International Journal of Electronic Commerce

Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/mjec20

Enhancing Targeted Advertising with Social Context Endorsement

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Published online: 05 Dec 2014.

To cite this article: Yung-Ming Li, Lienfa Lin & Shih-Wen Chiu (2014) Enhancing Targeted Advertising with Social Context Endorsement, International Journal of Electronic Commerce, 19:1, 99-128

To link to this article: http://dx.doi.org/10.2753/JEC1086-4415190103

Enhancing Targeted Advertising with Social Context Endorsement

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ABSTRACT: The success of online advertising depends on the degree of customer acceptance and corresponding click-through rate (CTR). The coverage of traditional online advertising is wide, but the CTR of display advertisements delivered by firms is relatively lower. Whereas targeted advertising can deliver appropriate advertisements to customers based on their traits (disturbance avoidance), advertisements can leverage the power of social influence to improve the degree of acceptance of advertisements. In this paper, by utilizing the power of social influence and context embellishment, we propose a personalized social context endorsement mechanism to enhance the effectiveness of advertisements. According to the results of an experiment conducted on Facebook, the proposed mechanism outperforms other benchmark approaches to improving the CTR and user impressions. This research effectively incorporates the theories of preference similarity, social influence, and moral sentiments and provides advertising sponsors and social media providers with a powerful system to conduct successful advertising campaigns.

KEY WORDS AND PHRASES: Online advertising, sentiment analysis, social context discovery, social media, social influence, social media.

In only a few years, the advent of social media has created a fundamental shift in human behavior. Social media meet core human needs (contacting, commenting, sharing, etc.) and consequently are becoming increasingly prevalent. In particular, the many emerging user-generated content services, such as social networking Web sites (e.g., Facebook, MySpace, Twitter), online review mechanisms (e.g., Epinions, cnet), and knowledge-sharing platforms (e.g., Wikipedia), have constructed a place to build relationships among people and have empowered people to publish their own opinions, experiences, creations, and other content.

The power of social influence is the ability attributed an actor to influence another actor's beliefs, attitudes, and behavior as a function of the social resources he or she commands [41]. Consumer research undertaken by Sociable Labs [35] shows that 38 percent of online shoppers have shared comments with friends about products they have purchased and 62 percent of online shoppers have read product comments shared by their friends on Facebook. According to a survey commissioned by DEI Worldwide [12], 70 percent of consumers have visited social media Web sites, such as social networking sites, blogs, and message boards, to get brand information. Among those surveyed, two-thirds of consumers agreed that online recommendations from other people were valuable, credible, and could influence their perceptions of a brand and hence influence their purchasing decision. It can be inferred that electronic word of mouth plays a vital role in online marketing strategies.

This research was supported by the National Science Council of Taiwan (Republic of China) under Grant NSC 101-2410-H-009-009-MY3.

International Journal of Electronic Commerce / Fall 2014, Vol. 19, No. 1, pp. 99–128.

ISSN 1086–4415 (print) / ISSN 1557–9301 (online)
DOI: 10.2753/JEC1086-4415190103

Many social network–based marketing strategies have been derived from this. For example, marketers can discover potential customers for market positioning by filtering the content that online users mention or discuss. To improve the customer relationship, social media sites offer an excellent platform for interacting with consumers and monitoring the feedback from consumers and their impression of the market. Impression[1] refers to the overall effect of something. It is the first and immediate effect of an experience or perception upon the mind: the sensation. In this paper, the impression of an ad is the average rating score by all users who received and gave an impression rating score for the ad. Marketers can also leverage the social influence of online opinion leaders by launching a social endorsement advertisement. A social media marketing industry report [36] indicated that 83 percent of marketers said that social media were important to their business. Among the variety of social marketing strategies, business exposure was considered to be the biggest issue of concern to companies.

One effective means of promotion in the social media is the distribution of behavior-targeting advertisements. The preferences of a user can be gleaned from the user profile, the topics the user likes, and the tastes of the user's friends. Many recommendation systems have been developed based on extracted preference information or friends' influence, and they have proved to be effective. Facebook has also launched Facebook advertisements [11], which assist advertisers by showing advertisements to a user based on demographic factors, such as location, age, or gender, and which can further engage the audience by incorporating social context into advertisements, such as displaying when someone's friend has liked an advertiser's Facebook page.

Social context is a little snippet of text that shows which friends have "liked" the page, event, or application linked with an ad. The so-called social context ads are based on the data collected on the likes and friends of users. According to Business Wire [7], reports show that social context ads are more effective. Likewise, Chan [8] also showed that advertising strategies using the social features of Facebook are more effective than traditional approaches.

Sponsored stories, another type of Facebook advertising, enable marketers to further amplify the distribution of stories that people have already shared with their friends, such as the "check-in" records at restaurants. However, according to a survey conducted by internet RETAILER [19], the average CTR for Facebook advertisements in 2013 was 20 percent, which is far behind the industry standard of 2.93 percent [21]. There may be a few reasons for this, in particular that (1) people are not on Facebook with the intent to purchase products and (2) the social context attached to the advertisements is not sufficiently powerful to resonate with the audience.

Although Facebook adopts the concept of social context advertisement, the social context attached to the advertisements delivered on Facebook is not sufficiently powerful to create resonance in the audience. For example, although one can see ads shared (i.e., "liked") by some friends, the format of the social context ad includes only the names of friends, without any other additional comments on the ad. In many cases, these friends may not be very close to the audience and their influencing power is not significant. Besides, the ad shared by the friends may not fit the interest of the audience.

The advertising strategy of Facebook is often tied in with fan page promotion, but there might be more critical factors that alter people's opinions of brands or products, such as a positive and experiential comment shared by a close friend or a trustworthy online user. It is common to see advertisements with only a few names of friends listed below them, who may barely know each other, or there may be advertisements that have been elaborately recommended to a particular person but it is still not clear why that person should be interested in them. As a consequence, the problems to be solved in this study are:

1. How should the power of social influence be leveraged to increase the CTR and the impression of online advertisements?
2. How should the personalized social context of a selected advertisement and a target user be chosen?

The first question is aimed at discovering the qualified "sender" to play the "endorser" role in advertising activities. To discover the influential endorser for a designated advertisement, we propose a new method for analyzing the sentiment of users' opinions and identifying those users who provide posts appraising the designated advertisement or brand.

The second question focuses on how to discover suitable "receivers" and send them a "personalized" advertisement wrapped in the strongest persuasive social context. To identify the appropriate target users (receivers) for a designated advertisement, we propose a new method that considers the factors of preference (degree of relevance of the designated advertisement to a user), quality (pervasiveness of a social context), and influence (social influence of a user on other users) to find the most suitable ad and social context appropriate to each target user.

In a world highly reliant on social networks, people are already becoming accustomed to sharing online experiences, opinions, or breaking news with friends and referring to others for advice. Thus, how to filter and extract the most positive, relevant, and potent content and entice the targeted customers to click on the advertisements is an important issue for both the marketers and the social media providers.

To resolve the above issues, a novel approach in this research is that the proposed mechanism will allow us to enrich the social context content with a positive or experiential comment shared by a close friend or a trustworthy online user. Specifically, by utilizing the power of social influence and context embellishment, we designed a new social context endorsement approach to advertising to enhance the attention the user pays to the ads. "Context embellishment" refers to some extra positive or persuasive information added to a designated advertisement to enhance the impression or the degree of acceptance of the advertisement by the target user.

To discover the appropriate social context, the main components of the proposed advertising system include a preference analysis module, a quality analysis module, and an influence analysis module. The system can discover and analyze the social contexts that are the most relevant to the advertisements and influential to the target users. The experiments were conducted using Facebook to validate the proposed mechanism. Our experimental results show that the proposed advertising approach of social context endorsement can significantly enhance the value of advertisements in terms of increasing both the CTR and the impression of the product.

The remaining parts of this paper are organized as follows: In the next section, the existing literature related to the research topics is reviewed. The third section details the components of the proposed system framework. The fourth describes the experimental data source, settings, and procedures. The experimental results and evaluation are discussed in the fifth. Finally, the sixth section concludes by stating the research contribution of this study and presenting future research directions.

Related Literature

Online Advertising

The Internet has created many new ways for marketers to promote their products and customer services. Two significant research domains can be distinguished within Internet advertising: display scheduling and personalized recommendation [21]. Display scheduling aims at maximizing the total CTR for all advertisements by appropriately managing display time and advertising space on the Web page. Common approaches are contextual and behavior-targeted advertising. These kinds of advertising systems scan the text of a Web site or user query input for keywords and return advertisements to the Web page based on those keywords. Goldfarb and Tucker [14] found that matching an advertisement to Web site content and increasing an advertisement's obtrusiveness independently can effectively increase intent to purchase. Aksakall [1] incorporated advertisement location and content issues for Internet display advertising to maximize the advertiser's revenue. Looking at banner advertising on the Internet, Bhatnagar and Papatla [5] examined the effect of search and navigation records, and Gallagher and Parsons [13] studied the effect of demographic customer profiles in investigating the reaction of customers based on their characteristics. Gopal et al. [15] empirically analyzed the impact of the interaction between the search channel and the content channel for keyword-based advertisements. The format of contextual advertisements may be pop-ups, banner, or textual advertisements, and they are widely implemented by search engines, such as Google AdSense, for content or keywords.

Personalized recommendation, on the other hand, is more "individualized" than targeted advertising, as it aims to assign a suitable advertisement to a single Web user rather than to a group of individuals. User information must be gathered in order to achieve this goal. Recommendation systems have been shown to be suitable for suggesting a wide range of products and services, such as books, restaurants, dry cleaners, plumbers, physicians, lawyers, financial institutions, and real estate brokers [3]. Content-based and collaboratively based approaches are usually applied to recommendation systems. Content-based approaches recommend items based on previous transactions and the features of an individual user [2], and collaborative filtering selects items based on the opinions of a group of other users who have a similar preference history [29].

However, both content-based and collaborative filtering rely heavily on subject user ratings, making it hard to recommend new items to users when there are insufficient related comments or rating records [38].

Since the advent of social media, an overwhelming quantity of user preference data, interaction records, and interest information has been created on it. Marketers can leverage these data to target their potential users more precisely and distribute the advertisements via the power of viral marketing and electronic word of mouth [6]. The study of social advertising is mainly related to the discovery of influential endorsers or opinion leaders [26]. The experimental studies conducted by Lim et al. [28] also found that, with the endorsement of an online store's satisfied customers who were similar peers, consumers' trusting beliefs about the store increased. The term "similar peers" means customers who are similar in their characteristics to the potential buyers. People who share common characteristics tend to perceive one another more positively and hence are more likely to trust one another. To achieve satisfied customer endorsement, the advertisement provider chooses to use the customers (endorsers) who have similar characteristics to the potential buyers (e.g., peers who are endorsers from the same university).

In the domain of measuring the success of online advertising campaigns, the CTR is the most common metric used [17]. It is calculated as the ratio of the total number of clicks obtained to the number of times that advertisements were delivered. In our research, we focused on developing an enhanced personalized advertising mechanism via the incorporation of social context endorsement. To further verify the effectiveness of the social contexts discovered using the developed mechanism, the CTRs and feedback on advertisements from users were collected and analyzed.

Social Influence

Social influence occurs when an individual adapts his or her behavior, attitudes, or beliefs to those of others similar to that individual [25]. Several scholarly studies on social and communication networks, opinion leadership, source credibility, and the diffusion of innovations have demonstrated the phenomenon that consumers influence other consumers [31]. Kiss and Bichler [22] have provided a wide review of the central measures generally used for selecting influencers/endorsers from customer networks for online marketing.

Influence does not necessarily require face-to-face interaction, but is based on information about other people [34]. The decisions of online users are usually affected by normative or informational factors [9]. Social impact theory states that people tend to conform to normative social influences and assumes that the social influence on the targets to be influenced is a function of strength, immediacy, and number of sources [23]. Individuals often obey social norms in order to gain an accurate understanding of social situations and to effectively respond to them [10]. Dynamic social impact theory views society as a self-organizing complex system in which individuals interact and have an impact on each other's beliefs; thus, it describes the diffusion of information through social systems [24].

In this research, by utilizing the theory of social influence on individuals' behaviors, thoughts, and preferences, we want to take advantage of social impact and amplify the effect of advertising via social context endorsement.

Opinion Sentiment Analysis

In social media, and on most online Web sites, people tend to record their feelings in a textual format. Therefore, there are many studies conducted on sentiment analysis based on textual data. Sentiment classification aims to automatically classify the text of written reviews from customers into positive or negative opinions.

There are two categories of approach for sentiment classification. One is to develop linguistic resources of sentiment orientation and structures of sentiment expression to classify texts [18]; the two main methods here are WordNet expansion and statistical estimation, such as the pointwise mutual information (PMI) measure. The second approach to analyzing sentiment is to train and deploy a sentiment classifier, which can be built using several methodologies, such as a support vector machine (SVM), maximum entropy, and naïve Bayes [36]. HowNet and the National Taiwan University Sentiment Dictionary (NTUSD) are the two main Chinese sentiment word dictionaries and are widely used in Chinese textual sentiment classification [36]. In this research, in order to discover positive comments about products for social endorsement, it was necessary to analyze the sentiment of the opinions of users. HowNet and the distant-weighted count were adopted to classify the polarity of sentiment words [37].

The System Framework

In this section, we describe the format of social context endorsement advertisements and describe the modules included in the proposed system framework. To improve the CTR of online social advertisements, we designed a personalized social context endorsement mechanism in order to discover the most influential social context as a personalized slogan attaching to advertisements by analyzing relevant social connections and activities.

Influential social context means a social context with a positive emotion icon on a designated advertisement shared by a close friend or a trustworthy online user who is the most relevant to the advertisement and influential to the target users. For example, consider the scenario that a marketer plans to conduct a promotional advertising campaign using social media. The marketer will first design the advertisements and select a set of directly relevant keywords for the product. According to the inputs, the social media provider can identify the people who have shared positive comments about the product. The influential social context (e.g., the opinions and the names of endorsers) can be discovered from the positive comments and be used to wrap with the advertisements. It should be noted that the endorsers (authors of opinions) are generally friends and famous people who are

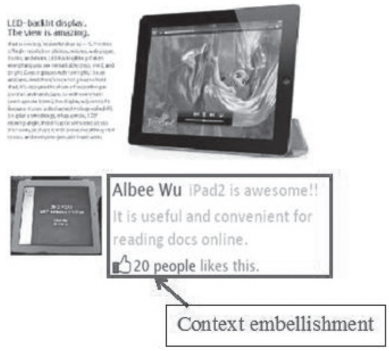

Figure 1. Example of a Context Embellishment Advertisement

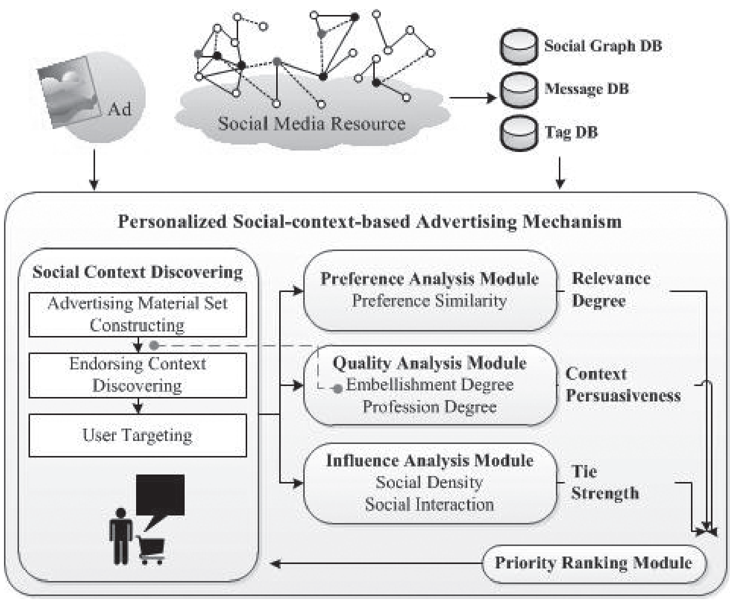

Figure 2. The System Framework

influential to the target users. Figure 1 is an example of a context embellishment advertisement.

For the proposed system, we considered the factors of preference, quality, and influence in the evaluation of the influential social context. The main components and procedures included in the proposed system are depicted in Figure 2.

Figure 2 illustrates the following aspects of the advertising mechanism:

1. *Social context discovering module*. According to the advertising material set (advertisements and product-related keywords) input by the advertiser, this module locates posts that include any of the

elements contained in the material set from the social network. The positive comments can be identified by sentiment analysis. The friends of the authors of the positive posts that are discovered are selected as the target users. For each target user, we selected the relevant advertisement and corresponding social context (friend's name and opinions) suited to that user.
2. *Preference analysis module.* Measures the similarity between the individual's preference and the advertisement category.
3. *Quality analysis module.* Measures the persuasiveness of a social context by evaluating the degree of embellishment of the post and the professional expertise of the author.
4. *Influence analysis module.* Computes the tie strength of an author to a specific target user based on the social density of the network and the intensity of social interactions between them.
5. *Priority ranking module.* Allocates appropriate weights to aggregate the scores generated from each module. The social context with the highest aggregated score will be chosen as the endorsement for the advertisement to deliver.

Social Context Discovery Module

The social context discovery module aims to discover posts that appraise the designated advertisement or brand. The main processes in the module include the relevant content set construction, endorsement context discovery, and user targeting.

Advertising Material Set Construction

The advertising material dictionary set is manually predefined and used for querying posts that contain any of the elements in the set. It includes the full name or unique nicknames of the product/service/brand and the links to the official Web site, content, or endorsement blogs. Examples are: RCset(McCafé) = McDonald's, mcdonalds, 麥當勞, 麥當當, www.mcdonalds.com, www.youtube.com/user/mcdonaldscorp/.

Endorsement Context Discovery

The social context apparent in the positive comments is identified by sentiment analysis, and the negative opinions are highlighted. It should be noted that posts published on social media have different characteristics from opinions posted on online review platforms. The discussions posted on social media are more instant, casual, and better reflect real life. It is likely that although one statement conveys a positive point, the next will complain about totally unrelated matters. Thus, in the proposed model, only the sentences containing the key content are analyzed, and the irrelevant sentences are filtered out and removed. However, because information-sharing posts (Web links or video sharing) usually contain textual explanations about the shared topic, in this case we take the whole part of a post into consideration.

To identify the sentiment words, the polarities of adjectives and adverbs should be evaluated. After parsing the sentences, the acquired adjectives and adverbs are extracted and matched with the positive and negative dictionaries to identify the polarity of the sentences. In addition, emoticons are helpful in expressing the ideas/feelings and understanding of others in socioemotional contexts [42]. Other research [32] has further validated that by using training data labeled with emoticons, the outcome of sentiment analysis has the potential of being independent of domain, topic, and time. Therefore, this study has also used emoticons as indicators of sentiment expressed in opinions. Since sharing in social media is generally short, emotional, subjective, and informal, emoticons are widely used at the end of sentences to illustrate the mood of the writer.

In this study, we used a group of experts composed of one professor, four doctoral students, and six graduate students. Their research area is the use of social comments to judge whether emoticons belong to a negative or positive emotion. The kappa statistic [16] is frequently used to test interrater reliability; generally, a kappa > 0.70 is considered satisfactory. The overall kappa statistic for this study was 0.92, indicating that the expert opinions in this study have high interrater reliability. The positive emoticons in this study were :), :D, XD, ^^, ^_^, :P, lol. The negative emoticons were :(, ;(, ><, = =, = =| | |. A sentence that contains a positive emoticon, adjective, or adverb gained a score of 1 point and a negative one was given a score of minus 1. The more positive sentiment terms a sentence has, the higher the polarity score of that sentence. The polarity of a sentence is measured by the average point score of all sentiment terms contained in the sentence and is formulated as

$$Polarity(s) = \frac{\sum_{sw_i \in \Phi_{sw}(s)} S\_point(sw_i)}{\left|\Phi_{sw}(s)\right|}, \tag{1}$$

where $\Phi_{sw}(s)$ denotes the set of sentiment terms (emoticons, adjectives, adverbs) in a sentence s, and $S\_point(sw_i)$ is the point score for a sentiment term sw_i (1 or −1) generated by the sentiment analysis.

After the polarities of all sentences in a post have been obtained, the degree of embellishment of the post is further measured by the average polarity of all the sentences included in a post and formulated as

$$ED(p) = \frac{\sum_{s_j \in \Phi_s(p)} Polarity(s_j)}{\left|\Phi_s(p)\right|}, \tag{2}$$

where $\Phi_s(p)$ represents the set of sentences expressed in a post p.

By manually checking the degree of embellishment assigned to the posts, we found that the most positive opinions or breaking news gained a high score of 0.7–1, and the scores for negative opinions were extremely low at below −0.95. Moreover, the percentage of posts scored around 0 was relatively low, which reflects the fact that when people share information they tend to emphasize why they are doing so to arouse the attention of their friends; therefore, in this research, the threshold of $ED(p)$ was set at 0, which effectively eliminated approximately 92 percent of negative posts.

User Targeting

After the analysis of the embellishment of the posts, the filtered posts are denoted as a relevant post set Φ_{RP}. The authors of the posts in set Φ_{RP} were selected into a candidate endorser set Θ_E. Finally, the friends of all users in the Θ_E were considered to be the target user set Θ_T. $Author(p)$ stands for the author of a post p and $\Theta_{Fd}(e)$ represents the set of friends of an endorser e. The processes are expressed as

$$\Phi_{RP} = \{p \mid ED(p) > 0\};\ \Theta_E = \{u \mid u = Author(p), p \in \Phi_{RP}\};$$
$$\Theta_T = \{t \mid t \in \Theta_{Fd}(e), e \in \Theta_E\}. \tag{3}$$

For each target user, the degree of fit of the designated advertisements and degree of influence of social contexts associated with the user were measured and ranked. Since the target users were located by extracting the friends of an endorser, the influential power of the endorsers should be analyzed and exploited in order to complement the weakness of the attraction of the advertisement itself.

Preference Analysis Module

The similarity between the designated advertisement and the user was measured to locate the preferred advertisement and associated social context endorsement, as people are more likely to embrace a new idea when it is familiar and relates to their previous experience, or when it matches their preferences. Most companies have their own official accounts in social media to communicate and improve their relationship with customers. People will "follow," "like," or subscribe in various ways to the official accounts of companies to get up-to-date news, interact directly with the marketers, or even exhibit their personal tastes. Hence, to extract the preference of a user, besides the topics which might usually be focused on, we also considered the categories of the official accounts of companies to which a user subscribes.

To estimate the fit between an advertisement and users' preferences, we adopted a treelike structure in this study. Several previous studies have employed the same structure, especially in the fields of product taxonomy [44] and semantic similarity in taxonomy [33]. We use the distance-based approach, which has been proved to outperform other approaches using keyword-based similarity evaluation [43], to estimate the similarity between an advertisement and a target user's preference. The category nodes of C_{ad} and C_u^i were assigned based on the classification of the advertisement and the ith official account the user joined, respectively; C_s represents the first common parent node of C_{ad} and C_u^i. The set of categories of the official account of companies to which user u subscribed is denoted by $\Omega(u)$. The preference similarity $PS_{ad,u}$ of the advertisement with a user can be calculated using the following formula:

$$PS_{ad,u} = \frac{1}{|\Omega(u)|} \cdot \sum_{i \in \Omega(u)} \left(\frac{2D_{root}}{D_{ad} + D_u^i + 2D_{root}} \right), \tag{4}$$

where D_{ad} represents the path distance between the category node of C_{ad} to the category node of the C_s, D_u^i denotes the distance from the category node of C_u^i to the category node of C_s, and D_{root} is the distance from C_s category node to root node.

Quality Analysis Module

This module aims to evaluate the persuasiveness of a social context, which is measured by two factors: the embellishment of the opinion and the profession of the author. The more positive and intense an expression of an opinion is, the more likely it is that the audience will be influenced. Meanwhile, an author who has particular expertise in the same domain of knowledge as the advertisement is apt to be considered more trustworthy when acting as a product representative. The former factor was addressed in the previous module, which was designed to eliminate negative opinions. The second factor, professional expertise, can be determined on the basis of two aspects: topic relevance and sharing intensity.

The set of the posts written by user u is denoted by $\Phi_P(u)$. We examined whether the post published by a user contained relevant words (mostly nouns) to evaluate the user's professional expertise. Professional expertise, PD_u, is yielded by the following equation:

$$PD_u = \frac{\sum_{p_i \in \Theta_P(u)} lookup(p_i) \cdot \left| \Phi_{interaction_{p_i}}(p_i) \right|}{\sum_{p_i \in \Theta_P(u)} lookup(p_i)}, \tag{5}$$

where $lookup(p_i)$ represents whether the post is relevant to the topic or not, $lookup(p_i) = 1$ indicates whether it contains words matching the components in a predefined product dictionary, and $lookup(p_i) = 0$ applies if this is not the case. $\Phi_{interaction}(p_i)$ is the set of interactions, such as reply, like, or share, performed by others with respect to a post p_i. $|\Phi_{interaction_{p_i}}| = |\Phi_{interaction}(p_i)| / \max_j(|\Phi_{interaction}(p_j)|)$ denotes the normalized value of interactions. The larger the number of feedback posts from other users to user u's posts that are relevant to the topic, the more likely it is that user u has professional expertise.

Finally, the context persuasiveness for user u and user u's post p about the advertisement is derived from the geometric mean in Equation (6):

$$CP_{u,p} = \sqrt{PD_u \times ED_p}. \tag{6}$$

Influence Analysis Module

The social influence of a user on other users is analyzed in this module. By analyzing the social closeness and interactions between the two, we can measure the tie strength between them. Social closeness (SC) measures the concentrations in a network and is calculated as

$$SC_{u_i,u_j} = \frac{\left|\Theta_{Fd}(u_i) \cap \Theta_{Fd}(u_j)\right|}{\left|\Theta_{Fd}(u_i) \cup \Theta_{Fd}(u_j)\right|}, \tag{7}$$

where $\Theta_{Fd}(u_i)$ and $\Theta_{Fd}(u_j)$ are the sets of user u_i's and user u_j's friends; the larger the value, the tighter the relationship, which indicates that they are more likely to be influenced by each other.

Social interaction (SI) is directional and takes real activities using social media into consideration. If a user frequently replies to, likes, or shares the posts of a specific user more than any others, it can be interpreted as being highly attentive to that user's opinions. There is a range of interactions that can take place in social media; we chose the reply, like, and share behaviors as indicators of social interaction because they are spontaneous and active ways of expressing oneself. If there is one user to whom we would like to contribute feedback over and above the average volume of interactions, then that user must be very important to us and could act as a valuable endorser. SI is measured as

$$SI_{u_i,u_j} = \frac{\left|\Phi p_{posted}(u_j) \cap \Phi p_{interacted}(u_i)\right|}{\left|\Phi p_{interacted}(u_i)\right|}, \tag{8}$$

where $\Phi p_{interacted}(u_i)$ is the number of posts user u_i interacted with and $\Phi p_{posted}(u_j)$ is the volume of the posts published by user u_j on the social networking sites. $|\Phi p_{posted}(u_j) \cap \Phi p_{interacted}(u_i)|$ represents the number of user u_j's posts that are feedback to user u_i's post. The larger the value is, the more likely it is that user u_j will be influenced by user u_i.

The tie strength indicating the impact of the influence of user u_j on user u_i can be formulated as

$$TS_{u_j \to u_i} = \sqrt{SC_{u_i,u_j} \times SI_{u_i,u_j}}. \tag{9}$$

Priority Ranking Module

The main purpose of this research was to find a suitable endorser with the strongest persuasive social context to enhance the effectiveness of the advertisement. The priority ranking module is a mechanism for evaluating the most suitable endorser ($TS_{u_j \to u_i}$ denotes the impact of the influence of user u_j on user u_i) with the most effective social context (CP_{u_j,p_k} denotes the context persuasiveness for user u_j and a positive opinion p_k related to the designated ad) added to a designated advertisement to a specific target user.

Because the approach used to target potential users in the proposed model was "friends of an endorser," which cannot guarantee the content-based fitness, the power of the endorser should be emphasized in order to complement the lack of attraction from the ad itself.

The degree of relevance of the ad to the user, $PS_{ad,u}$, indicates the degree of fitness of the advertisement. The role of social influence in the content validity of the social context becomes more important as advertisement fitness becomes weaker. Specifically, if an advertisement matches the preference of the targeted user very well, who introduces the advertisement to the user becomes less important and the wording of the content becomes more vital. By contrast, for an unfamiliar advertisement, the names of the endorsers should be the major factor highlighting the social context. Therefore, $PS_{ad,u}$ is assigned to the weight of content persuasiveness, and $(1 - PS_{ad,u})$ is allocated to that of the tie strength. The aggregated score of social context validation (SCV) is formulated as

$$SCV_{ad,u_i}^{u_j,p_k} = PS_{ad,u_i} \times CP_{u_j,p_k} + \left(1 - PS_{ad,u_i}\right) \times TS_{u_j \rightarrow u_i}, \tag{10}$$

where ad denotes the designated advertisements, u_i and u_j represent the advertisement receiver and product endorser, and p_k is a positive opinion related to the advertisement. After computing and ranking the scores of all the social contexts between a user and the advertisement, we can extract the topmost and place it as a second title attached to the advertisement.

Experiments

In this section, we describe the experiments used to verify the proposed advertising mechanism for personalized social context endorsement. The experiments were conducted on the popular social networking Web site Facebook. Facebook is the largest social networking site and continues to amass visitors across the globe.

As reported in a study of Internet use [39], in March 2011, 693 million unique visitors age 15 and over visited Facebook.com from a home or work computer worldwide to connect with friends. According to a social media industry report [36], Facebook is also the number one social media tool that marketers are willing to use, and Twitter, LinkedIn, blogs, and YouTube make up the rest of the top five, in that order. The content that users share on Facebook is of great variety, and the abundant amount of user-generated content is the best resource for developing sophisticated advertising mechanisms. Besides its well-constructed network structure, Facebook provides powerful application programming interfaces (APIs), which allow developers to request the network structures, personal data, and shared information of users and their friends with ease as long as permission tokens are obtained.

To discover the appropriate social context endorsement for a given advertisement input from the advertiser, the proposed mechanism was used to establish who had shared comments or information about the product and to examine what they said. The friends of the authors of the comments selected

Figure 3. First Page of Experiment 1

as social context endorsements were then targeted as the potential customers who would receive the advertisement along with the social context endorsement. If the interest of a user of the advertisement was effectively aroused, the user would show a greater tendency to click on the advertisement to obtain further information and the impression made by the advertisement or brand would be greater.

In the experiments, we developed a Facebook application called WhyShouldILikeIt and invited users to participate in the experiment. Basic information about participants was collected: their friends, status messages, the links they shared, and the messages or photographs uploaded. In Experiment 1, we focused on examining the impact of the social endorsement format on the impression of the advertisements. Those users who received the advertisements themselves were asked to score their impression of the advertisements before and after watching three kinds of different attachments, as shown in Figures 3 and 4. Users could also click the hyperlinks of advertisements to obtain detailed information, and the click-through record was collected for evaluation. To prevent click fraud, the clicks individuals made in the same advertisement with the same attachment were only recorded once. To justify whether our proposed advertising mechanism was superior to other benchmarks, the different variations of social context endorsement information wrapped in the same original ad (i.e., ads only, ads plus number of fans, ads plus name, and ads plus social context) were evaluated and compared by the respondents at the same time. Because the original ads were the same regardless of the different advertising mechanisms, the differences among the four elements of advertising information are just the variations of context embellishment (i.e., number of fans, names, social context) added to the original ads. The benefit of this experimental design is that the targeted users can see all the advertising information at the same time and make a better judgment about which advertisement will persuade the users, allowing the advertiser to improve the degree of acceptance for the advertisement.

In the second experiment, we focused on verifying the performance of the proposed mechanism. The interface for Experiment 2 is shown in Figure 5. The advertisements were displayed with different social context endorsements generated from different social context discovery approaches. The social context was

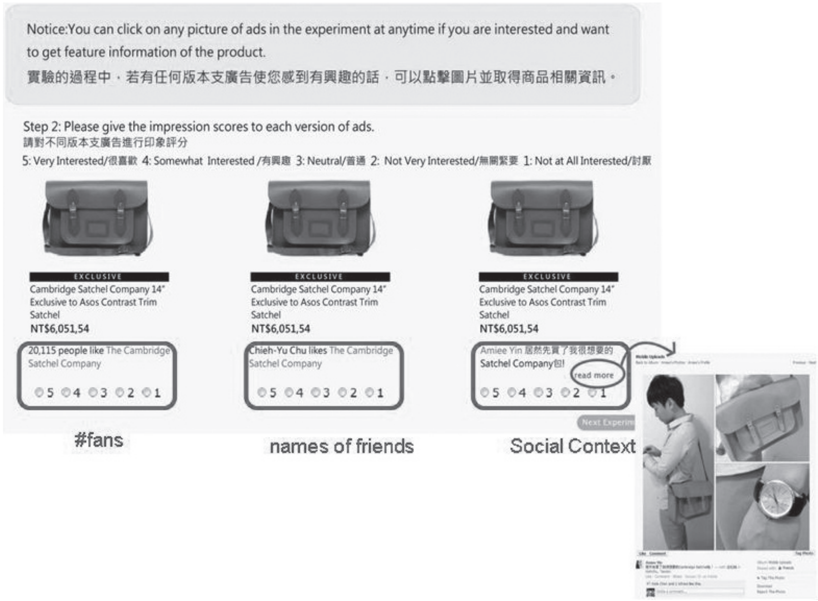

Figure 4. Second Page of Experiment 1

displayed in the same pattern: the name of a friend and the opinions the friend expressed. Users scored their impressions of the advertisements incorporating the distinct social contexts separately. The users' unique click-through actions were also recorded. To evaluate the effectiveness of our advertising approach, the experiment was conducted in accordance with other endorser discovery mechanisms (random, content-based, in-degree, and the proposed model). Among the existing social contexts, the random approach selects the endorsement context at random. The content-based method uses only the degree of embellishment as the selection criterion. Degree centrality is considered to be one of the most basic measures of social network analysis and has been used extensively in diverse research domains for measuring the network positions of actors with respect to the connections with their immediate neighbors. The in-degree of a node is a count of the number of ties directed to the node. When ties are associated with some positive aspects such as friendship or collaboration, in-degree is often interpreted as a form of popularity. Because the relationships on Facebook are bidirectional, we only used the in-degree formula to calculate the centrality of endorsers and determine the score of endorsement in the in-degree method. In the research, we used the links for friendship to measure the centrality of endorsers and determine the score of an endorsement context.

Data Collection and Description

Social Network Construction

The participants were invited to be involved through snowball sampling. Snowball sampling has proved to be a feasible method of studying the issue

Figure 5. Second Page of Experiment 2

of social networks [40]. Hence, it was used to construct the network structure of the experiments. Snowball sampling starts from a random sample of individuals drawn from a given population. Each one in the sample is asked to name N different persons. Those who are named and are not in the random sample form the first-stage network. Each one in the first-stage network is then asked to do the same thing for S times in order to complete the sampling process. In our experiment, S was set at 3 and N was set at 4. In other words, a specific network was formed by a continuous node-expanding process until a predefined maximum distance between connections (i.e., three hops) was reached. Initially 10 Facebook users were randomly selected. After filtering out those who were not willing to join the experiment, there were 7 users left, who were asked to perform the snowball sampling. Since we added a name conflict detection mechanism to prevent the overlapping of sampling in each stage, a total of 448 participants were generated through the snowball sampling with three (S) stages and four (N) name settings. After removing the people who were not interested in our experiment, we were left with a total of 376 unique participants, who formed the initial experimental social networks.

We used Graph API in Facebook to collect the user-generated content, including status, photographs, and shared links, from the nodes in the social network constructed. All the relevant content generated from the endorsers belonged to 92 unique users, and the target users generated from the "friends of endorsers" comprised 284 participants (52 percent male and 48 percent female). The characteristics of the constructed network are summarized in Table 1.

Consider a graph $G = (V, E)$. The clustering coefficient of a vertex indicates how concentrated the neighborhood of that vertex is. The clustering coefficient is defined as the ratio of the number of actual edges that there are between neighbors to the number of potential edges between neighbors. The clustering coefficient of a vertex n is calculated as $2e_n/(k_n(k_n - 1))$, where k_n is the number of neighbors of n, and e_n is the number of connected pairs between all neighbors of n. The distance between any two vertices is defined as the least number of edges required to connect the two. It is a measure of

Table 1. Data Descriptions for the Experimental Network.

Statistics for the experimental network	
Number of participants	284
Age	20–45
Gender	Male: 52% Female: 48%
Clustering coefficient	0.738
Average distance	1.852
Average degree of centrality	35.610

the efficiency of information or mass transport on a network. Let $d(v_1, v_2)$ denote the shortest distance between v_1 and v_2. Then, the average distance is calculated as $1/(n \times (n-1))\Sigma_{i \neq j} d(v_i, v_j)$, where n is the number of vertices in G. Degree centrality is defined as the number of links incident upon a vertex. It is a measure of network positions of actors in respect to the connections with their immediate neighbors. If d_i is the degree of vertex i, then the average degree centrality is calculated as $\Sigma d_i / |V|$.

Profile of Advertisements

Next, we describe the procedures involved in constructing the category tree and sampling the advertisements. First, by integrating the classification of products used by online B2C e-commerce sites such as Amazon and Yahoo and the category of fan pages on Facebook, we constructed a preference category tree that can be used for both product and user preference categorizations. In total, 18 leaf categories ({movies and tv; music; games}, {home appliances; arts, crafts and sewing; pet supplies}, {laptops, tablets, and notebooks; computer peripherals; software}, {camera, photo, and video; cell phones and accessories; MP3 players and accessories}, {clothing; shoes; handbags}, {personal care; makeup; skin care}) belonging to 6 parent categories ({movies, music, and games; home, garden, and tools; computer and peripherals; electronics; apparel, shoes, and accessories; health and beauty}) and 3 grandparent categories ({entertainment and living; electronics and computers; consumer products}) were adopted. The relationships among the different levels of categories were constructed in a treelike structure.

In the experiments, we randomly selected 108 advertisements collected from various channels, including Yahoo, ASOS, and KKBOX. The advertisements were grouped into six sets, and each set of advertisements included 18 advertisements matching 18 leaf categories. Each of the two experiments (Experiment 1 and Experiment 2) used three sets of advertisements. For the purpose of performance comparison, in Experiment 1, besides the proposed social context endorsement advertising strategy, we chose three other types of endorsement approaches as benchmarks. Hence, in Experiment 1 each person saw three sets ($18 \times 3 = 54$) of ads with four different formats. In the same way, in Experiment 2 we also included three other benchmarks to show the performance of our proposed mechanism. Hence, in Experiment 2 each person also saw 54 ads with four different formats. In total, each person saw 108 ads.

Experimental Procedures

We extracted the targeted users by expanding the friends of the people (endorsers) who shared positive comments about the product. Note that in the proposed mechanism, the friends of an endorser are just considered to be potential target users. The final target users should be those who have content-based fitness with the ad and can be highly influenced by the endorser. Therefore, in the proposed mechanism, for each user in the potential target user set, we computed not only the influential strength of every social context connecting the user but also the content fitness of the ad. For each targeted user, we evaluated the social context related to the designated advertisements. After the most appropriate social context had been generated, we invited the target user to visit our system and evaluate the advertisement attached to the social context endorsement.

The procedures for the social context endorsement discovery process are depicted in Figure 6 and can be described as follows:

1. The advertising material set was predefined, based on the advertisement input, and the set contained the identifiable product- or brand-related keywords.
2. We used the CKIP parser to separate the keywords from the sentences contained in the comments generated by the users in the sample network. Then, we applied the social context discovery module to label the polarity of each sentence. For each sampled ad, the irrelevant and negative messages were deleted from the social network, and users who did not befriend the authors were also deleted. The remainder comprised the ads' targeted social network. The authors of those comments were selected as candidate endorsers.
3. The friends of the candidate endorsers (denoted by dotted circles in Figure 6) were selected as the targeted users; for each of these, we considered the factors of preference, quality, and influence to evaluate the corresponding social context (endorser's name and positive comments) suited to that user. The details of the modules (social context discovery, preference analysis, quality analysis, and influence analysis) were elaborated earlier.

As a platform for online social activities, Facebook allows users to update personal information in many formats, such as status, photographs, and check-in records. We collected the data from the personal profiles and social activities of the 284 participants from April 2011 to April 2012. In total, 58,247 status messages were collected and split into 110,642 sentences; the total number of photographs was 77,671. However, most of these lacked annotation; only 31,845 of the photographs and 38,762 sentences were annotated with titles. The total number of links shared in the sampled network was 65,482, and 179,473 sentences were gathered. To compute the degree of embellishment

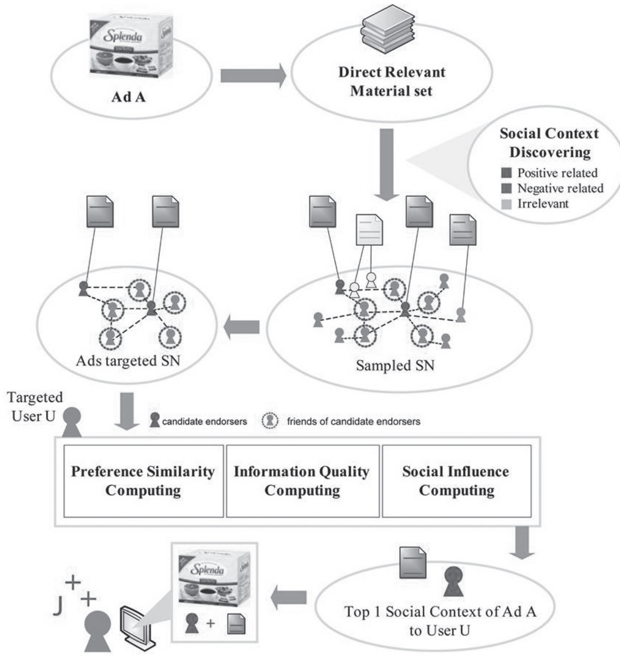

Figure 6. The System Flowchart

of each extracted sentence, the polarity of adjectives, adverbs, and emoticons was established by utilizing the CKIP technique and the dictionaries of positive and negative words listed in HowNet.

Computing Preference Similarity

To distribute an advertising campaign, increase business exploration, and maintain customer relationships, companies increasingly establish fan pages on Facebook. Fan pages can be seen as a resource for obtaining the latest news and favorable information. People are growing accustomed to "liking" the fan pages and expressing their support for and acquiring breaking news from particular firms. Thus, in the experiments, we identified the fan pages a user liked as the indicator representing a user's preference. A user commonly subscribes to the fan pages of several firms; thus, the average similarity of fan pages to the advertisement was calculated on the basis of the preference distances defined in the category tree.

Computing Information Quality

To determine a Facebook user's expertise, the proportion of relevant topics the user has mentioned and the amount of feedback from others were considered. We examined all the status messages of a user and matched them with the predefined dictionary. The professional expertise of the author increases with the number of product-related words mentioned. To protect against bias due to spammers, the count of likes for each message was also calculated; because the spammer has fewer friends, the likes and comments related to posted messages are also fewer. Even if the spammers posted a great deal of nonsense purporting to be relevant to the issue, the posts would eventually be filtered out. However, to avoid the scale problem of scoring different social contexts, the value of interactions was normalized to a range of 0–1.

Computing Social Influence

Users on Facebook can make friends with others by confirmed responses. The links of friends are thus bidirectional. Although the relationships on Facebook often come from real friendships, people still make new friends, such as befriending people who play the same Facebook game or a famous blogger. People tend to have greater trust in friends with higher familiarity. Thus, we used social closeness to measure the strength of relationships. To establish the degree of social interaction, we only considered the actions of a recipient in relation to the posts of the endorser, because we aimed to establish the impact of an endorser on the recipient of advertisements. Therefore, the comments that an endorser posted were examined and the number of likes, comments, and shares from the recipient were counted.

Results and Evaluation

To validate the effectiveness of the proposed social context endorsement mechanism for online advertising, we used the CTR of advertisements and user feedback as the performance indicators. The former is the most popular practical statistical measure for evaluating advertising effectiveness, and the latter allowed us to evaluate the improvement in the impressions made by the advertisements the target users received.

For the purpose of performance comparison, in Experiment 1, besides the proposed social context endorsement advertising strategy (denoted by Ads+SC), we chose three other types of endorsement approaches as benchmarks: bare banner advertisements (denoted by AdsOnly), advertisements with the number of fans on the fan page (denoted by Ads+#fan), and advertisements with the names of friends who were also fans (denoted by Ads+name). The first one is the most common type of advertisement, and the others are usually used by Facebook. In Experiment 2, we further compared the performance of our proposed social context endorsement approach with three other types of endorser-finding approaches (random, content-based, in-degree).

Click-Through Rate

The CTR of online advertisements can be calculated as the ratio of the number of users who clicked on an advertisement to the number of times the advertisement was delivered. This is defined as

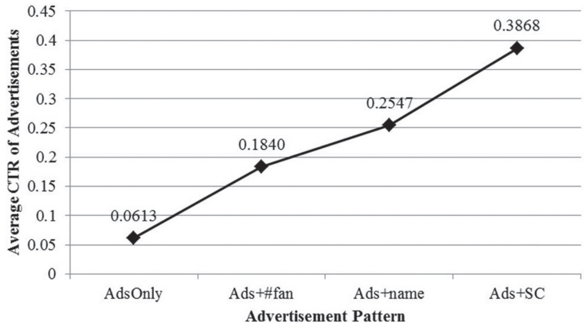

Figure 7. CTR Performances of Different Advertisement Patterns

$$CTR = \frac{Total\ \#\ of\ clicks}{Total\ \#\ of\ ads\ delivered}. \tag{11}$$

The results of the CTR with respect to various endorsement approaches (Experiment 1) are shown in Figure 7. We observed that by adding social information to the advertisements, people become more willing to click on the advertisements (advertisements with number of fans, advertisements with names of friends, advertisements with social contexts). The advertisements with number of fans and those with names of friends obtained a similar CTR. The results indicate that the effect of knowing why someone loves a product is stronger than only knowing who loves the product.

A paired sample *t*-test was used to statistically verify the significance of the difference in the advertising results (see Table 2). At the 95 percent significance level, all the test results showed that the strategy "social context" was significantly different, at 0.05, in relation to the other strategies. Therefore, this proves that our proposed strategy outperforms other strategies.

The CTR results in Experiment 2 are shown in Figure 8. These show that our proposed social context endorsement discovery mechanism outperformed other benchmarks, including the random approach, content-based approach, and in-degree approach.

Table 3 shows the statistical verification of the results, which confirms that our proposed mechanism outperforms other benchmark approaches at a significant level. The meaning of the token SC in Table 2 is the same as that of Social Context in Table 3. In Table 2, we consider the pattern of advertisement: Ads+SC is the advertising pattern we proposed. In Table 3, we consider the comparison between different approaches used to discover the fittest endorsement.

Our category tree comprises three main categories, and each main category has six leaf categories. Hence, 36 (6×6) advertisements were shown for each main category (e.g., entertainment and living, electronics and computers, consumer products). The results of the CTR with category of consumer products, electronics and computers, and entertainment and living are 3.721, 3.987, and 3.896, respectively. It can clearly be seen that the social context endorsement mechanism has a better result in the electronics and computers category

Table 2. Statistical Verification of Results of Experiment 1 Based on CTR Measurement.

Paired group		Mean	Standard deviation	Standard error mean	*t*	Sig. (two-tailed)
Ads+SC	AdsOnly	−3.2547	0.53566	0.03679	−8.847	0
	Ads+#fan	−0.20283	0.51645	0.03547	−5.718	0
	Ads+name	−0.13208	0.51656	0.03548	−3.723	0

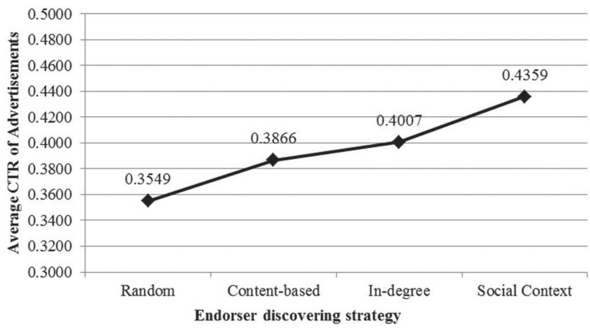

Figure 8. CTR Performance for Different Endorsement Discovery Strategies

Table 3. Statistical Verification of Results of Experiment 2 Based on CTR Measurement.

Paired group		Mean	Standard deviation	Standard error mean	*t*	Sig. (two-tailed)
Social context	Random	−3.13494	0.52186	0.03278	−7.517	0
	Content-based	−0.31011	0.51684	0.03348	−4.524	0
	In-degree	−0.1347	0.51677	0.03179	−3.781	0

than in other categories. This is mainly because mobile devices, such as the smartphone and tablet, have been so popularized that they are often held to be indispensable to daily life. The mobile environment and pervasive computing technology promote the development of products in the electronics and computers category. According to a report by Nielsen [30], over 54.9 percent of U.S. mobile subscribers now own smartphones, and approximately 70 percent of Americans who acquire new phones choose smartphones instead of feature phones; people are more interested in and pay more attention to these new products.

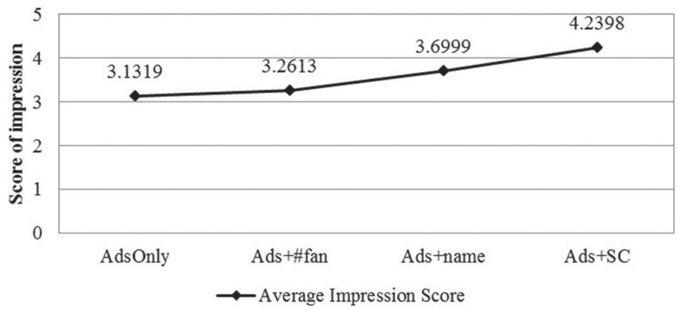

Figure 9. Product Impressions for Different Advertisement Patterns

Advertisements

Even though people are interested in the advertisements they receive, it is still quite likely that they will not click on the advertisements because of concerns about privacy and potential fraud [4]. Nonetheless, it is still of value to companies to increase the impression made by advertisements. Therefore, we also recorded the impressions of users in relation to different versions of advertisements and used the impression feedback of users as an evaluation measurement. The initial impression is the impression evaluation of the original ad (i.e., AdsOnly). In Experiment 1, we recorded the impressions of participants about the received advertisements expressed in four different formats. Those users who received the ads were asked to score their impression of the ads before and after watching three kinds of different attachments. The average impression scores of the various advertisement formats are shown in Figure 9. We can see that, with social context, the impression score of the advertisements increased to 4.2398 from the initial 3.1319 (social context–free advertisements).

The results for impression with category of consumer products, electronics and computers, and entertainment and living are 4.2539, 4.427, and 4.391, respectively. It is clearly found that the social context endorsement mechanism achieved a better result in electronics and computers than in other categories. The advent of social media has created a fundamental shift in human behavior: Sociable Labs [35] has shown that 38 percent of online shoppers have shared comments with friends about products that they have purchased, and 62 percent of have read product comments shared by their friends on Facebook. Our experimental results show that the social context endorsement mechanism has a better CTR in the electronics and computers category than in other categories. This outcome is consistent with the Nielsen Global Consumer Confidence Survey (2013) findings that the Internet is an important influence on consumers interested in buying new products, and the effects on the purchasing of electronics (81 percent) is the greatest.

We further separated the performances according to the initial scores to see the trend in relation to improved impressions, as shown in Figure 10. The results show that for those who initially disliked the advertisements, adding social context could enhance their impression of the product. The advantage of

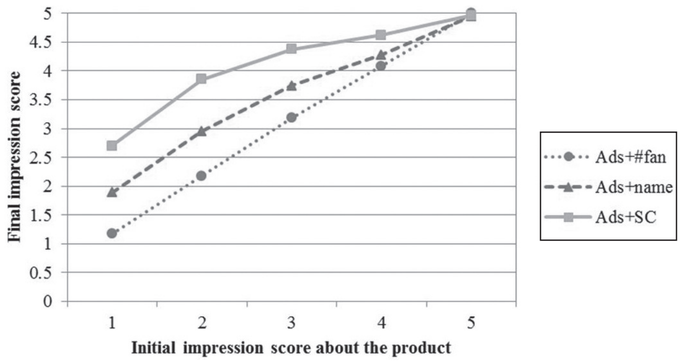

Figure 10. Increase in Ratio of Impressions in Experiment 1

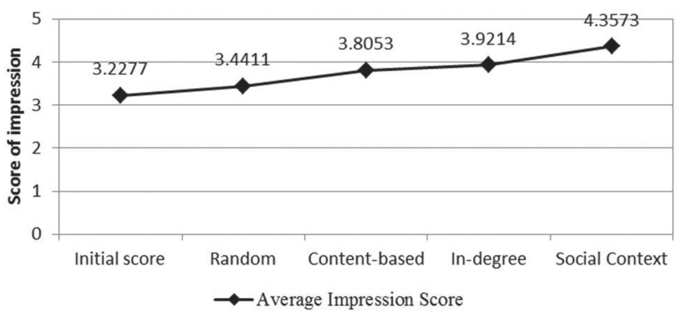

Figure 11. Advertisement Impressions for Different Advertisement Patterns

social context is particularly significant for an advertisement with an initially low impression.

In Experiment 2, we undertook the same evaluation of impression with respect to different social context endorsement discovery methods. As shown in Figure 11, social context–endorsed advertisements received a better impression score than other methods. The results also indicate that the "endorser" factor is more influential than the "opinion" factor, as the in-degree approach outperformed the content-based approach.

As Figure 12 shows, we found that the social context endorsement approach based on our proposed model obtained feedback with the highest level of improvement in the impression of the product. One interesting phenomenon is that the in-degree approach outperformed the content-based approach when the advertisements were of less interest to the target users. However, the opposite result was found when the advertisements were of greater interest to the target users. This coincides with the conjecture that if a person is not interested in the advertisements, the person who introduces them is more important than what is said. Yet, for those advertisements, the endorser is not as influential as the content of the opinions and advertisements.

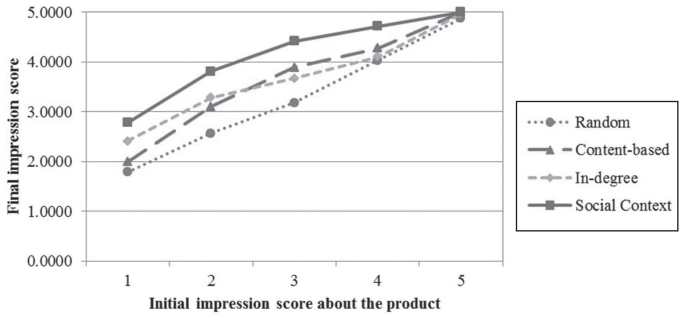

Figure 12. Increase in Ratio of Impressions in Experiment 2

Conclusions

The power of electronic word-of-mouth and viral marketing is inducing marketers to move away from their traditional marketing behaviors into social media, not only for the purpose of getting closer to their customers but also to increase their business exposure and consumer buying desires. There are two strategies commonly used to launch an advertising campaign on social media—social advertising and targeted advertising. Social advertising aims to leverage the influence of social opinion leaders in distributing information quickly and effectively along the networks.

With the overwhelming amount of content generated daily in social media, it is almost impossible for people to read each message that is created and distributed. However, a targeted advertising approach displays advertisements to potential customers according to the content they are viewing or the actions they perform; still, people can only receive relevant information and willingness to purchase cannot be enhanced significantly.

Besides, people tend to think of advertisements as spam and refuse to accept them even if an advertisement is nicely matched with user preference. A more sensitive advertising system should exploit the advantages of both social and targeted advertising approaches. In this research, utilizing the power of social influence and context embellishment, we developed a social context endorsement model to discover a close acquaintance who had posted positive comments on the product advertised, which were then leveraged as a social context endorsement for the advertisements. Our experimental results show that the proposed advertising approach of social context endorsement can effectively enhance the attention of users and increase both the CTR and the impression of the product.

Research Contributions

The success of online advertising is reflected in the degree of customer acceptance and corresponding CTR. Many researches [27, 28] have indicated that with the endorsement of satisfied customers who are similar peers, consumers' trusting beliefs about an online store will increase. Currently, most existing endorser-based advertisement systems did not take social relations and interaction into consideration. Facebook [11] considered social influence and celebrity endorsement in their proposed approach to advertising and launched the so-called social context ad in its performance advertising system. However, its CTR is far behind the industry standard [20]. There may be a few reasons for this, in particular that (1) people are not on Facebook with the intent to purchase products, and (2) the social context attached to the advertisements is not sufficiently powerful to resonate with the audience. To resolve the above issues, one novelty of this research is that the proposed mechanism allows us to enrich the social context content with positive or experiential comments shared by a close friend or a trustworthy online user. Specifically, by utilizing the power of social influence and context embellishment, we have designed a new social approach to context endorsement advertising to increase users' attention to the ads.

The practical contributions and managerial implications of this paper are summarized as follows. First, from a theoretical perspective, based on the preference similarity theory, social influence theory, and the theory of moral sentiments, we propose a novel personalized social context endorsement mechanism that combines the advantages of targeted and social advertising techniques to enhance the effectiveness of ads. The proposed system allows us to discover positive product-related opinions expressed on social media and to identify the appropriate target users to receive the ads with social context endorsement.

Second, from an empirical aspect, utilizing the Facebook platform, we have verified that adding social context information (number of fans, name of friends as fans, positive opinion of a friend) to the ads can effectively increase the CTR of the audience. We have also validated that social context endorsement can significantly enhance product impression, which is an important asset in creating business opportunities. According to the experiments, the proposed model had the biggest effect in increasing product impression. In addition to this, our results also show that when people dislike or are unfamiliar with an ad, the human influence approach performs better than the content quality approach, and vice versa.

Third, from a practical perspective, the proposed social context endorsement mechanism synergizes both the benefits of the targeted and social advertising approaches to enhance the value created by the ads. It provides advertising sponsors and social media providers with a powerful system for conducting advertising campaigns successfully.

Limitations and Future Research

There are several limitations and research issues that can be studied further. First, in our model the advertisements were collected from popular e-commerce sites, and they were largely in a picture format. The effect of different advertisement formats (e.g., textual, graphic, video) should be examined. Other factors that affect advertising performance (e.g., brand awareness, promotions) should also be investigated. Second, the user-targeting method of the proposed system is based on relationships (friends of endorsers). Other targeting methods could be developed to generate more exposure, such as a third-party relationship (e.g., a stranger who also plays your favorite game). Third, in this research, the social context endorsement was discovered from the targeted user's friends, but this could be extended to include appraisals by the public and famous people. Consolidating different types of opinions expressed by highly heterogeneous people is an interesting research avenue. Fourth, although we have showed the advantage of social context endorsement, the influential power of social context endorsement on various types of products could be compared and we could make further adjustments to the advertising strategy. Fifth, in this research, we just treat "reply," "like," and "share" equally when evaluating the social action between two users. To address the relative importance of different interactions (shares, comments, likes), we could assign these interactions different weightings. The artificial neural network (ANN) and analytic hierarchy process (AHP) are common approaches to deal with the uncertain weighting problem of parameter combination. In addition, the signaling relationship for shares, comments, and likes is as an emerging and open issue. Sixth, most comments are currently made due to the release of breaking news or favorable discount information. To encourage users to share comments about products, incentive mechanisms could be developed to obtain more positive comments. Last, due to privacy constraints, we were only able to collect social information from those users who were willing to authorize us to do that. The effectiveness of the proposed mechanism strongly depends on the amount of information shared in the social networks. If the participation scale is relatively small (e.g., fewer authors or fewer appraising comments), then the ad will have limited viewership. This will mean that firms may not find it attractive enough to implement. To increase information availability and encourage user participation, advertisers need to develop elaborate privacy management strategies and may need to introduce incentive mechanisms to attract users to join their fan pages.

NOTE

1. See http://en.wikipedia.org/wiki/Impression/.

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