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Evaluating the Impact of Posted Advertisements on Content Sharing Sites: an Unsupervised Social Computing Approach

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Abstract

During the last decade social media have greatly flourished, reaching rapidly the amazing figures of today. According to the Search Engine Journal (http://www.searchenginejournal.com/25-insane-social-media-facts/79645/): (a) currently 684,478 pieces of content are shared on Facebook every minute, (b) people are spending 1 out of every 7 minutes on Facebook when online, (c) 93% of marketers are using social media, however, only 9% of marketing companies have full-time bloggers and (d) around 46% of web users will look towards social media when making a purchase. It is obvious that businesses are tapping into social media, since they find them as a rich source of information and a business execution platform for product design and innovation, consumer and stakeholder relations management, and marketing. For this reason it is very useful to evaluate the impact of each posted advertisement. Towards this direction several supervised works have been presented in literature mainly focusing on traditional media. However, the impact of advertisements on new media (such as social networks, blogs etc.) has not been studied thoroughly yet. Additionally unsupervised impact evaluation is a very challenging problem. In this paper a novel unsupervised social computing approach is proposed that effectively performs both on open social media (twitter, blogs, microblogs etc) and on rule-stringent media (e.g. Facebook, LinkedIn etc). Our scheme algorithmically estimates the importance of each advertisement by considering both explicit interactions between advertisements and social media users and users' popularity. The proposed method operates without human intervention and training and it is applied on real content posted on social media. Experimental results provide an insight of the performance of our system and specific areas are detected for future research.

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Keywords: advertisements' impact ; social media; social computing; user popularity;

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1. Introduction

The world in which marketing operates has fundamentally changed. The rise of China, India and other emerging economies has demanded new market strategies to reach developing countries. At the same time, social concerns from environmental impact to corporate social responsibility are changing the relationships of companies to the societies in which they operate. Social Media and virtual worlds such as Second Life are giving new meaning to the concept of "place" in marketing. Collaborative projects such as open source software and Wikipedia are transforming the consumer into a co-creator.

On the other hand, the ever growing amount of user generated content and active participation over social media have recently attracted considerable public and scientific interest. Several studies estimate that the time spent on social networking websites is 20-25% of the total time spent on the internet, while more than 50% of social media users follow brands on social media (Van Belleghem et. al., 2011). A significant portion of this social media usage is critical for businesses to listen, monitor and respond. There exist many forums, blogs, news-sites and message-boards where customers express their opinions, complaints, questions, suggestions etc. regarding products and services. Businesses are increasingly becoming aware of this trend and devising strategies to best make use of this social media channel. It is now common to see ‘pages’ of various businesses on commonly used social networking websites. These pages are used by companies to make announcements and get feedback from customers about their products or services. Customers themselves use these brand pages for availing discounts, read reviews, access information, submit opinion etc. In some cases, companies (customers) are also using these pages for providing (accessing) customer service. Since the nature of brand page usage varies across ‘authors’ of user generated content, it is desirable for businesses to be able to prioritize the content for listening and responding.

Towards this direction, companies are increasingly investing in social media, indicated by worldwide marketing spending on social networking sites of about $4.3 billion (Williamson, 2011). One way to realize this aim is to create brand communities in the form of brand fan pages on social networking sites where customers can interact with a company by liking or commenting on brand posts (McAlexander et. al., 2002). Consumers who become fans of these brand fan pages tend to be loyal and committed to the company, and are more open to receiving information about the brand (Bagozzi and Dholakia, 2006). Moreover, brand fans tend to visit the store more, generate more positive word-of-mouth, and are more emotionally attached to the brand than non-brand fans (Dholakia and Durham, 2010). While preliminary research has been conducted on the success of marketing activities on social media, little is known about factors that influence brand post popularity, that is, the number of likes and comments on brand posts at brand fan pages (Ryan and Zabin, 2010). Management-oriented studies about brand post popularity are mainly descriptive; they provide no theoretical foundation and do not formally test which activities actually improve brand post popularity. For example, these studies suggest that companies should experiment with different brand post characteristics, such as videos, images, text, or questions (Keath et al. 2011). Current insights are thus limited, which has increased the call for research in the area of social media.

In this paper a novel unsupervised social computing approach is proposed, aiming at algorithmically estimating the importance of advertisements posted on social networks. To do so, first of all explicit interactions between advertisements and social media users are considered (systematic analysis of likes, comments and sharings). Additionally users’ popularity is also taken into consideration, since a popular user may exercise more influence to people around his/her micro-world than a non-popular user. The proposed scheme effectively performs both on open social media (twitter, blogs, microblogs etc) and on rule-stringent ones (e.g. Facebook, LinkedIn etc) and does not require human intervention and/or training. Experimental results over real social media advertisements provide insights of our system and specific areas are detected for future research.

The rest of this paper is organized as follows: Section 2 focuses on related works. The proposed scheme is described in Section 3. Experimental results are provided in Section 4 while Section 5 concludes this paper.

2. Related Work

Brand communities were found to be a successful tool for increasing sales (Adjei at al., 2010). In addition, they have the potential of improving the relationship between the consumers and the brand (Sicilia and Palazon, 2008) and may influence members’ perceptions and actions (Muniz and Schau, 2007). Brand communities facilitate interactions through exchange of opinions about the brand or a particular product among consumers, thus engaging their members in a form of Word-of-Mouth (WOM) communication (McAlexander et al., 2002). WOM was found to be a powerful tool for marketing, frequently used by individuals as a source of brand or product related information (Duana et al., 2008). As such it plays a significant role for increasing the brand commitment and purchase decision making (Harrison-Walker, 2001), leading ultimately towards increase in sales (Godes and Mayzlin, 2004). Moreover, many-to-many communication on social media platforms is characterized with exponential growth of the WOM volume. This form of message propagation is often referred to as viral marketing (Kaplan and Haenlein, 2011). In this new marketing era the terms engagement and participation became the central construct used to describe the nature of participants' specific interactions and/or interactive experiences (Brodie et al., 2011; Kietzmann et al., 2011). While certain interpretations focus on the cognitive and emotional aspects of engagement (Bowden, 2009), others refer to the concept of engagement primarily as a specific activity type or pattern, beyond purchase, resulting from motivational drivers (Van Doorn et al., 2010). On online platforms, this form of engagement is commonly referred to as online engagement and is addressed from the perspective of measuring undertaken actions, such as the click-through rates (CTR), page views, etc., with different measures being applied depending on the possibilities offered by the platform (Lehmann et al., 2012). Previous studies in the field of customer engagement in brand communities focused mostly on the consequences of engagement, including concepts of satisfaction (Bowden 2009), commitment and emotional attachment to the brand (Chan and Li 2010), empowerment (Fuller et al. 2009), consumer value (Schau et al. 2009), trust (Hollebeek 2011) and loyalty (Casalo et al. 2007). Moreover, achieving these marketing objectives was found to be of significant importance for the companies, leading towards increased profitability (Kumar et al. 2010).

On the other hand Social Media Marketing (SMM) can be defined as usage of the existing social media platforms for increasing the brand awareness among consumers (Drury 2008). Early studies in the field of SMM have focused on explaining the concept and providing theoretical foundations (Berthon et al. 2012). In addition, challenges of SMM were investigated, such as aggressive advertisement, lack of ecommerce abilities and invasion of user privacy (Bolotaeva and Cata 2010; Kaplan and Haenlein 2011). Apart from the challenges, many opportunities have also been recognized, such as raising public awareness about the company, product development through community involvement and gathering experience for the future steps by analysing the UGC (Bolotaeva and Cata 2010; Richter et al. 2011). More recent work has focused on empirical studies and particularly on ways companies may foster levels of customer engagement. Jahn and Kunz (2012) explore the factors that could convert consumers into loyal fans. In addition, De Vries el al. (2012) examine the popularity of brand posts, making an analogy between brand posts on Facebook and online advertising. Finally, an attempt to evaluate the effectiveness of SMM showed that a carefully managed Facebook advertising campaign increased the sales (Dholakia and Durham 2010). Still, as Wilson et al. (2012) point out, “these few studies only begin to touch on ways in which Facebook can be used to connect with customers.” Based on exploratory findings and practical examples, scholars have tried to generate guidelines for SMM. In general, guidelines that apply for online WOM, also apply to SMM: (1) sharing the control of the brand with consumers and (2) engaging them in an open, honest, and authentic dialog. Similarly, Parent et al. (2011) point out to the importance of continuous engagement and selection of appealing content to be communicated by the companies in order to increase the viral propagation. Still, these guidelines are mostly general and do not specify what “constitutes great content, and what will be most likely to be passed on.” In order to contribute in the direction of understanding the online customer engagement within brand communities on Facebook and derive implications for companies utilizing Facebook for marketing, Pletikosa and Michahelles (2013) develop a model which explains the relations between the characteristics of the content communicated by the company and the level of online engagement.

In summary, members of social networking sites can become fans of brands on dedicated brand fan pages. Brand fans can share their enthusiasm about the brand on these dedicated pages and be united by their common interest in the brand. Brand fan pages reflect part of the customers’ relationship with the brand and provide a source of information and social benefits to the members (Bagozzi and Dholakia 2006). On these brand fan pages, companies can create brand posts containing photos, videos etc; brand fans can then interact with these posts (Lisette et.al.,2012). This paper focuses on estimating brand post popularity, by considering the number of likes, comments and shares together with the popularity of users that perform these actions.

Finally another related area focuses on predicting content popularity across diverse domains tackling various applications. A survival analysis framework was used in (Lee et. al., 2010) to predict the overall number of comments by observing a thread for 2-3 days. Lerman and Hogg (2010) developed a stochastic model of user behavior that allowed prediction of popularity based on early user reaction to new content. Their study uses the social dynamics of Digg website where different users can vote for an article and change the way and location where it is presented on the website. Several Twitter specific scientific studies have also studied a related problem of predicting whether a tweet will be re-tweeted. Most of these studies (Petrovic et. al., 2011) concluded that the social features (number of followers, friends, lists etc.) have the maximum effect on retweetability. A collaborative filtering approach was used by Zaman et. al. (2010) to study the retweet behavior persistent among pairs of users. They used author information, number of the followers and number of words in the tweet for this study. Petrovic et. al. (2011) have used a passive-aggressive algorithm to predict the retweetability.

As also discussed above, though several of the very interesting previous works tackled the problem of predicting the content popularity, or estimating the brand awareness or even evaluating brand engagement, most of them are supervised and cannot be straightforwardly applied in the context of social networking sites. Furthermore most of them do not take into consideration user popularity and influence dynamics. These disadvantages are taken into consideration in this paper and a novel scheme is designed to evaluate the impact of posted advertisements.

3. The Proposed Advertisement Impact Estimation Scheme

The proposed architecture consists of five submodules: sentiment analysis, page segmentation, user popularity estimation, user-content interaction analysis and impact estimation. All these components are described next.

3.1. Page Segmentation and Sentiment Analysis

Unsupervised page segmentation is performed by an automatic wrapper, which exploits the format of social media sharing web sites to discover the underlying structure in order to finally infer and extract multimedia files (posts) and corresponding associated comments from the web pages. The system first identifies the section of the web page that contains the multimedia file to be extracted and then extracts it by using clustering techniques and other tools of statistical origin. The proposed system is an evolution of STAVIES (Papadakis, Skoutas et. al., 2005) and comprises of the transformation and the extraction module. These modules are further subdivided into components, each one responsible for a different task. The overall system architecture together with implementation issues can be found in (Ntalianis et. al., 2014).

On the other hand sentiment analysis is becoming a popular area of social media analysis, especially around user reviews and tweets. It is a special case of text mining, generally focused on identifying opinion polarity, and while it is often not very accurate, it can still be useful. In this paper we focus on 2 possible sentiment classifications for the comments, made in an advertisement post: positive and negative. Positive/negative comments are assumed as having a positive/negative impact on the posted ad. Towards this direction, in this paper we parameterize the NLTK Naive Bayes Classifier (Loper and Bird, 2002). In particular we incorporate the *sanders_twitter* twitter sentiment corpus with reviews categorized into pos (positive) and neg (negative) categories [http://www.sananalytics.com/lab/twitter-sentiment/], and a Naïve Bayes Classifier using boolean word feature extraction.

3.2. User Popularity, User-Content Interaction Analysis and Impact Estimation

In this subsection user popularity, user-content interaction analysis and impact estimation are described. To do so, first of all the following definitions are made:

Definition 1: Let U_i be the i^{th} user of a social network, $i = 1, \ldots, N$. *(a unique number could be ensured e.g. ideally by considering the exact time instance user U_i joined the network).*

Definition 2: The set FS_{U_i} of all friends of U_i is given by:

$$FS_{U_i} = \bigcup_{j=1}^{M} F_{U_i}^{j}, \qquad j = 1, \ldots, M \tag{1}$$

where $F_{U_i}^{j}$ is the j^{th} friend of U_i.

Definition 3: An "actual" friend $AF_{U_i}^{k}$, $k = 1, \ldots, L$ of U_i, is a user who frequently interacts (likes, comments, shares) with content posted by U_i or containing U_i.

Definition 4: Based on *Definition 3*, the set AFS_{U_i} of the "actual" friends of U_i is defined as:

$$AFS_{U_i} = \bigcup_{k=1}^{L} AF_{U_i}^{k}, \qquad k = 1, \ldots, L \tag{2}$$

where $AF_{U_i}^{k}$ is the k^{th} "actual" friend of U_i, and $AFS_{U_i} \subseteq FS_{U_i}$.

Definition 5: The largest the cardinality of set AFS_{U_i} the more popular the user U_i and probably the more influential. Users of a social network can be ordered according to their AFS_{U_i}, providing the users ordered list :

$$UOL = [U_r, U_h, U_o, \ldots], \text{ with } AFS_{U_r} \geq AFS_{U_h} \geq AFS_{U_o} \geq \cdots \tag{3}$$

Definition 6: For an advertisement AD_m^i, m=1, …, G, posted by a company C_i, three vectors are defined, $\mathbf{l}_{AD_m^i}$, $\mathbf{p}_{AD_m^i}$ and $\mathbf{c}_{AD_m^i}$, corresponding to likes, shares and comments the advertisement has received respectively:

$$\mathbf{l}_{AD_m^i} = [l_{U_r}^i, l_{U_h}^i, l_{U_o}^i, \ldots] \tag{4a}$$

$$\mathbf{p}_{AD_m^i} = [p_{U_r}^i, p_{U_h}^i, p_{U_o}^i, \ldots] \tag{4b}$$

$$\mathbf{c}_{AD_m^i} = [c_{U_r}^i, c_{U_h}^i, c_{U_o}^i, \ldots] \tag{4c}$$

where $l_{U_r}^i$ equals to 1 if user U_r has liked the respective advertisement and equals to 0 if she has not liked it. Similarly, $p_{U_r}^i$ equals to 1 if user U_r has shared the respective advertisement and equals to 0 if she has not shared it. Now regarding $c_{U_r}^i$, since the user U_r (and all users in general) can make both positive and negative comments, each comment passes through the sentiment analysis module (Subsection 3.1). Comment sentiments are aggregated and the total score is assigned to $c_{U_r}^i$. In summary, these three vectors visualize the interaction between users and advertisements and provide a first view of an advertisement's impact.

Definition 7: The ordering of set *UOL* (Eq. 3) is mapped to a weights vector $\mathbf{w}_U$ so that activities from popular users are strengthened while activities from non-popular users are weakened. Thus:

$$\mathbf{w}_U = [w_{U_r}, w_{U_h}, w_{U_o}, \ldots] \tag{5}$$

Definition 8: Let us denote as $L_{AD_m^i}$, $P_{AD_m^i}$ and $C_{AD_m^i}$ three variables that count the total number of weighted likes, shares and comments an advertisement has received respectively:

$$L_{AD_m^i} = \mathbf{w}_U^{\mathbf{T}} \mathbf{l}_{AD_m^i} = w_{U_r} \cdot l_{U_r}^i + w_{U_h} \cdot l_{U_h}^i + w_{U_o} \cdot l_{U_o}^i + \ldots \tag{6a}$$

$$P_{AD_m^i} = \mathbf{w}_U^{\mathbf{T}} \mathbf{p}_{AD_m^i} = w_{U_r} \cdot p_{U_r}^i + w_{U_h} \cdot p_{U_h}^i + w_{U_o} \cdot p_{U_o}^i + \ldots \tag{6b}$$

$$C_{AD_m^i} = \mathbf{w}_U^{\mathbf{T}} \mathbf{c}_{AD_m^i} = w_{U_r} \cdot c_{U_r}^i + w_{U_h} \cdot c_{U_h}^i + w_{U_o} \cdot c_{U_o}^i + \ldots \tag{6c}$$

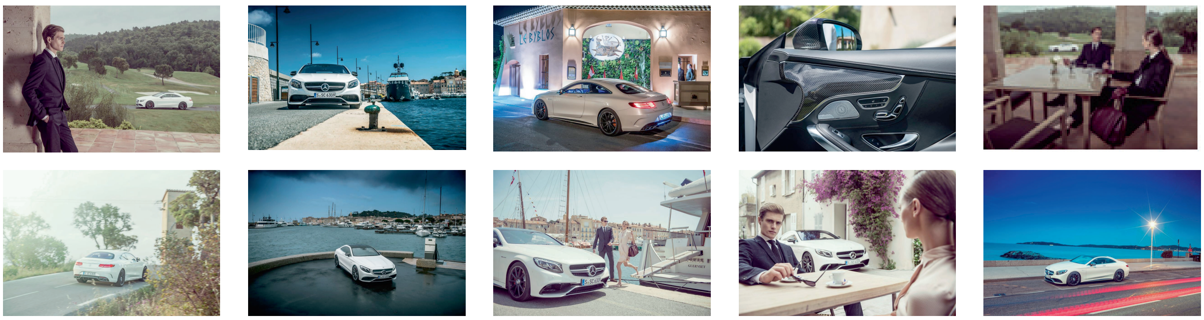
Definition 9: The impact of an advertisement AD_m^i, m=1, …, G, posted by company C_i can be calculated as:

$$I_{AD_m^i} = w_L L_{AD_m^i} + w_P P_{AD_m^i} + w_C C_{AD_m^i} \tag{7}$$

where w_L, w_P and w_C are 3 weights that determine the importance of likes, shares and comments respectively.

4. Experimental Results

In this section the overall performance of the proposed posted advertisements' impact evaluation scheme is analyzed. In order to evaluate our algorithms, we have gathered advertisements together with their associated content, from several official facebook pages regarding 30 different companies (Samsung, Apple, Mercedes, BMW, Subaru, Rolex, Casio, Adidas, Nike etc.). Recording has been performed on the 20th of July 2014 and for a time period of one month. This means that ads that have been posted between 20th of June and 20th of July have been kept, discarding all other posts. In parallel, the wrapper submodule gathered and associated to each advertisement its respective metadata (likes, shares, comments and persons that have liked/shared/commented on each ad). Now considering users' numbering/popularity and in order to follow the proposed methodology of Section 3, here three comments should be made: (a) our experiments are limited to the users that have liked the content of the 30 companies and thus we do not have to number all Facebook users, (b) even though we have limited the number of users that should be numbered, they were still too many (e.g. the page of Mercedes at https://www.facebook.com/MercedesBenz had 15,006,049 likes and thus the same number of associated users). For this reason user popularity was estimated per advertisement, (c) the wall and personal information of about 72% of the users that have interacted with the ads was hidden for non-friends and thus we could not evaluate their popularity. Furthermore, since in these pages usually likes are much more than shares and comments, only users that have commented have been considered for popularity evaluation. Additionally comments usually have a much larger influence. For this reason in this paper we set w_L=0.1, w_P = 1.6 and w_C = 9.3.



Metadata

Album title: #MBShootout St. Tropez (10 photos)

Post title: Oh, the sweet life on the Côte d'Azur. In cooperation with HUGO BOSS, GFWilliams Photographer traveled south to shoot the S-Class Coupé. Can you feel the breeze? Enjoy!

Post date: 20 July 2014

Number of Likes: 30,727

Number of Shares: 1,102

Number of Comments: 149

Fig. 1: A posted advertisement from Mercedes, containing 10 pictures, together with each associated metadata.

Next analysis of the results has been performed. Towards this direction and for visualization purposes, results for Mercedes are presented. In particular in Figure 1, the complete post of Mercedes S-Class Coupé is presented together with its associated metadata. The post contains 10 pictures, however analysis has been performed in album level and not for each particular picture. According to Eq. (5) and Figure 1, the 149 comments have been made by 134 unique users, only the profiles of 45 of them were open so that their popularity could be evaluated. Eq. (5) also defines their weights. In this paper weights were linearly distributed in the interval [10 1], where 10 was associated to the most popular user and 1 to the less popular with a step equal to 0.2. For the rest of the users the weight was also set to 1. We believe that, even arbitrary, this is a fair distribution for the specific experiment. However in other cases these numbers may significantly vary (some people's influence may be much larger compared to some others. e.g. the comment of a minister may have much more power than the comment of an unknown citizen). Thus this distribution should be further studied in future experiments.

Furthermore regarding $c_{U_r}^{i}$, since users make both positive and negative comments, each comment has passed through sentiment analysis. Tab. 1 presents some comments together with their sentiment analysis results. As mentioned, comment sentiments are aggregated and the total score is assigned to $c_{U_r}^{i}$ for user U_r and for every other user respectively. If the aggregation leads to a negative balance, then $c_{U_r}^{i}$ may have a negative value. Thus during multiplication and addition according to Eq. 6(a)-6(c) a negative $c_{U_r}^{i}$ will reduce the overall score. Based on the associated metadata $L_{AD_m^i}$ = 30,973.8, $P_{AD_m^i}$ = 1,117.6 and $C_{AD_m^i}$ = 192.1. And based on Eq.(7), $I_{AD_m^i} = 6{,}672{,}07$, which is a medium score(relevant to the scores of other advertisements), meaning that this advertisement had a medium impact to consumers.

Table 1. Some comments together with their sentiment analysis scores

User's Name		Isabel Salas	Onur Cengiz	Thandar Lay	Eddie Liu
Comment		Great shots!	WOW WONDERFUL Please One More Gift My Birthday	Very great	Really don't understand why Mercedes chose Hugo Boss. It's down-grade for S-Class.
Subjectivity	**Neutral**	0.2	0.1	0.1	0.0
	Polar	0.8	0.9	0.9	1.0
Polarity	**Pos**	0.7	0.7	0.8	0.2
	Neg	0.3	0.3	0.2	0.8

5. Conclusion

In this paper we have tried to algorithmically estimate the impact of advertisements posted on social media sites. Towards this direction explicit interactions between advertisements and social media users have been considered together with users' popularity. The main virtue of the proposed method is that it operates without human intervention. Experimental results from official facebook pages (gathering multicultural fans) regarding 30 different companies have illustrated the promising performance of the proposed scheme.

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