The Role of Emotions in Propagating Brands in Social Networks

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September 2014

Abstract

A key aspect of word of mouth marketing are emotions. Emotions in texts help propagating messages in conventional advertising. In word of mouth scenarios, emotions help to engage consumers and incite to propagate the message further. While the function of emotions in offline marketing in general and word of mouth marketing in particular is rather well understood, online marketing can only offer a limited view on the function of emotions. In this contribution we seek to close this gap. We therefore investigate how emotions function in social media. To do so, we collected more than 30,000 brand marketing messages from the Google+ social networking site. Using state of the art computational linguistics classifiers, we compute the sentiment of these messages. Starting out with Poisson regression-based baseline models, we seek to replicate earlier findings using this large data set. We extend upon earlier research by computing multi-level mixed effects models that compare the function of emotions across different industries. We find that while the well known notion of activating emotions propagating messages holds in general for our data as well. But there are significant differences between the observed industries.

Keywords Marketing, Social media, Word of mouth, Propagation, Google+, Mixed effects, Emotion, Text mining, Computational linguistics

1 Introduction

An important factor in marketing is the propagation of messages by word of mouth. This lends the marketer’s original message additional credibility and extends its reach. This is an essential contribution in the co-creation process of brands. The advent of social media and social networking sites gave marketing a broader access to people’s social circle and their word of mouth message networks. Despite its importance for marketing in general and brand management in particular, the precise mechanism of word of mouth message propagation in online social networks has not yet been adequately researched. In this paper we set out to fill this gap with additional insights, that will empower practitioners to better harness the power of word of mouth propagation across industries and help academia understand the different needs of consumers.

In order to do so, we harvested a large number of social media marketing messages. To the best of our knowledge, this is the most comprehensive study of brand marketing in social networking sites in general and the first one using Google+ data. We then computed their sentiment using advanced state of the art computer linguistic classifiers. Starting from well established Poisson-based regression models and extending to mixed effects models, we seek to trace the precise function of sentiment in marketing messages in the digital world. Due to the large number of observations, the results are expected to be very reliable.
This paper is organized as follows. We first distill the interdependencies between brand management, marketing and emotions in Section 2. Then we review other contributions towards a better understanding of emotions in social networks and word of mouth marketing in Section 3. In Section 4 we first describe our data and methods and then the results of our analysis in the subsequent section. Finally, we discuss our findings and offer some concluding remarks in Section 6.

2  Marketing, Brands and Emotions

At the beginning of the 21st century, marketing theory took a sharp turn. When conceptualizing marketing along the lines of the production of goods, many phenomena remained unexplained: For instance, brands and the involvement of consumers with brands could not be captured with a production logic. In contrast, a service-dominant logic is much more powerful in explaining especially the interactions between consumers and brands [Merz et al., 2009, Vargo and Lusch, 2004, 2008]. There, consumers work with brand managers in concert to co-create a brand. So instead of pure recipients of messages, consumers are attributed with an active role in the marketing and communication process [Hollenbeck and Kaikati, 2012]. This active role revolves around taking up messages that have been seeded by marketers and propagate them further, with possible own additions to the original message.

In essence, much of the co-creation process in marketing depends on word of mouth [Moldovan et al., 2011]. This is, the receiving and taking up and altering of a message by consumers. Holt [2002] describes that this also becomes one of the greatest challenges in the process. Due to the distance between brand managers and consumers, a lack of authenticity hinders much of the co-creation process. They find, however, that with increased use of word of mouth, authenticity becomes restored. This is also seconded by Chu and Kim [2011] who find that it is these connection properties that are intimately linked to word of mouth effects.

There are two aspects to bolstering the building of brands with word of mouth effects. One is the role of emotions, that in general are a very powerful vehicle in marketing. The study by Stokburger-Sauer et al. [2012] identifies the memorable brand experiences are one of the key drivers behind consumer–brand identification, and emotions are triggering these experiences more easily [Pham et al., 2013]. And the other one is the augmenting effect that brand communities can have.

Strictly speaking, an emotion is a feeling or a sensation that is a process within a human being. This narrow definition of emotion allows emotions to be triggered by external influences [Bagozzi et al., 1999]. While this distinction is perhaps worthwhile for psychological analyses, widening this definition, would apply the term emotion also to the triggering influence. This allows a more natural interpretation of emotions in texts. For instance a text that is sad will trigger the emotion of sadness in its readers. We use the term emotion in this latter, wider sense.

Emotions have various effects on the way marketing messages are received. In a word of mouth marketing context, for instance Berger and Milkman [2012] found that using the right emotions increases the likelihood of virality of a message. In their work they conclude that high-arousal emotions like awe and anger will increase the virality of a message. Less activating emotions, like sadness, work against the propagation of messages. Romani et al. [2012] arrive at different conclusions when diagnosing that anger and sadness as emotions in marketing messages will trigger negative word of mouth events.

Therefore, emotions in brand messages affect the degree of consumer involvement in the co-creation process.

An area that is or should be of elevated interest to marketers are brand communities [Schau et al., 2011].
Brand communities are groups of people that form around brands. They are not necessarily geographically close and might share nothing more than their common interest in a brand [Muñiz Jr. and O’Guinn, 2001]. Obviously, due to the centrality of a brand in these communities, they play an important role in the co-creation of the brand [Kozinets et al., 2010].

3 Word of Mouth in Social Networking

The advent of social media plays along well with the renewed understanding of marketing as omnidirectional co-creating process [Onishi and Manchanda, 2012, Kunz and Hogreve, 2011]. Instead of simply selling news to the masses [Iyengar and Kinder, 2010], social media allows for users selecting messages to propagate themselves. This makes social media ideal for word of mouth based marketing. Social networking sites (like Facebook) are a special case of social media that emphasizes shortness and multimedia over more elaborate texts.

When translating the mechanics of word of mouth marketing to the social networking arena, some equivalents become apparent [Matteo et al., 2013]. The propagation of a message can be achieved by using one of two forms of endorsement: a lesser and a more potent one. The details of these forms vary by implementation, but there is a general pattern. Each form of endorsement leads to the original message being injected into the news stream of users connected to the endorsing user. The lesser form of endorsement (Facebook’s likes, Twitter’s stars and Google’s +1s) leads to a less prominent injection and does not allow to enrich the original message with own content. The second form of endorsement (Reshares or Retweets) prominently adds the original story (possibly with additional information) to the users news streams.

The brand community has multiple equivalents. One is the official company sponsored social networking presence. There users can meet to retrieve seeded brand messages directly from the source. They can use these messages to propagate them further down their own stream of followers, possibly enriching it with their own respective contents on the way. Other brand community analogues are less formal communities or unofficial fan pages.

While word of mouth based marketing can be readily implemented using social media, in the past there have also been some challenges to companies discovered. Onishi and Manchanda [2012] find that social media and traditional mass media marketing can be hindering each other if not planned well. Only by taking into consideration the particularities of each channel can an optimal outcome be secured.

However, the greatest challenge perhaps is, that in social media in general but social networking in particular, brand managers are much harder pressed to anticipate what consumers want [Arango-Forero and Roncallo-Dow, 2013]. This is mainly because consumers can (and will) react instantly to seeds planted by the brand manager. Because of the nature of social media, these reactions can be far reaching, indeed. Take for instance the by now canonical example of the brand of a media manager that she managed to destroy during a flight from the US to Africa by posting a single negative message.

It is therefore crucial for brand managers to understand which messages lead to increased resharing of her brand messages. As stated above, the equivalent of word of mouth in social media is the two forms of endorsement. We have also established the notion, that emotions are viable predictors for the virality of social media messages. However, most current research is focused on single industries. For instance, both Berger and Milkman [2012] and Chevalier and Mayzlin [2006] focus on the book publishing industry. While informative, their research is hard to generalize, given their limited sample. The results described above draw an inconsistent picture with the role of emotions still being fuzzy. This is potentially due to the same emotions functioning differently across industries.
In this paper we want to focus on differences between industries. In this paper we focus on two key aspects of message sentiment and their effects on message endorsements: 1. How does message polarity affect message endorsements? 2. How does the use of emotions affect message endorsements?

In sight of the current state of the art, we offer the following hypotheses:

1. Messages with a positive polarity are more likely to be endorsed.
2. The use of (right) emotions in social media marketing messages increases the count of endorsements that message receives.
3. Not all emotions have the same effect across industries.

In the following section we are going to discuss both method and data we used to answer this question.

4 Research Design

In order to generate a complete picture of the determinants of emotional brand marketing in social media, a large host of brands needs to be analyzed. We used the Open Knowledge Foundation’s Brand Repository data base [Ope 2014]. At the time of analysis, that data base contained the names, identifiers and websites of 4151 different brands. To ensure comparability, we reduced this list further to contain only brands that used a .com top-level domain. This effectively excludes local and localized brands, focusing on internationally available brands. This step also excluded brands that did not use digital marketing at all, as demonstrated by their lack of a brand website. We further excluded any brands that either did not have a Google+ profile at all or one with a very limited +1 count ($p1 < 250$). The resulting list of 199 brands was then manually checked and each brand assigned to an industry. During the manual check and classification, we removed another 50 brands from the list that either had not posted anything on Google+ or that had slipped through our selection heuristic. Because brands from the automotive industry were somewhat underrepresented, we added nine randomly chosen brands to the list. In the end, 156 brands remained.

For each brand, all the posts to their Google+ page were retrieved using R [R Core Team 2014] and the plusser extension package [Waldhauser 2014]. This yielded 32409 posts in total. Table 1 gives the distribution of brands and posts over industries.

| Industry        | Pages | Posts |
|-----------------|-------|-------|
| Apparel         | 31    | 6368  |
| Automotive      | 11    | 2200  |
| Cosmetics       | 37    | 7742  |
| Electronics     | 14    | 2985  |
| Food/Beverages  | 43    | 8927  |
| Sports          | 8     | 1600  |
| Other           | 12    | 2587  |

Table 1: Number of analyzed brands and posts per industry.

Using the naive Bayes classifier implemented in the sentiment package [Jurka 2012], the messages’ polarity and emotionality were computed. The package delivers a negative-positive ratio to measure polarity based on keywords that occur in the message. To arrive at an estimation of sentiment, the package uses a similar approach for the emotions Anger, Disgust, Fear, Joy, Sadness, and Surprise.
As stated above, the key concept we seek to analyze is the propagation of a message in social networks. The analogue of word of mouth propagation in the online scenario is the higher form of endorsement: reshares. In order to be able to analyze and compare the distribution of reshares, we built two types of linear models. One type to establish a Google+ baseline that is interesting in itself, as Google+ has not yet received widespread academic attention, is a simple generalized linear model (GLM). We chose a GLM because the reshare counts of messages cannot be considered to be normally distributed. Rather, they represent rare (given the number of followers) events that are best modeled using a Poisson process. GLMs permit just that. The following equation summarizes our model.

\[ r \sim p + e + \text{cv} + \text{offset}(t) + \text{offset}(f) \]

On the left hand side, \( r \) represents the number of reshares a message has received. The variables \( p \) and \( e \) contain the polarity ratio and the emotions encoded within a message in six dimensions, respectively. There are other determinants that might influence reshare frequency independent to our analytical problem. Among those are message length and time of day the post was put online [Stieglitz and Dang-Xuan 2012, Cha et al. 2010, Suh et al. 2010, Yang and Counts 2010, Hochreiter and Waldhauser 2013]. Among other covariates that have been identified to be relevant for Twitter, but are not implemented in the Google+ search API are e.g. hashtags and media attachments. Message length and time of day are contained in \( \text{cv} \).

Poisson based regression assumes a constant window of measurement. In the case at hand, the window’s dimensions are given by the age of a post \( (t) \) and the number of followers it has been exposed to \( (f) \). While the age of the post can be reliably determined, we assume the number of page followers to have remained constant over the period of investigation and therefore take this figure as the number of followers the post has been exposed to. Both terms need to be included as offsets in the model to adequately model the relationships between the number of reshares and the message properties as described above.

This simple model is then extended to allow for brand and industry comparisons by using mixed effects models. Conceptually, we consider our selection of brands and industries to be random. Therefore, we model any effects due to industry and brand as random effects. We test both random intercept and random slope models against each other. \(^1\)

In this section we described our method of retrieving posts from Google+ and computing the posts’ sentiments. We proposed Poisson regression models to use sentiment to explain the reshare count of a message. In order to incorporate company and industry differences, we use mixed effect models. The results of our analyses will be given in the next section.

5 Results

In order to establish a baseline of message propagation mechanisms in Google+, we initially computed simple Poisson regression models. We started out with an empty model and included it as a reference \( (m_0) \). Next, we added variables to control for the message length (number of characters) and time of day (deviance from noon in hours). This formed model \( m_1 \). In a next step, we controlled for the number of comments and the number of +1s a message has received in \( m_2 \). Finally, in \( m_3 \) and \( m_4 \), the polarity and emotionality predictors were added. All models were tested successively against each other using standard Likelihood Ratio tests. All test yielded highly significant results with \( p < 2.2 \times 10^{-16} \). This is to be expected given the large sample

\(^1\)All modelling was done using the lme4 package [Bates et al. 2014]; graphics were produced using ggplot2 [Wickham 2009].
size. More appropriately, we compared the models using the AIC criterion. The results from this baseline estimation are given in Table 2.

|           | $m_0$  | $m_1$  | $m_2$  | $m_3$  | $m_4$  |
|-----------|--------|--------|--------|--------|--------|
| Intercept | 0.00   | 0.00   | 0.00   | 0.00   | 0.00   |
| Message length | 1.00   | 1.00   | 1.00   | 1.00   |
| Time of Day | 1.04   | 1.01   | 1.01   | 1.01   |
| Comments | 1.01   | 1.01   | 1.01   |
| +1s | 1.00   | 1.00   | 1.00   |
| Polarity | 1.00   |
| Anger | 1.05   |
| Disgust | 0.89   |
| Fear | 0.76   |
| Joy | 0.95   |
| Sadness | 0.95   |
| Surprise | 1.02   |

AIC: 926202.56 921079.66 794331.11 793457.15 786504.72

Table 2: Comparison of simple Poisson-based GLMs. Incidence Rate Ratios and model AIC.

In order to analyze and compare the effects of emotions on message propagation across industries, we computed multi-level models. There, messages are nested within industries. We compared two kinds of model types, all containing the same baseline fixed effects as $m_4$ above and one sentiment. We tested both model types for all seven sentiments (polarity and six emotions) using likelihood ratio tests. All tests produced overwhelming evidence that random slope models were required. Table 3 contains the incidence rate ratios that were computed using the models’ random effects into account for the different industries in the data set. The table’s $\sigma$ line describes the standard deviation of the random effects. The larger the value becomes, the more heterogeneous the function of this sentiment is across the surveyed industries.

|       | Polarity | Anger | Disgust | Fear | Joy | Sadness | Surprise |
|-------|----------|-------|---------|------|-----|---------|----------|
| Apparel | 1.01    | 0.86  | 0.73    | 0.63 | 0.94| 0.96    | 0.98     |
| Automotive | 1.00    | 1.14  | 1.75    | 1.12 | 1.01| 1.05    | 1.02     |
| Cosmetics | 1.00    | 0.96  | 0.88    | 0.83 | 1.02| 1.05    | 1.08     |
| Electronics | 1.00    | 0.55  | 0.74    | 0.77 | 0.83| 1.05    | 0.98     |
| Food/Beverages | 1.01    | 0.73  | 1.20    | 0.72 | 1.00| 0.96    | 1.24     |
| Sports | 1.00    | 0.94  | 1.94    | 0.96 | 1.03| 1.05    | 0.99     |
| Other | 1.02    | 1.04  | 0.52    | 0.85 | 1.07| 0.82    | 0.90     |
| $\sigma$ | 0.01    | 0.28  | 0.30    | 0.26 | 0.07| 0.09    | 0.09     |

Table 3: Varying functions of emotions as indicated by incidence rate ratios for message sentiment.

In this section we first established a base line for the function of sentiments in Google+ posts in the context of word of mouth marketing. We could validate previous findings for other forms of social media in the importance of covariates. We then proceeded with including random effects to model different industries. Using hypothesis testing, we conclude that more complex random slope models are required. In the next section we are going to discuss the implications of these findings.
6 Discussion & Implications

The results exhibited above allow for two important insights. One is that Google+ does not behave differently from other social networks, in terms of covariates explaining the likelihood of message propagation. The other key insight are the differences between industries in the function of sentiments.

6.1 Baseline

Looking at the results from $m_4$, it becomes evident that the findings by Berger and Milkman [2012] hold also for Google+. When controlling for message length and time of day, activating emotions like Anger or Surprise exhibit incidence rate ratios larger than 1. This indicates that every increase in Anger also leads to an increase in the likelihood of the message being reshared. As expected, the Sadness emotion is different. There, an increase in Sadness leads to a decrease in expected reshares. Due to the large number of brands and messages sampled and all results being significant, these results allow for a high degree of confidence.

6.2 Industry comparison

Turning to the comparison of the function of sentiments across industries reveals a different picture. When discussing random effects models, there are two key figures. One is the variability observed and the other one the random effects computed.

Figure 1 compares the variability in all seven sentiments of the industries observed. Disgust exhibits a very large variability, closely followed by Fear and Anger. The remaining emotions and Polarity appear to have almost constant effects across industries. While there is very little variation in Joy but also in Sadness and Surprise, negative but activating emotions like Anger, Disgust and Fear differ radically in their function across industries.

Figure 2 displays the different effects the measured emotions have on message propagation for brands of different industries. The high variability of Disgust is also clearly visible in its panel in this figure, while Joy and Sadness remain fairly constant. Looking at Anger, we find that most random effects indicate a negative effect on message propagation. Only the automotive industry can harness Anger successfully. The emotion of Disgust has some strong propagating effects also in the automotive and the sports industries. Fear is an emotion that is unpopular with consumers of goods from most industries but particularly apparel.

The findings of Berger and Milkman [2012] would suggest that Anger contributes to and Sadness hinders message propagation. We can confirm the function of Sadness in our data. For almost all industries, Sadness in the message leads to a decrease in the likelihood of a message being reshared. While brands from the automotive, cosmetics and electronics industries enjoy a slightly positive effect of Sadness, it is so small, that it can safely be ignored. This, however, is at odds with the results provided by Romani et al. [2012], that would expect sadness to lead to increased word of mouth effects. Our data does not support this.

Anger on the other hand does not behave as the predicted word of mouth driver. It is only the automotive industry that can benefit clearly from an angry emotion in its messages. There are barely noticeable effects for cosmetics and sports. Anger, however, clearly hinders message promotion in the industries of Electronics and Food/Beverages.

Recurring to the research questions we posited in the beginning, we have to conclude that message polarity does not only not vary across industries. Message polarity does not influence the likelihood of message propagation at all. There are, therefore, no connections between the polarity of a message and the strong form of endorsement.
Figure 1: Boxplot comparing the variability in sentiment effect across industries.
Figure 2: Effect of emotion on message propagation likelihood across industries.
Turning to the second question, it is apparent that there are stark differences in the functioning of emotions between the brands of different industries. The perhaps most important finding lies here: activating emotions do not function in the expected way for a majority of industries.

This has serious managerial implications. While traditional word of mouth based marketing literature asserts that activating emotions will *always* support the propagation of word of mouth, we find that this is only the case for select industries. Brand managers seeking to extend their involvement in the co-creation process are required to tread carefully in the light of these findings. While *Anger* will help in getting messages adopted by consumers for the automotive industry, managers responsible for electronics brands will need to avoid this emotion in their messages.

In the last instance, it appears that the brand co-creation process is more complicated than previously thought. With clear and significant differences in the function of sentiments between industries, brands and their advertisements remains a game for highly skilled players and careful considerations.

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