Electronic Word of Mouth (eWOM) in the Movie Industry

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ABSTRACT
This developmental paper aims to make use of Big Data, to establish how Electronic Word-of-Mouth or eWOM affects consumer behavior in the movie industry. For the purpose of this study, 134,998 reviews were collected for 1,238 movies. These reviews were taken from the IMDb website for movies shown from 2011 to 2013. To collect the extensive number of eWOM messages used for this paper’s dataset, a program utilizing the Python programming language was used to crawl and collect movie reviews and other relevant information. Sentiment Analysis making use of the Semantic Orientation Calculator (SO-CAL) would then be used to calculate the valence of the reviews and compare them to the star ratings given by the reviewers.

CCS Concepts
• Information systems→Data Mining

Keywords
Big Data; Data Mining; Online Reviews; Sentiment Analysis

1. INTRODUCTION
Electronic Word-of-Mouth (eWOM), more specifically Big Data, has been gaining more and more attention in the digital age. The sources of Big Data range from interconnected supply chains transmitting real-time to unstructured digital channels. Channels such as mobile applications and SNS are now made available for everyone through various technological devices. Because of the proliferation of ways to communicate, traditional Word-of-Mouth behavior has somehow gained higher significance and has fully translated itself into the online world [1]. Because of this great capacity for data exchange, organizations now have access to more information than it is capable utilizing effectively [2].

1.1 The Emergence of eWOM
Despite its importance, the effect of eWOM is difficult to quantify or to be analyzed correctly. As research on electronic communication is still growing, the definitions regarding the phenomenon still prove to be both contradicting and coinciding.

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Previous work has referred to this phenomenon as interactive marketing [3], Internet communication [4], Internet word-of-mouth and word-of-mouse [5], viral marketing [6], online feedback mechanisms [1], buzz marketing [7], stealth marketing [8], electronic word-of-mouth communication [9], electronic referral marketing [10], interactive or electronic word-of-mouth advertising [11].

Most eWOM studies examined its effect by customer review data. Also, many studies used review rating as the indicator of customer satisfaction [12, 13]. However, review rating may contain a group polarization problem. This pertains to the propensity of groups to take more extreme positions compared to the initial preferences of its individual participants [14-16]. Since people tend to put more attention on extreme opinion, a group polarization problem is more noticeable in eWOM [17].

1.2 Analyzing Online Reviews
When analyzing reviews, the actual degree of perception toward rating may differ significantly between reviewers. This is true even if two reviews give the same rating using the same scale. For example, two reviews have the same star rating but actual content can be very different: “It’s really not that bad”, “I fell asleep halfway through”. To avoid such problems, a few studies analyzed the contents of customer reviews instead of raw rating. Although such studies can analyze with increased reliability (on the assumption of high intercoder reliability), validity of those research is often questionable because of limited quantities in analysis. In addition, these studies, which used content analysis method, can easily make the mistake of making hasty generalizations or rash judgments. To cope with these problems, this study aims to analyze the review data through Big Data analysis.

Recently, Big Data analysis has received great attention in numerous areas. Big Data has been defined by Gartner as any collection of data which has three characteristics: volume, velocity, and variety [18]. Since Big Data is an emergent idea, IBM added an additional characteristic of Big Data, which is veracity, with Gartner’s 3 Vs. As Big data deal with enormous amount of data, like IBM’s argument, veracity become more important as time passes by. Therefore, this research focuses on the veracity of eWOM analysis by matching review ratings with actual review contents concurrently.

1.3 The Importance of Veracity
Understanding the affective content of a message is important because emotions differ in the level of activation they evoke [19]. However, regarding effectiveness of customer review by its direction, previous studies showed mixed results. One side of study argues positive customer reviews are more effective to
use [20]. On the other hand, some study emphasized negative customer reviews are more trustable [21-24]. There are also several studies that neutral reviews are more effective [25, 26]. These mixed results begin with a limited quantity of sample. Our research may solve these ambiguous results by adopting the Big Data analysis method.

Lastly, the time of reviews also need to be considered to clarify the ambiguous nature of eWOM. Before the product is released, eWOM could influence the consumers’ awareness of the product. On the other hand, after the release of the product, eWOM may influence consumers’ attitude towards the product. Understanding the changes in the affective content of eWOM based on the time of posting would influence the strategies used, either promoting simultaneously or retrosepectively, in line with consumer sentiment [27].

2. REVIEW OF LITERATURE

eWOM communication could pertain to positive or negative statements made available to a host of individuals and institutions online. It is made by potential, actual, or former clients about an organization, its services, or its products [9]. eWOM functions as an extended part of conventional communication means. As the world has moved towards web-based technologies, proxy means of communication has been established through blogs, forums, review sites, and social media [28].

With information derived through eWOM communication, customers could get feedback not only from the people they know, but also from complete strangers whose consumption behaviors prove to be similar or related to theirs [29-31]. Because of this, the consumption decisions of online consumers driven by the information they could get online ultimately affect sellers, whether online or offline.

Previous work has identified the various opportunities stemming from increased online consumer interchanges, as well as the threats they face because of them [32, 33]. Similarly, some research on the relationship between product choice and eWOM has been undertaken. One such experimental study focused on the utilization of online recommendation sources by users [34]. As such, eWOM proves to be the bridge that connects each and every user to the world, expanding ones reach beyond the confines of ones’ social circle.

2.1 Reliability of Online Recommendations

The evaluation process of consumers in relation to recommendation credibility proves to be an interesting phenomenon to examine. This is because more and more of these consumers make use of product information derived from the eWOM network. However such information could be deemed unreliable as it comes from a generally anonymous user base. The nature of the data in itself puts the credibility of the information up for discussion.

Compared to traditional WOM, the credibility of eWOM is scrutinized at a higher degree by consumers. This is especially true when dealing with product recommendations. Consumers would only believe reviews which they deem reliable. Previous research has revealed that credibility is one of, if not the chief qualification of utilizing eWOM. Such a study has found that customers’ purchase decision could be predicted by the credibility of the information source. Users who deem the review or recommendations as valid have no reason to disregard it [35].

In comparison to other attitude dimensions, the subject of people’s evaluation of credibility in the web is one which could potentially improve the understanding means of which eWOM is utilized. eWOM’s eventual emergence came primarily from online review sites, the amounts of which could range from hundreds to thousands of entries from a multitude of users worldwide. It was found that it was less likely that people recommend products featured in personal blogs to friends compared to those reviews from an independent review website [36]. This thereby leads users to assign more credibility to the latter. However, the influence of eWOM platforms in relation to the propensity to recommend the product was found to be limited to positive reviews, as the likelihood that the consumer would recommend a product with bad reviews decrease regardless of which eWOM platform the information came from.

With the constant growth and accessibility of the internet, the information from these online recommendations have crossed the realm of Big Data and analyses in relation to it. These Big Data analyses and Big Data in itself have been used to characterize the vast amount of complex information and methods that they need specialized technologies in order to visualize, manage, store, and examine.

With the advent of digital age, the Big Data era has emerged and made itself a necessity for the population at large, be it private individuals, or multinational organizations. This could potentially bring about the discovery and understanding of new technologies and sciences through the vast, exabyte scale amount of mobile, online, and sensor-generated information. This information could be acquired from the comprehensive, contextualized, and rich data available to businesses and organizations in light of digitalization.

2.2 The Effects of Reviews on Consumer Behavior

A positive relationship has been observed between review valence and consumer behavior across literature. Various factors, situational or otherwise, affect the response of users to the degree to which product information might be positive or negative. It can be said that involvement moderates the effects of negativity to users’ information processing. Those who focus on the outcome of product use gave more importance to negative than positive product information [21, 22]. Negative feedback, when incorporated even to exceptionally positive ones, adversely affected consumer attitude. In addition to this, it was found that the influence on attitude toward a brand of extremely negative reviews was strongest when compared to moderately negative and extremely positive reviews. It can thereby be said concurred that consumer attitudes are greatly affected by negativity, extremity, or more so, a combination of the two [24].

In this day and age, people refer to peer and critic reviews when considering products or services. Previous studies however, have not tackled this topic in depth. As such, information about the effects of reviews to the customer decision is minimal, or nonexistent. Prior research has found that both positive and negative reviews increase consumer awareness when consideration set theory is used to analyze the effect of online reviews to consumer choice. On the other hand, it was also found that positive reviews positively affects consumer attitudes as well. Furthermore, lesser-known products prove to be more responsive to such reviews, and that the expertise of a critic positively influences review impact, but only minimally [20].
2.3 The Role of Critics in Online Recommendation Systems

Getting the opinion of other people has always been a vital facet of data gathering and analysis. As resources like online review sites, blogs, and other social media platforms have become more prevalent, it is easier than ever to access other peoples’ insights and sentiments. The increase in popularity of new systems which deal with sentiment analysis as well as opinion mining has led to increased interest in the topic [37].

The power of critics has been well established in various fields, but the influence is even more prevalent in the field of entertainment. However, studies in relation to critic reviews and their effect to the market have hardly been the topic of academic writing. This influence is very important in the movie industry, as movies have very short life spans, and the production and other costs in relation to them prove to be quite high. Critics are could thereby be considered an opinion leader or influencer, being viewed by the public as someone knowledgeable or an authority figure in a particular area. They could also be considered predictors of popularity, or lack thereof [12].

The influence of critics in relation to creative goods such as literature, film, music, among others, has recently garnered a lot of scholarly interest [38, 39]. Critics prove to be valuable in the marketing process as they (1) serve as advertisements and provide information, (2) discover rising stars and create reputations, (3) create a product themselves in the form of reviews, and (4) influence preference because reviews could affect consumers’ perception or promote consumption [38]. Critics influence the choices of the people, get insights into the film, confirm the viewers’ opinion about the film, and be a point for discussion [40].

Because films are typically in theaters only for a brief period, one can make a distinction between the time when the decision to watch a movie was made, and the time when one has watched the film [44]. Studies as to whether pre-release WOM can explain and influence movie revenue thereby prove to be a good subject for research [45]. Previous studies show that negative eWOM has higher perceived effects than positive eWOM. They also show that these effects are greater for established sites compared to unestablished ones. Lastly, there are greater perceived effects for experience goods compared as opposed to search goods [46]. This leads us to the hypothesis:

Hypothesis 1: Positive prerelease eWOM has a stronger effect on Movie Sales Performance than negative pre prelease eWOM.

Previous research has also observed the relative helpfulness of the degree of positivity and negativity. Extreme and two-sided arguments would lead to question how effective extreme reviews are, versus moderate ones. Star ratings reflect attitude extremity [47], the degree of deviation from the middle point of the scale. This midpoint, most commonly depicted through a three-star review, could possibly reflect indifference or ambivalence, showing a reasonable measure of middle-ground attitude [48, 49].

It has been found that the credibility of communications is perceived to be higher when two-sided messages are used in advertising [50, 51]. The use of two-sided messages is also found to enhance brand attitude [50]. Hence, it could be implied that moderate reviews prove to be more effective than extreme ones. However, previous studies on reviews yielded varying implications. Two-sided arguments were found to be more credible for reviews of movies with moderate star ratings. These led to more positive attitudes about the films reviewed. Conversely, two-sided arguments were found to be less credible for films which experienced review extremity [26]. Therefore, we hypothesize that:

Hypothesis 2: The eWOM valence in the opening week will be less positive than that of the eWOM before the movie is released.

The aforementioned studies have however failed to consider timing in their studies. For products with short product life cycles, the decision as to when new products are launched is among the most significant strategy issues. These studies on the other hand did not tackle the relationship between the market and the timing of product. Movies, being a resource-intensive product proves to require longer lead times. Because of this, it becomes more difficult to forecast the competitive environment which awaits it at its subsequent release time. It is thereby important to understand the relevance of the environmental factors which influence its performance [52].

Previous studies have used a queuing theory framework to conceptualize the consumer’s movie adoption process in two steps—the time to decide to see the movie, and the time to act on the adoption decision. The parameter for the time-to-decide process captures the intensity of information intensity flowing from various information sources, while the parameter for the time-to-act process is related to the delay created by limited distribution intensity and other factors. This study has assumed that consumers act instantaneously on the motivating information they receive about the new product [44].

Current eWOM papers only consider star ratings and do not include content analysis. Since there is a large quantity of eWOM, it falls under Big Data. Degree of positivity or negativity considers valance of attitudes as opposed to simple existence of valence. To evaluate a product, awareness and attitude should be considered.
Awareness is more important than attitude. This is because knowing about a product is more important than actual perceptions about the product. Hence, before the release of the product, awareness is more important. On the other hand, after the release of the product, attitude becomes more important than awareness. Before the release of the product, the volume of eWOM is important. Therefore,

Hypothesis 3: Prior to the release of the movie, review volume has a stronger effect than review positiveness or negativeness.

On the other hand, after release of the movie, the feedback of the audience regarding the attractiveness of the movie. Degree of audience review is more important after release to the sales of the movie. Threshold on number of samples should be included to justify contents analysis. Timing should also be considered, thereby proposing that,

Hypothesis 4: Negative eWOM for subsequent weeks have a stronger effect on movie sales performance than positive eWOM for subsequent weeks

Since movie data are time sensitive, we should consider the time cycle of movies. Various media sources provide critical reviews to moviegoers and could easily be accessible [45, 53, 54]. These reviews could potentially provide value to advertising since the critics who make them are mostly not associated to studios in general. The effect of critical reviews to new films are found to be generally positive [12]. However, experience would come into consideration and further influence eWOM valence subsequent to the release of the films.

Expectations, be it its validation or negation is found to influence the satisfaction of consumers [55-57]. The higher the expectation given of film to be released, the greater the likelihood of disconfirmation attached to it. The related eWOM would thereby experience a decrease in its degree of positiveness. There is a higher chance that consumers view a film unfavorably after watching it if there was great expectations brought about by advertising, and general hype before its actual release [58].

4. METHODOLOGY

4.1 Data Collection

This study uses movie reviews as WOM messages from the Internet Movie Database (IMDB.com), a subsidiary website of Amazon.com. IMDB.com is currently the most popular and influential online database that provides extensive and influential source of information regarding movies, television shows, and celebrities. The information provided on the website includes financial information, cast, production crew, plot summaries, trivia, and reviews, among others. It is the leading online movie resource in the world with an aggregate viewership of 250 million unique monthly visitors and to add to that, the website is open-access to everyone on the web. These reasons help avoid probable bias in the demographic composition of the site’s online audience and therefore, is a valid source of reviews for movies.

As of October 2015, IMDb had about 185 million data items which include 3,487,955 movie titles, TV and entertainment programs. This number also include more than 6 million cast and crew members. Consumers rely on IMDb for a range of movie and television information that from local movie showtimes, ticketing, trailers, critic and user reviews to box-office data, editorial feature sections and watchlists.

To collect the extensive number of WOM messages used for this paper’s dataset, a program utilizing the Python programming language was used to crawl and collect movie reviews, dates when the reviews were published, usernames, and star ratings from the IMDb website for movies shown from 2011 to 2013. For 2011, 41,663 reviews were collected, for 2012, 47,180, and for 2013, 46,155, resulting to a total of 134,998 reviews collected from 1,238 movies shown within the timeframe for the study. Review publishing date information allow us to track the time period in the movie’s run a specific review belongs to. The pre-release period cover the stretch of time from the date the first movie review is posted to the specific date before the movie is officially released globally. Reviews written during this period capture the accumulation of the movie’s WOM before the opening date.

For other information regarding each movie, an affiliate of IMDb.com, BoxOfficeMojo.com was crawled. BoxOfficeMojo.com is the leading box-office reporting service website owned and operated by IMDb. Aside from the website being reliable, BoxOfficeMojo.com is well-designed and straightforward to find and collect information from, thus reducing possible errors in data collection. Information regarding annual movie lists, complete movie titles, worldwide and domestic grosses, genres, MPAA ratings, runtimes, production budgets, distributors, open and close dates, number of theatres at opening date and total, and weekly gross information were collected from the website. To be able to process the massive amount of data collected for this study, review details and movie information were matched together, organized, and compiled into one file for data analysis. Movie titles that do not have complete information were omitted in the study.

4.2 Control Variables

This study identified potential antecedents of WOM that may affect both independent and dependent variables. These factors are movie genres, MPAA ratings, Production Budget, and the Weeks of Release. Movie genres are generally accepted classification of movies based on its storyline (e.g. Action, Drama, Suspense, Sci-Fi). MPAA ratings, on the other hand, are used to classify movies based on content according to its suitability for viewing of specific audiences (e.g. G, PG, PG-13, and R). WOM activities can be affected by the movie’s intrinsic appeal and controversial buzz, if it exists, when the curiosity for the movie is high [45]. Next, production budgets is also considered as one of the control variables because there is significant evidence that high production budgets affect box-office revenues. Weeks of release also need to be controlled because movies shown longer will have more time to collect reviews. Number of theatres on opening dates and total

![Figure 2. The Impact of WOM Volume and Veracity on Movie Sales](image-url)
number of theatres were also controlled because, evidently, movies shown in more theatres will be getting more revenues. These variables were identified by other studies [1, 45] as important control variables are therefore also adopted in this paper.

4.3 Sentiment Analysis
To analyze the valence of movie reviews, this paper uses the Semantic Orientation Calculator. This method combines Wordnet and SentiWordnet. Current methods on sentiment analysis are explained below.

The approaches to sentiment analysis are currently grouped into four main methods—lexical affinity, keyword spotting, concept-level approach, and statistical techniques. Keyword spotting and lexical affinity matches words to specific emotions. On the other hand, knowledge-based systems utilize open resources, such as WordNet-Affect, SentiWordNet, and SenticNet, in order to obtain the semantic and affective evidence connected with the text.

4.3.1 Wordnet
Wordnet is a comprehensive English dictionary of nouns, verbs, adjectives, and adverbs. These words are classified synsets. Synsets are groups of synonyms. Each synset expresses a distinct meaning and are linked to other synsets in terms of conceptual-semantic and lexical relations. These results in a network of meaningful related words. Wordnet resembles a thesaurus because it classifies words into groups based on their meanings. Nonetheless, it differs from a thesaurus due to the following reasons: 1) Wordnet connects not just word forms/strings of letters but specific senses of the words. Therefore, words that are found to be in close distance between each other in the network are semantically disambiguated. 2) Wordnet identifies the semantic relations between words, as opposed to the Thesaurus which does not follow any definite pattern other than similarities in meaning.

4.3.2 SentiWordNet
SentiWordNet is a lexicon for opinion mining that uses Wordnet synsets. SentiWordnet assigns three sentiment scores for each synset: positivity, negativity, and objectivity. These scores describe how Objective, Positive, and Negative the terms contained in the synset within a range of 0.0 to 1.0. Their sum is 1.0 for each synset, therefore a synset may have a combination of nonzero scores across the categories.

4.3.3 The Semantic Orientation Calculator (SO-CAL)
Semantic Orientation (SO) measures the subjectivity and sentiment in natural language. SO estimates the sentiment polarity of the word, phrase, sentence, document including the strength of its positivity or negativity. Semantic orientation is useful in measuring popularity and marketing success to analyze written public opinion such as online reviews. SO-CAL classifies the polarity of an opinion in the text using dictionaries that annotate the semantic orientation, intensification, and negativity.

4.4 Testing the Accuracy of the Star Rating
Two judges independently read 284 reviews from one randomly chosen movie and assigned a star rating that is deemed appropriate for each user review. The scale used is similar to IMDB’s star rating, from 1 being the most negative to 10 as being the most positive review. These independent codings were then compared to the original star rating given by the user.

Actual star ratings given by the reviewer will be compared with the ratings given by the independent judges. This step will test the veracity of the given star ratings. The results will give the researchers an idea on the gap between star rating and movie reviews.

5. Discussion and Managerial Implications
Online word-of-mouth has been a source of insight and powerful information since the dawn of the internet age. Researchers have studied online reviews and how they affect product sales and consumer reaction. However, this paper shows that there is more to online e-WOM than is currently being researched. This paper contributes to movie-marketing and WOM research by investigating WOM. Particularly, this study focuses on WOM and its antecedents to help explain weekly box office sales. The study compares the explanatory power of volume of WOM, star power, and valence in analyzing box-office sales.

Results of this study would be pertinent in forecasting box-office sales. A good foresight on movie sales help studios and theatres better plan screening capacity to avoid sold-outs and empty screenings. Nonetheless, this is not the main purpose of the study at hand. Rather, the main point of this study is to illustrate how a forecasting model can significantly benefit from WOM information. To fulfill this task, we will use the set of independent variables and adopt the standard calibrating-forecasting approach. In contrast to Liu’s (2006) research, this research have collected WOM data from a total of 134,998 reviews collected from 1,238 movies shown within the timeframe for the study. Whereas, the previous study have collected WOM from only 40 movies. Another important point to be tested by this study are the star rating and its relationship with the valence of the movie reviews. This aspect was not explored in previous research. Most review websites sources use a star-rating to summarize aggregate movie evaluation information. Therefore, the veracity of star-rating and movie reviews are important WOM information. These two characteristics used individually or aggregated, will reveal possible relationships to box-office sales.

6. REFERENCES


