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Measuring Word of Mouth in Real-Time:

A Study of "Tweets" and Their Dynamic Relationship with Movie Sales and Marketing Efforts.

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ABSTRACT

Title:	Measuring Word of Mouth in Real-Time: A Study of “Tweets” and Their Dynamic Relation to Movie Sales and Marketing Efforts.
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Key Words:	*Word-of-Mouth, Sentiment, Twitter, Marketing, Sales*
Thesis Purpose:	This study aims to test whether electronic word-of-mouth in the form of comments on twitter are representative of overall word-of-mouth. The relationship between marketing, twitter comments, sales is tested and compared to word-of-mouth theory and previous studies.
Methodology:	A combination of cross-sectional research and case study research methodologies were used to understand Twitter messages using primarily quantitative analysis which was supplemented with qualitative analysis where appropriate to understand word of mouth on Twitter and its relationship with existing word of mouth theory.
Theoretical perspective:	The main theories that the study is based upon are theory concerning word-of-mouth and electronic word-of-mouth.
Empirical data:	The empirical data consist of approximately three million comments from twitter.com, box-office data and marketing information concerning 14 movies.
Conclusions:	Twitter can accurately represent the overall population’s WoM for the movie industry and accurately models the relationships between sales, marketing and word of mouth according to WoM theory. This study further demonstrates a practical method for monitoring word of mouth in real time and creates models that could be used to predict future outcomes. Furthermore, the study contributes to existing theory by helping to bridge the gap in understanding the difference between eWoM and traditional WoM by proving that the fundamental effects of WoM whether it is online or offline are the same.

Contents

1 Introduction

This introductory chapter provides the reader with a general introduction of the research area, word-of-mouth, and a review of previous literature. Based on the literature review, a problem discussion is presented, leading up to the aim of this research paper and how it can further our understanding in this field.

1.1 Background

1.1.1 Word-of-mouth

"Word of mouth is the most important element that exists"

- Gordon Weaver, executive VP of marketing for Paramount Pictures, 1984 (Bayus, 1985, p.31)

The fact that consumers acquire information concerning products and services from other people, especially family members and friends is well documented in marketing literature (Bayus, 1985). This interaction is generally referred to as word-of-mouth (WoM) and its influence on consumer behavior has long been an important topic for both marketing researchers and practitioners (Gruen et al., 2006). WoM can be defined as; informal communication between consumers regarding the ownership, usage, experience or characteristics of a product or service. (Steffes & Burgee, 2009; Sen & Lerman, 2007) It is usually interactive, swift and lacking in commercial bias (East et al., 2008).

According to previous research, WoM is one of the most powerful forces in the consumer marketplace (Sen & Lerman, 2007; Bansal & Voyer, 2000). Compared to all other sources of information consumers are being exposed to, WoM is considered the most credible and it has a strong influence on consumers' attitudes (Godes and Mayzlin, 2004; Brown & Reingen, 1987). Furthermore, research has shown that WoM has a significant impact on consumer purchase behavior (e.g. Richins & Root-Shaffer, 1988; Richins, 1983). Many practitioners therefore believe that the success of a product depends on the word-of-mouth that is generated (Godes and Mayzlin, 2004).

1.1.3 Electronic word-of-mouth

The evolution of the internet and social media has recently created the phenomena of electronic WoM (eWoM). One of the most significant aspects of the internet compared to previous mass communication technologies is its bi-directionality. The internet not only allows organizations to reach a vast audience at a low cost, but for the first time in human history individuals can also communicate their thoughts, reactions and opinions to a global community of internet users. (Dellarocas, 2003)

EWoM can be defined as a "statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the internet" (Hennig-Thurau et al. In Jansen et al, 2009, p. 2). EWoM and traditional WoM share the same fundamental similarities in purpose; however, differences also exist. Whereas traditional WoM interactions are immediate and intimate conversations, eWoM is usually an asynchronous process whereby sender and receiver are separated by both time and space. Furthermore, traditional WoM is generally conducted in small groups of two or more where the sender is known by the receiver. EWoM takes place on the internet giving it potentially unlimited reach, creating a one-to-world interaction rather than a one-to-one interaction. Finally, the power and influence of regular WoM stems from the credibility given to the message based on the strength of the relationship between the two parties. However, this does not apply to eWoM. On the contrary, research has shown that users rate anonymous sources of information as more important than strong or weak tie sources. (Steffes & Burgee, 2009)

EWoM exhibits similarities to traditional WoM in that it has a strong influence on consumers' purchasing behavior. However, it has magnified the impact of consumer-to-consumer communication in the marketplace (Mangold & Faulds, 2009). Furthermore, the amount of consumer-to-consumer communication through social media has seen a dramatic growth over the past decade, making eWoM a "major factor in influencing consumer behavior including awareness, information acquisition, opinions, attitudes, purchase behavior, and post-purchase communication and evaluation" (Ibid).

Recent studies, which are presented in more detail in the literature review, suggest that eWoM and traditional WoM exhibit the same patterns and that previous knowledge of traditional WoM can be used when studying eWoM. Results have also shown that eWoM could actually be representative of traditional WoM. However, the methods for measuring eWoM compared to traditional WoM are completely different. What makes eWoM significantly more interesting for practitioners and researchers is its accessibility. The public interaction that social media provides, makes it possible to monitor WoM discussions from an objective standpoint without interfering with it, making it highly interesting for research purposes.

1.1.4 Word-of-mouth terminology

This thesis separates WoM into three different categories. "Traditional WoM" is used when referring to offline WoM. "eWoM" is used when referring to electronic WoM. Finally "WoM" is used when referring to WoM as a general phenomenon. eWoM and traditional WoM might exhibit some differences due to how they are transmitted, but are fundamentally the same thing. The term "buzz" is also used in this paper and is used when talking about WoM in a quantitative way.

1.1.5 Social media

Social media is the umbrella term used for online platforms where users can participate, create and share content. Social media has its roots as far back as 1970, but it was not until the creation of MySpace in 2003 that social media exploded in popularity. This was followed by Facebook, YouTube and most recently Twitter in 2006. "Twitter is a real-time information network powered by people all around the world that lets you share and discover what's happening now" (twitter.com). Twitter is a microblog that lets people share short comments to a network of family, friends, associates or other people (Jansen et al. 2009).

Microblogging is a new form of eWoM that might have a big impact on the implications of eWoM. First of all, it allows people to share brand-affecting thoughts almost everywhere (i.e., while getting coffee, driving, shopping or sitting by their computer) to almost anyone that is "connected" (e.g. web, cellphone, email, instant messaging) on a scale that has not been seen before (Jansen et al., 2009). What also makes maicroblogs unique compared to other eWoM mediums is the fact that people are limited to writing short statements that are approximately the length of a newspaper headline and subhead, making it easy and quick to both write and read. Messages are also non-invasive as users choose who to receive updates from. Messages posted on microblogs such as twitter are also publically available data. This differs substantially from some other social media platforms, for example Facebook's protected service structure, because it makes the data easily accessible to anyone. What microblogging offers in the end is access to real-time opinions, which provide insight into consumers' reactions towards products and services at a critical junction of the decision-making and purchasing process. (Jansen et al., 2009)

Microblogging is also a fast growing phenomenon, with the amount of twitter users in the US growing from 2.7 million in 2008 to 18.1 million in 2009. Today, 55 million tweets are being made per day (Evan Williams, Twitter CEO, April 15th 2010 quoted on gigaom.com), making it the largest real-time source of public user opinions available. With these numbers there is no doubt that using twitter.com for mining user opinions offers an interesting opportunity for both researchers and practitioners. This makes eWoM a significant source of WoM, but very little previous research has been conducted testing WoM theory with eWoM data.

1.2 Literature review

The strong influence of traditional WoM on consumers' purchase behavior is well established in previous research. One such research conducted by Dye (2000) indicates that WoM drove 2/3 of purchases in the United States. Since the evolution of eWoM, there has been a renewed interest in researching WoM, with a focus on why people engage in it, its purpose and its impact (e.g. Dellarocas, 2003; Hennig-Thurau & Walsh, 2004). Several studies have looked at consumers' use of product ratings and online reviews of tangible products on websites such as Amazon, eBay, CNET and Epinions (e.g. Klein and Ford, 2003; Ratchford et al., 2003). Results from these studies have shown that consumers rely on eWoM for making purchase decisions.

There has been a lot of research on the topic of why consumers engage in WoM, such as Nardi et al. (2004) and Anderson (1998), with a significant amount looking at negative WoM, such as Richins (1983) and Blodgett et al. (1993). The consensus is that consumers who experience extreme satisfaction or dissatisfaction are more prone to engage in WoM. Previous research has also looked at why consumers seek opinions online such as Hennig-Thurau and Walsh (2004) and Goldsmith and Horowitz (2006). They conclude that consumer seek opinions online for several reasons but mainly to reduce risk and to make better buying decisions.

While the importance of WoM on consumer decision making processes and why people engage in WoM has been well established in previous research, nearly all existing WoM research is grounded in off-line research and experimentation (Steffes & Burgee, 2009). One study grounded in eWoM was conducted by Godes and Mayzlin (2004), who went about trying to measure the impact of eWoM on the ratings of TV shows using publicly accessible data in the form of Usenet newsgroups, which are discussion boards similar to forums. They state that the "existence of a publicly accessible reservoir of observable person-to-person communications is unprecedented." Using this method, the study could be conducted at minimal cost, especially compared to regular methods of gathering opinion data. They argue that their results support the idea that at least some aspects of eWoM are proxies for overall WoM. However, this is questioned by East, Hammond & Lomax (2008) who state "that there may be little correspondence between the content of consumer-generated media and face-to-face advice," they continue to state that eWoM is likely to become an increasingly important form of WoM.

Dellarocas and Narayan (2006) conducted a study based on the fact that the emergence of online communities has enabled organizations to monitor consumer-generated eWoM, in the form of user ratings online. Using eWoM they aimed to establish the populations' propensity to rate products online. Their results indicate that eWoM exhibits several relationships to previous research on offline WoM, suggesting that the antecedents of offline and online WoM are similar. This implies that previous research on offline WoM can apply to the online domain. They conclude that "these insights, together with the new ability to measure aspects of WoM in real-time by mining publicly available data from Internet communities, can lead to substantial advances in the ability of organizations to manage WoM."(Dellarocas and Narayan, 2006)

Davis and Khazanchi (2008) studied the influence of eWoM in the form of user reviews on e-commerce sales. In their study, they used sales data from an e-commerce website selling multiple products. Their results show that the volume of detailed reviews with pictures has a significant influence on changes in product sales. Liu (2006) used user comments from the yahoo movies message board (http://movies.yahoo.com) to measure eWoM patterns and their influence on box-office revenue. They used manual analysis of 12 136 comments about 40 movies during a five month period. Their results indicate that eWoM "offers significant explanatory power for box office revenue" (Liu, 2006, p. 86).

During the writing of this thesis (March 29, 2010), a paper was released by two authors working at HP Labs in California (Asur & Huberman, 2010). The paper has not yet been published or peer reviewed. The aim of their paper was to demonstrate how social media content could be used to predict real-world outcomes. The structure of their study and the data that they used is very similar to this study. Slightly different methods and variables are used, but the results from both papers are comparable. The purpose of study and this study are however substantially different in nature. Asur and Huberman conducted a scientific study with the aim of predicting future sales. However, their paper does not use or aim to contribute to WoM theory or investigate the marketing implications of such a system. This study on the other hand aims to further the understanding of eWoM in relation to traditional WoM as well as the implications for researchers and practitioners in the field of marketing and WoM. This study will be based on existing WoM theory in order to test eWoM. This study also tests more variables and their impact on sales in order to test a wide range of previously established and debated aspects of WoM. Furthermore, marketing efforts' impact on eWoM is also measured and analyzed using previous WoM theory. Asur and Huberman's study will be used in our theoretical framework and their results will, when appropriate, be compared to ours when the empirical data is analyzed because of the similarities in method.

1.3 Problem discussion

In previous research, traditional WoM has been shown to affect consumer purchase intentions and behavior. The evolution of eWoM has magnified the reach and impact of

WoM making it a dominant force in affecting consumer purchase behavior. Furthermore, the rapid growth of social media means that more and more people are sharing their opinions online. To study this evolution of WoM, the phenomena of microblogging and its particular characteristics, presented earlier, show great potential. People share thoughts on brands, products and experiences as they think it, wherever they are, in a simple format that is accessible by anyone, on a scale that has never been seen before (55 million tweets per day on twitter.com). The study by Jansen et al. (2009) showed that 19% of all tweets mention a brand.

However, very little research exists that studies the implications and possibilities of mining data from this enormous source of consumer opinions. Studies using far more limited sources of user opinions seem to indicate that eWoM might be a proxy for some aspects of regular WoM. If this is the case, the potential insights that might be extractable at a very low cost could be of great interest for both researchers and practitioners.

1.4 Research aim

The aim of this thesis is to see if eWoM in the form of comments on twitter are representative of overall WoM. As WoM is generally considered to have a significant impact on consumer purchase behavior, this study aims to test the correlation between eWoM on twitter and actual sales. Furthermore, the impact of marketing efforts on WoM is explored by studying their short term and long term impact on WoM. Whether WoM and eWoM do in fact follow the same patterns will be tested by analyzing the results using existing theory on WoM. The results will be compared to previous results, contributing to the understanding of the similarities and differences between eWoM and traditional WoM, and of how they relate to marketing and sales.

The methods used in this paper will also provide new insights into the potential of studying eWoM in the form of microblogging using new techniques for measuring WoM in real-time. These advances in the measuring of WoM offers marketers and researchers new tools that could have a significant impact on their ability to study and manage WoM at an unprecedented scale and speed at a significantly lower cost than traditional techniques.

1.5 Research Questions

Does eWoM on Twitter accurately represent overall WoM?

What is the relationship between marketing, WoM and sales?

1.6 Outline of the paper

In order to answer these questions, the following chapter presents WoM theories on which several hypotheses are formulated. This is followed by the third chapter in which the methodological considerations and research design is presented and argued for. An explanation of how the hypotheses will be answered will also be presented. The fourth chapter, results, tests the hypotheses by analyzing the results. An analysis of this study's results with regards to the existing theory is then presented. The study ends with a conclusion, where the researchers' own conclusions and explanations are made, as well as the implications of the study and future research topics are discussed.

2 Theoretical Framework

This section will begin with a model which illustrates the role of WoM in a marketing setting, which can be used to understand the relationship between marketing efforts, WoM and sales. This will be followed by presentation of previous WoM theories based on which our results will be tested. Hypotheses are formulated based on these theories to test whether data gathered from twitter behaves like traditional WoM. The standard null hypothesis testing method is used where each claim is tested and can only be accepted after showing a statistically significant result contrary to the null hypothesis.

2.1 A model for word-of-mouth

In marketing models form the 70s and 80s, sales was seen as the only relevant state variable in the system, and the focus was usually on the effects of marketing efforts on sales. Marketing efforts were seen as an input variable, and when WoM was included in the models it was modeled as a function of sales. (Bayus, 1985)

Based on previous research and the introduction of a new perspective on the role of WoM, Bayus (1985) developed the following model, mapping the interaction between marketing efforts, WoM and sales.

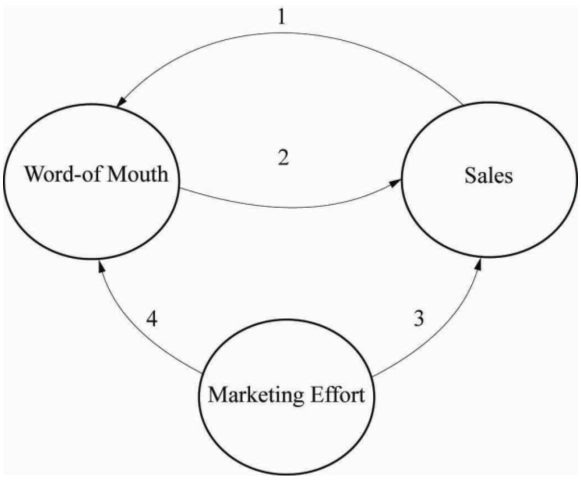

Figure 1: The conceptual model structure (Bayus, 1985)

In this model, sales influence the amount of WoM activity in the marketplace (1) (i.e. buyers expressing their opinions about a product). In turn, WoM influences actual sales (2). Marketing efforts have a direct impact on sales (3), but also influence WoM activity (4). Even though he doesn't define WoM, Bayus states that WoM should not be limited to only verbal communication. Godes et al. (2005) also brings out the discussion concerning the term WoM and its definitions, arguing that the term "social interaction" should be used instead. This can be in the form of face-to-face recommendations or just a stranger using a product. (Godes et al. 2005)

Bayus argues that viewing the marketing system in this way allows for new insights into marketing behavior possible. He points out the possible interaction between WoM and marketing efforts, stating that the current amount and type (i.e. positive or negative) of WoM might influence the effectiveness of current marketing campaigns. One example is that the influence between WoM and sales can create what he calls a "homeostatic or a positive feedback (growth) situation”. The implication of this being that the strength of path 3 relative to path 2 diminishes as sales increase. As WoM can increase sales and sales can increase WoM, at a certain point it might be possible cease the marketing efforts and still sustain the market share or even possibly increase it. Adding that “advertising heavily early in the product life cycle makes sense, since the ultimate goal is to let word of mouth take over.” On the topic of monitoring WoM, Bayus states that it could be done to measure the effects of marketing efforts and monitoring the amount generated by sales. If a lot of WoM is generated as a result of sales, the product will penetrate the market quicker and deeper.

2.2 Word-of-mouth

Yang and Zhang state that the content of the WoM people engage in can vary in two aspects, volume and valence. Liu (2006) suggests that valence produces the cognitive consequence of attitude while volume produces the cognitive consequence of awareness. Most previous studies have focused on examining either volume or valence due to limited data availability. (Liu, 2006)

Volume refers to the total amount of WoM interactions (Liu, 2006). It is well established in previous research that volume of WoM has a significant correlation with consumer purchase behavior and market outcome (e.g. Bowman & Narayandas, 2001; Liu, 2006; Davis & Khazanchi, 2008). Some studies on consumer reviews also argue that it is only the volume of reviews that matter, not the valence (Duan et al. 2005; Chen et al. in Davis & Khazanchi, 2008). The reason that is often presented in explaining this strong correlation is that the pure volume of WoM represents and influences consumer awareness. It is previously well established that increased awareness will lead to increased sales. The more WoM there is, the more likely it is that someone will be informed about the product, i.e. awareness of the product or service is increased. (Duan et al. 2008)

In the study by Godes and Mayzlin (2004) in which the impact of eWoM on TV ratings (number of viewers) was measured, the results obtained were unable to demonstrate a strong relationship between WoM and TV ratings. One possible reason for this is presented by Keller and Fay (in East et al., 2008) who in their study on what influences consumption found that “8% of advice was Web mediated, 70% was face-to-face, and 19% was by telephone”. The problem being “that there may be little correspondence between the content of consumer-generated media and face-to-face advice” (East, Hammond & Lomax, 2008). However; East et al. (2008) add that eWoM is likely to become an increasingly important form of WoM. In their conclusion, Godes and Mayzlin (2004) state that “First and foremost, more work is needed to identify the causal link between WoM and future sales” (p. 558).

> ***H1 Null:*** *The volume of twitter messages talking about movies does not correlate with future sales*
>
> ***H1 Alternative:*** *The volume of twitter messages talking about movies does correlate with future sales*

Valence refers to whether the WoM is positive or negative. In research that studies opinions, the term sentiment is often used when talking about valence. These studies usually classify sentiment into positive, negative and neutral, as an opinion can contain opinions or statements that contain no sentiment. Some examples of neutral sentiment are “I own a

Ford" or "I am flying to China with Air Asia." The actual effect valence has on sales is a topic that has been studied many times, but no clear consensus has been established. Positive WoM is usually either a direct recommendation to purchase a product or service, or an indirect recommendation. Negative WoM can be a criticism or complaint concerning a product or service. Both types of WoM are believed to influence purchase probability, with positive WoM encouraging it and negative WoM discouraging it. Valence is believed to influence consumers' attitude towards a product and therefore it has an impact on sales. Positive WoM increases expected quality, which improves consumers' attitude towards a product, whereas negative WoM reduces it.

The assumption is that purchase probability is a result of the relative amount and impact of positive WoM compared to negative WoM (East et al., 2008). It is also widely believed that negative WoM is more influential than positive WoM (Ibid). One study which is often cited when talking about the effects of positive WoM vs. negative WoM is Arndt (1967). This is one of the earliest studies that tried to measure how WoM affects purchase behavior. Arndt concludes that the influence of negative WoM is twice as strong as positive WoM. East et al. (2008) are critical to this assumption, stating that *"there is little evidence on this matter, which may relate to the difficulty of making accurate measurements in this field"* (East et al., 2008). In their study; East et al. (2008) studied the impact of negative WoM and positive WoM on purchase probability in multiple categories, using a mixture of role-play experiments and survey methods. Their results indicate that positive WoM has more effect than negative WoM in familiar categories. Furthermore, Zhu and Zhang (in Davis & Khazanchi, 2008) studied the effects of consumer ratings on sales of videogames and their results showed that a higher rating by only one point meant 4% higher sales. Their results suggest that valence is the best WoM attribute when it comes to predicting sales.

H2 Null: *Negative twitter WoM does not correlate with movie sales*

H2 Alternative: *Negative twitter WoM does correlate with movie sales*

H3 Null: *Positive twitter WoM does not correlate with movie sales*

H3 Alternative: *Positive twitter WoM does correlate with movie sales*

H4 Null: *The relative amount of positive WoM compared to negative WoM does not correlate with movie sales.*

H4 Alternative: *The relative amount of positive WoM compared to negative WoM does correlate with movie sales.*

There are two stages of WoM for consumers. The first stage is before a purchase decision, when a consumer listens to WoM in order to make a decision. If the consumer ends up purchasing the product, there is the potential that he/she might share his or her experience of the product to other consumers, which is the second stage. As it was illustrated in the model by Bayus (1985) presented earlier, this means that WoM not only influences sales it is also influenced by sales. Godes and Mayzlin (2004) identify the fact that WoM is not exogenous as a challenge when it comes to measuring the impact of WoM on sales. This has significant implications for the measuring of WoM, creating the need to understand the dynamic relationship between WoM and sales.

H5 Null: *The box office sales do not correlate with the future volume of twitter messages.*

H5 Alternative: *The box office sales do correlate with the future volume of twitter messages.*

What is problematic about WoM as a marketing tool is the fact that it is generated by the consumers and can therefore not be controlled directly by companies. As a result, the focus of research and what practitioners seek to understand is how companies can affect consumers' WoM communication. There have been two main methods that have been the focus of research on the topic of triggering positive WoM; the first is through advertising and promotion, and the second is through customer satisfaction.

Bayus (1985) stated that the notion that marketing efforts can affect WoM was suggested by several early studies, but never rigorously demonstrated. The results of his study show that word of mouth can be stimulated by increasing or decreasing marketing efforts. Yang and Zhang (2009) studied the effects of marketing efforts on WoM and their results show that marketing efforts do influence WoM. Marketing activities can for example generate interest from customers, activating them to search for further information through WoM.

H6 Null: *An increase in the volume of twitter messages as a result of marketing efforts cannot be measured.*

H6 Alternative: *An increase in the volume of twitter messages as a result of marketing efforts can be measured.*

The effect of customer satisfaction on WoM has been established in several studies. Oliver (1993) established that customer satisfaction is a factor in building customer loyalty. Ranaweera and Prabhu (2003) also conducted a study on customer satisfaction, concluding that it can generate positive WoM. Several studies in the service sector have validated the link between satisfaction and the likeliness of customer to engage in positive WoM (Knauer in Mangold et al., 1999). Furthermore, Wetzer et al.(2007) state that people share their feelings shortly after they have experienced a product or service.

In a study conducted by the US office of consumer affairs, the results indicate that satisfied customers usually share their experience and opinion with five other people (Knauer in Mangold et al., 1999). Dissatisfied customers, on the other hand, share their experience and opinion with nine other people. Due to how eWoM works, opinions are not shared to a limited amount of people but are instead shared openly. Previous research shows that people behave differently when engaging in eWoM compared to a regular face-to-face WoM situation. They demonstrate fewer inhibitions, display less social anxiety, and display less public self-awareness when communicating online. People engaging in eWoM tend to be more willing to disclose personal information and more honest and forthcoming in presenting their personal viewpoints. (Roed, 2003)

In a study conducted by Fiske (1980), the observation was made that negative WoM is usually rarer than positive WoM (East et al., 2008). This is confirmed by later studies such as Bowman & Narayandas (2001), where positive attitude towards brands was more common which leads to more positive WoM occurring than negative WoM. Results from the study conducted by Liu (2006) on consumer opinions of movies, also shows more positive WoM than negative WoM.

H7 Null: *Positive WoM in the form of twitter comments is not more common than Negative WoM.*

H7 Alternative: *Positive WoM in the form of twitter comments is more common than Negative WoM*

A few previous studies, which have been mentioned earlier, have looked at the impact of eWoM on box office revenue (Godes and Mayzlin 2004; Duan et al. 2005; Liu, 2006; and Asur & Huberman, 2010). This previous literature has established that the number of screens on which a movie is shown has a strong influence on box office revenue. The number of screens captures the distribution intensity, which provides information on the audiences' accessibility to movies. However, the amount of screens in and of itself is not a strong measure of expected sales as movie theaters rarely use their full capacity, with an estimated average capacity utilization of less than 20%. WoM works as third-party information for potential movie goers, which they might rely on in their decision-making process. WoM also constitutes the awareness of the potential audience and can help explain the variation in capacity utilization of the theaters. (Liu, 2006)

Previous research studies have also all indicated that volume of eWoM has a strong relationship to box office sales. The influence of valence has shown different results. Some studies on the effects of eWoM on sales question whether valence actually has an effect on sales as their results don't seem to support it (Liu, 2006; Davis and Khazanchi, 2007). Liu (2006) measured both the volume and valence of posts on yahoo movies message board and examined their impact on box office revenue. Their results indicate that valence has no explanatory power on box office sales. However, the most recent study conducted by Asur and Huberman (2010) shows that valence does provide some explanatory power for future box office sales. Volume of WoM is however shown to be the most important variable in explaining box office sales, with valence improving its explanatory power.

3 Methodological considerations

This chapter will begin with a presentation of the research method and why it has been chosen. This will be followed by a presentation of the data collection techniques used and procedures used for data analysis. The chapter will end with a reflection on the limitations of the chosen method.

3.1 Research Method

To better understand the goals of our research it is necessary to explain in detail the processes that underlie our results and conclusions. First and foremost it is important to elaborate on the philosophical stance taken by the researchers. Since our research is quantitative in nature it would be somewhat natural to assume a positivistic approach. However, our study looks at human nature and examines word-of-mouth in a microcosm (Twitter) that reflects society as a whole. Since it is a human system it is exceptionally difficult to prove causality as an outside observer on such a massive scale. Our research can show correlation but often has difficulty showing causation. Therefore, our research has aspects of both positivism and social constructionism. Our research takes the following aspects of positivism: it is independent, it needs to be defined in measurable units, it is reduced into simple terms such as volume and sentiment, it will have statistical probability and it is sampled in large numbers. Our research takes the following aspects of social constructionism: it is centred on human interest, aims to increase general understanding of the nature of electronic word-of-mouth and there may be theoretical abstraction upon further investigation (Easterby-Smith, 2008).

The ontological position of this paper is founded in constructionism. Constructionism views the world as created by and dependent on those within in the system in contrast with objectivism which asserts the world exists and the actors don't influence the nature of things (Bryman & Bell, 2003). Since we are looking at word-of-mouth it is very difficult to take a objectivist position, which would be most natural for quantitative research, because word-of-mouth by definition is a constructed social phenomena.

3.2 Research Design

The three criteria our research must meet are: reliability, replication and validity (Bryman & Bell, 2003). The reliability of our study is defined in the ability to repeat the study and get the same results. This will be possible; possibly with the original dataset within a year because the nature of our data source is open and published (Twitter is publishing all their data in the Library of Congress for researchers to access). This republishing of all the data makes they study exactly replicable. However, the validity of our studies will be accurate for the timeframe that our study was conducted over. Our study will have measurement validity, ecological validity, and external validity. The criterion of internal validity is hard to assess because we are looking at real word-of-mouth activity without any controls. Thus we are limited to studying correlation which does not necessarily mean causation. A different method of investigation would be required to confirm or deny causation (Bryman and Bell, 2003).

The research approach used is both deductive and inductive in different cases. Both approaches offer valuable techniques for understanding existing theory, testing theories and generating new theories. The deductive approach is most often associated with quantitative research and most often tests the existing theory (Bryman & Bell, 2003). A deductive approach is used while testing some of the larger assumptions such as identifying the correlation between word-of-mouth and sales. To understand causation and put it into a marketing context, the behavior observed must be looked at with an inductive approach. An inductive approach is used to generate theory; it generally looks at data and allows researchers to try and generate theory based on observed results (Bryman & Bell, 2003). The vast amount of data that is collected can be looked at in a qualitative fashion to further understand changes in the quantitative measurements. In such cases an inductive approach is necessary to fully understand and analyze the data collected.

The design our research takes is complex and a hybrid model because of the nature of the data we are working with. In most respects we are performing a quantitative study because of the immense amount of data we are working with (millions of Twitter messages). On the other hand we also use some qualitative methods such as determining sentiment (we are actually transforming qualitative data into quantitative data which will be further explained in the data processing section).

A cross-sectional research design is used in the study. The research question being answered requires many cases (movies) and looks for correlation to help elicit understanding. A cross-sectional research design is the logical choice because (1) more than one case is being studied, (2) each word-of-mouth message is at a single point in time, (3) quantitative and quantifiable data is being collected and (4) patterns of association are being studied to show correlation (Bryman & Bell). The weakness of this method of study is that we are limited to correlation because the variables cannot be manipulated like an experimental or quasi-experimental study which would show causation (Bryman & Bell, 2003).

The research also calls for some use of case study design to investigate deeper into quantitative data and explain causation which the cross-sectional research design lacks the ability to show. This mixed method research allows the researchers to fill in gaps in the cross-sectional research design, namely the requirement of internal validity, to allow for an understanding of causation on top of correlation (Bryman & Bell, 2003).

3.3 Data Collection

Sampling is very important for quantitative research and the key to making valid conclusions is a sample that is representative of the population (Easterby-Smith, 2008). The population that the research question is interested in is the general population and examines the representativeness and behavior of the sample in comparison with the overall population. The research conducted uses a systematic sampling procedure because it takes all the public data on Twitter that everyone posts and puts it into our database. The only sampling aspect of the research is whether Twitter users are representative of the population as a whole which is the research question. There are likely to be some under-represented demographics because the service is technological and relatively recent therefore a younger and wealthier skew would be expected. However, since this study is examining movie word-of-mouth it is generally within reach of everyone in the society and the users on Twitter should match the overall population's opinions as they are irrelevant to the technology and the potential demographic skew.

The method of data collection used is structured observation. Structured observation is observing behavior directly (Bryman & Bell, 2003). This method has many advantages over indirect methods because the participants being observed are actually performing the behaviors rather than saying or implying what they would or might do. This overcomes issues where participants say one thing and do another. The researchers using structured observation are in fact measuring real human behavior which brings a more accurate representation of reality.

The schedule used for the structured observation in this research in simple: if anyone mentions a movie name from our list of 40 movies it is observed and recorded into the database automatically by the software. This clear definition makes the research easily repeatable and allows researchers to aggregate the results to draw conclusions (Bryman & Bell, 2003). This method also fits naturally with the cross-sectional research design this study uses (Bryman & Bell, 2003).

The primary concerns which need to be addressed are reliability and validity when performing structured observation. A clear set of rules for observation is established to allow inter-observer effects to be minimalized (Bryman & Bell, 2003). This problem is addressed by automating all of the data collection with software allowing for one 'observer,' the software, to do all of the observations with perfectly consistent judgement. To address the issues of validity the research must address whether or not is has measurement validity. The first component of measurement validity is determining whether the research is measuring the proper variables to answer the research question. In this case the research needs either face, predictive, concurrent, construct or convergent validity (Bryman & Bell, 2003). The research in this paper meets face validity in that actual word-of-mouth is being observed and measured which for all intents and purposes should be considered word-of-mouth. It also has construct validity because the role of word-of-mouth in the larger marketing ecosystem is being examined used existing theoretical models and research. The second component of validity is addressing implementation error: was it implemented properly and do people modify their behavior (Bryman & Bell, 2003)? In the former case, the software used solves implementation issues by providing a uniform, consistent and fair observer. The latter case is not an issue because the observers have no knowledge that they are being observed other for this purpose. There is an underlying knowledge that anything published on the service is by definition public but no special consideration is given to our research in general.

Our primary data is collected from Twitter. Twitter is a social-network where users publicly write messages up to 140 characters long (140 characters is because of a SMS limitation because the system was originally intended to allow instant communication online and through text messaging). Currently, there are over 105 million users and 180 million unique visitors per month according to co-founder Biz Stone (gigaom.com).

The software collecting the data was written to mine search results from Twitter at 2 minute intervals. The timing was tweaked to balance the volume of data collection while maintaining a stable server and unrestricted access to Twitter. Faster collection rates overloaded our server and could get our server blocked from accessing Twitter for abuse. We collected data for 40 movies (12 movies were only early tests to ensure the software was functional and scalable while the other 28 movies were selected and used in the study because of release dates coinciding with our window of opportunity to do research and publish this paper) to collect data starting January 27, 2010 at the earliest.

The process the software collected data was in the following manner:
For every movie in the database (40 movies):

1. Collect last 15 messages containing the movie title (twitter search RSS feeds were used).
2. Check each message against last 15 messages entered to make sure duplicates are not entered.
3. If the message is new, it is inserted into the database in full with timestamp and source.

This process was repeated every 2 minutes for every movie.

Secondary sources for data were also required to fully understand how word of mouth and box office sales were related. IMDb's Box Office Mojo service was used for box office sales data. Ratings of movies were also gathered from multiple sources manually. The three sources for ratings were: IMDb, Rotten Tomatoes and Meta Critic. They were all collected on May 16, 2010 on movies that had three or more weeks of data collected. The users' (not critics') rating was used from all three sources because we are studying actual movie goers (not critics). Furthermore, TrailerAddict.com was used to find out marketing information, specifically when trailers and TV spots were released.

3.4 Data Processing

The data collected during the course of this study will be analysed using bivariate analysis and multivariate analysis. Bivariate analysis compares two variables in order to seek understanding of the relationship (Bryman & Bell, 2003). This type of analysis is the logical choice for addressing the broadest question in this research: does twitter buzz (eWoM) correlate with box office results? Bivariate analysis will allow investigation into the nature of the relationship between the two (correlation) but not prove causation (which is a previously stated limit of this research).

Multivariate analysis will also be employed to seek to further understand and gain meaning from the data collected. The other variables which will be investigated in this research are sentiment (the classification of meaning into positive, negative and neutral messages in word-of-mouth), the number of theaters a movie was playing in on the particular weekend, ratings and potentially marketing efforts from the movie companies such as a trailer release or other campaign during the lead up to a movie release. There are also calculated variables such as the positive-to-negative ratio, positive-to-neutral ratio and negative-to-neutral ratio which will be used in multivariate analysis

Variables	Type of variable
Box Office Sales	Dependent Variable, Independent Variable
Buzz (WOM)	Dependent Variable, Independent Variable
Positive Buzz	Independent Variable
Negative Buzz	Independent Variable
Neutral Buzz	Independent Variable
Positive to Negative Ratio	Independent Variable, Calculated
Positive to Neutral Ratio	Independent Variable, Calculated
Negative to Neutral Ratio	Independent Variable, Calculated
Number of Movie Theaters	Independent Variable
Movie Ratings (IMDB,Rotten Tomatoes, MetaCritic	Dependent Variable, Independet Variable
Marketing Efforts	Independent Variable

Figure 2: List of variables used in regression

Proper coding of the data is essential to ensure reliability. There will be very large challenges namely in the area of sentiment analysis with regards to codification. The sentiment analysis technique used for this research is an *enhanced term-counting method* (Kennedy & Inkpen, 2006). The *term-counting method* attempts to classify whether the sentiment is positive or negative by determining whether there are more positive or negative words in the text. If there are more positive words than negative words the selection of text is deemed to be positive and vice versa. If there are equal amounts of positive and negative words then the sentiment is classified as neutral. The *enhanced term-counting method* expands on this initial strategy by using *valence shifters* to understand words such as 'not' which alters positive and negative connotations of words. For example the text 'I did not like the movie' in a basic *term-counting method* would be classified positive because the word 'like' increases the positive count to one and there are no negative words. However, in the *enhanced term-counting method* the valence shifter 'not' is identified which reverses the sentiment associated with the word 'like' making it the opposite of 'like' which is negative. Therefore, 'not like' is identified as negative and the sentiment analysis performed is more accurate. The only major deviation made from this method was a special case for categorizing intent to see as positive. For instance 'I want to see iron man 2' was categorized as positive because it expresses intent to see the movie and could be said to influence those within the social group to see it with the author of the tweet. The opposite (valence shift) of wanting to see a movie was also taken into account 'I do not want to see iron man 2' would be categorized as negative.

There are more advanced sentiment analysis techniques discussed by Kennedy and Inkpen (2006) which involve machine learning (ML) but are beyond the capabilities of the researchers due to time and complexity. Machine learning techniques are superior to *enhanced term-counting methods* varying by approximately 60-70% (enhanced term-counting) to 80% (ML) (Kennedy & Inkpen, 2006).

The entire collection and processing was done on a Windows/Linux, Apache, MySql and PHP (W/LAMP) stack, which are the operating system, web server, database and programming lanuage. The data collection was done on the LAMP stack which was the primary source for all data. A secondary computer running a WAMP stack was used to do sentiment analysis and calculations. The technology used was chosen because of the stability and popularity of the systems. The other major factor in deciding how to handle data collection and processing was the knowledge of the researchers. In this case the researchers felt most comfortable working with the PHP programming language and MySql database to achieve what was necessary. Existing data collection software written by the researchers for previous applications was written in PHP and MySql; therefore it made sense to re-use these same proven techniques.

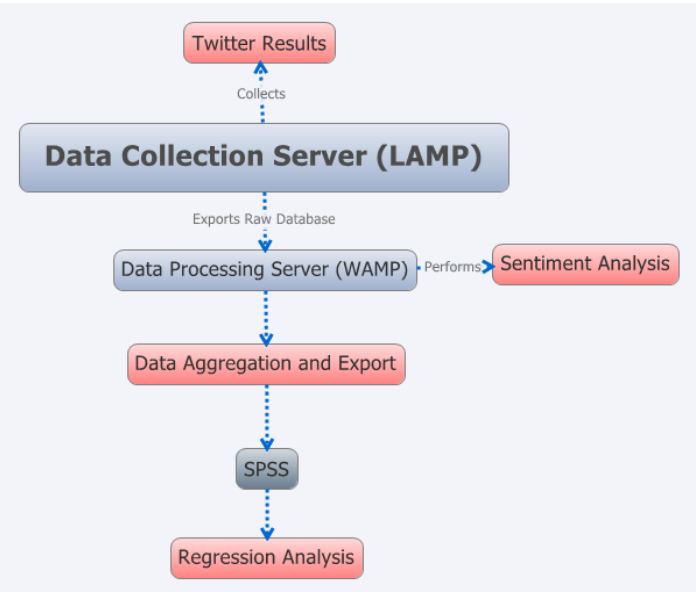

Figure 3: Data collection process

All the data once properly processed and coded was exported to Excel and SPSS. Excel helped in computing some of the calculated fields such as Positive-to-Negative Ratio (P/N Ratio). It was also used to synchronize some of the data according to release date. Some basic linear regressions were performed as well to help visualize the data before it was imported into SPSS. SPSS stands for Statistical Package for Social Sciences and is a statistics software program that helps do statistical analysis on datasets. It was used primarily as a tool to perform regression analysis on the data collected and calculated.

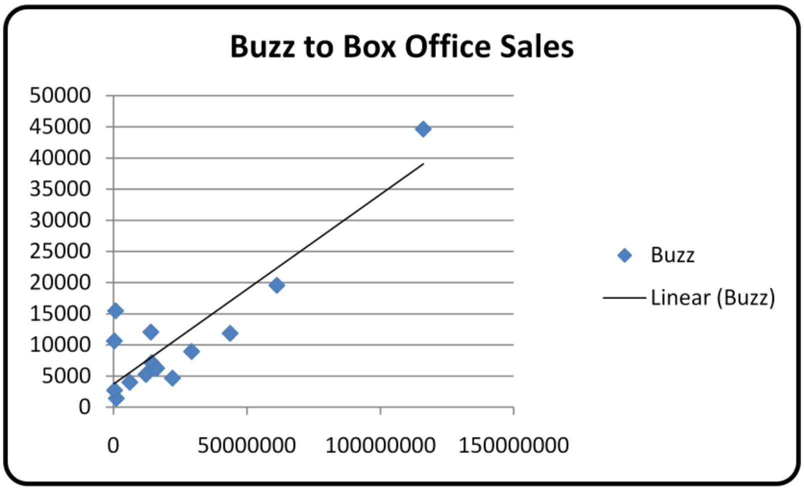

Figure 4: Linear relationship between buzz and sales

The method used to analyze the data was identical to Asur & Huberman (2010) "Our initial analysis of the correlation of the average tweetrate with the box-office gross for the 24 movies considered showed a strong positive correlation, with a correlation coefficient value of 0.90. This suggests a strong linear relationship among the variables considered. Accordingly, we constructed a linear regression model using least squares of the average of all tweets for the 24 movies considered over the week prior to their release." The data that was collected in this research also showed the same strong positive Pearson correlation (0.887). A Pearson correlation was used to detect linear relationships between the two scale variables. Therefore, this research also used linear regressions to model how twitter word of mouth correlates to box office sales.

Correlations

		Boxoffice1	Buzz1
Boxoffice1	Pearson Correlation	1	.887**
	Sig. (2-tailed)		.000
	N	14	14
Buzz1	Pearson Correlation	.887**	1
	Sig. (2-tailed)	.000	
	N	14	14

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 5: Correlation chart for buzz and box office sales

Each week was done as a separate regression because of the general pattern movie releases follow in terms of box office sales. The opening weekend is almost always the largest by a huge margin and the following weeks are generally mediated by word of mouth and reception of the movie by audiences. A single regression with all the weeks was attempted but the vast difference in coefficients across weeks made this approach impossible.

Every logical combination of all of our variables were tested to find the best model for each week. Furthermore, we studied the explanatory power of the first week on the second and third week as well as the second week on the third week. This was done to account for lag times that might be inherent in decision making processes of movie goers and the time it takes for information to spread across networks. While Twitter provides an instant communication mechanism, it does not communicate its messages to everyone (only a fraction of the population is on Twitter) and natural delays in information spreading may exist in a real system.

3.5 Limitations

While conducting the study there are some limitations due to the methods used and the actual implementation of said methods.

3.5.1 Data Collection

One of the central aspects of this research relies on data collection (data mining) from Twitter. There are explicit limitations put in place by Twitter to limit the amount of information one can collect in any given time interval. There are also limitations to how much of the information is published in the 'public timeline' which is the data visible to search queries. Therefore, it is impossible to get the full Twitter dataset but only a representative sampling of the dataset. Twitter's limit on how fast data can be collected from their service also limits the dataset that was collected because during episodes of extremely frequent message posting our service wouldn't be able to collect all of them because of frequency constraints. There were also limitations caused by the software and hardware used to collect the data. On two occasions the sheer volume of data being collected overloaded the software which caused the server to crash and require a reboot.

3.5.2 Sentiment Analysis

Sentiment analysis plays a crucial role in understanding the context of messages. Due to the scale of the research it there will be some level of error in classification. Minimizing this error is important and to ensure the highest level of accuracy possible an academic method of *enhanced term-counting* was used with training data which was randomly sampled off the data collected. More advanced methods of sentiment analysis exist, such as machine learning, but were beyond the scope of this paper for cost and time reasons.

3.5.3 Sampling Error

There is always potential for sampling error, this research seeks to limit the impact of this potential by investigating as large a sample as possible and gather the data in a structured manner that collects everything without prejudice. All specific data that was investigated manually was collected using the built in random function (in MySql database) when it was not time specific to minimize sampling error.

3.5.4 Selection of appropriate movies

Before analyzing the quantified results, a manual check of the data was conducted to evaluate the purity of it. Noise is expected to be present for all movies, but due to a variety of reasons some movies will have an unacceptable amount of noise. One of the primary reasons for unacceptably high levels of noise can be attributed to the genericness of the movie name. For example common phrases, given names and other generic movie names generate high levels of noise. Noise refers to comments that register as being about the movie but are actually concerning something else.

3.5.5 Type I and Type I Error

The possibility for Type I and Type II errors are unavoidable. The researchers consider the statistical significance of every variable at the 95, 99 and 99.9 confidence levels and take into consideration the likelihood based on multiple regressions using different formulas with similar variables to understand each variable's importance and role in explaining the data and creating a more accurate model. In cases of uncertainty or limited evidence (such as only one week being significant) the researchers err on the side of caution and fail to reject the null hypotheses.

3.5.6 Time and Budget Constraints

This research had a limited time frame to be conducted over which meant that compromises had to be made in movie selection, duration of monitoring, data analysis techniques and potentially other areas. Under ideal circumstances, more time could be spent in all areas but the researchers believe that even with these constraints the compromises made do not make the research any less valid and problems were controlled for as best as possible. Extensive testing of all methods was done and statistical significance was measured for all data analyzed to ensure the validity and reliability of the results.

3.5.7 Causation and Correlation

The largest problem with the research design was that the majority was done with a cross-sectional research design which allowed only correlation to be shown. Correlation does not necessarily mean causation. Under some circumstances causation was able to be shown using case study designs but not in all cases. This limits the scope and impact of this research and means further studies are required in some areas to prove the causation that may be implied by this research in some circumstances.

4 Results

In this chapter, the results of the study are presented. The chapter begins with a summary of the gathered data. The hypotheses will then be discussed, studied and analyzed one by one, followed by some notable overall results from the study

4.1 Overview of gathered data

During the period of roughly three months, approximately three million comments were collected from twitter.com concerning twenty eight movies. *Figure 5* shows the full list of movies for which data was gathered. However, several movies where excluded from the data set after studying the actual comments to make sure that nothing was skewing the data. Some of the movies (marked in red) were removed due some movie titles being used in circumstances that do not relate to the movie itself (noise). A few movies (marked in orange) were also excluded from the main data set, due to data on them being limited to only one or two weekends or none at all as work on results and analysis had to start before more weekends had passed. Only the first fourteen movies were used for the numbers that will be presented during this chapter, as they are the only movies for which three consecutive weeks of data exist. However, some of the other movies will be used to analyze aspects that do not relate to weekend box-office sales. Details on each movie can be found in the following table.

Movie	Opening weekend	Comment
Alice in wonderland	2010-03-05	
Green Zone	2010-03-12	
Repo men	2010-03-19	
The runaways	2010-03-19	
Hubble 3d	2010-03-19	
The girl with the dragon tattoo	2010-03-19	
How to train your dragon	2010-03-26	
Hot tub time machine	2010-03-26	
Diary of a wimpy kid	2010-03-26	
Clash of the titans	2010-04-01	
Why did I get married too	2010-04-02	
Letters to god	2010-04-09	
Death at a funeral	2010-04-16	
The back-up plan	2010-04-23	
Furry vengeance	2010-04-30	First and Second weekend only
A nightmare on elm street	2010-04-30	First and Second weekend only
Iron man 2	2010-05-07	First weekend only
Robin Hood	2010-05-14	No box-office numbers
Letters to Juliet	2010-05-14	No box-office numbers
Just Wright	2010-05-14	No box-office numbers
Edge of darkness	2010-01-29	Second and third weekend only
From Paris with love	2010-02-05	"Love" skewed the sentiment analysis
The last song	2010-03-31	Common expression
Date night	2010-04-09	Common expression
Kick-ass	2010-04-16	Common expression
The losers	2010-04-23	Common expression
Chloe	2010-03-26	Common expression (name)

Figure 5: List of movies monitored for this study

4.2 Hypothesis 1

As it has been well established in previous research that WoM has a significant correlation with sales, the first hypothesis investigates whether the volume of twitter comments concerning a movie correlates with a movie's future box office results.

> ***H1 Null:*** *The volume of twitter messages talking about movies does not correlate with future sales*
>
> ***H1 Alternative:*** *The volume of twitter messages talking about movies does correlate with future sales*

If WoM theory applies to eWoM in the form of twitter posts and eWoM is representative of overall WoM our results should indicate a significant correlation.

Previous research (Asur & Huberman, 2010) has shown that the volume of Twitter messages was a significant factor in determining box office sales. Asur and Huberman found the explanatory power of tweet rate (volume of twitter messages) preceding the opening weekend had a .80 adjusted R^2 (explanatory power) and .79 adjusted R^2 for the second week. However, their study did not look at the third week.

Total Buzz	Significance	Adjusted R^2
Week 1	0	0.769
Week 2	0	0.69
Week 3	0	0.807

[1]The results observed in this study showed .769, .69, and .807 adjusted R^2 to each of the respective weekends (first, second and third). All of these results were statistically significant with a significance value of 0 on SPSS which implies that the significance is above the .001 level (>99.9% confidence). The results show a significant correlation between buzz, in the form of twitter comments, during the week with box office results for the following weekend. It was important to test this variable again because it is foundational for this study and there has only been one previous study (Asur & Huberman, 2010) which was not peer-reviewed. The results in this study confirm the results of Asur and Huburman.

Total Buzz	Significance	Adjusted R^2
Week 2 -> Week 2	0	0.69
Week 1 -> Week 2	0	0.767
Week 3 -> Week 3	0	0.807
Week 2 -> Week 3	0	0.663
Week 1 -> Week 3	0	0.632

[2]To further test to what extent buzz predicts future sales, week one buzz was tested on both weekend two and three box office sales, and week two buzz was tested on weekend three box office sales. As could be expected, the results for predicting box office based on week one buzz were lower for weekend two than weekend one and the lowest for weekend three. Looking at weekend three, we can also see that week three buzz is the strongest in predicting weekend three box office (0.807), followed by week two buzz (0.663) and finally week one buzz (0.632). However, something interesting appears for weekend two as the results indicate that week one buzz is better at explaining weekend two box office than week two buzz is. Week one buzz predicts weekend two box office with almost the same precision as weekend 1 box office, with 0.769 and 0.767 respectively, compared to 0.69 which is how well week two buzz predicts weekend 2 sales. This implies a similar box office patterns for week one and two.

[1] Figure 6: Regression for buzz as a function of sales

[2] Figure 7: Regression for buzz as a function of sales using data from earlier weeks

Why week one is better at predicting weekend two box office is further discussed later in what we refer to as the "week two paradox".

As it has been established in previous research, it is important to take into account that some movies have a wider release than other movies. The following list shows the amount of theatres the 14 main movies in our data set were released in for the opening weekend. The difference between 34 theaters and 3728 is quite significant, which might have an impact on how well buzz can predict box office sales. In the study conducted by Asur and Huberman, this variable has a positive impact on predicting sales. Adding it to the regression might provide further precision to this study.

Movie	Theaters
Alice	3728
Greenzone	3003
Repo Men	2521
The Runaways	244
How to Train Your Dragon	4055
Hot Tub Time Machine	2754
Diary of a Wimpy Kid	3077
Clash of the Titans	3777
Why Did I Get Married Too	2155
Letters to God	897
Death at a Funeral	2459
The Back-Up Plan	3280
Hubble 3d	39
The Girl With The Dragon Tatoo	34

Figure 6: List of movies and theaters

Week 1

	Significance	Adjusted R^2
Theaters	0.366	0.366
Total Buzz (TB)	0	0.769
TB	0	0.895
+ Theaters	0.002	

Week 2

	Significance	Adjusted R^2
Theaters	0.013	0.364
Total Buzz (TB)	0	0.69
TB	0.004	0.691
+ Theaters	0.331	

Week 1 -> Week 2

	Significance	Adjusted R^2
Total Buzz (TB)	0	0.767
TB	0	0.888
+ Theaters*	0.003	

* Theaters for week 2

Week 3

	Significance	Adjusted R^2
Theaters	0.002	0.533
Total Buzz (TB)	0	0.807
TB	0	0.866
+ Theaters	0.029	

Week 1 -> Week 3

	Significance	Adjusted R^2
Total Buzz (TB)	0	0.632
TB	0	0.822
+ Theaters*	0.003	

Week 2 -> Week 3

	Significance	Adjusted R^2
Total Buzz (TB)	0	0.663
TB	0.014	0.711
+ Theaters*	0.109	

* Theaters for week 3

Figure 8: Regression for buzz and theaters as a function of sales

Theaters by themselves offer no significant explanation for box office results, but when combined with buzz they offer significant boost in the results. However, when combined with week two buzz, the significance of theaters is below acceptable levels. Overall, the buzz data from week two still seems to offer significantly weaker explanatory power for box office sales than week one and three. Conclusively, the overall results indicate a significant correlation between buzz and sales.

We reject the null hypothesis and conclude that the volume of twitter messages talking about movies does correlate with future sales.

4.2 Hypothesis 2

The existing theory about negative word of mouth argues that it discourages purchase behavior. To test this, the second hypothesis investigates the correlation between negative twitter and movie sales.

H2 Null: *Negative twitter WoM does not correlate with movie sales*

H2 Alternative: *Negative twitter WoM does correlate with movie sales*

To test this hypothesis, a negative correlation would have to be observed between negative WoM and box office results. Regression analysis was used to test how well the absolute amount of negative buzz explains sales.

Week 1	Significance	Adjusted R^2
Negative Buzz (NB)	0.001	0.556
NB + Theaters	0.014 0.136	0.608

Week 2 Week 1 -> Week 2	Significance	Adjusted R^2
Negative Buzz (NB)	0.004	0.476
NB + Theaters*	0.038 0.132	0.54

Week 3	Significance	Adjusted R^2
Negative Buzz (NB)	0.006	0.435
NB + Theaters	0.120 0.036	0.595

Figure 9: Regression for negative buzz and theaters as a function of sales

The results suggest that there is some explanatory power to the model (between .435 and .556) with statistically significant results. However, when combining negative buzz with theaters, none of the combined results show statistically significant results. Furthermore, when analyzing the regression for only negative buzz more closely, there is a positive coefficient since there is only one variable explaining a positive number (box office sales). To logically test the effect of negative buzz on box office sales it must be used in conjunction with other variables such as total buzz so that it may display a negative coefficient as expected which would mean negative buzz negatively impacts sales.

Week 1	Significance	Adjusted R^2
Total Buzz + Theaters	0 0.002	0.895
Total Buzz +Theaters + Negative Buzz	0 0.006 0.769	0.886

Week 2 Week 1 -> Week 2	Significance	Adjusted R^2
Total Buzz + Theaters	0 0.003	0.888
Total Buzz +Theaters + Negative Buzz	0 0.002 0.233	0.894

Week 3	Significance	Adjusted R^2
Total Buzz + Theaters	0 0.029	0.866
Total Buzz +Theaters + Negative Buzz	0 0.004 0.015	0.921

Figure 10: Regression for buzz, negative buzz and theaters as a function of sales

Using this method, SPSS shows negative WoM as having a negative correlation to sales, which would prove that negative buzz does indeed have a negative impact on movie sales. However, the significance of negative buzz is statistically insignificant in the first two cases. The results are therefore inconclusive as to whether negative buzz influences sales.

We fail to reject the null hypothesis and cannot conclude that negative twitter word of mouth does correlate with movie sales.

The results do however seem to indicate that negative buzz has increasing explanatory power as time passes. Furthermore, the negative buzz used for the first two weeks is based on buzz prior to the movie release; it is therefore from individuals who have not seen the movie. As has been demonstrated previously, using week two buzz for weekend two box office shows very unsatisfactory results which can be seen in *appendix 1*. Based on the results from week three we see indications that negative twitter word of mouth does have a negative impact on movie sales. However, more research is needed to confirm the impact of negative buzz on sales.

4.3 Hypothesis 3

Positive WoM is believed to encourage purchase behavior. However, this fact has been questioned as the results from some studies do not seem to support it. The third hypothesis therefore investigates whether positive WoM correlates with sales.

> ***H3 Null:*** *Positive twitter WoM does not correlate with movie sales*
>
> ***H3 Alternative:*** *Positive twitter WoM does correlate with movie sales*

To test this hypothesis, the total amount of positive buzz for movies will be used to see how well it correlates with future sales. The results will be compared to the results for total buzz from hypothesis one.

Week 1

	Significance	Adjusted R^2
Total Buzz (TB)	0	0.769
Positive Buzz (PB)	0	0.905
TB	0	0.895
+ Theaters	0.002	
PB	0	0.934
+ Theaters	0.03	

Week 2
Week 1 -> Week 2

	Significance	Adjusted R^2
Total Buzz (TB)	0	0.767
Positive Buzz (PB)	0	0.898
TB	0	0.888
+ Theaters*	0.003	
PB	0	0.926
+ Theaters*	0.039	

Week 3

	Significance	Adjusted R^2
Total Buzz (TB)	0	0.807
Positive Buzz (PB)	0	0.89
TB	0	0.866
+ Theaters	0.029	
PB	0	0.926
+ Theaters	0.024	

Figure 11: Regression for buzz, positive buzz and theaters as a function of sales

Only the strongest predictors are presented above. The full set of regressions, such as week two for predicting weekend two box office sales, can be seen in the appendices. The results observed in this study show .905, .898, and .89 adjusted R^2 for positive buzz, and .934, .926, and .926 adjusted R^2 for positive buzz in combination with theaters. All of these results were statistically significant with greater than 95% confidence. The strongest predictors for box office sales using positive buzz are the same ones that are the strongest using total buzz, i.e. buzz +theaters, with week one being the best predictor for weekend two box office results. The results show that positive buzz has more explanatory power in predicting sales than total buzz for all weeks, which indicates that positive buzz is a stronger attribute when predicting sales than the total amount of buzz. These results prove that positive buzz does correlate with sales.

We reject the null hypothesis and can conclude that positive twitter WoM does correlate with movie sales.

4.4 Hypothesis 4

In WoM theory, it is believed that purchase probability is a result of the relative amount and impact of positive WoM compared to negative WoM. Furthermore, it has been suggested that valence is the best WoM attribute when it comes to predicting sales. The fourth hypothesis will investigate the influence of the relative amount of positive WoM compared to negative.

> ***H4 Null:*** *The relative amount of positive WoM compared to negative WoM does not correlate with movie sales.*
>
> ***H4 Alternative:*** *The relative amount of positive WoM compared to negative WoM does correlate with movie sales.*

Since P/N Ratio is a calculated variable it cannot be used to explain movie sales alone. It has to be used in combination with other explanatory factors that it is connected to (Total Buzz, Positive Buzz, and Negative Buzz). Therefore, there is no stand-alone regression using P/N Ratio. Asur and Huberman (2010) found that P/N Ratio increased the explanatory power of their models when added into the regressions. To test the hypothesis, regressions where tested including both total buzz and P/N ratio with the following results.

Week 1	Significance	Adjusted R^2
Total Buzz	0	0.895
+ Theaters	0.002	
TB	0	
+Theaters	0	0.924
+P/N Ratio	0.046	

Week 2 Week 1 -> Week 2	Significance	Adjusted R^2
Total Buzz	0	0.888
+ Theaters	0.003	
TB	0	
+Theaters*	0.031	0.927
+P/N Ratio	0	

Week 3	Significance	Adjusted R^2
Total Buzz	0	0.866
+ Theaters	0.029	
TB	0	
+Theaters	0.001	0.939
+P/N Ratio	0.004	

Figure 12: Regression for buzz, theaters and positive/negative ratio as a function of sales

The results observed in this study show .924, .927, and .939 adjusted R^2 for Total buzz combined with theaters and P/N ratio. All of these results were statistically significant with greater than 95% confidence for all variables. The results observed in this study show that P/N ratio plays an important role in some of the key regressions and give some of the most accurate models for explaining box office results. The model presented above for predicting week two box office sales has the highest adjusted R^2 (.927) in all the regressions that have been tested. Overall, this regression model has some of the highest adjusted R^2 for all three weeks. It was the second best model for explaining week 1 box office sales. Furthermore, the highest adjusted R^2 (.96) for week 3 used: Positive Buzz, Theaters and P/N Ratio, to explain box office sales. [3]

Week 3		
PB	0	
+ Theaters	0.002	0.96
+ P/N Ratio	0.009	

The results indicate that valence in the form of relative amount of positive WoM compared to negative is indeed one of the best attributes when it comes to predicting sales.

We reject the null hypothesis and can conclude that the relative amount of positive word of mouth compared to negative word of mouth correlates with movie sales.

4.5 Hypothesis 5

Previous research has established that WoM not only affects sales, it is also affected by sales. In an effort to understand the dynamic relationship between sales and WoM, the fifth hypothesis investigates the correlation between box office results and future buzz.

> ***H5 Null:*** *The box office sales do not correlate with the future volume of twitter messages.*
>
> ***H5 Alternative:*** *The box office sales do correlate with the future volume of twitter messages.*

[3] Figure 13: Regression for positive buzz, theaters and positive/negative ratio as a function of sales

To test this hypothesis, a regression is done using buzz and box office from all three weeks and weekends. The results are compared to previously presented results for how well buzz predicts box office.

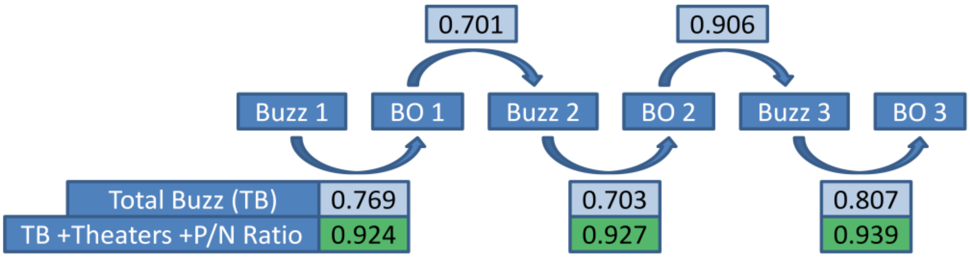

Figure 14: Regression for sales as a function of buzz, and buzz and theaters as a function of sales

The upper boxes show the results for the correlation between box office sales and buzz during the following week. The results observed in this study show .701 and .906 adjusted R^2 for the each respective week (second and third). The results show that a significant correlation between box-office results and the amount of total buzz the following week. Box office weekend two actually explains buzz week three better than week three buzz (before including valence and amount of theaters) explains box office results weekend three. A feedback loop as Bayus (1985) suggested seems to be present, where buzz and box office sales show a strong relationship, above .7, to one another in all six regressions.

To further test this hypothesis, the underlying data was investigated for the first Monday after the movie release date.

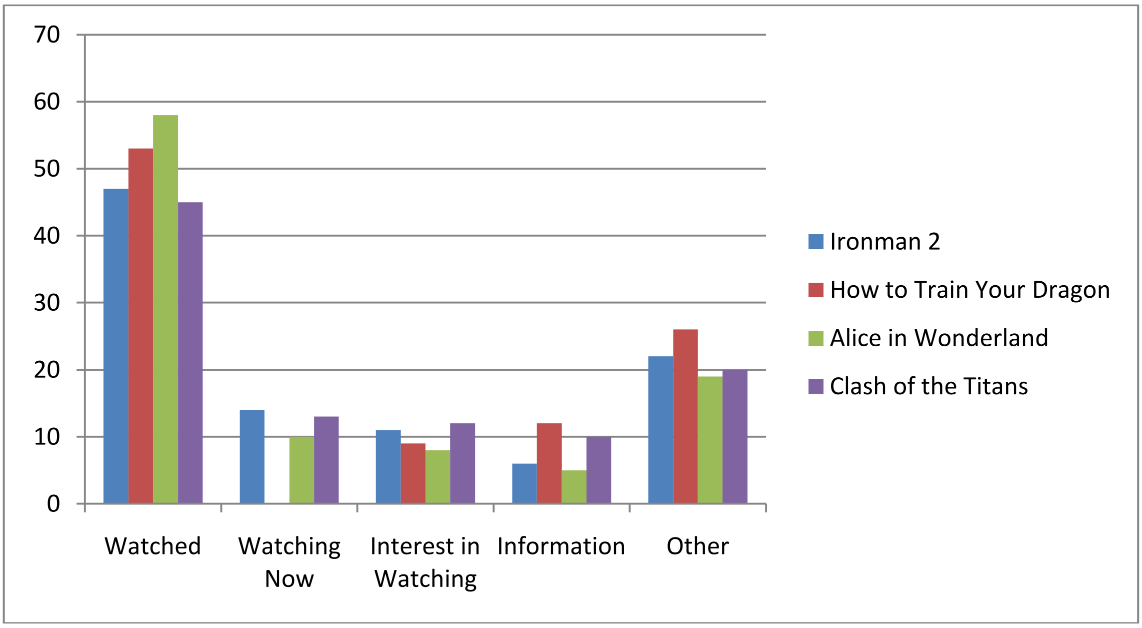

Figure 15: Classification of comments following the first weekend

The five categories were:

- Watched – people who talk about their experience, opinion, or stating they had seen the movie
- Watching Now – those expressing that they were seeing the movie at the moment or that day
- Interest in Watching – those expressing interest in seeing the movie without any time dimension

- Information – information posts such as trailers, movie time, release locations, etc.
- Other – posts without classification (disinterest in seeing, noise, related materials such as games, previous versions of a movie) and posts in other languages

The results clearly show that around 50% (45-58%) of the buzz after the movie releases is directly from people who have just watched the movie. If you include those indicating they are watching it at that moment/that day the number rises to between 53-68%. These numbers may in actuality be higher because of the languages not understood by the researchers. It is clear that the box office sales are influencing word of mouth on Twitter.

In this instance we can not only reject the null hypothesis proving there is a correlation between box office sales and the future volume of twitter messages, but show that box office sales caused the messages on twitter.

4.6 Hypothesis 6

Previous research has established that WoM marketing not only affects sales directly, but also influences and generates WoM. This can be seen in "*Figure 1.1 The conceptual model structure (Bayus, 1985)"* presented in the theory chapter. The sixth hypothesis will investigate the influence of marketing efforts on twitter buzz.

> ***H6 Null:*** *An increase in the volume of twitter messages as a result of marketing efforts cannot be measured.*
>
> ***H6 Alternative:*** *An increase in the volume of twitter messages as a result of marketing efforts can be measured.*

To test this hypothesis, access to marketing budgets and a detailed account of the marketing efforts would be ideal, but this is not information that is made public and was therefore not available for this paper. However, the main form of marketing used for movies are trailers, that are released over a period of time leading up to the premiere, with the first trailer sometimes being released up to six months before the premiere. The release dates of these trailers are easily found (TrailerAddicts.com was used to find release dates). To test this hypothesis we will therefore look at when trailers were released and study if there is a notable increase in short term and long term buzz following the release of a trailer. We are however limited by the timeframe of our data collection, which in most cases was not long enough prior to the premiere of the movie to cover the release of the trailers, so only a limited amount of buzz data covering a release of a trailer is available for analysis. Three movies with enough time prior to the premiere to cover the release of a trailer where found; Iron Man 2, A Nightmare on Elm Street and Death at a Funeral. Charts for the evolution of their buzz will be presented. In each chart, the release of a trailer is pointed out with a red arrow.

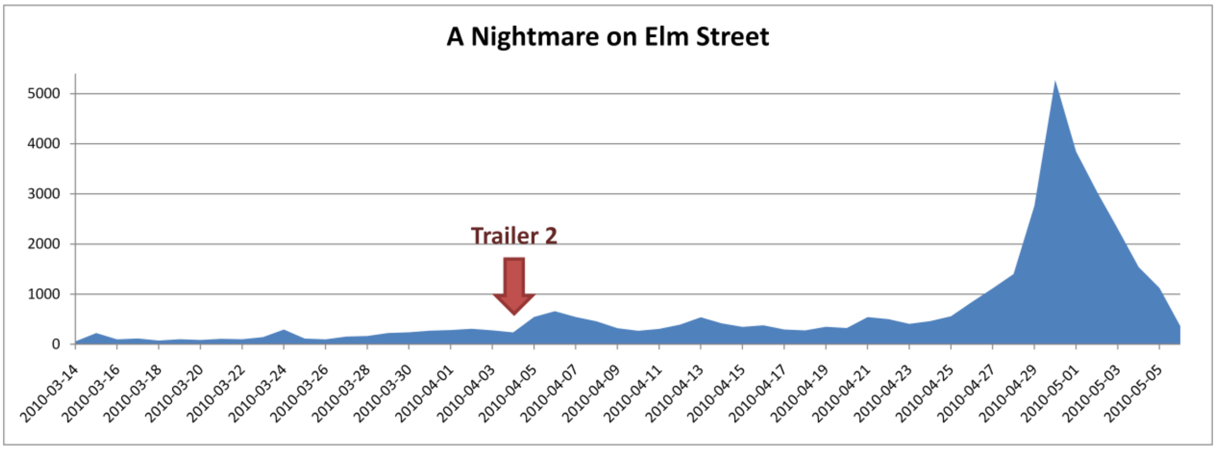

Figure 16: Evolution of buzz of "A Nightmare on Elm Street" following the release of a trailer

Looking at the buzz evolution for "A Nightmare on Elm Street", there is a clear spike in the buzz following the release of a trailer. The charts for "Iron Man 2" and "Death at a Funeral", presented further down, show similar spikes.

Digging into the comments, it can be confirmed that the increase in buzz does originate from the trailer. In the comments concerning the trailer for "A nightmare on elm street" a lot of people point out the fact that there is actually a new trailer for the movie with comments such as the following.

"New trailer of "A Nightmare on Elm Street" (starring Kellan Lutz) http://bit.ly/dmhugK"

"There's another new Nightmare On Elm Street trailer out! I know it's a remake - but what can ya do?"

Other comments reveal other interesting things, such as the following:

"Whaaat!?! There's a new Nightmare on Elm Street movie coming out??"

This comment does not refer to the actual trailer, but it points to the fact that this person became aware of the movie as a new trailer got released. There is a strong chance that he/she either saw the trailer or heard about the movie or trailer through WoM, either in the form of eWoM or regular WoM. This is an indication that the release of the trailer helped increase awareness about the movie.

Furthermore, other comments also express sentiment towards the movie as the new trailer got released, such as the following comments:

"Just seen the trailer for 'A Nightmare on Elm Street' starring @KellanLutz_ omg it looks soooo scary!!!"

"Oooo a nightmare on elm street looks good!!"

These people are expressing positive sentiment as a result of seeing the trailer. Other people are also expressing neutral and negative sentiment and newfound awareness about the movie as a result of seeing the trailer.

"Just saw the trailer for the new A Nightmare On Elm Street. Dont look too bad but I aint impressed yet..."

"Wow nooooo why they makin a nightmare on elm street. What The Fuck? They need to leave the old movies alone"

Looking at the chart for Iron Man 2, the two distinct spikes leading up to the release of the movie also coincide with the release of trailers. Following the release of the "Feature trailer", the daily comments concerning the movie went from ~60 to over 1500 in 1 day.

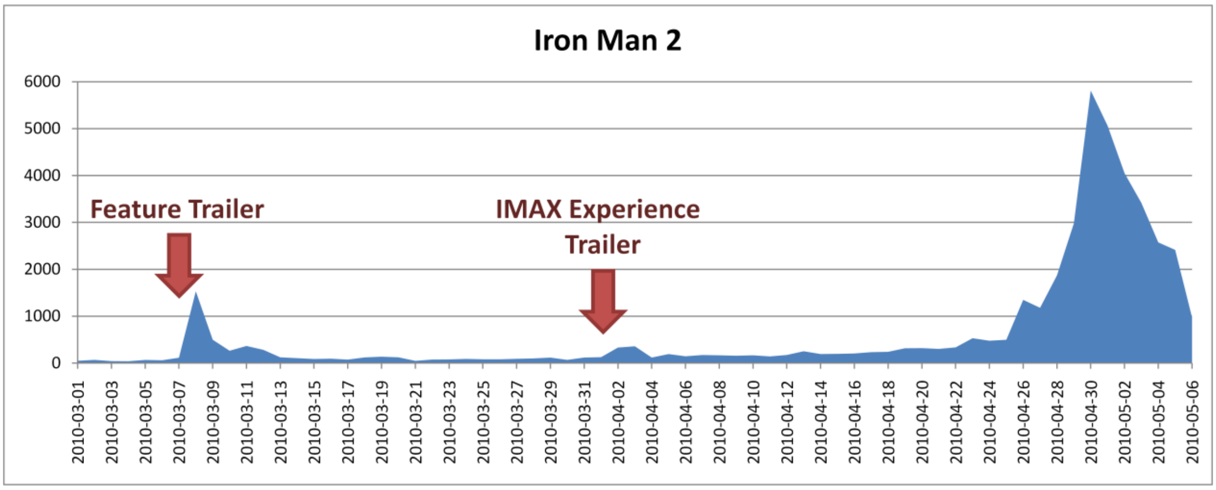

Figure 17: Evolution of buzz of "Iron Man 2" following the release of two trailers

The effect on buzz from the marketing efforts in the form of a trailer can clearly be seen in this example, with the release of the "feature trailer" undeniably having a strong effect on WoM in the form of twitter comments. Looking at the specific comments, a lot of positive comments concerning the newly released trailer are present, such as the following:

"New Iron Man 2 trailer is AWESOME!!! Can it be may 7th now??"

"Really wants to watch ironman 2 after seeing the trailer....http://bit.ly/aCu0bz"

"Just saw the #Ironman 2 trailer - consider my world rocked."

The comments clearly indicate that it was the trailer that initiated the increase in buzz. The overall sentiment towards the movie as a result of the trailer is predominantly positive. The comments also indicate that the marketing had a direct effect on purchase intentions. The "IMAX Experience trailer" is a shorter trailer than the "Feature Trailer" and does not show anything new in the form of content from the movie, but is instead to promote the movies' release in IMAX theaters. Though this trailer does not generate the same bump in WoM as the previous one, it still manages to create a noticeable increase in twitter comments.

The third movie for which the buzz was recorded during a marketing effort is "Death at a Funeral" for which 4 TV spots where released. The exact timeframe for which these TV commercials where broadcasted is not known, but it can be concluded that they started being broadcasted around the 17th as this is when comments concerning a TV commercial start appearing on twitter.

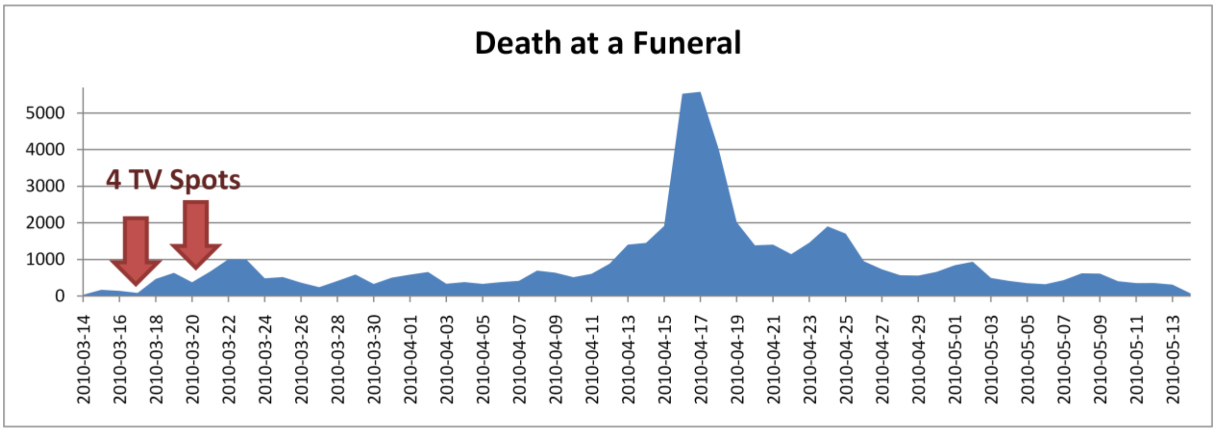

Figure 18: Evolution of buzz of "Death at a Funeral" following the release of four TV spots

The TV commercials were later uploaded on the internet on the 20th which would explain the second bump. Looking at the specific comments, awareness about the movie was clearly created. The comments however express mixed sentiments about the movie, with a lot of negative sentiment being expressed due to the fact that it is a remake of a British movie. Here are some of the comments from the 18th of March:

"Just saw the preview for the movie "death at a funeral" looks pretty funny actually! wanna see it!"

"I CANNOT believe they made a re-make of "Death at a Funeral". Absolutely RIDICULOUS!"

"THE HOLY FUCK? a Death At a Funeral remake/US version? REALLY? REALLY? was the british one NOT IN ENGLISH?"

For this movie, as in the other three cases, there seem to be a strong relationship between marketing efforts and spikes in eWoM in the form of twitter comments. However, what is also interesting to study is the long term effects of this kind of marketing on buzz. To test this, we take the average amount of twitter comments the week before the marketing efforts and the average amount the two weeks after the short term spikes, we could see if there is a significant jump in long term buzz as a result of the marketing.

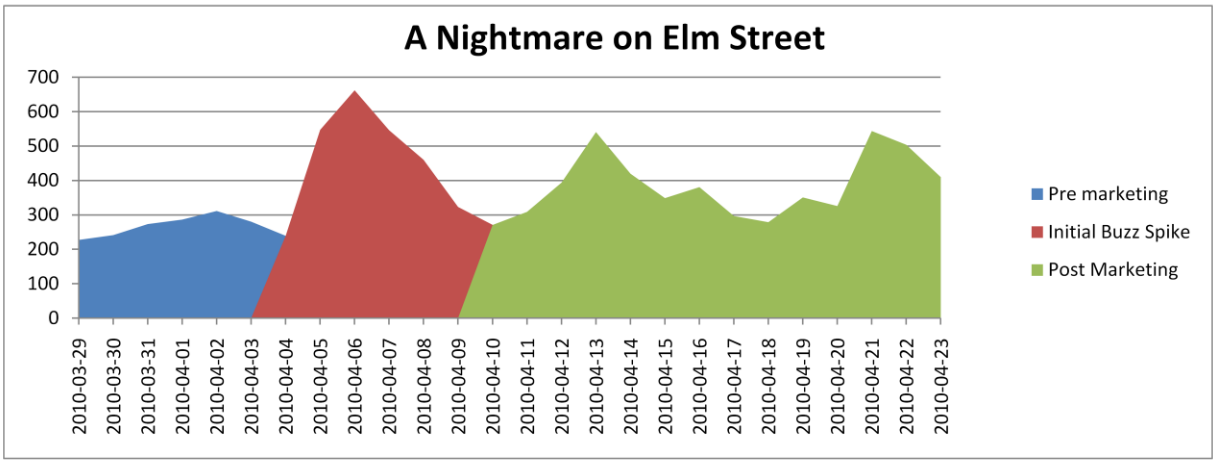

Figure 19: Closer look at Evolution of buzz of "A Nightmare on Elm Street" surrounding the release of a trailer

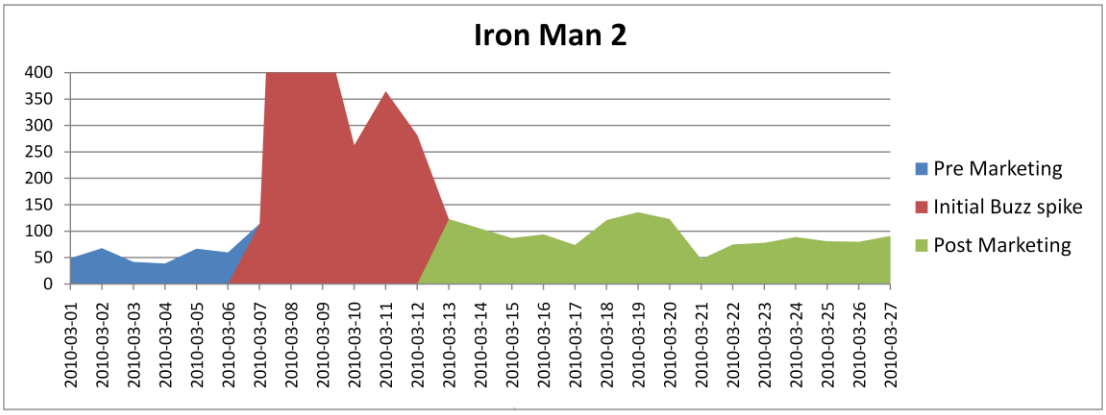

Figure 20: Closer look at Evolution of buzz of "Iron Man 2" surrounding the release of a trailer

For these two movies, a slight jump in buzz can be identified after the initial spike surrounding the advertisement. The average amount of comments before the trailer for "A Nightmare on Elm Street" is ~265 comments per day. After the initial buzz spike surrounding the release of the trailer, the average comments per day are ~384. For "Iron Man 2" The average comments per day jump from ~63 comments per day to ~92 comments per day. This represents an average jump in comments of ~45%. Looking at Death at a Funeral, a slightly higher jump in buzz can be identified.

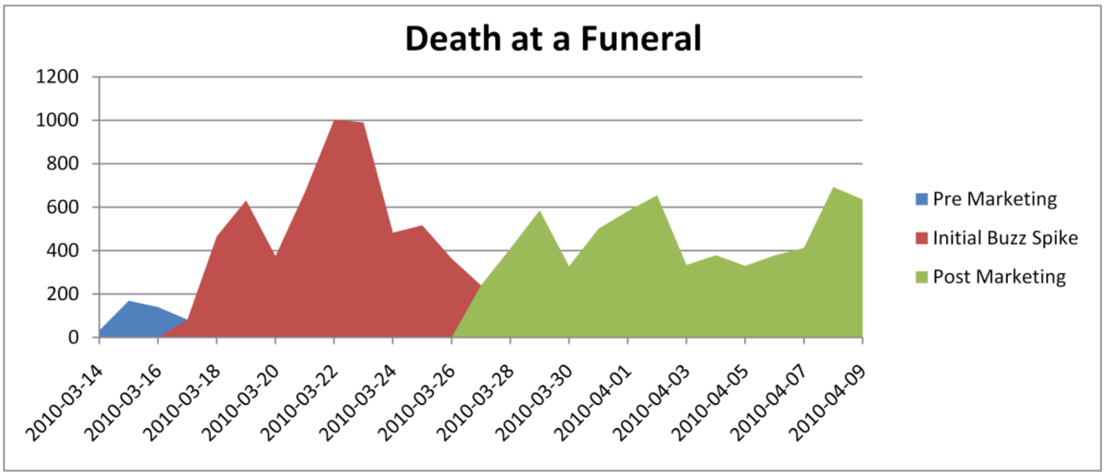

Figure 21: Closer look at Evolution of buzz of "Death at a Funeral" surrounding the release of four TV spots

The amount of buzz before the release of the trailer is very limited, but the average buzz during the three days before the 4 TV spots is ~130 comments per day. After the campaign, the average number of comments jumps to ~462. This represents jump of over 250% in buzz. The results for all three movies seem to indicate that marketing efforts in the form of trailers and TV spots increases awareness and has a long term impact on WoM. The data is however too limited to be conclusive as more data prior to the marketing effort would be needed to identify the average number of comments during a longer period, and the natural growth in WoM as the release of the movie approaches.

To conclude, in analyzing all these movies a significant spike in WoM directly following the release of a trailer or TV spots could be identified. In studying the comments it was also clear that the WoM was generated by the marketing campaign. The data also indicates a long term increases in WoM as a result of marketing efforts.

We reject the null hypothesis and can conclude that an increase in the volume of twitter messages as a result of marketing efforts can be measured.

4.7 Hypothesis 7

Previous studies on WoM have identified that positive WoM is more common than negative WoM, which is what this seventh hypothesis aims to investigate is the ratio of positive and negative twitter comments.

> ***H7 Null:*** *Positive WoM in the form of twitter comments is not more common than Negative WoM.*
>
> ***H7 Alternative:*** *Positive WoM in the form of twitter comments is more common than Negative WoM*

To test this hypothesis, the total amount of positive comments for all movies will be compared to the total amount of negative comments. The charts below show the evolution of the ratio of positive comments to negative comments for all movies during the 14 weeks for which data was collected.

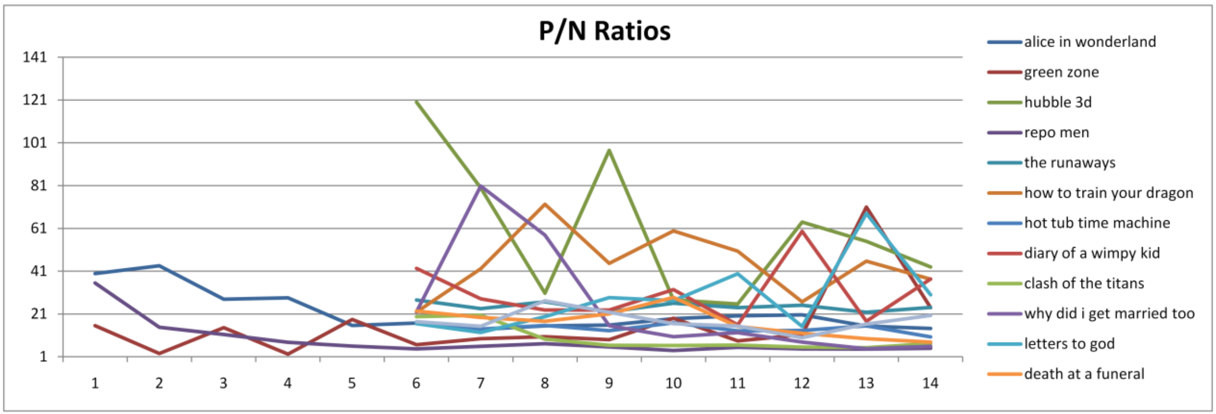

Figure 22: The evolution of P/N ratios for all movies

Grouping all the results into one chart produces a very chaotic chart, but what is notable is the fact that the ratio of positive comments is above 1.0 for all movies, all fourteen weeks, with the lowest number being 2.2 for "Green Zone" week 4. These results show that the amount of positive twitter comments on a weekly basis are always more common than negative comments. Below is a chart of the average P/N ratio for all movies.

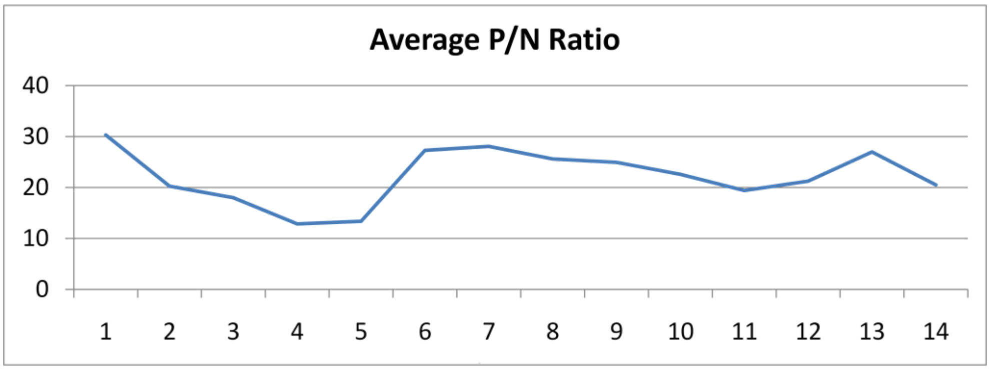

Figure 22: Average P/N ratios for all movies

The amount of positive WoM in the form of twitter comments varies between ~13 to ~30 times as many as negative ones during the 14 weeks of data collection. Overall, positive comments are on average ~22 times more common than negative ones in our data set.

We reject the null hypothesis and can conclude that Positive WoM in the form of twitter comments is more common than Negative WoM.

4.8 Notable results

4.8.1 Week two paradox

One of the most fascinating results comes from the second weekend of box office sales. It has been dubbed the 'week 2 paradox' because the second weekend of box office sales is the hardest to predict and does not correlate well with any of the models established based on the week 2 data. The strongest correlation observed was between the first week's data and the week 2 box office results. Previous research by Liu (2006) showed similar results with the second week having the lowest adjusted R^2 in their model at .765 while the first week had .902 and third had .820. Based on the data available, no explanation for this phenomenon could be found. A discussion around this paradox and possible explanations that could be studied in future research are presented in the conclusion.

4.8.2 Understanding positive buzz

The most conclusive part of this research was that positive buzz has the strongest correlation with actual box office sales. The best model that explained box office sales was the third week box office sales being explained by positive buzz, theaters and positive-to-negative ratio which had an adjusted R^2 or .96. In virtually all of our best models positive buzz was a factor with the exception of using week 1 buzz to predict week 2, in which it give the second best results with a small margin. The difference in explanatory power between the model using total buzz (.927) and the model using positive buzz (.926) was .001

The marketing implications for positive word of mouth can be understood by some case study analysis. For example if *Clash of the Titans* and *How to Train Your Dragon* are compared, they launched in approximately the same number of theaters (3777 to 4055 respectively). Clash of the Titans had a total buzz of 19570 prior to week 1 and How to Train Your Dragon had 11860. The relative amount of positive was very close after they both opened (graph below). However, as time progressed the relative amount of positive buzz for How to Train Your Dragon went higher and higher while Clash of the Titans steadily decreased.

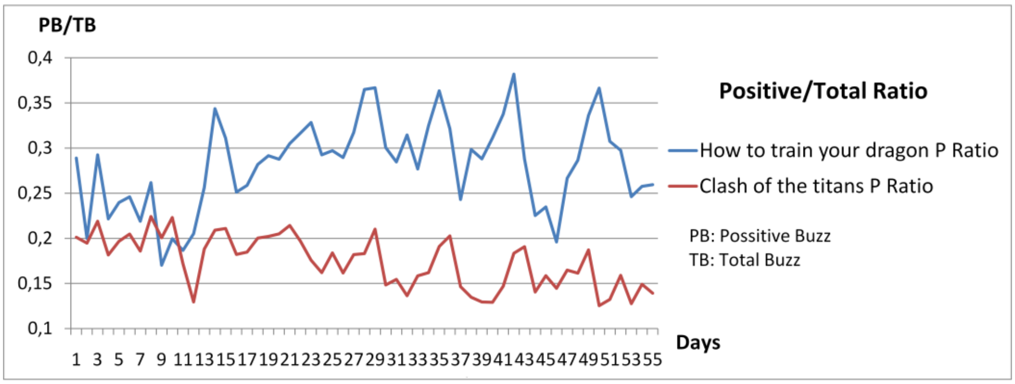

Figure 22: Evolution of relative amount of positive comments for "How to Train Your Dragon" and "Clash of the Titans"

The result of this divergence in the relative amount of positive buzz (we use relative amounts to account for the difference in total volume of buzz to compare these movies) is that How to Train Your Dragon, which earned two thirds of what Clash of the Titans earned the opening weekend, starts to consistently make more money every day after the second weekend.

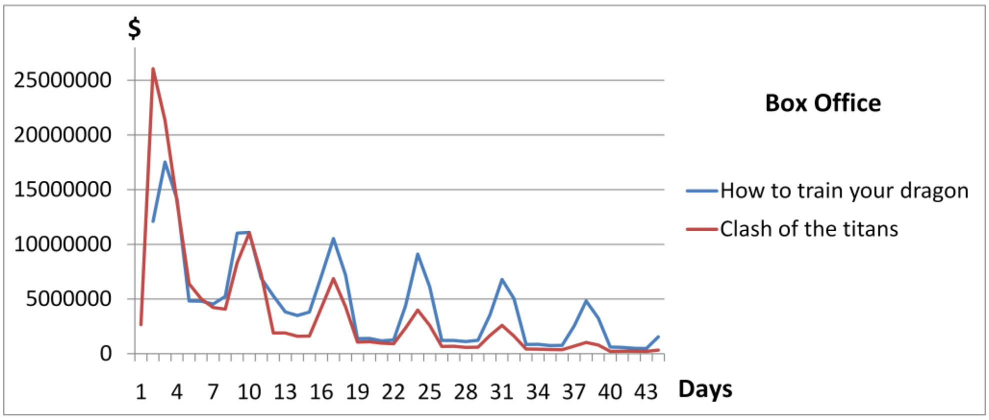

Figure 22: Evolution of box office sales for "How to Train Your Dragon" and "Clash of the Titans"

While our regression analysis can only show correlation, a deeper look into the data with side by side comparisons using a case study method like this, allowed us to gain more insight into the causation which we conclude to be positive buzz. This is backed up strongly by user ratings which place How to Train Your Dragon as one of the most favorably rated movies of all time according to IMDb.

4.8.3 Sentiment and Rating

One of the sets of variables studied was user ratings from three of the major sources for movie ratings (IMDb, Rotten Tomatoes and MetaCritic). Regressions testing if ratings could be predicted by the ratio of positive to negative sentiment were attempted. The expected result would be the rating could be explained by the positive-to-negative ratio. However, the only set of ratings which could be explained by this data was the Rotten Tomatoes data which had .432 adjusted R^2 with 99% significance. For comparison the IMDb ratings had an adjusted R^2 of .058 with 79% significance and Meta Critic had .125 adjusted R^2 with 88% significance. Neither of the other two movie rating services had much explanatory power and they were statistically insignificant regardless.

No strong predictive model could be created for predicting movie ratings based on sentiment. This could be the result of the different ways rating services calculate their own ratings. It could also be due to the time ratings were collected, expectations, or inadequacy of the enhanced term-counting method to account for degrees of satisfaction. This does not mean these ratings are irrelevant in understanding box office sales; merely that this study cannot predict them based on the methods used.

5 Analysis

In this chapter, the results will be analyzed in relation to existing theory of WoM and compared to earlier results from eWoM studies in order to answer the research questions of this thesis. The analysis aims to provide insight into how eWoM in the form of comments on twitter behave in relation to marketing and sales in comparison to theory based on traditional WoM and other studies of eWoM. The chapter is divided into three parts, with the first looking at the influence of volume and valence on sales. The second looks at the influence of sales on WoM. The third and last part looks at the impact of marketing efforts.

5.1 Explanatory power of volume and valence

One of the most established facts in WoM theory based on traditional WoM, is the fact that the volume of WoM has a significant correlation with sales. Looking at eWoM, one of closest studies to this study was Godes & Mayzlin (2004) who studied the relationship between Usenet discussion and TV ratings (viewership numbers). In their study they were unable to find a strong link between WoM and TV ratings (amount of viewers). Usenet was the precursor to much of the online communities found in 2010, but never reached a wide audience. It was also earlier in the evolution in the use of the Internet and therefore it may not have been representative of the overall population. This study is six years later and the adoption of social media is prevalent in the US where the box office data used is geographically covering. Godes & Mayzlin (2004) encouraged further research should be done in the area investigating this link.

The results of this study show that WoM in the form of comments on twitter are in line with what is expected according to WoM theory, it is fairly conclusive that word of mouth on Twitter has a strong correlation with box office sales (varying from .690 to .807 on total buzz). This study's results agree with later studies done by Liu (2006) and Asur & Huberman (2010) which indicated that volume offered significant explanatory powers in predicting box office sales. As in these previous studies, including the amount of movie theaters to capture the distribution intensity gave even stronger results. With only these two variables, future box office results could be predicted with an adjusted R^2 of between .866 and .895. These strong results indicate that the volume of comments on twitter could be a strong indication of overall volume of WoM.

The other main variable in WoM is valence, which is also believed to have an impact on sales as it influences consumers' attitude towards a product. Several studies on traditional WoM indicate that both positive and negative WoM influence purchase behavior. However, in studies using eWoM, there has been some controversy on whether valence influences sales or not. Some studies argue that valence is very important for understanding sales such as Zhu & Zhang (in Davis & Khazanchi, 2008). The results of other studies such as Liu (2006) found valence to be insignificant in explaining sales. The amount of data they had at their disposal to analyze was however limited by the manual techniques used to quantify and classify WOM.

The results found in this study directly contradict the results of Liu (2006) which found that positive and negative valence never had any statistically significant role in their box office forecasting model. Furthermore, this study also had results that better predicted box office sales than Liu (2006) in the first three weeks. The results from Liu (2006) were .902, .765 and .820 for the first three weeks respectively; while this study's results were .934, .812 (or .927 using first week to predict the second week) and .960. This study also showed that positive word of mouth was a critical factor in increasing the model's fit. This study also confirmed some aspects of Asur & Huberman (2010) such as valence (sentiment analysis) can improve box office sales predictions. However, their study found that valence only became relevant after release. This study confirmed their results for negative word of mouth which appears to only become a significant variable in predicting box office sales after release but not before. Positive word of mouth, on the other hand, was found to be a significant variable in predicting box office sales before release. This result contradicts both Asur & Huberman (2010) which argue that valence is important only afterwards, and Liu (2006) which argues that valence is not important at all.

With regards to the ratio of positive to negative word of mouth the results behaved as expected. Since positive word of mouth was a significant variable from pre-release to the third week and negative only became a significant variable in the third week, the ratio of positive to negative word of mouth only became significant in the third week.

Overall, the results of this study seem to be in line with theory on traditional WoM, in confirming that valence does seem to have an impact on sales. However, because of the techniques used, this study fails to shed any further light on the debate on whether negative or positive WoM has more impact. The only contribution that can be made to this debate is that the results indicate that positive WoM has stronger explanatory power in predicting future sales than negative WoM.

5.2 The influence of sales on volume of WoM

The fact that WoM influences sales is well established in research using both traditional WoM and eWoM, but the topic of how sales influences WoM seems not to have been covered in eWoM studies. Bayus (1985) modeled the relationships between word of mouth, sales and marketing efforts. This model suggests a dynamic relationship between sales and WoM, with both variables influencing each other.

This research therefore tested the Bayus model of the interaction between sales and word of mouth and how they both influence one another. Predicting the second week of buzz based off the first weekend's box office sales yielded an adjusted R^2 of .701 with greater than 99.9% confidence. Predicting the third week of buzz based off the second weekend box office sales yielded a much stronger explanatory power with an adjusted R^2 of .906 which also had greater than 99.9% confidence. These results do confirm a correlation between box office sales and word of mouth on Twitter. The causal link can also be confirmed with case study analysis. It was evident that much of the word of mouth generated after a movie release was caused by people watching the movie.

Bayus even theorized that word of mouth could generate sales better than marketing efforts at a point where the sales generated enough word of mouth to generate more sales. This idea was tested in this study by understanding the growth and decline of a movie's box office sales. Movie marketing efforts are almost exclusively focused on the time period leading up to the release, so for the purposes of this study it can be generally assumed that there was very little marketing going on after release. While no movie in this sample generated substantially more money after opening weekend (there were two exceptions but this can be attributed to limited releases that later increased the amount of theaters showing the movie substantially), the longevity of some movies was clearly correlated with word of mouth that initial sales generated. Asur & Huberman (2010) observed one movie, *The Blind Side*, which jumped from $32M to $40M the second week in box office sales and explained it with a large increase of positive word of mouth. This study had no such case matching this exact phenomenon. The best example of this phenomenon in this study was *How to Train Your Dragon*, which eclipsed the much larger *Clash of the Titans* in terms of box office revenue after the first week due to positive word of mouth.

This study showed that there is certainly a correlation between sales and word of mouth and also showed that sales were also the cause of the word of mouth. These results confirm the Bayus (1985) model of the relationship between word of mouth and sales accurate in this particular industry (movies) and medium (Twitter).

5.3 The influence of marketing efforts on WoM

The existing WoM theory concerning marketing efforts states that marketing efforts lead to increased volume of word of mouth. One such study by Yang and Zhang (2009) states that "the influence of Marketing Efforts on Word of Mouth is shown obviously." This study set out to test and confirm this fact by studying the effects of movie trailers and TV advertising on the total amount of twitter comments.

The amount of data available for this particular purpose was limited due to the long timeframe in which trailers are released before the opening weekend and the limited timeframe available to gather data. The few cases in which data was available, do however show strong indications that WoM in the form of Twitter comments experiences a significant increase as a result of the release of a trailer or TV campaign. Regarding the long term effects on WoM, the limited data made it impossible to draw any conclusion, but the data does seem to suggest that a permanent increase in WoM is achieved due to increased awareness after a marketing campaign. This study confirms that marketing efforts can demonstrably increase word of mouth on Twitter.

6 Conclusion

This sixth and final chapter will discuss the findings of the results and analysis in relation to the research questions and aim presented in the beginning of this study. The aim was to see if eWoM in the form of comments on Twitter where representative of overall WoM by testing its relationship to sales and marketing and comparing it to WoM theory. On the basis of this research objective the empirical data was analyzed, which has led us to the conclusions presented in this chapter. The practical as well as theoretical contributions of the study are outlined and discussed. Finally, the chapter provides suggestions for future research that could further contribute to the field.

6.1 The effects of WoM on sales

One of the main facts established in previous research, is the fact that volume of WoM has a strong correlation with sales. In this study, the correlation between the volume of comments gathered from Twitter concerning individual movies and the actual box office sales for those movies was proven to be very strong. This confirms that volume of WoM is a good indicator of future sales, and that WoM in the form of twitter comments is a good representation of the overall relative volume of WoM concerning different movies. Another aspect of WoM which has been widely covered in previous research is the effect of valence on sales. Both positive and negative WoM is believed to influence sales, with positive WoM having a positive effect and negative WoM having a negative effect. Studies on traditional WoM have shown results that confirm this belief, while results in eWoM studies have been contradictory. This study found positive WoM to be a significant variable in predicting box office sales, which indicates that it has a strong influence on sales. A good example of how the relative amount of positive WoM seems to influence sales is presented in the case of *How to Train Your Dragon* compared to *Clash of the Titans*. *How to Train Your Dragon* which had a relatively high amount of positive WoM experienced significantly higher sales in later weeks compared to *Clash of the Titans* which had significantly bigger opening weekend, but experienced a lot lower relative amount of positive WoM when people who saw it started sharing their opinions. No clear consensus could however be made on negative WoM as the data seems to indicate that it doesn't start to play a significant role until week three. The results of this study overwhelmingly support that word of mouth on Twitter correlates with sales which is the expected result based on theory. Therefore, our study confirms much of the existing literature about how word of mouth is expected correlate sales.

While this study confirms that the theory is relevant for Twitter and the movie industry, the theoretical debate concerning the relative influence of volume and valence is not conclusively settled by this research. The results of this study show that both volume and valence are important. Total buzz is a significant variable in explaining box office sales. The total amount of positive buzz generally has more explanatory power, this is however a measure of the volume of valance, while negative buzz and pure valance in the form of positive to negative ratio are inconclusive until the third week. Therefore, the researchers have to conclude that volume is more important than valence though valence enhances the models substantially. Whether this conclusion can be extended beyond the movie industry is unknown and would require a more diverse set of data to analyze to draw any definitive conclusion about the importance of each factor. Some industries may be more or less affected by valence based on industry factors such as the type of product or service, competition, pricing and other aspects. Volume also could be more or less important in some industries based on pre-existing awareness and perceived brand value, brand positioning, and purchasing decision cycles. The strong results from this study could be attributed to several factors that are relevant for the movie industry; for example the high competition and high rotation of movies offered (new movies being released weekly), which creates a limited window of opportunity to see the movie in theaters. Movies are social and experiential in nature which might make consumers more prone to share their experience with others, and also rely on WoM in their decision-making process. Movies are also a low cost and low risk purchase, which might factor into the decision making process.

Where this study offers new insight and extends existing knowledge is in the fact that it confirms social media sources, specifically Twitter, as a reliable and significant source of WoM. Since it was possible to use Twitter to accurately monitor WoM in real time and build models to predict future sales, similar techniques should be able to offer significant insights in other industries as well. The specific results of this study may not be helpful for other industries but the method for monitoring and modeling other industries could be very relevant.

6.2 The relationship between marketing, WoM and sales

The previous section covered the influence of WoM on sales, but one aspect that has not been covered to the same extent in previous research is the influence of sales on WoM. Recent studies using eWoM have mostly overlooked this aspect of the interaction between WoM and sales. However, understanding the dynamic relationship between the two might be key in understanding how to influence both sales and WoM. Another aspect which is of great interest for both practitioners and researchers is the role of marketing in influencing both sales directly and indirectly through WoM. The key theoretical model being tested in this study is Bayus's model (1985) which shows how marketing efforts, word of mouth and sales are all connected and influence one another.

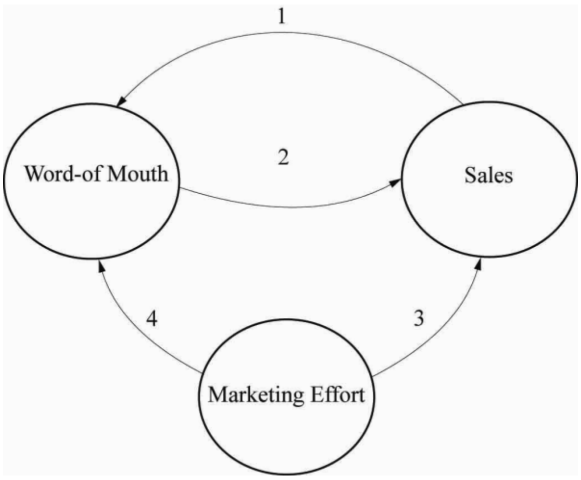

Figure 1: The conceptual model structure (Bayus, 1985)

Connection 2 was presented earlier, the ability to influence sales through word of mouth. This section will focus on *connection 1* and *connection 4*. The results from this study were able to confirm *Connection 1* in which sales influence WoM. The results show that sales have a strong correlation with future buzz. Not only was correlation shown between sales predicting buzz, causation was also shown with further investigation into what specifically was being said. Results showed that approximately 50% of all WoM after the premiere of a movie were comments by individuals who had seen the movie or where currently watching it. The implications are that after consumers have had a chance to experience a movie, it is their opinions that will constitute the majority of the WoM that is communicated. This two way interaction between WoM and sales creates a loop that Bayus theorized could generate enough WoM to generate sales better than any marketing efforts. Data from this study was able to identify that movies with a feedback loop consisting of a higher percentage of positive comments also saw a significantly more favorable evolution of sales over time. These results confirm the concept of a strong two way interaction between WoM and sales.

Connection 4, which is the connection between marketing efforts and WoM, is a connection that is well covered and established in previous research. To further confirm that comments on twitter follow the expected patterns based on existing theory, this connection was tested and confirmed by looking at the impact of trailers and TV advertising on Twitter WoM. An immediate spike could be identified in the amount of comments being shared concerning the particular movie following the marketing effort. While the short term effects where very clear, the long term effects were not strong enough to draw any definitive conclusion on the long term effects of this kind of marketing. Furthermore, the effects of marketing on WoM where not nearly as strong as the impact of sales on WoM.

The only link in Bayus' model (1985) which was untested was the effect of marketing efforts on sales which could not be tested due to the private nature of marketing efforts and spend in regards to movies. Due to this fact no quantitative measure could be used to account for marketing efforts in the regression analysis. However, the rest of the model was conclusively shown to accurately model word of mouth on Twitter with regards to the movie industry.

This study showed that there is certainly a correlation between box office sales and word of mouth concerning movies, and that the sales are also the cause of a significant amount of future word of mouth. Furthermore, the influence of marketing efforts on WoM could also be measured. **These results confirm the Bayus (1985) model of the relationship between marketing, word of mouth and sales is accurate in this particular industry (movies) and medium (Twitter).**

6.3 Theoretical and practical contributions

The main contribution of this study is the demonstration that real-time electronic word-of-mouth has become widespread enough to accurately model the overall population's WoM for at least one major industry. This study has demonstrated a practical method for how to monitor word of mouth in real time and created models using linear regression analysis that could be used to predict future outcomes.

The study further contributes to existing theory by helping to bridge the gap in understanding the difference between eWoM and traditional WoM by proving that the fundamental effects of WoM whether it is online or offline are the same. The scale of this study eliminates the potential for weak links between offline and online WoM presented in earlier small scale studies. It should be noted that not all online sources of WoM are created equal and that the source must be an accurate enough representation of the population.

Twitter modeled the overall population well because of a large and diverse user base in an industry that appealed to all demographic segments.

The method presented also makes it possible for both researchers and practitioners to gather more WoM data, on a scale of many orders of magnitude, without any interaction with consumers which gives it greater reliability, faster collection times and lower costs. The technology offers the possibility to classify the sentiment and quantify the results in real-time, which offers things such as; up to date information on consumer opinions, the ability to measure the success of marketing campaigns in real-time and the possibility to accurately prediction future sales with greater accuracy. These are only a few of the use cases that the researchers have come up with and believe many more valuable practical and theoretical applications exist. Movies are a static medium where, once the movie is released, no changes are made to it during the time it is shown in theaters. For other industries consumer feedback in the form of positive and negative comments could be used as feedback in the development of products which lead to improvements and future products. The applications for non-static industries and industries that need to respond quickly to consumers' feedback are potentially even greater than the movie industry.

We hope that this research helps open a door for researchers and practitioners to the possibility of using this way of measuring WoM, moving the field towards the use of eWoM as a basis for research and market intelligence.

6.4 Future research

6.4.1 Applying the methods to other industries

The aim of this study was to test the viability of using comments on twitter as a source of WoM. The results achieved by using a very simple method were beyond what was expected when this project started. Far more advanced and accurate methods (presented in the method chapter) already exist that can be used for this type of study, which should only increase quality and accuracy of the results. The next step is to apply these methods on other industries to test the overall generalizability of the results found in this study.

6.4.2 The week two paradox

What has been dubbed "the week two paradox" was presented in the results, but no explanation based on the data available was able to explain why week two buzz showed weaker results in predicting weekend two box office sales. The results indicate that the second week correlated best with the first week's data. Based on this correlation the researchers have hypothesized that movie goers interested in seeing a movie are most likely to go in the first two weeks regardless of what is said about the movie. There is potentially a 'new' factor in seeing a movie where some people want to see or will see a movie simply because it's new before opinions are formed by others around them. After a certain point in time the amount of people who have pre-committed to seeing a movie or are affected by a 'new' factor is likely to go down dramatically. Therefore, the movie goers that purchase tickets later after release are probably the most sensitive to reviews, rating and opinions of others. Further investigation into decision making processes and intentions would have to be studied to fully understand this aspect of the phenomenon.

Another factor that could help explain this phenomenon is the nature of human networks and how information traverses it in the real world. As discussed previously, Twitter is a form of instant communication but since it is only used by a fraction of the population it has some inefficiency in modeling real human behavior. In reality, information takes longer to spread through social networks. Therefore, some type of delay between first opinions, feedback and actual decision making processes being affected may exist. This would explain why the amount of negative buzz becomes a stronger explanatory variable in the third week while being relatively weak during the first and second week.

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Appendices

Appendix No. 1: Regressions for different variables as a function of sales

Week 1	Significance	Adjusted R^2
Theaters	0.366	0.366
Total Buzz (TB)	0	0.769
TB	0	0.895
+ Theaters	0.002	
TB	0	0.748
+ P/N Ratio	0.978	
TB	0	0.924
+Theaters	0	
+P/N Ratio	0.046	
Positive Buzz (PB)	0	0.905
PB	0	0.934
+ Theaters	0.03	
Total Buzz	0.692	0.928
+Theaters	0.046	
+ PB	0.034	
PB	0	0.897
+ P/N Ratio	0.854	
PB	0	0.934
+ Theaters	0.023	
+ P/N Ratio	0.333	
Negative Buzz (NB)	0.001	0.556
NB	0.014	0.608
+ Theaters	0.136	
NB	0.002	0.532
+ P/N Ratio	0.552	
NB	0.01	0.638
+ Theaters	0.067	
+ P/N Ratio	0.199	

Week 2	Significance	Adjusted R^2
Theaters	0.013	0.364
Total Buzz (TB)	0	0.69
TB	0.004	0.691
+ Theaters	0.331	
TB	0	0.673
+ P/N Ratio	0.551	
TB	0.004	0.684
+Theaters	0.268	
+P/N Ratio	0.405	
Positive Buzz (PB)	0	0.812
PB	0	0.81
+ Theaters	0.379	
Total Buzz	0.344	0.810
+Theaters	0.362	
+ PB	0.026	
PB	0	0.799
+ P/N Ratio	0.639	
PB	0	0.802
+ Theaters	0.314	
+ P/N Ratio	0.474	
Negative Buzz (NB)	0.012	0.377
NB	0.099	0.464
+ Theaters	0.113	
NB	0.008	0.392
+ P/N Ratio	0.276	
NB	0.049	0.507
+ Theaters	0.088	
+ P/N Ratio	0.191	

Week 3	Significance	Adjusted R^2
Theaters	0.002	0.533
Total Buzz (TB)	0	0.807
TB	0	0.866
+ Theaters	0.029	
TB	0	0.837
+ P/N Ratio	0.099	
TB	0	0.939
+Theaters	0.001	
+P/N Ratio	0.004	
Positive Buzz (PB)	0	0.89
PB	0	0.926
+ Theaters	0.024	
Total Buzz	0	0.921
+Theaters	0.004	
+ PB	0.015	
PB	0	0.927
+ P/N Ratio	0.203	
PB	0	0.96
+ Theaters	0.002	
+ P/N Ratio	0.009	
Negative Buzz (NB)	0.006	0.435
NB	0.120	0.595
+ Theaters	0.036	
NB	0.001	0.576
+ P/N Ratio	0.047	
NB	0.011	0.757
+ Theaters	0.013	
+ P/N Ratio	0.016	

Appendix No. 2: Regressions for different variables as a function of sales based on previous weeks

Week 1 -> Week 2	Significance	Adjusted R^2
Theaters	Null	Null
Total Buzz (TB)	0	0.767
TB	0	0.888
+ Theaters*	0.003	
TB	0	0.746
+ P/N Ratio	0.97	
TB	0	0.927
+Theaters*	0.031	
+P/N Ratio	0	
Positive Buzz (PB)	0	0.898
PB	0	0.926
+ Theaters*	0.039	
Total Buzz	0.681	0.920
+Theaters	0.055	
+ PB	0.043	
PB	0	0.889
+ P/N Ratio	0.962	
PB	0	0.928
+ Theaters*	0.026	
+ P/N Ratio	0.289	
Negative Buzz (NB)	0.004	0.476
NB	0.038	0.54
+ Theaters*	0.132	
NB	0.005	0.443
+ P/N Ratio	0.599	
NB	0.028	0.562
+ Theaters	0.238	
+ P/N Ratio	0.074	

* Theaters for week 2

Week 1 -> Week 3	Significance	Adjusted R^2
Theaters	Null	Null
Total Buzz (TB)	0	0.632
TB	0	0.822
+ Theaters*	0.003	
TB	0.001	0.599
+ P/N Ratio	0.92	
TB	0.001	0.839
+Theaters*	0.002	
+P/N Ratio	0.175	
Positive Buzz (PB)	0	0.741
PB	0.001	0.821
+ Theaters*	0.028	
Total Buzz	0.473	0.813
+Theaters	0.029	
+ PB	0.507	
PB	0	0.717
+ P/N Ratio	0.992	
PB	0.001	0.817
+ Theaters*	0.396	
+ P/N Ratio	0.024	
Negative Buzz (NB)	0.013	0.366
NB	0.156	0.579
+ Theaters*	0.022	
NB	0.017	0.32
+ P/N Ratio	0.67	
NB	0.086	0.517
+ Theaters*	0.228	
+ P/N Ratio	0.041	

* Theaters for week 3

Week 2 -> Week 3	Significance	Adjusted R^2
Theaters	Null	Null
Total Buzz (TB)	0	0.663
TB	0.014	0.711
+ Theaters*	0.109	
TB	0	0.697
+ P/N Ratio	0.152	
TB	0.007	0.768
+Theaters*	0.064	
+P/N Ratio	0.085	
Positive Buzz (PB)	0	0.776
PB	0.002	0.8
+ Theaters*	0.146	
Total Buzz	0.497	0.790
+Theaters	0.164	
+ PB	0.073	
PB	0	0.801
+ P/N Ratio	0.14	
PB	0.001	0.844
+ Theaters*	0.072	
+ P/N Ratio	0.069	
Negative Buzz (NB)	0.036	0.26
NB	0.403	0.523
+ Theaters*	0.019	
NB	0.013	0.346
+ P/N Ratio	0.137	
NB	0.144	0.604
+ Theaters*	0.017	
+ P/N Ratio	0.102	

* Theaters for week 3