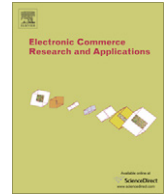




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Identifying influential reviewers for word-of-mouth marketing

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ABSTRACT

The key to word-of-mouth marketing is to discover the potential influential nodes for efficiently spreading product impressions. In this paper, a framework combined with mining techniques, a modified PMI measure, and an adaptive RFM model is proposed to evaluate the influential power of online reviewers. An artificial neural network is adopted to identify the target reviewers and a well-developed trust mechanism is utilized for effectiveness evaluation. This proposed framework is verified by the data collected from Epinions.com, one of the most popular online product review websites. The experimental results show that the proposed model could accurately identify which reviewers to select to become the influential nodes. This proposed approach can be exploited in effectively carrying out online word-of-mouth marketing, which can save a lot of resources in finding customers.

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1. Introduction

Under the current global economic structure, firms face extreme competition from competitors around the globe. In order to survive, appropriate marketing strategies are desired to raise sales and the loyalty of customers. Prior study reveals that, under the whole cost structure of firms, only the marketing costs have significantly increased over the last 50 years (Sheth and Sisodia 1995). The advancement of technology drives down the manufacturing and managerial costs but, at the same time, raises the marketing cost rapidly (Weber 2002).

With lower costs, higher speed, and externality effects, marketing on the Internet has advantages over traditional media. However, its effectiveness is still uncertain. To resolve this problem, the development of recommendation mechanisms based on the information of the products, purchase history and personal preference, and data-mining techniques (Cho and Kim 2004, Zhang and Jiao 2007) would be helpful for sending information to the customers who are most possibly interested in them. Nevertheless, most of the existing recommendation mechanisms did not consider the factor of influential power between online users. Customers' purchase decisions would be largely influenced by the product comments provided by someone we trust, rather than the firms' advertisements (Jurvetson 2008). Identifying the potential influencers could help enterprises improve effectiveness of their online marketing strategies through word-of-mouth information propagation.

Originally, word-of-mouth marketing is an action for informally sharing experiences and spreading information among consumers whenever they are satisfied or dissatisfied with specific products (Anderson 1998, Mangold et al. 1999). In many markets, customers are strongly influenced by the opinions of their peers (Richardson and Domingos 2002). Word-of-mouth marketing refers to marketing techniques that utilize the customers' social networks to increase brand awareness through self-replication and message diffusion (Kiss and Bichler 2008). The customers' social networks would affect the adoption of individual innovations and products (Strang and Soule 1998) and reduce the risk of consumers' purchasing decision making (Murray 1991, Godes and Mayzlin 2004). Online user reviews would influence other users' perception of product and could be considered as part of the word-of-mouth marketing (Duan et al. 2008). Measuring the influential power of the reviewers is essential in word-of-mouth marketing because the quantified influential strength can be used to discover the nodes most appropriate for spreading product information speedily, widely, and effectively.

In the current paper, utilizing opinion-mining techniques combined with modified Pointwise Mutual Information (PMI) (Turney and Littman 2003) and adaptive RFM (Recency, Frequency, and Monetary) (Hughes 2005) models, we develop a framework to evaluate the influential capability of online reviewers and recommend appropriate ones to support word-of-mouth marketing. PMI and RFM measures are aggregated based on artificial neural network (ANN) weight learning model to represent the overall influential strength of a reviewer. The developed framework is further empirically experimented and verified by the data collected from Epinions.com,

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one of the most popular online product review websites. As the relationships between trust and influence are very tight, we use a trust network mechanism to evaluate the effectiveness of our framework in discovering influential reviewers. A reviewer with a higher trust value not only reveals that there are more users trusting her/him but also indicate that she/he could influence more users. Compared with the results developed by popular author and review rating approaches, our proposed model has a higher accuracy rate in predicting the influential strength of the reviewers.

The remaining part of the current paper is organized as follows. In Section 2, we discuss existing literature related to our research topics. In Section 3, we propose the system architecture and the methodologies applied in this work. Section 4 describes the experimental data source, settings, and procedures. The experimental results and evaluations are discussed in Section 5. Section 6 concludes our research contributions and presents future research directions.

2. Literature review

2.1. Word-of-mouth marketing

Word-of-mouth marketing, also called viral marketing, is a new marketing method that uses electronic communications (e.g. e-mail) to trigger brand messages throughout a widespread network of buyers. Dobele et al. (2005) studied several real marketing cases and analyzed why firms need word-of-mouth marketing, how to apply technology to it, and how to use it successfully. In general, discovering influential nodes is one of major avenues of word-of-mouth marketing research (Duan et al. 2008, Kiss and Bichler 2008). A common approach for identifying influential online reviewers is to compare the accumulated ratings of the reviews or the authors (Turney 2002). Review mining is another method to discover the influential reviewers; without the public rating information, the influential strength of an article or an author on others' purchasing decisions could be evaluated based on the content of reviews (Yu et al. 2008).

Moore (2003) investigated the branding influence based on the word-of-mouth marketing environment. In the case of Microsoft, the number of Microsoft's Hotmail users increases rapidly by utilizing the contacts of each user. Although Microsoft spent only a small budget on marketing, its membership grew by 12 million in 18 months (Jurvetson 2008). Leskovec et al. (2006) proposed a model to investigate user behaviors in a large community and identified the growth and effectiveness of the social network. Richardson and Domingos (2002) utilized a probabilistic model to analyze the probability of a customer's purchasing that is strongly dependent on whether his/her friends also have purchased the same product. However, they did not focus on identifying the influencers in a customer social network to induce the potential customers with business opportunities.

Several works on word-of-mouth marketing are based on social networks (Strang and Soule 1998, Duan et al. 2008, Jurvetson 2008, Kiss and Bichler 2008). However, most of them focus on the observation of business situations or on the calculation of social network spreading. It is hard to acquire a practical model that can be easily and effectively applied to business strategy development. In this research, we address the issue of word-of-mouth marketing from the aspect of influential reviewer discovery. Our presented work focus on develop a framework that can support the enterprise to successfully operate word-of-mouth marketing.

2.2. Online reviews and opinion mining

Online reviews are closely associated with word-of-mouth marketing in a Web environment. People tend to read the product re-

views written by other experienced users before making a purchase decision. In other words, these reviews are equipped with some kind of influencing power over the readers. A prior study on Amazon.com reviews suggested that reviewers may engage in experience sharing of questionable practices and promote specific agendas to build their expert identities (David and Pinch 2005). Examining the effect of online book reviews on the relative sales at Amazon.com and Barnesandnoble.com, Chevalier and Mayzlin (2003) found that an improvement in reviews leads to an increase in sales. Reinstein and Snyder (2005) suggested that online movies reviews from professional critics have positive effect on increasing the customer demand. In addition, Basuroy et al. (2003) also pointed out that movie reviews have a significant impact on the performance of companies.

Opinion mining can be applied to measure the influencing level of a review or comment. Zhan et al. (2007) emphasized the important role of writing and referring to product reviews on the Internet. Dobele et al. (2007) identified the key points about the success or failure of message passing in word-of-mouth marketing. By collecting and categorizing many cases about message-passing behaviors for several different products, they showed that "emotion" has more impact than "the expectation of the recipient" in the successful message passing. In general, people tend to be influenced by subjective expressions involving strong words and objective reaction statements are generally not considered important because they lack "emotions" to affect the purchasing decisions of others (Dobele et al. 2007).

Regarding the methodologies to implement opinion mining, many scholars focus on the identification of the author's attitude and opinion-mining techniques are mostly applied in the binary classification of reviews (e.g. positive or negative tendency) (Drozdenko and Drake 2002, Hu et al. 2004, Ding et al. 2008). Scoring mechanisms considering multi-dimensional factors will be more feasible for the review valuation. In reality, there are already some social data sets distributed on the Web, which are helpful in simplifying the data-collecting process for opinion mining (TrustLet 2008).

2.3. RFM measure

Hughes (2005) proposed the RFM analytical model to measure the values of customers for enterprises in 1994. With RFM analysis, firms could discover the potential and valuable customers easily by observing their past behaviors. Newell (1997) showed that the RFM method is very effective in customer segmentation. Actually, this simple and direct measure has been used in direct marketing for a number of decades (Baier et al. 2002). Obviously, those customers who recently purchase (Recency), who purchase many times (Frequency), and who spend more money (Monetary) typically represent the best targets for new offerings (McCarty and Hastak 2007). Regarding the RFM applications, Drozdenko and Drake (2002) applied hard-coding techniques to assign weights to the three variables in RFM analysis. This is the so-called "judgment-based RFM" because the procedures are developed based on the judgments of marketers. Chan (2008) proposed a novel approach that combines customer targeting and customer segmentation for campaign strategies. In our work, RFM will be used to evaluate the values of online reviewers while some modifications will be made to fit the characteristics of the experimental data source.

2.4. ANN (artificial neural network)

An artificial neural network (ANN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionistic approach (Wikipedia-ANN 2008). ANN is particularly appropriate for solving

complex problems with several variables. It has been used extensively for solving business problems and can be used as an element of business intelligence. For example, Kuo and Chen (2004) utilized a fuzzy neural network to learn the rules produced from order selection questionnaires in electronic commerce. Cao and Marc (2006) created an ANN model for a reputation agent to evaluate the capabilities of selecting products and services in an e-tourism environment. Chiang et al. (2006) developed an ANN model to predict and explain consumers' choice between Web and physical stores. Our study also exploits this technique to build a feasible model to achieve an accurate identification of influential reviewers.

2.5. Trust mechanism

Trust is a relationship of reliance and is also a willingness to rely on an exchange partner in whom one has confidence (Moorman et al. 1993). It is an expectancy that the behaviors of people (or objects of trust evaluation) will follow a predetermined manner (Ammeter et al. 2004) and this manner is the behaviors of others they trust. Trust can be used to indicate the strength level of relationships among people without performing a detailed investigation of intention (Simmel and Frisby 2004). Munns (1995) stated that trust is a relation personal to an individual, and arises from the experiences and influences on that individual.

Trust has been described as “central to all transactions” between individual or organizational actors in economics (Dasgupta 2000). It strengthens the motivations of people to do transactions and the benefits of each transacting target can be evaluated accordingly. Morgan and Hunt (1994) theorized, modeled, and tested the success of relationship marketing and found that commitment and trust are key factors. Brockand and Barclay (1997) studied the relationships between buyers and sellers and showed that trust is based on character, motives, intentions, and role competence and judgment. Dunn (1988) indicated that trust is helpful for decision support in a scenario where there is uncertainty about the actions that will be undertaken by others. In other words, a trust mechanism is an important and effective component of our purchase decision, although we are not familiar with the product.

The product reviews written by a trustable reviewer normally have higher impacts. On the other hand, the product reviews of an influencer should be trusted by more people. Due to these features, the trust score is a clear and appropriate pointer to potential nodes. In this research, we use a trust indicator to measure the

effectiveness of our influencer identifying framework in the current study.

3. The model

The proposed model analyzes the content of after-use reviews provided by online users and the reviewing activities of these authors to identify the potentially influential reviewers. Fig. 1 displays the main components and procedures included in the system architecture.

In the framework, the comments written by each reviewer are first analyzed by text-mining techniques and quantified by a modified PMI (Pointwise Mutual Information) measure based on an established subjective work set. In the meantime, the reviewing recency and frequency of the authors are quantified to measure the RFM scores of the reviewers. Then, the PMI- and RFM-based scores are combined to determine whether a reviewer has the infective ability and is valuable in word-of-mouth marketing. To aggregate these two scores better, an ANN (artificial neural network) technique is used to implement the weighting mechanism. The well-trained ANN model further outputs a list of ranked influential reviewers. Finally, we utilize a well-developed trust mechanism to evaluate the effectiveness of our proposed influential reviewers discovering mechanism. The units in this architecture are detailed in the following subsections.

3.1. Word-set expansion

The semantics of an article are usually determined by some specific keywords, which are clear and easy to interpret. The semantic identification is greatly helpful for judging the tendency of a review. A trustable reviewer should write relatively fair comments on the products. From the viewpoint of the consumers, an influential review should not only express the merits but also point out the defects of the products. Also, previous work has indicated that the reviewers who express extreme justification (e.g. all positive or all negative comments) are less likely to be trusted (Jindal and Bing 2008). If a reviewer can fairly reflect the advantages and disadvantages of a product, the review contents likely would include more subjective and emotional words which express his/her satisfaction or dissatisfaction with a product. In this research, the positive and negative perspectives of words are combined to carry out the review analysis. However, we do not focus on classifying a review

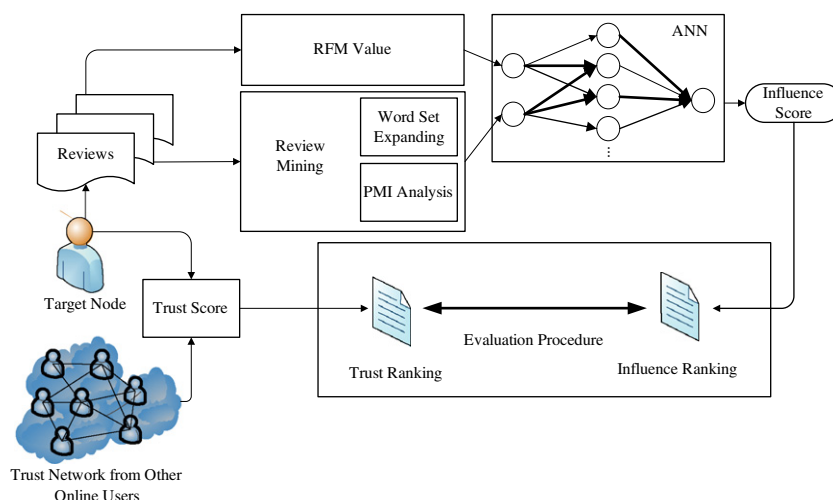


Fig. 1. System concept and architecture.

to be positive or negative, but instead we use the “quantity of emotional expression” such as the number of subjective terms in a review to measure the influential strength of a review.

Turney and Littman (2003) defined two sets of words, the positive (S_p) and negative (S_n) sentiments, as:

$$S_p = \{\text{good, nice, excellent, positive, fortunate, correct, superior}\},$$

$$S_n = \{\text{bad, nasty, poor, negative, unfortunate, wrong, inferior}\}.$$

Here, we integrate both word sets into a word set S_{p+n} , which covers the subjective words with positive or negative semantics.

$$S_{p+n} = S_p + S_n.$$

In order to prepare a word set with a sufficient number of subjective words, we recursively expand the set of S_{p+n} from the WordNet online semantic lexicon. WordNet (Miller 1990, 1995), a large collection of lexical semantic relations built at Princeton University, is perhaps one of the most important and widely used lexical resources for natural language processing systems (Conlon et al. 2004, Malucelli et al. 2006). It is an online lexical database which links the six major semantic relations (Miller 1995) such as synonymy, antonymy, hyponymy, hypernymy, meronymy, and holonymy. The English nouns, verbs, adjectives, and adverbs are grouped into sets of synonyms, each representing a distinct lexicalized concept (Miller 1990). There are more than 118,000 different word forms and more than 90,000 different word senses included in WordNet. It provides a more effective combination of traditional lexicographic information and modern computing (Miller 1995) that allows users to use it under program control for extracting the semantic relations.

A word set S_{p+n}^k represents a word set generated by expanding the S_{p+n} in k degrees. For example, S_{p+n}^1 includes the 14 original items and S_{p+n}^2 consists of the 14 items and all their synonyms. The ingredients of S_{p+n} will carry a complete meaning of “subjective words” which can reach our expectations.

3.2. PMI strength measure

PMI models were originally used to measure the strength of the semantic association between words (Turney and Littman 2003). The value of PMI between two terms t, t' is formulated as

$$PMI(t, t') = \log_2 \frac{P_c(t, t')}{P_r(t)P_w(t')},$$

where $P_c(t, t')$ is the probability that term t and term t' co-occur in a defined set of documents and $P_r(t)$ and $P_w(t')$ are the probability that terms t and t' appear in these documents, respectively. The log of the ratio corresponds to a form of correlation, which is positive when the terms tend to co-occur and negative when the presence of one term makes it likely that the other term is absent.

In this research, PMI is modified to measure the strength score of a review. We use the concept of PMI to measure the semantic association from the matched terms in a review and the word set. Denote n_{tr} as the number of terms t occurring in the target’s review r and N_r as the number of all the words in review r . N_s represents the number of words in the word set S_{p+n}^k that includes term t' . The PMI value for a term t in a review and t' in the word set is modified as

$$PMI(t, t') = \begin{cases} \log_2(f_r(t)f_w(t')), & \text{if } t = t' \\ 0, & \text{if } t \neq t', \end{cases}$$

where

$$f_r(t) = \frac{n_{tr}}{N_r},$$

$$f_w(t') = \frac{1}{N_s}.$$

Note that, as the number of words in each review could be unequal, we used a relative occurring frequency in the modified PMI measure. The PMI measure of a review should consider all the matched words in the whole review article. Thus, the PMI value for a review R is written as

$$PMI_R = \sum_{t \in R} PMI(t, t'), \forall t' \in S_{p+n}^k.$$

As this formulation will produce a negative score, the PMI score of a review R is standardized as

$$PMI_{R_std} = \frac{PMI_R - PMI_{min}}{PMI_{max} - PMI_{min}},$$

where PMI_{min} and PMI_{max} are the lowest and highest PMI values of the reviews analyzed. Finally, we can obtain the target reviewer’s score by averaging all the standardized PMI scores of the reviews written by the target reviewer:

$$PMI_{Avg} = \frac{\sum_{R \in A} PMI_{R_std}}{|A|},$$

where A is a set of reviews written by the target reviewer and $|A|$ is the total number of these reviews.

3.3. RFM measure

The RFM model was initially proposed to measure the values of customers for enterprises (Hughes 2005). With RFM analysis, firms could estimate the potential of customers by observing their past purchasing behaviors. In this research, we modify the RFM model to evaluate the influential strength of the reviewers. Based on the characteristics of online product reviews, only the Recency and Frequency indexes of RFM analysis are adopted. Monetary value is excluded because of its measurement difficulty. In practice, users (reviewers) generally share experience or knowledge with the community voluntarily and their efforts have no direct relationships with pecuniary revenues.

3.3.1. Recency model

“Recency” in the original RFM model is measured by the duration between the last purchase and current dates. In this research, the “Recency” of a typical reviewer is interpreted as the time range between the current date and the latest written date of a reviewer and is measured in days. For a reviewer i , the Recency value γ_i is explicitly formulated as

$$\gamma_i = C - l_i,$$

where l_i is the last written date of reviewer i and C is the current date. Before being combined with other index values, γ_i needs to be standardized. Recency standardization is slightly different from general standardization procedures because higher Recency values indicate lower market values. The standardized Recency value is formulated as:

$$Std_{\gamma_i} = \frac{\gamma_{max} - \gamma_i}{\gamma_{max} - \gamma_{min}},$$

where γ_{min} and γ_{max} are the lowest and highest Recency values of the reviewers analyzed. The formulation reveals that the lower the Recency value γ_i , the higher the standardized Recency value Std_{γ_i} .

3.3.2. Frequency model

Frequency in the original RFM model represents the number of purchases in a specific time range. A similar definition is applied in this research. It is used to indicate the number of writings of an author during a specific time range. We separate the time periods

into three time ranges and aggregate those reviews written during each time range:

- $\theta_{<90}$: The number of writings made within 90 days,
- θ_{90-365} : The number of writings made between 90 and 365 days,
- $\theta_{>365}$: The number of writings made over 365 days.

The segmentation of the three time ranges is based on the characteristics of the product types and reviews. As most of the data are electronic products and their life cycles are shorter than general products, it is appropriate to segment the time periods into the three ranges. The reviews of each author are classified into the three categories. It is apparent that the reviews written in different time ranges represent different importance levels. The Recency score of a reviewer is calculated by aggregating the weighted frequencies of the reviews written during each time range. Similarly, the Recency scores need to be standardized before they can be utilized in combination with other measures.

3.4. ANN ranking mechanism

We use the machine-learning approach to estimate the overall influence score, which considers the above indexes (PMI, Recency, and Frequency). The relationships among these elements are complex and cannot be indicated by linear models because they are associated with uncertain human behaviors, motions, and attitudes. Linear or static weighting of these three scores cannot represent the scenarios in reality. ANN is particularly appropriate and effective for solving various complex problems. These kinds of complex human behaviors are appropriate for construction by massive data training and learning in ANN. Therefore, in our research, all the scores are fed into an ANN model for weighting adjustment. The ANN-based weighting mechanism can adaptively allocate appropriate weight distributions among the three scores. Finally, a list of ranked reviewers is generated according to their overall influence scores.

3.5. Trust network value calculation

The relationships between trust and influence are very tight. A reviewer with a higher trust value not only reveals that there are more users trusting her/him but also indicate that she/he could influence more users. Although trust is effective in influencing the purchasing decisions of others, we do not adopt it directly as an element of our influencer identifying model. Instead, we use SCN (Social Connection Number) as the evaluation indicator to measure the effectiveness of our proposed model. One main reason is that most of the online product review communities still have not offered any trust mechanisms. It is difficult for firms to include a trust measure to identify influential reviewers. In addition, a trust mechanism is more beneficial to the veteran than to the novice because experienced reviewers have wider social networks for trust measurement. Instead, we use a trust network mechanism to evaluate the effectiveness of our framework in discovering influential reviewers. If the reviewers discovered by our model also have a high trust value, the effectiveness of our model can be justified.

Generally, trust value can be measured by aggregating the relationship evaluations scored by mass users. Trust evaluation should consider the human relationships, as time passes, the accumulated trust value will become more and more objective. Since the trust relationships among the reviewers can add benefits to product information spreading, some online discussion forums have provided the mechanisms for users to evaluate the reviewers with whom they trusted. These scores can be used to represent the trust levels of authors. For example, Epinions.com offers a mechanism to evaluate the trust values of other users and edits their own “Web

of Trust” (WOT) (Victor et al. 2008). By utilizing the trust evaluation mechanism, users can establish their friend lists as well as blacklists. A social network of trust relationship based on these friend lists can be further used to evaluate the opinion-propagating ability of a reviewer.

The purpose of utilizing a trust network in our model is to evaluate the influence of a reviewer. As the trust value is a fair indicator to judge his/her influence, we are interested in estimating how many people trust a target reviewer. We use an SCN to measure the possible influence of a node based on the trust relationships between users. The construction of SCN is a recursively extracting process to aggregate all possible indirect trust relationships. The SCN value for a reviewer i is formulated as

$$SCN_i = n_i + \sum_{j \in tr_i} \delta SCN_j,$$

where n_i is the number of nodes who trust node i , tr_i is a set including these nodes, and symbol δ denotes the decay rate of trust strength. In practice, the social connections among the members could be directly observed through their trust ratings and the indirect trust relationships between two nodes can further be developed from the extraction process. Note that multiple connections between two nodes are likely to appear because people may connect to friends via different paths. If a node has already been visited in the previous extracting procedures, the redundant node should be erased. For example, in Fig. 2, there are three paths of trust relationship between A and D. Node D will be included in the first degree extraction (path $A \rightarrow D$) because it has a direct connection with node A but the redundant node Ds, discovered during the second degree extraction (path $A \rightarrow B \rightarrow D$) and the third degree extraction (path $A \rightarrow B \rightarrow C \rightarrow D$) will be excluded.

The pseudo-codes of the recursive procedure for relationship extraction are described as follows:

```

int k; //The extracting level
long rec(long Nk){//The target node is trusted by N people in level k
    if (k < 2 || Nk == 0){
        return dup(Nk);
        //If no one trusts the node or the relationship ends in level 1,
        return the number of people who trust the target node.
    }
    else {
        return  $\delta^{k-1} * \text{dup}(N_k) + \text{rec}(N_{k-1})$ ;
        //Return cumulative SCN and erase redundant connections.
    }
}
    
```

Note: dup(•) is a function is used to remove duplicate nodes.

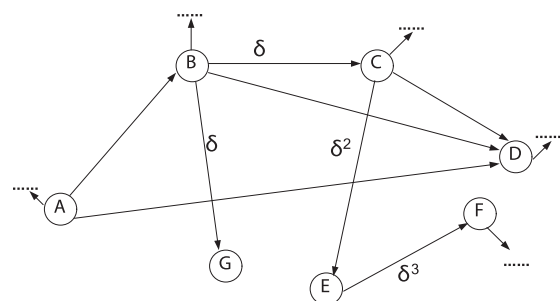


Fig. 2. SCN extraction of the reviewers.

4. Experiments

4.1. Data source

The data used in this experiment were collected from Epinions.com, which was established around 2000. It is a popular open platform, which provides user-generated reviews on various types of products. It also provides a simple trust mechanism for users to evaluate the reviewers. Several researchers (Turney 2002, Massa et al. 2007, Victor et al. 2008) have conducted studies on the review forum of Epinions.com. Thus, the stability and objectivity of its data should be plausible.

The retrieval date of these reviews was May 14, 2008. According to our observation (Fig. 3), there are relatively more reviewers and product reviews in the “Electronics” and “Computers & Software” categories. The reviews of these two catalogs account for approximately half of all collected reviews, so we retrieve training data from the “Electronics” and “Computers & Software” categories. The training data set includes 4573 reviews written by 82 reviewers, which were randomly selected from 8 sub-categories of “Electronics” catalog – “Home Audio,” “Video,” “Communications,” “Car Audio,” “Optics,” “Outdoor Electronics,” “Cameras and Accessories,” and “PDA & Handhelds” and five sub-categories of “Computers & Software” category such – “Hardware,” “Computer & Video Games,” “Web Sites & Internet Services,” and “Software.”

The training data set was used to train the ANN model parameters, and decide the optimal parameter values of word-set expansion level and decay rate of indirect trust relationship. These three parts represent two-thirds of all reviews. We think the situation is due to our starting point in collecting data. In other words, the on-line platform for writing product reviews is constructed by computer and networks. It is reasonable that most users are familiar with products related to electronics and information technology. The centralized data distribution also has some advantages. It makes the main character of data can be identified easily and the applying range of our model is also cleared. Then, we randomly selected the testing data from all the sub-categories in “Electronics” and “Computers & Software” categories but excluded the reviews which were already included in the training dataset. In general, each review was written by 1 author whose SCN value was larger than 0. There are 16 reviewers having written 276 product reviews belonging to “Electronics” category and 12 reviewers writing 108 product reviews included in “Computers & Software” category.

4.2. Word-set expansion and PMI score

To analyze the semantics of the training and testing reviews retrieved from Epinions.com, an appropriate word set S_{p+n}^k should be built. In order to perform subjective word matching effectively, it is necessary to carry out a sufficient expansion on the original word set S_{p+n} . As WordNet has defined related subjective words well and listed their synonyms, we use it to find out the synonyms of the words in the original word set for further word-set expansion.

Specifically, all the synonyms of the words in S_{p+n}^1 are extracted from the WordNet word base and added into word set S_{p+n}^1 to generate a new word set S_{p+n}^2 . This process is recursively conducted until six levels of word-set expansion are constructed. The word-set expansion results are shown in Table 1. The size of a word-set will grow rapidly according to expansion level k value and the number of word matches will also increase due to a larger word-set S_{p+n}^k . Clearly, different values of k will lead to different PMI values and further influence the predicting results. Table 1 shows that number of words in a word-set with expansion level k ($k = 1, \dots, 6$).

The PMI values of the reviews with respect to different word-set expansion levels ($1 \leq k \leq 6$) can be calculated. That is, each reviewer will have 6 PMI scores with respect to the six different word-set expanding levels. Utilizing the training data set, we can decide the appropriate word-set expansion level k . In Section 4.6, we will discuss the selection of word-set expansion level.

The procedures of word matching are listed in the following:

- (1) Start from the original word set.
- (2) Execute keywords matching all the reviews in the data set with the word set.
- (3) Record the matching counts and calculate the PMI strength score of each review.
- (4) Average the review score of each reviewer.
- (5) Increase the k value and repeat steps (2)–(4) to acquire different level PMI scores.

Table 1
Word-set expansion results.

K	1	2	3	4	5	6
Number of words in S_{p+n}^k	14	142	578	1241	2148	3223

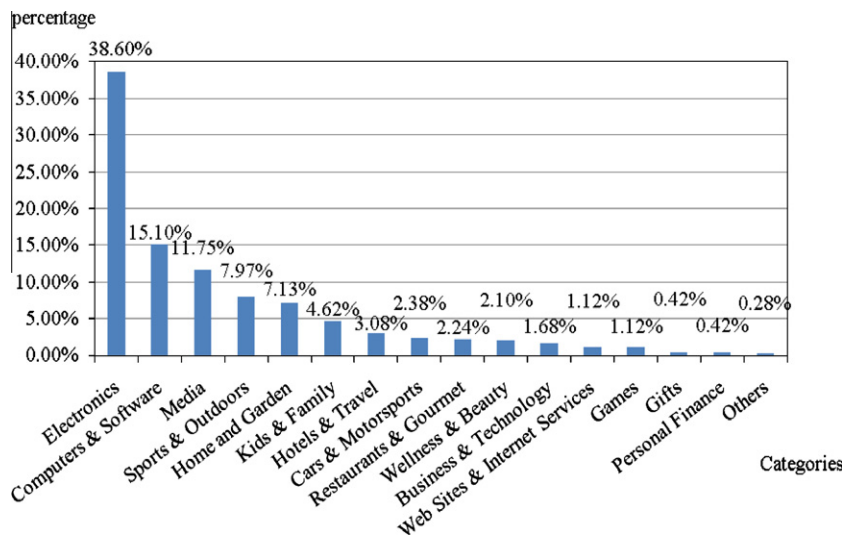


Fig. 3. The distribution of reviews in different category.

4.3. RFM score

The time-related attribute of the review is used to calculate the Recency and Frequency values of a reviewer. The two indicators are directly associated with the reviewers. Reviewers will receive higher standardized Recency and Frequency values if they write reviews continuously. This would be helpful for identifying influential nodes. An analysis of the RFM values reveals significant differences between different reviewers.

4.4. Trust score

As mentioned above, the relationships between trust and influence are very tight. The trust value will become objective as the value is evaluated by mass users for a sufficiently long time period. Epinions.com has already been equipped with a trust-scoring mechanism. Using this mechanism, users can create their own friend lists and blacklists, which include the reviewers they trust or distrust. The situation of a user's trust could be obtained by checking his/her profile. For example, in Fig. 4, the information of "Web of Trust" for one of our collected users is displayed at the left-hand side of his/her profile's page (notice that considering the user privacy, we replace the user name with an asterisk).

In our experiments, we used the trust list rather than the block list for trust score calculation. We calculate the SCN values of the reviewers in Epinions.com as the objective measures to evaluate the effectiveness of different approaches in identifying the influential reviewers. The SCN value, an overall trust value of a reviewer aggregated from direct and indirect trust relationships, is used to measure the possible influential range of reviewers. Starting from the link of "View all members who trust", we could calculate his/her first level SCN value. Then, we can further calculate the second level SCN value by exploring the links of the users who trust this user. The processes of SCN value calculation are detailed in Section 3.5.

4.5. Artificial neural network training

A three-layer artificial neural network was applied to predict the influence score of the reviewers. The NNTool in MATLAB 2006 is used in this experiment. Table 2 lists parameters adopted in the network training. All network types are feed-forward back-propagation. The network is composed of three layers: input layer, hidden layer, and output layer. The input layer has three

Table 2

Parameters for neural network training.

Parameters	Value
Network type	Feed-forward back-propagation
Number of neurons in hidden layer	50
Training function	TRAINLM
Performance function	MSE
Epochs	150
Goal	0
Mu	0.001
Mu_dec	0.1
Mu_inc	10
Mu_max	10,000,000,000
Max_fail	5

neurons: PMI, Recency, and Frequency. The hidden layer is the main processing component for generating the network structure. Fifty neurons are applied in the hidden layer to build the network structure. The output layer has only one neuron to generate the predicted result, which is sequentially compared with the standardized trust score for network training. Epoch stands for the number of learning cycles in each network. One hundred and fifty is an appropriate number for our experiment because the MSE values were close to zero. A larger epoch value does not provide apparent effects. Mu is the adaptive learning rate that changes according to the variation of MSE.

4.6. Parameters selection

In the experiments, an ANN model constructed with 50 neurons in a hidden layer is adopted. The settings of the ANN model have been detailed in Section 4.5. In order to select better parameters (PMI level and decay rate), we divided the full training data into training set (80%) and validating set (20%). The PMI, Recency, and Frequency scores of each reviewer included in the training set are fed into the ANN model. Then, the validating set is used to validate the performance of model which trained with a specific parameter pair. In order to determine the most appropriate parameter values with better performance, we compare the performance of the experiments according to different combinations of word-set expansion levels ($k = 1, 2, \dots, 6$) and decay rates ($\delta = 0.1, 0.2, \dots, 1$). The effectiveness performance is evaluated based on the MAPE (Mean Absolute Percentage Error) metric:

Web of Trust

d**** trusts:

1. P****
2. a****
3. J****
4. J****
5. t****

▶ View all 162 members whom d**** trusts

d**** is trusted by:

1. a****
2. g****
3. l****
4. p****
5. k****

▶ View all 523 members who trust d****


Web of Trust

Trust d****

Block d****

Whom should I trust?

d**'s Profile**

 About d****

LEAD in Electronics

(POPULAR AUTHOR) - Top 10

Epinions.com ID: d****

Location: California

Member Since: Oct 04 '99

Homepage: [My Reviews](#)

Favorite Websites: [My Complete Review Index](#)

[My Flat TV Buying Guide](#)

[Review.shop](#)

Activity Summary

Reviews Written: [850](#)

Member Visits: 82,892

Total Visits: 6,464,398

I love to push buttons on electronic (audio and video) equipment. It makes me happy. [more](#)

d**'s Recent Opinions**

Date Written	Review Title	Product / Topic	Product Rating	Review Rating
Jan 04 '10	Panasonic RP-HTX7	Panasonic RP-HTX7	★★★★★	Very Helpful

Fig. 4. User profile page of Epinions.com.

Table 3
Parameter selection results.

k	1	2	3	4	5	6
δ						
0.1	1.222763	1.115599	1.083815	0.739229	1.569439	1.594041
0.2	0.811729	1.065123	0.971794	0.877263	1.631737	1.584756
0.3	0.664860	1.000941	0.978604	0.77697	1.584953	1.350964
0.4	0.849885	0.798237	1.017242	0.837631	1.520523	1.297554
0.5	0.746417	0.789464	0.976858	0.853228	1.489285	1.232578
0.6	0.802712	0.777556	0.946689	0.570369	1.500788	1.254329
0.7	0.836332	0.789084	1.009532	0.886847	1.50293	1.231015
0.8	0.817978	0.747584	0.921297	0.824756	1.238224	1.048989
0.9	0.905375	0.760606	0.924659	0.828024	1.237317	0.98466
1	0.905130	0.760606	0.924659	0.824756	1.174292	0.999692

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right|,$$

where A_t is the t th actual standardized SCN value extracted from the trust network mechanism, and F_t is the t th forecasting value of influential strength generated from the ANN model and n stands for the total number of data where $t \in \{1, 2, \dots, n\}$. Table 3 shows the MAPE results under the six different word expansion levels and various trust decay rates.

As a smaller MAPE represents a more accurate result, we can observe that the four-level word-set expansion with 0.6 decay rate has the best MAPE performance in the experiments. Thus, in the following experiments, the parameter set ($k^* = 4, \delta^* = 0.6$) is used. From the results, we can also observe that while k is greater than 4, the MAPE values become larger as the expansion level increases. If the word-set expansion level is too high, the word-set includes too many synonym words so as to blur the identification of semantic orientation of reviews. Contrarily, an insufficient word-set (k value is smaller than 4) might not rightly present the semantic orientations.

5. Results and evaluation

After we achieved the trained ANN model and the appropriate parameter values for representing word-set expansion level and trust decay rate, we use the settings to predict the influence ranking of the reviewers included in the testing data set. We first conducted an experiment which used the testing data included in the “Electronics” catalog and then extended to other scenarios. The Recency and standardized Frequency values of the reviewers in the “Electronics” catalog are displayed in Table 4.

Table 4
Recency and frequency values.

ID/period	Recency Days	Frequency		
		<90 days	90–365 days	>365 days
ASourdough4	20	0.090	0.260	0.650
AtlantaGreg	94	0.013	0.026	0.962
Corona79	68	1.000	0.000	0.000
Dkozin	35	0.207	0.272	0.522
Howard_Creech	50	0.030	0.080	0.890
Hwz1	890	0.000	0.000	1.000
JIMILAGRO	1418	0.000	0.000	1.000
Jvolzer	97	0.016	0.339	0.645
Njpoteri	1518	0.000	0.000	1.000
Porcupine1	91	0.050	0.350	0.600
Readsteca	121	0.000	0.234	0.766
Sarahrose12	69	0.083	0.000	0.917
Theheidis	232	0.000	0.067	0.933
Tucknroll	851	0.000	0.000	1.000
Williamrender	1484	0.000	0.000	1.000
Zan720	1079	0.000	0.000	1.000

Table 5
Influential score ranking.

Reviewer ID	Predicted value	Rank
ASourdough4	0.80414	4
AtlantaGreg	0.74056	5
Corona79	0.73896	6
Dkozin	0.81824	3
Howard_Creech	0.95182	1
Hwz1	0.94761	2
JIMILAGRO	0.52945	9
Jvolzer	0.59398	8
Njpoteri	0.11858	16
Porcupine1	0.14036	15
Readsteca	0.39470	12
Sarahrose12	0.16267	14
Theheidis	0.61034	7
Tucknroll	0.43411	10
Williamrender	0.22284	13
Zan720	0.39588	11

Table 5 shows the experimental results. A ranking list for choosing the influential nodes is generated. The ranking is based on the predicted value that represents the possibly influential value for a reviewer. Enterprises could easily identify the ones who have more influential power through the ranking list.

“Popular author” and “Review rating” are two common approaches used to evaluate the influential strengths of the reviewers and reviews (Chevalier and Mayzlin 2003). To judge the effectiveness of our model, these two common ranking mechanisms are compared with our method. The reason for choosing these two methods is because they cover “human connections” and the “value of writings.” Having a higher author rating may indicate that the reviewers are popular and/or their product reviews are helpful to the customers in choosing suitable products. These reviewers have a greater influence on the consumers (Yu et al. 2008).

Popular author ranking is one of the ranking mechanisms offered by Epinions.com. It chooses popular authors on a monthly basis, and the newest ranking of this month can be looked up in real time. The popular authors are classified into different product categories to make this mechanism more complete and effective. The popular author ranking of each node for “Electronics” and “Overall” categories in 2008 is collected for evaluation. Although the nodes have different rankings in these two categories, their relative positions are the same. Therefore, the popular author ranking is displayed by one ranking set only.

The sales of products are greatly influenced by the professional product reviews and the impact of review ratings on product sales has been mentioned by prior studies (Reinstein and Snyder 2005, Sawhney and Eliashberg 1996). Review rating is another common ranking mechanism applied by Epinions.com that allows users to rate each review article. When someone posts a review, every online member can give a rating to the review. In other words, each review has a composite score that is evaluated by other online users. The average scores of all the reviews written by each author are utilized to decide the overall review rating. The ranking is generated from these average scores. The review rating represents the comments of their readers and it should reflect the feeling of people correctly. It also indicates the values of these articles for online users.

MAPE is used to measure the effect of this result and is calculated by the following equation:

$$MAPE_R = \frac{1}{16} \sum_{i=1}^{16} \left| \frac{R_{Ti} - R_{Pi}}{R_{Ti}} \right|,$$

where R_{Ti} stands for the trust ranking of each reviewer and R_{Pi} is the predicted ranking. By comparing this with the trust ranking, the MAPE values can be acquired as shown in Table 6.

Table 6
Ranking and MAPE value.

ID/method	Ours	Popular author	Review rating	Trust
ASourdough4	4	4	12	5
AtlantaGreg	5	5	16	4
Corona79	6	10	7	7
Dkozin	3	2	8	3
Howard_Creech	1	1	4	1
Hwz1	2	3	6	2
JMILAGRO	9	12	13	9
Jvolzer	8	6	15	8
Njpoteri	16	16	1	14
Porcupine1	15	11	10	14
Readsteca	12	7	14	13
Sarahrose12	14	13	3	12
Theheidis	7	8	9	11
Tucknroll	10	9	5	10
Williamrender	13	15	2	14
Zan720	11	14	11	6
MAPE	0.144946	0.310921	1.049976	0

As shown in Table 6, the proposed method has a lower mean absolute percentage error rate than the other two. The proposed influential power prediction method for word-of-mouth marketing has approximately 85% accuracy rate. Our method was based on the quantity of emotional expression to determine the strength of influence. While similar to review rating, our method appears to perform better. Even though our method did not consider the popularity of the author, it still appears to be a better mechanism than those mechanisms taking the popularity of the author into account. Overall, our method performed approximately 50% better than popular author mechanism did and approximately 85% better than review-rating mechanism did.

Fig. 5 graphically displays the absolute percentage error with trust ranking for every reviewer. Obviously, the absolute errors of the review-rating method are higher than others. Our proposed influential power prediction method has a lower absolute error rate than the other two methods. The lower error rate means higher accuracy. In other words, it means the result of our influential prediction method is closest to the benchmark in the real-world trust-ranking mechanism.

We then conducted the experiments using the data included in “Computers & Software” category and the data included in combined “Electronics” and “Computers & Software” categories. The results are showed in Fig. 6. We can observe that our proposed approach outperforms other two benchmark approaches in all three scenarios. The accuracy rate in the “Electronics” catalog is better than that in the “Computers & Software” catalog. The phenomenon

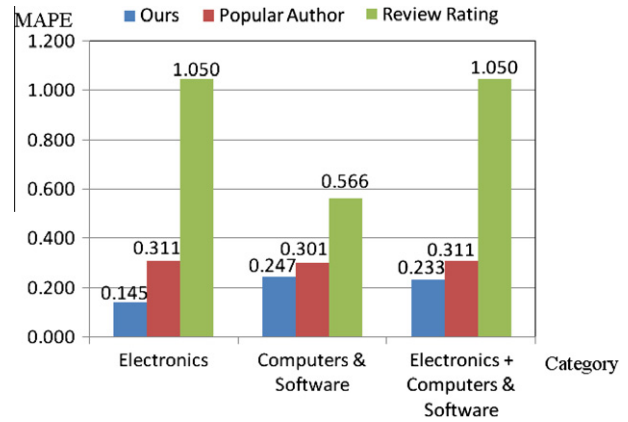


Fig. 6. The MAPE values in different catalogs.

is due to the fact that in the training data set, the reviews from the “Electronics” catalog is more than those from the “Computers & Software” catalog. As a result, we can also find the accuracy performance of combined “Electronics” and “Computers & Software” categories is better than that of the “Computers & Software” catalog but worse than that from the “Electronics” catalog.

6. Conclusion

Although the advancement of IT technology and the Internet reduces the cost of marketing behaviors such as advertising, the “uncertainty” problem still exists. Many enterprises waste many resources on invalid online marketing. Word-of-mouth marketing is a new and effective marketing method that is based on the power of “word of mouth” for saving many resources and avoiding possible trouble in mass marketing. Finding potential reviewers who are powerful to others and willing to spread positive product impressions efficiently is the key to word-of-mouth marketing. Via the Internet, the recommendations from other online users’ product comments have a more influential power than traditional advertising does. In this work, an innovative mechanism to find potentially influential reviewers is proposed. The text-mining techniques and the RFM analysis were combined to calculate the influential power of real online users through their reviews. The trust score, which is composed of thousands of human connections, is applied for effectiveness evaluation. The results showed that the proposed model could accurately identify which reviewers to select to become the influential nodes.

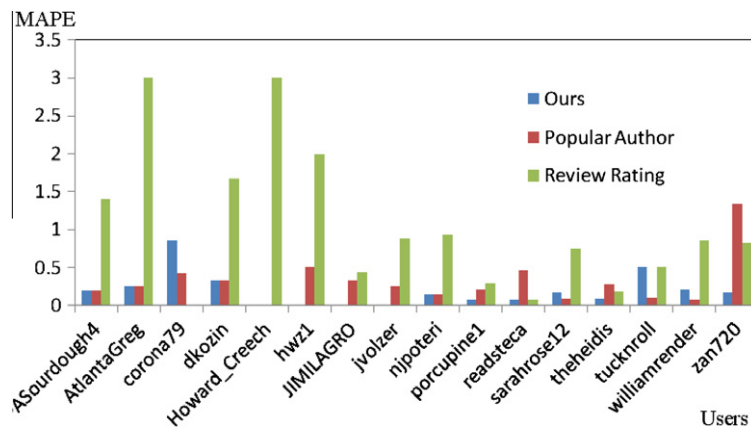


Fig. 5. Absolute percentage error of the reviewers.

6.1. Research contributions

This method assists in carrying out online word-of-mouth marketing, which can save a lot of resources in finding customers. Online word-of-mouth marketing can spread product information widely to a large number of potential customers. It widens the range of marketing and provides more chances to enterprises. For firms, the influential power of each reviewer can be measured clearly and the reviewer most worthy of being marketed can be easily identified by the proposed model. After the influential nodes have been appropriately identified, firms are able to develop some special marketing strategies to take advantages of these potential reviewers. For instance, enterprises can provide free trial versions of the new products or special discounts to these targeted customers/reviewers. This proposed method provides a helpful and effective name list of reviewers to improve marketing behaviors.

There are several reasons why our proposed model is more efficient than those presented by other studies.

First, our method is composed of several key factors contributing to a reviewer's influence. By opinion mining, the values of reviews can be identified easily. The current paper does not focus on judging reviews that are positive or negative but focuses on "quantity of emotional expression" in reviews. This mechanism can quantify the infectiveness of the reviews. Further, the RFM analysis helps pick up the reviewers who are productive in writing good reviews and catch the market trend.

Second, the ANN training process sharpens the model to be close to the real trust value. By thousands of training processes, the system learns the patterns extracted from real data. Sufficient training makes the model become closer to our expectation. When the testing data are processed by a well-trained network considering several dimensions of factors, better predictions are produced.

Third, popular author rating considers the hit numbers of reviews only. In the study, the contents of reviews are not analyzed and their qualities are not guaranteed. It is possible to have a situation with high hit numbers for a particular reviewer, but she/he may not provide the right information to consumers. For instance, the review written by a popular author may not meet the expectations of readers, but the hit number is still recorded by the website. Generally, people are attracted by the "popular author" fame. Even if they feel disappointed after reading, it still increases the hit number of the review continuously.

Fourth, the review-rating mechanism of finding valuable reviewers is incomplete and may lead to bias. It is not appropriate for sole use, especially while the data have not previously been filtered or classified. The most serious problem in this mechanism is that it does not consider the RFM characteristic of reviewers. Anyone who has just written one or two highly rated reviews will obtain a high averaged rating. It is likely that those reviewers who have written hundreds of reviews may have similar or even lower scores than the ones who have only written one or two reviews, because most online reviews have high ratings and the characteristics of reviewers' RFMs are ignored.

6.2. Research limitations

There are also some limitations in our research. First, our model is constructed based on product reviews from several different categories, especially from "Electronics" and "Computers & Software". We know that different products have different characteristics in using experiences and life cycles. Unrelated product reviews and reviewers may lead to inaccurate results in the current model. Adjusting training data source and RFM time for different kinds of products should be beneficial. Second, our model reflects the relative influence among the nodes in the social network, but the actual influence value for each reviewer is not measured. The current

model is mainly built based on the present social structure. A more sophisticated model evaluation considering future influence diffusion coverage strength can be further developed. Third, in the current model, the expansion of a trust network, SCN tracing process, is calculated based on a constant decay rate of social connections. In real world, trust decay rate can be a derived variable based on the social relations of two nodes. In this scenario, more computing resources are required to calculate the accurate influence value of each node.

6.3. Directions for future research

Several potential directions to extend the study are as follows. First, as the data description ranged mainly from electronics and computers to media in the dataset, the current model thus can only reflect the electronic category. A comparison with various types of products can be further developed. A possible solution is to clarify the reviews in advance. Second, the profile of the company or brand attribute can be considered. Retrieving related review data according to the distinguishing characteristics of the enterprise may generate a more appropriate recommendation. Third, a flexible weighting mechanism is another factor to be considered. A flexible weighting mechanism not only makes the model fit enterprises' needs better but also saves computing resources. Fourth, this research focuses on the discovery of influential reviewers. It would therefore be interesting and useful to develop further an information diffusion framework based on the identified reviewers. Lastly, besides the study in the system development perspective, the exploration of the ethical issue in exploiting these discovered influential reviewers for word-of-mouth marketing is also an interesting and important research topic.

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