BRAND MESSAGES ON TWITTER: PREDICTING DIFFUSION WITH TEXTUAL CHARACTERISTICS

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ABSTRACT

Chris J. Vargo: Brand Messages On Twitter:
Predicting Diffusion With Textual Characteristics
(Under the direction of Joe Bob Hester)

This dissertation assesses brand messages (i.e. tweets by a brand) on Twitter and the characteristics that predict the amount of engagement (a.k.a. interaction) a tweet receives. Attention is given to theories that speak to characteristics observable in text and how those characteristics affect retweet and favorite counts. Three key concepts include sentiment, arousal and concreteness. For positive sentiment, messages appeared overly positive, but still a small amount of the variance in favorites was explained. Very few tweets had strong levels of arousal, but positive arousal still explained a small amount of the variance in retweet counts. Despite research suggesting that concreteness would boost sharing and interest, concrete tweets were retweeted and shared less than vague tweets. Vagueness explained a small amount of the variance in retweet and favorite counts. The presence of hashtags and images boosted retweet and favorite counts, and also explained variance. Finally, characteristics of the brand itself (e.g. the number of followers the brand had, the number of users it followed and its overall reputation of the brand) boosted retweet and favorite counts, and also explained variance.

To God, my wife Laura, my family and my friends. Thank you for giving me the energy to pursue the career of my dreams.

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PREFACE

This work was inspired primarily by two books by which I was intrigued, “Made to Stick” by Chip Heath and Dan Heath and “Contagious” by Jonah Berger. You will see some of the core concepts of these books tested here. The idea of why certain things catch on (get shared) on social media is a puzzle with an infinite amount of pieces. This dissertation offers two or three pieces to this puzzle. I hope other scholars will contribute more.

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Chapter 1: Literature Review

The Origin of Brands on Social Media

Almost every popular consumer brand now has a social media presence (Brandwatch, 2013). Still, the history of brands' activity on social media is relatively new. Facebook was perhaps the first social networking service adopted by brands (Borhani, 2012). In 2006, when Facebook decided to open profiles to anyone 13 and older, brands began to create profiles on the service (Borhani, 2012). Initially, brands signed up for the same account as consumers. They had access to the same user interface. Brands could "friend" people, post messages and respond to friends. Some argue that major businesses did not seriously pay attention to Facebook until 2007 when the "group page" functionality was added (Richmond, 2007). This separated brand accounts from regular users. Brands were given a message board feature like those often found on Web pages. Two-way communication could occur with consumers inside of the group pages, but brands no longer acted as users outside of these pages. By December 2007, Facebook had over 100,000 businesses registered for what it now calls "pages." Pages are currently the primary method that brands use to post content to Facebook. Here, brands can freely post messages and interact with consumers. By "liking" a page, a consumer can receive updates on new content via his or her "news feed." Additionally, sponsored content options (i.e. promotions and advertising) now exist on the service. Here, information is targeted to consumers who do not directly opt to

receive information. While Facebook continues to evolve, these basic functionalities have been present for almost six years.

Following Facebook in 2006, Twitter gained popularity as a micro-blogging service. In a world of many social media services, Twitter differentiates itself in two ways: messages are public and brief. The majority of information created by users is open for all to see (Vieweg, 2010). This is different from Facebook, on which the majority of the content is perceived to be private (e.g. person-to-person) or semi-private (e.g. person to a contained network of people) (Kwak et al., 2010). Twitter has placed an emphasis on being a public medium by calling itself "…a platform for you to influence what's being talked about around the world…" (About Us, 2010). Users of Twitter follow other users, but relationships are often not reciprocal. Few users gather many followers, while many users gather a few (Vargo, 2013a). Users follow a mix of sources ranging from news services to celebrities. Like Facebook, messages from those users are curated into a person's news feed. Those messages (i.e. "tweets") are posts or status updates. The term is as much a play on the size of the message as it is on the audible similarity to Twitter. A tweet can be a combination of any 140 characters. The origin of the character limit can be traced to Twitter's origin as a text messaging service, but it is now embraced as a distinctive characteristic of the service.

In its formative years, Twitter was primarily used on desktop computers. Now, 75 percent of Twitter's traffic is generated from mobile devices (Protalinski, 2013). Twitter reaches a large segment of the world, touting 215 million active users (Protalinski, 2013). Despite having more users under the age of 30, Pew Research shows that major demographics of all varieties in America are represented on Twitter (See Table 1).

Table 1 – Twitter Demographics

Gender		Race		
Men	Women	White	Black	Hispanic
18%	17%	14%	27%	28%

Age			
18-29	30-49	50-64	65+
30%	17%	13%	5%

Education			
< High School	> High School	Some College	College +
16%	15%	20%	19%

Household Income					Urbanity	
> $30k	$30k - 49,999k	$50k - $74,999k	$75k +	Urban	Suburban	Rural
15%	16%	20%	22%	21%	18%	11%

Source: Pew Research Center's Internet & American Life Project Spring Tracking Survey, April 17 - May 19, 2013. N = 1,895 adult internet users 18+.

While people can broadcast any topic they choose, Catone has developed a typology of tweets (2008). Catone's typology relies on the concept of a meme. Biologist Richard Dawkins first proposed the term "meme" in 1976. The term was coined to describe a biological occurrence in which lots of individual units (the cultural equivalent of genes) undergo variation, selection and retention (Heath, Bell, Sternberg, 2001). His idea also accounted for constant competitions that memes go through. He noted that cultural memes do not compete solely on truth or newsworthiness alone. Instead other factors, such as novelty, dictate which memes are selected and retained in society. This may explain why Syria does not trend highly on Twitter, but sports, humor and entertainment do (Goel, Watts & Goldstein, 2012). Dawkins was perhaps one of the first to study how ideas propagate using a variation, selection and retention approach (Heath, Bell and Sternberg, 2001). Memes are not new to the social media era. For much of history, certain memes have

survived competition in the marketplace of ideas. Dawkins provides examples in his book that include chain letters and rumors (1976).

In a content analysis of Twitter, Catone finds that memes do exist on Twitter. His definition of memes however, varies slightly (2008). First, he recognizes that not everything posted to Twitter is intended to be a meme. Users post status updates of everyday occurrences (i.e. what a user ate for lunch or delays experienced at an airport). Second, there are short-term memes, which he defines as temporal events that are of interest to a larger audience. Conversations can last from a few minutes to a few hours. For example, a television show will have some buzz before, during and for a short time after the show airs. The final type of discussion widely observed on Twitter refers to long-term memes. Long-term memes are topics of interest that people talk about for days, weeks or even months. Catone observes politics and new video games as examples of longer-term discussions happening on the service (2008).

Across all three types, chatter involves the everyday occurrences and interests of users. Consumers interact with brands daily. It is no surprise, then, that users engage in brand conversations on Twitter. In a 2012 study, a projected 39 percent of all Americans tweeted about a brand (Borhani). Moreover, 29 percent follow a brand on Twitter. Coupled with the finding that people of all demographics are found to have user profiles, Twitter is a viable space to engage with consumers.

Twitter has always been open for businesses to join. At no point during registration does Twitter delineate whether the new registrant is a person, business or organization. Unlike Facebook, which delineates brands from people by giving them pages instead of user profiles, brands on Twitter are provided with the same service as individuals. Brands can interact with other users freely. Outside of paid advertisements, a brand cannot interact with a consumer on

Facebook until the user "likes" the brand's page. The increased interactivity and visibility that Twitter affords has sparked the interest of brands. 97 percent of major brands have active Twitter accounts as of 2013. Brandwatch's survey found that while 25 percent of brands' accounts only broadcasted messages, 69 percent of accounts broadcasted and engaged with consumers. The survey also found that more brands engaged in two-way communication on Twitter than on Facebook. Brands are beginning to interact so much that 66 percent of brands on Twitter created new accounts in the past year. The primary motive for the new accounts is to keep interactions (e.g. customer service and support) separate from accounts that primarily broadcast messages. Brands are also sending more tweets than ever before; 45 percent of brands tweet 10 to 49 messages per week.

Over time the service has introduced brand friendly features. Advertisement options now exist on Twitter. Brands can pay Twitter to gain exposure with non-followers. Brands can inject messages into a user's timeline; they may also opt for a sponsored spot in the user recommendation panel. Brands are, in turn, suggested to targeted users. In the trends panel, topics can be sponsored. Recent multimedia improvements allow brands to display a wider array of content in tweets. Images can now be displayed inline below the text of a tweet. Users no longer need to "activate" (e.g. click or tap) a tweet to see photos included with tweets. When a tweet is activated, video and other multimedia content can be embedded (e.g. slideshows and graphics).

With the additional features that Twitter affords, brands have moved beyond earlier models of social media marketing that largely entailed the rebroadcasting of existing marketing messages to a social media service. Many different areas of a business have a social media focus

that includes Twitter. Only 66 percent of social media teams reside in marketing, corporate communications and public relations departments (Solis & Li, 2013).

Brand Behavior and Goals on Social Media

Dedicated social media staffs exist inside all types of business units, including: human relations, product development, advertising, customer experience, information technology, executive, legal and marketing research teams. Social media are used to support many different aspects of a brand. In a study of brands on Twitter, Borhani found several use cases (2012). (1) Brands now monitor the conversations of consumers. By analyzing mentions of their brands, they can listen and learn. Digging further into social data, brands can look at users by demographic, by the moods they evoke or even the words they mention. (2) Brands gain customers and stakeholders via Twitter. (3) Brands broadcast marketing materials, such as coupons and promotions. (4) Brands use Twitter to broadcast public relations messages, such as important news. (5) Twitter can be used to engage in public conversations with employees about a brand. (6) Personal connections are made with users through engaging with them in everyday chatter. (7) Customer service is rendered and issues are solved via Twitter.

Yan argues all of these behaviors should abide by nine rules of social media engagement (2011). These rules help to effectively build a brand on Twitter. (1) All communication directly with consumers must foster a sense of membership or citizenship with the brand. (2) Messages should stick to the core values of the brand. (3) Messaging should encourage the audience to engage in a dialogue. (4) Listening to that dialogue should help the organization find a competitive advantage. (5) Dialogue should also inform the brand's vision, and differentiate how that vision is different than other brands. (6) Ensure that consumers are properly interpreting the core values and missions of the brand. (7) Interactions with consumers must be positive, and thus

build positive brand associations. (8) Interactions must also boost the perceived quality of the brand and not devalue it. (9) Finally, broadcasted (i.e. non-customer service) messages should build greater awareness of the brand by targeting audiences that it has not yet reached.

These rules pertain to brand management (2, 4, 5, 6, 7, 8) and brand engagement (1, 3, 7, 9). This dissertation focuses on a particular aspect of brand engagement. When consumers respond to messages broadcasted from a brand, this engagement is public (Montalvo, 2011). As such, others see it. This dissertation is specifically interested in cases where consumers share and pay attention to brand messages on Twitter with friends (i.e. by "retweeting" or "favoriting" them). When consumers share these messages, the content spreads. Solis and Li found that the most widely shared goal of social media strategists was to market their content as widely as possible to consumers (2013).

The key difference between a retweet and a favorite is the intentional sharing function that comes with retweeting. When a user performs a retweet, that message is rebroadcasted. This sharing function allows new users, ones following the person who just performed the retweet, to see that tweet in their timelines. When this interaction occurs for a brand, its organic reach grows. The more retweets a brand generates for a message, the more people see it, at no cost to the brand.

The favorites function started out as a bookmarking tool (About Us, 2010). Users of twitter "favorited" tweets to easily find them later. In 2010, Suh et al. found that only 57.5% of all users of Twitter had ever favorited a tweet, and only 7.2% had favorited 100 things or more (2010). Since then, its usage appears to have become more mainstream. Now, in addition to bookmarking, the favorite function also serves as an equivalent to Facebook's "like" button (Noland, 2013). Users favorite tweets to let authors know they appreciated the tweets.

Twitter has also blurred the lines between favoriting and retweeting with the advent of the "Discover tab." "The Discover tab surfaces the best content from around Twitter and is personalized for you" (Using the Discover Tab, 2014). As such, it curates tweets that have been favorited by the users that a user follows. It displays those favorites to that user inside of the Discover tab. In this instance, a favorite is similar to a retweet. Finally, the complete list of favorites for any user can been seen by visiting that user's profile. This function does not exist for retweets. When the favorite interaction occurs for brands, their organic reach also grows. While it may not be as straightforwardly quantifiable as a retweet, the more retweets brands garner for a message, the more people see the message at no cost to the brand. Retweets and favorites are two separate types of interactions. While their functions are similar, it is conceivable that there would be scenarios when certain tweets would have more of one than another. This dissertation will attempt to predict both.

How can consumers be encouraged to engage with marketing content and share it with their social networks? This question has no simple answer. Many scholars have realized that the most successful marketing campaigns were ones that went "viral" (Gladwell, 2002). Rarely do viral marketing campaigns go viral (Goel, Watts & Goldstein, 2012). There are times when a marketing campaign spreads through social networks. People can spread the word like wildfire. This observation has piqued interest in marketers and scholars alike.

Virality

This dissertation uses the term "virality" as a term for times when a message spreads through a social network. The continuum approach to the measurement of virality is adopted (Goel, Watts & Goldstein, 2013; Hofman, 2013; Watts & Dodds, 2007). Some messages are viral, and some are not. Moreover, some messages will also be more viral than others. Virality

was first used to describe the widespread diffusion of a piece of information. This meaning aligns with early uses of the word from the 18th century, during which it was used to describe prolific growth (Wilkes, 1825). In communication, sociology and many other disciplines, virality is talked about in a diffusion sense (Watts & Dodds, 2007; Goel, Watts & Goldstein, 2012). Here, information, advertisements or products are the "virus" that is spread. The patterns of how information is dispersed in networks of people are analyzed.

In the marketing and advertising fields, Phelps et al. pin the origin of the word virality and defined it as the rapid spread of a marketing tactic through a network of highly connected people (2004). When writing a short column for *Boardwatch Magazine,* Knight linked marketing with virality (1997). The new term viral marketing was born. The article was enamored with how quickly the Internet could enable new products and services to gain popularity (2004). Companies could manipulate "the network effect" of the Internet and reach millions of people that were connected. The article cited the first example of viral marketing as Hotmail, the widely used email service. Knight claimed that by putting a footer on every email that invited others to sign up, Hotmail was able to manipulate the network of millions of people who were connected. The result was 50 million signups. "This [viral marketing tactic] spreads organically like a virus as people use the medium to communicate with friends" (Knight, 1999, p. 50).

Phelps offered a definition for viral marketing, calling it an extremely successful example of "word-of-mouth advertising." He recognized that individuals and their exchanges of messages are the primary drivers of the virality. This definition also mentions the greater body of word of mouth (WOM) literature in advertising and marketing. This accomplished body of research is rather extensive and has been around for roughly 50 years (Dichter, 1966).

One key similarity between Dichter's first writings on WOM and the viral marketing literature is the way in which diffusion has been portrayed. Many people pass on a message. Because many people are connected to many more people, that message spreads across a population of people. This is a core principal in the WOM literature and in this dissertation. As Goel, Watts and Goldstein notice, a large initial cascade is rarely enough for something to be truly viral (2013). Instead, it must pass from person to person. As a result, the amount of times a message is passed on can be a good measure of how wide that message spreads across a network.

Viral Marketing is Not Viral

The term virality implies contagious. Imagine the flu; it can spread like wildfire. Each person infects a large percent of people with whom they come in contact. Two years ago, Chris' father-in-law had the flu. He gave it to his entire family. Chris' wife gave it to him. And then, Chris gave it to his entire family. This flu was truly viral. Information is not shared like the flu on social media (Goel, Watts & Goldstein, 2013; Hofman, 2013; Watts & Dodds, 2007; Berger, 2012). The majority of content posted online does not spread like wildfire, but some things do become wildly popular. When content is somehow special, does it spread like the flu?

Goel, Watts and Goldstein suggest that diffusion online appears to be much less contagious (2012). The average cascade generated from any individual is small relative to the number of people to whom that person is connected. Using interactions of people on social networks (i.e. Yahoo Kindness, Yahoo Voice, Zync, Twitter and Friendsense) the researchers noted that information rarely traveled far from its origin (2012). Often, messages were only shared from the originating source. Even for very popular users, sharing rarely went beyond the first generation. Overall, the researchers noted the "low infectivity" across the networks. Most messages were not shared. When they were, they were not shared often. Even on the rare

occurrence when a message was passed on for many generations, those multi-generational shares did not account for a large percentage of the times the content was shared. This phenomenon was also observed on the social bookmarking service Digg. Stories that spread mainly through a submitter's social neighborhood proved not to be very popular (Lerman & Galstyan, 2008). This phenomenon was observed for even the "top users" of Digg (i.e. the users with the most followers). While these users did tend to get the most amount of "up votes," their social networks were not enough to make content spread widely across the network.

Returning to the flu analogy, when Chris' father-in-law shared the flu, Chris got the flu, but not directly from him. The flu was passed from Chris' father-in-law, to his mother-in-law, to his wife and finally to him. Many scholars have shown that multigenerational sharing of information rarely occurs on online social networks (Anderson et al., 2013; Hofman, 2013; Watts & Dodds, 2007). Newer research suggests that this is even true of Twitter accounts with many followers (Anderson et al., 2013). If the flu were like what these scholars have observed on social media, you may expect that Chris's father-in-law would have passed the flu on to one or two people, and the spread would have stopped there.

For this dissertation, it is then expected that messages (i.e. tweets) from brands will have low infectivity. Popular brands will likely have many followers, and therefore, many people listening to their messages (Vargo, 2013a). Still, few will pass them on to others (i.e. by Retweeting those messages).

RQ1a: How frequently are brand messages shared on Twitter?

RQ1b: How frequently are brand messages favorited on Twitter?

Influential Followers vs. a Ton of Followers: Which is Better?

Regardless of the general level of infectivity on Twitter, brands want to maximize their propensity for their messages to be shared. As brands grow fan bases on Twitter, academic research stands at odds on how best to accumulate followers with this goal of infectivity in mind. Should a brand accumulate the largest follower count possible on Twitter to maximize message dissemination? Or, should a brand care about attracting influential opinion leaders first and foremost?

The most popular theory in the communications discipline that discusses this process is two-step flow. Many theories have been connected to two-step flow. It came in the early era of mass communication theory, at a time when the mass media had previously been thought to have an all-powerful effect. This effect was thought to exist on all types of decision-making. The mass media was thought to control our opinions on everything from news to consumer behaviors (Weimann, 1994). From this view, two-step flow emerged as one of the leading new models that explained how consumers were influenced (Weimann, 1994; Katz and Lazarsfeld 1955; Lazarsfeld, Berelson, and Gaudet 1968). The theory explained how the media and a select group of influential people worked in a network of communication to influence the masses.

In the decades after the introduction of the two-step flow, the idea of opinion leaders (i.e. influentials) was revived in communication theory (Weimann 1991; Weimann 1994). Opinion leaders were thought of as the people that ordinary people turned to for information and advice. Shifting from the traditional definition of a leader as someone who actively guides and directs, an opinion leader was thought of as, "not an authoritative, charismatic or leading figure but rather a position of an expert among his or her peers, a source of advice on a particular issue or subject" (Weimann, 1994; p. 71). Weimann goes beyond opinion change to innovation and

provides evidence that opinion leaders drive the diffusion of innovations. He shows that, in some cases, the success of a new product may hinge on whether influential people adopt the product early in the adoption process.

The two-step flow argument reappeared in popular nonfiction with Gladwell's *The Tipping Point* (2002). Gladwell vividly describes a group of people as similar to Paul Revere for their ability to disseminate information quickly and efficiently. He claims that these people have a "set of social gifts" that separates them from everyday people. In using terminology such as "influentials," "connectors," "mavens" and "salesmen" these people have the ability of influencing tons of people around them. Borrowing from the book title, these people can provide a certain advantage that tips the scale of public opinion. Gladwell provides examples of people throughout history who had exceptionally large social networks. When they chose to spread an idea, product or even a restaurant recommendation, their influence was exceptional. Gladwell argues that just one influential can start a momentous cascade of WOM. Just a few of these people combined can provide enough of a social cascade to spread an idea to full adoption in a community. Since Gladwell coined the phrase influentials, a renewed interest in targeting those that tend to influence many has resurfaced. In a review of influentials research, Roch concludes, "in business and marketing, the idea that a small group of influential opinion leaders may accelerate or block the adoption of a product is central to a large number of studies" (2005).

Berger has sharply refuted the notion that social epidemics are driven by a small group of people (2012). Berger does not refute that influential individuals do exert influence over others. But he specifically challenges the notion that these individuals are the key catalysts in product diffusion or opinion change. He refutes Gladwell's argument that restaurants become popular by

the power of a few influential individuals (2002). Instead, he depicts diffusion as a grassroots effort. For something to catch on, many people talk to their few friends. They talk to them because whatever they encountered or observed is something great. Because they have ample time in conversations, they are likely to tell their friends. Many talking to many start the largest social cascades. Berger argues while each individual may only influence a small amount of others, these numbers add up when ideas are "contagious."

Watts and Dodds modeled the patterns of cascades (2007). They define cascades as the process whereby something, typically information or knowledge, is successively passed on to others. Cascades vary in how widely they are spread (i.e. the amount of diffusion they receive). Watts and Dodds argue that cascades are more complicated than understood by the opinion leader research. They refute the idea that influentials are vital to the formation of public opinion (2007). The researchers supply evidence in the form of computerized social networks. In simulated models, Watts and Dodds built a network of 10,000 individuals. Each individual was given an influence threshold (i.e. a tolerance level that must be satisfied before that individual would pass along a message). The researchers tested the "influentials hypothesis by setting different levels of connectedness for certain actors in the network. Some were central to the network and well connected. Others were isolated in the network and had few connections. Inspired from Gladwell's *The Tipping Point*, a small percent of the total actors had many connections, and the rest had relatively few. After the networks were configured, one person was picked at random as a starting point. Then, based on the acceptance thresholds, people either did or did not pass on the message. If they did pass on the information, the people they were connected to then received that information. Those people then decided whether or not to pass on the information based on their threshold and so on. After repeating the experiment a thousand

different ways the researchers found that the largest cascades began with average actors. Under most of the social conditions that the researchers considered, they found that large cascades were not started by influentials. Instead, the drivers of widespread diffusion were easily influenced individuals. The researchers note that, under the majority of all scenarios, influentials were only modestly more important than average individuals.

Hofman has also shown that the largest social cascades do not occur when a single person introduces content, but when many people introduce content (2013). Hofman, too, observed the viral diffusion method on Twitter. He shows that for a viral video, typically each person that introduces the content garners a few additional adoptions. While some adoptions are greater than others, no one adoption can attribute for a large amount of diffusion (2013). Quercia et al. too found that the largest cascades came from users with a large amount of followers (2011). They, therefore, suggested that marketers target a large number of potential influencers, thereby capturing average effects.

It is for these cases, that this dissertation will adopt the Watts and Dodds observation that a large audience drives virality and that diffusion can be most reliably caused by masses of easily influenced people (2007). As such, this dissertation expects that brands with more followers will reach more people.

RQ2a: What effect will the number of followers have on the average number of shares (i.e. retweets) that brand's tweets receive?

RQ2b: What effect will the number of followers have on the average number of favorites that brand's tweets receive?

With all of the literature on influentials and opinion leaders, it is hard to completely downplay the existence of some social order of influence. In all reality, as many researchers have noted, when dealing with macro-level judgments, one scenario cannot always be correct (Anderson et al., 2013). In predictive models dealing with large data, large amounts of predictive errors occur. Moreover, there are certainly times when the influentials have been shown to result in large social cascades of diffusion (Watts & Dodds, 2007; Anderson et al., 2013). Still, knowing the effect that follower counts have on diffusion will put into prospective its importance as a social media metric of influence. Cha et al. warn that this statistic is often overhyped, which they explain in their paper entitled the "Million Follower Fallacy" (2010). The researchers found that users with large amounts of followers were not consistently influential. The most followed users were observed as being particularly unsuccessful at spawning large amounts of retweets. Instead, the authors suggest that retweets are driven by the content value of a tweet.

Brand Differences by Type

It is also likely that the level of infectivity of brand messages will vary by the type of brand. When considering the typology of different brands, differences emerge. Some brands generate more WOM than others. A 2006 survey showed that 94 percent of consumers talked about computers and restaurants, while only 65 percent talked about personal care products, and 45 percent talked about athletic shoes (Allsop, Bassett & Hoskins, 2007). On the receiving end, not all brands are equal in the amount of information people seek. 18 percent of respondents sought information about financial products, while only eight percent of respondents provided it. Conversely, 15 percent of respondents actively provided information about politics to their friends, while only 10 percent sought that information. In another study, book categories on Amazon were a positive indicator of the amount of eWOM generated for any specific book

(Amblee & Bui, 2008). Some categories had more reviews than others. This dissertation will survey many different types of brands. Taking these findings, the expectation is that the amount of WOM generated will vary by brand type.

RQ3a: On average, do certain types of brands tend to have messages shared (i.e. retweets) more than other types?

RQ3b: On average, do certain types of brands tend to have messages favorited more than other types?

Brand Differences by Connection Type

In WOM networks, information travels through people who are connected through social ties (Dichter, 1966). Those ties can be friendships, professional relationships or through an Internet service, such as following a user on Twitter. Any possible social setting in which people interact can be thought of as a network (Rosen, 2009). Brands are connected to users on Twitter. The most common scenario for popular brands is to have a uni-directional tie with their consumers (Vargo, 2013a). Consumers follow brands. Some brands on Twitter form a closer bond with their customers by returning the favor (i.e. following them back on Twitter). This conscious choice by the brand may seem innocuous. However, networks with lots of reciprocity are often more balanced, stable and harmonious (Prell, 2011). When dealing with marketing, WOM theory has also shown that relationships do matter in networks.

Researchers wanted to discover how three piano teachers received referrals for new students (Brown & Reingen, 1987). To discover the network of people that led to the referrals,

researchers contacted each of the current students. Each was asked how he or she had been referred to the teacher. If a student named a person as the referrer, that person was contacted. This process was repeated until the path was traced back to the teacher, or the path could not be traced further (e.g. the person was non-responsive). The networks were traced and a final list of 118 people was constructed. Next, a letter was mailed to each participant, each with a list all the other 117 actors in the network. The subjects were asked to look through the list and identify whom they knew and how well they knew them. Strong friendships, or strong ties, were more influential and most often traced the flow of referral. Close friends successfully referred close friends. Weak ties, however, seemed to bridge different subgroups of people.

In an eWOM recreation of the same methodology, Brown, Broderick and Lee conducted a social network analysis of an online community (2007). The research showed that strong ties (e.g. close interpersonal relationships) were less relevant when compared to the 1987 study. Participants seemed to have a relationship with the online service itself, not individual users on the site. Many consumers have ties with brands on Twitter (Vargo, 2013a). For this dissertation, two types of ties can be observed between brands and consumers: a mutual tie or a unidirectional tie. Some brands choose to follow many users. Other brands may only follow employees, or a select group of people. Those that follow many tend to have mutual ties with their followers. Some brands "follow back," or follow new users in hopes those people will follow them. Brands that follow many will have more mutual ties. By default, it is safe to assume that these ties are weak, when compared to close personal friends. Still, research shows that even weak ties have strong word-of-mouth influence (Goldenberg, Libai & Muller, 2001). This dissertation will investigate the differences in the way brands follow users. Specifically, it will investigate if those

differences influence the amount of eWOM generated. The research suggests that brands that seek more mutual ties with consumers will generate more eWOM.

RQ4a: Will the number of users a brand follows predict the number of shares (i.e. retweets) its messages receive?

RQ4b: Will the number of users a brand follows predict the number of favorites its messages receive?

Message Content and Virality

Guerini, Stapparava and Ozbal echo the fact that consumers have resistances to spreading information (2011). They suggest another reason for why content may catch on in a network of people. "Virality is a phenomenon strictly connected to the nature of the content being spread, rather than to the influencers who spread it" (p. 506). They suggest that analysis of influencers accounts for *how* content spreads, not *why* content spreads. This argument can be restated as: the probability of influencing people is controlled by the content. The nature in which the content spreads is a result of the network and its influentials.

There is tremendous variation in the WOM literature surveyed here. Even the term "word-of-mouth" is used interchangeably with "word of mouth" (Liu, 2006; Dichter, 1966). Still, at the core of these studies, two variables emerge: the messages that consumers share with each other and the networks of people through which these messages pass. This dissertation argues that the messages are just as important as the networks. In the WOM literature, little attention has been paid to characteristics of the message.

Rosen makes the promising observation that products that evoke strong emotional reactions also have more WOM (2009). He provides examples of emotions: fear, surprise, excitement and delight. These emotions make consumers talk about products to their friends. He finds that these emotional reactions occur when a product exceeds a consumer's expectations, or when a company has created a product so good that the consumer has an amazing experience. While helpful to develop a hypothesis that emotional content is talked about more, Rosen does not test it. This dissertation looks to provide solid ground on which such a claim might stand. It will test message characteristics that could possibly bolster diffusion (i.e. sharing) of messages across eWOM networks. Berger sums this thinking up best by saying,

> "We all have friends who are better joke tellers than we are. Whenever they tell a joke, the room bursts out laughing. But jokes also vary. Some jokes are so funny that it doesn't matter who tells them. Everyone laughs even if the person telling that joke isn't all that funny. Contagious content is like that – so inherently viral that it spreads regardless of who is doing the talking. (Berger, 2012, p. 14)"

This dissertation looks at these types of "contagious" messages closely. Are there brand messages that are the viral equivalent of a hilarious joke? WOM literature shows that brands have advantages and disadvantages when it comes to virality on Twitter. In one sense, major consumer brands have a large amount of followers (Vargo, 2013a). This allows their messages to be heard by many, including potential opinion influencers (Rosen, 2009). However, credibility is a big mediating factor of WOM diffusion (Dichter, 1966; Blackwell, Miniard & Engel, 2006). Consumers are skeptical of information that comes directly from brands (Breazeale, 2009). Then again, scholarship shows that brands can generate WOM through seeding opinion leaders (Godes

& Mayzlin, 2009). The question still remains, can brands and products reach out to consumers directly and generate eWOM effectively? RQ1 will test this question.

Yes, WOM can explain how messages from brands spread. As discussed, it can often too explain why. But these theories tend to ignore the properties of the messages that get passed on. Certainly, some messages are more likely to be spread than others. Shifting to the content of the message, there properties of a message that can be quantified and observed. Goel, Watts and Goldstein have shown that some of the most shared content on Twitter come from unsuspecting places (2013). The strongest networks do not always drive the most diffusion. On Twitter, messages are simple 140 character messages, supplemented with multimedia or a hyperlink to a story. Are there characteristics of the message that might increase the diffusion? The following is an introduction to scholarship that addresses the characteristics of textual messages, and how those characteristics influence the diffusion of these messages.

Emotion

Humans react certain stimuli with emotion. These emotional reactions are powerful and abundant in humans. Certain stimuli can evoke specific psychological reactions (Zajonc, 1980). Emotions have a powerful influence over everyday perception, attention, memory and learning (Dolan, 2002). Scholars have shown that, ultimately, these effects alter decision making (Dolan, 2002). The bulk of empirical work on emotions has come from psychology and neuroscience disciplines (e.g. Agres, Edell & Bubitsky, 1990; Dolan, 2002). Given the broad effect emotions have on decision making, it has since been applied to marketing and advertising (Heath, 2012). Through methods like experiments and analysis of neural activity, the activation of emotions can be studied. Participants are presented with advertising stimuli and their responses are recorded. That reaction can be analyzed to see how it alters behaviors and attitudes.

Understanding how emotion is processed in the human brain helps us appreciate how deeply the human brain is affected by emotion. Human brains process emotion before facts (Zajonc, 1980). As counter-intuitive as that may sound, evidence shows that before the human brain can apply any sort of reasoning or interpretation to stimulus, it reacts with emotion. This means that when presented with an emotional advertisement, a human's initial reaction has little to do with predispositions that person may have to that product (Wood, 2012). In fact, only after the emotional reaction can an individual begin to think rationally. There are obvious limitations to this finding. Not everyone cries at a funeral, and not everyone smiles at a baby. Outward expressions of emotion come after an internal emotional reaction, after the brain has time to apply reasoning and cognitive resistance. Still, scholars have provided evidence that the brain is wired with an emotional circuit that activates before the brain has time to cognitively process that information (Bagozzi, Gopinath & Nyer, 1999). After humans have time to think, a second emotional circuit is activated with cognition, and that process can correct or alter an initial emotional reaction (LeDoux, 1998). Have you ever seen someone start to laugh at a joke and then stop after finding it to be in bad taste? This is a good example of both emotional circuits working in opposition.

Emotions and Advertising

Many have observed and written about how emotionally charged advertisements garner an initial "gut reaction" (Heath, 2012). These reactions can be overtly apparent, in a chuckle or a furrowed brow, but all emotional reactions are not necessarily visible (Wood, 2012). Just as facial expressions are measurable, so is emotional response. Scholars suggest that gut reactions, when induced with the right emotion, can influence our subsequent behavior (Dolan, 2002).

Moreover, newer scholarship has shown that emotional reactions can make advertising more effective (Wood, 2012).

But how specifically is an advertisement charged with emotion? Consumers are skeptical to any type of marketing content, such as advertisements and marketing material (Dichter, 1966). Consumers apply all types of cognitive resistances to advertisements (Rizvi, Sami & Gull, 2012). Emotion actually precedes these types of cognitive resistances. Consumers may very well be able to apply all types of reasoning to whatever informational content is inside of an advertisement. Emotional content, however, may be immune to skepticism.

In a test of this hypothesis, advertising scholars set out to see if skeptical consumers would react differently to informational and emotional advertising (Obermiller, Spangenberg & MacLachlan, 2005). Those that tested as highly skeptical to advertising tended to like, rely on and attend to informational advertising less when compared to the emotional counterparts (Wood, 2012). It has been suggested by some scholars that the number of consumers skeptical of advertising has grown in the recent decades (Rizvi, Sami & Gull, 2012).

Additional evidence shows that in advertising, emotional reactions can be better predictors of effectiveness than commonly used evaluation metrics, such as surveys (Wood, 2012). Wood argues that measuring the gut reaction subjects have to advertisements is extremely important, and that measurement is currently missing in the way most major advertising campaigns measure emotion. In what is better known in psychology as "System 1" processing, the intuitive, immediate and effortless responses that come from advertisements may indeed be the emotional responses that should be measured. Wood argues that most advertising research measures "System 2" responses, which are slower, effortful and analytical. Wood argues that current advertising surveys measure emotion after subjects have had time to cognitively process

the advertising stimuli, thus measuring System 2 responses. The researchers measured facial reactions to advertisements. While maybe not precognitive, the researchers argued that initial facial reactions were closer to "System 1" in nature (Zajonc, 1980). The results showed that simple emotional response is more predictive of effective advertising than the widely used measures of persuasion, brand linkage and even message delivery.

Researchers have pinned emotional response as a key characteristic of successful advertising campaigns. The challenge, then, for advertisers has been to (1) monitor or evaluate the amount of emotion evoked from advertisements and (2) measure the effects (i.e. WOM, ad evaluation, attitude toward the ad, or even purchase behavior). The emotion itself that is the most effective persuader for advertising is very much up for debate.

There are many emotions that advertising content can elicit. Dobele et al. identified eight key emotions found in psychology research. They then examined how often those emotions occurred in successful advertising campaigns (2007). The researchers were interested in discovering if any one emotion might account for an increased likelihood of sharing a viral marketing campaign with a friend. Nine campaigns were coded for the presence of surprise, joy, sadness, anger, disgust and fear. The only emotion that was resoundingly present across all of the campaigns was surprise. The second and third most observed emotions were joy and sadness. When taken together, the two emotions accounted for eight of the nine viral campaigns. The researchers note that the element of surprise "catches the imagination of the recipient" and this reaction drives the recipient to share that experience with friends. Derbaix & Vanhamme supports this observation by using the "critical incident technique" to show that the intensity of surprise is significantly correlated with the frequency of word of mouth in subjects (2003).

There are several books and a rather large body of literature on emotion as it pertains to advertising and emotion (Agres, Edell & Bubitsky, 1990; Heath, 2012). The body of psychological studies on emotion goes even deeper, and encompasses entire journals, such as *The Journal of Emotion*. These experiments are usually conducted in controlled settings where participants are subjected to advertisements and their results are recorded. These studies focus on human reaction (Bagozzi, Gopinath & Nyer, 1999). This dissertation focuses on the message characteristics of micro-blogging messages. The content is the key variable, not participant responses. There is little doubt that the aforementioned studies have proven to be extremely helpful. For practitioners, it is important to look at what emotions yield positive results, and to copy test advertisements in order to get the strongest emotional response. This dissertation will study the same phenomenon in reverse. The following studies have taken this approach and measured emotional content of advertisements using empirical methods.

Emotion as a Measured Characteristic of Text

Textual characteristics need to be agreed upon, and have concrete definitions for how and when they exist in order to be part of a valid content analysis (Riffe, Lacy & Fico, 2005). When dealing with emotion and content analysis of characteristics, the body of work on emotion is much narrower. Digging deeper to textual characteristics, three key areas exist: specific emotions, sentiment and arousal. For this dissertation, I have chosen to focus on the latter two, given the lack of empirical research on specific emotions. Little is known about how specific emotions are manifested in text and the subsequent behaviors those emotions evoke when they exist. The effects of arousal, sentiment and text are better understood. Alternatively, by measuring specific combinations of arousal and emotion, more descriptive accounts of emotion can be provided.

Perhaps the most common way that emotion has been measured in content analysis is in terms of sentiment valence. Most commonly measured in scales ranging from positive to negative, sentiment is usually a measurement of how positive or negative a combination of words is, expressed through words with associated sentiment scores (Barrett & Russell, 1998). Studies from several disciplines have concluded different things in terms of sentiment and what it tells us about how consumers will interact with content.

Berger and Milkman looked at sentiment valence and the virality of news stories on the New York Times website (2011). They found stories with positive sentiment tended to be shared more than negative ones. Hansen et al. (2012) challenged Berger and Milkman's results and hypothesized that news content was more likely to be retweeted on Twitter if negative. For non-news tweets, they relied on the self-enhancement literature, which suggests that people share positive information about themselves. They found that, for news stories, negative sentiment predicted the amount a tweet was rebroadcasted, while for non-news content, positive sentiment drove the diffusion.

By adding the dimension of "generation," Angelis et al. (2012) arrive at a similar conclusion. They posited that people are more likely to generate positive stories that contain their personal experiences. However, those same people are likely to gossip about others' negative experiences. Again, an explanation is found in self-enhancement theory, which suggests that people engage in public behaviors that project them in a positive image.

Through surveys, Heath found that undergraduates were more likely to pass along central, or neutral information (1996). When given a preference between good and bad news, people were willing to pass along bad news over good news. However, Heath draws a distinction of domains, saying that in emotionally negative domains, such as child abuse, people

are willing to pass along bad news, even when it is exaggeratedly bad (1996). Conversely, people are inclined to transmit exaggeratedly good news in emotionally positive domains.

When content takes the form of a folk story or urban legend, the more negative the story, the greater chance that story will be passed on (Donavan, Mowen, and Chakraborty, 1999). Researchers manipulated a fictional urban legend regarding a kangaroo wearing a Gucci jacket. They found that when the overall sentiment for the story was negative, subjects were more likely to pass on the story to their friends than when compared to a positive manipulation of the same story.

Similarly, Kamins, Folkes and Perner (1997) tested whether consumers were more likely to spread rumors with positive as opposed to negative outcomes. While consumers self-reported that they would be more likely to spread negative rumors, a field test found this to be only partially true. Personal relevance was a mediator to whether a consumer would pass on negative information. Consumers tended to share positive personal stories but not negative ones. If the subject of the rumor was perceived to be about a rival, negative stories were more likely to be spread. When rumors were about people with no connection to the consumer, neither positive nor negative stories were more likely to be shared.

This finding is echoed by Dang-Xuan et al. (2013) who looked at messages broadcast by influential Twitter users in the parliamentary elections in Germany. The higher the level of emotion, in either a positive or negative direction, the more often content was retweeted. While it is likely that the actual Twitter users who rebroadcast the messages had connections to the content (i.e., they supported a candidate), it is unlikely that the content was directly about them. In this large field test, actual tweets and actual retweet counts were used as variables. Sentiment was automatically coded and verified for validity with a manual content analysis.

The general consensus of the literature surveyed here suggests that emotionally charged messages tend to be more viral. Both in positive and negative valence, sentiment seems to evoke interest.

RQ5a: Will brand messages with positive valence be shared (i.e. retweeted) more than messages with neutral or negative sentiment?

RQ5b: Will brand messages with positive valence be favorited more than messages with neutral or negative sentiment?

Emotion as a Measured Characteristic of Text: Arousal

In addition to being positive or negative, emotions also differ in the level of physiological arousal (i.e. level of activation) they evoke (Barrett & Russell, 1998). Emotive content can contain evoke high or low amounts of arousal. This dissertation defines arousal as a dimension independent of affect, as does Berger (2012). Arousal is not just driven by positive affective emotions, but by negative ones as well (Berger, 2011). Disgust and fear can carry as much arousal as awe (Berger & Milkman, 2011). Some pleasant words imply activation (i.e. elated, thrilled); others imply deactivation (i.e. serene, calm). Some unpleasant words imply activation (i.e. upset, distressed); others imply deactivation (i.e. lethargic, depressed). Words denoting activation and deactivation also vary in valence. Some activation words are pleasant (i.e. thrilled, excited), some unpleasant (i.e. tense, jittery). Some deactivation words are pleasant (i.e. relaxed, calm), others unpleasant (i.e. down, lethargic) (Bagozzi, Gopinath & Nyer, 1999).

The theory of arousal stems from Berlyne's research in 1960. He defined arousal as how "wide awake" and "ready to react" someone was. He found that while extreme levels of arousal discouraged learning, moderate to high levels fostered learning. Other scholars have broadened arousal to mean how stimulated, or excited, one is (Health, 2012).

Kroeber-Riel (1979) expanded Berlyne's research and further tested arousal. In what he calls "phasic activation," he finds that people can be activated by advertising copy and illustration. His research demonstrates that arousal occurs first in the reticular activation system of the brain, which is located near the stem. From there, it travels and awakens many other cortical units, readying them for action. These cortical units are capable of behaviors like information processing. By activating them, the likelihood that a behavior will occur increases. Kroeber-Riel refutes Berlyne's assertion that too much activation can thwart information processing by differentiating two types of activation: tonic activation, a longer lasting effect, and phasic activation, a temporal effect. He finds that a high degree of tonic activation can indeed result in cognitive decline. However, he provides evidence that advertisements do not provide tonic activation. Instead, his research shows that advertisements, given their temporal nature, are more likely to arouse in the phasic sense. Kroeber-Riel posits that, for advertising, the higher the amount of phasic activation, the higher amount of information processing. His research supported this hypothesis in an experimental setting. Higher activation levels led to higher recall values. He concludes, "Advertisements that fail to arouse will have no effect, as the information conveyed by the advertisement will not be processed efficiently" (p. 546).

Heath, Bell, Sternberg show that memes are more likely to be passed on when they contain the arousing emotion disgust (2001). In their proposed emotional selection hypothesis, they predict that memes are selected and retained in the social environment based on their ability

to tap emotions that are common across individuals. In a series of experiments, they compared their emotional selection hypothesis with an informational selection hypothesis. The premise was that people would be more likely to pass along information that was plausible, useful and practical. Their alternative hypothesis predicted that people would value stories that produced favorable emotional reactions. According to this entertainment hypothesis, stories would succeed when they were able to evoke a strong emotion because these stories were better crafted and more entertaining. The authors found evidence of their emotional selection hypothesis and demonstrated that people were more willing to pass along memes with higher levels of emotion; however, their research was limited to the emotion of disgust and did not explore why emotional selection occurs.

The interaction of emotion and arousal can yield powerful effects. For fear-laden advertisements, Agres, Edell, and Bubitsky (1990) found that the greater the amount of arousal, the more intense the response is for that advertisement. Arousal was the second most influential factor on attitude toward the ad, brand attitude and behavioral intent.

Gorn, Pham, and Sin manipulated the moods of participants and then showed them either positive or negative advertisements (2012). When ads were ambiguous in tone, the manipulated mood colored judgments of advertisements that were not particularly positive or negative. When ads had a positive or negative tone, those tones largely prevailed. In a second study, mood and arousal levels were manipulated separately. In the arousal condition, the valence of advertisements were polarized in either a positive or negative direction. Regardless of how participants' moods were manipulated, arousal intensified the tone of the advertisements. Positive ads seemed more positive and negative ads seemed more negative. The researchers concluded that the "excitation transfer" of the arousal state enhanced the tone of advertisements.

Similarly, Sanbonmatsu and Kardes show that arousal can mediate the amount of persuasion yielded from advertisements (1988). In manipulating arousal by having people exercise, those who were in arousing (i.e. activated, awake) states were more likely to find advertising to be persuasive.

Berger and Milkman (2011) demonstrated that news stories evoke different levels of arousal. That arousal can be a predictor of the number of times a news story is shared (Berger, 2011). The researchers suspected that highly arousing emotions of both positive and negative valence would drive the propensity in which *New York Times* articles would be shared. The researchers looked at arousing emotions: awe, anger and anxiety. These emotions were compared to sadness, a deactivating emotion. Control variables were used for how featured, practical, interesting and surprising the content was. The most dominating factor in the regression analysis was whether the content included at least one arousing emotion. The researchers recreated these findings via a laboratory experiment, where arousal levels were induced by asking participants in the activation group to exercise. Participants who were activated were willing to share stories with friends more than participants who were not activated. Similarly, Peters, Kashima and Clark used survey responses to show that students were more likely to share social anecdotes about other students that contained interest, surprise, disgust and happiness (2009). Anecdotes that did not contain arousing emotions garnered little interest from the students, and they were not likely to pass them on to others. This study lacked control variables for the content. Possible mediating variables, such as how funny or interesting the students found the anecdotes to be, were not investigated.

Considered together, these studies provide a strong argument for arousal as an instigator of behaviors. When specifically applying this knowledge to brand content on Twitter, there are

several studies that suggest arousal motivates behavior. Arousal appears to evoke stronger responses to advertisements (Gorn, Pham & Sin, 2012; Agres, Edell & Bubitsky, 1990; Kroeber-Riel, 1979). It also makes people more likely to share memes and recommend content to people (Berger & Milkman, 2011; Peters, Kashima & Clark, 2009; Heath, Bell, Sternberg, 2001). These studies suggest that positive arousal will boost the likelihood that brand messages will be shared more on Twitter.

RQ6a: Will brand messages with positive arousal be shared (i.e. retweeted) more than messages with neutral or negative sentiment?

RQ6b: Will brand messages with positive arousal be favorited more than messages with neutral or negative sentiment?

Defining Concreteness

Emotion is a very powerful concept, and does indeed alter behavior. However, other characteristics of text have been studied as they pertain to advertising effects (see Percy, 1982 for a concise review of studied characteristics). After review of these other characteristics, perhaps the most applicable to the temporal, terse nature of microblogging messages is Paivio's dual-coding theory. In this theory, two concepts are outlined: concrete and abstract. The mutually exclusive terms concrete and abstract are *abstract* in the early scholarship (Lambert, 1955). Percy offers the definition, "concrete words are generally described as those that refer to objects, persons, places, or things that can be seen, heard, felt, smelled or tasted (1982, p. 108). Abstract words "refer to those things that cannot be experienced by our senses" (Percy, 1982, p. 108).

Percy's focus appears to be on nouns. Heath and Heath similarly define concrete information as the degree in which a sensorial experience is evoked (2007). Other scholars support this view (Macklin, Bruvold & Shea, 1985; Rioux, Regan & Schmitt, 1990; Percy, 1982). Heath and Heath open the possibility to adjectives by providing the example of "V8" as a concrete term and "high-performance" as abstract. Both appear to be adjectives of the word "engine." Vague and ambiguous terms are abstract. For instance "big data" is abstract and "Hadoop" is concrete. Heath and Heath suggest that the inclusion of "buzz words" or grandiose words can make a piece of text more abstract (2007).

Many alternative definitions exist for concrete and abstract. Imaging ability, or how many images a word can bring to mind, is an early definition of concrete (Lambert, 1955; Paivio, 1963; Sadoski, Goetz & Fritz, 1993; Rossiter & Percy, 1978). Consider the difference in the terms "food" and "steak dinner." While both could describe the same thing, steak dinner may evoke more visual imagery. A third definition approximates to how explicit a message is explained (Dickson, 1982; Krishnan, Biswas & Netemeyer, 2006). In this case, abstractness means ambiguity. The advertising slogan "sale today" would be abstract, in which "20% off today only" is concrete. Regardless of definition, the concreteness has been conceived as an inherit characteristic of any given piece of text. The abstractness and concreteness measurements have usually been measured on a scale ranging from one (very abstract) to seven (very concrete).

The measurement of concreteness did differ in the seminal article. Lambert had participants recall as many words out loud as they could for a given word (1955). Here, he noticed that concrete nouns elicited more responses. The stimuli were assembled from the most frequently used English and French words. All of the words had no apparent "emotional implication," thereby controlling the effect of emotion. The researches labeled a word concrete if

the word was “touchable” or “manipulable.” English concrete nouns included words “garden,” “house,” “food” and “child,” whereas abstract words included “peace,” “honor,” “thought” and “idea.” Across both languages, concrete words produced more associations.

This finding, while basic and perhaps incomplete in methodological rigor, sparked the interest of other psychologists. They tested more effects that concrete words might have on participants. Paivio investigated adjective-noun word pairings and the effect on learning (1963). His hypothesis was that nouns act as “conceptual pegs” on which adjectives can be hung. He argued that conceptual pegs provide “codes of learning.” Given Lambert’s findings on associations and concreteness, he surmised that the best codes would be those that have the most associations, and therefore, would be the most concrete. The more associations a word had, the easier it would be to remember. Paivio paired adjectives with concrete nouns. Abstract nouns were left in isolation. The concrete nouns referred to “specific things or events” while abstract nouns were “more general” (e.g. technical-advertisement vs. discourse). Higher levels of recall were observed for the adjective concrete pairings when compared to the abstract nouns. In 1965, Paivio replicated the study using concrete and abstract nouns with no adjectives (e.g. coffee and soul). Again, concrete words had greater recall. He found that concrete nouns evoked higher amounts of imagery, were more meaningful and were more familiar than abstract nouns. Several studies have gone on to show that concrete words are more positively associated with comprehension (Begg and Paivio, 1969; Paivio, 1971; Sheehan, 1970).

Wharton took the basic findings of dual-coding theory and applied them to textbook comprehension in an educational setting (1980). Wharton modified narrative passages from history textbooks. Some were purposely left untouched. Others were altered to be more concrete and image evoking. In addition, an empirical test was created via surveys to help determine

phrases that evoked "mental imagery." Wharton asked participants to identify phrases that evoked, "clearer, stronger, pictures" in their minds. When reading the concrete phrases in textbook passages, college freshmen scored significantly higher on comprehension. He also found that 24 percent more of the students considered the concrete treatments interesting.

In another study that used historical narratives, Sadoski et al. investigated the effects of concreteness on familiarity, comprehensibility, interestingness and recall (1993a). The narratives were paragraphs drawn from textbooks and historical articles that dealt with historical figures. Concrete text was more interesting and more comprehensible than abstract text.

In an extended analysis of the sentence data from the previous study, Sadoski et al. constructed a path model to test the causal assumptions regarding the effects of concreteness on interestingness (1993b). Concreteness had strong effects on interestingness. Sadoski used schema theory to explain the results, which asserts that high interest material is better understood. The assumption here is that concrete words are generally more familiar to readers, and this familiarity creates a more elaborate schema with which to identify. Given the well-proven link between concrete language, comprehension and familiarity, he posits that concreteness also bolsters interestingness.

Short texts ranging from *Readers Digest* to math and science passages from textbooks were also tested for abstractness and concreteness (Sadoski, Goetz & Rodriguez, 2000). Again, concrete texts were more comprehensible and more interesting than abstract text. As perhaps a byproduct of understanding and interest, recall was also higher for concrete text. The effects of concreteness, familiarity and interestingness were also assessed against reader engagement. The authors formally expanded dual-coding theory by asserting that the "referential connection"

between concrete language and mental imagery evoked interest and affective engagement. The researchers note that it is "this link that makes the content seem to come to life" (p. 87).

Concreteness and Advertising

Advertising and marketing disciplines alike have also addressed abstractness and concreteness as defined by dual-coding theory. Here the general premise across the literature is that concreteness is a property of an advertising message that can bolster attitudes and persuasion. Interestingly, the hypothesized influence of concreteness is positive, and scholars have not identified situations where abstractness may be more influential. Unlike the Elaboration Likelihood Model where specific scenarios are illustrated given when to use either peripheral or central cues, concreteness is always assumed to be superior to abstractness (Petty, Cacioppo & Schumann, 1983)).

Several definitions of concreteness exist in the advertising domain. The definitions, while not at complete odds with each other, do vary. Rossiter and Percy put forth the hypothesis: the more images an advertisement evoked in a subject, the greater the consumer response (1978). In what they called "visual imaging ability," advertising copy was manipulated to be "superlative and explicit." The authors chose a household consumer product, beer. They then altered advertisements. Advertising copy for one concrete condition read, "winner of 5 out of 5 taste tests in the U.S. against all major American beers and leading imports." Whereas an abstract condition read, "Bavaria's finest beer." The concrete treatment generated almost twice the favorable attitude toward the new brand of beer.

Dickson asserts a slightly different definition (1982). that while statistics such as "5 out of 5" can elicit positive results as in Rossiter and Percy's example, they can also be abstract (1982). Dickson's findings suggest that when statistics are overly abstract, they are likely not

influential. The inspiration of the investigation came from the abundance of public health and safety initiatives that used statistics in campaigns (e.g. quitting smoking, inoculating children, reducing highway driving speeds and conserving energy). Other scholars have shown that these campaigns used "abstract statistical information" and were also very ineffective (Nisbett et al., 1976). Generic statistics were compared to concrete statistics, which provided "anecdotal information that describes a particular event or object in detail" (p. 398). This type of information was dubbed "concrete case-history product information." Conditions were created in which very basic written arguments were incorporated into advertisements using statistics. In comparison, more detailed arguments were created that described a specific event in great detail. Participants scored better on recall for the concrete conditions. Additionally, participants identified the concrete advertisements as more vivid in their memories.

In yet another divergent definition, when focusing on advertising cues that dealt with the price of products, Krishnan, Biswas and Netemeyer found that the concreteness of the price cue mediated the effectiveness of the advertisement (2006). Short text claims, such as "A $100 value" were not as effective as "Last Week $200, Now $100." The authors argued by adding context to the price, the cues were made concrete. The researchers define concreteness as "the degree of detail and specificity about the price comparison being made" (p. 95). Concrete price cues were more effective than the abstract versions. A similar view of concreteness was adopted by Feldman, Bearden and Hardesty when they defined concreteness as the "degree of detail and specificity about objects, actions, outcomes and situational context" (p. 124, 2006). The researchers surmised that the more vivid advertising claims were (through descriptions), the less cognitive effort required to process information (Bettman, Luce & Payne, 1998).

Macklin, Brovold and Shea equate concrete advertisements to ones that thoroughly describe the features and benefits of a product or service (1985). They concede that this is easier to do for a product that has many features to describe, such as a computer or a camera. They adopt the "availability-valence" hypothesis. In this scenario, increased amounts of cognitive elaboration boost persuasion. Cognitive elaboration is activated when messaging is concretely structured. When consumers cognitively elaborate, multiple related pathways are engaged. The concept "associative pathways" implies that a particular concept, when concretely elaborated, is connected to many other pathways in the human brain. Those pathways can be stimulated simultaneously. When these pathways are stimulated, a person can access information with less effort. This can ultimately lead to increased persuasion.

Ci's doctoral dissertation offers perhaps the most exhaustive study of abstractness and concreteness on advertising copy (2008). He adopts a second definition of the abstractness-concreteness continuum as it pertains to advertising copy: generality vs. specificity. Here, unlike the seminal articles that defined concreteness as the extent to which visual imagery was evoked (e.g. Lambert, 1955), a noun is considered concrete when it refers to a specific concept. A noun is abstract if it has sub-concepts below it. The more sub-categories an object includes, the more abstract the object becomes. Consider the Ferrari 330 GTC. It is likely that the reader will picture a slick sports car. Alternatively, the term sports car has many sub-categories and is, in turn, more abstract. In Ci's view, specific concepts with no sub-concepts are concrete, while general concepts are abstract. Using content analysis instructions from existing scholars, scores of concreteness were created for advertising copy (Dube-Rioux, Regan & Schmitt, 1990). Ci found that concreteness had significant positive effects on attitudes toward advertisements and products.

From Concreteness to Interest to Virality

The research surveyed here on concreteness and abstractness spans from education to advertising. Even inside of the advertising discipline, a wide range of effects have been studied and observed, from attitudes to purchase intentions (e.g. Dickson 1982; Fernandez and Rosen 2000; MacKenzie 1986; Percy 1982). Concreteness appears to have even more effects.

In perhaps the most in-depth analysis of concrete text, Rubin attempted to dissect the reasons why oral traditions (i.e. stories, epics, songs and poems) were remembered and then passed on to others (1995). The oral traditions, while all spoken by nature, involved very specific, detailed bits of information that have been successfully passed down thousands of generations. Stories included rhymes such as *Eenie Meenie.* Rubin outlined constraints of the traditions that allowed the rhyme to be transmitted almost flawlessly. Taking psychological understandings of how the brain functions and theories regarding how memories are created and recalled, Rubin attempts to explain why some stories get shared more than others. He identifies three characteristics of stories that control how they are remembered and recalled: sound patterns, meaning or story structure and imagery.

In his broader concept of imagery, he found various characteristics of concrete text that played roles in whether a story was remembered or passed on to others. Rubin discovered that concrete details increase the sense that a narrative is accurate. He has shown that for successful oral traditions, the details and story structures largely remain the same. He further suggests concrete details that increase emotionality. As mentioned in the previous chapter, increasing emotionality likely makes content more viral. He also finds that concrete language is more intimate and immediate. This personal connection with readers makes them identify with the text on a deeper level. As discussed in the WOM chapter, messages that are personal are subjected to

less scrutiny and are usually more persuasive and attitude changing as a result. All of these effects could be linked to increased virality and are ripe for investigation.

Rubin, in his study of oral traditions, does identify concrete material as more likely to be passed on, but he does so indirectly by mentioning concreteness in the context of a successful oral tradition. No formal experiment was conducted to test the linkage of the two concepts.

Heath and Heath posit that information that is concrete is easier to understand (2007). This assertion is widely supported by education literature (Wharton, 1980; Sadoski, 1993a; Sadoski, 1993b). Using a term borrowed from Gladwell's *The Tipping Point,* Heath and Heath argue that, because abstraction makes an idea harder to comprehend, "sticky" ideas are usually concrete. Indeed, Rubin's investigation shows that concrete ideas are more memorable (1995). Rubin shows how oral traditions travel from person to person and generation to generation, and argues that concrete elements are more likely to survive transmission because they are easier to understand and remember.

But even if concrete ideas tend to "stick" in the environment more than abstract ones, little discussion has been generated about the sharing of concrete information. After all, this dissertation is dedicated to the virality of brand messages. Sure, more memorable tweets may be the ones that are shared the most, but the link is not explicit. Memorability and recall aside, the increased interest that concrete messages generate may empirically link concrete messages to viral messages and test the assumptions of Rubin (1995).

Bakshy et al. investigated URLs inside of Twitter messages (2011). The researchers found a correlation between "interesting links" and increased diffusion. The researchers asked survey participants, obtained via Amazon Mechanical Turk, to rank the "interestingness" of Web pages that were linked inside of tweets. Those Web pages that "Turkers" (i.e. users of

Mechanical Turk) agreed were interesting were found inside of tweets that were shared more often. Moreover, several variables failed to explain how viral content became. In particular, the positivity of the sentiment associated with the content did not predict virality. Turkers were also asked how likely they would be to recommend the content they read to friends, imagining if they had encountered the content on their own Twitter feed. Interestingly, Turkers did not accurately predict actual shares.

It has been shown that concrete information is more interesting than abstract information (Wharton, 1980; Sadoski, 1993a; Sadoski, 1993b; Goetz & Rodriguez, 2000). Interest has also been thought of as a state of arousal (see the previously discussed in the arousal section of this paper) (Peters, Kashima & Clark, 2009). This effect can actually result in immediate behavioral change. Interest is a positively arousing emotion that can cause excitement (Berger, 2012). It is because of this arousing state that several scholars have linked interesting content to more viral content. Berger and Iyengar (2012) and Berger and Schwartz (2011) argue that if a message or product is interesting, it will have more online WOM. For a full review of the arousal literature, see the arousal chapter of this dissertation.

Berger offers an argument for interestingness that goes beyond arousal (Berger & Milkman 2012). He claims that online social interaction between friends is rarely immediate, except for instant messaging exchanges. For example, when a friend tags another friend in a tweet, there is no expectation for that friend to immediately respond. This is largely because that friend may be working, busy or simply away from an Internet-connected device. Because online exchanges between friends on Twitter are not immediate, there is time for messages to be crafted. Berger argues this time alters the expectations. He contends that when two people meet and exchange pleasantries with each other, the conversation generated is usually not clever.

Instead, through their observation, they have noticed that these conversations tend to be rather similar (e.g. regarding the weather or a sporting event that occurred for a local team). Berger noticed that while it is entirely possible to have these everyday exchanges via publicly facing social media services, like Twitter, they largely don't occur. While it has been noted that people do tend to share everyday activities, they rarely do so and expect others to respond directly to those messages as if having an everyday conversation. Instead, when engaging with others via public social media services, there is an inherit expectation for those conversations to be interesting. In comparison to off-the-cuff conversations, people expect these messages to be worthy of sharing and worthy of being seen by others. Berger and Milkman's have provided some early work that supports this notion for online conversations (2011).

Furthermore, interestingness and curiosity have been linked together, often with interest as a dependent measure of curiosity (Loewenstein, 1994). Especially in tweet form, microblogging content is terse. Assuming that people are at least somewhat curious when browsing through their Twitter feeds, it is entirely possible that curiosity may explain the drive to seek interesting information. Knowing that people seek out interesting information can further explain its popularity and intrigue, as others may be curious in the same way.

For these reasons, this dissertation will ask: if concrete text tends to be more interesting, and more interesting information tends to be shared and sought after online, will concrete information be shared more?

RQ7a: Will concrete brand messages be shared (i.e. retweeted) more than abstractly worded messages?

RQ7b: Will concrete brand messages be shared (i.e. favorited) more than abstractly worded messages?

Other Characteristics of a Social Media Message

Departing from psychology and advertising disciplines, computer science scholars have given the most focused attention to the virality of social media messages. These studies investigate more explicit characteristics of messages that exist on social networking services. The aim for these studies is prediction. A typical computer science question in this area of literature is: Given a set of properties for a message on a social networking service, what combination might explain how popular a message gets? Unlike the psychological concepts examined earlier (e.g. concreteness and emotion), these features are more quantitative in nature and are usually byproducts of the message itself (e.g. does a tweet contain a URL or the number of people who commented on a tweet). These properties are also called "metadata." Computer scientists have studied the metadata of messages on various social networking and social media services with the hopes of establishing predictive models. The majority of these studies gather data from services where data access is easily accessible. The literature is not exhaustive across all social networking services due the issues with data collection that exist on some services, such as Facebook (Vargo, 2013b).

Perhaps the first service that was extensively studied was Digg. On this service, users can post links that they find interesting. By posting a link, they share it with their friends and with the larger body of Digg's users. As content gets positive feedback, or up votes, it also becomes more prominently featured on the website. Researchers found that the most discriminative piece of metadata associated to the popularity of posts (i.e. thumbs ups) was the number of comments a

story generated (Jamali & Rangwala, 2009). The researchers created a predictive model and were able to, in some cases, predict the popularity of Digg posts using the number of positively valenced comments a given post received. Dubbed as buzz and appreciation variables, this finding is echoed by Guerini, Strapparava and Ozbal (2011). On Twitter, this is most similar to favoriting a tweet. Therefore, it could be that the more favorites a given tweet receives, the more retweets it may obtain.

RQ8: Will the number of favorites a brand message receives predict the number of times it is shared (i.e. retweeted)?

In perhaps the most exhaustive analysis of metadata that is readily retrievable via the Twitter API, Suh et al. looked at the metadata associated with tweets and whether any of those variables could predict the number of times a tweet would be retweeted (2010). Dependent variables included the number of URLs and the number of hashtags. To build a predictive model, first a random set of 10,000 tweets was selected. Interestingly, of these tweets only 219 had been retweeted more than 20 times, suggesting that the overall number of tweets retweeted many times was quite low. Then the researchers continued with an extremely large set of 74 million tweets to test the model. URLs and hashtags had strong positive relationships with the likelihood a tweet would be rebroadcasted.

RQ9a: Will brand messages with URLs be shared (i.e. retweeted) more than messages without a URL?

RQ9b: Will brand messages with URLs be favorited more than messages without a URL?

RQ10a: Will brand messages with hashtags be shared (i.e. retweeted) more than messages without a hashtag?

RQ10b: Will brand messages with hashtags be shared favorited more than messages without a hashtag?

At the time of this dissertation, 300 million users are active on Google+ (Gundotra, 2013). The site acts as a social layer for Google services and allows users to share content with other registered users. While it does not limit the size of posts like Twitter, it is still considered a service in which friends share short messages. Researchers have shown that a post is three times as likely to have a high number of shares if that post has an image (Guerini, Staiano, & Albanese, 2013). The authors cite the "rapid cognition" model, which states that a user has a relatively short period of time in which to view a post. An image is an example of a stimulus that engages rapid cognition. By including images, this type of cognition is more fully engaged. Cognition allows users to process the information and begin to understand the content at a level beyond basic browsing or skimming. Conversely, the authors suggest that text-only posts involve more "linguistic-elaboration" and are less likely to be shared because of a user's propensity to engage in rapid cognition. Described as visual cues, the authors conclude that photos grab more attention. This additional attention, coupled with cognition is a cocktail that the authors imply leads to increased amounts of sharing.

RQ11a: Will brand messages with an image be shared (i.e. retweeted) more than messages without an image?

RQ11b: Will brand messages with an image be favorited more than messages without an image?

Summary of Literature Review

This dissertation has summarized large bodies of work from several different disciplines: psychology, marketing, computer science, communication, education and sociology. Each field contributes a piece to the immensely large puzzle that is virality. This dissertation chose to sum up the characteristics of messages that enhance diffusion. There are many other theories that might further explain the motivations that people have in sharing content with each other. Moreover, the understanding of the content that is being shared across these social networks appears to be in its infancy. Still, this dissertation has exposed several large areas of social science that have not explicitly been tested with social networking services such as Twitter. This is especially true when it comes to brand messages. The entire bulk of advertising literature discussed here deals with traditional advertisements as stimuli. While a small amount of research shows brands can generate WOM, no studies were found to show that process as it originates from brand messages online, nevertheless how brand messages are spread on Twitter.

Scholars seem to be more interested than ever with how information spreads through networks of people, especially online. While this may be due to the fact that, for the first time, large datasets of online social interactions are now available, this dissertation suggests that the interest is both economic and cultural. Understanding why content goes viral is a marketer's

dream. It is also very telling of what kinds of content society values. These opportunities to test existing social science theory alongside the potential rewards that lie in solving even a tiny piece of this gigantic puzzle warrant this investigation.

RQ12a: To what extent can the independent variables identified in this study be used to predict the number of retweets for brand messages on Twitter?

RQ12b: To what extent can the independent variables identified in this study be used to predict the number of favorites for brand messages on Twitter?

Chapter 2: Method

Selection of the Brands

A myriad of popular consumer brands exists. To satisfy the hypotheses from the literature review, a few criteria for brand selection emerged. To test RQ3, brands from multiple product categories were chosen. Also, due to the low infectivity of messages on Twitter, the most popular consumer brands were chosen (Goel, Watts & Goldstein, 2012). This was done to ensure that sharing (i.e. the number of times those brand tweets are retweeted) was prevalent enough to observe and predict. *AdAge Megabrands* was used as a measure of the most popular consumer brands (2012). The list ranks brands by U.S. advertising spending. The top 200 brands are reported each year, dating back to 2006. Brands are not separated into product categories. To address this issue, brands were assigned to a corresponding product category. At least 20 major categories emerged. To limit the scope, only brands with at least three other parity products were considered. Four categories had at least four brands (See Table 2). In all, 17 brands were selected. All 17 Twitter usernames are included in Table 3.

Table 2 – Brands Included in Study

Insurance Companies	Banks	Cable and Satellite Companies	Department Stores
Progressive	Citibank	Comcast	Macy's
Nationwide	Bank of America	Time Warner Cable	J.C. Penney
Liberty Mutual	Wells Fargo	DirecTV	Kohl's
AllState	PNC	Dish	Sears
State Farm			

Table 3 – Twitter Handles for Brands in Study

Insurance Companies	Banks	Cable and Satellite Companies	Dept. Stores
Progressive	Citibank	comcast	Macys
Nationwide	BofA_News	TWC	jcpenney
LibertyMutual	WellsFargo	DirecTV	Kohls
AllState	PNCNews	dish	Sears
StateFarm			

Research suggests that the reputation of a brand be accounted for when comparing eWOM. In a study of eBooks on Amazon, Amblee and Bui found that the reputation of a brand can influence the amount of eWOM generated for that brand (2008). They observed that when authors had great reputations, more eWOM was generated for their books (2008). This dissertation, therefore, added a control for how reputable a brand is in its final predictive models (RQ12). This limits the impact of reputation on the other predictor variables.

To establish this control, a reputation score must be readily available for each of the selected brands. The Reputation Institute founded by social scientists Fombrun and Riel has been tracking reputations of brands since 1997. Its *Reputation Pulse* index measures the corporate reputations of the largest U.S. companies based on consumers' trust, esteem, admiration and good feeling about a company (Johndrow & Schneid, 2013). The 2013 survey included responses from 4,719 respondents. The survey asked consumers about each company found in the Forbes list of U.S. companies with the largest revenues. Based on responses, it assigned each company a score from zero to 100. All of the 17 brands selected had brand reputation scores.

Variables

The dependent variables in this study are the number of retweets and favorites for each tweet in the sample. Independent variables are the number of followers, number of friends,

number of statuses (tweets), number of times listed, number of favorites, number of @username mentions in the tweet, number of URLs in the tweet, number of hashtags in the tweet, length of the tweet in characters, and length in words, presence of a photo in the tweet, positive valence, positive arousal and concreteness of the tweet.

Retrieving Tweets from Twitter

Python was used to access the Twitter API. An API is a way for third-party services to connect to Twitter and call its functions. This dissertation used the Twitter API to retrieve tweets. Version 1.1 of the API was used. It was queried using the statuses/user_timeline call. Tweets sent from these 17 brand accounts were downloaded for 92 days. The tweets ranged from October 12, 2013 to January 12, 2014. For the Python data collection script, see Appendix 1. To initiate the data collection process, an initial download of the 3,200 of the most recent tweets from each brand was conducted. Tweets that were newer than two weeks were discarded and retrieved later when they had reached two weeks of age. Then, every two weeks, a new crawl was conducted for each brand, retrieving only new tweets from that brand that were at least two weeks old. This was done under the premise that the majority of retweets and favorites would happen within the first two weeks of a tweet being sent. By waiting two weeks to collect a tweet's metadata, this dissertation hoped to capture the majority of that tweet's all-time diffusion.

The news feed feature of Twitter would suggest that only newer tweets on Twitter are seen, and therefore, retweeted and favorited. Still, it was plausible to think that brand messages on Twitter could continue to be retweeted after the two week maturation period. To validate this decision, 200 of the most recent tweets that were at least 24 hours old were downloaded on January 15 at 7:00 p.m. for each of the 17 brands. Then, for 24 consecutive days, the same tweets

and their corresponding metadata were downloaded at the same time each day. Table 4 shows how the count of retweets varied over time. After 14 days, all brands' total retweet counts increased by less than 1% of the total retweet count, except Comcast, which increased by 1.2%. A similar outcome for favorites is assumed, given the same constraints for news feed exposure.

Table 4 – Daily Retweet Percentages

	Cumulative % of Total RTs by Day			Total RTs
Brand	1	7	14	
AllState	98.64%	99.66%	100.34%	294
BofA_News	99.76%	99.69%	100.00%	1271
Citibank	98.14%	99.22%	99.38%	1288
Comcast	96.20%	97.84%	99.03%	12885
DirecTV	100.34%	100.17%	100.09%	25399
dish	100.29%	100.29%	100.21%	2806
jcpenney	100.00%	100.93%	100.00%	324
Kohls	98.08%	99.23%	100.00%	260
LibertyMutual	87.57%	97.77%	99.94%	1617
Macys	97.52%	99.01%	100.00%	202
Nationwide	99.77%	99.77%	99.77%	437
PNCNews	99.35%	101.30%	101.30%	154
Progressive	100.00%	100.00%	100.00%	44
Sears	100.43%	100.43%	100.00%	230
StateFarm	99.43%	99.71%	99.71%	349
TWC	99.81%	100.17%	100.07%	46642
WellsFargo	99.31%	99.42%	100.00%	864
Average	98.51%	99.68%	99.99%	5592

* Some values exceed 100% due to retweets being deleted (by the user).

When the same three-month period of data was harvested for each brand, the data collection concluded. With each tweet, came its accompanying metadata. This included the number of times the tweet was retweeted and favorited. The metadata also includes the other variables used in the analysis. For the complete list, see Table 5.

Table 5 – Tweet Metadata

Metadata	How its calculated
Followers	The number of Twitter accounts following the account.
Statuses	The number of times the account has updated its status (i.e., tweeted).
Friends	The number of Twitter accounts the account follows.
Listed	The number of Twitter lists that include the account.
Year	The year the Twitter account was created.
URLs	The number of URLs in the tweet
Mentions	The # of Twitter accounts mentioned by username in the tweet.
Media	Whether or not a photo was included in the tweet.

Messages starting with @ were excluded from this analysis. This decision was made based on the limited exposure that these types of messages receive. Twitter's news feed is designed to not show these messages by default. As such, a substantially smaller percentage of people see these tweets. Given the limited audience of these messages, the retweet and favorite distribution for these messages is inevitably different, and therefore, confounding to this analysis.

Initially, 9,908 tweets were included in the analysis. For the retweet count, further statistics show that the average is not precise, with the 95% confidence interval mean's lower bound value at 23.18, and the upper bound value at 38.00. With the median at 3.0 and the mode at 1.0, the distribution is extremely skewed toward the upper end of the range with a skew of 34.99. Indeed, a handful of outliers appear to have shifted the mean. Upon inspection of these outliers, 89 of the 90 most retweeted tweets were retweets themselves. These retweets originated from other accounts. This dissertation aims to measure the diffusion of content that was authored by the brands themselves. Therefore, all tweets starting with "RT" were labeled as retweets and removed from the analysis.

This adjustment resulted in a new corpus size of 7,578. Brands sent 4.85 tweets per day (*SD* = 4.22). The range was rather large. On average, any given brand's tweet was retweeted eight times and favorited seven times. Variance across brands was high. PNC only averaged one retweet per tweet (*SD* = 1.62), and Macy's averaged 32 retweets per tweet (*SD* = 63.55). PNC averaged zero favorites per tweet (*SD* = .88), and Macy's averaged 40 (*SD* = 63.14) favorites per tweet. For a complete picture of the descriptive statistics, see Appendix 2.

Human Reliability Check: Sentiment, Arousal and Concreteness

Sentiment, arousal and concreteness must be calculated. Ultimately, this dissertation relies on computer-automated measures for these predictor variables. In order to use these measures, two reliability checks were performed. The first was a human reliability check for the concepts. The aim here was to see if people could reach a consensus when these concepts were present in the stratified sample of brand tweets. 80 undergraduate students were recruited through the University of North Carolina at Chapel Hill's Journalism and Mass Communication student research participant pool. The students were given instructions on how to detect sentiment, arousal and concreteness in tweets. See Appendix 3 for the instructions given to each student. The students were then asked to score each tweet across the three dimensions according to Bradley and Lang's normative rating procedure (2010). The full instructions can be found at the end of Appendix 3.

According to Riffe, Lacy and Fico, to reach an assumed level of agreement of 90%, a sample size of 100 would suffice (2005). The ANEW measurement scale had nine levels, while the concreteness scale had 6 levels. Since the maximum number of levels was nine a sample size of 1000 was used. 20 sets were created, each consisting of 50 different tweets. Tweets were

randomly displayed using the service Qualtrics. Each set of tweets was taken at least four times by four different assessors.

Krippendorff's alpha was used as the statistical measure of agreement between the coders. Across all 20 sets of tweets, initial agreement and reliability scores were low, $a = .21$. To reach an acceptable range, scales were conflated to logistic values. Sentiment and arousal scores of 6 and above were assigned a 1. Concrete scores of 4 and higher were also assigned a 1. All remaining values were assigned 0. This recoding scheme essentially conflated neutral and positive classes. These adjusted scales were conflated to allow detection of positive sentiment (or non-positive sentiment), positive arousal (or non-positive arousal) and concreteness (or abstractness). The lack of agreement on negative and low arousal classes was likely due to the nature of the brand messages themselves. Only .05% of tweets had complete consensus on negative sentiment, low arousal and low concreteness. Across all concepts, agreement was marginal, $a = .643$.

This author studied the coded data and looked at completion times. From proctoring the content analysis, a pattern emerged. A significant amount of participants left the study very early. Upon inspection of the completion times, the average completion time was 44.14 minutes. This was 6.78 decisions per minute. However, the standard deviation was 19.05 minutes. 20 coders completed the study in approximately thirty minutes, or 10 decisions per minute. Computer loading times and the initial training session at the beginning were not subtracted from these averages, because they were quantified known. This author estimates the training session at 15 minutes. Given a 15-minute training session, 50% of the coders made 300 decisions in 29 minutes, or approximately one decision every six seconds. This still did not account for loading times and the time to read each tweet. The author suspects that a majority of the coders

completed the task too quickly. Looking at survey agreement, a pattern emerged. All possible combinations of coders were subjected to Pearson correlation with each other. The average completion time was 58 minutes (or 43 minutes, subtracting for training). This difference was substantial, about a second greater for each decision.

As a result, the simple agreements were substantially higher: 91% for concreteness, 91% for sentiment and 89% for arousal. Because classes were highly skewed (i.e. high arousal, high concreteness, positive sentiment), Krippendorff's alphas were substantially lower than simple agreements. 67% of tweets were labeled as positive in sentiment by coders, 60% of tweets were concrete and 58% had positive arousal. Final alpha values were $a = .764$ for concreteness, $a = .746$ for sentiment and $a = .768$ for arousal. For a complete list of agreement and alphas by survey, see Appendix 4. Acceptable inter-annotator agreement was reached on the representative sample. Next, the entire corpus was calculated across the three dimensions using pre-established wordlists for each concept.

Scales needed to be conflated to reach agreement on arousal, concreteness and sentiment. The full, unscaled computerized variables, while described below for better understanding of the content analysis, were not used in regression or ANOVA procedures. Instead, the conflated variables were used as described above.

Computer Automated Measure of Arousal

The content of each tweet was measured for arousal with Bradley and Lang's Affective Norms for English Words (ANEW) (2010). The project is actively developed by the University of Florida's Center for Emotion and Attention. The most recent version of ANEW consists of 2,476 words that have been assessed along three dimensions of emotion based on the work of Osgood, Suci, and Tanenbaum (1957): affective valence (pleasant to unpleasant), arousal (calm

to excited) and dominance (controlled to in control). The ANEW list was chosen specifically for its measurement of arousal. Other word lists such as AFINN (Nielsen, 2011) or SentiStrength (Thelwall, Buckley and Paltoglou, 2011) score words on only one dimension (valence). The ANEW list provides the mean score and standard deviation in each dimension for each word on a nine-point scale.

A Python script was used to compare the text of each tweet in the corpus with the ANEW list. Each tweet was stripped of hashtags symbols and then tokenized. See Appendix 5 for the Python code used to calculate scores for all three concepts (arousal, sentiment and concreteness). Each tokenized word was then compared to the ANEW list. Other scholars have applied the same method (Bird, Klein, and Loper, 2009). A mean score for arousal was computed by averaging the scores for all ANEW words in the tweet. If the tweet did not contain any of the ANEW words, it was scored 5, implying no positive or negative arousal.

Computer Automated Measure of Sentiment

The previously mentioned sentiment methods were applied for the sentiment concept. Two wordlists and one standalone program were used to derive three separate measures of sentiment: AFINN, ANEW and SentiStrength. For AFINN and ANEW the arousal coding process was duplicated using the sentiment wordlists. A Python script tokenized and compared the words in tweets to the wordlists. A sentiment score was computed by taking the mean value of all scored words found in a given tweet. If the tweet did not contain any words in the wordlist, it was scored 5 for the ANEW measure and 0 for AFINN, meaning it was neither unpleasant nor pleasant on the given scales.

In addition, the program SentiStrength was also used to calculate sentiment. The program was called with the following parameters: exlamations2, noDictionary, noMultipleLetters and

scale. Exlamations2 allowed exclamation marks to be counted as positive 2 sentiment for non-subtractive sentences. NoDictionary prevented SentiStrength from attempting to correct spellings using its own built in dictionary. NoMultipleLetters prevented the program from using the presence of additional letters in a word to boost sentiment. These features that were overrode could be useful for informal text that has the presence of words that are misspelled, or where characters are repeated for emphasis (i.e. I am realllly happy). These brand messages appeared to be free of these informalities, and had very few spelling errors. Therefore, any of these corrections would likely be error prone.

Computer Automated Measure of Concreteness

Brysbaert, Warriner and Kuperman published a corpus of 37,058 English words, 2,896 two-word expressions and the corresponding concreteness scores for those words (2013). 4,000 participants judged the word pairings. Participants were instructed to rank word concreteness based on the extent to which words evoked senses and motor responses according to Paivio's dual-coding theory (1963). The researchers noted that the participants focused on visual and haptic experiences when making decisions. A mean score for concreteness was computed by averaging the concreteness scores for words in the tweet.

Establishing Reliability for Computer Coded Variables

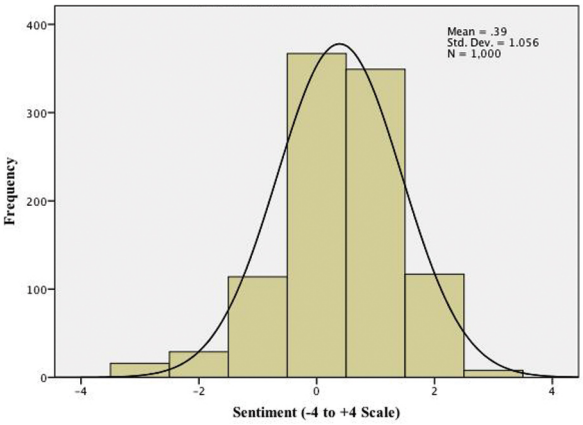
Because the automated process of assigning scores for arousal, sentiment and concreteness rely on the averages of pre-existing wordlists, it was inevitable for errors to occur. For example, only the SentiStrength sentiment analysis program accounts for negation. Moreover, no models account for linguistic twists such as sarcasm or irony. While it is unknown how often major consumer brands use negation, irony and sarcasm, those remain possibilities. For these reasons, another reliability check was performed. For the human coded set of 1,000

tweets, human scores were compared to computerized scores, which were conflated per the same specification as human coded tweets.

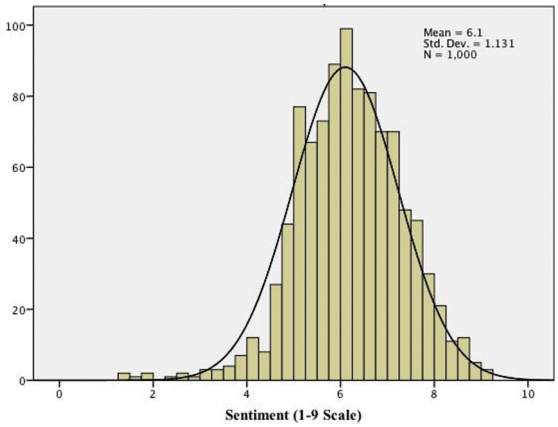
Before conflation, sentiment scores for human scores tended to skew positive in comparison with all other computer sentiment measures (See Figure 1).

Figure 1 – The Distribution of Sentiment Measures

Sentistrength



Human Assessors



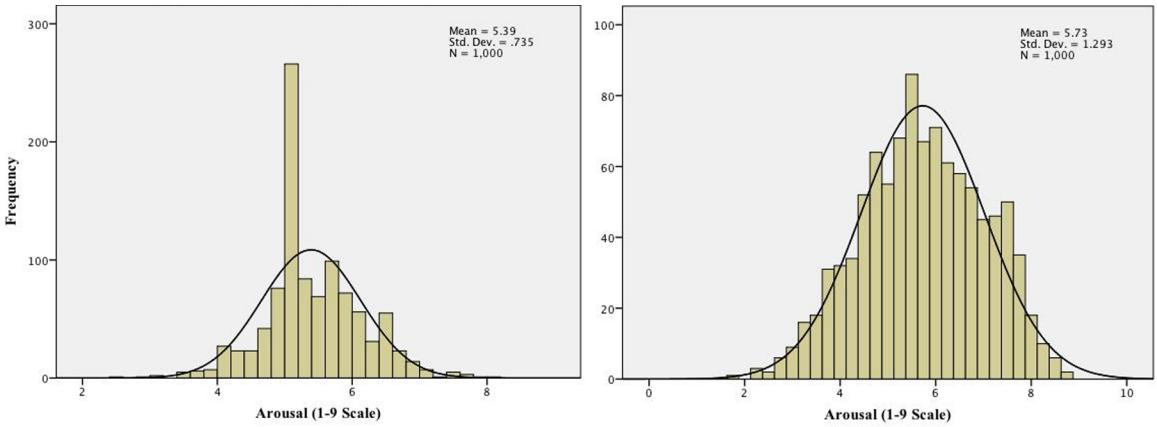
To better mirror the positively skewed distribution, first sentiment scores were increased by 25% of the scale's total, if the score was greater than 0. While this improved correlations, it did not offer enough additional agreement. Upon inspection of tweets containing these high scores, it was observed that a majority of tweets that scored high in sentiment also included capital letters as a point of emphasis (e.g. "@Macys: We are having a GREAT sale today!"). Additionally, highly positive tweets also included exclamation points. These two features were added as boosters to the sentiment and arousal scoring Python scripts. As such, when a tweet contained either an exclamation point or words with capital letters that were associated with positive sentiment, that word's score was boosted by +1 unit. Sentistrength already accounted for exclamation points, so only boosting was added as an additional

parameter. Through all manipulation and an unsuccessful regression attempt using all three sentiment measures, SentiStrength prevailed with the highest percent agreement. When scales were conflated, SentiStrength agreed with the human assessors 88.5% of the time and had *a* = .739.

Arousal followed suit; after adjusting for capitalized words and exclamation points, an agreement of 84.7% was reached with *a* = .687. The majority of error appeared to be the result of a large number of scores being initially coded as "5," or neutral, due to a lack of any features (See Figure 2).

Figure 2 – The Distribution of Arousal Measures

ANEW (Computerized) Human Assessors



Human-coded concreteness scores also skewed positively when compared to the computerized counterparts. After reconfiguring the Python script to include all username mentions (i.e. @chrisjvargo) as the default proper noun score (+ 6), distributions were comparable. This suggests that users found mentioning other Twitter users as illuminating

characteristics. The robustness of the extremely large wordlist prevented a large portion of scores from being coded as neutral. An agreement of 87.1% was reached with $a = .731$.

Creating Interactions for Concreteness

Paivio's dual coding theory defines concreteness as the ability to evoke imagery (Begg and Paivio, 1969; Paivio, 1971; Sheehan, 1970). As such, interaction variables were created for instances where concretely worded tweets also appeared with images (as denoted by the media variable from the Twitter API). If a tweet contained an image and was concrete, it was assigned a 1. All other tweets were assigned a 0. Here, the propensity to evoke imagery would be boosted, because the Tweet itself had an image.

As an exploratory measure, another interaction of concreteness with the presence of hashtags was created. Again, the assumption was that in this instance additional context would be created, and that context would boost imagery. If a tweet contained a hashtag and was concrete, it was assigned a 1. All other tweets were assigned a 0.

Preparation for Regression

For the regression statistics you see here, the nominal variables (number of users following a brand, number of users a brand follows, reputation score, retweet count, and favorite count) were prepared for regression using the following methods. The measurement level was adjusted to 10 even fields. Variables were binned appropriately to one of the 10 values based on the cutoffs. Outlier values more than three standard deviations away from the mean were replaced with the cutoff value for that variable. Values for ANOVAs remained unaltered.

Chapter 3: Results

RQ1: Retweet and Favorite Counts

RQ1a: How frequently are brand messages shared on Twitter?

Addressing RQ1a, the mean retweet count for a brand tweet is 7.96 (*SD* =7.25). A 95% confidence interval around the mean reveals a relatively precise measurement, with the lower bound being 7.38 and the upper bound being 8.53. However, even after removing retweets from the sample, the variable still remains skewed at 10.72 (*SE* = .028). The skewness is reflected in the median value of 2 and the standard deviation of 25.56. While the variance is high, only four tweets received retweet counts higher than 500. For a list of the top 25 most retweeted tweets, see Appendix 6.

RQ1b: How frequently are brand messages favorited on Twitter?

Addressing RQ1b, the mean favorite count for a brand tweet is 6.99. A 95% confidence interval around the mean reveals a relatively precise measurement, with the lower bound being 6.40 and the upper bound being 7.58. The variable is slightly more skewed than the retweet count at 12.01 (*SE* = .028). The skewness is reflected in the median value of 2 and the standard deviation of 26.29. While the variance is high, only four tweets received favorite counts higher than 500. For a list of the top 25 most favorited tweets, see Appendix 7.

RQ2: Number of Followers

RQ2a: What effect will the number of followers have on the average number of shares (i.e. retweets) that brand's tweets receive?

A regression analysis of follower counts on retweet counts offers a small, but significant, amount of explanatory power, $b = .384$, $t(7576) = 36.242$, p =.000. Follower counts explain a significant proportion of the variance in retweet counts, $R^2 = .148$, $F(1,7576) = 1313.451$ p =.000.

RQ2b: What effect will the number of followers have on the average number of favorites that brand's tweets receive?

A larger effect is revealed when a regression analysis is performed with the dependent variable of favorite count. The regression was again highly significant, $b = .527$, $t(7576) = 54.002$, p =.000. Follower counts explain a greater, significant proportion of the variance in favorite counts, $R^2 = .278$, $F(1,7576) = 2916.242$ p =.000.

RQ3: Differences by Brand

RQ3a: On average, do certain types of brands tend to have messages shared (i.e. retweets) more than other types?

A one-way ANOVA was performed to detect differences between the four types of brands. There was a significant main effect for brand type, $F(3,7574) = 30.754$, $p = .000$. See Table 6 for full results.

Table 6 – Retweet Means by Brand Type

	Sum of squares	df	Mean square	*F*-Ratio	Sig.	Post hoc analysis Mean	1	2	3	4
Between Groups	59579.351	3	19859.784	30.754	.000	1 = 6.08				*
Within Groups	4891060.662	7574	645.770			2 = 3.88			*	*
Total	4950640.013	7577				3 = 7.11		*		*
						4 = 11.9	*	*	*	

Notes: Bonferroni Post hoc; *Significance Level 0.05 ($p < 0.05$); 1 = Insurance Companies; 2 = Banks; 3 = Cable & Sat. Companies; 4 = Dept. Stores

A Bonferroni post-hoc test was performed to see if groups were significantly different from each other. Significant interactions are denoted in Table 6. Banks received fewer retweets than cable and satellite companies, and department stores. Insurance companies received fewer retweets than department stores. Cable and satellite companies received fewer retweets than department stores. Finally, department stores received more retweets than insurance companies, banks and cable and satellite companies.

RQ3b: On average, do certain types of brands tend to have messages favorited more than other types?

When comparing favorites as the dependent variable, there was a significant main effect for brand type, $F(3,7574) = 89.923$, $p = .000$. See Table 7 for full results.

Table 7 – Favorite Count by Brand Type

	Sum of squares	df	Mean square	*F*-Ratio	Sig.	Post hoc analysis Mean	1	2	3	4
Between Groups	180074.501	3	60024.834	89.923	.000	1 = 4.94				*
Within Groups	5055728.283	7574	667.511			2 = 4.20				*
Total	5235802.784	7577				3 = 3.23				*
						4 = 14.3	*	*	*	

Notes: Bonferroni Post hoc; *Significance Level 0.05 ($p < 0.05$); 1 = Insurance Companies; 2 = Banks; 3 = Cable & Sat. Companies; 4 = Dept. Stores

A Bonferroni post-hoc test was performed to see if groups were significantly different from each other. Significant interactions are denoted in Table 7. Insurance companies, cable and satellite companies, and banks all received fewer favorites than department stores.

RQ4: Following Counts

RQ4a: Will the number of users a brand follows predict the number of shares (i.e. retweets) its messages receive?

A Pearson correlation reveals that retweet counts and follower counts are positively correlated, $r = .176$ ($p = .000$). This would suggest that as follower counts increase, so do the number of retweets a brand receives for its messages.

RQ4b: Will the number of users a brand follows predict the number of favorites its messages receive?

For favorite count, a stronger positive relationship is shown, $r = .294$ ($p = .000$). This too suggests that as follower counts increase, so do the number of favorites a brand receives for its

messages. For a detailed look at how the relationship for retweet count and favorite counts are observed in regression, see the results for RQ12.

RQ5: Sentiment

RQ5a: Will brand messages with positive valence be shared (i.e. retweeted) more than messages with neutral or negative sentiment?

A one-way ANOVA was performed to detect whether tweets labeled with positive sentiment had a higher mean for retweet count than ones that did not. There was a significant main effect for sentiment, $F(1,7576) = 59.320$, $p = .000$. Positively worded tweets have more retweets, $M = 10.16$, $SE = .534$, $SD = 22.212$, than non-positively worded tweets, $M = 5.65$, $SE = .216$, $SD = 13.168$.

RQ5b: Will brand messages with positive valence be favorited more than messages with neutral or negative sentiment?

For the outcome variable of favorite count, a significant main effect was also shown, $F(1,7576) = 55.391$, $p = .000$. Positively worded tweets have more favorites, $M = 9.18$, $SE = .538$, $SD = 33.48$, than non-positively worded tweets, $M = 4.70$, $SE = .250$, $SD = 15.22$.

RQ6: Arousal

RQ6a: Will brand messages with positive arousal be shared (i.e. retweeted) more than messages with neutral or negative sentiment?

A one-way ANOVA was performed to detect whether tweets labeled with positive arousal had a higher mean for retweet count than those that did not. There was a significant main effect for arousal, $F(1,7576) = 7.304$, $p = .007$. Tweets with positive arousal have more retweets, $M = 8.60$, $SE = .431$, $SD = 29.129$, than non-positively arousing tweets, $M = 6.98$, $SE = .344$, $SD = 18.859$.

RQ6b: Will brand messages with positive arousal be favorited more than messages with neutral or negative sentiment?

For favorite count, no main effect was found, $F(1,7576) = 2.748$, $p = .097$. Positively arousing tweets, $M = 7.39$, $SE = .421$, $SD = 28.457$, were similar to non-arousing tweets, $M = 6.37$, $SE = .412$, $SD = 22.589$.

RQ7: Concreteness

RQ7a: Will concrete brand messages be shared (i.e. retweeted) more than abstractly worded messages?

A one-way ANOVA was performed to discover whether tweets labeled as concrete had a higher mean for retweet count than those that did not. There was a significant main effect for concreteness, $F(1,7576) = 14.957$, $p = .000$). Concretely worded tweets appear to have fewer retweets ($M = 5.68$, $SE = .545$, $SD = 21.125$), than abstractly (a.k.a. vaguely) worded tweets ($M = 8.52$, $SE = .340$, $SD = 26.517$).

RQ7b: Will concrete brand messages be shared (i.e. favorited) more than abstractly worded messages?

However, for favorite count the main effect was not significant, $F(1,7576) = 1.070$, $p = .301$). Concretely worded tweets ($M = 6.36$, $SE = .627$, $SD = 24.318$) were similar to abstractly worded tweets ($M = 7.14$, $SE = .343$, $SD = 26.752$).

When considering a 2x2 design of image and concreteness on retweet counts there was a significant main effect, $F(3,7574) = 67.985$, $p =.000$ and all interactions were significant. See Table 8 for full results.

Table 8 – 2x2 ANOVA (Image x Concreteness) Comparison of Retweet Means

	Sum of squares	df	Mean square	*F*-Ratio	Sig.	Post hoc analysis Mean	1	2	3	4
Between Groups	129817.316	3	43272.439	67.985	.000	1 = 12.58		*	*	*
Within Groups	4820822.697	7574	636.496			2 = 3.83	*		*	*
Total	4950640.013	7577				3 = 17.19	*	*		*
						4 = 6.60	*	*	*	

Notes: *Significance Level 0.05 (p < 0.05); 1 =Image and Concrete; 2 = No Image, Concrete; 3 = Image, Not Concrete; 4 = No Image, Not Concrete

When considering a 2x2 design of image and concreteness on favorite counts there was a significant main effect, $F(3,7574) = 128.131$, $p = .000$. All interactions were significant (see Table 9 for the full results).

Table 9 – 2x2 ANOVA (Image x Concreteness) Comparison of favorite Means

	Sum of squares	df	Mean square	*F*-Ratio	Sig.	Post hoc analysis Mean	1	2	3	4
Between Groups	129817.316	3	43272.439	67.985	.000	1 = 12.58		*	*	*
Within Groups	4820822.697	7574	636.496			2 = 3.83	*		*	*
Total	4950640.013	7577				3 = 17.19	*	*		*
						4 = 6.60	*	*	*	

Notes: Post hoc is Bonferroni; *Significance Level 0.05 (p < 0.05); 1 = Image and Concrete; 2 = No Image, Concrete; 3 = Image, Not Concrete; 4 = No Image, Not Concrete

When considering a 2x2 design of hashtags and concreteness on retweet counts there was a significant main effect, $F(3,7574) = 35.186$, $p = .000$. The hashtags, not concrete group had a substantially higher mean than all other groups. For significant interactions see Table 10.

Table 10 – 2x2 ANOVA (Hashtag x Concreteness) Comparison of Retweet Means

	Sum of squares	df	Mean square	*F*-Ratio	Sig.	Post hoc analysis Mean	1	2	3	4
Between Groups	68047.920	3	22682.640	35.186	.000	1 = 6.22			*	
Within Groups	4882592.093	7574	644.652			2 = 4.80			*	
Total	4950640.013	7577				3 = 10.77	*	*		*
						4 = 4.32			*	

Notes: Post hoc is Bonferroni; *Significance Level 0.05 (p < 0.05); 1 = Hashtag and Concrete; 2 = No Hashtag, Concrete; 3 = Hashtag, Not Concrete; 4 = No Hashtag, Not Concrete

When considering a 2x2 design of hashtags and concreteness on favorite counts there was a significant main effect, $F(3,7574) = 9.486$, $p = .000$. Only one interaction was significant. The hashtag, not concrete group had a higher mean than the no hashtag, not concrete group. See Table 11 for full results.

Table 11 – 2x2 ANOVA (Hashtag x Concreteness) Comparison of Favorite Means

	Sum of squares	df	Mean square	*F*-Ratio	Sig.	Post hoc analysis Mean	1	2	3	4
Between Groups	19599.688	3	6533.229	9.486	.000	1 = 6.22				
Within Groups	5216203.096	7574	688.699			2 = 4.80				
Total	5235802.784	7577				3 = 10.77				
						4 = 4.32			*	

Notes: Post hoc is Bonferroni; *Significance Level 0.05 (p < 0.05); 1 = Hashtag and Concrete; 2 = No Hashtag, Concrete; 3 = Hashtag, Not Concrete; 4 = No Hashtag, Not Concrete

RQ8: Favorites Predicting Retweets

RQ8: Will the number of favorites a brand message receives predict the number of times it is shared (i.e. retweeted)?

A Pearson correlation of favorite count on retweet counts shows a significant correlation r = .695, p = .000.

RQ9: URLs

RQ9a: Will brand messages with URLs be shared (i.e. retweeted) more than messages without a URL?

A one-way ANOVA was performed to detect whether tweets with URLs had a higher mean for retweet count. There was no significant main effect for URLs, $F(1,7576) = 3.131$, $p = .077$. Tweets with no URLs have more retweets ($M = 8.70$, $SE = .525$, $SD = 26.169$), than those with URLs ($M = 7.59$, $SE = .354$, $SD = 25.253$). The difference was not significant.

RQ9b: Will brand messages with URLs be favorited more than messages without a URL?

However, for favorite count there was a significant main effect $F(1,7576) = 27.080$, p = .000. Tweets with no URLs ($M = 9.23$, $SE = .622$, $SD = 31.050$) have a higher average than tweets with a URL ($M = 5.89$, $SE = 23.538$).

RQ10: Hashtags

RQ10a: Will brand messages with hashtags be shared (i.e. retweeted) more than messages without a hashtag?

A one-way ANOVA was performed to detect whether tweets with hashtags had a higher mean for retweet count than those without. There was a significant main effect for hashtags, $F(1,7576) = 43.053$, p =.000. Tweets with no hashtags have fewer retweets ($M = 4.42$, $SE = .330$, $SD = 17.156$), than those with one hashtag ($M = 9.91$, $SE = .495$, $SD = 29.006$)

RQ10b: Will brand messages with hashtags be shared favorited more than messages without a hashtag?

For favorite count, there was a significant main effect for hashtags, $F(1,7576) = 21.531$, $p = .000$ Tweets with no hashtags have fewer retweets ($M = 5.11$, $SE = .442$, $SD = 27.895$), than those with a hashtag ($M = 8.03$, $SE = .399$, $SD = 22.983$).

RQ11: Images

RQ11a: Will brand messages with an image be shared (i.e. retweeted) more than messages without an image?

A one-way ANOVA was performed to detect whether tweets with an image had a higher retweet count than those without an image. There was a significant main effect for images, $F(1,7576) = 183.673$, $p = .000$). Tweets with images have more retweets ($M = 16.15$, $SE = 1.126$, $SD = 42.420$), than tweets without images ($M = 6.07$, $SE = .245$, $SD = 19.256$).

RQ11b: Will brand messages with an image be favorited more than messages without an image?

For favorites, another significant main effect was found $F(1,7576) = 381.220$, $p = .000$. Tweets with images have more favorites ($M = 18.98$, $SE = 1.3$, $SD = 48.971$), than those without images ($M = 4.23$, $SE = .205$, $SD = 16.051$).

RQ12: "All in" predictive model

RQ12a: To what extent can the independent variables identified in this study be used to predict the number of retweets for brand messages on Twitter?

Finally, using all the predictor variables outlined in RQ2 to RQ11, a linear regression analysis was applied for retweet count. See Table 12 for the full results.

Table 12 – Summary of Multiple Linear Regression Analysis for Retweet Count

	B	SE(B)	β	t	Sig. (p)	Tolerance
(Constant)	-.180	.050		-3.630	.000	
Followers	.344	.011	.344	30.038	.000	.773
Images	.540	.028	.211	19.223	.000	.847
Hashtags	.241	.021	.115	11.378	.000	.989
Insurance Company (Control)	.319	.030	.114	10.599	.000	.871
Following	.083	.010	.083	8.158	.000	.974
Concreteness	-.159	.025	-.063	-6.258	.000	.987
Arousal	.042	.021	.020	2.012	.044	.996

*Sentiment, URLs and other brand type controls excluded (explained no unique variance significantly)

RQ12b: To what extent can the independent variables identified in this study be used to predict the number of favorites for brand messages on Twitter?

Follower count, the presence of an image, the presence of a hashtag, the control variable for the brand type of insurance company, following count, concreteness and arousal explained a marginal amount of variance in retweet counts, $R^2 = .231$, $F(5,7571) = 323.963$, $p = .000$. Moreover, the Beta weights were all positive, with the exception of concreteness. In a test for multicollinearity, all predictor variables' tolerance values remained close to one with (.773 to .996) suggesting that multicollinearity was not an issue.

Using all the predictor variables outlined in RQ2 to RQ11, a linear regression analysis was also applied for favorite count. See Table 13 for the full results.

Table 13 – Summary of Multiple Linear Regression Analysis for Favorite Count

	B	SE(B)	β	t	Sig. (p)	Tolerance
(Constant)	-.089	.048		-1.841	.066	
Followers	.375	.013	.375	29.80	.000	.548
Images	.506	.027	.197	18.98	.000	.800
Hashtags	.169	.020	.081	8.52	.000	.961
URLs	-.130	.021	-.061	-6.20	.000	.887
Reputation	.133	.012	.133	11.47	.000	.644
Following	.073	.010	.073	7.57	.000	.926
Insurance Company (Control)	-.175	.031	-.063	-5.628	.000	.698
Concreteness	-.089	.023	-.035	-3.77	.000	.986
Sentiment	.070	.019	.035	3.64	.000	.945

*Arousal and other brand type controls excluded (explained no unique variance significantly).

Follower count, the presence of an image, hashtags, the presence of a URL, reputation score, following count, the insurance company brand type control, concreteness and sentiment explained a marginal amount of variance in favorite counts, $R^2 = .345$, $F(5,7568) = 442.557$, $p = .000$. The Beta weights were all positive, except the insurance company control, URL and concreteness. In a test for multicollinearity, all variable's tolerance values remained closer to one than zero (.548 to .986) suggesting that multicollinearity was not an issue.

Chapter 4: Conclusion

How Viral are Brand Messages?

This dissertation looked at 17 of the most popular consumer brands on Twitter. In an exhaustive review of 7,578 messages from these brands over three months, not one "viral" tweet was found. This finding supports Goel, Watts and Goldstein's finding that diffusion online is most often not contagious (2012). The average cascade generated from any individual was small relative to the number of people to whom that person was connected. Anderson, Goel and Hofman consider 10,000 shares a benchmark for virality on Twitter; here the maximum was 594 (2013).

While brand messages are generally not shared enough to be viral, brands do appear to garner more attention when compared to the entire population of Twitter users. Suh et al. found that for an unfiltered corpus of 74 million Tweets, only an additional 2.9 million retweets were created (2010). On average, each tweet garnered .04 retweets. Here, the brand message corpus of 7,578 garnered 60,287 retweets, or 7.96 retweets. Brand messages are shared more than the entire population of Twitter's tweets.

While Suh et al. did not measure the average number of favorites per tweet, they note that their "study shows that the favorite feature is not heavily used" (pg. 7). In their data set, they found that 42.5% of tweets was posted by users with no favorited items. The data from this dissertation suggests that the use of favorites has dramatically increased since 2010. Brand tweets were favorited almost as much they were retweeted (6.99 vs. 7.96). Therefore, we can

assume that favorite counts for brands are also higher than the norm for all of Twitter. This is likely because of the high follower counts of brands on Twitter. Vargo found in a random sample of 1.2 million users, the mean follower count was 1,876. All of the brands have over 10,000 followers on Twitter.

Follower Counts

Given that brands have large follower counts, it is of little surprise that follower counts were the strongest predictor of retweet counts and favorite counts in both the initial regressions and the final "all in" regression. Simply put, the more followers a brand had, the more interactions it received. This gives support to the "diffusion through the masses hypothesis" set forward by various scholars (Goel, Watts & Goldstein, 2013; Hofman, 2013; Watts & Dodds, 2007). The more people following a brand, the more that brand's messages will be shared. As Watts and Dodds predict, this was likely caused by small amounts of sharing by many individuals (2007). However, according to Goel, Watts and Goldstein, the average cascade generated from any brand was small relative to the number of people to whom that brand was connected (2012). When initial cascades from large nodes are small, the messages are unlikely to travel far from their origins. Brands are, therefore, unlikely to have messages travel to followers of their followers across the network of Twitter.

Differences by Brand Type

Significant differences in retweet counts and favorite counts by brand and brand type exist. Notably, banks tend to receive very few interactions, while department stores receive many more interactions. Interestingly, brand reputation appeared to have no influence on these differences. Reputation appeared to be independent of these social media interactions. These results suggest that different benchmarks exist for different products and services. Support is

given to the findings of other researchers who found that different products receive different amounts of attention online (Allsop, Bassett & Hoskins, 2007; Amblee & Bui, 2008).

Through regression, it does not appear that the brand type itself offers much explanatory power of how often a message will be shared. Insurance companies are retweeted slightly more and favorited slightly less than other brand types. Outside of this difference, the type of brand itself appears irrelevant. This gives hope that the findings here for the other characteristics are often independent of brand type, and that these findings could be applicable to many brand types.

Sentiment

The sentiment analysis part of this paper revealed that brand messages were excessively positive on Twitter. Most brand messages included exaggerated positive characteristics such as exclamations and uppercase words. An effort to quantify how positive a brand message was largely unsuccessful. Even to the author, no apparent measurement levels for sentiment surfaced. Messages appeared to be positive or not. A small handful of the corpus may have been negative, but no consensus could be reached. Even tweets that used negative words usually had an overall positive connotation to the students who performed the content analysis.

Still, it appears that positively worded tweets were favorited more than non-positive ones. Regression analysis shows that a little explanatory power can be gained from this knowledge. In the case of retweets, sentiment was not included in the final regression, as other predictor variables explained the same variance with more accuracy. Positive emotion did offer a small amount of explanatory power in the final regression for favorite count, but the beta weight was only slightly positive.

Brand messages were almost always related (directly or indirectly) to the product or service from which the message came. They were also generally positive. Together, these

messages appeared to be performing the "self-enhancement" function as described by Hansen et al. (2012). Brands tended to serve messages that were non-news related and pertained to the brand. As self-enhancement theory suggests, the messages were positive. The results show that brand messages tend to be favorited more, but not shared more. Little support is offered for those that suggest non-news stories, when positive, are shared more (i.e. Hansen et al., 2012; Angelis et al., 2012; Dang Xuan et al., 2013).

The reason for the lack of support may be because of a lack of degree (a.k.a. polarity) in the positive sentiment. Heath suggests that for exaggeratedly positive domains, such as brand messages on Twitter, people will only share stories when messages are exaggeratedly positive (1996). The messages found here were positive in tone, but the positivity could be simply an artifact of the self-enhancement behavior of brands. These messages, while slightly positive overall, lacked the emotional charge found in the work of scholars like Dang Xuan et al. (2013).

Arousal

Arousal had a result similar to sentiment. Through an analysis of means, those tweets with positive arousal did tend to be retweeted and favorited more than those without positive arousal. Positive arousal did offer a very small amount of explanatory power in the final regression for retweets count, but the beta weight was rather small. In the case of favorite count, arousal was not included in the final regression, as other predictor variables explained the same variance with more accuracy.

The content analysis phase of this dissertation revealed that tweets with uppercase words and exclamation points also tended to have higher amounts of arousal. Unlike sentiment, this author is optimistic that measuring arousal with more levels of measurement is possible, as certain tweets appeared to have varying level of arousals.

While Berger remains vocal that arousal encourages people to react to and share messages, this dissertation was unable to find levels of arousal so distinct and compelling that would elicit such a response (2011, 2012; Berger & Milkman, 2011). Instead, the manual content analysis revealed that most tweets were slightly arousing (6 out of 9). Arousing emotions like disgust did not emerge in brand messages (see Heath, Bell and Sternberg, 2001). Moreover, it is unclear exactly how a brand message activates someone to the point that the person feels "wide awake" or "ready to react" as described by Heath (2012). It may be possible for brands to evoke greater levels of arousal, and high levels of arousal may have greater effects, but no such examples were found in this dissertation.

Concreteness

The presence of a concretely worded tweet alone was not enough to garner more retweets and favorites. When considering the interaction of concretely worded content and other characteristics that might boost concreteness (images and hashtags), differences emerged. While concrete messages with URLs were shared more than vague messages with URLs, non-concrete content was shared more regardless of whether an image was present. Hashtags appeared to be a better predictor than concreteness. Messages with hashtags were retweeted and favorited more than concretely worded tweets. The significant interactions didn't lend themselves to any known theories, and as such were not entered into the final regression.

Concreteness did explain a significant amount of variance in the final regressions (retweets and favorites). However, the direction of the Beta was completely unexpected. Non-concrete (a.k.a. vague or ambiguous) content was shared and favorited more than concrete content. This held true through regression analysis. Concreteness offered negative explanatory

power. This suggests that there is some type of novelty in abstractly worded messages that causes them to be shared and favorited more.

In one sense, visual imaging ability, as defined by Rossiter and Perry, is supported (1978). Brand messages with images made it easier to picture scenarios. Images added context and provided detail. As dual-coding theory would suggest, brand messages with images were retweeted and favorited more. However, when considering the text alone, more abstract messages prevailed. Bakshy et al. found that "more interesting" content is, indeed, shared more on Twitter (2011). If true, it would suggest that concrete information is generally more uninteresting on Twitter. This would stand at odds with the greater body of research that suggests that concrete textual passages boost interest in readers (i.e. Wharton, 1980; Sadoski, 1993a; Sadoski, 199b; Goetz & Rodriguez, 2000).

Heath and Heath provide a definition of concreteness that seems at odds with how concreteness was measured here (1995). In their work, they show how concrete text is usually "stickier" (i.e. easier to recall and remember) than abstract text (see also Rubin, 1995). It could be that on Twitter, a medium known for its brevity, the stickiest messages are very short and novel. The novelty of messages that are short may also be abstract due to the fact that very few words are used.

Other Characteristics of the Brand

The number of users a brand followed did positively explain a small amount of the variance in retweet and favorite counts. The more users a brand follows, the more interactivity it receives. This supports some early exploratory work by Brown, Broderick and Lee (2007). Brands that make stronger ties with their consumers (i.e. by following users back as opposed to a uni-directional tie) may see a small benefit in the engagement they see as a result.

Finally, the overall reputation of a brand did explain a small amount of variance in retweet and favorite counts. This works reinforces Amblee and Bui's work and shows that reputation can have residual effects on sharing (2008). Consumers may indeed be more likely to share messages from brands with good reputations.

Images

Finally, tweets with images were retweeted more and shared more. (Moreover, in the final regressions, the presence of an image was the second most influential predictor variable in both models. The r^2 for images alone was above .10 for both retweets and favorites. Support is given to dual-coding theory (see Concreteness heading above). In addition, support is given to the "rapid cognition" model, which states that a user has a relatively short period of time in which to view a post. That short window is important. If an image is present, the amount of engagement that can occur within that time is boosted. This theory is given a reasonable amount of support as it pertains to brand messages on Twitter (Guerini, Staiano, & Albanese, 2013).

The Difference between Favorites and Retweets

For the limited domain of brand messages, the data here contradicts Suh et al. in that favorites can indeed predict retweets (2010). Still, the predictive model is not overly powerful, as one might expect, $R^2 = .483$, $F(1,7576) = 7064.622$ p =.000. This data suggests that retweets and favorites, while related, are not duplicate measures. They do appear to serve as different behaviors and should be treated as such. Retweets were slightly more common ($M = 7.96$, $M = 6.99$). The two were significantly correlated with a Pearson correlation of .695, but not quite to the degree of .8, which would suggest collinearity.

Overall Conclusion

The final regression analyses were done with careful regard to multicollinearity. Only variables that could explain unique variance in the outcome variables were selected. The total amounts explained were $R^2 = .231$ for retweets and $R^2 = .345$ for favorites. While the majority of variance still remained unexplained, the results seem realistic. Each of the aforementioned variables had a small, but significant impact on the interaction a tweet received. Some may read this dissertation and see it as a failure to see "the reason" why brand messages are shared or favorited on Twitter. This author would reply that there is likely no one reason why a message is shared. Instead, many factors are working in concert with each other, or many factors can cause a retweet (or favorite), but one factor does not cause a retweet the majority of the time. Instead, a regression that predicts all retweets of brand messages might look like a puzzle with many pieces needed to reveal the entire picture.

There are, without a doubt, many more variables that can be measured in regards to the content of a brand message on Twitter. This dissertation opened the discussion by measuring the most commonly discussed characteristics of a textual message on a social networking service as they pertained to sharing and diffusion. It is the hope of this author that more of the unexplained variance will be addressed in future studies.

Chapter 5: Discussion & Limitations

Arousal for Retweeting, Sentiment for Favoriting

It is the suspicion of this author that the aforementioned fundamental difference between a favorite and retweet may have something to do with the one key difference observed here. Positive arousal seemed to predict retweets but not favorites. Positive sentiment predicted favorites but not retweets. As shown, the practice of favoriting tweets on Twitter has exploded since 2010. No evidence suggests that retweeting has. This author suggests that favoriting is a somewhat less active form of engaging with a brand.

From what Berger and others have written about arousal, we know that it activates and encourages a whole host of behaviors (2012). Could it be that more activation is required to gain a retweet? Consumers may indeed need more incentive to retweet. After all, it is an endorsement of a brand. That endorsement is shared with friends. Guerini, Stapparava and Ozbal echo the fact that consumers have resistances to spreading information when it comes to branded content (2011). It could be that arousal is needed in these scenarios but not in cases of simply "favoriting" or liking content. In these cases, it may just be that consumers slightly prefer positive content as opposed to negative content.

Concreteness

Concreteness seems to discourage retweeting and favoriting. This finding appears to confound Heath and Heath's "Made to Stick" observation (2007). But does it? Heath and Heath

describe concrete text as “sticky.” But what makes content sticky on Twitter? Heath and Heath do a great job of showing stories that were unique and easy to remember. Could it be that the more detailed and specific a tweet is, the less likely it is to standout in the universe of tweets?

Figure 3 – A Taco Bell Tweet

Figure 3 shows an example of a tweet that would have been scored as ambiguous in this content analysis. Yet, this tweet had almost eight times as many shares as any other tweet in this dissertation. This tweet is boosted by an ephemeral event. This message references an external event and latched on with perfect timing. Paivio defines concreteness as referring to “specific things or events” (1963). While this message is vague textually, it makes a specific reference to a pop cultural event (i.e. “bae” is emergent Internet slang for the word babe). It also can mean “before anything else.” This clever double meaning was enough to send it viral. It’s timing was also perfect. The slang was new. Could it be that tweets that seize the moment are the ones that are shared more, regardless of a vivid description of an event? If so, a future measure of concreteness as it applies to the timing of extraneous events may provide a better measure of concreteness.

More Linguistic Properties

It is the hope of this author that several different areas of this dissertation are expanded. First and foremost, more work is needed at the intersection of linguistics and virality. While the structures and properties of social networks have been well studied, the content of those messages remains understudied. At the same time, linguistics and the automated detection of linguistic characteristics continues to rapidly expand. Properties of tweets that go beyond sentiment and emotion exist. Linguistic properties such as hedging (uncertainty), negation, sarcasm and uniqueness are just a few areas in which these brand tweets may show more variance than sentiment and arousal alone. At the time of writing this dissertation, no papers attempt to link these properties to the virality of a message. Such studies would be exploratory, but potentially groundbreaking.

This dissertation is one of the first major studies of diffusion that relied on the ANEW arousal wordlist. There is more work to be done in the expansion of this wordlist to the online domain. While the wordlist did have good accuracy on the words that were included, the list was short. An expansion of more terms would likely boost the reliability and allow researchers to incorporate more of a full-scaled measurement to arousal, as opposed to a one-level approach.

Expanding Brand Types

This dissertation provides clear evidence that not all types of brands are equal on Twitter. Along those lines, a full explication of why certain brands are shared more than others would likely yield interesting results. Only one explanation is eliminated in this study: reputation. All other possibilities, such as novelty, excitement and interest, remain valid inquiries. One possible reason that Macy's may have been more popular is because of the content of its messages. Macy's appeared to tweet deals and coupons to its followers. Do those types of messages get

shared more than others? Promotions directly connected to price are concrete by definition, but they also save consumers money. This is yet another possible motivation for WOM, one discussed as "social currency" in *Contagious* (Berger, 2012). People want to strengthen their bonds with others by sharing information that they believe will be helpful. It is logical that promotions would be shared with friends.

Such promotions would likely not exist for all brands to the same extent as others. Some brands have more temporal, dramatic promotions, while others, such as insurance companies, appear not to run temporary promotional discounts as often. This author encourages others to think about how else brands differ on the content they deliver. Perhaps categorizing tweets into some non-mutually exclusive categories, such as informational, promotional, humorous and competitive, would yield insight into diffusion. While emotion and concreteness may correlate with some of these categories, the categories themselves may have stronger predictive power.

The True Power of Images

The inclusion of images into the analyses here was limited to simply their presence. However, a deeper dive into the actual characteristics of the images and the extent to which they are exciting or arousing may have greater predictive power. Not all images are the same in regard to their ability to capture interest (Gundotra, 2013). Newer methods are surfacing that would allow researchers to quantify properties of images and incorporate them into regression models. This is no longer limited to the metadata surrounding an image, but instead to the actual visual characteristics such as brightness, patterns, colors, shapes, animals and faces. Does the presence of human faces make a difference? How about the presence of animals? What about cool colors versus warm colors? These characteristics could always be identified through manual content analysis, but now, new methods can allow computer-assisted investigation as well.

Training Content Analysts

Finally, this author feels that the largest shortcoming of this study was the lack of agreement on initial human-coded samples of brand messages on Twitter. Many possible explanations for this exist. It was a student sample. There was low motivation to be accurate. The task was laborious. The tweets lacked dominant features. But regardless of the impact of these limitations, one thing could have boosted reliability, an initial training session.

If students were given a pre-test of tweets with known, gold standard responses, their responses could have been automatically checked for error. If students disagreed on a concept, they could have then been offered some supplementary training on how to detect that concept. This process could be repeated as much as needed until the student agreed across all concepts with the gold standard data. If after a reasonable amount of tries the student could not reach agreement with the gold standard data, the student's responses could be automatically disregarded from the study. This author will be sure to build an interactive training session like this for all future studies.

Injection and Selection of Tweets with Characteristics

Another logical way to approach the data collection to this study could have involved the manual selection of tweets. In this study, there was a lack of brand tweets that were strong in negative sentiment and negative arousal. If a sample was hand selected, such problems could have been alleviated. Millions of tweets from hundreds of brands could have been pre-screened for sentiment and arousal using the computerized methods in this study. Inducting a sample that the computer believed was polarized in sentiment and arousal may have created more dramatic results in the regression analysis.

Moreover, through the content analysis stage, tweets could have been manually manipulated to have polarized sentiment and arousal by the researcher. These doctored tweets would not have an outcome variable, as they were never actually broadcasted. But this could have helped train both the human coders and the computerized methods. Ultimately, assessing agreement on polarized examples would test the feasibility to reliably detect these concepts.

Truly Detecting Virality

Along these lines, if a future attempt in the prediction of brand messages that are truly viral is attempted, a much larger sample will be needed. Alternatively, a sample could be inducted by handpicking those that went viral. This dissertation focused on the everyday, commonplace messages and when they did and did not have interactions. Focusing on truly viral tweets would inherently be the opposite. The more evidence of tweets that were truly viral, the more likely the findings would be significant. The regressions outlined in this dissertation were significant due to the large sample size. A study of truly viral brand messages on Twitter would likely not be afforded that luxury unless the researcher went to great lengths to capture as much evidence of virality as possible.

APPENDIX 1: PYTHON SCRIPT FOR DATA COLLECTION

```
# Twitter REST API v1.1 GET statuses/user_timeline script
# oauth2 library must be installed

import oauth2 as oauth
import urllib2 as urllib
import json
from time import sleep

# replace XX with credentials. Sign up at https://dev.twitter.com/
access_token_key = "XX"
access_token_secret = "XX"

consumer_key = "XX"
consumer_secret = "XX"

_debug = 0

oauth_token    = oauth.Token(key=access_token_key, secret=access_token_secret)
oauth_consumer = oauth.Consumer(key=consumer_key, secret=consumer_secret)

signature_method_hmac_sha1 = oauth.SignatureMethod_HMAC_SHA1()

http_method = "GET"


http_handler  = urllib.HTTPHandler(debuglevel=_debug)
https_handler = urllib.HTTPSHandler(debuglevel=_debug)

'''
Construct, sign, and open a twitter request
using the hard-coded credentials above.
'''
def twitterreq(url, method, parameters):
  req = oauth.Request.from_consumer_and_token(oauth_consumer,
                                              token=oauth_token,
                                              http_method=http_method,
                                              http_url=url,
                                              parameters=parameters)

  req.sign_request(signature_method_hmac_sha1, oauth_consumer, oauth_token)

  headers = req.to_header()

  if http_method == "POST":
    encoded_post_data = req.to_postdata()
  else:
    encoded_post_data = None
    url = req.to_url()

  opener = urllib.OpenerDirector()
  opener.add_handler(http_handler)
  opener.add_handler(https_handler)

  response = opener.open(url, encoded_post_data)

  return response

#### Remember to:
#### Go Grab a two week old Tweet from your profile, and set that id as start_id
#### Correct screen_name?
#### Correct outfile?


start_id = int('422488243985473536')
stop_id = int('421159514009006080')
filenum = str(00)
print str('starting AllState')

def fetchsamples2():
  global start_id
  global filenum
```

```
  url = "https://api.twitter.com/1.1/statuses/user_timeline.json"
  parameters = {'screen_name': 'AllState',  # name of twitterer
            'include_rts': 1,  # Include retweets
                'count': 200, # number of tweets (200 max)
                'max_id': str(start_id),    # start from this tweet and work back
                'since_id': str(stop_id)}  # dont get any tweets older than this, cause we already got them
  response = twitterreq(url, "GET", parameters)
  data = json.load(response)
  with open('out_AllState'+filenum+'.txt','w') as outfile:
      json.dump(data, outfile)
  for tweet in data:
      start_id = tweet['id_str'].encode('utf-8')
      print start_id
      created = tweet['created_at'].encode('utf-8')
  start_id = int(start_id) - 1
  print start_id
  tempfilenum = int(filenum) + 1
  filenum = str(tempfilenum)
  print filenum

# range = 16 will collect up to 3,200 tweets if count = 200
for i in range(16):
  if __name__ == '__main__':
    fetchsamples2()
    sleep(5)
```

APPENDIX 2: SUMMARY OF TWEETS COLLECTED

Brands	Avg. Retweet Count	*SD*	Avg. Favorite Count	*SD*
Sears	3.80	3.23	0.91	1.10
Allstate	5.69	6.40	5.95	27.67
BofA	4.03	6.29	7.93	20.47
Citibank	4.10	10.79	1.89	5.54
Comcast	4.73	11.27	4.07	18.40
DirectTV	6.95	39.64	9.02	51.93
Dish	12.11	27.05	19.11	36.43
JCPenney	7.97	20.61	9.68	23.78
Kohls	7.74	30.23	13.13	52.32
LibertyMutual	32.28	63.55	40.07	63.14
Macys	2.74	3.73	1.19	3.17
Nationwide	0.87	1.62	0.48	0.89
PNC	1.76	3.67	1.05	1.86
Progressive	14.29	44.05	6.18	30.73
State Farm	8.90	29.04	2.60	10.32
TWC	4.55	6.07	2.76	8.56
WellsFargo	6.32	12.12	2.88	5.58
Total	7.96	25.56	6.99	26.29

APPENDIX 3: STUDENT RELIABILITY INSTRUCTIONS & SAMPLE SURVEY

Below are instructions that will be presented to respondents at the beginning of the survey. I will read the instructions to them as they review it. After they receive the general instructions on sentiment, arousal and concreteness the survey will begin.

<PAGE ONE OF SURVEY>

Hi. My name is Chris Vargo. I am a Ph.D. candidate here at UNC Chapel Hill. I am currently working on research that looks at tweets. This is part of my dissertation in which I am completing under the guidance of Dr. Joe Bob Hester. I am interested to see if I can find characteristics of tweets that make them "viral," or shared more with others. Since I study advertising and public relations, I am interested in tweets that are sent from brands, like "Bank of America" or "Time Warner Cable." We will talk about the specifics in just a minute, but first I need to talk to you about consenting and agreeing to help me with this study.

There are no anticipated risks to you if you participate in this study. To avoid strain on your eyes, take short breaks and look away from the computer screen for no less than 15 seconds. Also, to avoid long periods of sitting, feel free to stretch periodically.

This session will last one hour. The incentive to you of completing this study is 1/3rd of your research requirement in the class in which you signed up for this study through. Your name will be sent to your instructor or professor; it will verify that you participated. Should you have to leave early, you will still receive full credit for this study.

Taking part in this study is completely voluntary. If you choose to be in the study you can withdraw at any time without consequences of any kind. You can choose to skip any question, if you so feel. Participating in this study does not mean that you are giving up any of your legal rights. You may talk about this study freely to others.

The responses here will be kept anonymous and no personal information will be collected. The records of this study will be kept private.

If you have questions or want a copy or summary of the study results, contact me via the email you used to sign up for the study: cjvargo@live.unc.edu.

Thank you. By taking the survey, participants are voluntarily agreeing to take part in the study. Now, let's advance to the instructions.

In this survey you will be presented with 50 tweets. Quickly read the tweet when it pops up on your screen, as you would if you were casually browsing messages on Twitter (or any other social media). Don't worry about studying it. Pay no attention to conventional grammar, hashtags, or to your liking or disliking of some words, or the tweet in general.

Following each tweet will be a short set of questions. Go with your immediate gut answer for each question.

<BEGIN PAGE TWO>
Sentiment Instructions

After reading a tweet, the first thing we need you to decide is the sentiment of that tweet. Sentiment is can be positive, neutral or negative. We are concerned with the overall tone of the tweet.

Some tweets are positive. For instance:

@Macys: Yay #awards shows! Just gonna slip into a swank dress & practice our red carpet walk. So much fun.

Focus on the feeling. Does it use positive words? Does it sound happy? Can you imagine the person that wrote the tweet as smiling, or being happy?

If you've said yes to any of these questions – locate the emotion below that best describes the emotion in the tweet. Once you've found the emotion, label the tweet with the corresponding score (6 through 9) with the button below.

Slightly Positive	*Moderately Positive*	*Very Positive*	*Extremely Positive*
6	7	8	9
Alert	Excited	Elated	Ecstatic
Calm	Relaxed	Serene	Content

If the sentiment is not positive – consider negative sentiment. Consider the example:

@Comcast: 30% of customers don't like Dish and return to cable. Why? Poor service, bad customer support and awful channel selection.

Does the tweet use negative words? Does it sound negative? Can you imagine the person that wrote the tweet as upset, or unhappy?

If you've said yes to any of these questions – pick the emotion below that best describes the emotion in the tweet. Once you've found the emotion, label the tweet with the corresponding score (1 through 4) with the button below.

Slightly Negative	*Moderately Negative*	*Very Negative*	*Extremely Negative*
4	3	2	1
Tense	Nervous	Stressed	Upset
Bored	Depressed	Unhappy	Sad

Does the tweet sound neither negative nor positive, but instead factual or without emotion? If the tweet sounds like:

@StateFarm: With the New Year, comes new purchases. If you're considering buying a new vehicle, use these IIHS Top Safety Picks.

If the tweet does not use positive or negative words, consider scoring the tweet a 5, for neutral or no sentiment.

<BEGIN PAGE THREE>

Arousal Instructions

Next you are going to code for arousal. Here I don't mean arousal in the *sexual* sense. Instead, arousing tweets are ones that use an energized voice. If the message sounds like it came from a person that just consumed a large amount of caffeine, it is highly arousing. Arousal is often also called activation or animation. These tweets can sound alert, excited or elated.

@Sears: Run to your local Sears now! 50% off all fitness apparel today! Going fast!

Arousal is *not just for positive sentiment*. Arousing emotions can also be negative. When a tweet is tense, nervous or stressed it also has a high amount of arousal.

@Comcast: This game is intense! We can barely watch with one eye open. Who will win? So anxious.

tweets with low amounts of arousal sound subdued, bored, depressed, relaxed, or serene. If you imagine the author as not animated, but very inactive, code the tweet as having a low amount of arousal. Consider these two tweets:

@DirecTV: Yawn. What is everyone watching on this cold, dreary Sunday?

@Starbucks: Relax. Destress. Tazo Refresh Tea.

Consider the tweet on an arousal scale of 1 to 9. 1 being the most subdued, 9 being the most active. Consider the scales below. Look at the scale that matches the sentiment you just chose in the first part of this exercise. Pick the arousal state that you feel best matches the tweet. Take the corresponding number as your answer.

POSITIVE AROUSAL STATES

Low (subdued) arousal					*High (active) arousal*			
1	2	3	4	5	6	7	8	9
Calm	Relaxed	Serene	Contented	Neutral	Happy	Elated	Excited	Alert

NEGATIVE AROUSL STATES

Low (subdued) arousal					*High (active) arousal*			
1	2	3	4	5	6	7	8	9
Bored	Depressed	Unhappy	Sad	Neutral	Upset	Stressed	Nervous	Tense

<BEGIN PAGE FOUR>
Concreteness Instructions

We need you to consider one more thing about each tweet: how concretely worded it is.

Concrete tweets:
- Describe a specific event or scenario vividly.
- Engage your senses when you imagine that scenario.
- Use descriptive words that enhance the meaning of the tweet.

Vague tweets:
- Don't describe a specific event or scenario vividly.
- Are hard to picture in your mind.
- Use generic words that have many different meanings.

The purpose of this test is to discover how well these tweets render clear, vivid pictures in your mind.

For example, compare these two tweets.

@Starbucks: Are you swamped today? Relax with a hot specialty drink.

@Starbucks: Too many books to read for class today? Take a minute to relax with a piping hot Caramel Flan Latte!

Both of these tweets could describe the same thing. The second one however is clearer, stronger and more active to your senses. You can picture being busy with schoolwork. You can also picture a latte better than you can a "hot specialty drink."

These two tweets are vague:

@Sears: Remember to always love one another.

@Kohls: Have a great weekend!

These tweets are vague statements. They really don't describe clear, strong situations. As you read these tweets aloud, they do not appear to elicit your senses.

The following three questions below will be asked of you. After you've made your answers take all three scores into account and deliver your overall score for how concrete the tweet is.

A) How clearly does the tweet describe a specific event or scenario?

Vague			*Concrete*		
1	2	3	4	5	6
Very unclear	Unclear	Somewhat unclear	Somewhat clearly	Clearly	Very clearly

B) How effective is the tweet at engaging your senses when you imagine it?

Vague			*Concrete*		
1	2	3	4	5	6
Very ineffective	Ineffective	Somewhat Ineffective	Somewhat Effective	Effective	Very Effective

C) How ambiguous is the words used in the tweets?

Vague			*Concrete*		
1	2	3	4	5	6
Very ambiguous	Ambiguous	Somewhat ambiguous	Somewhat specific	Specific	Very specific

D) Finally, given your evaluation of all the criteria of concreteness, what is your overall score of concreteness for this tweet?

Vague			*Concrete*		
1	2	3	4	5	6
Very Vague	Vague	Somewhat Vague	Somewhat Concrete	Concrete	Very Concrete

<END OF INSTRUCTIONS, BEGIN EXAMPLE SURVEY>

tweet 1 of 50:

@ Macy's: We are having an extremely great sale today. Half off all David Yurman earrings!

Q1) What is the sentiment of this tweet? Select the score with the most appropriate emotion:

Extremely Negative	*Very Negative*	*Moderately Negative*	*Slightly Negative*	*Neutral Sentiment*	*Slightly Positive*	*Moderately Positive*	*Very Positive*	*Extremely Positive*
1	2	3	4	5	6	7	8	9
Upset	Stressed	Nervous	Tense	Informational	Alert	Excited	Elated	Ecstatic
Sad	Unhappy	Depressed	Bored		Calm	Relaxed	Serene	Content

<ONLY SHOWN IF RESPONDED WITH A POSITIVE SENTIMENT (6-9) FOR Q1>
Q2a) *U*se this scale to identify the level of arousal for this tweet. Select the score with the most appropriate emotion:

Low (subdued) arousal					*High (active) arousal*			
1	2	3	4	5	6	7	8	9
Calm	Relaxed	Serene	Contented	Neutral	Happy	Elated	Excited	Alert

<ONLY SHOWN IF RESPONDED WITH A POSITIVE SENTIMENT (1-4) FOR Q1>
Q2b) Use this scale to identify the level of arousal for this tweet. Select the score with the most appropriate emotion:

Low (subdued) arousal					*High (active) arousal*			
1	2	3	4	5	6	7	8	9
Bored	Depressed	Unhappy	Sad	Neutral	Upset	Stressed	Nervous	Tense

<ONLY SHOWN IF RESPONDED WITH NEUTRAL SENTIMENT (5) FOR Q1>
Q2c) Use this scale to identify the level of arousal for this tweet:

Low (subdued) arousal					*High (active) arousal*			
1	2	3	4	5	6	7	8	9

Q3) How clearly does the tweet describe a specific event or scenario?

Vague			*Concrete*		
1	2	3	4	5	6
Very unclear	Unclear	Somewhat unclear	Somewhat clearly	Clearly	Very clearly

Q4) How effective is the tweet at engaging your senses when you imagine it?

Vague			*Concrete*		
1	2	3	4	5	6
Very ineffective	Ineffective	Somewhat Ineffective	Somewhat Effective	Effective	Very Effective

Q5) How ambiguous are the words used in the tweets?

Vague			*Concrete*		
1	2	3	4	5	6
Very ambiguous	Ambiguous	Somewhat ambiguous	Somewhat specific	Specific	Very specific

D) Finally, considering your answers for questions 3 through 5, what is your overall score of concreteness for this tweet?

Vague			*Concrete*		
1	2	3	4	5	6
Very Vague	Vague	Somewhat Vague	Somewhat Concrete	Concrete	Very Concrete

<QUESTIONAIRE WILL REPEAT 50X, EACH TIME PIPING IN A DIFFERENT TWEET>

APPENDIX 4: STUDENT-TO-STUDENT AGREEMENTS AND KRIPPENDORFF'S ALPHAS

	Percent Agreements			Krippendorff's Alphas		
Survey #	Concreteness	Sentiment	Arousal	Concreteness	Sentiment	Arousal
1	88%	90%	88%	0.78	0.73	0.76
2	88%	96%	72%	0.85	0.44	0.60
3	98%	94%	78%	0.83	0.56	0.95
4	98%	90%	94%	0.79	0.86	0.90
5	96%	86%	84%	0.72	0.68	0.88
6	92%	88%	90%	0.74	0.78	0.80
7	92%	88%	92%	0.76	0.82	0.79
8	96%	84%	94%	0.67	0.79	0.89
9	88%	98%	96%	0.96	0.92	0.67
10	92%	90%	88%	0.75	0.74	0.78
11	88%	86%	86%	0.70	0.69	0.76
12	88%	92%	92%	0.84	0.84	0.74
13	90%	86%	86%	0.70	0.72	0.68
14	92%	88%	94%	0.67	0.87	0.83
15	90%	88%	86%	0.76	0.71	0.75
16	80%	96%	92%	0.92	0.84	0.58
17	90%	90%	96%	0.80	0.90	0.77
18	98%	84%	84%	0.64	0.66	0.92
19	92%	90%	92%	0.78	0.71	0.67
20	82%	82%	84%	0.62	0.66	0.63
Total	90.9%	89.3%	88.4%	0.76	0.75	0.77

APPENDIX 5: PYTHON SCRIPT THAT CALCULATES SCORES FOR AROUSAL

```
import csv
import re
import sys
WORD_PAT = re.compile("[-'\w!]+")
WORD_PAIR = re.compile("[-'\w!]+[ /\\:;,.]+[-'\w+!]+")
USER_PAT = re.compile('@\.?\w+')
NUM_WORD_COLUMNS = 23

CONCRETENESS_SCORES_FN = 'arousal_scores.csv'
## ANEW arousal scores were saved as a two column csv with column one being the word and
## column two being the score for that word.
## Here, other wordlists could be used, as long as data for words is formatted as above.
## Script for sentiment were essentially the same, excepting for the average variable (see line 146)
## See line 112 for the input file (Tweets to be coded). Data must be formatted one tweet per line,
## and saved as a .txt file
## Output file will be saved as .csv, with averaged score, boosting scores for caps and !
## and the words used to calculate the score
OUTPUT_FN = 'out.csv'
BANG_BOOST = 1
CAP_BOOST = 1

def tokenize(text):
    """
    >>> tokenize('foo bar bat')
    ['foo', 'bar', 'bat']
    >>> tokenize('foo bar! bat!')
    ['foo', 'bar!', 'bat!']
    >>> tokenize('for cold-weather-related car damage:')
    ['for', 'cold', 'weather', 'related', 'car', 'damage']
    >>> tokenize('much http://www.rolltide.com love')
    ['much', 'http', 'www', 'rolltide', 'com', 'love']
    >>> tokenize('SO PUNK LOVE MUCH!! http://www.rolltide.com #happy #love')
    ['SO', 'PUNK', 'LOVE', 'MUCH!!', 'http', 'www', 'rolltide', 'com', 'happy', 'love']
    """
    """
    # Only if supporting bigram scores:
    #>>> tokenize('foo a cappellas bar')
    #['foo', 'a cappellas', 'bar']
    #>>> tokenize('acid rains acid acid tests')
    #['acid rains', 'acid', 'acid tests']
    """
    word_scores = get_word_scores()
    tokens = []
    pos = 0
    while pos < len(text):
        pair_match = WORD_PAIR.search(text, pos)
        if pair_match:
            pair = text[pair_match.start(0):pair_match.end(0)].strip("-'")
            if pair.strip('!').lower() in word_scores:
                tokens.append(pair)
                pos = pair_match.end(0)
            else:
                word_match = WORD_PAT.search(text, pos)
                word = text[word_match.start(0):word_match.end(0)].strip("-'")
                if '-' in word:
                    if word.strip('!').lower() in word_scores:
                        tokens.append(word)
                    else:
                        tokens.extend(word.split('-'))
                else:
                    tokens.append(word)
                pos = word_match.end(0)
        else:
            word_match = WORD_PAT.search(text, pos)
            if word_match:
```

```
                word = text[word_match.start(0):word_match.end(0)].strip('-')
                if '-' in word:
                    if word.strip('!').lower() in word_scores:
                        tokens.append(word)
                    else:
                        tokens.extend(word.split('-'))
                else:
                    tokens.append(word)
                pos = word_match.end(0)
            else:
                break
    return tokens


word_scores = None
def get_word_scores():
    global word_scores
    if word_scores is None:
        word_scores = {}
        with open(CONCRETENESS_SCORES_FN) as f:
            for line in f:
                word, score = line.split(',')
                word = word.lower()
                word_scores[word] = float(score)
    return word_scores


def remove_at_mentions(text):
    """
    >>> remove_at_mentions('@user blah')
    ' blah'
    >>> remove_at_mentions('foo @user blah')
    'foo  blah'
    >>> remove_at_mentions('@.user blah')
    ' blah'
    """
    return re.sub(USER_PAT, '', text)


def preprocess(tweet):
    return remove_at_mentions(tweet)


def main():
    word_scores = get_word_scores()
    maxlen = 0
    with open('in.txt') as infile:
        with open(OUTPUT_FN, 'wb') as outfile:
            csvwriter = csv.writer(outfile)
            csvwriter.writerow(
                ['tweet', 'average', 'numscores', 'cap_boost', '!_boost'] +
                [ 'word%d' % (n+1) for n in range(0, NUM_WORD_COLUMNS)])
            for tweet in infile:
                bang_boost_total = 0
                cap_boost_total = 0
                tweet = tweet.strip()
                text = preprocess(tweet)
                tokens = tokenize(text)
                token_scores = []
                for token in tokens:
                    if word_scores.get(token.strip('!').lower()):
                        score = word_scores[token.strip('!').lower()]
                        if '!' in token:
                            score += BANG_BOOST
                            bang_boost_total += BANG_BOOST
                        if token == token.upper():
```

```
                        score += CAP_BOOST
                        cap_boost_total += CAP_BOOST
                    token_scores.append((token, score))
            words = [token for token, score in token_scores]
            if len(words) > maxlen:
                maxlen = len(words)
            if len(words) < NUM_WORD_COLUMNS:
                words = words + \
                    ['' for i in range(NUM_WORD_COLUMNS-len(words))]
            scores = [score for token, score in token_scores]
            score = sum(scores)
            try:
                avg = score / len(scores)
            except ZeroDivisionError:
                avg = 5
            csvwriter.writerow([tweet, avg, len(scores),
                cap_boost_total, bang_boost_total] + words)
    # print maxlen # if we need to see the max words length


if __name__=='__main__':
    main()
```

APPENDIX 6: THE TOP 25 MOST RETWEETED TWEETS FROM BRANDS

# of RTs	Brand	Tweet
594	Macys	Now Starring: #RobertPattinson as the (unbelievably gorgeous) new face of @Dior Homme #DiorRob http://t.co/OCSiQrH6b3 http://t.co/9e4Ni1IuDC
568	Macys	Do all hedgehogs age as well as @Sonic_Hedgehog? He hasn't aged a bit since 1991 when we first met! http://t.co/lvFBeQqzRg
514	JCPenney	Tweet #AmexJCP, get $10 back 1x on $50+ qual purchs at JCPenney w/synced Amex Card! (RegLtd Exp 12/31) Terms: http://t.co/xF7oyZGY95
511	Dish	Back-to-back Christmas Full House episodes begin 12/14! Want a happy home, "You got it, dude." http://t.co/ygQPYEvubk http://t.co/nbCPEeDypZ
451	Macys	How proud are you @MicheleMahone?! @AustinMahone did an amazing job! #MacysParade
426	State Farm	Commit to safe driving & you could win a Kelly Clarkson concert at school! http://t.co/HugEWSG5Tf #CelebrateMyDrive http://t.co/3xMTYg1Q6M
400	State Farm	Excellent performance by @Z100NewYork Hometown Hero winner @matthunter123! #Z100JingleBall http://t.co/jRQ3zH06IX
369	LibertyMutual	RETWEET if you can't wait to cheer on #TeamUSA. Only 50 days until the 2014 #Olympic Winter Games! #TeamLM http://t.co/FrWt6onVRX
344	Macys	Hey @HelloKitty, looking cute up there! #MacysParade http://t.co/MLByN72n1R
331	LibertyMutual	RETWEET if like @JazmineFenlator, you won't take no for an answer. #RISE #TeamUSA http://t.co/Hg3Qfoa47W
290	Macys	#MacysParade starts soon! Excited to see @DuckDynastyAE, @AustinMahone & @CherLloyd? Tell 'em. http://t.co/ym7Vgp36fq
270	TWC	It's #MoreSportsMonday w/ the @BuffaloBills! RT & Follow us for chance to win a signed helmet http://t.co/TUVpln93UF http://t.co/SQRs4XOOco
250	TWC	Wrestling Fans! RT & Follow us for a chance to win a @WWE Encyclopedia & WWE2K14 video game for #MoreSportsMonday: http://t.co/TUVpln93UF

250	TWC	Happy #MoreSportsMonday! RT & Follow us for your chance to win a @TeamVic signed football: http://t.co/TUVpln93UF
249	TWC	Today's #MoreSportsMonday prize is all about @UFC! RT & Follow us for a chance to win: http://t.co/TUVpln93UF http://t.co/5Iu05QlYyz
246	Macys	The BIG day is tomorrow...9am to noon! @jimmyfallon, are you ready? #MacysParade http://t.co/HLb4yS1nIC http://t.co/fQv0giEytG
244	Kohls	Everyone's talking about #GetJenniferThere. Where is she going? @TheAMAs! And she's going to need your help: http://t.co/U5XYlTxrxw
243	Kohls	Oh no! @JLo is stuck in traffic on the way to @TheAMAs and needs your help! Vote #JLoRoofRun or #JLoHitch. http://t.co/U5XYlTxrxw
230	Kohls	The paparazzi are in @JLo's way! Make sure she gets to @TheAMAs stage in time. Vote #JLoUseThem or #JLoLoseThem now. http://t.co/FuPbpIReLa
229	TWC	Happy #MoreSportsMonday! RT & Follow us for a chance to win a signed @WWE Encyclopedia & WWE2K14 video game: http://t.co/TUVpln93UF
214	Kohls	Ok guys, @JLo needs your help again! Vote #JLoTunnel or #JLoJailBreak to get her to the @TheAMAs. http://t.co/U5XYlTxrxw
212	TWC	#MoreSportsMonday is a must have for @WWE fans! RT & Follow us for a chance to win: http://t.co/TUVpln93UF http://t.co/q39QN4fsZc
207	TWC	It's #MoreSportsMonday & we've got swag from the @KCChiefs! RT & Follow for a chance to win! http://t.co/TUVpln93UF http://t.co/OVCCRwFzLj
204	Dish	"Merry Christmas, Charlie Brown." Watch Snoopy and gang NOW on DISH Anywhere! http://t.co/hYIQWibV6s http://t.co/CQYPcvGHa9
202	TWC	We're giving away signed @WWE merch for #MoreSportsMonday! RT & Follow us for a chance to win! http://t.co/TUVpln93UF http://t.co/5t0UeFgMfM

APPENDIX 7: THE 25 MOST FAVORITED BRAND TWEETS

# of Favs.	Brand	Tweet
686	LibertyMutual	RETWEET if like @JazmineFenlator, you won't take no for an answer. #RISE #TeamUSA http://t.co/Hg3Qfoa47W
654	Dish	Back-to-back Christmas Full House episodes begin 12/14! Want a happy home, "You got it, dude." http://t.co/ygQPYEvubk http://t.co/nbCPEeDypZ
582	Macys	Do all hedgehogs age as well as @Sonic_Hedgehog? He hasn't aged a bit since 1991 when we first met! http://t.co/lvFBeQqzRg
453	JCPenney	Ready to jingle like your last name's Kringle? Check out some of our top #BlackFriday deals on Pinterest! http://t.co/AhPXRyZZKZ
414	Macys	#Macys #BlackFriday doors open at 8pm! What are you snagging first? We're headed for these: http://t.co/aGLYVDlX95 http://t.co/nmyGghuKuu
401	Macys	Now Starring: #RobertPattinson as the (unbelievably gorgeous) new face of @Dior Homme #DiorRob http://t.co/OCSiQrH6b3 http://t.co/9e4Ni1IuDC
380	State Farm	Excellent performance by @Z100NewYork Hometown Hero winner @matthunter123! #Z100JingleBall http://t.co/jRQ3zH06IX
380	Macys	#MacysParade starts soon! Excited to see @DuckDynastyAE, @AustinMahone & @CherLloyd? Tell 'em. http://t.co/ym7Vgp36fq
380	DirectTV	The @DuckDynastyAE #QuackMatch game is BACK for the holidays! Come play here: http://t.co/QWidpRrbt5 http://t.co/AuakY7Iv4z
363	Macys	How proud are you @MicheleMahone?! @AustinMahone did an amazing job! #MacysParade
319	LibertyMutual	A brother in arms in the #USArmy and on #TeamUSA. @RicoSled23, thank you for your service. #ThrowbackThursday http://t.co/akIoPzJMVv
301	BofA	Watch #BofA Corporate Social Responsibility head Andrew Plepler discuss our #CSR philosophy: http://t.co/5JXrrybuxD
292	Kohls	The paparazzi are in @JLo's way! Make sure she gets to @TheAMAs stage in time. Vote #JLoUseThem or #JLoLoseThem now. http://t.co/FuPbpIReLa

289	JCPenney	We're thankful to @the_USO. Watch as @BlakeShelton sings a salute with the help of our digital choir. #JingleMingle http://t.co/rvAJGry7UD
274	TWC	Duck the halls & get ready for the second annual @DuckDynastyAE Christmas special airing tonight at 10/9c. http://t.co/0ddLkupp4o
272	Macys	Hey @HelloKitty, looking cute up there! #MacysParade http://t.co/MLByN72n1R
268	Dish	"Merry Christmas, Charlie Brown." Watch Snoopy and gang NOW on DISH Anywhere! http://t.co/hYIQWibV6s http://t.co/CQYPcvGHa9
263	DirectTV	Play the @DuckDynastyAE Holiday #QuackMatch game on our Facebook page here: http://t.co/zUbSnRJTv0 http://t.co/ChHnBTpjQW
244	JCPenney	If the tiara fits... http://t.co/Rk6Twpnnjm http://t.co/Ugz6t1KOOx
243	JCPenney	You're not dreaming! Get 30-50% off all bed and bath during our White Sale. http://t.co/qIxyiF1G8g http://t.co/SFVxMEpOnl
240	JCPenney	Bottoms up! #DecorTip #DIY http://t.co/Oid1ZPnq3Q
239	Kohls	Head to our Facebook page and let us know your favorite @JLo #GetJenniferThere moment for a chance to win. http://t.co/IxQNhmMOYt #AMAs
235	LibertyMutual	WATCH #TeamUSA athlete @jenhudak share who inspires her to #RISE and overcome in this video: http://t.co/LWK6xrHA0O #Roadtosochi
234	Kohls	Everyone's talking about #GetJenniferThere. Where is she going? @TheAMAs! And she's going to need your help: http://t.co/U5XYlTxrxw
234	Kohls	Success! Thanks for helping us get @JLo to @TheAMAs in time for her performance! #GetJenniferThere http://t.co/jABGChA8pw #AMAs

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