$AD\text{-}LENGTH_i$	.214	1.000			
3	$HUMOR_i$	.235	-.006	1.000		
4	$TWEET\text{-}VOL_i$	.458**	.173	.144	1.000	
6	$SENT\text{-}INDEX_i$	.224	-.079	.081	-.009	1.000

Note: The positive pairwise correlation between $TWEET\text{-}VOL_i$ and $AD\text{-}METER_i$ denotes significant relationship between these variables.

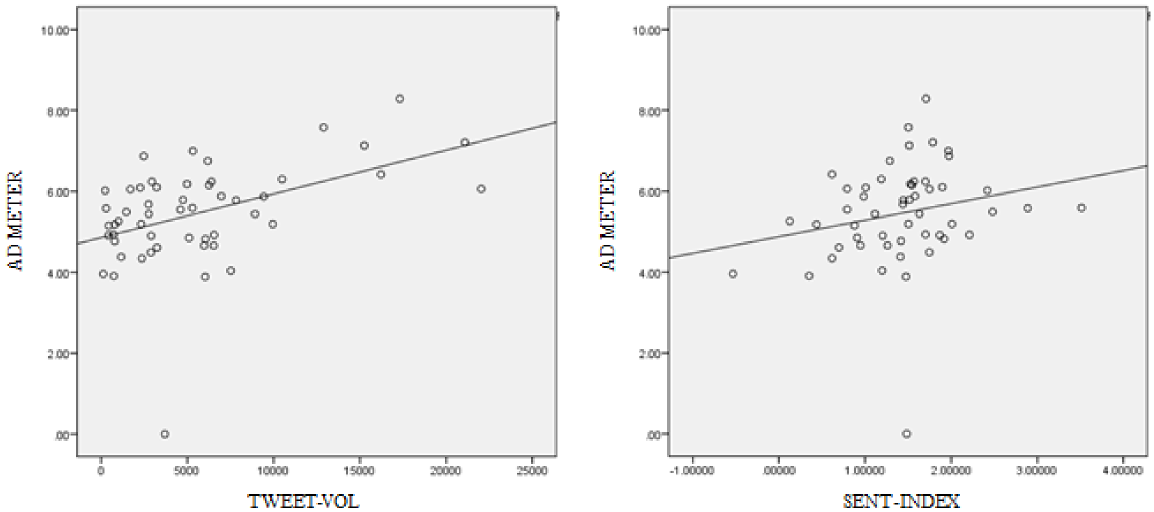

Figure 6: Scatter Plots relating *AD-METER* to *TWEET-VOL* and *SENT-INDEX*

Notes: The scatter plots above denote positive correlations for $TWEET\text{-}VOL_i$ and $SENT\text{-}INDEX_i$ with $AD\text{-}METER_i$.

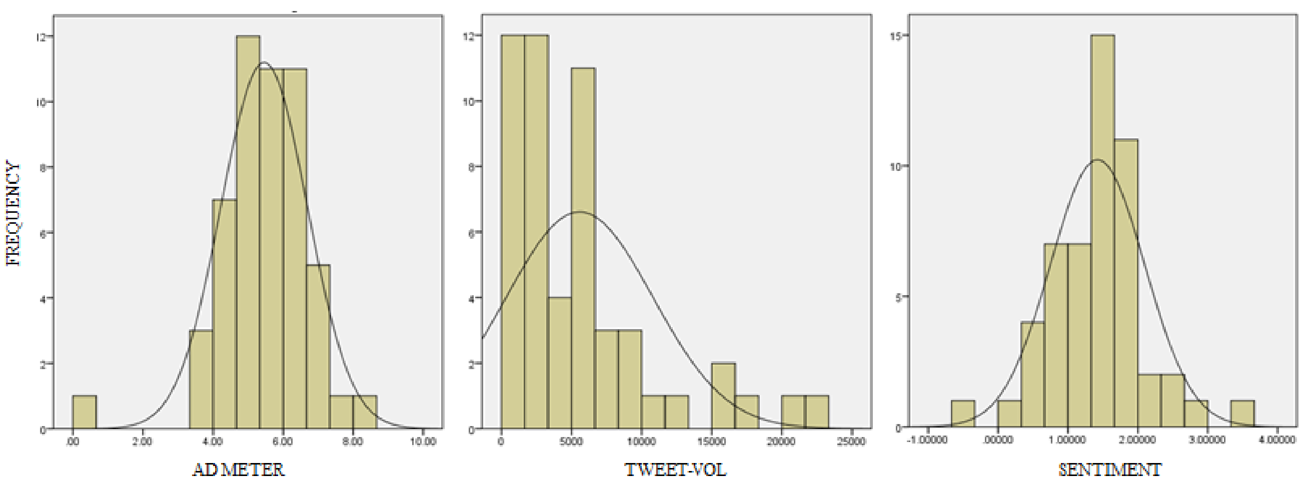

Figure 7: Histograms of *AD-METER*, *TWEET-VOL* and *SENT-INDEX*

Note: These histograms denote normal distributions for $AD\text{-}METER_i$ and $SENT\text{-}INDEX_i$ while a power-law distribution for $TWEET\text{-}VOL_i$.

Analysis & Results

As validation of our framework, we employed four Bootstrapping Linear Regression Models (Efron & Tibshirani [10]) with 1,000 bootstrap replications in examining the relationship between characteristics of Super Bowl ads and social media WOM measures with performance ratings obtained from *USA Today AD-METER*. The fundamental notion of bootstrapping is that inferences about a population from a dataset can be made by resampling from that dataset and conducting an estimation on the resampled dataset. Bootstrapping is most appropriate for small sample size dataset (as is the case in this study) and has been shown to be sound (Kim [21]). In addition, due to the large number of participants (525,000 unique tweet contributors), the large number of tweets (660,000) and the Super Bowl being the premiere advertising event of the year, we assert that pragmatism and external validity are supported in this dataset.

In this study we also employed a stepwise regression approach of Super Bowl ad characteristics and social media measures on *AD-METER* rating. Model 1 sets the baseline in relating control variables of Super Bowl ad likeability measures (*AD-LENGTH* and *HUMOR*) to *AD-METER* rating. Model 2 appends to Model 1 by relating the social media measure of sentiment (*SENT-INDEX*) for each Super Bowl ad with its *AD-METER* rating. Model 3 appends to Model 1 by adding the social media measure of Twitter message volume (*TWEET-VOL*) with its respective *AD-METER* ratings. And Model 4 combines both Model 2 and 3 in relating *TWEET-VOL* and *SENT-INDEX* to *AD-METER*. Discussion of the four models follows.

Relating Super Bowl ad characteristics to Ad Meter rating

$$AD\text{-}METER_i = \beta_0\text{*intercept} + \beta_1\text{*}AD\text{-}LENGTH_i + \beta_2\text{*}HUMOR_i + e_i \qquad (2)$$

Eq. 2 or Model 1 examined Super Bowl ad characteristics, specifically $AD\text{-}LENGTH_i$ and $HUMOR_i$ with $AD\text{-}METER_i$. Significant coefficients with a p-value at the 10% level were found between the predictors of $AD\text{-}LENGTH_i$ (β_1= .010) and $HUMOR_i$ (β_2 =.507) with $AD\text{-}METER_i$. The adjusted R-squared for Model 1 was a low 6.3%. This shows that our selected Super Bowl ad characteristics of humor and length of ad have a positive but weak relationship with ad performance. Intuitively ads with longer broadcast length and associations with humor are more likely to relate to higher ad performance. This sets a baseline for our results, which Table 8 outlines.

Relating Super Bowl ad characteristics and sentiment to Ad Meter rating

$$AD\text{-}METER_i = \beta_0\text{*intercept} + \beta_1\text{*}AD\text{-}LENGTH_i + \beta_2\text{*}HUMOR_i + \beta_3\text{*}SENT\text{-}INDEX_i + e_i \qquad (3)$$

Eq. 3 or Model 2 examined Super Bowl ad characteristics and the social media measure of $SENT\text{-}INDEX_i$ with $AD\text{-}METER_{\text{i}}$. Predictor $SENT\text{-}INDEX_i$ (β_3 = .426) was significant in relation to $AD\text{-}METER_{\text{i}}$. The adjusted R-squared for Model 2 was 13.7% signifying a marginal ability of the model to explain $AD\text{-}METER_{\text{i}}$. This finding shows the relevance of sentiment generated by social media in relation to ad performance. The coefficient for $AD\text{-}LENGTH_i$ (β_1= .011) is marginally significant at p-value of 10% while $HUMOR_i$ (β_2 =.454) is not significant in this model. Table 8 outlines the results.

Relating Super Bowl ad characteristics and tweet volume to Ad Meter rating

$$AD\text{-}METER_i = \beta_0\text{*intercept} + \beta_1\text{*}AD\text{-}LENGTH_i + \beta_2\text{*}HUMOR_i + \beta_3\text{*}TWEET\text{-}VOL_i + e_i \qquad (4)$$

Eq. 4 or Model 3 examined Super Bowl ad characteristics and the social media measure of $TWEET\text{-}VOL_i$ with $AD\text{-}METER_{\text{i}}$. Predictor $TWEET\text{-}VOL_i$ (β_3 = .00009) was significant in relation to $AD\text{-}METER_{\text{i}}$. The adjusted R-squared for Model 3 was 29.7% signifying a good ability of the model to explain $AD\text{-}METER_{\text{i}}$. This finding shows the relevance of volume of ad tweets generated by social media in relation to ad performance. Intuitively an increase of 10,000 tweets for an ad relates to a significant increase of .9 in the $AD\text{-}METER_{\text{i}}$ index. Both $AD\text{-}LENGTH_i$ (β_1= .006) and $HUMOR_i$ (β_2 =.354) are not significant in this model. Table 8 outlines the results.

Relating Super Bowl ad characteristics, sentiment and tweet volume to Ad Meter rating

$$AD\text{-}METER_i = \beta_0\text{*intercept} + \beta_1\text{*}AD\text{-}LENGTH_i + \beta_2\text{*}HUMOR_i + \beta_3\text{*}TWEET\text{-}VOL_i + \beta_4\text{*}SENT\text{-}INDEX_i + e_i \qquad (5)$$

Eq. 5 or Model 4 examined Super Bowl ad characteristics and the social media measures of $SENT\text{-}INDEX_i$ and $TWEET\text{-}VOL_i$ with $AD\text{-}METER_{\text{i}}$. Predictors $TWEET\text{-}VOL_i$ (β_3 = .00009) and $SENT\text{-}INDEX_i$ (β_4 = .430) were highly significant in relation to $AD\text{-}METER_{\text{i}}$. The adjusted R-squared for Model 2 was 37.6% signifying a stronger ability of the model to explain $AD\text{-}METER_{\text{i}}$. This finding shows the relevance of both volume of ad tweets as well as sentiment generated by social media in relation to ad performance. Both $AD\text{-}LENGTH_i$ (β_1= .007) and $HUMOR_i$ (β_2 =.3) were not significant in this model. Table 8 outlines the results.

Table 8: Bootstrap Linear Regression of $AD\text{-}METER_i$ on both Super Bowl and social media measures

	Model 1	Model 2	Model 3	Model 4
	β_i	β_i	β_i	β_i
Dependent Variable	*AD-METER$_i$*	*AD-METER$_i$*	*AD-METER$_i$*	*AD-METER$_i$*
AD-LENGTH$_i$	.010(.006)+	.011(.006)+	.006(.005)	.007(.005)
HUMOR$_i$	.507(.292)+	.454(.290)	.354(.254)	.3(.236)
TWEET-VOL$_i$			.00009(0)***	.00009(0)***
SENT-INDEX$_i$		.426(.145)**		.430(.130)**
cons	4.95(.311)***	4.308(.372)***	4.665(.31)***	4.014(.323)***
N	51	51	51	51
R-squared	.101	.189	.339	.429
Adjusted R-squared	.063	.137	.297	.376
replications	10000	10000	10000	10000

+ <.1, * <.05, **<.01, ***<.001.
β – beta coefficient with bootstrapped standard error in parenthesis.

DISCUSSION

This section presents the summary of the findings of the study as part of the *present* stage of the modified CUP SMA methodological framework. The framework, via its *identify*, *capture* and *understand* stages, processed 660,000 tweets during the 2014 Super Bowl and validated that social media measures, specifically volume of Twitter messages surrounding brands and ads (WOM), have value in relating Super Bowl ads to performance outcomes. In particular social media measures of brands and ads are relevant to ad ratings. This is evidenced by such ads as Budweiser's 'BestBud' and 'Hero's welcome' that generated a high volume of brand and ad messages as well as being rated highly in the Ad Meter rating. In addition, those ads with a higher proportion of positive WOM are more likely to obtain higher ad ratings as well. Thus we note a corollary between positive ads such as Budweiser's 'BestBud' and highly negative ads such as Sprint with their respective Ad Meter ratings. In short, social media measures can be a supplementary indicator of ad performance, especially for acquiring instant feedback at a low cost.

This framework shows resiliency and usefulness in extracting and analyzing social media measures for Super Bowl ads. This framework is generalizable to other domains as well in supporting the relevancy and pertinence of SMA research. In addition, such analytics may provide practitioners with accurate information in developing successful WOM strategies or campaigns for promoting successful consumer engagements. With this framework managers are able to make quality decisions quickly and accurately instead of relying on intuition, and researchers can use the tool to further explore social media inquiries.

Scholars have recommended other techniques in this stage including visual analytics using word clouds and social network maps (Stieglitz and Dang-Xuan [39]). Figure 8 illustrates an example of word clouds using Wordle.net generated from a sample of tweets for the Budweiser brand. This tool is useful in identifying frequently used terms accompanying the term 'Budweiser' such as 'commercial' and 'puppy' which could aid in design of hashtags or keywords for future ads. In addition, the words 'coke' and 'doritos' are also frequently mentioned alongside 'Budweiser' although at a lower frequency indicating competitors the firm should take notice of. Figure 9 shows the network maps of Twitter users who forwarded (also known as retweets) tweets containing the term 'Budweiser'. This map also identifies those individuals who were pushing WOM surrounding 'Budweiser' to their network of followers. Such individuals may be valuable to the Budweiser brand and should be considered for influencer marketing or other marketing actions.

Social media (Sasser et al. [37]) represent a nascent yet overwhelmingly popular IT phenomenon permeating all facets of the Internet. As social media are transferring more of the control of brand promotion into the hands of consumers, businesses are in flux in dealing with social media. Scholars have ascertained that analytics is critical in understanding social media (Davenport & Harris [7]). Thus this study contributes to the area of SMA research by implementing a framework that shows evidence of the value of social media predictors in relation to Super Bowl ad ratings. This framework is useful to both practitioners and researchers alike in demonstrating an SMA implementation and providing evidence of the value of social media.

Figure 8: Word cloud for Budweiser tweets created using Wordle.net

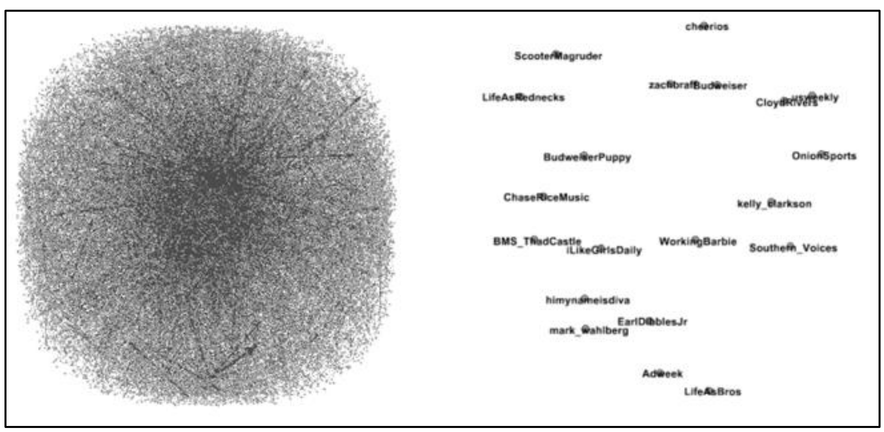

Figure 9: Network analysis graph of Twitter users that retweeted ‘Budweiser’ tweets. Shown here are for all users (left figure) and filtered by those generated more than 50 retweets (right figure).

CONCLUSION

Consumer engagement in social media is virtually unexplored (Schultz & Peltier [38]). Simultaneously businesses continuously seek better monitoring of their social media ROI but face immense challenges in measuring social media investments. This reflects the paucity of research in the area of SMA. We fill this gap by implementing a SMA methodological framework to allow practitioners to concretely measure social media indicators in relation to their brands and to gain a better understanding of consumers’ view of their brands. Specifically our framework shows how social media WOM surrounding Super Bowl XLVIII ads are identified, captured and analyzed in relating to their performance as measured by the *USA Today* Ad Meter ad likeability rating. We validated the framework by providing evidence that social media measures, namely volume of Super Bowl ad Twitter messages and sentiment, positively correlate with ad rating. Thus we contributed a systematically-researched and well-evaluated a SMA methodological framework that enables businesses to successfully monitor their investments as well as to facilitate the work of researchers in expanding on future social media inquiries.

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