Electronic Word-of-Mouth Spread in Twitter as a Function of Message Sentiment

Benny Bornfeld, Sheizaf Rafaeli, Daphne Ruth Raban
Faculty of Management
University of Haifa
Haifa, Israel
bennyb@ruppin.ac.il, sheizaf@rafaeli.net, draban@univ.haifa.ac.il

Abstract **- Which is more viral, positive or negative electronic word-of-mouth? Can you tell which of the following tweets will spread more in Twitter: "saw the movie … last night, must see it" or "saw the movie … last night, avoid at any cost"? This study is about electronic Word-Of-Mouth spread as a factor of its sentiment. Some theories support a negative bias, while others support a positive bias. Some suggest that both biases are possible, depending on the product type. This paper presents the main theories, related studies and the results of quantitative research based on movie related tweets containing sentiment polarity. Due to the dual nature of Twitter, as mass medium and social network, the research focuses on Twitter's social sub network which contains ordinary users having a small to medium number of followers. The main findings are that tweets with positive sentiment polarity spread 15-20 percent more than tweets containing negative sentiment polarity.**

Keywords-Information flow; Information Dissemination; Sentiment Analysis; electronic Word Of Mouth; Twitter.

I. INTRODUCTION

Word-of-mouth (WOM) is known to have a strong influence on the user's purchase decision. In addition to marketing aspects, message spread or virality is important for intellectual, learning and political reasons. Several books on this topic were recently published; amongst them are "Going Viral" [1] and "Memes in Digital Culture" [2].

The recognition of the importance of WOM in the two-step flow theory dates back to Lazarsfeld and Katz [3]. Electronic Word-Of-Mouth (eWOM) is an important product-related message spreading mechanism. The Internet-based WOM, eWOM, travels fast and can potentially reach very large audiences. One of the most salient Internet services today is Twitter. Twitter is a powerful platform for spreading many kinds of messages, including eWOM. Some eWOM messages carry a negative sentiment polarity and others carry positive or neutral polarity. Does message sentiment polarity influence the extent of message spread? The old marketer's belief that "bad is stronger than good" dominated the pre-Internet WOM era. Is this negative bias still dominant in the Internet social networks of today? Or is the spirit of Facebook's only “Likes” and no “dislikes” catching in the eWOM communication?

Looking at the question of eWOM spread and influence as a function of the eWOM sentiment polarity, there are several theories and evidence, elaborated in the next sections, which provides support for both directions. Those contradicting directions were the trigger for this study, hoping to make a contribution to this open question.

The rest of the paper is structured as follows: In the theoretical background, we present differing views by the Negativity Bias and Product Moderator Theory, followed by an overview of the data source, Twitter. In the related work section, we discuss and summarize related work on this and similar topics. We continue with presenting the research hypotheses and the method followed by a discussion of the finding. We finalize with conclusions and future work section.

II. THEORY

Looking at the question of WOM spread and influence as a function of the WOM sentiment polarity, several theories and evidence provide support for both directions. Some theories postulate that negative is more influential and some claim that positive is more influential. Others state that both directions are valid and the effect depends on the type of the product. In principal, message dissemination depends on two factors: the message value and the messenger’s preference. The information value theories presented here are (1) the negativity bias and (2) the product moderator theory which distinguishes the bias according to different product types.

A. *Negativity bias*

When examining the literature and theory related to the WOM and sentiment polarity, there is strong evidence for the negativity bias. Several articles [4][5][6] show evidence in support of the WOM negativity bias for products and services. They report that negative WOM is twice to 4 times stronger than positive WOM. These sources fit the statement "Bad is stronger than good", which is the title of an article [7] . They state that "The greater power of bad events over good ones is found in everyday events, major life events (e.g., trauma), close relationship outcomes, social network patterns, interpersonal interactions, and learning processes. Bad emotions, bad parents, and bad feedback have more

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impact than good ones, and bad information is processed more thoroughly than good". Cheung and Thadani [8] provided a mapping of studies showing the prevalence of the negativity bias over a broad range of areas from information processing, memories, feedback, emotion, marital status, WOM, impression formation, choice, value and frames and customer satisfaction. Baumeister et al. [7] present a social evolutionary argument that this cross-area prevalent phenomenon shows that it is a human adaptive mechanism. They postulate that "The relative strength of bad over good is an adaptive response of the human organism to its physical and social environment. In view of how pervasive the relative strength of bad is, it seems unlikely that this pattern is maladaptive". They explain why it is more adaptive in the following manner -"bad events signal a need for change, whereas good ones do not. If satisfaction and pleasure were permanent, there might be little incentive to continue seeking further benefits or advances. The ephemeral nature of good feelings may therefore stimulate progress (which is adaptive). If bad feelings wore off, however, people might repeat their mistakes, so genuine progress would best be served by having the effects of bad events linger for a relatively long time." More evidence and possible explanations to the negativity bias is summarized in the work of Rozin and Royzman [9].

Another argument in support of the negative bias is the rarity argument. This argument claims that since negative information is rarer, it is highly informative by definition. In order to support the rarity argument, we first need to describe and validate the positivity dominance in languages. Rozin and Royzman [9] provide a summary of evidence based on the work of Osgood [10], showing that positive adjectives are used more frequently. They present a study done on 17 languages, which validated the positivity bias. Quantitative analysis studies by Blenn et al. [11] and Asur and Huberman [12] observed that there are more positive than negative tweets. The biased feedback features provided by social networks platforms like Facebook's “Like” and Google's “Plus One” contribute to the overall positive polarity in social networks. Back to the rarity argument, given the positivity bias in language, negative information is rarer and therefore more informative.

The reliability argument: In many online systems, such as recommender systems, the anonymity of the writer makes the user suspicious as to the credibility of the information, especially towards positive information. Lam et al. [13] studied the credibility issue and gave the following example: “consider a dishonest seller on eBay who wishes to increase his feedback score. He could create a large number of identities and use them to leave himself positive feedback.” According to attribution theory [40], the reader may attribute the positive information to the reviewer self-serving or other non-product-related reasons, leading him to discount positive information.

B. *Product type moderator theory*

Trying to settle the contradicting findings in different studies, several studies postulated and provided evidence that the effect is subject to the product type. Two contemporary studies, of “hedonic vs. utilitarian” and “promotion vs. prevention consumption” products, relate to the same basic factor of product type. Zhang et al. [14] draw on regulatory focus theory and propose that: "the consumption goals that consumers associate with the reviewed product moderate the effect of review valence on persuasiveness". Higgins et al. [15] who phrased the regulatory focus theory provide the following description of their theory: "A promotion focus would involve a state of eagerness to attain advancement and gains where as prevention focus would involve a state of vigilance to assure safety and non-losses".

Based on Attribution Theory, Sen and Lerman [16] examined the usefulness of published consumer reviews for the reader. They claim that: "trust that the reviewer’s opinions are based on external (product, or other related aspect) and not internal (subjective, or reviewer related) reasons will determine the review’s usefulness to the reader." Attribution theory examines whether the reader attributes the reviewer’s opinions to product related motivations, or believes that they are motivated by self-serving or other non-product-related reasons. The authors find that: "compared with the utilitarian case, readers of negative hedonic product reviews are more likely to attribute the negative opinions expressed, to the reviewer's internal (or non-product related) reasons; and therefore are less likely to find the negative reviews useful". Referring to the previously mentioned study, hedonic products map to product with promotion consumption goals and utilitarian products map to products with prevention consumption goal.

C. *The Messenger’s preferences*

Messages spread only if the messengers decide to pass them. In WOM communication, the messengers have the choice to pass the message or not. One factor on their pass-or-not decision would be the message value, which was discussed in the previous paragraph. Another important factor is their subjective preference. In his seminal book, "The Presentation of Self in Everyday Life", Goffman writes about how people present themselves in a way they want to be perceived by others. Berger and Milkman [17] stated that “Consumers often share content for self-presentation purposes [18] or to communicate identity, and consequently positive content may be shared more because it reflects positively on the sender. Most people would prefer to be known as someone who shares upbeat stories or makes others feel better rather than someone who shares things that make people angry or upset”. People often relate the message to the messenger. This is the perception in the roots of the phrase "shooting the messenger". Relating this theory to the question of eWOM dissemination in social

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networks, people will prefer to repeat positive eWOM in order to present themselves in a positive way.

D. Theory summary

Message dissemination depends on the information value and the messenger preference. Regarding the information value, there are more theories and evidence in support of a negative bias. The prevalence of the negativity bias across many areas, the adaptive argument, the rarity argument and the reliability issue associated mainly with positive eWOM lead to the hypothesis that negative messages spread more. On the other hand, the reliability is less of an issue in Twitter because the follower knows who sent the message. The regulatory focus theory, present the moderator role of product type. It predicts a positive bias for hedonic promotion consumption goal products. Since movies are definitely a hedonic, promotion consumption goal product it predicts that negative information will be "discounted". Regarding the messenger preference, the need to present oneself in a positive light contributes to a positive bias.

E. The research framework

The research question is: Does the eWOM message sentiment polarity influence the extent of message dissemination?

We studied the dissemination of eWOM in Twitter as a function of message sentiment polarity. This study examined the spread of tweets via the retweet mechanism in the movies domain. Hence, the presentation and discussion of related work focus on studies which share one or more of this research characteristic.

F. Twitter

Twitter is currently the most popular microblogging service. Microblogging is a broadcast medium in the form of blogging, which differs from typical blogging by its small content length. Twitter enables its users to send text-based posts called tweets to their followers. A tweet length is up to 140 characters. Users may subscribe to other users' tweets - this is known as "following" and subscribers are known as "followers". Tweets are publicly visible by default. Twitter carries hundreds of millions of tweets per day.

Like social network sites, profiles are connected through an underlying articulated network, but these connections are directed rather than undirected. The number of user's followers varies from zero to millions. Among the many ordinary users which have up to hundreds of followers there are some highly followed users. Those highly followed celebrities, politicians, news channels, corporations and others use this network as a mass medium communication channel. Participants have different strategies for deciding who they follow - some follow thousands, while others follow few. Some follow only those that they know personally, while others follow celebrities and strangers that they find interesting. In the following section, we further discuss if Twitter can be considered to be a social network.

Several social conventions were introduced and then embraced by the service users' community itself. The most notable conventions are:

1. Reply: a way to reply to, or to mention another user. Syntax: @user (e.g., @barackobama)
2. Hashtag: a way to indicate the message topic. Syntax: #topic (e.g., #iranelections)
3. Retweet: forwarding others messages to your followers. Syntax: RT @user (e.g., RT @ladygaga). This spreading mechanism plays a major role in this research method and in many other studies and services. We elaborate on its role when answering question 5 in the next section.

III. RELATED WORK

Related work covered in this section presents studies which asked similar questions or methods. This review aims to bridge theory, methods and their findings.

The related work is divided into the following research questions:

1. From studies related to valence effect on product eWOM: What is the effect of positive versus negative product eWOM on message dissemination and influence in Twitter and in recommender systems?
2. Moving from product related information to the neighboring non-product information dissemination, several studies researched the following question: What is the effect of positive versus negative polarity on non-product related message dissemination and influence in Twitter and other media channels?
3. To show the practical relevance of this question, several studies asked: Does eWOM polarity influence product sales?
4. To validate the selection of Twitter as the data source, several studies examined the question: Is Twitter a social network?
5. Due to the key role of the retweet mechanism, several studies explored the question: What are the roles and characteristics of the retweet mechanism?

1. Spread and influence of positive and negative product eWOM in Twitter and in recommender systems.

The question of dissemination and influence of messages within online social network was explored from three different angles: the nodes, the arcs, and the substance.

1. The networks' node angle is focusing on the people and asking: who is influential?
2. The network structure angle examines the ties (arcs) between people and exploring how the networks structures affect the spreading.

3. The content angle examines spread as a function of the message content attributes, such as topic, emotion and sentiment (this is this research angle)

Barbagallo et al. [19] studied tweets containing tourist information about the city of Milan in Italy. They found that negative posts are retweeted more. Sen et al. [16] researched online reviews and found support for the negative bias. In addition, they observed that: "in the case of hedonic products however, readers were more likely to discount than value the negative reviews. Readers found 72% of reviews “not helpful” as compared to 28% being “helpful”".Jansen et al. [20] Twitter-based eWOM research covered products from several industries. They found that on average 50% of the tweets were positive and 33% were critical of the company or product. Zhang et al. [14] conducted an experiment in which they measured the reaction to positive and negative Amazon product reviews. The reviews covered two types of products: a promotion consumption goal product and a prevention consumption goal product. In accordance with Attribution Theory, they found that: "For products associated with promotion consumption goals, consumers show a positivity bias, whereby they rate positive reviews as more persuasive than negative ones. Conversely, consumers show a negativity bias for products associated with prevention consumption goals". In the preventive consumption product, the experiment participants were suspicious towards positive reviews. One common perception is that some of those reviews might be written by non subjective reviewers, such as the product seller. On the other hand, negative reviews for promotion consumption product were attributed to the reviewer’s subjective perspective. With regard to Attribution Theory, there is a difference between classic recommender systems and Twitter. In recommender systems, the reader has no information/acquaintance with the review writer. Therefore, she derives the attributes from cues in the review content. In Twitter, the reader is presumed to be familiar with the person she is following who sent the tweet.

2. *What is the effect of positive versus negative content on non-product related message (e.g., news) dissemination and influence in Twitter and other media types?*

Several scholars examined the dissemination of non product related content, such as news, articles and phatic communication. Berger and Milkman [17] studied the spread of NY Times articles by email. They found that the spread is related to activation "Content that evokes either positive (awe) or negative (anger or anxiety) emotions characterized by activation (i.e., high arousal) is more viral. Content that evokes deactivating emotion (sadness) is less viral". Stefan and Dang-Xuan [21] studied German politics related tweets and found that emotionally charged Twitter messages (positive or negative) tend to be retweeted more often and more quickly compared to neutral ones. Hansen et al. [22] Twitter based research found that negative news and positive phatic communication are more viral. They proposed that "if you want to be cited: Sweet talk your friends or serve bad news to the public". Somewhat contradicting results were presented by Bakshy et al. [23] . They found that tweets containing URLs linking to positive stories where more dominant in the top retweeted list. Thelwall et al. [24] studied tweets peaks around large events. They observed that "popular events are normally associated with increases in negative sentiment strength and some evidence that peaks of interest in events have stronger positive sentiment than the time before the peak". The rise in both positive and negative sentiment is at the expense of neutral tweets. Another interesting observation by this research supports the writers subjectivity claim: "a surprisingly small average change in sentiment associated with popular events (typically 1% and only 6% for Tiger Woods’ confessions) is consistent with events affording posters opportunities to satisfy pre-existing personal goals more often than eliciting instinctive reactions".

3. *How does eWOM polarity influence sales?*

The very practical question regarding the relation between eWOM and sales was addressed by several studies. Many of them chose to focus on the movies industry. Some studies took the challenge of solving the eWOM and sales chicken and egg question, using time series analysis. Some studies aimed at finding sales predictions based on eWOM characteristics, such as influencers, overall chatter and message sentiment. Some of those studies are based on recommender systems while others are Twitter based.

Liu et al. [25] found that positive Twitter WOM increases movie sales while negative WOM decreases it. They divided the tweets to pre-consumption (e.g., I want to watch the movie) and post consumption (e.g., the movie was….). They found that the strongest effect on movie sales comes from pre-consumption tweets where the authors express their intention to watch. Asur and Huberman [12] presented evidence that although eWOM volume is the main predictor for movie sale, sentiments extracted from Twitter can be utilized to improve the forecasting power of social media. Addressing the chicken and egg problem [26] conducted a study based on reviews from recommender web sites. They state that WOM is both a precursor to and an outcome of retail sales and that WOM polarity significantly influences the WOM volume. Those studies, showing the relation between sentiment, WOM and sales provide ground for tying the terms of influence and spread.

4. *Is Twitter a social network?*

Twitter's popularity, the buzz around it, the open nature of its communication and the opportunity it provides for computational social science research has made it a fertile ground for scientific research. Twitter combines characteristics of both mass media, broadcasting news and advertisement and characteristics of social network with relations and interaction between the users. The question of the nature of Twitter and how its users perceive it has implications to this research and others which explore phenomena within social networks.

The 2010 article "What is Twitter, a Social Network or a News Media?" by Kwak et al. [27] addressed this basic question by conducting a large scale quantitative analysis. They showed that Twitter is not a classic social network: “In its follower-following topology analysis I have found a non-power-law follower distribution, a short effective diameter, and low reciprocity, which all mark a deviation from known characteristics of human social networks [28].Among reciprocated users we observe some level of homophily”. Huberman et al. [28] studied the interaction between users on Twitter and came to the following conclusion: "most of the links declared within Twitter were meaningless from an interaction point of view. Thus the need to find the hidden social network; the one that matters when trying to rely on word of mouth to spread an idea, a belief, or a trend".

Other studies took a more qualitative approach. Gruzd et al. [29] conducted a case study on Barry Wellman's twitter followers and friends and stated: "there is a possibility that Twitter can form the basis of interlinked personal communities—and even of a sense of community. The analysis of Barry’s Twitter network shows that it is a basis for a real community, even though Twitter was not designed to support the development of online communities". Boyd et al. [30] examined tweets and retweets and found that "Spreading tweets is not simply to get messages out to new audiences, but also to validate and engage with others". Marwick [31] conducted a research by tweeting questions to Boyd's Twitter followers and analyzing their answers. Among them was a question aimed at understanding to whom are they tweeting. They found that some users "imagined their audience as people they already knew, conceptualizing Twitter as a social space where they could communicate with pre-existing friends".

A comparison to another "quasi social" network may shed some light on this question. Social questions and answers sites, such as Yahoo! Answers also possess a dual nature. Golbeck [32] showed that this service fully meets the Golbeck's accessibility, relationship and support criteria for a web-based social network. Furthermore, a study by Rechavi and Rafaeli [33] showed that within this service there are actually two interdependent networks, a social and an informational network.

5. What are the roles and characteristics of the retweet mechanism?

Twitters' retweet feature receives a lot of attention in Twitter-based studies. Some studies provide descriptive data concerning retweet probability. Some studies correlate it against other characteristics, such as number of followers, number of friends, tweeting rate, mentions, hashtags, urls, etc. Other studies try to predict the retweet probability based on the user and content characteristics. Besides its obvious role in message spreading, several researchers claim that the retweet is an important indicator of influence in Twitter.

In a world where endless amount of information is flowing through social networks, competing for the user's attention, the message sender has to overcome the basic passivity of the message receiver. Based on retweets, Romero et al. [34] propose an algorithm to determine the influence and passivity of users based on their information forwarding activity (retweets).They see the retweet as an action performed by the retweeterer. Driving the user to take an action indicates influence. Cha et al. [35] compared three possible measures of influence, indegree, retweets and mentions. They argue that: "it is more influential to have an active audience who retweets or mentions the user. Retweets are driven by the content value of a tweet, while mentions are driven by the name value of the user.". Zaman et al. [36] built a model for retweet probability based on the tweeterer and the tweet content. Suh et al. [37] conducted a large scale study of retweets and found that "URLs and hashtags have strong relationships with retweetability. Amongst contextual features, the number of followers and followees as well as the age of the account seem to affect retweetability, while, interestingly, the number of past tweets does not predict retweetability of a user’s tweet".

Boyd et al. [30] studied retweeting as conversational practice and claim that: "While retweeting can simply be seen as the act of copying and rebroadcasting, the practice contributes to a conversational ecology in which conversations are composed of a public interplay of voices that give rise to an emotional sense of shared conversational context. For this reason, some of the most visible Twitter participants retweet others and look to be retweeted. This includes users of all kinds, but notably marketers, celebrities and politicians". A research on celebrities influence in Twitter [38] defined influence in the following manner: "the ability to, through one's own behavior on Twitter, promote activity and pass information to others". He found that retweet-based influence is the most significant type of influence.

A. Related work summary

Most product related WOM studies report a negative bias. Some studies derive from the regulatory focus theory and show the moderator role of the product type, leading to a positive bias in hedonic promotion consumption goal products. Studies on non-product content dissemination, such as news, present contradicting results. Some studies focus on the emotions the message arouses and the message affordance. Several studies support the two ways relationship between the movie's Tweets dissemination and its box office success. Several studies pondered over the nature of Twitter and found that it exhibits also social network characteristics. Studies that focused on the role of Twitter's retweet feature found that it plays an important role in the social sub-network and that retweet is an indicator of influence.

In light of the theory and related work, there were three motivations for this research:

1. The contradicting evidence from different studies.
2. The tension between theories supporting positive versus negative bias.
3. Modest availability of evidence based on updated high volume data collected from online social networks.

In order to be consistent with the view of Twitter as a social network, the focus of the research is on WOM flow between ordinary users and not WOM originating from the highly followed users.

Related studies show that this research stands on solid ground when choosing Twitter as the data collection field, examining the retweet dissemination and choosing to study the movies domain.

IV. RESEARCH HYPOTHESES

Consistent with other researches which used movies and other products tweets and the language positivity bias previously described -

H1: There are more positive than negative tweets in movie-related Twitter messages.

Following the theory and studies that show support for more spread of positive polarity messages in hedonic, promotion consumption goal -

H2: Positive polarity movie tweets will spread more, in number of retweets and audience size, than negative polarity movie tweets.

V. METHOD

The method is based on measuring the message dissemination (the dependent variable) as a function of the message sentiment polarity (the independent variable). The basic categorical values in sentiment polarity are positive, neutral and negative. The retweet mechanism drives dissemination. The collected data contains tweets about movies which came out between the end of 2011 and the beginning of 2012. The focus was on new movies since they were more tweeted about. The rationale of choosing movies was discussed in the related work section. Due to the dual nature of Twitter as mass medium and social network, the research focuses on Twitter's social sub network which contains ordinary users having medium number of followers. The cutoff number below which we considered a user to be an ordinary user was having 1000 followers. This number was chosen due to its being the round number above Dunbar's number for social group size and wanting to address a significant portion of Twitter users. 70% of twitter users have 50-1000 followers (Figure 4). The reason there is a lower limit of 50 followers is that there was almost no retweet activity for tweets sent by users with fewer than 50 followers.

A. *Research process description*

This section describes the research process and results, discussing the rationale of the different steps, challenges and results. The main steps were:

1. Data collection
2. Data cleaning
3. General tweets and retweets statistics
4. Followers analysis
5. Sentiment classification
6. Manual sentiment classification
7. Naïve Bayes classification endeavour
8. Study of tweets dissemination as a factor of the sentiment

1) *Data Collection*

About half a million movie related tweets were collected during 4 months using a service by a company called GNIP [39] (see Figure 1). GNIP provides full access to tweets which was not available directly from Twitter in the time this data was collected.

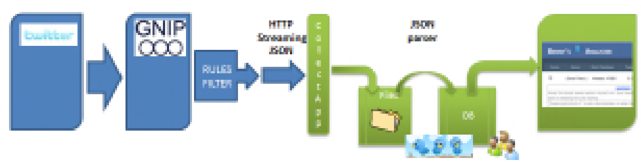

Figure 1. Tweets collection architecture.

2) *Data Cleaning*

After the tweets collection step, where ~500,000 tweets containing movie names were collected, the large data set was analyzed using an application that we've developed for this purpose, called Twitter Analyzer. The application main features are presenting, sorting and filtering all tweet's and user's fields. It also calculates and aggregates number of retweets and exposure.

Manual inspection of the tweets using the Twitter Analyzer indicated that many of the tweets do not contain WOM content. The first step was cleaning the data set in order to get a higher percentage of WOM content. The cleaning process first step was removing several movies related tweets which contained a large number of non WOM content. The second step was using a white list for filtering tweets which contained words indicating that the user had seen the movie (was, were, went to, saw, have seen, had seen, watched, is). After the cleaning process, the clean data set contained 21,000 tweets. Eventually we verified that our data set contained low level of spam in it (less than 3%).

3) *General tweets and retweets statistics*

For the second hypothesis, we're interested in the retweet mechanism and followers count. The relative share of retweets to the overall traffic is described in Table 1. It is based on the initial data set of 108,000 tweets. The data shows that ~9% (7/78) of the tweets were retweeted and that 22% of the total number of tweets is due to retweets.

4) Followers

Analysis of the number of followers showed that the distribution is according to a power law and 70% of the users have 50 – 1000 followers (see Figure 2). The power law distribution of number of followers is the reason that the 100 most retweeted tweets (~1%) are responsible for about half the retweets in the data set.

TABLE I :MESSAGE TYPE DISTRIBUTION IN THE INITIAL DATASET.

Retweets	22%
Original tweets that were retweeted	7%
Tweets that were not retweeted	71%
Total	100%

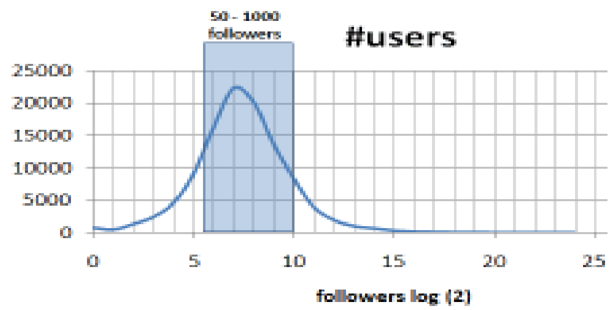

Figure 2: Distribution of users according to the number of followers (log 2).

5) Sentiment Classification

The following categories were defined (*):

- Positive (e.g., "… WAS SOOOOOO GOOD!!!! ")
- Negative (e.g., "… is the first movie where i actually fell off to sleep...#flop")
- Neutral (e.g., "Just saw … and now I think Im Keke Palmer singing all these slow jams lmao")

(*) Two other categories were used to classify the tweets, "Not Relevant" and "Before" (e.g., "going to see the movie"). Due to their relatively low number, they were joined with the Neutral category in order to simplify the analysis.

The following classification guidelines were set:

- In cases where the tweet contained both positive and negative content (e.g., "the movie was too long but interesting"), it was classified as neutral.
- The sentiment classification refers to the movie and not to the general sentiment of the tweet. For example, the following tweet: "had a great time with my friend but the movie been boring" was classified as negative.

6) Manual classification

Two human coders classified 8,600 tweets according to the categories described above. The 8,600 tweets were sampled randomly from the clean data set and contained all the messages that were retweeted and part of the messages that were not retweeted. The human coders' inter-classification-agreement rate was ~84% (7195/8600). Those 7195 classified tweets (Table 2) were used for the dissemination analysis. This data set is called the classified set. The main result of this stage is that the ratio between negative and positive eWOM is 0.18 (7.3/40.4).

7) Naïve Bayes classification endeavour

Having a large tweets data set, our goal was to use the manual classification to train a Naïve Bayes classifier. The low percentage of negative tweets (~7%) led to a relatively high classification error rate which made it unsuitable for usage as a reliable classifier for the larger data set. Unbalanced data sets are a known issue with naïve bayes classifier.

8) Tweets dissemination as a factor of the sentiment

The overall ratio: The overall ratio between negative and positive retweet count was 0.18 (table 3), which is the same as the ratio between negative and positive tweets.

Ordinary users' retweet ratio: A closer examination of retweets count for ordinary users (50 – 1000 followers) showed that positive retweets are retweeted about 15% more on average (Figure 3). Further, neutral tweets get retweeted more times (Table 3) than both positive and negative tweets, this is due to a lot of retweets of neutral tweets that were tweeted by highly followed users.

TABLE II: MANUAL SENTIMENT CLASSIFICATION DISTRIBUTION RESULTS.

Retweets	Negative	Positive	Neutral	Total
Quantity	527	2907	3761	7195
Percent	7.3%	40.4%	52.3%	100%

TABLE III: SUM OF THE TIMES THE TWEETS GOT RETWEETED.

Retweets	Negative	Positive	Neutral	Total
Count(*)	173	976	5365	6514(**)
%	2.7%	15%	82.3%	100%

(*) After removing the highest record in every category
(**) Retweets from the classified data were counted from the large data set

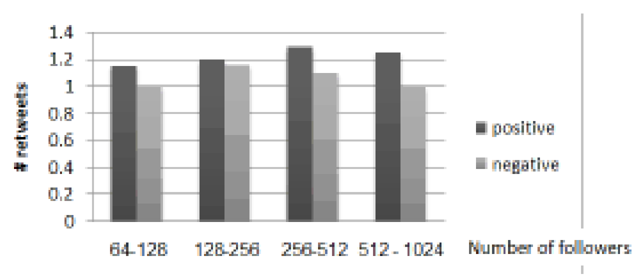

Figure 3: Average number of the times a tweet was retweeted for ordinary users.

TABLE IV: TOTAL EXPOSURE OF TWEETS.

Tweets	Negative	Positive	Neutral	Total
Count(*)	233349	1289641	4867790	6390780
%	3.6%	20%	76.4%	100%

Exposure ratio: Counting the number of users who received the tweet, the negative/positive ratio for the total exposure

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was again 0.18 (3.6% / 20% in Table 4). Consistent with the previous observation, neutral tweets get the highest exposure.

Ordinary users' exposure ratio: A closer look at the distribution of exposure count of users who received (exposed to) the retweet showed a significant difference of ~15%-20% more positive tweets in the range of 100-600 exposure level (Figure 4).

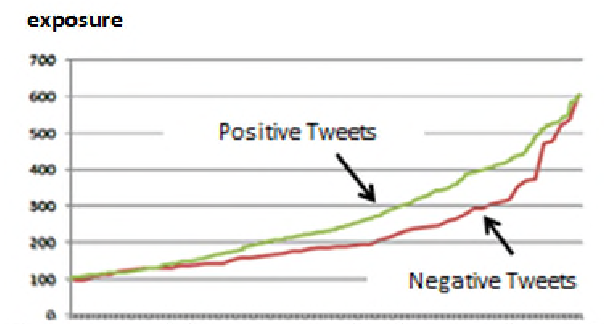

Figure 4: Retweet exposure distribution in the 100-600 exposure range.

9) Dissemination as a factor of sentiment - results summary

The negative/positive ratio of ~0.18 was consistent over the full classified tweet set. This ratio, showing positive dominance over negative in the original tweets (Table 2) is consistent with other studies, such as Blenn et al. [11] and Asur and Huberman [12]. When focusing on ordinary users, in the 100-1000 followers range, there is a positive bias: positive tweets are retweeted more times (Figure 3) and positive retweets exposure is higher (Figure 4).

B. Results summary

General characteristics and statistics of the retweet mechanism: Retweets constitute 7% of all tweets, and counting the repeats they amount to ~29%. The retweets are power law distributed. Some tweets are retweeted in high numbers, 1% of the tweets that were retweeted were responsible for 50% of the total number of retweets.

Followers' distribution: 70% of the users have 50 to 1000 followers. This is the group that is referred to as ordinary users in our analysis. There is a lower boundary of 50 followers below which there are almost no retweets.

Tweets dissemination:

- Full classified data set (7195 tweets):
  - Positive tweets outnumber negative tweets by a ratio of 5.5 (1 / 0.18).
  - Neutral tweets are the most retweeted.
- Ordinary users subset (50 – 1000 followers) (4627 tweets):
  - There was a positive bias of (15%-20%) in dissemination measurements

1) Limitations

The generalization power of these findings is somewhat limited due to the focus on one product type in a specific network. Nevertheless, Twitter is a very big network and movie related tweets are popular (see Asur and Huberman [12]).

VI. DISCUSSION

Our findings support H1 by showing that there are five times more positive than negative sentiment polarity tweets. This is consistent with the language positivity bias. An alternative explanation is that since the dataset contains tweets about movies, most people enjoy the movie they see and avoid going to movies which they will not like by reading reviews and getting recommendations from friends. Regarding the main hypothesis, this study provides support for H2 which predicts that positive sentiment polarity tweets spread more than negative tweets in the social sub-network of Twitter. While the dissemination results of the full classified set showed no preference to positive or negative polarity, a closer look at the ordinary users showed a positive bias of about 15%-20%. These results support the regulatory focus theory and messenger preference, both predicting a positive bias / negative discount, for promotion consumption goal product, such as movies.

The limited explanatory of power of 15-20% suggests that there are other significant factors that affect messages dissemination, such as content, attributes, structure and user characteristics. Some of them are described in the studies referenced in this paper.

The justification of using Twitter as our data field relies on the existence of a social sub-network for ordinary users. Marwick [31] and Gruzd et al. [29] claimed that Twitter has social network aspects in addition to mass medium characteristics. We extricated the social sub-network by restricting the analysis to ordinary users, those with 50-1000 followers. This is a novel approach, following Liu et al. [22] who also split their Twitter users by follower count. Empirically, there are two findings which support the dual approach view. With a cutoff parameter of 600-1000 followers we found significant differences in sentiment dissemination and in tweets length between the two groups.

A repeated finding shows high exposure and number of retweets of neutral tweets. This can be explained in light of the two sub networks approach. Most of the neutral tweets are tweeted by highly followed users. Those highly followed users are often channels of information.

VII. CONCLUSION AND FUTURE WORK

Positive tweets get the stage on the social sub network of Twitter with the topic of movies. Furthermore, the positivity bias hypothesis for hedonic promotion consumption goal products received support in these data.

Future work: A complimentary focus on the same question can study the results for eWOM spread on different products. It may be interesting to compare a promotion consumption goal product with a prevention consumption goal one. Message dissemination of the same product (movies) can be studied in other social networks and compared to the results presented here.

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