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SECOND SCREENS AND SOCIAL SOUNDTRACK

A Dissertation in
Information Science and Technology

by

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ABSTRACT

The use of second screen devices (e.g. smartphones, tablets, etc.) integrated with social media technology facilitates social interaction about broadcast media events. I refer to such facilitation as the social soundtrack. The research presented in this dissertation deals with three research objectives surrounding the social soundtrack of Super Bowl XLIX, considered as the broadcast media event, on three social media platforms (*Twitter, Instagram and Tumblr*) on topical categories (*commercials, music and game*) at three phrases (*Pre, During and Post*).

In the first research objective, I perform statistical analysis on more than 3M, 800K and 50K posts from Twitter, Instagram and Tumblr, respectively to evaluate the change of social soundtrack conversations regarding the identified categories at the three specified phases. I identify the predominant phase and category of interaction across all three social media platforms. Results show significant phase-category relationships for all three social media platforms. The *During* phase is identified as the predominant phase for all three categories on all social media platforms regarding absolute volume of conversations. Concerning predominant category identification, the game category is prominent in a majority of the social soundtracks for all phases, with the exception of Tumblr with dominant peaks for music and/or commercials relative to game in all three phases.

The second research objective evaluates the relationship between social media conversing and search (Google) queries, concerning commercials. The causality analysis step of relationship evaluation shows that volume and attitude of social media conversations directly cause the web search for the respective brands. The attitude of social conversation is referred to the average sentimentality aggregated over time. Results also quantify the relationship social media conversing volume and attitude hold with searching volume for the set of brands on the social
media platforms. I also find that more individual brands go viral in the Post phase, highlighting the potential impact of cross channel advertising effects.

The third research objective deals with 1) phase based significance on two content aspects of the social soundtrack (attitude and formality) among the three categories and 2) finding the relationship that these two content aspects independently have with different attributes of second screen interaction (volume of conversations, patterns used in social media texts, number of sentences, and number of unique words). From the perspective of significance, the results show that attitude score (i.e., average sentimentality) of Super Bowl commercials dominates that of other categories throughout all social media platforms in all three phases. However, when broadening the scope to the social soundtrack formality, it is music that becomes the emergent category in all three phases. Regarding investigation of the relationship that attributes have with attitude and formality, it is found that URL based recommendation and undirected broadcast pattern in social media posts has positive correlation with viewers’ attitude in Pre and Post phases respectively, while undirected broadcast has positive correlation for Twitter and Tumblr with formality with the exception of Instagram where URL based recommendation has positive influence on formality in Pre and Post phases. The analysis shows that commercials dominate other categories in attribute-attitude relationship, but it is the music category that dominates in attribute-formality relationship compared to the other two categories in Pre and Post phases.

Evaluation of the research objectives is achieved by quantitative analysis of the identified communication platforms during Super Bowl XLIX. The outcome of this research has potential to help retailers identify the temporal shift of conversations on topical categories related to In-Real-Life (IRL) events broadcast. More specifically, marketers and content creators can utilize such results to identify the optimal time and forum to relay and disseminate their respective messages during major broadcast media events. Future research may take similar approaches as taken here,
while offering cross-comparison results among multiple broadcast media events to offer further valuable insights to retailers.
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Chapter 1

Introduction

Television (TV) is a social medium that connects people through the shared broadcast of programs. Before the rise of the internet, TV was considered to be a form of traditional mass media that enabled one way communication with one-to-many mapping. A TV program was centrally produced by a network channel and was received often, by large group of audiences but in no way could the audiences send feedback to the source or share their opinions. So the social element of traditional TV was limited and was based on watching of TV shows together and sharing reactions to the content in the same physical space. The social interactions concerning TV content were restricted to small groups within a confined space. This limited social linkage did not provide affordances for experiencing TV together with remote viewers, as the traditional TV experience lacks the necessary features for distant communication.

Role of Internet and Social Network

Digitization and the rise of the internet blur the boundaries between types of media, and smudge the distinction between individual and mass audiences. Rise of the internet substitutes the one-to-many traditional TV with interactive TV with the possibility of many-to-many mode of communications. Secondly, the notion of anonymous receivers is no longer entirely valid as the receivers can create identity in an online discussion forum regarding a TV show. The internet turns TV into a potentially interactive medium rather than it being one way as it was before. The interactivity enables the viewers to communicate with each other and address social issues using digital media tools particularly social networks.
Social networking sites allow people to create and maintain a network of friends or colleagues. By displaying pictures in their profile and delineating the social tastes, ties, favorites, and relationship statuses via social networks, the users make their identities in cyberspace. Users get involved with information exchange by means of writing on the “wall” of Facebook or posting tweets on Twitter, and hence contribute to virtual community building where people exhibit specific interests, know each other as participants of the same group, and possess a sense of belonging and allegiance toward the community.

With the advent of internet technology and the emergence of online social networking, the communicative possibility of TV have greatly expanded as the merging of technologies now allows a number of social activities and conversations concerning TV content via social networks (e.g., Facebook, Twitter, Weibo, etc.). This combination of TV and online social networks forges a social TV that imparts feelings of togetherness and communication among people in dispersed locations, though the influence of social media on social relationships is still a debatable issue (Pollet, Roberts, & Dunbar, 2011). Several researchers feel that social media interaction is a sterile form of social exchange compared to face-to-face communication. This form of communication may result in negative outcomes (e.g., loneliness, depression, restlessness, etc.) and therefore weakens the neighborhood feeling and community ties (Hafner, 2003; McKenna & Bargh, 1998). Others believe that social media and social networks open a new avenue of social communication that allows groups and relationships to be shaped by the exchange of resources such as information, influence, social support, knowledge, etc. between the actors (i.e., users) and, therefore, augment social connectivity (Haythornthwaite, 1996). The social network has embedded itself within the modern TV culture, and it acts as a social soundtrack for TV content, with a variety of implications for mass communication (Morales & Shekhawat, 2013). Social soundtrack is witnessed as a fundamentally new mode of human communication. TV broadcast has been augmented with vast amount of audience feedback that are predictive of audience
decisions of what to watch and how to interpret what they see. This new mode of communication reconceives how political campaigns of the future will be won, how marketers will sell, and over time this mass-interactive medium will give rise to new forms of news and entertainment.

Second Screen Phenomenon

While the use of handheld devices has redoubled over the past decade, TV remains the most popular and powerful entertainment media in the world. The objective of next generation connected devices is to link the TV with the computing/communication device.

Engaging TV with more than one computer technology simultaneously is referred to as second screen phenomenon. When combined with social media, this second screen phenomenon has the potential to be an important social soundtrack for a variety of cultural experiences. Based on televised broadcasts of TV shows, the social soundtrack is an interesting communication interactivity that can be both real time (e.g., during the live broadcast) and non-real time (e.g., not during the live broadcast). This social commentary happens on social networks. Engaging in chats via social soundtrack about a show is becoming a common way to discover new programs and decide what to watch. Once a show airs, social commentary often takes place for hours and days. As a result, cable providers and advertisers have new opportunities to engage their audience over longer spans of time. The integration of online social networks as the interactive medium with televised broadcasts marks the emergence of a new usage phenomenon augmenting the social possibilities of TV and other mass communication (Morales & Shekhwat, 2013). This new usage phenomenon is referred to as instantiation of the second screen (TV and computing device), although there may be multiple screens involved (TV and several computing devices). With the second screen phenomenon, the TV is the base device and the secondary screen is the computer (desktop or laptop), tablet, or smartphone. The secondary screen enables the social
soundtrack, the conversation with others, regarding the particular televised broadcast of a TV program.

The second screen is no longer a trend but an integral aspect of media experiences now - more than 84% of handheld device owners use their devices while watching TV shows. Several studies show a greater frequency of usage of smartphones and tablets while the TV program is being aired. The studies distinguish the higher percentage of comments or posts in the social network, about the content that is being watched. So tracking people’s preferences through the social networks and social media is now possible via second screen. There are certain events that happen In-Real-Life (IRL) (e.g. Super Bowl, Academy Awards, Music Video Awards, etc.) that are anchored temporally and do not lend themselves to recordings for later viewing, unlike a seasonal TV show. Hence, the second screen interactions about an IRL event leads to a social soundtrack fixed in duration. These IRL events that have multiple facets, often generate substantial social soundtracks. The popularity of an IRL event intuitively increases the social soundtrack volume from the perspective of postings on social media platforms. The information in the social soundtrack may refer to different event aspects (e.g., actors, directors, costumes, characters, themes, etc. for a show; players, coach, style, etc. if the event is a sporting event; or brand, sale, customer preferences, etc. for advertisements). It is seen that the big sporting events and the Academy award show are the prime second screen territories (Zhachary & Greenwood, 2014). In a separate study on commercials televised live during the Oscar, there is 19% increase in click through rates for real time ads compared to controlled ads from the perspective of second screen insights (Gevelber, 2015). In another study viewers paid more attention to commercials while watching the Super Bowl than commercials televised during normal primetime TV

1 www.clickz.com
programs (Yelkur, Tomkovick, & Traczyk, 2004). The second screen phenomenon serves channel providers and marketers to gather contextual insights about the viewers, as they share feelings and information about the content of broadcast IRL media using second screens. The second screen technology also leads to increasing brand and IRL event engagement as mining and analysis of the second screen experience opens opportunities for tailoring content to individual consumers. Potential customers are excited about the control they have of their media consumption. So the second screen experience is considered a big wave with respect to broadcast of IRL events where this *convenience innovation* adds significant value from perspective of change in consumer behavior. The second screen offers insights into consumer’s mind while the primary screen (i.e. TV) remains the optimum screen for viewing. With a majority of users hopping between secondary devices and TV, brands should aim to provide custom app experiences that keep viewers engaged and coming back for more. For today's multi-device-using audience, providing great content and facilitating social sharing can increase the chance of an ad campaign to receive widespread attention while broadcasting an IRL event. Consumers are no longer stuck with a set choice for how to consume media. By means of exploitation of users’ second screen experiences, where the content can go viral, the cable providers and retailers can keep viewers engaged with the show or televised brand. Marketers can create compelling campaigns by amplifying and adding value to what people are interested in when they turn to their second screens. TV viewers often want to know more about what they're watching, and brands can capture their interest in these moments of curiosity. So if there is something big happening on the first screen (TV), it will affect what is happening on the second screen, too.

As the second screen interaction is embedded within the media broadcast of IRL events and acts as social soundtrack of the events content, the attributes of second screen interaction such as number of sentences per social media post, communication style using second screens, volume of conversation, etc. have implications for the formality / attitude of viewers, diffusion of
information, influence over public opinions, decision making, and technological future of mass communication to name a few. The second screen interaction via social media integrates different modalities of communication such as reciprocity, broadcasting, and reference-sharing etc., with different kinds of content (e.g., text, images, URLs and videos). This flexibility leads to the plausible assertion that social media interaction using second screens renders changes in social interaction behavior for the pop culture.

There has been little academic research concerning this increasingly important second screen interaction related to IRL event and little practitioner research beyond that the phenomenon is occurring. The analysis of the second screen interaction attributes associated with broadcast of IRL events is also scarce. The emergence of social media and the second screen changes the viewing habits of the audience from strictly passive to more active, and it is potentially impactful as an emerging social behavior.

In this research, I consider Super Bowl XLIX as one such IRL broadcast media event. It happens once a year and is a major event especially in the U.S. The Super Bowl event itself comprises multiple topical sub-events that are labeled as categories. In my research I took three such categories known as 1) Super Bowl commercial, 2) Super Bowl music, and 3) Super Bowl game. I select three popular social media platforms (Twitter, Instagram, and Tumblr) as the data collection sites to research the changes in second screen interactions related to Super Bowl XLIX in three temporal phases; a) Pre phase, b) During phase, and c) Post phase. In my dissertation, I present three research objectives described in the next three chapters. In the first research objective I investigate the use of the secondary screens during the Pre, During, and Post phases of the Super Bowl XLIX, specifically examining if viewer interactions concerning commercials, game, and music categories differ in Pre, During, and Post event phases. In the second research objective, I consider Super Bowl XLIX commercials as the domain for both social soundtrack conversations and web searching data. Google is used as the medium of web search. Here I
investigate the influence of social media conversations on web search along with causality
analysis, and also examine the change in viral propagation of tweets on Twitter and change in
web search volume about the brands between two phases (Pre and Post) of an event. In third
objective, I examine a) if formality and attitudes extracted from viewer interactions concerning
Super Bowl commercials, game, and music categories differ in Pre, During and Post phases, and
b) evaluate the relationship the attributes of second screen interaction has with the attitudes and
formality extracted from viewer interactions concerning Super Bowl commercials, game, and
music categories in each of the event’s phases. I also measure the comparative effect of categories
on this evaluated relationship.

This research is important as the degree and manner of usage of secondary screens in
conjunction with IRL broadcast media events can facilitate retailers, broadcasters, and artists to
manage branding and awareness campaigns by understanding the relationship among phase-
category pairs and different social media platforms via social soundtrack conversations. As online
information sharing is becoming a more powerful marketing venue, understanding the causality
between social soundtrack and web search along with degree of influence of one temporal data on
the other can provide significant business insights to retailers in managing online brand
awareness. Additionally it helps to understand the relationship between interaction features,
patterns of interactions, and attitude of viewers, along with the effect of different social media
platforms on social soundtrack conversations. Findings also shed light on social interaction in
cross technology usage of second screens, and the impact on information sharing and diffusion of
viewership.

I provide three research objectives in the next three chapters. All three chapters comprise
the following sections: 1) Introduction, 2) Literature review, 3) Research Questions, 4) Data
Collection and Research Design, 5) Methodology, 6) Results, 7) Discussion and Implications, 8)
Limitations, and 9) Conclusion. Each section is further subdivided into relevant subsections.
Chapter 2 delineates the first research objective regarding evaluation of relationship between Super Bowl phases and Super Bowl categories from the perspective of second screen conversation on social soundtrack mediums and investigates the temporal significance of emerging categories (phases) across phases (categories). The literature review of chapter 1 deals with prior research on how social media helps information sharing, and how the second screen assists in sharing the feelings among viewers of a TV show, particularly media broadcast for IRL events, to name a few. The research question section is associated with multiple research hypotheses from the perspective of the phase-category relationship regarding change in social soundtrack conversations via second screens. The data collection and research design section speaks about the volume of data collected in three social media platforms, how the data is collected, and how the phases and categories are identified. The methodology section illustrates the relevant statistical procedure to test the research questions regarding measurement of the phase-category relationship and temporal emergence of phases and categories, while the findings of the tests are represented in the results section supported by tables and figures. The discussion and implications section discusses the results and the importance. Finally the limitations are specified.

Chapter 3 talks about the second research objective related to the causality analysis prior to quantify the relationship 1) between the attitude and web search, and 2) between volume of second screen interaction and web search from the context of Super Bowl commercial category. The literature review section sheds light on prior research on the interplay among social media conversation, information sharing, digital advertisement and web searching activities. The research question section identifies the research questions and associated research hypotheses corresponding to a) linkage between social media and web search, and b) change in viral effect on Twitter in Super Bowl phases. The data collection and research design section tells about the volume of data collected in three social media platforms, identification of commercial category,
extracting of the brand names from Super Bowl commercial, collection of web search data from a major search engine, how the volume and attitude from brand mentioning on the social soundtrack are measured, and how viral tweets are estimated from Twitter. The methodology discusses the relevant data structure and procedures used to test the social soundtrack-web search causality and relationship, and to test the difference in viral tweets in phases. The findings are mentioned in the results section with tables and figures. The next section discusses the results and its implication for brand marketing. Finally, the chapter concludes by specifying the limitations in the study.

Chapter 4 describes the third research objective regarding a) phase-wide change in formality and attitude of each of three Super Bowl categories, and b) relationship the attributes of second screen interaction and the attitudes and formality concerning Super Bowl commercials, game, and music categories in each event’s phases. The literature review section discusses the previous research on formality and attitude of second screen interaction via social media. The research question section handles the pertinent research questions and associated hypotheses related to a) temporal phase-wide shift in attitude and formality of the social soundtrack regarding Super Bowl categories, and b) correspondence between social soundtrack attributes and viewer attitude/formality. The data collection and research design section has to do with the quantity and procedure used to collect data on Twitter, Instagram and Tumblr, the conversion of data into a continuous scale, and the organization of data based on a relevant data structure. The methodology section takes care of the estimation of social soundtrack formality and attitude, and identifies the relevant statistical test and learning procedure to test the research questions. The result section represents the findings from the test in the form of tables and figures. Like chapter 2 and chapter 3, the discussion and implication section explores the results and the importance on viewer’s temporal shift on topics related to IRL events. Next section concludes with the future work and limitations.
The final chapter synthesizes the exploration of analysis done in my dissertation and will discuss the work and issues that are not presented in this research and will be taken care of in the future along with the extension of current work that remains unexplored in present study.
Chapter 2

Second Screen Interaction on Social Soundtrack for an IRL Event

Given the near ubiquitous use of online social media sites with access to mobile technology, the conversational aspects concerning broadcast media events have greatly increased, as the synergy of these technologies permits online social dialogues to occur by viewers. The combination of online social media platform and mobile technology permits online conversations that convey feelings of togetherness and communication among people, often in dispersed locations. Social media platforms and mobile technologies have embedded themselves alongside the modern broadcast medium, facilitating the creation of a social soundtrack for the event.

The social soundtrack is an interesting conversational form of information sharing and interaction that can be both real time (i.e., during the live broadcast) and non-real time (i.e., before or after the live broadcast) based on the timing of event. The social soundtrack concerning such events can happen on various social media platforms. The integration of these social media platforms as the conversational media in conjunction with communicating about in real life events using mobile devices marks the emergence of a phenomenon that greatly augments prior social aspects of such broadcast mediums. This technology affordance for online conversation about an event is referred to as the second screen phenomenon, although there may be multiple (i.e., more than two) screens involved.

In the second screen phenomenon, the broadcast media event is shown on the base device where the viewing occurs (i.e., usually the largest screen), while the secondary screens are the computing devices (e.g., tablet, smartphone) that facilities the conversation. It is the secondary screen that allows for creation of what I refer to as the social soundtrack, the online conversation
with others regarding a real life event. The social soundtrack participants, which are the viewers of the event, exchange social media comments via second screen devices in terms of sharing of messages (Mukherjee & Jansen, 2014). The interchange of information can happen live (i.e., during the event) or when the event is not live (i.e., before or after of the event, relative to the start and end of the event). The content of posts in the social soundtrack may contain different aspects such as actors, directors, costumes, characters, and themes for a show; players, coach, and style if the event is a sporting event, or brand, sale, or customer preferences if the event is an advertisement. TV broadcast of the events that happen In-Real-Life (IRL) (e.g. Super Bowl, Academy Awards, Music Video Awards, Grammys, sports, broadcast of natural disasters etc.) are unique happenings with substantial social tracks, as these events do not lend themselves to recordings for later viewing, unlike, for example, a seasonal TV show.

Therefore, the second screen interactions about an IRL broadcast event leads to a social soundtrack that is fixed in duration, with the period bounded by the event’s Pre and Post phases, including the event’s During phase. The popularity of an IRL event intuitively increases the volume (i.e., number of posts) of social soundtrack from the perspective of commentary left on social media platforms. For this research, I consider Super Bowl XLIX as one such IRL broadcast media event. It happens once a year and is a major happening, especially in the US.

Aside from being just a sporting experience, the Super Bowl event involves multiple topical sub-events of interest, which I label as categories. For the game itself, the teams, coaches and the players are important for viewer engagement. The Super Bowl commercials also hold distinct appeal for many viewers and have become a cultural phenomenon, alongside the game itself. The music performances conducted during the halftime show are also an important facet of this most popular media event in the US. In this research, I investigate the social soundtrack for each of these three Super Bowl XLIX categories.
There has been limited academic research concerning the increasingly important second screen phenomenon and little systemic practitioner investigation. In this research, I investigate the use of the secondary screens during the Pre, During, and Post phases of Super Bowl XLIX, specifically examining if viewer interactions concerning commercials, game and music categories differ in Pre, During, and Post event phases. I select three popular social media platforms (Twitter, Instagram, and Tumblr) as my data collection sites to research the changes in second screen interactions throughout the phases of Super Bowl XLIX.

This research is important in highlighting the changing nature of viewership, moving from a passive to a more active role. Findings can indicate the technological affordances of mobile devices in moving the traditionally passive role a viewer into a more active, participator role. This is important practically as the degree and manner of usage of secondary screens in conjunction with IRL broadcast media events can facilitate retailers, broadcasters, and artists to manage branding and advertising campaigns by understanding the relationship among phase-category pairs and different social media platforms via social soundtrack conversations. Finally, findings shed light on social communication in relationship to the schedule of IRL broadcast media events, the social interaction in cross technology usage for second screens, and the effect of social soundtrack on pop culture and human information processing.

The rest of the paper is organized as follows. Section 2 introduces the background research from the perspective of information sharing via social soundtrack, integration of TV and secondary screens and media broadcast of IRL events. Section 3 provides detailed explanation of my research questions and hypotheses. Then, Section 4 presents the data collection and research design in details. Section 5 demonstrates the methodology to evaluate the research questions and hypotheses, followed by the result, along with discussion and implication in Section 6 and Section 7 respectively.
Literature Review

Social Media and Information Sharing

There has been prior research on information seeking and information sharing via social sites to augment user enrichment. For example, it was claimed that content and technology gratifications were the two key factors that drive user satisfaction with social media communication (Liu, Cheung, & Lee, 2015), which was reflected in a study that experimented with Facebook groups focusing on discussion related to diabetes and found out that the user community aimed to construct the identity and recognition by information integration (Greene, Choudhry, Kilabuk, & Shrank, 2011). Different dimensions of user’s motivation of using social media to share personal experiences and information were analyzed, which in turn influenced the social support between anonymous users (Oh & Syn, 2015). In a field study, Joannah-Sin (2015) investigated the variation in problematic informational outcomes with the use of different social mediums between genders while in another research, Jansen, Sobel and Cook (2011) classified ecommerce information sharing behavior of the youth that used multiple social media platforms. In the context of production, flow and consumption of information via social media communication within virtual communities, a significant homophily among the user categories was found in Twitter (Wu, Hofman, Mason, & Watts, 2011). In another field study on social networks, it was claimed that weaker ties in social graph played more dominant role in dissemination of novel information through social media platforms (Bakshy, Rosenn, Marlow, & Adamic, 2012). Regarding research on information sharing about media broadcast, it was claimed that end user enrichment enhanced the social possibilities of broadcast events via information sharing with event related user generated content on social media (Alliez, 2008). All these works focused on the user’s information sharing behavior supported by social networking platforms. My
research builds on this prior work by specifically introducing the concept of the social soundtrack as an information sharing conversation medium.

Integration of TV and Second Screen

There has also been research concerning second screen interactions on social media platforms from the perspective of end user engagement and generation of social media posts regarding TV shows. Prior research found that Twitter was increasingly used as real time audience communication channel for sharing TV experiences where the viewers were creating parallel narratives for events via second screen (Lochrie & Coulton, 2012). A modest interest among users was observed in using secondary screen to share information while viewing TV shows (Courtois & D’heer, 2012). In an experiment with engagement of users with second screens, users’ second screen behavior were examined concerning where and when people switch their attention between the primary and second screen (Leroy, Rocca, Mancas, & Gosselin, 2013). Prior research had also observed that sufficient social media is generated via texting on different social media sites using second screens (Lenhart, 2012). While conducting the social possibilities of TV affected by second screens, viewers’ sentiments concerning US National Football League teams were analyzed by mining social media tweets in order to enable the viewers to better select the interesting programs (Zhao, Zhong, Wickramasuriya, & Vasudevan, 2011). In other research related to generation of online social interactions, the resulting buzz of specific American reality show related tweets on the TV screen were investigated during the show (Benton & Hill, 2012). It exhibited that the specific tweets with new information resulted in more user engagement than the general tweets during airing of TV show. In a separate research concerning engagement of users about seasonal TV shows via second screen, predominant conversation patterns in TV show-related social media posts during live and after live broadcast
of US TV shows were examined and found that the different conversation patterns became predominant when the TV show was broadcast live compared to when it was not in the air (Mukherjee, Wong, & Jansen, 2014). Regarding viewers’ conversation in groups about a TV show it was found that viewers generated substantial social media when the show was not being transmitted (Mukherjee & Jansen, 2015b). Examining the conversational patterns at the interplay of second screen, social soundtrack and TV for different cultural biases, social media conversational patterns differed between US and non-US TV shows both in real time transmission and after live broadcast (Mukherjee & Jansen, 2015a). However, none of this prior research measures the temporal interaction effects of social networks and second screens concerning IRL events, which is what I examine in this research.

**IRL Event Based Social Media Conversation**

As the prevalence of seasonal TV (i.e., a broadcast show scheduled over several weeks with new episodes released at intervals) has decreased, my research focus is on what I refer to as IRL broadcast media events. These broadcast media events are those IRL events that are anchored temporally and do not lend themselves to delayed viewing (i.e., recording and watching at a later time). These IRL events can also generate substantial social media conversation (Lenhart, 2012; Lindsay, 2011; Oulasvirta, Rattenbury, Ma, & Raita, 2012). Regarding research on natural disasters, Palen (2008) studied how social media is successfully used in wide range of organizations for crisis and disaster management from the perspective of recovery capabilities. In a separate study, Sakaki, Okazaki and Matsuo (2010) analyzed the real time Twitter interactions concerning earthquakes and proposed an earthquake reporting system. For sports related events the value of social media tools helped sports marketers and retailers to enhance the relationship marketing process (Williams & Chinn, 2010). Adidas used Twitter to become the most-talked-
about brand in FIFA 2014 (Ruvolo, 2014). The digital mediatization of Olympic 2008 was intensified in terms of amount and types of content posted in different social media platforms (Hutchins & Mikosza, 2010). Tang and Cooper (2012) evaluated the relationship between the gender groups and the use of social media for Olympics 2008. Wang, Can, Kazemzadeh, Bar and Narayanan (2012) analyzed the public sentiment for the 2012 US presidential election while in a distinct research, focused group of users with similar biases were identified based on prior users’ behavior on Twitter for the 2012 US presidential election (Lin, Margolin, Keegan, & Lazer, 2013).

Integration of Prior Research

For this research, the specific IRL broadcast media event, I examined is Super Bowl XLIX. Prior research studies on the interplay among second screens, IRL broadcast events, and social media regarding Super Bowl is limited. The growing presence of Super Bowl 2012 was measured by tracking the number of comments posted particularly in Twitter compared to that in 2011 (Dumenco, 2012). Twitter was used as the social media platform to assess people’s interest in car-related commercials aired during Super Bowl 2012 and tweet patterns were analyzed to identify the relationship between tweets and nature of commercials (Lee, Kim, Kim, & Han, 2014b). Regarding research of participation using second screens on content analysis of TV shows, the second screen interaction on Twitter was studied to address the creation of consumer interest in brands televised during Super Bowl 2014 (Shin, Byun, & Lee, 2015). Though the aforementioned research speaks to the usage of social networks to analyze viewer interactions concerning an event, prior research failed to investigate in a systemic manner the interplay among temporal phases of an IRL event, different social media platforms, and the multiple inherent categories within the social soundtrack via second screens, which I do in this research. Also, prior
research has been mainly limited to single social media platform, while I investigate three social media platforms in this research.

**Motivation for the research**

As such, from prior works, there are several unanswered questions concerning the second screen conversation concerning IRL events. *How is social media technology used during the live broadcast of an IRL event? How does the media broadcast of IRL events influence the social soundtracks? How does an IRL event based social commentary in the social soundtrack influence interaction on different aspects of the event in phases?* These are some of the questions that motivate my research on investigating the relationship between Super Bowl phases and Super Bowl categories on the social soundtrack from multiple social media platforms.

**Research Question**

The social environment influences and shapes individual human behavior (Ashford & LeCroy, 2009). The making of broadcast media events that are more social therefore influences human communication in a socially mediated way, affecting human thoughts and actions. The viewers of an IRL event use second screens to post messages concerning the broadcast event on online social media platforms, which are the medium of conversation to build social relationships. Therefore, the social soundtrack can both influence and shape the social environment via the information sharing of the participants.

For clarity, I define three of my key constructs:

(1) **Second screen** – Computing device used for posting social media content to the social soundtrack.
(2) **Social soundtrack** – Collection of social media posts from second screens concerning a particular event.

(3) **IRL broadcast media event** – Happening anchored temporally and not lending itself for delayed viewing.

Within the spectrums of US broadcast media events shows, there are certain programs that draw a great deal of social media attention. Among these, I consider Super Bowl XLIX in my research, as it was the most-watched American television program in history, at the time of the study, with an average audience of 114.4 million viewers (Schalter, 2015a). Due to the high degree of viewership for the Super Bowl, companies (e.g., Budweiser, Nationwide, McDonalds etc. for Super Bowl XLIX) sponsor expensive commercials televised during the event. An integral aspect of the Super Bowl event, Super Bowl commercials have become a cultural phenomenon of their own, alongside the game. A considerable number of people watch the event primarily to see and discuss the commercials. In addition to the game and ads, popular and iconic performers and musicians (e.g., Katy Perry, Lenny Kravitz and Missy Elliot for Super Bowl XLIX) take part in the half time show on game day.

In my research, I select three social network platforms for social soundtrack data collection, Twitter, Instagram and Tumblr. Twitter is one of the most popular micro-blogging sites. Most micro-blogging services share commonalities and are used for discussing brands (Jansen, Zhang, Sobel, & Chowdury, 2009). Instagram is a medium of communication where users perform capturing and online sharing of images and videos (Hu, Manikonda, & Kambhampati, 2014a). Tumblr is second largest microblogging service after Twitter. It supports eight types of posts such as 1) images, 2) videos, 3) audios, 4) text, 5) answer, 6) links, 7) quotes, and 8) chat (Chang, Tang, Inagaki, & Liu, 2014).

There is considerable discussion in the social soundtrack on three aforementioned categories of game, commercials, and music, not only during but before and after the Super Bowl
event. I term these temporal phases of Super Bowl event oriented social soundtrack conversation periods as: 1) *Pre* phase, 2) *During* phase and 3) *Post* phase. The *Pre* phase highlights the audience interaction and starts weeks ahead of the event day and continues until the event starts, with the opening kick-off. The *During* phase is the period of the live broadcast of the event, in this case from kick off to final second of the game. *Post* phase is the social sound track beginning the moment the event is over extended to some point of time in the future.

In my research, I classify the second screen interactions into three broad Super Bowl-related second screen categories: 1) commercials, 2) music and 3) game to identify the dependence of these categories among Super Bowl phases: 1) *Pre*, 2) *During*, and 3) *Post*.

Again, for clarity, I define two more my key variables:

1. **Event Category**: Classification of posts within the social sound track concerning an event sub-topic.

2. **Event Phase**: Distinct period of an event for temporal classification of social sound track posts.

For this research, I believe social soundtrack conversation regarding the specific Super Bowl categories changes in various Super Bowl phases. The social soundtrack conversation will also most likely change in specific Super Bowl phases for different categories. So, my premise is that there is a phase-category relationship in second screen conversations that exists for each of the three social media platforms. Based on this intuition, I formulate my first research question testing the relationship among Super Bowl phases and categories for each of these three social media platforms.

*RQ1. Does there exist a social soundtrack relationship w.r.t. volume of posts among Super Bowl categories and Super Bowl phases based on the social media platform?*
This research question informs retailers and marketers curious as to the dominance of the specific category in a specific phase during second screen communication on specific platforms. In a previous study based on a survey of Super Bowl XLIV viewers (Johnson & Lee, 2011), the primary contributor to viewer’s enjoyment was the competitiveness of the game itself with the specific teams competing. This indicates significantly more enjoyment based on the level of fandom towards a specific team. The next largest category was the Super Bowl commercials that were rated higher than the Super Bowl musical entertainment (e.g., pre-game show, the national anthem, the halftime entertainment etc.). The ad agencies engage to buy their slots and build up the ads days before the game and practice follow ups afterwards as prices rise for the leftover slots as the game gets closer (Farhi, 2014). On the other hand, NFL uses halftime show as the revenue stream to contribute significantly in post-Super Bowl tour profit (Florio, 2014). So, the Super Bowl categories have temporal aspects before, during and after the IRL event. To examine the phase-category relationship, I define the following hypotheses.

Hypothesis 01: There exists a relationship w.r.t. volume of posts among Super Bowl categories and Super Bowl phases in second screen conversations on Twitter.

Hypothesis 02: There exists a relationship w.r.t. volume of posts among Super Bowl categories and Super Bowl phases in second screen conversations on Instagram.

Hypothesis 03: There exists a relationship w.r.t. volume of posts among Super Bowl categories and Super Bowl phases in second screen conversations on Tumblr.

The first research question identifies the phase-category (in)dependence but does not identify the change in second screen interactions in Super Bowl categories among Super Bowl phases. Neither does it determine the change in interactions in Super Bowl phases among Super Bowl categories. This leads me to formulate my second and third research questions that are characterized by interplay of specific Super Bowl categories and three Super Bowl phases.
RQ2. Does volume of second screen conversation w.r.t Super Bowl categories in the social soundtrack significantly differ among Super Bowl phases?

RQ3. Does volume of second screen conversation w.r.t Super Bowl phases in the social soundtrack significantly differ among Super Bowl categories?

The second and third research questions highlight multiple perspectives. The social soundtrack conversations related to the categories via social networks enlighten the commercial opportunities (Zhang, Jansen, & Chowdhury, 2011) at the intersection of the social networks, the broadcast media event, and second screens. Communication via second screens identifies the adaptation of social media as the driver of interaction from the perspective of the viewing audience, whilst the event is (not) broadcast live. I examine my second research question by forming three research hypotheses.

_Hypothesis 04: There is a significant difference in volume of second screen conversation in the social soundtrack related to Super Bowl commercials among the Super Bowl phases._

_Hypothesis 05: There is a significant difference in volume of second screen conversation in the social soundtrack related to Super Bowl music among the Super Bowl phases._

_Hypothesis 06: There is a significant difference in volume of second screen conversation in the social soundtrack related to the Super Bowl game among the Super Bowl phases._

Hypothesis 04, Hypothesis 05, and Hypothesis 06 are tested with the absolute volumes of categorical conversations in continuous scale among Super Bowl phases. Here absolute volume in continuous scale means that the volume of conversation is converted as a ratio between volumes of social media interaction at an instant to the best of highest values of volume among all records among all Super Bowl categories. I are also curious to test the hypotheses w.r.t relative volumes
of conversations of a specific category in a specific phase and interested to find out the dominant phase w.r.t relative volumes across three conversation categories. I have an intuition that the inter-phase relative volumes of conversation for a specific category (i.e., relative volumes of posts for a particular category over three different phases) may yield a different scenario compared to that with absolute continuous scale volumes of postings of a specific category over three phases. I further formulate three hypotheses for research question 2 taking relative volumes of posts into account.

*Hypothesis 07:* There is a significant difference in relative volume of second screen conversation in the social soundtrack related to Super Bowl commercials among the Super Bowl phases.

*Hypothesis 08:* There is a significant difference in relative volume of second screen conversation in the social soundtrack related to Super Bowl music among the Super Bowl phases.

*Hypothesis 09:* There is a significant difference in relative volume of second screen conversation in the social soundtrack related to the Super Bowl game among the Super Bowl phases.

Each of the six aforementioned hypotheses addresses Super Bowl commercials; music and game categories separately among the Pre, During, and Post Super Bowl phases.

Testing with intra-phase relative volumes of posts for the categories is synonymous to testing with the absolute volumes of categories as the intra-phase relative volume for a particular category represents what percentages of total volume of conversation in a time frame belongs to that category in a specific phase. The total volume of conversation in a period is the summation of posts corresponding to each of these three categories at that time.

So, research question 3 begets three hypotheses.
Hypothesis 10: There is a significant difference in volume of second screen conversation in the social soundtrack in Pre-Super Bowl phase among Super Bowl categories.

Hypothesis 11: There is a significant difference in volume of second screen conversation in the social soundtrack in During-Super Bowl phase among Super Bowl interaction categories.

Hypothesis 12: There is a significant difference in volume of second screen conversation in the social soundtrack in Post-Super Bowl phase among Super Bowl interaction categories.

Hypothesis 10, Hypothesis 11, and Hypothesis 12 are tested with the absolute volumes of phase based conversations in continuous scale among Super Bowl categories. Here absolute volume in continuous scale is the ratio between volumes of social media interaction at an instant to the highest value of volume among all records in a particular phase.

The hypotheses related to third research question address the significance of Pre, During and Post-Super Bowl phases separately for Super Bowl commercials, music and game categories in the social soundtrack communication.

Data Collection and Research Design

Super Bowl XLIX took place on the 1st of February (Sunday) 2015 in University of Phoenix Stadium, Arizona, USA. The kick-off time was 6:30 PM Eastern. The NBC channel broadcast the event. Super Bowl XLIX is considered the most watched program in American television history (Patra, 2015), at the time of the study. The average number of viewers was 114.5 million, reaching 118 million during the half time show (Wikipedia, 2015d).
I collected data related to Super Bowl XLIX from the 10th of January 2015 and continued till the 24th of February 2015, as shown in Table 2-1. Three social media platforms were used as data collection sites. To collect data, I embedded the respective APIs and tokens for Twitter, Instagram and Tumblr in corresponding scripts with search queries. There was a list of queries that includes: ‘superbowlxlix’, ‘superbowl49’, ‘superbowlcommercial’, ‘superbowlAd’, ‘halftimeshow’, ‘superbowlhalftime’, ‘sb49’ and ‘football’. The aim of forming this list of queries was to collect data for this research using each term as a search query on all three social media platforms. The query list was formed with these terms as they occurred most frequently as tags (e.g., #superbowlcommercial, #superbowlxlix, #halftimeshow, #superbowl49 etc.) in a sample data set for all social media platforms collected against the seed query named “superbowl”. The sample data was collected for 48 hours (i.e. from 01/06/2015-16:00:00 to 01/08/2015-16:00:00) to identify the potential search queries, and the sample data was not included in the data set used in this analysis.

<table>
<thead>
<tr>
<th>Volume</th>
<th>Twitter</th>
<th>Instagram</th>
<th>Tumblr</th>
</tr>
</thead>
<tbody>
<tr>
<td>Volume</td>
<td>3,112,789</td>
<td>811,262</td>
<td>51,569</td>
</tr>
</tbody>
</table>

**Data Collection in Super Bowl Phases**

The data collection period for Super Bowl XLIX is divided into three temporal phases (i.e., Pre, During and Post) to evaluate phase-category (in)dependence. Table 2-2 shows the date and time of each Super Bowl phase.

| Table 2-2. Start and end dates and time for Super Bowl phases |
Super Bowl Phase | Start Date-Time | End date-Time
--- | --- | ---
Pre | 1/10/2015-00:00:00 | 2/1/2015-18:29:59
During | 2/1/2015-18:30:00 | 2/1/2015-22:30:00
Post | 2/1/2015-22:30:01 | 2/24/2015-00:00:00

I further display the distribution of the posts collected during three Super Bowl phases on three social media platforms in Table 2-3 and Table 2-4. Table 2-3 shows the data collected during each Super Bowl phase, while Table 2-4 shows the mean per hour posting during each phase. From Table 2-3, it is noticed that though the volume of posts for Pre and Post-Super Bowl phases are higher than that During phase, the rate of second screen interaction for Pre and Post-Super Bowl phases is lower than the During Super Bowl phase (see Table 2-4).

Table 2-3. Volume of collected Super Bowl XLIX social media data in Pre, During and Post phases on social media platforms

<table>
<thead>
<tr>
<th>Social Media</th>
<th>Pre Phase</th>
<th>During Phase</th>
<th>Post Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>1,753,458</td>
<td>35,525</td>
<td>1,323,806</td>
</tr>
<tr>
<td>Instagram</td>
<td>452,761</td>
<td>16,459</td>
<td>342,042</td>
</tr>
<tr>
<td>Tumblr</td>
<td>24,695</td>
<td>6,544</td>
<td>20,330</td>
</tr>
</tbody>
</table>

Table 2-4. Hourly mean volume of collected Super Bowl XLIX social media data in Pre, During and Post phases on social media platforms

<table>
<thead>
<tr>
<th>Social Media</th>
<th>Pre Phase</th>
<th>During Phase</th>
<th>Post Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>3,211.46</td>
<td>8,881.25</td>
<td>2,500.76</td>
</tr>
<tr>
<td>Instagram</td>
<td>829.23</td>
<td>4,114.75</td>
<td>630.86</td>
</tr>
<tr>
<td>Tumblr</td>
<td>45.23</td>
<td>1636</td>
<td>38.39</td>
</tr>
</tbody>
</table>

As I considered Twitter, Instagram and Tumblr, I further explored the data types posted on Instagram and Tumblr. Table 2-5 and Table 2-6 display different types of posts supported by Tumblr and Instagram respectively and the number of postings collected. From Table 2-5, it is observed that among all three phases, there are three major types of postings on Tumblr. Blogs
containing images hold the top position, followed by texts and videos. Audio has the least count in the *During* phase, while for *Pre* and *Post* phases, Answer is the least. From Table 2-6, on Instagram, I have only two types of media posts. I noticed that people post images considerably more than videos.

Table 2-5. Volume of type of posts in Pre, During and Post phases on Tumblr

<table>
<thead>
<tr>
<th></th>
<th>Pre Phase</th>
<th>During Phase</th>
<th>Post Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Answer</td>
<td>15</td>
<td>10</td>
<td>17</td>
</tr>
<tr>
<td>Audio</td>
<td>112</td>
<td>2</td>
<td>53</td>
</tr>
<tr>
<td>Chat</td>
<td>32</td>
<td>30</td>
<td>47</td>
</tr>
<tr>
<td>Link</td>
<td>526</td>
<td>22</td>
<td>334</td>
</tr>
<tr>
<td>Image</td>
<td>18,112</td>
<td>3662</td>
<td>14,027</td>
</tr>
<tr>
<td>Quote</td>
<td>74</td>
<td>44</td>
<td>79</td>
</tr>
<tr>
<td>Text</td>
<td>3975</td>
<td>2426</td>
<td>4262</td>
</tr>
<tr>
<td>Video</td>
<td>1849</td>
<td>348</td>
<td>1511</td>
</tr>
<tr>
<td></td>
<td>24,695</td>
<td>6544</td>
<td>20,330</td>
</tr>
</tbody>
</table>

Table 2-6. Volume of type of posts in Pre, During and Post phases on Instagram

<table>
<thead>
<tr>
<th></th>
<th>Pre Phase</th>
<th>During Phase</th>
<th>Post Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image</td>
<td>424,384</td>
<td>15,049</td>
<td>313,644</td>
</tr>
<tr>
<td>Video</td>
<td>28,377</td>
<td>1,410</td>
<td>28,398</td>
</tr>
<tr>
<td></td>
<td>452,761</td>
<td>16,459</td>
<td>342,042</td>
</tr>
</tbody>
</table>

**Super Bowl Interaction Categories**

Once I collected the data from all three social networks, I classify the collected data into the three categories (commercials, music, and game) of second screen interaction for each social media platform. The categories were identified by means of the keywords collected from relevant websites. The keywords are in lower case letters and are extracted from websites regarding Super Bowl commercials (Anonymous, 2015; Staff, 2015), Super Bowl music (Wikipedia, 2015b, 2015d), and Super Bowl game (Schalter, 2015b).
The list of Super Bowl commercial keywords contains the ad titles (e.g., ‘mercedes’, ‘coca cola’, ‘wix’ etc.), titles of the themes / videos for the ads (e.g., ‘real strength’, ‘like a girl’ etc.), the popular name of the brands (e.g., coke, burrito etc.), hashtags associated with the spots (e.g., ‘#realstrength’, ‘#likeagirl’, ‘#itsthateasy’ etc.) and the first and last names of actors participated in Super Bowl commercial videos (e.g., ‘william’, ‘dafoe’, ‘braylon’, ‘o neil’, ‘o- neil’, ‘jeff’, ‘bridges’ etc.). I extract 47 brands from relevant websites (Anonymous, 2015; Staff, 2015) for my research.

The list of Super Bowl music keywords contains the first name and last name of the performers of the halftime and the pre-game show (e.g., ‘lenny’, ‘kravitz’, ‘katy’, ‘perry’ etc.), terms that describes the half time show (e.g., ‘shark’, ‘palm’, ‘beach’, ‘flames’ etc.) and the songs (e.g., ‘teenage dream’, ‘california gurls’ etc.).

The list of keywords relate to the Super Bowl game contains the first name and last name of the players, coaches, umpires, referees, commentators (e.g., ‘brady’, ‘julian’, ‘edelman’ etc.), the field positions (e.g., ‘rusher’, ‘quarter back’, ‘quarter-back’, ‘red zone’ etc.), teams (‘patriot’, ‘seahawks’, ‘hawks’ etc.) and other key terms related to game (e.g., ‘punt’, ‘fumble’, ‘tackle’, ‘intercept’, ‘goal’, etc.).

I assign the posts on social media platforms in Super Bowl commercials, in Super Bowl music, or in Super Bowl game categories, depending on the presence of terms from the respective keywords lists. These keywords are crosschecked with the presence of the terms; either in the body of the text or in form of hashtags in Twitter and in the tag-lists against the search results for Instagram and Tumblr. The terms are used as search queries for data collection on all three social networking platforms.

I do not assign the posts to any category that has terms from more than one keyword category list. For Twitter and Tumblr, I check the presence of the terms in tweets and blogs, while for Instagram the terms are checked in the caption of the posts. I have 190,410 Twitter postings,
70,305 Instagram postings and 9,705 Tumblr postings that belong to more than one category. I did not incorporate these mixed category postings in this research, as I consider Super Bowl categories as mutually exclusive. Apart from that, there are 99,523 tweets and 1,000 Tumblr posts, not included in the analysis; that do not belong to any category, such as soccer related tweets, as “football” is used as the search query for data collection. In Asian, European and African countries “football” is synonymous to soccer, unlike USA and Canada.

Figure 2-1. Snapshot of example postings for commercial, music and game postings on Twitter

Figure 2-2. Snapshot of example postings for commercial, music and game postings on Instagram
Figures 2-1 to 2-3 display example snapshots of Super Bowl commercials, Super Bowl music, and Super Bowl game category postings on Twitter, Instagram and Tumblr respectively.

I constructed a three 3x3 (phase x category) contingency table from the distribution of the categories for second screen Super Bowl conversations on Twitter, Instagram and Tumblr respectively, as shown in Table 2-7.

Table 2-7. 3x3 contingency tables for Twitter, Instagram and Tumblr of phase and category

<table>
<thead>
<tr>
<th>Super bowl phase</th>
<th>Commercials</th>
<th>Music</th>
<th>Game</th>
<th>Twitter Category Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre</td>
<td>350,259 (57.0%)</td>
<td>506,035 (57.5%)</td>
<td>737,011 (55.5%)</td>
<td>1,593,305 (56.4%)</td>
</tr>
<tr>
<td>During</td>
<td>10,525 (1.7%)</td>
<td>12,029 (1.4%)</td>
<td>11,057 (0.8%)</td>
<td>33,611 (1.2%)</td>
</tr>
<tr>
<td>Post</td>
<td>253,745 (41.3%)</td>
<td>362,113 (41.1%)</td>
<td>580,082 (43.7%)</td>
<td>1,195,940 (42.4%)</td>
</tr>
<tr>
<td>Total</td>
<td>614,529 (100%)</td>
<td>880,177 (100%)</td>
<td>1,328,150 (100%)</td>
<td>2,822,856 (100%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Super bowl phase</th>
<th>Commercials</th>
<th>Music</th>
<th>Game</th>
<th>Instagram Category Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre</td>
<td>92,864 (55.6%)</td>
<td>136,431 (54.2%)</td>
<td>185,784 (57.6%)</td>
<td>415,079 (56.0%)</td>
</tr>
<tr>
<td>During</td>
<td>2,683 (1.6%)</td>
<td>5,748 (2.3%)</td>
<td>6,249 (1.9%)</td>
<td>14,680 (2.0%)</td>
</tr>
<tr>
<td>Post</td>
<td>71,464 (42.8%)</td>
<td>109,458 (43.5%)</td>
<td>130,276 (40.4%)</td>
<td>311,198 (42.0%)</td>
</tr>
<tr>
<td>Total</td>
<td>167,011 (100%)</td>
<td>251,637 (100%)</td>
<td>322,309 (100%)</td>
<td>740,957 (100%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Super bowl phase</th>
<th>Commercials</th>
<th>Music</th>
<th>Game</th>
<th>Tumblr Category Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre</td>
<td>6,934 (48.6%)</td>
<td>7,560 (51.2%)</td>
<td>5,914 (50.0%)</td>
<td>20,408 (49.9%)</td>
</tr>
<tr>
<td>During</td>
<td>2,594 (18.2%)</td>
<td>1,834 (12.4%)</td>
<td>1,889 (16.0%)</td>
<td>6,317 (15.5%)</td>
</tr>
<tr>
<td>Post</td>
<td>4,746 (33.2%)</td>
<td>5,370 (36.4%)</td>
<td>4,023 (34.0%)</td>
<td>14,139 (34.6%)</td>
</tr>
</tbody>
</table>
After data collection, I segregate the count of posts collected for all three social media platforms and for all three Super Bowl categories into five minutes intervals. I further segregate the categorical time-count data as Pre, During and Post phases by annotating the time shown in Table 2-2. So, each social soundtrack has phase-commentary and category time counts (five minutes) that are used as the units of analysis in testing the research hypotheses corresponding to research questions 1 through 3 pertaining to phase-category relationship.

**Methodology**

I use SPSS to evaluate my hypotheses for all three research questions. For first research question, I perform chi-square tests to determine the phase-category relationship. For examining the second and third research questions, I use one way ANOVA. Before performing one way ANOVA on the absolute volume count data, I need to convert it into a continuous scale. So I express the continuous scale absolute volume as the ratio between the value at time $t$ and the best of the highest counts recorded in three Super Bowl phases (category), as shown in equation 1. For equation 1, $j$ represents the phase (category) and $t$ represents an instance of five minute time window. The continuous scale of count data satisfies the normality condition. $T_i$ denotes the range of time windows for each phase (category). For a specific phase, $T_i$’s for categories are same but for a specific category, $T_i$’s for phases are different$^4$.

\[ \frac{\text{Value at time } t}{\text{Best of highest counts recorded in three Super Bowl phases (category)}} \]

$^4$ Range of five minute time intervals in *During* phase is shorter than that in *Pre* and *Post* phases
scaled_count\textsubscript{t}^i = \frac{volume\textsubscript{t}^i}{\text{MAX}\{\text{max}\{volume\textsubscript{t}^1_k\}, \text{max}\{volume\textsubscript{t}^2_k\}, ..., \text{max}\{volume\textsubscript{t}^j_k\}\}} \tag{1}

To compute relative count data, I put absolute volume in both the numerator and the denominator in equation 2. In equation 2, \(i\) represents the phase and \(j\) represents the category.

\[ rel\_count\textsubscript{t}^j = \frac{volume\textsubscript{t}^j + 1}{\sum_j volume\textsubscript{t}^j + 3} \text{ at time } t, \tag{2} \]

The denominator includes a constant (i.e. 3) to avoid the zero division if at a particular time frame for a social network, the volumes for all three categories for a specific phase become zero. As there are three categories, I add 1 to the volume of each category (i.e. numerator) that sums up to 3 in the denominator\(^5\).

The data concerning scaled volume and relative volume maintain the normality condition. Therefore, I apply Games-Howell (GH) test as the post hoc analysis to identify the dominance of specific interaction category in specific phase in phase-category space. I use GH test as the data violates the homogeneity of variance (significance of Levene’s statistic < 0.05), but the data does follows the equality of means assumption (significance of Welch’s statistic < 0.05).

For first research question, I perform the chi-square test using SPSS on 3x3 phase-category contingency tables (see Table 2-7), where each cell \(C^k_{i,j}\) gives the observed frequency of second screen interaction in Super Bowl phase \(i\) for interaction category \(j\) on social network platform \(k\).

In SPSS, I run two separate ANOVA tests to evaluate the second and third research questions. The critical value of the \(F_{\text{ANOVA}, (2, 120)}\) is 2.996 at the 95% confidence interval (\(\alpha = 0.05\)). For research question two, the second screen interactions in five minute time intervals for each category over the three phases are used as the unit of analysis or independent variable and denominator of equation 1 is the best in the set of highest counts recorded in all three phases. For

\(^5\) There are five minute time windows in Tumblr where the volumes for all three categories are recorded zero in a specific phase.
research question three, the second screen interactions in five minute time intervals for each phase over three categories are used as the unit of analysis or independent variable and denominator of equation 1 is the largest of the highest counts recorded for all three Super Bowl categories. The ANOVA test identifies that the mean of the tweet counts in five minute time interval of at least one phase (category) is significantly different from others for each category (phase).

Results

Research Question 1

Chi-square tests were carried out to test three hypotheses associated with the first research question. I have three 3x3 contingency tables for Twitter, Instagram and Tumblr in Table 2-7. \( \chi^2_{\text{critical}} = 9.49 \) with df = 4 at \( \alpha = 0.05 \).

_Hypothesis 01: There exists a relationship between Super Bowl categories and Super Bowl phases in second screen conversations on Twitter._

From 3x3 contingency table shown in Table 2-7 for Twitter, I carry out the chi-square test where \( \chi^2(4, 0.05) = 4501.75 \) and p-value << 0.05. For Twitter, there exists a relationship between Super Bowl phases and Super Bowl categories. Hypothesis 01 is fully supported.

_Hypothesis 02: There exists a relationship between Super Bowl categories and Super Bowl phases in second screen conversations on Instagram._

I perform the chi-square test on the 3x3 contingency table for Instagram shown in Table 2-7. The \( \chi^2(4, 0.05) = 891.36 \), p-value << 0.05. The result supports hypothesis 02 and show the existence of phase-category relationship for Instagram.
**Hypothesis 03:** There exists a relationship between Super Bowl categories and Super Bowl phases in second screen conversations on Tumblr.

The chi-square test on 3x3 contingency table for Tumblr (see Table 2-7) supports hypothesis 03 as the test results $\chi^2(4, 0.05) = 190.25$ with p-value $<< 0.05$. So, there exists a dependency between Super Bowl phases and Super Bowl categories on Tumblr.

To identify the dependence between specific interaction category and specific Super Bowl phases, I examine the second and third research questions. Identifying the dependence of categories of conversation on phases of an IRL event will facilitate the retailers, broadcasters and music companies to focus on the conversation of specific category in a specific phase to increase the sales of brands, promote the popularity of the broadcast network and formulate the strategies of launching the music videos of particular artists.

**Research Question 2**

I performed one way ANOVA tests to evaluate three research hypotheses related to research question 2. The volume of social soundtrack on a particular Super Bowl category are in continuous scale formed using equation 1 to test hypotheses 04 through 06.

**Hypothesis 04:** There is a significant difference in volume of second screen conversation in the social soundtrack related to Super Bowl commercials among the Super Bowl phases.

I evaluate hypothesis 04 on Twitter, Instagram and Tumblr. The top portion in Table 8 displays the F statistic with the p–values. It is seen that there is a significant difference in Super Bowl commercial-related social conversation among Super Bowl phases for all social media platforms.
Hypothesis 05: There is a significant difference in volume of second screen conversation in the social soundtrack related to Super Bowl music among the Super Bowl phases.

I test hypothesis 05 on Twitter, Instagram and Tumblr. The middle portion in Table 8 displays the F statistic with the p-values. It is seen that there is a significant difference in Super Bowl music-related social conversation among Super Bowl phases for all social media platforms.

Hypothesis 06: There is a significant difference in volume of second screen conversation in the social soundtrack related to Super Bowl game among the Super Bowl phases.

I test hypothesis 06 on Twitter, Instagram and Tumblr. The bottom portion in Table 2-8 displays the F statistic with the p-values. It is seen that there is a significant difference in Super Bowl game social conversation among Super Bowl phases for all social media platforms.

Table 2-8. ANOVA statistics w.r.t continuous scale absolute volume on Super Bowl Commercials, Super Bowl Music and Super Bowl Game categories

<table>
<thead>
<tr>
<th>Social Media Platform</th>
<th>Super Bowl Commercials category</th>
<th>Super Bowl Music category</th>
<th>Super Bowl Game category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>69.74</td>
<td>0.00</td>
<td>70.49</td>
</tr>
<tr>
<td>Instagram</td>
<td>72.78</td>
<td>0.00</td>
<td>63.58</td>
</tr>
<tr>
<td>Tumblr</td>
<td>97.79</td>
<td>0.00</td>
<td>92.50</td>
</tr>
</tbody>
</table>

I define the phase(s) as the predominant Super Bowl phase(s) if the mean(s) of that phase(s) is (are) significantly higher than that of the remaining phase(s) compared among the
Super Bowl categories. To test the predominant Super Bowl phase(s) among the Super Bowl categories, I perform the GH test.

For hypothesis 04, the During Super Bowl phase emerges as the predominant Super Bowl phase for second screen interaction in Super Bowl commercials (see top portion in Table 2-9).

For hypothesis 05, again the During Super Bowl phase is predominant in Super Bowl music categories (see middle portion in Table 2-9) on all social media platforms.

For hypothesis 06, During Super Bowl phases become predominant relative to the Pre and Post Super Bowl phases for Twitter in Super Bowl game category (see bottom portion in Table 2-9).

Table 2-9. Dominant phases and T statistic (* denotes significance) for other phases with emerging phases w.r.t continuous scale absolute volume for all Super Bowl categories

<table>
<thead>
<tr>
<th>Social Media Platform</th>
<th>Dominant Phase</th>
<th>T values with other phases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>During</td>
<td>Pre: 12.55* Post: 23.57*</td>
</tr>
<tr>
<td>Instagram</td>
<td>During</td>
<td>Pre: 17.79* Post: 20.73*</td>
</tr>
<tr>
<td>Tumblr</td>
<td>During</td>
<td>Pre: 30.63* Post: 32.19*</td>
</tr>
</tbody>
</table>

Super Bowl Music Category

<table>
<thead>
<tr>
<th>Social Media Platform</th>
<th>Dominant Phase</th>
<th>T values with other phases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>During</td>
<td>Pre: 16.70* Post: 25.24*</td>
</tr>
<tr>
<td>Instagram</td>
<td>During</td>
<td>Pre: 11.37* Post: 13.16*</td>
</tr>
<tr>
<td>Tumblr</td>
<td>During</td>
<td>Pre: 36.71* Post: 38.25*</td>
</tr>
</tbody>
</table>

Super Bowl Game Category

<table>
<thead>
<tr>
<th>Social Media Platform</th>
<th>Dominant Phase</th>
<th>T values with other phases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>During</td>
<td>Pre: 16.11* Post: 21.07*</td>
</tr>
<tr>
<td>Instagram</td>
<td>During</td>
<td>Pre: 19.71* Post: 23.34*</td>
</tr>
<tr>
<td>Tumblr</td>
<td>During</td>
<td>Pre: 45.95* Post: 46.96*</td>
</tr>
</tbody>
</table>

I provide Figures 2-4 to 2-6 depicting the hourly mean of postings on all three social media platforms for all three categories over three phases of Super Bowl XLIX.
Figure 2-4. Hourly mean of Super Bowl commercials interactions during Pre, During and Post phases for all social media platforms

Figure 2-5. Hourly mean of Super Bowl music interactions during Pre, During and Post phases for all social media platforms
Figure 2-6. Hourly mean of Super Bowl music interactions during Pre, During and Post phases for all social media platforms

Hypothesis 04 through 06 are tested with the continuous scale absolute volumes of categorical conversations among Super Bowl phases finding that *During* phase becomes predominant for all three categories across three social media platforms. It is obvious that *During* phase will be the dominant as the means of conversations in *During* phase are substantially higher than the *Pre* and *Post* phases as displayed in Figures 2-4 to Figure 2-6.

The ANOVA test of hypothesis 07 through 09 gives the following results displayed in Table 10. Hypothesis 07 through 09 are evaluated using relative volumes computed using equation 2.

The top portion in Table 2-10 displays the F statistic with the p–values. It is seen that there is a significant difference in relative volume of posts concerning Super Bowl commercials among Super Bowl phases for all social media platforms. Hypothesis 07 is fully supported.

The middle portion in Table 2-10 displays the F statistic with the p–values. It is seen that there is a significant difference in relative volumes of Super Bowl music related social conversation among Super Bowl phases for all social media platforms. Hypothesis 08 is fully supported.
The bottom portion in Table 2-10 displays the F statistic with the p–values. It is seen that there is a significant difference in Super Bowl game social conversation among Super Bowl phases for all social media platforms. Hypothesis 09 is fully supported.

Table 2-10. ANOVA statistics w.r.t relative volumes on Super Bowl Commercials, Super Bowl Music and Super Bowl Game categories

<table>
<thead>
<tr>
<th>Social Media Platform</th>
<th>Super Bowl Commercials category</th>
<th>F_{ANOVA}(2, 12859)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td></td>
<td>129.58</td>
<td>0.00</td>
</tr>
<tr>
<td>Instagram</td>
<td></td>
<td>28.27</td>
<td>0.00</td>
</tr>
<tr>
<td>Tumblr</td>
<td></td>
<td>8.61</td>
<td>0.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Social Media Platform</th>
<th>Super Bowl Music category</th>
<th>F_{ANOVA}(2, 12859)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td></td>
<td>154.54</td>
<td>0.00</td>
</tr>
<tr>
<td>Instagram</td>
<td></td>
<td>81.87</td>
<td>0.00</td>
</tr>
<tr>
<td>Tumblr</td>
<td></td>
<td>5.60</td>
<td>0.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Social Media Platform</th>
<th>Super Bowl Game category</th>
<th>F_{ANOVA}(2, 12859)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td></td>
<td>381.369</td>
<td>0.00</td>
</tr>
<tr>
<td>Instagram</td>
<td></td>
<td>128.681</td>
<td>0.00</td>
</tr>
<tr>
<td>Tumblr</td>
<td></td>
<td>26.59</td>
<td>0.00</td>
</tr>
</tbody>
</table>

To test the predominant Super Bowl phase(s) among the Super Bowl categories w.r.t relative volumes, I perform the GH test.

Table 2-11. Dominant phases and T statistic (* denotes significance) for other phases with emerging phases w.r.t relative volume for all Super Bowl categories

<table>
<thead>
<tr>
<th>Social Media Platform</th>
<th>Super Bowl Commercials Category</th>
<th>Super Bowl Music Category</th>
<th>T values with other phases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>During</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instagram</td>
<td>Post</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tumblr</td>
<td>Pre and Post (Mean of Pre is Higher)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Pre: 15.32*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Post: 17.73*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

To test the predominant Super Bowl phase(s) among the Super Bowl categories w.r.t relative volumes, I perform the GH test.
For hypothesis 07, the During Super Bowl phase emerges as the predominant Super Bowl phase for relative volume of second screen interaction in Super Bowl commercials for Twitter, while it is the Post phase that appear as the predominant for Instagram. Both Pre and Post phases are predominant for Tumblr (see top portion in Table 2-11).

For hypothesis 08, again the During Super Bowl phase is predominant w.r.t relative volume of posts in Super Bowl music categories on Twitter and Instagram social media platforms; but for Tumblr, it is both Pre and During phases that pop up as the predominant (middle portion in Table 2-11).

For hypothesis 09, Post-Super Bowl phase becomes predominant w.r.t the relative volume of posts in comparison with the Pre and During Super Bowl phase for Twitter in Super Bowl game category (see bottom portion in Table 2-11). Interestingly, though Pre and During mark their presence as predominant, there is no significant difference between Pre and During phases for the Super Bowl game category on Instagram. For Tumblr, During phase is predominant for relative volume of second screen conversations on game.

The relative volume of game-related conversation in During phase is less than that in Post phase for Twitter unlike relative volumes of Super Bowl commercials for Twitter and Super Bowl music. For Instagram, Post phase is predominant for Super Bowl commercials category unlike Super Bowl music, where During phase is strong. For Tumblr, though During phase is
predominant in game category, *Pre* phase plays the lead in other two categories. So I observe an interesting mixed response for identifying predominant phases in category based social soundtrack.

I believe that though the absolute volume of second screen conversations related to a particular category in *During* phase is much higher than that in *Pre* and *Post* phases, the relative volumes for that category in *During* phase may be less as the absolute volumes of conversations in other two remaining categories in *During* phase is considerably higher than that in *Pre* and *Post* phases. If there are three categories say X, Y and Z, the relative volume of second screen conversations related to category X at time $t_1$ is the ratio between count of category X related discussion and summation of second screen conversations on category X, category and category Z (see equation 2) at $t_1$. For example the relative volume of game-category is the ratio between game-related conversations to the total volume of posts over different times in *During* phase. This ratio for *Pre* and *Post* phases for Twitter is greater than that in *During* phase as game-related discussions on Twitter is much higher than commercials and music-related conversations in *Pre* and *Post* phases compared to that in *During* phase. The result implies that the relative volumes can also be the important metric of observation besides the absolute volume from the perspective of retailers, broadcasters and entertainment industries as measurement of relative volumes yield different result for category specific inter-phase conversations.

**Research Question 3**

For research question 3, I stick to the continuously scaled values of absolute volume, as it tests the difference in social conversation over three categories in a specific phase. Here the testing of hypotheses corresponding to research question 3 is contained within specific phase.
For research question 3, I evaluate the difference in second screen interaction among Super Bowl categories in each phase. Here, the second screen interactions in five minute time intervals of each Super Bowl phase among three categories are used as the unit of analysis. A separate ANOVA test identifies that means of the tweet counts in five minute time interval of at least one Super Bowl category is significantly different from the others for each phase. The volume of social soundtrack on a particular Super Bowl phase are in continuous scale formed using equation 1 to test hypothesis10, hypothesis 11 and hypothesis 12.

Table 2-12. ANOVA statistics w.r.t absolute volume for Twitter, Instagram and Tumblr in Super Bowl phases

<table>
<thead>
<tr>
<th>Social Media Platform</th>
<th>Pre Super Bowl phase</th>
<th>During Super Bowl phase</th>
<th>Post Super Bowl phase</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$F_{ANOVA}^{(2, 19686)}$</td>
<td>$p$-value</td>
<td>$F_{ANOVA}^{(2, 144)}$</td>
</tr>
<tr>
<td>Twitter</td>
<td>20,684.88</td>
<td>0.00</td>
<td>4.56</td>
</tr>
<tr>
<td>Instagram</td>
<td>9,184.81</td>
<td>0.00</td>
<td>90.53</td>
</tr>
<tr>
<td>Tumblr</td>
<td>270.90</td>
<td>0.00</td>
<td>66.35</td>
</tr>
</tbody>
</table>

The top portion in Table 2-12 displays the F statistic with the p–values for each of the social media platforms. It is seen that there is a significant difference in second screen conversations in Pre-Super Bowl phase among Super Bowl categories for all social media platforms. Hypothesis 10 is fully supported.

The middle portion in Table 2-12 displays the F statistic with the p–values for each of the social media platforms. It is seen that there is a significant difference in second screen
conversation in the *During* Super Bowl phase among categories for Twitter, Instagram and Tumblr. Hypothesis 11 is fully supported.

The bottom portion in Table 2-12 displays the F statistic with the p–values for each of the social media platforms. It is seen that there is a significant difference in second screen conversation in the *Post* phase among Super Bowl categories for all social media platforms. Hypothesis 12 is fully supported.

### Table 2-13. Emerging categories and T statistic (* denotes significance) for other categories with emerging categories w.r.t continuous scale volume for all Super Bowl phases.

<table>
<thead>
<tr>
<th>Social soundtrack</th>
<th>Dominant category</th>
<th>Pre-Super Bowl Phase</th>
<th>Post-Super Bowl Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Twitter</strong></td>
<td>Game</td>
<td>Commercials: 205.74*</td>
<td>Music: 125.10*</td>
</tr>
<tr>
<td></td>
<td>Game</td>
<td>Commercials: 135.77*</td>
<td>Music: 70.00*</td>
</tr>
<tr>
<td></td>
<td>Music</td>
<td>Commercials: 18.50*</td>
<td>Game: 21.92*</td>
</tr>
<tr>
<td><strong>Instagram</strong></td>
<td>Game and music</td>
<td>Commercials: 3.10*</td>
<td>Game: 0.72</td>
</tr>
<tr>
<td></td>
<td>(music has higher mean)</td>
<td>p-value= 0.76</td>
<td></td>
</tr>
<tr>
<td><strong>Tumblr</strong></td>
<td>Game and music</td>
<td>Commercials: 13.55*</td>
<td>Music: 1.34</td>
</tr>
<tr>
<td></td>
<td>(game has higher mean)</td>
<td>p-value= 0.38</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Commercials</td>
<td>Music: 10.33*</td>
<td>Game: 10.56*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Twitter</strong></td>
<td>Game</td>
<td>Commercials: 155.17*</td>
<td>Music: 106.84*</td>
</tr>
<tr>
<td><strong>Instagram</strong></td>
<td>Game</td>
<td>Commercials: 100.40*</td>
<td>Music: 36.37*</td>
</tr>
<tr>
<td><strong>Tumblr</strong></td>
<td>Commercials and music (mean of music is higher)</td>
<td>Commercials: 1.89 p-value = 0.14</td>
<td>Game: 12.61*</td>
</tr>
</tbody>
</table>
I call the category(s) as emerging Super Bowl category(s) if the mean(s) of that category(s) is (are) significantly higher than that of the remaining one(s) compared over the Super Bowl phases. To test the emerging Super Bowl category(s) among the Super Bowl phases, the GH test is performed. Table 2-13 presents the combined results of post-hoc analysis for hypotheses 10 through 12.

For hypothesis 10; the second screen interaction related to Super Bowl game category is dominant on Instagram and Twitter, and Super Bowl music is the dominant category on Tumblr in Pre phase (see top portion in Table 2-13). For hypothesis 11, game and music becomes predominant on Twitter in the During phase, though Super Bowl music category has higher mean of second screen interaction. On Instagram and Tumblr, the Super Bowl game and Super Bowl commercials are dominant categories respectively (see middle portion in Table 2-13). The GH test for hypothesis 12 identifies Super Bowl game as the dominant category on Twitter and Instagram in Post phase. On Tumblr, postings related to both Super Bowl music and Super Bowl commercials become dominant as no significant difference is found between these two categories (see middle portion in Table 2-13). For relative volume of conversations perspective Super Bowl game category is predominant in majority of the phases for majority of social networks unlike Super Bowl commercials, predominant from continuous scale absolute volume perspective.

In Pre and Post phases the game related discussions have the dominance over other two categories for Twitter and Instagram. In Tumblr, it is either Super Bowl music or Super Bowl commercial related conversations become stronger than game for all three phases. I believe that feelings for videos related to the ads for the commercials and the performances concerning the music entertainments can be better described in blogs compared to game related activities as majority of game related activities are supposed to be momentary and therefore can be posted predominantly as tweets and media post captions.
I refrain from testing the significance of emerging categories in a specific phase from relative volume perspective as testing with intra-phase relative volumes of posts for the categories is synonymous to testing with the continuous scale absolute volumes of categories in that phase.

**Discussion and Implications**

**Discussion of Results**

In this research, I investigate three research questions pertaining to second screen interactions highlighting the use of three social networks in sharing information in the social soundtrack about Super Bowl XLIX, in three phases, *Pre*, *During* and *Post*, of the IRL media event broadcast. Three categories (commercials, music and game) concerning the Super Bowl event are formed for each of *Pre*, *During* and *Post* phases. The first research question addresses the (in)dependence among the phase and categories. The second research question is concerned with the change in the rate social interaction via second screens across the three phases for each of three categories. The third research question addresses the change in peoples’ interest among phases for the categories. The results of research question 1 establish my intuition regarding existence of phase-category relationship.

The second research question is tested based on absolute volume converted to a continuous scale w.r.t. highest record and the relative volume of social soundtrack conversations respectively. For scaled absolute volume of conversation, it is found that the *During* phase remains the dominant relative to its *Pre* and *Post* phase counterparts for all categories across all three social media platforms.

The relative volume of second screen interactions concerning Super Bowl music during live broadcast media event of Super Bowl (i.e., *During* phase) eclipses that in *Pre* and *Post*
phases for the Super Bowl music category on Twitter and Instagram. For Super Bowl commercials I get a mixed response where During and Post phases are predominant on Twitter and Instagram respectively. Both Pre and Post phases are dominating During phase on commercials related posts on Tumblr. Interestingly for Tumblr, the second screen interaction for the Super Bowl game category is significantly high in the During phase, but for Twitter, the discussion in Pre and Post phases outperform that in the During super Bowl phase.

I further explore interest in Super Bowl categories in each phase in terms of second screen interaction on different social media platforms. From absolute volume of conversation with continuous proportion perspective, it is observed that people indulge in discussion on the Super Bowl game before, during, and after the broadcast media event for Twitter and Instagram, though it is jointly prevalent with Super Bowl music in During phase. For Tumblr, the interactions related to Super Bowl commercials and music surpass the game-related buzz.

**Implications**

Concerning the practical implication of the findings, the increased rate of interaction via second screens in the During phase of IRL broadcast media events leads to the increased rate of potential diffusion of information about different event categories. This information sharing is done by distributing, publishing, and commenting via various types of posts or artifacts (e.g. text, audio, image, video, etc.) among users on social media platforms. Peoples’ interest about events like the Super Bowl is much higher than other conventional broadcast media programing. So, the excitement and the curiosity of different aspects of Super Bowl (e.g. brands, songs, artists, teams, etc.), weeks before the media event’s broadcast of the kickoff may drive the second screen interaction to shoot up During live transmission of the game.
In my research, the social communication via second screens among viewers concerning the Super Bowl game category dominates relative to the other categories on Instagram in all three phases of the social soundtrack. The Super Bowl game category also has the paramount importance on Twitter in Pre and Post phases taking relative volume feature into account. This discussion on diverse facets of the game will inevitably help the star players of the winning team to appear center stage of creating business opportunities.

Different brands may compete to hire those players as their prospective ambassadors of their products or service (Mathre, 2014). People generally idolize the sports stars and the artists. So, the logo of the brands that sponsor them will have a great impact on demography of masses (Gianatasio, 2015a). This eventually may increase the sales of the product indirectly and generate profit. In the During phase of Super Bowl, the rate of second screen interaction related to commercials and music rise significantly on Twitter compared to Pre and Post-event phases (see Figure 2-4 and Figure 2-5). For Tumblr, the brands remain the focus of the second screen communication in the During phase of Super Bowl (see Figure 2-4). Retailers, advertise their brands or services at the Super Bowl, targeting the viewers engaged on these social media platforms as potential consumers. The real time sentiment analysis of evolving stream of social conversation via social soundtrack (Guerra, Meira Jr, & Cardie, 2014) eventually helps the retailers or entertainment industries to launch a social-based recommender system framework (Ma, Zhou, Liu, Lyu, & King, 2011) benefitted by the phase wise information extracted from different social media platforms. So, technology has temporal influences on social soundtracks for media broadcast IRL events.

In my study, the proportion of absolute volume of social soundtrack related to Super Bowl music outshines other two categorical discussion during weeks before the kickoff starts (see top portion of Table 2-13). Music and entertainment industries can set strategies and timings to launch new releases by mining the social soundtrack mediums concerning the popularity of the
songs as the artists perform *During* halftime show (see middle portion of Table 2-11) or in pre-game sessions (see Tumblr row in top portion of Table 2-13). This marketing analysis can provide potential insights into potential sales and revenue (Gianatasio, 2015b). The growth of social interaction via second screen *During* live broadcast media event increases the possibility of direct communication between brands and consumers. Integrating broadcast media events’ social soundtracks via social networks shrinks the virtual distance between brands and consumers, thus highlighting a rise in potential brand recall, boosting advertising campaigns, and enhancing sale possibilities via word-of-mouth advertising (Jansen et al., 2009). The stronger message association due to the presence the second screen interaction generates higher purchase intent among the consumers of the brands (Schivinski & Dabrowski, 2014).

**Strength and Limitations**

As in all studies, there are limitations to this research. The first limitation is that for instance I have garnered 3 million tweets while there is 28 million tweets reported during telecast of Super Bowl. This is because I have used the public APIs that has the restricted access to collect the data for my research for all three social soundtrack. Although increase data may strengthen my findings, my substantial amount of data used in this research shed significant insights. Secondly, there may exists the spam messages or automatically generated messages that can be shared/reposted /retweeted. This may affect my result. My present study did not filter out such spam or bots, which I will focus in my future work.

In terms of strengths, I believe the my research findings present significant insights in identifying the temporal significance of shift in second screen based social media conversations on Super Bowl XLIX categories and phases. I analyzed the categories and phases relationship from several angles, showing statistically significant relationships. I used a large quantity of data
from multiple social media platforms, which is rarely done. Finally, I also introduced and clearly
defined the constructed, which can be the basis for future research.
Chapter 3

Impact of Social Media Conversation on Web Search Concerning IRL Event Branding

The combination of social media sites and mobile devices greatly augments the opportunity for conversational information sharing concerning in-real-life (IRL) events, especially ones that are broadcast. This harmony of technologies allows for social conversations via online social media platforms, such as Facebook, Twitter, Weibo, or vk. These online social media sites, with mobile devices for access, have embedded themselves alongside the broadcast medium, affording what I refer to as the social soundtrack for IRL events (Mukherjee et al., 2014).

The social soundtrack is an interesting conversational information sharing activity that can happen on various social media platforms both in real time (i.e., during the event) and non-real time (i.e., before or after the event). The integration of these social media sites as the conversational medium in conjunction with mobile devices for ubiquitous access marks the emergence of a phenomenon that greatly augments prior social aspects of broadcasting. This novel technology synergy is referred to as the second screen phenomenon, although there may be multiple (i.e., more than two) screens involved that augment delivering and consuming information (Chyi & Chadha, 2012; Google, 2012).

With the second screen phenomenon, as shown in Figure 1, the broadcast media event is shown on the primary screen (i.e., typically the largest display) where the viewing occurs, while the secondary screen is the computer device (e.g., usually a smartphone but might also be desktop, laptop, or tablet) (Covey, 2010; Phalen & Ducey, 2012). The second screen phenomenon facilitates the information sharing that occurs on one or more social media platforms. Second screens facilitate the producing and consuming of online communication, creating a social
commentary channel among those engaging in the social soundtrack. The social soundtrack participants exchange social media posts related to the IRL event via second screen devices by sharing of comments (Mukherjee et al., 2014) to a social media site. It is the combination of the secondary screen and social media technologies that allows for the creation of the social soundtrack, the online conversation with others regarding an IRL broadcast event, such as the Super Bowl, Academy awards, Grammy awards, etc. TV broadcasts of IRL events are associated with substantial social soundtracks, as these events do not lend themselves to recording for later viewing, unlike a seasonal TV show, for example.

Figure 3-1. Overview of the second screen phenomenon, with primary screen, computing devices, and social media sites facilitating the creation of the social soundtrack
Hence, the second screen interactions about an IRL event lead to a social soundtrack that is fixed in duration, with the period bounded by the event’s Pre (i.e., period ending at the start of the event) and Post (i.e., period beginning after the event ends) phases. Super Bowl XLIX is one such IRL broadcast media event. It occurs once a year and is a major happening, especially in the US. The Super Bowl event involves multiple sub-categories of interest. Among them, Super Bowl commercials have become a cultural phenomenon in their own right, along with the game itself. A considerable number of people watch the Super Bowl primarily to see and discuss the commercials (UsaToday, 2014).

There has been limited academic research concerning the increasingly important second screen interaction phenomenon and little systemic practitioner investigation. In this study, I explore the relationship between volumes and attitude of social soundtrack conversation and web searching concerning Super Bowl XLIX commercials. I consider Super Bowl XLIX commercials as the domain for both social soundtrack conversations and web searching data (i.e., search terms submitted to search engines, such as Google). Search data is typically not considered social media, so this research is a comparison across different online channels of the important and expensive branding events that are Super Bowl commercials. As the driver for most of online commerce, especially advertising, web search is a critically important economic indicator (Kulkarni, Kannan, & Moe, 2012).

As online information sharing is becoming a more powerful marketing venue, one key question that arises is how the interaction among broadcast advertising, social media, and web search impact brands. Understanding this relationship can provide significant business insights to retailers in managing online brand awareness.
Literature Review

A symbiotic relationship exists between TV advertising and social media as connectivity

technologies change consumer behaviors towards broadcast advertising.

Social Media and Information Sharing

In prior research on information seeking and information sharing to augment user
enrichment, Alliez (2008) showed that end user enrichment enhances the social aspects of
broadcast events with information sharing via user generated. Zhang, Jansen, and Chowdhury
(2011) showed that social media can be an effective brand engagement tool. Sun, Wang, Chen
and Fu (2014) dealt with the challenge of providing personalized content by mining the
information generated via social media to develop a media recommendation framework. Liu,
Cheung and Lee (2015) claimed that content and technology gratification are key factors that
drive user satisfaction with social media communication. In a field study, Joannah-Sin (2015)
investigated the variation in problematic informational outcomes with the use of different social
soundtrack mediums between genders. The derived user satisfaction via second screen social
soundtrack conversations augments other social possibilities. Alpar, Engler and Shulz (2015)
claimed that information recipients would be influenced by the quality of information and social
cues that prompted business vendors to incorporate the social aspects of the advertising message.
In other research, Oh and Yeon-Syn (2015) analyzed the different dimensions of users’
motivation for using the social soundtrack to share personal experiences and information and, in
turn, influencing social support among anonymous users. Regarding IRL events, Zhao, Zhong,
Wickramasuriya and Vasudevan (2011) extracted sentiments about US National Football League
teams by analyzing their opinions in tweets. Lin, Margolin, Keegan and Lazer (2013) identified
users with similar biases based on prior users’ behavior on Twitter for the 2012 US presidential election. Twitter sentiment was capitalized to characterize the political violence during elections in Pakistan (Younus et al., 2014).

**Social Media and Advertising**

The rapid growth of the social soundtrack that augments information sharing may enable social media channels to become the primary mode of advertising (Barsamian, 2001; Haley, 2006). There are some studies that have examined the influence of social media on brand advertising. Keller and Fay (2012) claimed that social soundtrack mediums are the platforms where consumers share their opinions about the products via electronic word-of-mouth (eWOM) and thereby influence product sales. Regarding brand engagement, De Chernatony (2001) showed that when consumers become the promoter of the brand value, alongside the retailers, they participate in social conversations about the products. In another study, Carroll (2005) argued from the user engagement perspective that advertisement strategies create involvement, participation, and social media distribution. Advertising of brands in the social media environment generates inter-personnel connectedness by means of information sharing (Willie, 2007). Advertisers are using ads to try to encourage potential consumers’ online interactive behavior on different social media mediums using second screens. Therefore, the rapid expansion of social media usage leads to the reinforcement of the impact of TV advertising in terms of a resurgence of its ability to develop brands (Stipp, 2011), as such connectedness facilitates eWOM brand awareness. Fleming, Reitsma, Parrish, and Jaddou (2012) observed that product fan-pages impact the possibility of product purchase, consideration, and recommendation. Young (2014) identified that consumers using traditional and digital media simultaneously has replaced the single traditional linear advertising media, such as TV. Baracho,
Silva and Ferreira (2012) identified the feelings and opinions of customers about brands and vehicle parts in the automobile domain. Liu (2012) analyzed sentiments to predict sales performance, while reviews were used to rank products and retailers (McGlohon, Glance, & Reiter, 2010).

**Social Media and Web Search**

Though the aforementioned studies speak to the impact of online conversations on brand advertisement, they do not identify the role of users’ information behavior concerning web search for brands. In web search, consumers are in an information seeking mode. There are studies that hint that eWOM advertising might stimulate web searches (Keller & Fay, 2012; Rockwood, 2012). Graham and Havelina (2007) examined the relationship between WOM advertising and brand interest behavior (i.e., brand search in the web, brand website visits etc.). The relationship is important because Fulgoni and Morn (2009) showed that increased web search is related to both online and off-line purchase behavior. Zhang, Jansen and Spink (2009) identified the relationship between attributes of search queries and the ranking of the web advertising results against those queries using a time series approach, with better ranked results getting more consumer interaction. The information searching in response to the brand advertisement prompts consumers to turn to a search engine as their first action related to the brand communication (Lecinski, 2012). Regarding the impact of the social soundtrack on brand search, Neff (2013) claimed that social soundtrack interaction played a positive role on brand engagement for Coca Cola, although the researcher was skeptical of its influence on short-term sales.
Integration of Prior Research

For this research, the specific IRL broadcast media event, I examine is Super Bowl XLIX, specifically Super Bowl commercials. There are a handful of studies that examine the impact of social soundtrack conversation on Super Bowl commercials. The Super Bowl is the highest rated IRL event in US advertising and considered one of the biggest marketing venues (Tomkovick, Yelkur, & Christians, 2001). Nail (2007) claimed that pre-game TV coverage of the Super Bowl influences post-game online conversations on social media. Siefert, Kothuri, Jacobs, Levine, Plummer, and Marci (2009) showed that the Super Bowl commercials that generate higher level of emotional attachments resulted in more social media buzz. In another study, Steinberg and Shultz (2011) identified that humor and meaningful cause-related conversation helps to maximize the Super Bowl brand investment.

Though the aforementioned research speaks to the usage of social media to analyze viewer interactions concerning brands, the prior research fail to investigate the synergies among temporal phases of an IRL event, various social media platforms facilitating the social soundtrack, and web search activity driven by the use of social media in discussing brands. Also, prior studies have been mainly limited to one social media platform, whereas this research examines three social media platforms.

Motivation for the research

From a review of prior work, there are several unanswered questions concerning second screen interaction and web search activity concerning IRL events. How do different social media platforms affect web search? How does the media broadcast of IRL events influence web search? How does the social commentary in the phases of an IRL event stimulate web searching activity
concerning that IRL event? What impact does attitude about brands have on web search concerning an IRL event? These questions form the basis of my research.

**Research Question**

The social environment influences and shapes individual human behavior (Ashford & LeCroy, 2009). Making broadcast media events more social therefore influences the human communication act of information sharing in a socially-mediated way that can affect thoughts and behaviors. Viewers of an IRL event use a social media site as a channel of communication conversing by posting via second screens the online messages centered on the broadcast event to build social relationships. Therefore, the social soundtrack can influence and shape the social environment.

For clarity, I define some of my key constructs:

1. **Second screen** – Computing device used for posting social media content to the social soundtrack when simultaneously engaging with media on a primary screen or IRL event
2. **Social soundtrack** – Collection of social media posts from second screen interactions by individuals conversing about a particular event
3. **IRL broadcast media event** - Happening anchored temporally and not lending itself for delayed viewing
4. **Web search** – The act of submitting a keyphrase to a search engine in order to retrieve information about a topic

Social media sites allow for information sharing posts about broadcast media events to be accessed by viewers in a variety of ways. The community members can join in discussions while getting ready, while watching, or reflecting on the event. They can have their comments viewed,
shared, and responded to by other members communicating in the social soundtrack. Such social soundtrack conversations may or may not be active during the live telecast of the event. Second screen technologies, such as smartphones, tablets, laptops, and even desktops, greatly facilitate the social soundtrack information sharing by allowing the conversations to occur nearly anytime and anywhere.

Within the spectrum of US broadcast media happenings, there are certain IRL events that draw considerable social media attention. Such events include the Oscars award ceremony, music video awards shows, Grammys award show, and sporting games. My research focuses on Super Bowl XLIX, as this program was the most-watched American television broadcast event in history, at the time of the study, with an average audience of 114.4 million viewers (Wikipedia, 2015d). Due to the high level of viewership in the Super Bowl, companies pay for expensive commercials that are televised during the broadcast. The commercials are an integral aspect of the Super Bowl broadcast, and these commercials are an event in their own right.

In my research, I select three social media platforms for the social soundtrack data collection, which are Twitter, Instagram and Tumblr. Twitter is one of the most popular microblogging sites and is also used by brands for communication (Zhang et al., 2009). Instagram is a social media medium where users perform online sharing of images and videos (Hu et al., 2014). Tumblr is the second largest microblogging service after Twitter. It supports eight types of posts including 1) images, 2) videos, 3) audios, 4) text, 5) answer, 6) links, 7) quotes, and 8) chat (Chang et al., 2014). I chose Google as the search engine, using Google Trends, as the data collection channel for the search terms.

There are considerable discussions in the social soundtrack concerning Super Bowl commercials, before, during and after the game. I term these phases of the Super Bowl as: 1) Pre phase, 2) During phase, and 2) Post phase. The Pre phase highlights the audience lead up conversation in social media and starts weeks ahead of the game day. I label the conversations on
the game day as occurring in *During* phase. The *Post* phase is the social soundtrack data beginning when the game day is over until that point the data collection ends.

**Social Influence on Web Search**

If the Super Bowl commercials have a branding effect, my premise is that a relationship should exist between the information shared via social soundtrack conversations and the volume of search data from the perspective of the brands in phases. Based on this perception, I formulate my first research question to test the influence between social soundtrack conversing and web searching in phases of an IRL event. I evaluate the information aspect of social soundtrack conversations based on influence of both 1) relative volume and 2) attitude of social media conversations on web search related to brands. As in (Kucuktunc, Cambazoglu, Weber, & Ferhatosmanoglu, 2012), I define attitude as the inclination towards the positive or negative sentiments. I form two research questions based on these two aspects of information sharing on social soundtrack about brands.

*Research Question1. Is there a relationship between relative volumes of social soundtrack conversations on brands and web searching of brand data in Super Bowl phases?*

*Research Question2. Is there a relationship between attitudes of social soundtrack conversations on brands and web searching of brand data in Super Bowl phases?*

These research questions can inform retailers and marketers about the influence of commercials’ related activity (conversations and/or web search) on information seeking behavior pertaining to brands. As foundational research questions, I would expect, if the buzz about the ads and the ads themselves had an effect on behavior outside of social media, I would expect to see an impact on search activity.
To examine the research question 1, I define the following hypotheses, each for one social media platform.

*Hypothesis 01: There is a significant relationship between relative volume of social soundtrack conversations and web searching data for Twitter.*

*Hypothesis 02: There is a significant relationship between relative volume of social soundtrack conversations and web searching data for Instagram.*

*Hypothesis 03: There is a significant relationship between relative volume of social soundtrack conversations and web searching for Tumblr.*

The research question 2 regarding evaluation of social soundtrack attitudes on brand related web search is examined by the following three hypotheses each for one social media platform.

*Hypothesis 04: There is a significant relationship between attitude of social soundtrack conversation and web searching data for Twitter.*

*Hypothesis 05: There is a significant relationship between attitude of social soundtrack conversation and web searching data for Instagram.*

*Hypothesis 06: There is a significant relationship between attitude of social soundtrack conversation and web searching data for Tumblr.*

**Difference of Viral Effect**

In addition to measuring the relationship between social soundtrack and web search, I examine the viral effect related to each individual brand that differ significantly between Pre and Post phases (i.e., before and after happening the IRL event) in social soundtrack. I exclude During phase due to insufficiency of search volume granularity on the search engine available on game day (Heisler, 2008). I limit my evaluation of examining the viral effect only for Twitter...
based on the percentage of retweets present in each phase for each brand. I mention it as a limitation that the other two social media platforms lacks this “retweeting” feature.

I formulate a research hypothesis for each Super Bowl brand to examine the difference of viral effect between two phases on Twitter as:

_Hypothesis 07: There is a significant difference in viral effect regarding individual brands between Pre and Post Super Bowl phases on Twitter._

Understanding the difference whether brand-related tweets go viral before or after the event will facilitate companies to understand what and when people share brand related information.

**Data Collection and Research Design**

Super Bowl XLIX occurred place on the 1st of February (Sunday) 2015 at University of Phoenix Stadium, Arizona, USA. The kick-off time was 6:30 PM Eastern. The NBC channel broadcast the event, with an average of 114.5 million viewers, reaching to 118 million viewers during the half time show (Wikipedia, 2015d).

As shown in Table 3-1, I collected data related to Super Bowl XLIX from the 10th of January 2015 and continued through the 24th of February 2015 on each of the three social media platforms. To collect data from each platform, I utilized the respective APIs and tokens for Twitter, Instagram, and Tumblr in corresponding scripts with search queries.

The queries that I used include: ‘superbowlxlix’, ‘superbowl49’, ‘superbowlcommercial’, ‘superbowlAd’, ‘superbowlhalftime’, ‘superbowl2015’, ‘2015superbowl’, ‘sb49’ and ‘football’. The aim of forming this list of queries was to collect data for this research using each term as a search query on all three social media platforms.
The query list included the terms that occurred most frequently as social media tags (e.g., #superbowlcommercial, #superbowlxlix, etc.) in a collection of sample data for all social media platforms collected against the seed query named “superbowl”. I collected the sample data for 48 hours (i.e. from 01/06/2015-16:00:00 to 01/08/2015-16:00:00) to identify the potential queries for this research, and the sample data was not included in the data set used in this research.

Table 3-1. Volume of collected Super Bowl XLIX social media data by social media platforms

<table>
<thead>
<tr>
<th>Social Media Platform</th>
<th>Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>3,112,789</td>
</tr>
<tr>
<td>Instagram</td>
<td>811,262</td>
</tr>
<tr>
<td>Tumblr</td>
<td>51,569</td>
</tr>
</tbody>
</table>

**Design of Social Soundtrack and Web Search Data Collection**

For my hypotheses, I divide the data collection period into three temporal phases to test the change in viral effect. Table 2 shows the date and time of each of the temporal phases.

I count game day as the During phase and is used for research question 1 and research question 2 only. The game started at 2/1/2015-18:30:00 and continued till 2/1/2015-22:30:00. I consider that the During phase respectively includes these 4 hours; the first 18 and half hours of the game day (2/1/2015-00:00:00 to 2/1/2015-18:39:50), and the remaining one and half hours of the day (2/1/2015-22:30:01 to 2/1/2015-23:59:59). For evaluation of research hypothesis 07, I do not include the game day in my analysis, as unlike the social soundtrack data, I cannot annotate sufficiently the granularity of Google search data during this time frame for my research (Heisler, 2008). From a research design perspective (for hypothesis 07 only), search data collected on a single day become inconsistent for analysis with that collected over multiple days in other phases.
The Pre phase spans from the moment the data collection for social soundtrack starts and continues till the beginning of the game day. The Post phase begins the day following game day and continues until that point the social soundtrack data collection ends.

Table 3-2. Start and end dates and time for Super Bowl phases (*Denotes for comparison but not included in analysis of hypothesis 07)

<table>
<thead>
<tr>
<th>Super Bowl Phase</th>
<th>Start Date-Time</th>
<th>End date-Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre</td>
<td>1/10/2015- 00:00:00</td>
<td>2/1/2015-18:29:59</td>
</tr>
<tr>
<td>During*</td>
<td>2/1/2015-18:30:00</td>
<td>2/1/2015-22:30:00</td>
</tr>
<tr>
<td>Post</td>
<td>2/1/2015-22:30:01</td>
<td>2/24/2015-00:00:00</td>
</tr>
</tbody>
</table>

In my research regarding social soundtrack-web search relationship, I deal with 47 commercials (Anonymous, 2015; Staff, 2015). The list of Super Bowl commercial keywords contains the ad titles (e.g., ‘mercedes’, ‘coca cola’, ‘wix’ etc.), titles of the themes / videos for the brands (e.g., ‘real strength’, ‘like a girl’ etc.), the popular name of the brands (e.g., coke, burrito etc.), hashtags associated with the spots (e.g., ‘#realstrength’, ‘#likeagirl’, ‘#itsthateasy’ etc.) and the first and last names of actors participated in Super Bowl commercial videos (e.g., ‘liam’, ‘neeson’, ‘braylon’, ‘oineil’, ‘o-neil’ etc.). I check the presence of these keywords, extracted from relevant websites (Anonymous, 2015; Staff, 2015), in the social media posts, while social media posts are collected based on the list of search queries. I generate the list of search queries based on the terms that occurred most frequently as tags in the sample data, not included in data set. I use the keywords list for Super Bowl commercials formed to determine the sub-list for each of these 47 brands such as upcoming movie trailers (e.g., 50 Shades of Gray, Jurassic World 3D), products (e.g., Mercedes, Skittles), services (e.g., Esurance, TurboTax), technologies (e.g., Microsoft, Mophie), mobile games (e.g., Game of War, Heroes Charge) etc. I segregate the Super Bowl commercials keywords list into 47 sub-lists by identifying the ad title, titles of the theme / video, hashtags and the names of the actors participated to promote the ad for each of
these 47 brands. So, a social media post belongs to a particular brand if the post contains the corresponding keywords from the keyword sub-list concerning that brand.

I collect the search data regarding web queries from Google Trends for evaluation of my hypotheses, where the query list contains the brand names of the commercials extracted from the web sites (Anonymous, 2015; Staff, 2015) (e.g. ‘mercedes’, ‘budweiser’, ‘pepsi’, ‘skittles’, ‘microsoft’ etc.). The brands either sponsor the championship or pay for advertisements during the media broadcast. The search data shows the relative interest of users over days for those brands. The spans of search data collection for Pre and Post phases are same as that for social media data, as shown in Table 3-2.

I segregate the count of social soundtrack posts collected for all three social media platforms on Super Bowl commercials into daily (24 hours) intervals to keep the same dimensionality as that of search engine data (i.e., continuous scale). I compute relative counts of the postings in social soundtracks for all three social media platforms by using equation 1 to maintain the same scale that the searching data exhibits (0 to 100) for examining the research hypotheses. I define relative count as relative volume in my research.

\[
rel\_count^j = \frac{\text{Count\_of\_post}^j_i}{\max_{i,j}(\text{Count\_of\_post}^j)} \times 100
\]

(3-1)

In equation 3-1, \(i\) and \(j\) denote the day and the social media platform, respectively. For normalization, the relative count values lie in the range of 0 to 100. Max function selects the highest value from the set of frequencies for days across all three phases on \(j^{th}\) social media platform.
Measuring Attitude

To evaluate research question 2, I need to measure the attitudes about each brand for all three social media platforms. Measurement of attitude involves the computation of sentiment of the postings that is carried out in two major stages. The first stage deals with mining emoticons from the postings on all three social soundtrack mediums, while the second stage determines the presence of positive and/or negative words. Before carrying out the stages, the pre-processing steps are carried out as: a) remove the hashtags, b) remove the usernames addressed by “@” and “RT” within the messages, c) remove the special characters such as “@”, “RT”, “via” and URLs, d) replace all contraction of verb forms to the corresponding verbs (e.g., “’ll” to “will”, “’ve” to “have”, “’re” to “are”) e) replace all negations (“neither”, “nor”, “never”, “no”, “negative”, “not”, “n’t”, “won’t” etc.) to “not”, f) replace a sequence of repeated characters by two characters (e.g., “cooooool” to “cool”, “oooooh” to “ooh” etc.), g) lowercase the letters and expand the acronyms in the posts to its meaning extracted from relevant online resources (Fisher, 2012; Howard, 2009; Rouse, 2015). I execute sentence level parsing of the texts based on the punctuations (e.g. “.”, “?”,”!” etc.) and/or emoticons as used in (Hogenboom et al., 2013) before performing the stages. Once the sentence level parsing is done, I remove the punctuations after extracting emoticons.

Extracting Emoticons

I extract the emoticons from the social soundtrack messages posted in all three social networking platforms by preparing two emoticon sentiment lexicons. I categorize the lexicons as “positive” sentiment lexicon and “negative” sentiment lexicon. The lexicons are prepared from available online resources (ComputerUser, 2014; Wikipedia, 2015a). I combine these online lists
of positive and negative emoticons into the corresponding lexicons, while leaving out duplicate entries. I do not weigh the intensity of the emotions, but I do assign the emoticons either positive (e.g., “:-D”, “:-)”, “:-)” “:o” etc.) or negative (e.g., “: (”, “:-{(”, “:-_” “v.v”, “D8”, “:c” etc.). I assign the polarity of sentences contained in Twitter texts, Instagram captions, and Tumblr blogs either as positive or negative, depending on the presence of positive and negative emoticons. I exclude neutral emoticons from my research.

Presence of Positive and Negative Words

Once the data cleaning and pre-processing of texts is complete, I follow the second stage to determine the existence of positive and negative words. I use online sentiment lexicon (Liu & Minqing, 2004) used in (Liu, Hu, & Cheng, 2005) to form my lexicons of positive and negative words, while removing the duplicating entries. In determining the attitude of the sentences by means of presence of positive / negative words, I split the sentences into tokens and assign the polarity according to the following logic.

\[
\begin{align*}
&\text{if ("not" } \notin \text{ sentence}_i \land \text{pos_word}_j \in \text{ sentence}_i \land \text{index("not") < index(pos_word}_j))

&\quad \text{count(polarity}_{\text{neg}}) + 1;

&\text{else if ("not" } \notin \text{ sentence}_i \land \text{pos_word}_j \in \text{ sentence}_i)

&\quad \text{count(polarity}_{\text{pos}}) + 1;

&\text{if ("not" } \notin \text{ sentence}_i \land \text{neg_word}_j \in \text{ sentence}_i \land \text{index("not") < index(neg_word}_j))

&\quad \text{count(polarity}_{\text{pos}}) + 1;

&\text{else if ("not" } \notin \text{ sentence}_i \land \text{neg_word}_j \in \text{ sentence}_i)
\end{align*}
\]
\[ \text{count}(\text{polarity}_{\text{neg}}) + \cdot \]

Table 3-3 shows the polarity of the example statements based on presence of positive and negative words.

Table 3-3. Example statements and polarity

<table>
<thead>
<tr>
<th>Statement</th>
<th>Polarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>“it is not at all worth viewing”</td>
<td>negative</td>
</tr>
<tr>
<td>“the katy perry show was amazing”</td>
<td>positive</td>
</tr>
<tr>
<td>“i will not miss the telecast of halftime show”</td>
<td>positive</td>
</tr>
<tr>
<td>“first 15 min of the game was boring”</td>
<td>negative</td>
</tr>
</tbody>
</table>

**Estimating Attitude**

Once the polarity of the statements of tweets, captions, or blogs related to each commercial are determined w.r.t the presence of emoticons and sentiment words, I compute the polarity score at the sentence level. Next, I aggregate the score at single tweet, caption, or blog level. Once posting level attitude score is computed, further aggregation is carried out on the number of messages posted within the 24 hour time window.

I assign a scale of rating for the emoticons and the sentiment words. I provide more positive or negative weight on positive and negative emoticons than that for positive and negative words as emoticons simulate the nonverbal cues that dominate verbal cues (Burgoon & Saine, 1978) (i.e., the text messages) and hence an important emotion/intention indicator for viewers. The texts coupled with emoticons have higher sentiment than the messages without emoticons.

The weight scale I chose is as follows. Negative emoticons: -2, negative words: -1, positive words: +1, positive emoticons: +2 and 0 for neutral emoticons. A positive word with a “not” and a negative word with a “not” immediate before it are counted as negative and positive word respectively. I am assigning equal weights with opposite signs for positive and negative
emoticons and assign same positive and negative weight for positive and negative words but with opposite signs as in (Kramer, 2010). So, the attitude score I compute using formula 3-2 for a specific Super Bowl category in a specific phase.

\[
S_{tk} = \frac{1}{N} \cdot \sum_{i=1}^{M} \left(2 \cdot PosEmot_j^i + 1 \cdot PosWord_j^i - 1 \cdot NegWord_j^i - 2 \cdot NegEmot_j^i\right)
\]  

(3-2)

Here, I term \(S_{tk}\) as the average attitude score of postings aggregated in a particular 24 hour time window \(t_k\). \(N\) = total number of postings within \(t_k\). \(PosEmot_j^i, PosWord_j^i, NegWord_j^i, NegEmot_j^i\) are positive emoticons, positive words, negative words and negative emoticons for sentence \(j\) in posting \(i\). \(M\) is the count of sentences in posting \(i\). Higher \(S_{tk}\) indicates more positive attitudes. The steps of attitude measurement for all three social soundtracks are performed for each Super Bowl commercial to evaluate research question 2.

Once computation of relative counts and attitude scores are done for social soundtrack conversations, I organize the social and search data as balanced panel data (Berrington, Smith, & Sturgis, 2006b) for all three social soundtrack mediums where each of the 47 brands has relative counts of social soundtrack conversations and web search across total number of days for data collection (i.e. 46 days). So, the balanced panel dataset can be viewed as a three dimensional space where the dimensions are 1) brands (47 brands), 2) time stamps (46 days) and 3) the relative volumes and attitude score for online channels (Twitter, Instagram, Tumblr and Google). As there are three social media platforms, I have three such posting-searching data panels. In my dataset, I have a total of 2162 records (47x46) each with relative counts and attitude scores for three social media platforms along with relative counts for one search engine. Each record is the unit of analysis in my study to evaluate my hypotheses.
**Viral Tweet Ratio**

To evaluate hypothesis 07, I compute the daily viral tweet ratio as proportion of retweets (RT) that is present in the posts for Twitter in 24 hour time window. Retweet (RT) is a specific category of pattern which can be recognized by presence of “‘ RT @’, ‘ RT: @’, ‘RT@’, ‘retweeting @’, ‘retweet @’, ‘ (via @)’, ‘ RT (via @)’, ‘ thx @’, ‘ HT @’ or ‘ r @’ ” in the tweets. I measure the daily proportion of retweets for each and every Super Bowl commercial separately for Pre and Post phases. Retweets are the mediums that help a tweet to go viral on Twitter (Zarrela, 2009). The daily ratio of viral activity is the unit of analysis to evaluate hypothesis 07.

**Methodology**

**Social Influence on Web Search**

To identify influence in RQ1 and RQ2, I follow two separate methods. The first one is the Granger causality test, which is a statistical hypothesis test that identifies whether one time series data is capable of forecasting the other (Granger, 1969) as the volume and attitude score of social soundtrack and the volume of web search are the time series data. I also test whether the reciprocal causality exist between two time series data. If volume and attitude of social soundtrack independently cause web search, the reciprocal causality tests whether web search can cause volume and / or attitude of social soundtrack separately. Before performing Granger causality test, I need to make the time series data stationary.

The second method that I use is panel data regression with fixed and random effects (Bell & Jones, 2015; Schmidheiny & Basel, 2011) on brands to quantify the relationship between conversing on the social soundtrack and searching on the Web. In the regression model, Google
search data is the response variable, while the relative volume and attitude metrics of social soundtrack data concerning brands are the cofactors. I conduct the Hausman specification test to discover the preferred model (fixed or random) and observe time effects on the linkage between social postings and web searching. The fixed effects model assumes that individual specific effect is correlated with the independent variable, while for random effects there is no correlation between individual specific effect and independent variables. I set the movie brand “50 shades of gray” as the baseline for brand effect in the fixed effect model. I are estimating the pure effect of web searching by controlling the unobserved heterogeneity with the addition of dummy variables for each brand in the fixed effects model.

**Difference in Viral Effect**

For examining hypothesis 07, I use Welch’s independent sample t-test to measure the significant difference in viral ratio between Pre and Post phases as the variance and sample size of the data in two phases are unequal (i.e., 22 samples in Pre phase and 23 samples in Post phase). The level of significance is maintained at $\alpha = 0.05$.

The relative volume of continuous scale data such as social soundtrack conversations, brand attitudes, viral tweets and relative search volume follow the approximate normal distribution.
**Results**

**Social Influence on Web Search**

**Granger Causality Procedure**

The web search and the social conversation data are to be made stationary time series data before applying the Granger causality test on all three social media platforms. I perform unit root test and number of differences required for the volume and attitudinal scores for social conversation and relative volume of web search data and find out that after the first difference the data becomes stationary for Twitter, Instagram and Tumblr.

Once the data has become stationary, I apply Granger causality test separately 1) between volume of web search (X) and volume of brand related social soundtrack conversation (Y) and 2) between volume of web search (X) and attitudinal score of social soundtrack conversations related to brands (Z). The number of lags is included according to minimum AIC information criterion. Table 3-4 provides the optimal number of lags that generates minimum AIC values for 1) (Y, X), and 2) (Z, X) for Twitter, Instagram and Tumblr.

<table>
<thead>
<tr>
<th></th>
<th>Twitter</th>
<th></th>
<th>Instagram</th>
<th></th>
<th>Tumblr</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lags</td>
<td>AICmin</td>
<td>Lags</td>
<td>AICmin</td>
<td>Lags</td>
<td>AICmin</td>
</tr>
<tr>
<td>(Y, X)</td>
<td>8</td>
<td>1.429</td>
<td>9</td>
<td>1.395</td>
<td>8</td>
<td>1.347</td>
</tr>
<tr>
<td>(Z, X)</td>
<td>7</td>
<td>-0.083</td>
<td>7</td>
<td>-0.726</td>
<td>8</td>
<td>2.787</td>
</tr>
</tbody>
</table>

I test whether social soundtrack volume (Y) *cause* brand search volume of Google (X) with optimal lags (see Table 3-4) for Twitter, Instagram and Tumblr respectively. Additionally, I also evaluate whether social soundtrack attitude (Z) *cause* Google search volume (X) with
optimal lags (see Table 3-4) for Twitter, Instagram and Tumblr respectively. Table 3-5A holds the F-statistic with p-values of the models for all three social media platforms.

Table 3-5A: Result for Granger causality for all three social media platforms (‘*’ denotes significance causation, M->N means M Granger causes N)

<table>
<thead>
<tr>
<th></th>
<th>Twitter F-statistic</th>
<th>p-value</th>
<th>Instagram F-statistic</th>
<th>p-value</th>
<th>Tumblr F-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Y, X): Y-&gt;X</td>
<td>3.335</td>
<td>0.0008*</td>
<td>5.165</td>
<td>5.87e-07*</td>
<td>6.7768</td>
<td>8.21e-09*</td>
</tr>
<tr>
<td>(Z, X): Z-&gt;X</td>
<td>2.461</td>
<td>0.016*</td>
<td>1.066</td>
<td>0.383</td>
<td>2.01</td>
<td>0.042*</td>
</tr>
</tbody>
</table>

From Table 3-5A, the causality of Google search volume by social soundtrack volume is observed for all three social media platforms (p-values < 0.05). For the Granger causality test between attitude and search volume, it is noticed from p-values that for Twitter and Tumblr, social soundtrack attitude causes web search, while for Instagram, the null hypothesis (i.e., social soundtrack attitude does not cause Google search) cannot be rejected.

Next, I evaluate the reciprocal causation taking into account whether Google search causes social soundtrack volume and social soundtrack attitudes in the specified lags, shown in Table 3-5B represent the result of reciprocal causation done by means of Granger causality test.

Table 3-5B: Result for reciprocal causality for all three social media platforms (‘*’ denotes significance causation, M->N means M Granger causes N)

<table>
<thead>
<tr>
<th></th>
<th>Twitter F-statistic</th>
<th>p-value</th>
<th>Instagram F-statistic</th>
<th>p-value</th>
<th>Tumblr F-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(X, Y): X-&gt;Y</td>
<td>3.920</td>
<td>0.0001*</td>
<td>1.764</td>
<td>0.070</td>
<td>5.736</td>
<td>2.99e-07*</td>
</tr>
<tr>
<td>(X, Z): X-&gt;Z</td>
<td>0.486</td>
<td>0.846</td>
<td>0.813</td>
<td>0.576</td>
<td>0.843</td>
<td>0.565</td>
</tr>
</tbody>
</table>

From Table 3-5B, it is noticed that Google search causes volume of social soundtrack conversations for Twitter and Tumblr, while the reciprocal causation is not supported for Instagram. Regarding social soundtrack attitude, none of the social media platforms support the alternative hypothesis (i.e., Google search causes social attitude about brands).
**Panel Data Regression**

Once the result of Granger causality is achieved, I perform regression analysis on the panel data for each social media platform in R to quantify the relationship and compute the results of both fixed effects and random effects model. For panel data regression, I consider the forward direction of relationship (i.e. social soundtrack volume and attitude cause web search related to brands) as the social soundtrack volume directly cause Google search in all three social media platforms and brand attitudes also cause Google search in majority of social networks in forward direction of causal relationship. In my regression equation, attitude scores and relative counts of the social soundtrack conversations are explanatory variables, while the Google search data is the response. For random effects model, R takes “50 shades of gray” as the baseline, as the first in the brand list. I perform Hausman specification test (Hausman, 1978) to choose either fixed or random effects model. The Hausman test results, displayed in Table 3-6, show that the p-values for all three social media platforms are less than 0.05, which indicates the fixed effects model is preferable to use.

Table 3-6: Hausman specification test between fixed effects and random effects models for three social media platforms

<table>
<thead>
<tr>
<th>Social Media</th>
<th>F(46, &gt;120)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>201.27</td>
<td>&lt;2.2e-16</td>
</tr>
<tr>
<td>Instagram</td>
<td>162.47</td>
<td>&lt;2.2e-16</td>
</tr>
<tr>
<td>Tumblr</td>
<td>201.09</td>
<td>&lt;2.2e-16</td>
</tr>
</tbody>
</table>

The test result of hypotheses 01-03 are displayed in Table 3-7, along with the test results of hypotheses 04-06.
Table 3-7. Coefficient estimate of regression for relative counts and attitude with coefficient of determination (R2) in different social soundtrack mediums (* denotes significance, i.e. p-value < 0.05)

<table>
<thead>
<tr>
<th></th>
<th>Rel Vol Estimate</th>
<th>t-value</th>
<th>p-value</th>
<th>R2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>4.723*</td>
<td>3.955*</td>
<td></td>
<td>0.0015</td>
</tr>
<tr>
<td>Instagram</td>
<td>11.862*</td>
<td>1.143</td>
<td>7.221</td>
<td>0.335</td>
</tr>
<tr>
<td>Tumblr</td>
<td>8.617*</td>
<td>0.952*</td>
<td>3.676</td>
<td>2.118</td>
</tr>
</tbody>
</table>

From Table 3-7, it is seen that the estimates of relative volume for all three social media platforms are significant (p-value <0.05). Regarding research question 1, it is seen that each unit increase of posts on Twitter, Instagram and Tumblr significantly increases the Google search concerning brands by 4.72 times, 11.862 times and 8,617 times, respectively. It infers that there is a significant relationship between relative volume of social soundtrack conversations and web search regarding brands. So hypothesis 01, 02 and 03 are satisfied.

Regarding influence of social soundtrack attitude on Google brand search, it is observed from Table 3-7 that for Twitter and Tumblr, the relationship between social media attitude and Google search on brands is significant. For Instagram, the conversing attitude-search relationship is insignificant, though it has the positive correlation (i.e., 1.143 : 1). For Twitter, each unit increase of aggregated attitude on tweets significantly increase the web search 3.96 times, while for Tumblr, the search significantly increases 0.95 times with each unit increase of blog attitudes. So hypothesis 04 and hypothesis 06 are satisfied, while hypothesis 05 is not supported.

I also measure the fixed effect of brands on the posting-searching association. The baseline is again the movie brand “50 shades of gray”. The coefficients are shown in Figures 3-2a and 3-2b for better clarity.
Figure 3-2a. Brand fixed effect in volume of social conversations and web search association w.r.t “50 shades of gray” on three social media platforms for first set of brands

Figure 3-2b. Brand fixed effect in volume of social conversations and web search association w.r.t “50 shades of gray” on three social media platforms for second set of brands
From Figures 3-2a and 3-2b, it is observed that “Budweiser” brand has the greatest significant impact of relationship between social conversing and web searching (Twitter: 69.21, Instagram: 64.67, Tumblr: 68.67), which matches with the view corroborated by (Jarboe, 2015). It is followed by the car commercials and “Coco Cola” brand (Twitter: 65.45, Instagram: 59.54, Tumblr: 64.45) compared to the baseline “50 Shades of Gray” on all social media platforms. It is worth mentioning that the brand fixed effect on social conversing-web searching association follows a similar pattern for all three social soundtrack mediums.

Figure 3-3 displays the time effect on social-search relationship for each platform. The result of fixed effect model exhibits that conversation related to several brands from the perspective of relative volume and attitude influence web searching in relation to the baseline (i.e., “50 Shades of Gray”).

Figure 3-3. Time fixed effect in social conversations and web search association w.r.t “10th Jan 2015” on three social media platforms (**” represents significance)
Table 3-8. Fixed effect in social conversations and web search association w.r.t “50 shades of gray” on three social media platforms

<table>
<thead>
<tr>
<th>Car Brands</th>
<th>Twitter estimate</th>
<th>Instagram estimate</th>
<th>Tumblr estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>BMW</td>
<td>67.61*</td>
<td>63.79*</td>
<td>64.58*</td>
</tr>
<tr>
<td>Dodge</td>
<td>63.52*</td>
<td>58.40*</td>
<td>62.53*</td>
</tr>
<tr>
<td>Jeep</td>
<td>61.97*</td>
<td>55.80*</td>
<td>59.13*</td>
</tr>
<tr>
<td>Kia</td>
<td>57.46*</td>
<td>50.46*</td>
<td>56.36*</td>
</tr>
<tr>
<td>Lexus</td>
<td>55.94*</td>
<td>55.26*</td>
<td>55.60*</td>
</tr>
<tr>
<td>Mercedes</td>
<td>65.97*</td>
<td>60.29*</td>
<td>62.87*</td>
</tr>
<tr>
<td>Nissan</td>
<td>63.57*</td>
<td>58.88*</td>
<td>62.70*</td>
</tr>
<tr>
<td>Toyota</td>
<td>59.04*</td>
<td>58.69*</td>
<td>57.75*</td>
</tr>
<tr>
<td>Fiat</td>
<td>35.16*</td>
<td>33.50*</td>
<td>33.35*</td>
</tr>
<tr>
<td>Chevrolet</td>
<td>26.18*</td>
<td>23.15*</td>
<td>26.01*</td>
</tr>
</tbody>
</table>

Table 3-8 provides the fixed effects estimates of car related commercials which exist at the higher ends relative to the baseline, particularly for first eight cars in Table 3-8. Moreover, it is worth noting the “Sprint” and “Nationwide” commercials have significantly negative fixed effect on social conversing-web searching relationship concerning brands on all three social media platforms (i.e., Nationwide: Twitter: -9.32, Instagram: -10.89, Tumblr: -11.16 and Sprint:: Twitter: -6.40, Instagram: -5.42, Tumblr: -5.52). Thus, 43 out of 46 brands have significant positive or negative fixed effects (i.e. p-value > 0.05), while “Terminator”, “Jurassic World” and “Mophie” have insignificant effects on social soundtrack-web search relationship. Out of 43 brands that show significant effect, 41 brands show positive and 2 show negative effect (i.e., “Sprint” and “Nationwide”) relative to the baseline.

The time effect shows the specific days that contribute to the social conversation-web search relationship in relation to day 1 (i.e. 10th Jan 2015) from the perspective of relative count and attitude perspective. It is seen from Figure 3-3 that the trend of social influence on web search concerning brands changes from negative to positive starting from Pre phase and ending at Post phase. The social-search influence is significantly positive in particularly during and the majority of the time in Post phase, while it is negative and insignificant in major portions of the
Pre phase for all three social media platforms. The time effect reaches its peak on 2nd Feb 2015 (just after the game day) on all three platforms. It is important to note that time effect too follows a similar patterns for all three social media platforms.

Table 3-9 displays the dates where the time effects are individually significant on Twitter, Instagram and Tumblr.

Table 3-9. Time effect in social conversations and web search association w.r.t “10th Jan 2015” on three social media platforms (“*” denotes the significance)

<table>
<thead>
<tr>
<th>Day</th>
<th>Twitter estimate</th>
<th>Instagram estimate</th>
<th>Tumblr estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>12-Jan</td>
<td>-4.11</td>
<td>-4.87*</td>
<td>-4.02</td>
</tr>
<tr>
<td>30-Jan</td>
<td>6.99*</td>
<td>5.79*</td>
<td>5.78*</td>
</tr>
<tr>
<td>31-Jan</td>
<td>6.89*</td>
<td>5.15*</td>
<td>5.52*</td>
</tr>
<tr>
<td>1-Feb</td>
<td>10.96*</td>
<td>8.80*</td>
<td>10.26*</td>
</tr>
<tr>
<td>2-Feb</td>
<td>30.42*</td>
<td>26.00*</td>
<td>24.62*</td>
</tr>
<tr>
<td>3-Feb</td>
<td>7.11*</td>
<td>4.99*</td>
<td>5.17*</td>
</tr>
<tr>
<td>5-Feb</td>
<td>4.93*</td>
<td>4.48</td>
<td>4.79*</td>
</tr>
<tr>
<td>6-Feb</td>
<td>4.44</td>
<td>3.94</td>
<td>4.61*</td>
</tr>
<tr>
<td>7-Feb</td>
<td>9.33*</td>
<td>9.01*</td>
<td>9.55*</td>
</tr>
<tr>
<td>8-Feb</td>
<td>6.36*</td>
<td>5.49*</td>
<td>6.45*</td>
</tr>
<tr>
<td>13-Feb</td>
<td>5.46*</td>
<td>4.96*</td>
<td>4.84*</td>
</tr>
<tr>
<td>14-Feb</td>
<td>6.38*</td>
<td>6.61*</td>
<td>5.77*</td>
</tr>
<tr>
<td>15-Feb</td>
<td>6.63*</td>
<td>6.31*</td>
<td>6.38*</td>
</tr>
<tr>
<td>16-Feb</td>
<td>4.57*</td>
<td>4.12*</td>
<td>4.18*</td>
</tr>
<tr>
<td>21-Feb</td>
<td>4.95*</td>
<td>4.24</td>
<td>4.92</td>
</tr>
<tr>
<td>22-Feb</td>
<td>5.18*</td>
<td>4.61</td>
<td>4.88*</td>
</tr>
</tbody>
</table>

Number of significant time effect in Post phase: 12
Number of significant time effect in Pre phase: 2

From Table 3-9, it is found that Post phase dominates relative to Pre phase from perspective of number of days, with significant time effects on relationship between social conversing and web searching concerning brands. From 30th Jan 2015 and 3rd Feb 2015, from 7th
Feb 2015 to 8th Feb 2015, and from 13th Feb to 16th Feb, time effect on social-search association is significant for all three social media platforms.

For better understanding, I provide Figures 3-4a and 3-4b to highlight the average attitude of brands averaged over number of days in three phases. From Figures 4a and 4b, it is observed that “Sprint” and “Nationwide” have negative attitudes for all three social media platforms, which is witnessed as significant negative contribution to the relationship between social conversation and web search (see Figure 3-2a) w.r.t. “50 Shades of Gray”. Beechler (Beechler, 2015) noted that 77.3% of second screen conversation related to “Nationwide” were negative. On the other hand, it is observed from Figures 3-4a and Figure 3-4b, that brand “Budweiser” holds the highest average daily attitude scores on all social media platform, which is again noticed by the highest significant fixed effect estimate on social soundtrack-web search linkage.

Figure 3-4a. Attitude scores of the first set of brands averaged over number of days on three social media platforms
Difference of Viral Effect

I evaluate hypothesis 07 for Twitter only to find the difference in retweets between Pre and Post phases for each commercial. I have an intuition from the time effects that more Super Bowl commercials displays higher mean of retweets in Post phase. I perform Welch’s t test on the samples in Pre and Post Super Bowl phases.

Table 3-10. Average Retweets on Twitter and average relative traffic volume on Google search engine in Pre and Post phases for Super Bowl commercial brands

<table>
<thead>
<tr>
<th>Brands</th>
<th>Google</th>
<th>Twitter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre</td>
<td>Post</td>
</tr>
<tr>
<td>50 Shades of Grey*</td>
<td>0.069</td>
<td>0.41</td>
</tr>
<tr>
<td>Avocado</td>
<td>0.469</td>
<td>0.467</td>
</tr>
<tr>
<td>BMW</td>
<td>0.895</td>
<td>0.901</td>
</tr>
<tr>
<td>Budlight</td>
<td>0.342</td>
<td>0.348</td>
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<tr>
<td>Budweiser</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>Cash of Clans*</td>
<td>0.67</td>
<td>0.734</td>
</tr>
<tr>
<td>Brands</td>
<td>Pre</td>
<td>Post</td>
</tr>
<tr>
<td>----------------------</td>
<td>-------</td>
<td>-------</td>
</tr>
<tr>
<td>Chevrolet*</td>
<td>0.47</td>
<td>0.53</td>
</tr>
<tr>
<td>Coca Cola*</td>
<td>0.87</td>
<td>0.90</td>
</tr>
<tr>
<td>Dodge*</td>
<td>0.85</td>
<td>0.89</td>
</tr>
<tr>
<td>Doritos</td>
<td>0.18</td>
<td>0.196</td>
</tr>
<tr>
<td>Dove*</td>
<td>0.56</td>
<td>0.38</td>
</tr>
<tr>
<td>Eat24*</td>
<td>0.51</td>
<td>0.64</td>
</tr>
<tr>
<td>Esurance*</td>
<td>0.269</td>
<td>0.332</td>
</tr>
<tr>
<td>Fiat</td>
<td>0.56</td>
<td>0.619</td>
</tr>
<tr>
<td>Fast and Furious*</td>
<td>0.50</td>
<td>0.65</td>
</tr>
<tr>
<td>Game of War</td>
<td>0.518</td>
<td>0.545</td>
</tr>
<tr>
<td>Geico*</td>
<td>0.778</td>
<td>0.85</td>
</tr>
<tr>
<td>GoDaddy*</td>
<td>0.48</td>
<td>0.504</td>
</tr>
<tr>
<td>GrubHub</td>
<td>0.519</td>
<td>0.603</td>
</tr>
<tr>
<td>Heros Charge*</td>
<td>0.682</td>
<td>0.831</td>
</tr>
<tr>
<td>Jeep*</td>
<td>0.815</td>
<td>0.87</td>
</tr>
<tr>
<td>Jurassic World 3D*</td>
<td>0.155</td>
<td>0.283</td>
</tr>
<tr>
<td>Kia</td>
<td>0.805</td>
<td>0.826</td>
</tr>
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<td>Lexus</td>
<td>0.797</td>
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<td>McDonalds*</td>
<td>0.487</td>
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<td>Mercedes</td>
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<td>0.41</td>
</tr>
<tr>
<td>Nationwide*</td>
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<td>0.23</td>
</tr>
<tr>
<td>Nissan*</td>
<td>0.85</td>
<td>0.89</td>
</tr>
<tr>
<td>Pepsi</td>
<td>0.714</td>
<td>0.72</td>
</tr>
<tr>
<td>Pitch Perfect 2*</td>
<td>0.238</td>
<td>0.414</td>
</tr>
<tr>
<td>Pizza Hut</td>
<td>0.523</td>
<td>0.518</td>
</tr>
<tr>
<td>Skechers*</td>
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<td>0.78</td>
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<td>Skittles*</td>
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<td>0.336</td>
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<tr>
<td>Snickers*</td>
<td>0.317</td>
<td>0.423</td>
</tr>
<tr>
<td>Sprint*</td>
<td>0.797</td>
<td>0.864</td>
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<tr>
<td>Squarespace*</td>
<td>0.39</td>
<td>0.54</td>
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<td>Terminator</td>
<td>0.24</td>
<td>0.23</td>
</tr>
<tr>
<td>T Mobile</td>
<td>0.826</td>
<td>0.827</td>
</tr>
<tr>
<td>Tomorrowland*</td>
<td>0.322</td>
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<tr>
<td>Toyota</td>
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<td>0.931</td>
</tr>
<tr>
<td>Turbo Tax*</td>
<td>0.459</td>
<td>0.655</td>
</tr>
<tr>
<td>Verizon</td>
<td>0.791</td>
<td>0.794</td>
</tr>
<tr>
<td>Victoria’s Secret*</td>
<td>0.53</td>
<td>0.52</td>
</tr>
<tr>
<td>Wix.com</td>
<td>0.62</td>
<td>0.60</td>
</tr>
</tbody>
</table>
Brands with significant higher web search from Pre to Post
Brands with significant lower web search from Pre to Post
Brands with no significant change in web search from Pre to Post

<table>
<thead>
<tr>
<th>Brands</th>
<th>Google</th>
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<th>Twitter</th>
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<tr>
<td></td>
<td>Pre</td>
<td>Post</td>
<td>t-val</td>
<td>p-val</td>
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<tr>
<td>Brands with significant higher</td>
<td></td>
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<td>17</td>
<td></td>
</tr>
<tr>
<td>web search from Pre to Post</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Brands with significant lower</td>
<td></td>
<td></td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>web search from Pre to Post</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brands with no significant</td>
<td></td>
<td></td>
<td>29</td>
<td></td>
</tr>
<tr>
<td>change in web search from Pre</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>to Post</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Note: Notable increases in traffic are in bold italics and notable decreases in traffic are in bold between Pre and Post phases. The brands that exhibit significant change from Pre to Post in at least one online channel are denoted in bold with ‘*’ shaded brands have no significant correlations.

Table 3-10 displays the Welch’s t-test result. I also perform Welch’s t test on relative volume of web search for each and every commercial between Pre and Post phases. As the relative volume of social soundtrack influences the brand search and the time effect on this conversing-searching linkage is dominating in Post phase, I believe that the mean web search for each brand in the Post phase will be higher.

It is observed from Table 3-10 that hypothesis 07 is satisfied by 19 brands. Out of 19 brands, 16 commercials show a notable increase of viral effect from Pre to Post Super Bowl phases, while 3 shows the reverse trend, which supports my intuition of having more number of brands that show significantly higher viral effect in the Post phase compared to Pre phase. Comparison in Google search on brands between two phases also support the belief that the more number of brands exhibit significant web search in Post phase relative to Pre phase. The results corroborated by Table 3-10 is in conformity with the contribution of time effect on social soundtrack-web search relationship (see Figure 3-3).
Discussion and Implications

Discussion of Results

In this research, I evaluate the relationship between volume of social media posts and web searching data concerning Super Bowl commercials, the relationship between attitude of social media posts and web searching data concerning Super Bowl commercials, and the difference in retweet proportions of postings on Twitter and difference in web searching activity on Google between Pre and Post phases.

Social Influence on Web Search

I examine the relationship between second screen based social conversations highlighting the use of three social networks and users’ searching on a web search engine using Super Bowl XLIX commercials. The influence of the social soundtrack on web search is tested from the perspective of relative volume of brand interactions and the brand attitude derived from social soundtrack.

The results of Granger causality identifies that brand related discussion on social soundtrack directly causes Web search on brands from the perspective of social soundtrack volume and attitude with the exception of Instagram where the corroborated social attitude does not directly cause Google search. It is important to note that reciprocal causation exists from the perspective of volume for Twitter and Tumblr where Google search on brands also contribute to generation of brand-related social soundtrack.

My results of panel data regression show that social soundtrack conversation significantly influences web search for the overall set of brands that corroborates the view observed in Granger causality test. The unit increase of relative volume and brand attitude significantly increase the
web search on all social platforms with the exception on Instagram where the relationship between social soundtrack and web search is not significant. It is important to note that the regression model with fixed effects explained about 82% of the variance ($R^2$) in the social-search longitudinal data in all three social media platforms. I also test the brand fixed effects and time effects on the social soundtrack-web search linkage w.r.t. to baselines. It is observed that “Budweiser” brand has the highest contribution followed by “Coco Cola” and car-related commercials, especially “BMW”, “Mercedes”, “Dodge”, “Jeep,”, “Toyota”, “Nissan”, “Lexus” and “Kia”) w.r.t the baseline “50 Shades of Gray”. “Sprint” and “Nationwide” have the significant negative estimates, which is corroborated by the average attitude scenario. From the time effects, it is observed that days indexed in Post phase have the significantly positive contributions on the tested relationship for all three social media platforms. So, there are certainly individual differences for brands based on the actual commercials shown during the IRL event and consumer reaction to those commercials once the event is over. The social soundtrack conversations on all three social media platforms and the web search engine concerning the commercials increases in the Post phase, perhaps viewers engage more on commenting and sharing feelings about the commercials and videos pertaining to the brands on all three social media platforms compared to that in Pre phase.

**Difference in Viral Effect**

I examine the difference in proportion of retweets out of second screen interactions on Twitter and of searching activities on a web search engine concerning each Super Bowl XLIX commercials, between two phases, Pre, and Post. My research addresses the change in viral effect contained in social soundtrack commentary on Twitter by computing the retweet ratio
concerning brands. I also see the change in searching data on Google concerning Super Bowl brands and number of searches for each brand between the two phases.

My statistical results show that 19 Super Bowl brands exhibit significant differences in viral effect between the two phases on Twitter, where 16 brands shows increased viral effect from Pre to Post phase and 3 brands show the reverse trend (i.e., Twitter- increase : decrease : no significant change = 16 : 3 : 28). However, it is observed that from Pre to Post phase, web search activity increases significantly for a considerable number of brands (increase : decrease : no significant change = 17 : 1 : 29). It is interesting that, higher traffic on retweets and web searching data in the Post phase compared to the Pre phase for brands is reinforced by the time effect findings.

**Implication**

My findings show that significantly positive influence brand volume of traffic and attitude have on the brand-related web search. There are several brands that show strong positive as a result of the broadcast commercials (“Budweiser”, “Coco Cola”, “BMW”, “Mercedes”, “Dodge”, “Jeep”, “Toyota”, “Nissan”, “Lexus” and “Kia”, “Clash of Clans”, “Microsoft”, “Pepsi”, “Geico” etc.) and the related social soundtrack on three social media platforms and associated h web searching. Given the increased correlation between the conversations on the social soundtrack and web searching, there is certainly a relationship between conversing and searching as shown by the causality analysis, which can have a positive effect for the brands in both direction as causality can be reciprocal in some social media platforms from the perspective of influence of web search on brand related interaction.
A few brands showed significantly negative estimates (“Sprint”, “Nationwide”). This also supports the view of brand effects on social-search bonding. The time effect shows that majority of days in the Post phase contributes to the conversing-searching relationship.

Regarding practical implications of these research findings, I believe that increased potential diffusion of information concerning these brands days especially during and after the media broadcast of the IRL event may drive increase web searching concerning those brands while it is at a lesser degree before the media broadcast of the IRL event in the days immediate before the event when the curiosity and excitement about the upcoming commercials is definitely higher than that in weeks before the game day. Both web search and social soundtrack conversations significantly rise in the During phase.

Retailers and advertisers will also be curious concerning the variation of traffic in terms of viral effect of social soundtrack conversations concerning brands and information seeking via web searching in two phases of IRL events. It is observed that there are individual brands (i.e. 16 brands for Twitter) that show higher proportion of average retweets in Post phase, while 3 brands (“Dove”, “Nationwide” and “Victoria’s Secret”) show higher proportion of average retweets in Pre phase. The similar scenario is enacted for brand-related web searching, where the number of brands (i.e. 17 brands for Google) show increases in searching in the Post phase is considerably higher than those that display decreases in searching in the Post phase (i.e. “Dove”). So, for at least seven brands (such as “50 Shades of Gray”, “Chevrolet”, “Clash of Clans”, “Jurassic World 3D”, “Jeep”, “TurboTax”, “Fast and Furious”), the commercial are most likely causing an significant increase in terms of web searching and an additional viral effect on Twitter in the Post phase.
I believe that viewers sharing of information in terms of relative volumes and attitude towards the brands increase during the live broadcast of the event and once the event is over via social media postings compared to that when the items are unseen, at which point the information diffusion focus shifts from one brand to other (e.g., “Clash of Clans”, “Turbo Tax”, “Jeep” has increased viral effect in the Post phase, while for “Dove”, “Nationwide” and “Victoria’s Secret”, the Pre phase is dominating). The attitude towards breweries, beverages, and car commercials is stronger compared to other commercials’ products, as observed from their fixed effects estimates during live broadcast and post-event days, as supported by observed time effects. Before the telecast, there may be excitement or inquisitiveness as a topic of conversation, but post event analysis of different aspects concerning the display of the brand ad on social media dissipates once the event has ended. People seem to be engaged more on information sharing about those brands after the broadcast in terms of expressing the attitude and tweet circulation, which brands may be able to convert to clicks and online purchases. The information sharing concerning the
Super Bowl commercials days after broadcast combined with the impact of the actual commercials may drive an increase in information seeking via web concerning the brand names once the broadcast is over, which is most likely what a brand would strive to accomplish with such an expensive broadcast commercial.

It is also interesting to observe that average magnitude of relative volume of web search is considerably more in the Post phase for brands at individual level. Retailers should monitor the brands that cause a rise in web searching and leverage such opportunities to promote their sales and accrue more profit or by cross selling. This points to the need for a coordinated multi-channel marketing effort across all online channels.

The insight of variability in fixed effect estimates of brands and time, the brand attitude scores, viral effect in phases and phase-wide brand search by greater second screen interactions within the social soundtrack relative to an IRL media broadcast may increase the sales of the product indirectly and generates profit or brand loyalty in the long term. So, specific brands have much to gain by monitoring the Pre and Post phase broadcast conversations within the social soundtracks. Thus, eWOM advertising in the social soundtrack impacts web search by consumers now interested in the brands.

**Strength and Limitation**

As in all research, there are limitations. The first limitation is that I have garnered 3 million tweets, while there is 28 million tweets reported during telecast of Super Bowl (Gibbs, 2015). This is because I have used the public APIs to collect the data for my research for all three social soundtrack platforms instead of using full data, which may overcome the limitations of the public APIs for collecting data. Using the firehose to collect the data may strengthen my findings. However, I do collect substantial data for my research.
Also, I consider attitude of social soundtrack conversations as one of the independent variables in my research. In my study, I did not capture the actual sentimentality of the texts as the positiveness and negativeness may neutralize each other at some sentence level or post level averaging. In future work, I will focus on deriving the amount of sentiments (i.e., positive and negative) besides computing attitude, as sentimentality and attitude are two different metrics (Kucuktunc et al., 2012). However, I do investigate the attitude of the overall social media postings.

Finally, to test the viral effect of social soundtrack, I have used Twitter out of three social media platforms as my data for Instagram and Tumblr lack the repost / reblog features. The results will definitely be reinforced if I can test the viral effect for Instagram and Tumblr, along with the Twitter. I will focus to maintain the repost and reblog features in my future work, while collecting the media data on IRL events.

Although having these limitations, I believe the my research findings present significant insights in identifying the relationship between second screen based social media conversations and web search concerning brands in Super Bowl XLIX.
Chapter 4

Attitude and Formality in Second Screen Conversations on IRL Event

The integration of social and mobile technologies allows for shared conversations and interactions via social media platforms (Golbeck & Hansen, 2011). The integration of broadcast media events, mobile technologies, and social media sites has forged synergic online interactions that can impart feelings of togetherness, information sharing, and conversation among people in dispersed locations. The social networking and mobile technologies have embedded themselves alongside media broadcasts, facilitating the creation of a social soundtrack (i.e., online conversation) for events and associated content, such as advertising.

This occurrence is referred to as the second screen phenomenon, although there may be multiple (i.e., more than two) screens involved. With the second screen phenomenon, the broadcast media event is shown on the base device (i.e., typically the largest screen) where the viewing occurs, while the secondary screen is the computing device (e.g., desktop, laptop, smartphone, tablet) via which the interaction occurs by leveraging one or more social media technologies. The use of secondary screens affords the creation of what I refer to as the social soundtrack, the online interaction with others regarding the particular broadcast program. The effect on the role of the viewer is profound, as the nature of viewership is transiting from a passive to an active one.

Viewers’ exchange information related to the event via second screen devices in terms of posting of comments (Mukherjee et al., 2014). The exchange of information can happen live or when the show is not transmitted live. The social media exchanges for such events can happen on different social networks platforms. The integration of these networks as the interactive medium
for second screen posting concerning televised broadcasts marks the augmenting of prior limited social aspects of the broadcast medium. There are certain events that happen In-Real-Life (IRL) (e.g. sporting event, award shows, etc.) that are anchored temporally and do not lend themselves to recordings for later viewing, unlike a seasonal TV show. Hence, the second screen interactions about an IRL event lead to a social soundtrack fixed in duration. These IRL events many times generate substantial social soundtracks. The popularity of an event intuitively increases the social soundtrack volume from the perspective of postings on social media platforms. The information in the social soundtrack may refer to different event aspects (e.g., actors, directors, costumes, characters, themes, etc. for a show; players, coach, style etc. if the event is a sporting event; or brand, sale, customer preferences etc., for advertisements).

In this research, I consider Super Bowl XLIX as one such IRL broadcast media event. The Super Bowl happens once a year and is a major happening, especially in the US. The Super Bowl involves multiple categories of interest. First, for the game itself, the teams, coaches and the players are important for viewer engagement. Second, the Super Bowl commercials hold pronounced appeal for many viewers. Lastly, the musical performances conducted at the halftime show are the third important facet of this most popular IRL event.

There has been little academic research concerning the increasingly important second screen interaction phenomenon related to IRL events and limited systemic practitioner inquiry. Apart from the volume of conversations, changes in language style indicate the credibility and rapport building between people in second screen conversations who don’t know each other while change in attitude detect audience reactions to events’ content (i.e., social listening). In this research, I investigate 1) the use of second screens in the Pre, During, and Post phases of Super Bowl XLIX, specifically examining if formality and attitudes extracted from viewer interactions concerning Super Bowl commercials, game, and musicals categories differ in each of event’s phases, and 2) examining the relationship social soundtrack features that includes varied patterns
of the postings have with the attitudes and formality extracted from viewer interactions concerning Super Bowl commercials, game, and music categories in each of event’s phases. I select three popular social media platforms (Twitter, Instagram, and Tumblr) as our data collection sites to research the a) the changes in formality and attitude of second screen interactions, and b) relationship of attributes of postings with attitude of second screen interactions throughout each of the phases for each category of Super Bowl XLIX.

This research is important as the degree and manner of usage of secondary screens in conjunction with IRL broadcast media events can facilitate retailers, broadcasters, and artists to manage branding and awareness campaigns by understanding the relationship among phase-category pairs for formality/informality and attitude of viewers, along with the effect of different social media platforms on social soundtrack conversations. Additionally it helps to understand the relationship between interaction features, patterns of interactions, and attitude of viewers, along with the effect of different social media platforms on social soundtrack conversations. Findings also shed light on social interaction in cross technology usage of second screens, and the impact on information sharing and diffusion of viewership. Results also highlight the changing nature of viewership from a totally passive to a more active one.

**Literature Review**

End users exchanging viewer generated content greatly enhances the social possibilities of TV (Alliez, 2008; Wu et al., 2011; Zhao & Lindley, 2014). There has been prior research on analyzing sentiment/attitude of social media conversations, but the formality research on social media conversations is scarce. Understanding the social soundtrack formality and sentiment of the conversations can shed light on the goals, needs, and desires of the conversation participants while viewing an event.
Formality of Social Media Conversation

Sabater (2013) examined Facebook messages of native and non-native English speakers to identify the stylistic variations in their online writing. The result showed that non-native speakers exhibited more formal traits in a university context. In another study on postings of two communities on Twitter, it was found that there was marked difference in formality and tone between the two user groups and the underlying differences of communication goal was cited as the reason (Paris, Thomas, & Wan, 2012). In a separate research using WhatsApp in an university set-up, Alamri revealed that, over time, instructors discourse became informal (Alamri, 2015). Similar characteristics were found for blogs that claimed to be more informal, and it was shown that the personality of author influenced the formality of text (Nowson, 2006). Yates (Yates & Orlikowski, 1992) claimed that the cultural or literacy practices rather than the technology imparted weightage in the difference in stylistic formality observed in online communication between native and non-native speakers of English. Lan (2000) proposed that linkage between linguistic formality and linguistic correctness was a key player to promote more formal style in online writing. Though these studies did formality testing on computer mediated communication, social media is considered as a difficult medium to process the conversation as it does not follow the conventional style of communication (Nowson, Oberlander, & Gill, 2005).

Sentiment / Attitude of Social Media Conversation

Some of the early research on Twitter sentiments was done by (Bermingham & Smeaton, 2010; Go, Bhayani, & Huang, 2009; Pak & Paroubek, 2010). Kuoloumpis, Wilsom and Moore (2011) investigated the utility of linguistic features for detecting the sentiments of Twitter posts,
while Go, Bhayani and Huang (2009) used emoticons assigned to Twitter messages to identify the users mood.

In the era of Web 2.0, individuals share their opinions and reviews via social networking sites, microblogs, personal blogs to name a few, and this occurs in real time. Regarding application-oriented research, Baracho, Silva and Ferreira (2012) analyzed social networks, identified the feelings and opinions of customers about brands and vehicle parts in the automobile domain. Liu (2012) analyzed sentiments to predict sales performance, while reviews were used to rank products and the retailers (McGlohon et al., 2010). O’Connor, Balasubramaniyan, Routhledge and Smith (2010) showed that Twitter sentiment is linked to the public opinion regarding election polls. Bollen, Mao and Zeng (2011) used Twitter-based sentiments to predict stock market movements. Twitter data, movie views, and blogs were analyzed to predict box office revenues for movies (Asur & Huberman, 2010; Joshi, Das, Gimpel, & Smith, 2010; Sadikov, Parameswaran, & Venetis, 2009). Hong and Skiena (2010) evaluated the relationship between US football betting and opinion polls. Zhao, Zhong, Wickramasuriya and Vasudevan (2011) extracted viewers sentiments also about US National Football League teams by analyzing their opinions in the form of tweets. Lin, Margolin, Keegan and Lazer (2013) identified focused group of users with similar biases based on prior users’ behavior on Twitter for the 2012 US presidential election. Twitter sentiment was capitalized to characterize political violence during elections in Pakistan (Younus et al., 2014). Kim, Cha and Sandholm (2014) proposed a new route navigation system to avoid crime hotspots based on Twitter sentiments.

Kucuktunc, Cambazoglu, Weber, and Ferhatosmanoglu (2012) derived attitude from the online positive and negative sentiments. In their research, they have define sentimentality and attitude as two different metrics. While sentimentality measured the amount of sentiment, the attitude computed the inclination. The notion that attitude influences the behavioral intentions were supported in research on advertising and technology adoption (Curran & Lennon, 2011).
Lukka and James (2014) received mixed response from the perspective of attitude towards Facebook advertising among three groups of users.

**Prior Research**

For this research, the specific IRL broadcast media event I examine is Super Bowl XLIX. Lee, Ham, Kim, and Kim (2014a) used Twitter as the social media platform to assess people’s interest in Super Bowl 2012 car commercials. Shin, Byun and Lee (2015) studied the second screen interaction on Twitter to address the creation of consumer interest in brands televised during Super Bowl 2014. Hartmann and Clapper (2014) analyzed the effect of brand advertising on viewership in Super Bowl 2012 framework and found that the ads made the association between brands and the viewership. Though the aforementioned research spoke to the usage of social networks to analyze viewer interactions, they did not investigate the interplay among formality and/or attitude of conversations in temporal phases and the multiple inherent categories of IRL events on various social media platforms within the social soundtrack. Also, prior research has been mainly limited to single social media platform, while I examine second screen conversations across multiple platforms.

None of these prior research studies assessed the temporal interaction effects of social networks and second screens from the formality and sentiment/attitude perspective concerning live broadcast of major IRL events. Neither did they assess the temporal interaction effects of social networks and second screens from the temporal strength of linkage between social soundtrack features, patterns, and the content of second screen conversations from attitude perspective concerning live broadcast of major IRL events. Understanding the temporal aspects of attitude/sentiment within the social soundtrack has implications for leveraging social media within a variety of domains.
As such, there are several unanswered questions concerning second screen interaction concerning IRL events. *How is social networking technology used during the broadcast of an IRL event? How does the media broadcast of IRL events influence the social soundtracks from the perspective of attitude and formality on different dimensions of IRL event? How does social soundtrack regarding the media broadcast of IRL events influence the human attitude and formality towards different dimensions of IRL event? How does language construct in social media discourse affect formality and attitude regarding IRL events?* These are some questions that motivate our research.

**Research Question**

It is known that human information behavior is influenced and shaped by the social environment (Ashford & LeCroy, 2009). Therefore, technology and processes making broadcast media events more social, influences human communication in a socially mediated way that affects human thoughts and actions. The once passive viewers now take an active role using second screens with social networking as mediums of communication by posting social media concerning the broadcast event in order to build a social relationship. Therefore, the social soundtrack can influence and shape the social environment.

For clarity, I define three of our key constructs:

(1) **Second screen** – the computing device used for posting content to the social soundtrack.

(2) **Social soundtrack** – the collection of social media posts from second screens about an event.
(3) **IRL broadcast media event** – a happening that is anchored temporally, not lending itself for delayed viewing.

Social media sites allow for feelings about IRL broadcast media events to be shared and then commented on by other viewers in a variety of ways. Due to the second screen phenomenon, viewers can join in opinion exchange while watching the event and have their postings observed and responded to by other members engaging in the social soundtrack. Such interactions may or may not be during the live telecast of the events. The second screen technologies greatly facilitate these social interactions to occur anytime, including during the broadcast media event itself.

Within the umbrella of IRL broadcast media events, there are certain ones that are associated with substantial social soundtrack volume. The Oscars award ceremony, music video awards shows, the Grammys award show, and sport games are such events. Among these, I consider Super Bowl XLIX in our research, as it was the most-watched American television program at the time, with an average audience of 114.4 million viewers (Wikipedia, 2015c). As a result of the high degree of viewership, companies purchase expensive ads televised during the Super Bowl broadcast (e.g., Budweiser, Nationwide, McDonalds etc. for Super Bowl 2015). Super Bowl commercials, an integral aspect of Super Bowl event, have become a cultural phenomenon of its own, alongside the game. A considerable number of people watch the event primarily to see and discuss the commercials. In addition to the game and ads, popular and iconic performers and musicians (e.g., Katy Perry, Lenny Kravitz for Super Bowl 2015) take part in half time shows on event day and are also a draw for viewers.

In our research, I classify second screen interactions appearing in the social soundtrack into three event categories: a) commercials, b) musicals and c) game. There is considerable sharing of feelings in the social soundtrack on three aforementioned categories not only throughout but before and after the Super Bowl event. I label these temporal phases of the Super
Bowl social soundtrack as: a) Pre phase, b) During phase and c) Post phase. The Pre phase is the audience interaction beginning sometimes weeks ahead of an event and continuing until the event start, for our research the kick-off of Super Bowl 2015. The During phase is the period of the live broadcast of the event, from kick off to the final second of the game. The Post phase is the social soundtrack beginning the moment the event is over until the end of data collection.

For precision, I define these two key event variables:

(1) **Event Category**: classification of posts within the social sound track concerning an event sub-topic

(2) **Event Phase**: a distinct period of an event for temporal classification of social sound track posts.

Most micro-blogging technologies share some commonalities (Jansen et al., 2009). In our research, I select three social media platforms for data collection: Twitter, Instagram and Tumblr. Twitter is one of the most popular micro-blogging sites, used as the platform of communication for the social soundtrack. Instagram is a medium of communication where users perform capturing and online sharing of images and videos (Hu et al., 2014). Tumblr is second largest microblogging service in the US after Twitter. It supports eight types of posts, which are images, videos, audios, text, answer, links, quotes, and chat (Chang et al., 2014).

In this research I 1) analyze phase wide change in second screen formality and attitude among Super Bowl categories, and 2) quantify the relationship between a) social soundtrack features and second screen attitude, and b) social soundtrack features and second screen formality.
Change in Second Screen Formality and Attitude

I have an intuition that formality and attitude extracted from the social soundtrack conversation regarding specific categories change by phases. As in (Kucuktunc et al., 2012), I define attitude as the inclination towards the positive or negative sentiments and find out attitude scores as an aggregation of positive and negative sentiments extracted from second screen interaction. I identify attitude of a post by aggregating the positive and negative sentiments contained in the post. I further aggregate the post level attitude over time. The social soundtrack content characteristics will also most likely change in specific Super Bowl phases for different categories. These changes in attitude and formality of language shed light on the manner of information processing and dissemination with the social soundtrack.

Based on this intuition, I frame our research questions that evaluate the change in attitude and formality of the second screen conversation within the Super Bowl XLIX phase-category space.

**RQ1.** Does attitude of second screen conversation w.r.t Super Bowl phases in the social soundtrack significantly differ among Super Bowl categories?

**RQ2.** Does formality of second screen conversation w.r.t Super Bowl phases in the social soundtrack significantly differs among Super Bowl categories?

These research questions highlight multiple perspectives. The formality and attitude extracted from social soundtrack conversations related to the categories via social networks enlighten the commercial opportunities at the intersection of social networks, broadcast media events, and second screens. Though there are challenges of harnessing, analyzing, and interpreting social soundtrack postings, as user generated content in social media sites is unstructured and dispersed (Kaplan & Haenlein, 2010), retailers have the opportunity for awareness of consumer feelings and attitudes, in real time, via attitude analysis of social media
postings (Rambocas & Gama, 2013). By means of formality analysis of the social soundtrack, marketers get an impression of the degree of involvement of the potential consumers where highly involved consumers shun formality and thrive on casual style (Mattern et al., 2012). Communication via second screens identifies the adoption of social networks as the driver of interaction from the perspective of the participating audience, whilst the event is (is not) broadcast live.

The first research question analyzes the change in second screen attitude of the social soundtrack over Super Bowl categories respectively on each of the three social media platforms. This research question is examined by the following hypotheses.

Hypothesis 01: There is a significant difference in social soundtrack attitude of second screen conversation in the Pre phase among Super Bowl categories.

Hypothesis 02: There is a significant difference in social soundtrack attitude of second screen conversation in the During phase among Super Bowl categories.

Hypothesis 03: There is a significant difference in social soundtrack attitude of second screen conversation in the Post phase among Super Bowl categories.

The hypotheses 01, 02 and 03 address the Super Bowl phases separately for Super Bowl categories based on second screen attitude.

Similarly, the second research question begets three hypotheses

Hypothesis 04: There is a significant difference in social soundtrack formality of second screen conversation in the Pre phase among Super Bowl categories.

Hypothesis 05: There is a significant difference in social soundtrack formality of second screen conversation in the During phase among Super Bowl categories.

Hypothesis 06: There is a significant difference in social soundtrack formality of second screen conversation in the Post phase among Super Bowl categories.
The hypotheses 04, 05 and 06 address the Super Bowl phases separately for Super Bowl categories based on second screen formality.

**Relationship between Features and Content**

In this study, I extract the social soundtrack features in addition to count of posts that correspond to (a) pattern of viewers’ conversation, (b) number of sentences in the postings, and (c) number of unique words present in the texts of the posts. The identifiers for categories of patterns for social soundtrack conversation that are common to each of the three social media platforms are described by Table 4-1.

Table 4-1. Categories of social soundtrack conversation patterns common to three social media platforms

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Referral (RF):</td>
<td>Any full length or shortened URL.</td>
</tr>
<tr>
<td>Response (RS):</td>
<td>Postings intentionally engaging another user by means of ‘@’ symbol which does not meet the other requirements of containing referrals.</td>
</tr>
<tr>
<td>Broadcast (BC):</td>
<td>Undirected statements (i.e., does not contain any addressing) which allow for opinion, statements and random thoughts to be sent to the author’s followers. Any undirected statement followed by questions ‘?’ belongs to Broadcast (BC) category.</td>
</tr>
</tbody>
</table>

In addition to the patterns of social conversations presented in Table 4-1, Twitter has the specific category of pattern known as Retweet (RT) which can be recognized by presence of "‘RT: @’, ‘retweeting @’, ‘retweet @’, ‘(via @)’, ‘RT (via @)’, ‘thx @’, ‘HT @’ or ‘r @’ ” in the tweets. Instagram and Tumblr contains the patterns presented in Table 4-1. The Referral (RF) category contains full length or shortened URLs within tweets directed to another user for
Twitter. For Instagram and Tumblr, RF categories may contain the URLs for images and videos in addition to general full length or shortened URLs.

The priority order of this classification of tweets for Twitter is: RT > RF > RS > BC. For Instagram captions, and Tumblr blogs I set the priority order as: RS > RF > BC. The sentences of the posts are parsed based on the punctuations such as “:”, “?” and “!” The number of unique words within each posting is determined by excluding the stop words and the hashtags present in the sentences of each post.

**Social Soundtrack Attitude**

I have an intuition that relationship between interaction features present in social media postings and the attitude extracted from the social soundtrack conversation regarding specific categories changes in phases. The social soundtrack feature-attitude linkage will also most likely change in specific phases for different categories. These feature-attitude relationships of language shed light on the manner of information processing and dissemination with the social soundtrack.

Based on this intuition, I frame our research question that deals with influence of interaction features on attitude of social media conversations in each phase on different categories.

*RQ3. Do the features of social soundtrack conversations on different social media platforms relate to the attitude of social media conversations concerning Super Bowl XLIX in each Super Bowl phase?*

While evaluating the research question 3, I also examine the phase-wide relative contributions of three categories on feature-attitude relationship.
Social Soundtrack Formality

I frame our next research question to evaluate the feature-formality relationship in the second screen conversation within the Super Bowl XLIX phase-category space as:

*RQ4. Do the features of social soundtrack conversations on different social media platforms relate to the formality of social media conversations concerning Super Bowl XLIX in each Super Bowl phase?*

While evaluating the research question 4, I also examine the phase-wide relative contributions of three categories on feature-formality relationship.

The research question 3 and research question 4 are evaluated by linear regression method on balanced panel data.

Data Collection and Research Design

Super Bowl XLIX occurred place on the 1st of February (Sunday) 2015 at University of Phoenix Stadium, Arizona, USA. The kick-off time was 6:30 PM Eastern. The NBC channel broadcast the event, with an average of 114.5 million viewers, reaching to 118 million viewers during the half time show (Wikipedia, 2015d).

Data Collection in Super Bowl Phases

As shown in Table 4-2, I collected data related to Super Bowl XLIX from the 10th of January 2015 and continued through the 24th of February 2015 on each of the three social media platforms. To collect data from each platform, I utilized the respective APIs and tokens for Twitter, Instagram, and Tumblr in corresponding scripts with search queries.
The queries that I used include: ‘superbowlxlix’, ‘superbowl49’, ‘superbowlcommercial’, ‘superbowlAd’, ‘superbowlhalftime’, ‘superbowl2015’, ‘2015superbowl’, ‘sb49’ and ‘football’. The aim of forming this list of queries was to collect data for this research using each term as a search query on all three social media platforms.

The query list included the terms that occurred most frequently as social media tags (e.g., #superbowlcommercial, #superbowlxlix, etc.) in a collection of sample data for all social media platforms collected against the seed query named “superbowl”. I collected the sample data for 48 hours (i.e. from 01/06/2015-16:00:00 to 01/08/2015-16:00:00) to identify the potential queries for this research, and the sample data was not included in the data set used in this research.

Table 4-2. Volume of collected Super Bowl XLIX data by social media platforms

<table>
<thead>
<tr>
<th>Platform</th>
<th>Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>3,112,789</td>
</tr>
<tr>
<td>Instagram</td>
<td>811,262</td>
</tr>
<tr>
<td>Tumblr</td>
<td>51,569</td>
</tr>
</tbody>
</table>

I segregate the data collection period into three temporal phases. Table 4-3 shows the date/time of each Super Bowl phase.

Table 4-3. Start and end times for the three Super Bowl phases

<table>
<thead>
<tr>
<th>Super Bowl Phase</th>
<th>Start Date-Time</th>
<th>End Date-Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre</td>
<td>1/10/2015-00:00:00</td>
<td>2/1/2015-18:29:59</td>
</tr>
<tr>
<td>During</td>
<td>2/1/2015-18:30:00</td>
<td>2/1/2015-22:30:00</td>
</tr>
<tr>
<td>Post</td>
<td>2/1/2015-22:30:01</td>
<td>2/24/2015-00:00:00</td>
</tr>
</tbody>
</table>

I display the distribution of the posts collected during three Super Bowl phases on three social media platforms in Table 4-4 and Table 4-5. Table 4-4 shows the data collected during each Super Bowl phase, while Table 5 shows the mean posts per hour during each phase. I notice that the volume of posts for Pre and Post phases is higher than that During phase (see Table 4-4),
and the rate of second screen interaction is lower for Pre and Post phases than the During phase (see Table 4-5).

Table 4-4. Volume of Super Bowl XLIX data in Pre, During and Post phases on social media platforms

<table>
<thead>
<tr>
<th>Platform</th>
<th>Pre Phase</th>
<th>During Phase</th>
<th>Post Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>1,753,458</td>
<td>35,525</td>
<td>1,323,806</td>
</tr>
<tr>
<td>Instagram</td>
<td>452,761</td>
<td>16,459</td>
<td>342,042</td>
</tr>
<tr>
<td>Tumblr</td>
<td>24,695</td>
<td>6,544</td>
<td>20,330</td>
</tr>
</tbody>
</table>

Table 4-5. Hourly mean volume of Super Bowl XLIX data in Pre, During and Post phases on social media platforms

<table>
<thead>
<tr>
<th>Platform</th>
<th>Pre Phase</th>
<th>During Phase</th>
<th>Post Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>3,211.46</td>
<td>8,881.25</td>
<td>2,500.76</td>
</tr>
<tr>
<td>Instagram</td>
<td>829.23</td>
<td>4,114.75</td>
<td>630.86</td>
</tr>
<tr>
<td>Tumblr</td>
<td>45.23</td>
<td>1636</td>
<td>38.39</td>
</tr>
</tbody>
</table>

Super Bowl Interaction Categories

With data from all three social networks, I classify the data into the three categories (commercials, music, and game) of second screen interaction for each social media platform. I identify the categories by means of the keywords collected from relevant websites. The keywords are in lower case letters and extracted from websites regarding Super Bowl commercials (Anonymous, 2015; Staff, 2015), music (Wikipedia, 2015b, 2015d), and game (Schalter, 2015b).

The list of Super Bowl commercial keywords contains the ad titles (e.g., ‘mercedes’, ‘coca cola’, etc.), titles of the themes / videos for the ads (e.g., ‘real strength’, ‘like a girl’ etc.), the popular name of the brands (e.g., coke, burrito etc.), hashtags associated with the spots (e.g., ‘#likeagirl’, ‘#itsthateasy’ etc.) and the first and last names of actors participated in Super Bowl
commercial videos (e.g., ‘neeson’, ‘braylon’, ‘o neil’ etc.). The query list of Super Bowl halftime keywords contains the first name and last name of the performers of the halftime and the pre-game show (e.g., ‘lenny’, ‘katy’, ‘perry’ etc.), terms that describes the half time show (e.g., ‘shark’, ‘palm’, ‘flames’ etc.) and the songs (e.g., ‘teenage dream’, ‘california gurls’ etc.). The query list of keywords related to Super Bowl game contains the first name and last name of the players, coaches, umpires, referees, commentators (e.g., ‘brady’, ‘julian’, ‘edelman’ etc.), the field positions (e.g., ‘rusher’, ‘quarter back’, ‘red zone’ etc.), teams (‘patriot’, ‘seahawks’, etc.) and other key terms related to game (e.g., ‘punt’, ‘fumble’, ‘tackle’, etc.). I then assign the posts on each social media platform in Super Bowl commercials, in Super Bowl music, or in Super Bowl game category, depending on the presence of terms from the respective keywords lists. A post may belong to multiple Super Bowl categories if that post contains terms from more than one categorical keywords list.

Table 4-6. Phase x category for Twitter, Instagram and Tumblr

<table>
<thead>
<tr>
<th>Phase</th>
<th>Commercials</th>
<th>Music</th>
<th>Twitter Game</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre</td>
<td>350,259</td>
<td>506,035</td>
<td>737,011</td>
</tr>
<tr>
<td>During</td>
<td>10,525</td>
<td>12,029</td>
<td>11,057</td>
</tr>
<tr>
<td>Post</td>
<td>253,745</td>
<td>362,113</td>
<td>580,082</td>
</tr>
<tr>
<td>Phase</td>
<td>Instagram</td>
<td>Game</td>
<td></td>
</tr>
<tr>
<td>Pre</td>
<td>92,864</td>
<td>136,431</td>
<td>185,784</td>
</tr>
<tr>
<td>During</td>
<td>2,683</td>
<td>5,748</td>
<td>6,249</td>
</tr>
<tr>
<td>Post</td>
<td>71,464</td>
<td>109,458</td>
<td>130,276</td>
</tr>
<tr>
<td>Phase</td>
<td>Tumblr</td>
<td>Game</td>
<td></td>
</tr>
<tr>
<td>Pre</td>
<td>6,934</td>
<td>7,560</td>
<td>5,914</td>
</tr>
<tr>
<td>During</td>
<td>2,594</td>
<td>1,834</td>
<td>1,889</td>
</tr>
<tr>
<td>Post</td>
<td>4,746</td>
<td>5,370</td>
<td>4,023</td>
</tr>
</tbody>
</table>

I construct a three-(phase X category) table from the distribution of the categories for second screen Super Bowl interactions on Twitter, Instagram and Tumblr respectively, as shown
in Table 6, where each cell $C_{i,j}$ gives the observed frequency of second screen interaction in Super Bowl phase $i$ for Super Bowl category $j$ on social network platform $k$.

I did not assign the posts to any category that has terms from more than one keyword lists. For Twitter and Tumblr, I check the presence of the terms in tweets and blogs, while for Instagram the terms are checked in the caption of the posts. I have 190,410 Twitter postings, 70,305 Instagram postings, and 9,705 Tumblr postings that belong to more than one category. I did not incorporate these mixed category postings in this research, as I considered Super Bowl commercials, Super Bowl halftime show and Super Bowl game category as mutually exclusive variables. Apart from that, there are 99,523 tweets; not included in the analysis; that don’t belong to any category, such as soccer-related tweets, as “football” is used as the search query for data collection. In Asia, Europe and South American countries “football” is synonymous to soccer, unlike US and Canada.

Research Design

Change in Formality and Attitude among Categories

Once I collected the data, I segregate the count of posts collected across the weeks for all three social media platforms across all three Super Bowl categories into five minutes intervals. I then further segregate the categorical time-count data as Pre, During and Post phases, by annotating the times shown in Table 3. I derive the formality and attitude for each post in each of these five minute phase-category subsets by identifying variation in part-of-speech (POS) uses for formality and extracting emoticons followed by presence of positive/negative words for sentiment from messages posted in all three social soundtrack mediums using equation 4-1.

$$rel\_value_i = \frac{Score_i}{\max \{Score_j\}} \quad (4-1)$$
\(^i\) denotes the index of the five minute time slot within a specific phase and \(j\) is the specific content score (i.e., attitude or formality) of the posting. For attitude \(\text{Max}\) function returns the highest value of attitude score / formality score within a phase. This relative scaling is done for all three social media platforms. So, each social soundtrack has category time counts (five minutes) of attitude and formality scores for each phase that I use as the unit of analysis in testing the first two research questions.

**Relationship between Features and Content**

In addition to segregation of posts into five minute time counts from the perspective of attitude and formality, I discriminate the five minute counts for each of the social features including the volume of posts, patterns of communications, number of sentences and number of unique words across all three categories for all three social media platforms.

I then further segregate the categorical time-count data regarding volume of posts, patterns of conversations exist in posts, number of sentences present in the posts and number of unique words in sentences of posts for Pre, During and Post phases, by annotating the times shown in Table 3 for each of the social media platforms. I transform the five minute time count data regarding volume, each of the social features and the derived attitude into a relative scale using equation 1. Superscript \(j\) in equation 1 is the specific attribute of the posting. \(\text{Max}\) function returns the highest value of the count for a specific attribute within a phase. Here, the attributes are: 1) volume of posts, 2) each of the conversation patterns, 3) sentences, and 4) unique words. This relative scaling is done for all three social media platforms.

Once the computation of relative scaling of the attributes is done for the social soundtrack conversation for each of the three social media platforms, I organize the categorical time count data into a balanced panel (Berrington, Smith, & Sturgis, 2006a) data for all three social media platforms.
platforms where each of the three categories has relative values of the social soundtrack attributes across total number of five minute slots for data collection in each phase. Panel data, known, as cross-sectional time series data, can control variables whose behavior cannot be observed (i.e., behavior of Super Bowl categories). In our study, for each phase, the balanced panel dataset can be viewed as a three dimensional space where the dimensions are 1) Super Bowl categories (commercial, music, game), 2) Time stamps for each category (number of five-minute time slots. i.e., 6558, 49 and 6534 for Pre, During and Post phases respectively) and 3) the relative attributes along with relative formality and attitude scores for social soundtrack mediums (Twitter, Instagram, Tumblr). As there are three social media platforms, I have three such balanced longitudinal data panels for relative values of the attributes with attitude / formality for each phase. In our dataset, I have a total of 19674 (3 x 6558) records, 147 (3 x 49) records and 19062 (3 x 6354) records each with relative values of attributes for three social media platforms for Pre, During, and Post phases respectively. Each record is the unit of analysis in evaluating the research question 3 and research question 4 for each phase and for each social media platform.

Methodology

I analyze the formality and attitude of each of the tweets, Instagram media postings and Tumblr blogs to calculate the respective scores. I then aggregate these scores within each of these five minute time intervals. Prior to any analysis, I follow the following pre-processing steps as: a) remove the punctuations from the sentences of the posts (do it for formality only), b) remove the hashtags, as this does not contribute to the frequency of POS tags, c) remove the usernames addressed by “@” and “RT” within the messages, d) remove the special characters such as “@”, “RT”, “via” and URLs, e) replace all contraction of verb forms to the corresponding verbs (e.g., “’ll” to “ will”, “’ve” to “ have”, “’re” to “ are”) f) replace all negations (“neither”, “nor”,


“never”, “no”, “negative”, “not”, “n’t”, “won’t” etc.) to “not”, g) replace a sequence of repeated characters by two characters (e.g., “coooool” to “cool”, “ooooh” to “ooh” etc.), f) lowercase the letters and expand the acronyms in the posts to its meaning (examples shown in Table 4-7) extracted from relevant online resources (Fisher, 2012; Howard, 2009; Rouse, 2015).

Table 4-7. Example acronyms and their expansions

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>gr8, gr8t</td>
<td>great</td>
</tr>
<tr>
<td>f2f</td>
<td>face to face</td>
</tr>
<tr>
<td>ftw</td>
<td>for the win</td>
</tr>
<tr>
<td>lol</td>
<td>laughing out loud</td>
</tr>
<tr>
<td>omg</td>
<td>oh my god</td>
</tr>
</tbody>
</table>

**Measuring Formality**

By means of formality analysis of the posts, I quantify the stylometric variations of social soundtrack expressions over different phases and categories. Once the pre-processing is done, I use Stanford POS Tagger (Group) to identify the POS tags from the tokenized postings on all three social media platforms. I use the standard tag-set defined by Penn Treebank to identify the tags from the tokens by means of Stanford POS Tagger. As I am using the F-score as defined in (Heylighen & Dewaele, 1999), I put the tags belonging to particular subclasses into the corresponding super class (e.g., “JJ”, “JJR” and “JJS” into superclass “JJ”; “RB”, “RBR” and “RBS” into superclass “RB” etc.).

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6 ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html
The tagging is followed by calculation of F-score using the formula for a specific Super Bowl category in a specific phase.

\[ F_{t_k} = \frac{0.5}{N} \sum_{i=1}^{N} \left[ \text{nn}_i + \text{adj}_i + \text{prep}_i + \text{art}_i - \text{pro}_i - \text{vrb}_i - \text{adv}_i - \text{intj}_i + 100 \right] \]  

(1)

Here, \( F_{t_k} \) is the average formality of the aggregated POS frequencies expressed in percentages of the number of words belonging to a particular POS category with respect to the total number of words in the posting \( i \) in a particular five minute time window \( t_k \). \( N \) = total number of postings within \( t_k \). \( \text{nn}_i, \text{adj}_i, \text{prep}_i, \text{art}_i, \text{pro}_i, \text{vrb}_i, \text{adv}_i, \text{intj}_i \) are frequencies of noun, adjective, preposition, article, pronoun, verb, adverb and interjection respectively in the excerpt of posting \( i \).

By means of formality analysis, I calculate the average F-score in five minute time counts in phase-category space, which is the unit of analysis for testing the second research question.

**Measuring Attitude**

Attitude measurement of the postings involves two major stages. The first stage deals with mining emoticons from the postings on all three social soundtrack mediums, while the second stage determines the presence of positive and/or negative words. Before carrying out the stages, the pre-processing steps are carried out as in formality measurement except the removal of punctuations. I execute sentence level parsing of the texts based on the punctuations (e.g. “.”, “?”, “!” etc.) and/or emoticons as used in (Hogenboom et al., 2013) before performing the stages. Once the sentence level parsing is done, I remove the punctuations after extracting emoticons.
Extracting Emoticons

I extract the emoticons from the social soundtrack messages posted in all three social networking platforms by preparing two emoticon sentiment lexicons. I categorize the lexicons as “positive” sentiment lexicon and “negative” sentiment lexicon. The lexicons are prepared from available online resources (ComputerUser, 2014; Marks, 1997; Wikipedia, 2015a). I combine these online lists of positive and negative emoticons into the corresponding lexicons, while leaving out duplicate entries. I do not weigh the intensity of the emotions, but I do assign the emoticons either positive (e.g., “:-D”, “:-)”, “:-)”, “:+o” etc.) or negative (e.g., “: (”, “:-("”, “:-_”, “v.v”, “D8”, “:-c” etc.). The polarity of sentences contained in Twitter texts, Instagram captions, and Tumblr blogs are assigned either as positive or negative, depending on the presence of positive and negative emoticons. I exclude neutral emoticons from our research, focusing on non-neutral sentiments.

Presence of Positive and Negative Words

Once the data cleaning and pre-processing of texts was complete, I follow the second stage to determine the existence of positive and negative words. I use online sentiment lexicon (B. Liu & Minqing, 2004) used in (B. Liu et al., 2005) to form our lexicons of positive and negative words, while removing the duplicating entries. In determining the attitude of the sentences by means of presence of positive / negative words, I split the sentences into tokens and assign the polarity according to the following logic.

Step 1: if ( (“not” ∈ sentence_i ∧ pos_word_j ∈ sentence_i) ∧ (index(“not”) < index(pos_word_j)))

\[
\text{count}(\text{polarity}_{\text{neg}}) + +;
\]
Step 2: else if ("not" $\notin$ sentence$_i \land$ pos_word$_j$ $\in$ sentence$_i$ )

$$\text{count}(\text{polarity}_{\text{pos}}) + \; ;$$

Step 3: if ("not" $\in$ sentence$_i \land$ neg_word$_j$ $\in$ sentence$_i$ ) $\land$ (index("not") <

$$\text{index}$$ (neg_word$_j$)))

$$\text{count}(\text{polarity}_{\text{pos}}) + \; ;$$

Step 4: else if ("not" $\notin$ sentence$_i \land$ neg_word$_j$ $\in$ sentence$_i$ )

$$\text{count}(\text{polarity}_{\text{neg}}) + \; ;$$

Table 4-8 shows the polarity of the example statements based on presence of positive and
negative words.

<table>
<thead>
<tr>
<th>Statement</th>
<th>Polarity</th>
<th>Logic Step</th>
</tr>
</thead>
<tbody>
<tr>
<td>“it is not at all worth viewing”</td>
<td>negative</td>
<td>1</td>
</tr>
<tr>
<td>“the katy perry show was amazing”</td>
<td>positive</td>
<td>2</td>
</tr>
<tr>
<td>“i will not miss the telecast of halftime show”</td>
<td>positive</td>
<td>3</td>
</tr>
<tr>
<td>“first 15 min of the game was boring”</td>
<td>negative</td>
<td>4</td>
</tr>
</tbody>
</table>

Estimating Attitude

Once the polarity of the statements of tweets, captions, or blogs related to each commercial are
determined w.r.t the presence of emoticons and sentiment words, I compute the polarity score at the
sentence level. Next, I aggregate the score at single tweet, caption, or blog level. Once posting level
attitude score is computed, further aggregation is carried out on the number of messages posted
within the 24 hour time window.

I assign a scale of rating for the emoticons and the sentiment words. I provide more positive or
negative weight on positive and negative emoticons than that for positive and negative words as
emoticons simulate the nonverbal cues that dominate verbal cues (Burgoon & Saine, 1978) (i.e.,
the text messages) and hence an important emotion/intention indicator for viewers. The texts coupled with emoticons have higher sentiment than the messages without emoticons.

The weight scale I chose is as follows. Negative emoticons: -2, negative words: -1, positive words: +1, positive emoticons: +2 and 0 for neutral emoticons. A positive word with a “not” and a negative word with a “not” immediate before it are counted as negative and positive word respectively. I am assigning equal weights with opposite signs for positive and negative emoticons and assign same positive and negative weight for positive and negative words but with opposite signs as in (Kramer, 2010). So, the attitude score I compute using formula 4-2 for a specific Super Bowl category in a specific phase.

\[
S_{tk} = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{M} \left( 2 \cdot PosEmot_{ij} + 1 \cdot PosWord_{ij} - 1 \cdot NegWord_{ij} - 2 \cdot NegEmot_{ij} \right) 
\]

Here, I term \( S_{tk} \) as the average attitude score of postings aggregated in a particular 24 hour time window \( t_k \). \( N \) = total number of postings within \( t_k \). \( PosEmot_{ij} \), \( PosWord_{ij} \), \( NegWord_{ij} \), \( NegEmot_{ij} \) are positive emoticons, positive words, negative words and negative emoticons for sentence \( j \) in posting \( i \). \( M \) is the count of sentences in posting \( i \). Higher \( S_{tk} \) indicates more positive attitudes. The steps of attitude measurement for all three social soundtracks are performed for each Super Bowl category.

As with measuring the formality, I have the average sentiment score in five minute time counts in phase-category space, which is used as the unit of analysis for testing the first six research hypotheses.

Change in Formality and Attitude among Categories

For examining the research questions, I use one way ANOVA. Both the formality and attitude data follow approximate normal distribution. I apply the Games-Howell (GH) test as the post hoc
analysis to identify the dominance of specific interaction category in the specific phase of phase-category space. I use the GH test as the data violates the homogeneity of variance (significance of Levene’s statistic < 0.05), but it follows the equality of means assumption (significance of Welch’s statistic < 0.05).

In SPSS, I run two separate ANOVA tests to evaluate the first two research questions. The critical value of the $F_{\text{ANOVA}}(2, > 120)$ is 2.996 at the 95% confidence interval ($\alpha = 0.05$).

The ANOVA test identifies that the mean of the formality / attitude scores in five minute intervals of at least one phase (category) is significantly different from others for each phase.

**Relationship between Features and Content**

I use panel data regression with fixed and random effects (Bell & Jones, 2015; Schmidheiny & Basel, 2011) on balanced panel data to evaluate the relationship between the features of social soundtrack conversations and content formality and attitude concerning Super Bowl categories. In the regression model, relative attitude and formality scores are the dependent variable, while the relative values of social soundtrack features (i.e., volume, patterns of social soundtrack conversations, number of sentences, and number of unique words) are the cofactors.

For clarity, I provide Table 4-9 to list the cofactors within a five minute time window in a relative scale used in the panel data regression.

<table>
<thead>
<tr>
<th>Social media platform</th>
<th>Cofactors</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter, Instagram, Tumblr</td>
<td>volume</td>
<td>Aggregated relative number of postings</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>Aggregated relative number of postings with “@” symbol</td>
</tr>
</tbody>
</table>
I conduct the Hausman specification test to discern the preferred model (fixed or random) (Hausman, 1978). The fixed effects model assumes that individual specific effect is correlated with the independent variable, while for random effects there is no correlation between individual specific effect and independent variables. I set the Super Bowl commercials as the baseline category for finding relative categorical effect in the fixed effects model. I are estimating the pure effect of social soundtrack features by controlling the unobserved heterogeneity with the addition of dummy variables for each category in the fixed effects model.

Results

Change in Formality and Attitude among Categories

Research Question 1

I test hypothesis 01, 02 and 03 related to attitude for Twitter, Instagram and Tumblr interactions, respectively. The top, middle and bottom portion in Table 4-10 displays the F-statistic with the p–values for each Super Bowl phase. It is seen that there is a significant difference in average attitude of second screen conversations in all three phases among Super
Bowl categories for all three social media platforms, with an exception of Twitter in the *During* phase (hypothesis 02) with a low effect size (i.e., partial $\eta^2 = 0.033$).

Table 4-10. ANOVA statistic for attitude in phases

<table>
<thead>
<tr>
<th>Social Media Platform</th>
<th>$F_{\text{ANOVA}}$</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pre Phase</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Twitter</td>
<td>202.25</td>
<td>0.00</td>
</tr>
<tr>
<td>Instagram</td>
<td>1058.74</td>
<td>0.00</td>
</tr>
<tr>
<td>Tumblr</td>
<td>302.67</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>During Phase</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Twitter</td>
<td>2.41</td>
<td>0.09</td>
</tr>
<tr>
<td>Instagram</td>
<td>15.80</td>
<td>0.00</td>
</tr>
<tr>
<td>Tumblr</td>
<td>23.04</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>Post Phase</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Twitter</td>
<td>367.25</td>
<td>0.00</td>
</tr>
<tr>
<td>Instagram</td>
<td>765.66</td>
<td>0.00</td>
</tr>
<tr>
<td>Tumblr</td>
<td>184.78</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 4-11 presents the combined results of post-hoc analysis (GH test) for three research hypothesis. Surprisingly, the GH test from Table 11 shows that second screen conversations related to Super Bowl commercials category exhibit significantly more attitude in all three phases for all three social soundtracks, except in the *During* phase for Twitter. In *During* phase, no category is significant in measuring second screen attitude, while in the *Post*- phase, attitude about commercials is associated with that related to game for Twitter. Viewers exchange positive sentimental feelings significantly more for commercials via second screens in all three social soundtracks, except Twitter in *During* phase.

Table 4-11. Post-hoc test for emerging categories w.r.t attitude in phases

<table>
<thead>
<tr>
<th>Platform</th>
<th>Significant category</th>
<th>T-values with other categories</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Twitter  | Commercials | Musicals: 17.48* | Game: 3.44*
Instagram | Commercials | Musicals: 26.72* | Game: 43.74*
Tumblr    | Commercials | Musicals: 16.17* | Game: 20.15*

Platform    | Emerging category | T-values with other categories
Twitter     | None          | 
Instagram   | Commercials   | Musicals: 3.04* | Game: 5.43*
Tumblr      | Commercials   | Musicals: 3.83* | Game: 6.18*

I provide Figure 4-1, Figure 4-2 and Figure 4-3 to depict the change in daily attitude for each Super Bowl category on all three social media platforms.

![Daily attitude for Three Categories](image)

Figure 4-1. Daily attitude from social soundtrack for three categories on Twitter
Research Question 2

I test each of hypotheses 04, 05, and 06 for Twitter, Instagram and Tumblr. The top, middle and bottom portion in Table 4-12 displays the F-statistic with the p–values for Pre,
During and Post-Super Bowl phases. It is seen that there is a significant difference in average formality of second screen conversations in all three phases among Super Bowl categories for all three social media platforms.

Table 4-12. ANOVA statistic for formality in phases

<table>
<thead>
<tr>
<th>Social Media Platform</th>
<th>Pre Phase</th>
<th>During Phase</th>
<th>Post Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F\textsubscript{ANOVA} (2, 19668)</td>
<td>p-value</td>
<td>F\textsubscript{ANOVA} (2, 144)</td>
</tr>
<tr>
<td>Twitter</td>
<td>570.85</td>
<td>0.00</td>
<td>66.26</td>
</tr>
<tr>
<td>Instagram</td>
<td>126.38</td>
<td>0.00</td>
<td>15.97</td>
</tr>
<tr>
<td>Tumblr</td>
<td>148.07</td>
<td>0.00</td>
<td>6.94</td>
</tr>
</tbody>
</table>

I classify the category(s) as emerging (predominant) Super Bowl category(s) if the mean(s) of that category(s) is (are) significantly more than that of the other category(s) over each of the phases. To test the emerging category(s) among the phases, the GH test is performed. Table 4-13 presents the combined results of post-hoc analysis for hypotheses 04, 05 and 06.

The GH test from Table 4-13 shows that musicals category is more formal for Twitter in all three phases, while for Tumblr musicals is associated with commercials as the predominant categories in all three phases. For Instagram, though formality in game conversations becomes predominant in all three phases, musicals appears strong along with game in During phase. Viewers engage in more formal interactions for musicals in all three social soundtracks, except Instagram in Pre and Post phases.
Table 4-13. Post-hoc test for emerging categories w.r.t formality in phases

<table>
<thead>
<tr>
<th>Platform</th>
<th>Emerging category</th>
<th>T-values with other categories</th>
<th>Pre Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>Musical</td>
<td>Commercials: 31.24* Game: 23.22*</td>
<td></td>
</tr>
<tr>
<td>Instagram</td>
<td>Game</td>
<td>Commercials: 15.46* Musicals: 3.58*</td>
<td></td>
</tr>
<tr>
<td>Tumblr</td>
<td>Commercials and Musicals, mean of Commercials is higher</td>
<td>Musicals: 0.12, Game: 15.53* p-value: 0.99</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Platform</th>
<th>Emerging category</th>
<th>T-values with other categories</th>
<th>During Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>Musical</td>
<td>Commercials: 9.68* Game: 8.93*</td>
<td></td>
</tr>
<tr>
<td>Instagram</td>
<td>Musical and Game, mean of Musical is higher</td>
<td>Commercials: 4.86* Game: 0.54, p-value: 0.85</td>
<td></td>
</tr>
<tr>
<td>Tumblr</td>
<td>Commercials and Musicals, mean of Musical is higher</td>
<td>Commercials: 1.61, Game: 5.18* p-value: 0.25</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Platform</th>
<th>Emerging category</th>
<th>T-values with other categories</th>
<th>Post Phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Twitter</td>
<td>Musical</td>
<td>Commercials: 21.49* Game: 11.73*</td>
<td></td>
</tr>
<tr>
<td>Instagram</td>
<td>Game</td>
<td>Commercials: 22.83* Musicals: 9.04*</td>
<td></td>
</tr>
<tr>
<td>Tumblr</td>
<td>Commercials and musicals, mean of musical is higher</td>
<td>Commercials: 2.15, Game: 9.37* p-value: 0.08</td>
<td></td>
</tr>
</tbody>
</table>

I provide Figures 4-4, 4-5 and 4-6 to depict the change in daily attitude for each Super Bowl category on all three social media platforms.
Figure 4-4. Daily formality from social soundtrack for three categories on Twitter

Figure 4-5. Daily formality from social soundtrack for three categories on Instagram
Relationship between Features and Content

Research Question 3

The Hausman specification test results indicate that the fixed effects model is preferred one, as the p-values are < 0.05. The estimates of regression coefficients of the social soundtrack features (cofactors) identify how much second screen attitude changes over time on average per category when the respective cofactor is increased by one unit.

Table 4-14. Fixed effects model results for Twitter

<table>
<thead>
<tr>
<th>Phase</th>
<th>Cofactors</th>
<th>Coeff</th>
<th>p-value</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre</td>
<td>volume</td>
<td>-1.096</td>
<td>6.3e-09*</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>-0.140</td>
<td>0.002*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>0.152</td>
<td>0.000*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>retweet</td>
<td>-0.109</td>
<td>0.009*</td>
<td></td>
</tr>
</tbody>
</table>
I present the results of fixed effects regression model done on the panel data for Twitter in all three phases in Table 4-14. From Table 4-14, I find that attitude score will increase by 15% and 118% in relative scale with one unit increase of URL-based recommendations or referral (RF) pattern and number of sentences respectively in Pre phase for Twitter, while for unit increase of other cofactors the attitude score reduces. In During phase, though the coefficients of the majority of cofactors are large and positive, they are not significant (p-value > 0.05) in measuring the effect of the cofactors on the attitude of the tweets. Interestingly, in the Post phase, attitude increases by 55% and 11% with unit increase of mention (RS) and undirected broadcast (BC) conversation patterns, respectively. It is important to note an increased number of tweets decreases attitude significantly in the Pre phase, while in the other two phases, the effect is not significant (i.e., p-value > 0.05).

Table 4-15. Fixed effects model results for Instagram

<table>
<thead>
<tr>
<th>Phase</th>
<th>Cofactors</th>
<th>Coeff</th>
<th>p-value</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>broadcast</td>
<td>-0.303</td>
<td>6.8e-12*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>1.178</td>
<td>9.3e-10*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>0.159</td>
<td>0.102</td>
<td></td>
</tr>
<tr>
<td>During</td>
<td>volume</td>
<td>-0.589</td>
<td>0.850</td>
<td>0.44</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>8.879</td>
<td>0.363</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>9.668</td>
<td>0.321</td>
<td></td>
</tr>
<tr>
<td></td>
<td>retweet</td>
<td>9.375</td>
<td>0.338</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>9.382</td>
<td>0.337</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>0.799</td>
<td>0.798</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>0.857</td>
<td>0.300</td>
<td></td>
</tr>
<tr>
<td>Post</td>
<td>volume</td>
<td>-0.013</td>
<td>0.694</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>0.550</td>
<td>0.002*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>-0.135</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>retweet</td>
<td>-0.068</td>
<td>7.1e-07*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>0.110</td>
<td>7.8e-09*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>-0.036</td>
<td>0.366</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>-0.225</td>
<td>0.004*</td>
<td></td>
</tr>
</tbody>
</table>
During the **Pre** phase, Instagram media post attitude increases by 45% and 27% for unit increase of referral (RF) and sentences respectively in relative scale, while for unit increase of other cofactors, the Instagram attitude reduces, matching with that of Twitter in the **Pre** phase.

In the **During** phase, Instagram attitude increases 66% with unit increase of sentences in Instagram caption while it decreases significantly (p-value < 0.05) by 110% and 140% with unit increase of cofactors: 1) unique words and 2)volume of posts respectively. The social soundtrack conversation patterns do not have any significant effect on attitude in **During** phase. In the **Post** phase, among the social soundtrack features, the unit increase of undirected broadcast (BC) and number of sentences elevate the Instagram attitude by 22.5% and 23.1%. The positive effect of mention (RS) on attitude is insignificant (i.e., p-value > 0.05). It is important that volume of posts significantly reduces social soundtrack attitude in all three phases.
Table 4-16. Fixed effects model results for Tumblr

<table>
<thead>
<tr>
<th>Phase</th>
<th>Cofactors</th>
<th>Coeff</th>
<th>p-value</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre</td>
<td>volume</td>
<td>-0.915</td>
<td>2.2e-16*</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>0.123</td>
<td>0.220</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>0.477</td>
<td>1.7e-06*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>-0.016</td>
<td>0.873</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>1.076</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>-1.532</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td>During</td>
<td>volume</td>
<td>-1.34</td>
<td>0.063</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>0.665</td>
<td>0.522</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>0.572</td>
<td>0.594</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>0.429</td>
<td>0.694</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>1.491</td>
<td>0.061</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>-0.107</td>
<td>0.862</td>
<td></td>
</tr>
<tr>
<td>Post</td>
<td>volume</td>
<td>-1.114</td>
<td>2.2e-16*</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>-0.749</td>
<td>2.0e-09*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>-0.468</td>
<td>0.000*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>0.801</td>
<td>7.7e-11*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>1.282</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>-1.546</td>
<td>2.2e-16*</td>
<td></td>
</tr>
</tbody>
</table>

Table 16 represents the results of fixed effects model on the panel data for Tumblr in all three phases. From Table 16, in Pre phase, it is observed that URL based recommendation or referral (RF) and number of sentences has the positive effect on Tumblr attitude. Unit increase of referral pattern and number of sentences increase the attitude by 48% and 108% respectively. In During phase, the relation between social soundtrack attitude and none of the social soundtrack features are significant, while in Post phase it is the undirected broadcast and number of sentences that show the positive relation with Tumblr attitude. One unit increase of broadcast and number of sentences result 80% and 128% growth in attitude. Other social soundtrack conversation features are negatively related with attitude in a relative scale. It is worth noting that the increase of volume of posts reduces the attitude score in Tumblr, as seen in Twitter and Instagram.
Figure 4-7. Effect of music and game in relation to commercials for all three social media platforms across three Super Bowl phases

Figure 4-7 depicts the effects of music and game categories on linkage between social soundtrack features and attitude. It is seen from Figure 4-7 that for Instagram and Tumblr, music and game categories have reduced effect on feature-attitude linkage relative to Super Bowl commercials in all three phases. A similar scenario is observed in Pre phase for Twitter. In During phase for Twitter, music and game categories have higher fixed effects relative to commercials. In Post phase alternating scenario is observed. Music has lower effect, while game has higher estimate of effect in relation to Super Bowl commercials. The estimates of category fixed effects in During phase for Instagram and the game category estimate in During phase for Twitter are not significant, as p-values are > 0.05. So, Super Bowl commercials have more effect on the relationship between social soundtrack features and attitude in majority of phases for all social media platforms.
**Research Question 4**

On the balanced panel data, I run linear regression models introducing fixed and random effects for each phase and for all three social media platforms. I consider Super Bowl commercials as the base line category for both fixed effects and random effects model. The Hausman specification test indicates that fixed effects model is preferred over the random effects model for all three phases on Twitter, Instagram and Tumblr.

<table>
<thead>
<tr>
<th>Phase</th>
<th>Cofactors</th>
<th>Coeff</th>
<th>p-value</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre</td>
<td>volume</td>
<td>-10.881</td>
<td>0.014*</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>-12.747</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>-0.949</td>
<td>0.344</td>
<td></td>
</tr>
<tr>
<td></td>
<td>retweet</td>
<td>-4.545</td>
<td>3.4e-06*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>12.450</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>9.282</td>
<td>0.040*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>-5.768</td>
<td>0.011*</td>
<td></td>
</tr>
<tr>
<td>During</td>
<td>volume</td>
<td>80.546</td>
<td>0.344</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>353.830</td>
<td>0.183</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>365.918</td>
<td>0.167</td>
<td></td>
</tr>
<tr>
<td></td>
<td>retweet</td>
<td>377.716</td>
<td>0.156</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>362.745</td>
<td>0.172</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>-57.913</td>
<td>0.495</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>2.812</td>
<td>0.899</td>
<td></td>
</tr>
<tr>
<td>Post</td>
<td>volume</td>
<td>-17.534</td>
<td>1.7e-07*</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>-18.667</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>-5.679</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>retweet</td>
<td>-9.381</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>16.544</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>16.747</td>
<td>6.9e-07*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>-8.708</td>
<td>0.000*</td>
<td></td>
</tr>
</tbody>
</table>

I present the results of fixed effects regression model results from the panel data for Twitter in all three phases in Table 4-17. From Table 4-17, I find that formality will increase by 12.45 times and 9.28 times in relative scale with one unit increase of undirected broadcast (BC)
pattern and number of sentences respectively in Pre phase for Twitter, while for unit increase of other cofactors the formality reduces significantly except referral (i.e. p-value > 0.05). In During phase, though the coefficients of the majority of cofactors are large and positive, they are not significant (p-value > 0.05) in measuring the effect of the cofactors on the formality of the tweets. In Post phase, formality increases 16.54 times and 16.75 times with unit increase of undirected broadcast (BC) pattern and number of sentences respectively. It is important to note that increased number of tweets decreases formality significantly in Pre and Post phases, while in During phase the effect is positive but not significant (i.e., p-value > 0.05).

I present the results of fixed effects regression model performed on the panel data for Instagram and Tumblr in all three phases in Table 4-18 and Table 4-19 respectively.

<table>
<thead>
<tr>
<th>Phase</th>
<th>Cofactors</th>
<th>Coeff</th>
<th>p-value</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre</td>
<td>volume</td>
<td>2.834</td>
<td>0.011*</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>-4.173</td>
<td>0.057</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>10.758</td>
<td>1.4e-05*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>-5.720</td>
<td>0.009*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>-3.349</td>
<td>7.6e-13*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>-2.845</td>
<td>0.021*</td>
<td></td>
</tr>
<tr>
<td>During</td>
<td>volume</td>
<td>18.262</td>
<td>0.141</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>39.692</td>
<td>0.662</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>24.200</td>
<td>0.785</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>27.728</td>
<td>0.758</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>-13.142</td>
<td>0.083</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>-25.610</td>
<td>0.175</td>
<td></td>
</tr>
<tr>
<td>Post</td>
<td>volume</td>
<td>1.967</td>
<td>0.091</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>-8.815</td>
<td>1.4e-06*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>3.731</td>
<td>0.010*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>-8.519</td>
<td>2.8e-06*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>-3.890</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>-8.543</td>
<td>9.9e-08*</td>
<td></td>
</tr>
</tbody>
</table>
From Table 4-18, I find that formality will increase by 10.76 times in relative scale with one unit increase of URL-based captions (RF) in the Pre phase for Instagram; however, the a unit increase of other cofactors reduces the formality significantly. In the During phase, the coefficients of the majority of cofactors are large and positive except sentences and unique words; however, they are not significant (p-value > 0.05) in measuring the effect of the cofactors on the formality of the Instagram captions. In the Post phase, formality increases 3.73 times with a unit increase of referral (RF) pattern. It is important to note that increased number of postings with captions increases formality significantly in Pre and Post phases, while in During phase the effect is also positive but not significant (i.e., p-value > 0.05). The variance explained (R^2) in Pre and Post phases in Instagram is lower than that explained in During phase.

I present the results of fixed effects regression model done on the panel data for Tumblr in all three phases in Table 4-19. I find that formality significantly increases by 19 times and 41.19 times in relative scale with one unit increase of undirected broadcast (BC) pattern and number of sentences respectively in the Pre phase for Tumblr, while for unit increase of other cofactors the formality reduces significantly. In the During phase, the coefficients of the cofactors are large and positive, but they are not significant (p-value > 0.05) in measuring the effect of the cofactors on the formality of the Tumblr blogs. In Post phase, formality increases 25.7 times and 43.21 times with unit increase of undirected broadcast (BC) pattern and number of sentences, respectively. It is important to note that the increased number of Tumblr postings reduces formality significantly in Pre and Post phases, while in During phase the effect is positive but not significant (i.e., p-value > 0.05). Unlike Instagram, variance explained (R^2) in Tumblr by the model in During phase is lower than that explained in Pre and Post phases.

Table 4-19. Fixed effects model results for Tumblr
<table>
<thead>
<tr>
<th>Phase</th>
<th>Cofactors</th>
<th>Coeff</th>
<th>p-value</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre</td>
<td>volume</td>
<td>-44.977</td>
<td>2.2e-16*</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>-14.988</td>
<td>1.2e-14*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>-7.306</td>
<td>0.000*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>19.034</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>41.195</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>-7.036</td>
<td>3.8e-08*</td>
<td></td>
</tr>
<tr>
<td>During</td>
<td>volume</td>
<td>7.848</td>
<td>0.679</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>12.579</td>
<td>0.647</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>26.479</td>
<td>0.352</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>17.810</td>
<td>0.539</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>1.796</td>
<td>0.931</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>8.161</td>
<td>0.618</td>
<td></td>
</tr>
<tr>
<td>Post</td>
<td>volume</td>
<td>-43.561</td>
<td>2.2e-16*</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>mention</td>
<td>-19.534</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>referral</td>
<td>-9.922</td>
<td>7.4e-06*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>broadcast</td>
<td>25.700</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sentences</td>
<td>43.211</td>
<td>2.2e-16*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>unique words</td>
<td>-8.462</td>
<td>2.8e-10*</td>
<td></td>
</tr>
</tbody>
</table>

In fixed effects regression model, I also evaluate the effect of categories (i.e. unobserved variable) on the linkage between social soundtrack features (cofactors) and the quantified formalities (response) in each phase for all three social soundtrack platforms.

Figure 4-8 depicts the effects of music and game categories on linkage between social soundtrack features and formality on three social media platforms. It is seen from Figure 8 that music and game categories have significant increased effect on feature-formality linkage relative to Super bowl commercials in all three phases for Twitter and Instagram while for Tumblr the same scenario observed in the Post phase. In Pre, though relative fixed effects of music and game categories are positive, the effects of game in Pre phase is not significant (p-value > 0.05) and in the During phase, there is no significant effect of music and game categories relative to commercials, though the effect of game is least in Tumblr During phase. The fixed effects of Super Bowl music category is best on relationship between social soundtrack feature and formality of the content in all phases for Tumblr. For Twitter and Instagram, among the three categories, the fixed effects of Super Bowl commercials is least, while the fixed effects of music
and game are the highest on the relationship between social soundtrack feature and formality of the content in all phases respectively.

**Figure 4-8.** Effect of music and game in relation to commercials for all three social media platforms across three Super Bowl phases

### Discussion and Implications

#### Discussion of Results

In this research, I investigate four research questions pertaining to change in formality and attitude expressed in second screen interactions and quantifying the relationship between second screen attributes with content aspects (i.e., attitude and formality) of social soundtrack highlighting the use of three social networks concerning Super Bowl XLIX, in three phases, Pre,
During and Post, of the IRL media event broadcast. Three categories (commercials, musicals and game) concerning Super Bowl 2105 are formed for each of Pre, During, and Post phases.

**Change in Formality and Attitude among Categories**

While identifying predominant categories w.r.t second screen formality, interestingly the musical category appears strong for Twitter in all three Super Bowl phases. For Instagram, formality in the game category is significantly more than other categories in all three phases, while in During phase musicals is associated with game. For Tumblr, commercials and musicals jointly surface as the emergent categories in all three Super Bowl phases (see Table 4-12 and Table 4-13). Finding the emergent categories w.r.t second screen attitude, it is interesting to observe that Super Bowl commercials shines as the emergent category in all phases for all three social soundtracks, except in During phase for Twitter in which no category proves significant (Table 4-10 and Table 4-11). It seems that Super Bowl commercials draws more positive attitude compared to other two categories.

**Relationship between Features and Content**

From the second screen features-content relationship point of view, I consider second screen interaction attributes (see Table 4-9) as the cofactors. From conversation patterns perspective, it is observed that in Pre phase for all social soundtrack platforms referral or URL based recommendations (RF) pattern has the positive influence on social soundtrack attitude, while the other patterns have significant negative influence (see Table 4-14, Table 4-15, and Table 4-16). It may be that before kickoff, second screen users shows more excitement and curiosity about the upcoming commercials, halftime shows or different issues of the game itself by sharing the
information via URLs. This URL based messages may have more positive word or emoticons to
display their moods, particularly about commercials. As from Figure 4-7 it is observed that Super
Bowl commercials outshines other two categories in majority of phase-social media interplays. In
the Post phase for Twitter, none other than response or mention (RS) pattern has positive
influence on attitude. I believe the getting responses (RS) against the queries or statements
published on Twitter after the event generates more attitudinal score (see Table 4-14). For
Instagram and Tumblr, the undirected broadcast has positive relationship, while other
classification patterns have negative impact (see Table 4-15 and Table 4-16). Surprisingly, the
classification patterns do not have significant relationship with attitude in During phase, as
observed for all three social media platforms.

For feature-formality relationship, it is the undirected broadcast pattern (BC) and number of
sentences that have the significant positive influence on formality of second screen discourse in
Pre and Post phases for Twitter and Tumblr (see Table 4-17 and Table 4-19) while for Instagram
surprisingly the URL based recommendations (RF) shows positive relationship with second
screen formality in Pre and Post phases. Other communication patterns show significantly
negative relationship with formality except BC for Twitter and Tumblr and RF for Instagram. The
classification patterns do not have significant impact on formality in During phase for all three
social media platforms, as observed for attitude in second screen interactions.

The percentage of variance of Second screen attitude and formality data is better
explained in During phase compared to other two phases (see R² values from Table 4-14, Table 4-
15 and Table 4-16 for attitude; Table 4-17 and Table 4-18 for formality) for majority of social
media platforms except Tumblr (see table 4-19) where the reverse scenario is observed.
Implications

Change in Formality and Attitude among Categories

In our research, the increased rate of communication via a second screen during live broadcast media events leads to the increased exchange of feelings about different event categories by sharing, publishing, and commenting via various types of posts (e.g. audio, image, video, etc.) on social media platforms. Peoples’ interest in events like the Super Bowl is much higher than conventional broadcast media programing. Those concerned about such interests can monitor the social soundtrack for information and insights. In our research, regarding second screen attitude it is important to note that viewers involve in more sentimental discussions related to Super Bowl commercials compared to other categories in all three phases over all three social soundtracks. So, the brands or retailers sponsoring the ads should tap the feelings exchanged about the commercials and identify the facets of the potential consumers alongside the quality / content of the ads to formulate the business policies and programs. Integrating broadcast media events’ social soundtracks via social networks highlights a rise in potential brand recall, boosting advertising campaigns, and enhancing sale possibilities via word-of-mouth advertising.

Regarding second screen formality, the Games-Howell test exhibits the musical category dominates relative to the other categories in all three phases of the majority of social soundtracks, except on Instagram, where formality in the game category is higher. This may increase the personalization of the music products and marketing, allowing brands to communicate with viewers in a manner they are comfortable with. The analysis on the manner of discussion on diverse facets of the musicals will inevitably help the music and entertainment industries to create potential business opportunities by identifying the moments in the halftime show where viewers engage in different writing styles (Lukin, Moore, Herke, Wegener, & Wu, 2011).
**Relationship between Features and Content**

On relationship between attitude of second screen interactions and second screen conversation features, our research shows that URL-based recommendation has a positive relation with human attitude quantized from the social media posts in *Pre* phase. I pre-suppose that people engage more on expressing feelings by viewing particularly the trailers of ads / videos of commercials published weeks before the actual broadcast (Newton, 2015), as Figure 4-7 captures that fixed effects of Super Bowl commercials outperforms that of other two categories on the relationship between features of social soundtrack conversations and content attitude. Different brands that come forward to track the feelings on diverse facets of the commercials in the *Pre* phase will inevitably help the retailers to eventually increase the sales of the product and generate profit. Tapping the mention/response (RS) based interaction between viewers on Twitter in *Post* phase also facilitate retailers to identify the attitude of viewers about the products and hence get hold on the respective strength or weaknesses of the brands. The increased rate of communication via a second screen during live broadcast media events does not always lead to the increased exchange of feelings about different event categories, as it is seen that increase of volume of postings reduces the attitude scores. This may lead to increased insight into human information behaviors (Bernard J. Jansen & Rieh, 2010), as I believe that quality of posts is preferred over the quantity of uninformative posts to impart feelings.

Regarding formality of second screen interactions, the significant reduction in formality of tweets in categories for unit increase of social soundtrack conversation patterns, except undirected broadcast (BC), across phases indicates that viewers using RS, RF or RT patterns in their tweets are less formal viewers compared to those use BC for Twitter. In *Pre* and *Post* phases for Instagram, referral or URL based recommendations (RF) pattern has the positive influence on social soundtrack formality, while the other patterns have significant negative
influence. For Tumblr, the blogs with more undirected broadcast patterns (BC) become more formal in Pre and Post phases, while blogs containing more of other conversation patterns become less formal. From a feature-formality influence perspective, the relative volume of postings has positive relation with Instagram formality, while for Tumblr it is negative. From category effect perspective, it is also observed that music category has higher estimates of fixed effects on social soundtrack feature-formality relationship which is supported by the view in change in formality in phases among categories both on Twitter and Tumblr. For Instagram, game category outperforms other two categories in the strength of feature-formality linkage in all three phases. This seems to infer that the media based posts that contain URLs in Twitter and Tumblr are more formal relative to Instagram. It is also observed that game category has higher estimates of fixed effects on Instagram feature-formality relationship, while the impact of commercials is the lowest. Thus, the viewers can be identified with the moments when the change in stylometric variation for categories in different phases occurs. Moreover the lesser formality regarding commercials on feature-formality setting, may allow brands to communicate with viewers in a less formal manner which may uplift the degree of brand personalization.

**Strength and Limitation**

As in all research, there are limitations. The first limitation is that I have garnered 3 million tweets, while there is 28 million tweets reported during telecast of Super Bowl (Gibbs, 2015). This is because I have used the public APIs to collect the data for our research for all three social soundtrack platforms instead of using full data, which may overcome the limitations of the public APIs for collecting data. Using the firehose to collect the data may strengthen our findings. However, even with this, I collected substantial amount of data for the research reported here.
Secondly, there may exist spam messages or automatically generated messages that can be shared/reposted/retweeted. This may affect our results. Our present study did not filter out such spam or bots which I will focus in our future work.

Also, I consider attitude of social soundtrack conversations as one of the independent variables in our research. In our study, I did not capture the actual sentimentality of the texts as the positiveness and negativeness may neutralize each other at some sentence level or post level averaging. In future work, I will focus on deriving the amount of sentiments (i.e., positive and negative) besides computing attitude, as sentimentality and attitude are two different metrics (Kucuktunc et al., 2012).

Although having these limitation, I believe the our research findings present significant insights in identifying the temporal relationship between feature attributes and content of second screen based social media conversations (i.e., attitude and formality) along with temporal shift in content aspects concerning Super Bowl XLIX categories.
Chapter 5

Conclusion

In our research, I analyze three research objectives regarding second screen interactions on Super Bowl XLIX.

The first research objective is associated with three research questions to determine the dependence between the three phases with three categories and temporal significance of categories (phases) among phases (categories). It seems that there is a dependence between IRL phase and IRL category from the perspective of volume of second screen interaction. It seems that During phase dominates Super Bowl Pre and Super Bowl Post phases for each of three categories. The investigation of finding emerging category(s) in each temporal phase, I find that volume of Super Bowl game related discussion dominates before, during and after the live broadcast of Super Bowl XLIX on Twitter and Instagram while for Tumblr people engage more on discussions related to Super Bowl commercials and Super Bowl music than game. The three research questions are examined from the perspective of human information processing in terms of the volume and pace of comments posted as acts of information sharing.

In our second research objective, I evaluate two research questions related to the relationship the volume and attitude extracted from second screen interactions concerning Super Bowl XLIX commercials as presented in the social soundtrack have with the web searching concerning the brands for this IRL event. Measuring the relationship consists of two stages. The first stage is to evaluate the causality and reciprocal causality between 1) web search and volume of social soundtrack interactions, 2) web search and second screen attitude extracted from each of the three social soundtrack mediums. It seems that attitude and volume of brand related
discussions on majority of social soundtrack directly cause the web search on brands while the reciprocal causation (i.e., web search causes second screen interaction) is observed from the perspective of volume of social soundtrack conversations. The second stage quantify the correlation between 1) volume of second screen interaction and web search and 2) attitude from second screen interactions and web search by fixed effects regression model. The unit increase of volume and attitude of brand related conversations significantly increase the brand search on the web particularly for Twitter and Tumblr. The brand and time fixed effects are also measured to address the endogeneity of the correlations (to take care of unobserved variables) in the model. I observe that Post phase contribute more on the social soundtrack influence on web search concerning brands. I further examine the change in retweets (viral effect) in Twitter to test the difference in viral effects between two temporal phases concerning Super Bowl XLIX commercials. The change in search volume in Google between two phases is also tested. It seems that there is higher traffic pertaining to the retweet propagation and web search after the live broadcast of Super Bowl. The research questions are investigated from the perspective of information processing as a form of eWOM advertising in conjunction with traditional broadcast advertising, both in terms of the volume and attitude of comments posted in social soundtrack mediums and queries submitted for web search in Google.

The third research objective I analyze four research questions regarding content of second screen interactions of Super Bowl XLIX. All of these questions are examined from the perspective of human information processing in terms in terms of formality and attitude to the social soundtrack comments. The first two research questions identify the emerging Super Bowl category of discussion in each of the three super bowl phases from the perspective of second screen formality and second screen attitude extracted from the social soundtrack conversation on all three social media platforms. Though formality of social soundtrack is a complex issue, I ventured to address some issues regarding change of topical second screen formality concerning
discussion on IRL event. The investigation on formality exposes that the Super Bowl music that becomes emerging category in majority of social soundtrack in all three phases from the perspective of significant change in phase based formality among categories. While evaluating the emerging category from the perspective of attitudes of social soundtrack conversation, I find the Super Bowl commercials dominate the rest in majority of social media platforms in all three phases. The remaining two research questions examine the relationship the social soundtrack features that includes varied patterns of the postings have with the attitudes and formality extracted from viewer interactions concerning Super Bowl commercials, game, and music categories in each of event’s phases by means of fixed effects regression model. I find URL based recommendation and undirected broadcast pattern in social media posts has positive correlation with viewers’ attitude in Pre and Post phases respectively while the music category has significant contribution in attribute-formality relationship compared to other two categories in Pre and Post phases. No significant influence and category fixed effects are observed in During phase. This research provides contributions concerning understanding user behavior and interaction in terms of the shift in users' temporal attitude and formality concerning effects of categories treated as unobserved variables in the IRL event which is an emerging avenue of social soundtrack research.

**Future Research Plan**

**Multiple Samples of Domain**

In this research I have collected data on Super Bowl XLIX context. Though the findings indicate an important aspect regarding a change in people’s TV viewing and interaction habits with the presence of second screen, the underlying theoretical framework of the inferences can be
reinforced with tests on multiple sample of Super Bowl data happened in each year. I collected data for Super Bowl 50 held on 7th February 2016 on Twitter, Instagram and Tumblr and will run the analysis on Super Bowl 50 data. The results will be compared with that of Super Bowl XLIX data. I have an intuition that the comparative analysis will shed lights on different aspects of the Super Bowl categories.

**Broader Exploration of Social Soundtrack Features**

While investigating the relationship between social soundtrack features and social soundtrack content in the third research objective, the social soundtrack features are limited into different text based patterns of second screen conversations on three social media platforms. The type of posts (images, videos etc.) of Instagram and Tumblr are not considered as the variables in determining the relationship (Chang et al., 2014; Hu et al., 2014). For Instagram only the captions are considered. Moreover the tweets can be classified in several different categories that are not listed in the study of third research objective. In my study I mainly look into conversational (Referral and Response), pass along (Retweet) and phatic (Broadcast) tweets for Twitter. Apart from that each class of tweet can be divided into several categories, e.g., pass along class contains endorsement category apart from Retweet, phatic communication includes greetings and note-to-self categories etc. Those categories can be formed with micro level research regarding broader exploration of the different features and characteristics related to the semantics of the conversation posted in social networks (Dann, 2010). In my future research, I will analyze the impact of such micro-level categories on social media content. The result may differ with the incorporation of those categories/subcategories.
Causality Analysis between Content and Features

While quantifying the relationship between social soundtrack features and content of social media conversations, I consider the unidirectional relationship where the social soundtrack features are considered as the independent variables and the contents are adjudged as the response. In this research I do not examine the bi-directionality of this relationship. For example, the sentiment of a message may cause an individual to retweet the message. In my future work I will measure the causality analysis in the reverse direction to measure the reciprocal relationship. Moreover I need to evaluate the direction of causality and the strength of relationship between second screen formality and second screen attitude.

Measuring “Informality”

Social media is considered as a difficult medium to process the conversation (Nowson et al., 2005) and I have computed the formality scores of conversations based on a traditional framework of formality described in a prior research (Heylighen & Dewaele, 1999). In my research I computed the formality score based on the presence of the different parts of Speech exist in the texts. I do not consider the impact of emoticons and abbreviations while measuring the formality scores in a different framework as stated in (Mosquera & Moreda, 2011). The abbreviations present in the postings are expanded as described in the relevant websites in my research. I have determined the (in)formality score with the presence of non-correlated variables such as positive / negative emoticons, interjections present in the text and the number of abbreviations but did not measure the temporal significance of the informality across Super Bowl phases and Super Bowl categories. I will also measure the bi-directionality and strength of the relationship that (in)formality has with the social soundtrack features.
Measuring formality/informativity in a space constrained framework different from the traditional infrastructure will help to identify the degree of concision viewers adopt to express their feelings temporally. Using social media often means learning to use language in a somewhat different way where we are forced to notice the potency of concision even if we don’t always use those strategies in our everyday writing.

Measuring Sentimentality

In my research I have incorporated attitude rather than sentimentality for research objective 2 and research objective 3. I have portrayed the aggregated attitude as the average summation of positiveness and negativeness over posts which is further aggregated over a specified time window. Here positiveness and negativeness may neutralize each other at some sentence level or post level averaging. Thus the actual sentimentality regarding particular Super Bowl category or specific brand is not captured. The sentimentality is an important subtask of affective computing which in turn is a study to interpret, process and simulate human feelings or emotions. I will focus on finding the temporal change in category/brand specific positiveness or negativeness of comments to reflect the sentimentality of the topic. I already computed the frequency of positive/negative words at the sentence level and post level. I have to determine the relevant methodology to carry out the experiment related to change in sentimentality of the viewers’ second screen interaction and will make a comparative analysis between second screen attitude and second screen sentimentality. Further evaluation will be performed on linkage between the conversation patterns and the second screen sentimentality in bi-directional fashion.
Subjectivity Analysis

Subjectivity refers to how someone’s judgment is shaped by personal opinions and feelings instead of outside influences. Computing subjectivity of social media is an important avenue of affective computing. Public opinion, perceptions and emotions are the critical factors in sharing and dissipation of information about aspects of IRL events on social media. The viewers have become increasingly engaged to Twitter, Facebook, Weibo and other social media sources to learn and share thoughts about different topics of IRL events (brands, performers etc.). It is necessary then for those seeking information, to develop an understanding as to the particular role that social media plays in communicating impacts and opportunities provided by different aspects of IRL events. So subjectivity, as a process of socialization is needed to discuss how the role of the individual has changed from the passive consumer of information to actively validate the information that they and others consume and generate the new information on IRL event topics in a temporal fashion. I will analyze the subjectivity of the social soundtrack pertaining to different topics/categories of Super Bowl in temporal phases as it is essential for retailers and channel owners to examine issues of legitimacy and subjectivity as well as understanding the distinction between active and passive participants in social soundtrack conversations.

Despite having the limitations of my research objectives discussed, I believe that my research contributes to understanding human information sharing and information seeking behavior and interaction via social soundtracks in conjunction with viewing mass media broadcasts of IRL events in an emerging avenue of social soundtrack research that can potentially impact numerous fields, including the role of viewership in pop culture.


Appendix A

Publications on Second Screens (IRL event)


Partha Mukherjee and Bernard Jansen, “Influence of Attitude and Tone in Second Screen Conversations”, submitted in International Journal of Human Computer Interaction, Taylor & Francis, UK
Appendix B

Publications on Second Screens (Seasonal TV Shows)


Partha Mukherjee, Jian-Syuan Wong and Bernard Jansen, “Patterns of Social Media Conversations Using Second Screens”, in sixth ASE international conference on Social Computing 2014 (SocialCom’14), Stanford, CA, USA.


VITA

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PhD (Information Sc. & Technology, PSU), M.S (Comp Sc., Univ. of Tulsa), M.S (Comp. Sc., ISI, India), B.S (Mech Engg, JU, India)

Subjects of Interest
Online Advertising, Machine Learning (supervised, unsupervised and reinforcement learning), Artificial Intelligence, Data Mining, Theory of probability, Stochastic modeling, Analysis of social networks

Computer Skill Set
Programming Languages: C, Objective C, J2SE (JAVA), MATLAB, HTML5, shellscript, Awk, Python, PHP, JavaScript
DBMS: MySQL, MS-Access, Oracle.
Statistical Package: Minitab 16, R-2.15.1, SPSS.
Operating Systems: Windows XP/ 7.0, Sun Solaris, Linux (Red Hat/ Ubuntu), MAC OSX
IDEs: Netbeans, Eclipse, Xcode, JCreator
Online Teaching Tools: Camtasia 8.6., NeoSpeech
Hardware Description Language: VERILOG HDL

Award
- Participant in Research Presentation at Penn State Graduate Exhibition in March 2015:
  - Ranked first in Social and Behavioral Research Presentation.
  Link: http://www.gradschool.psu.edu/exhibition/awards/?year=2015

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Selected Publication
Partha Mukherjee, Brad Kozlek, Allan Gyorke, Cole Campese and Bernard Jansen, “Designing Mobile and Socially Networked Learning Assistant”, in MERLOT Journal of Online Learning and Teaching (JOLT), Vol. 10, No: 3, December 2014, pp; 351-373

Reference
Provided as per suggestion