Abstract

There are three main research results in this project. First, high cost and uncertainty are problems of marketing. Online social advertising is more powerful than firm's advertisements. Our research results showed that our model outperforms general methods in diffusing information/advertisements through social network. Our work can accurately point out which online users to be selected to become the endorsers. In the electronic commerce applications, the proposed mechanism helps to target the right endorsers, and the diffusion model can then be applied. Second, we propose a novel marketing intelligence system for monitoring the opinion variation/market trends in online social media. Accordingly, our experimental results show that with the support of the proposed marketing intelligence system, we found the consideration of user credibility and opinion quality is essential for aggregating microblog opinions. The proposed mechanism can effectively discover market intelligence for supporting decision makers. Third, three different social decision support mechanisms are proposed to support different product purchasing decision process scenarios. These proposed mechanisms can successfully incorporate the incomplete opinions from online social network and further speed up the process in support users' purchasing decision.

Keywords: Online advertising, Microblog, Diffusion mechanism, Influence model, Market trends, Sentiment classification, Credibility assessment

摘要

在這份結案報告裡有三個主要成果。首先，昂貴的成本和不確定性是造成行銷的困難點。線上社群廣告的作用遠遠超出公司的官方廣告。根據我們的研究結果發現，本研究中所提出的通過社會網絡傳播信息/廣告散佈的模型優於現下一般性的方法。本研究中所提出之模型能夠準確地指出哪些線上用戶最適合成為產品代言人來進行產品推廣。在電子商務應用中，本機制的目標，有助於挑選正確的代言人，並給予資訊擴散的建議。第二，我們提出了一個新穎的行營情報系統，藉此監測社群媒介中的市場趨勢。根據我們的實驗結果發現，審視聚合微網誌意見確實有助於判讀市場趨勢，且用戶信譽和發文質量皆是必不可少的。本研究中所提出的機制能有效地發現市場情報以支持決策者。第三，我們提出了一個社群支援機制，協助社群媒介的線上用戶可實現社會評價支援。本機制可以成功地吸納社群媒介中朋友們的意見，加速使用者的決策過程，協助做出購買決策。

Keywords: 線上廣告，微網誌，散佈機制，影響力模型，市場趨勢，情感分類，信譽評估，社群支援，決策分析

1. Introduction

In recent years, social media, such as Facebook, Twitter and Plurk, have flourished and raised much attention. Social media provide users with an excellent platform to share and receive information and give marketers a great opportunity to diffuse information through numerous populations. An overwhelming majority of marketers are using social media to market their businesses, and a significant 81% of these marketers indicate that their efforts in social media have generated effective exposure for their businesses [22]. With effective vehicles for understanding customer behavior and new hybrid elements of the promotion mix, social media allow enterprises to make timely contact with the end-consumer at relatively low cost and higher levels of efficiency [20]. Social advertising is a kind of recommendation system, of sharing information between friends. It takes advantage of the relation of users to conduct an advertising campaign. Since the World Wide Web (Web) is now the primary message delivering medium between advertisers and consumers, it is a critical issue to find the best way to utilize on-line media for advertising purposes [7, 23].

Right after the blooming of the Web 2.0 applications, such as Wikipedia, blogs, and forums, social media appeared and grew quickly as the descendant of blog from mid 2006 and has become an increasingly influential social media which empowered the Internet users to publish their creations, opinions and spread new content via interactions. Today, the largest microblog platform, Twitter has over 100 million users and generates 55 billion posts per day according to its report at the end of April 2010. The name of “Microblog” is coined because of its 140-characters limitation for each post. Several characteristics of microblog are widely discussed as in [13]. Marketing intelligence (MI) is an important pillar of business intelligence.

MI system is designed to fulfill four needs from business managers: (1) identify opportunities and threats from the market environment (2) help managers to know more about the competitors (3) help preempt competitors’ actability (4) aid effective marketing decision making [35]. Many MI systems are proposed to cope with traditional types of web content, such as product reviews on forums [8] or weblog usages [3]. However, there are not much works on effectively discovering well-rounded marketing intelligence over microblogs while microblog platform is new and having its unique characteristics. Numerous posts are produced every second on microblog, which makes microblogs a great source to observe customers’ opinion over campaigns and the new products/services rolled out by business in real-time.

The social support has been defined in numerous ways. According to seminal work by House [9], social support is one of the important functional contents of relationships that can be categorized into four broad types of supportive behaviors or acts:

1. *Emotional support*. It involves the provision of empathy, love, trust, and caring.
2. *Instrumental support*. It involves the provision of tangible aid and services that directly assist a person in need.
3. *Informational support*. It focuses on the provision of advice, suggestions, and information that a person can use to deal with problems.
4. *Appraisal support*. It involves the provision of information that is useful for self-evaluation purposes – in other words, constructive feedback and affirmation.

The speed and frequency of users' communication in micro-blogosphere is faster and more frequently than blogosphere. The message length in micro-blogosphere should not exceed 140 characters, makes users could write and read message more easily and efficiently. According to the above light-weight communication, the advance of Internet, and flourished smart phone device technologies, users are able to conveniently and timely share information or ask for social support everywhere and expect to get responses momentarily.

2. Research Goals

In the social advertising part, the advertisers should disseminate advertising messages by information sharing between people and increase the resonance so as to widen the coverage and keep the advertisement alive. However, currently, they still lack of an appropriate advertising mechanism, which helps marketers to diffuse their advertisements effectively and improve resonance among users. Besides, the existent sharing mechanisms have a problem of excess sharing between friends. Users often share information with all of their friends, who will cause a negative impression if friends are not interested and reduce the efficiency of advertisements. As a result, social spam has become a severe problem confronted by users of social media. Sharing information over the network can improve people's reputation and develop their social capital [30]. However, sending too many unsolicited and irrelevant messages to friends will make them feel uncomfortable and even harm the development of social capital.

In the marketing intelligence part, to derive marketing intelligence system on microblogs, the volume of posts (the massive number of opinions) is overwhelming on microblogs. Hence a problem rises and interests us: Can we develop a system framework to summarize and extract valuable knowledge from opinions automatically? Several sub-problems emerge as we consider the design of the automatic microblog summarization system. First, the opinions about topic of a user's query may focus on many different aspects. For example, when people talk about a company, they may comment on specific service, product or even environmental issues of the company.

Therefore, it's important to know that aspects and topics concerned by customers. Second, in what form the opinions should be summarized to? And how to convert tons of opinions into that compact type? Third, when summarizing the opinions, should we discriminately treat opinions comes from different expresser because of their different level of credibility?

In the social support part, our research mainly focuses on the provision of social appraisal support within micro-blogosphere. We propose a mechanism, which composes with social network analysis (SNA), intuitionistic fuzzy set (IFS) and technique for order preference by similarity to ideal solution (TOPSIS) to achieve social appraisal support for online users.

3. Literature Review

The issue of online advertising has aroused much academic interest and been spotlighted for decades. Online advertising can usually be categorized into two types: 1) targeted advertising, which delivers advertisements based on the user's preference profiles; 2) social advertising, which delivers the advertisements to influential users determined by social relationship [19]. Social relationships and social interaction are powerful because they can act as trusted referrals and reinforce the fact that people influence people and have become the crucial components in social advertising [1]. Some researchers measure the influential strength by analyzing the number of network links and users' relationships and interaction in the network to identify the influential nodes for social advertising [19, 32]. Therefore, studying social influence can help us to better understand why certain information is transmitted faster than others and how we could help advertisers and marketers design more effective campaigns [5]. Researchers analyze information diffusion in the social network based on the individual's characteristics. Some of them are based on bond percolation, graph theory or a probabilistic model to extract the influential nodes, considering the aspect of dynamic characteristics, such as distance, time, and interaction and so on [15, 16]. Others exploit social network analysis techniques, to evaluate the influential nodes from the aspect of the node's structural position, such as degree centrality, closeness centrality [17]. The design of diffusion mechanism is conceptually similar to that of computer network multicast process. Multicast is a network technology for the delivery of information to a specific group using the most efficient strategy to deliver the messages over each link of the network [33].

Feature extraction, meronyms acquisition, opinion mining, sentiment analysis, and credibility assessment are basic components for deriving marketing intelligence system. To deal the task of production feature extraction, the authors of [13] generate a set of frequent features by finding out frequent terms and prune the feature set by calculating term compactness and redundancy. In [23], Red Opal system also uses frequent noun and noun phrases for feature extraction. Within the ontology engineering communities, it's been recognized that natural language texts provide a rich source for extracting semantic relations, such as hyponyms and meronyms. In [8, 24], how hyponym relations can be acquired automatically using linguistic patterns has been studied. Major applications of opinion mining are product review mining [13, 23, 24], recommendation systems [26]. Sentiment classification is to identify the sentiment (or polarity) of retrieved opinions. There are two major categories of approaches for this task. One approach is to develop linguistic resources of sentiment orientation and structures of sentiment expression then classify text based on the developed resources as in [13]. The second approach to analyze sentiment is to train and deploy a sentiment classifier, which can be built with several methodologies such as SVM, Maximum Entropy and Naïve Bayes [36]. Prior to the Internet era, several important criteria, like source, receiver, message, medium and context, have been addressed to assess credibility of information contains in presswork and interpersonal communication [31]. In [28], the authors states that authority leads to credibility. A more authority source makes the information more credible. Some researches adopt link analysis on web pages and provides authority indicators of web page, such as HITS and Pagerank proposed [18]. Also, trust relation in social network is also a promising solution to online credibility as described in [4].

The aim of Multi-Criteria Decision-Making (MCDM) technique is to identify the best, compromised or optimal solution from all feasible alternatives evaluated on multiple criteria [14]. TOPSIS is an appropriate tool for the multiple attribute decision-making problems [10]. It simplifies the complex human decision-making process into the distance and relative closeness coefficient measurements. In order to handle the vague information from social network and deal with the multi criteria fuzzy decision making problems for users, the intuitionistic fuzzy sets could be applied to represent the characteristics of alternatives and the criteria value are given by fuzzy numbers [21].

4. Methodology

In this section, we describe the proposed framework in detail. First, we designed a social diffusion mechanism to disseminate advertising information via social endorsers. Second, we develop a marketing intelligence system to summarize the opinions on the web. Third we proposed a social support mechanism to help users make decisions via their social network in the micro-blogosphere.

4.1 Social Diffusion Mechanism

The process of our diffusion mechanism (ADPlurker) is shown in Figure 1 and detailed as follows.

1. The endorser discovery engine is triggered to identify the influential users

(referred to as social endorsers) who have high preference in the advertisements of the sponsors (user A in Figure 1). The components of the endorser discovery engine are described in subsection 3.2.

2. The system delivers relevant advertisements of the sponsors to identified social endorsers using a recommended list of their friends with strong propagation capability for forwarding further advertisements.
3. After the social endorsers receive the advertisements, they share the received advertisements with their friends spontaneously (users B, C, D in Figure 2) with the support of the recommended list of friends further generated by the endorser discovery engine.
4. The endorser discovery engine sends a corresponding list of friends to all the users who receive the advertisement respectively.
5. The social advertisement diffusion proceeds continuously by repeating step

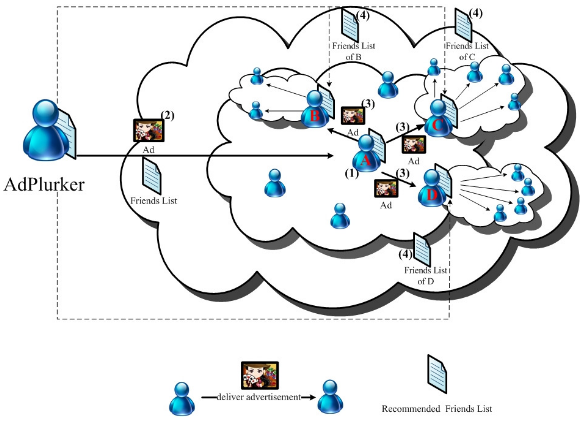

Figure 1. Process of social diffusing mechanism

Note that the proposed social diffusion mechanism is different from spamming. The friends selected by the endorser discovery engine are based on quantitative measurement of the factors, such as user preference, network influence, and propagation strength. Effective information diffusion on social networks is grounded in the relevance of individual preference and the closeness of social relations. Therefore, the main functionality of the proposed social endorser discovery engine is to identify the nodes with the strong propagation capabilities in disseminating relevant messages as widely as possible. In order to identify the appropriate social endorsers to achieve a better diffusing performance, in this research, we not only consider the static factors (individual preference and link structure of relationship), but also dynamic factors (social activeness, social interactions, and social similarity) in the evaluation of nodes' propagation capabilities—transmitting information towards the most suitable friends and spreading it further.

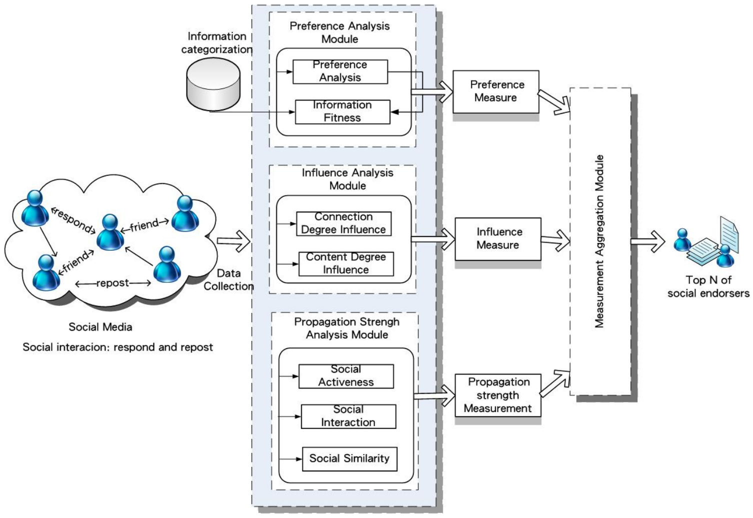

Figure 2. Architecture of endorser discovery engine

Figure 2. shows the main components and procedures of the proposed endorser discovery engine. Our proposed system architecture includes four modules: Preference Analysis" module; "Influence Analysis" module; "Propagation Strength Analysis" module; and "Measurement Aggregation" Module. The details related to each module are described as follows.

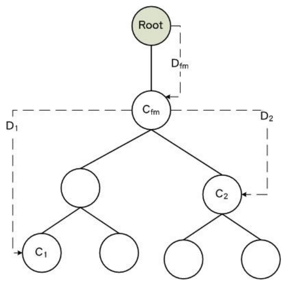

Figure 3. Category tree

In the preference analysis module, we establish the category tree of advertisement and use the same tree to define the user's preference tree. Furthermore, we utilize a distance-based approach [34] to calculate the similarity between preference tree and category tree. As shown in Figure 3, assume C_1 and C_2 stand for the target category of the advertisement and the closest category of the user's preference respectively and C_{fm} represents the first mutual parent node of C_1 and C_2 in a catalog tree. The fitness degree of the advertisements to a user can be calculated by the following formula:

$$Sim_p(C_1,C_2)=\frac{2D_{fm}}{D_1+D_2+2D_{fm}}$$

where D_1 (D_2) is the length of the path from C_1 (C_2) to C_{fm} and D_{fm} is the distance of the path from C_{fm} to the root node in the category tree .

In the influence analysis module, the connection degree (individual influence) and content degree (personal content influence) are included in our system. First, we use mutual relationship (friendship) to measure the connection degree influence as, in practice, the mutual degree represents the number of friends a user has. Mutual degree for user *i* is measured as:

$$Md(i) = \sum_{j=1}^{n} E_{ij} ,$$

where E_{ij} is 1 if an edge from node *i* to *j* exists and an edge from node *j* to node *i* exists, too, otherwise it is 0. Second, we measure the content degree influence of a user by the number of total responses and message forwards from people. We denoted |Φ| as the total number of the elements in a set Φ. The formula for content degree measure can be expressed as:

$$Cd(i) = \frac{|\Phi_{response(i)}| + |\Phi_{forward(i)}|}{|\Phi_{post(i)}|} ,$$

where $\Phi_{post(i)}$ stands for the set of the messages posted by user *i*, $\Phi_{response(i)}$ represents the set of the responses on user *i*'s posts , and $\Phi_{forward(i)}$ is the set of *i*'s posts forwarded by others. The aggregate network influence measure is the sum of the mutual degree value $Md(i)$ and the content degree value $Cd(i)$.

Social activeness is used to calculate the activity intensity of a user. We calculate the activeness of a user by the number of post records during a period of time in the social platform. The formula is defined as below:

$$Sa(i) = \frac{\sum_{t=1}^{T} |\Phi_{messages(i,t)}|}{T} ,$$

where $\Phi_{messages(i,t)}$ is the total number of messages posted by user i at time period t.

Social similarity aims to measure the similarity degree between two people from implicit social structure and behavior, such as friend-in-common and content-in-common. Denote $F(i)$ as a set of user *i*'s friends. The similarity of a friend-in-common between user *i* and friend *j*, is measured as:

$$Sim_{cf}(i,j) = \frac{F(i) \cap F(j)}{Max(F(i), F(j))} .$$

In addition, semantic analysis can be used to measure the social similarity in the aspect of content-in-comment and to discover the potential preference of users [2]. Figure 4 shows the process of semantics similarity analysis.

Figure 4. The process of semantics similarity analysis.

The term frequency (TF) for term m in a post p is calculated as:

$$tf_{m,p} = \frac{freq_{m,p}}{\max_i (freq_{i,p})} ,$$

where $freq_{m,p}$ is the raw frequency of term *i* appearing in post *p* and $\max_i(freq_{i,p})$ is the number of times the most frequent index term, l, appears in post *j* . The inverse document frequency (IDF) for term m is formulated as:

$$idf_m = \log\frac{N_p}{n_m},$$

where N_p is the total number of posts and n_m is the number of posts in which term *p* appears. Then, the relative importance of term m to post p can be obtained by calculating:

$$w_{m,p} = tf_{m,p} \times idf_m .$$

Finally, we measure the content similarity degree between people by a cosine similarity metric. The number of terms (keywords) selected for analyzing a person's document in a collection or corpus is denoted as *M*. The similarity of corpus (content-in-comment degree) between user *i* and friend *j* is defined as:

$$Sim_{cc} = \cos(\vec{i}_M, \vec{j}_M) = \frac{\vec{i}_M \cdot \vec{j}_M}{|\vec{i}_M||\vec{j}_M|},$$

where $\vec{i}_M$ and $\vec{j}_M$ are the document vectors in the *M* dimensional term space for user *i* and friend *j*.

Finally, the similarity score is measured by the sum of friend-in-common and content-in-comment scores. That is, social similarity between user *i* and friend *j*, is formulated as:

$$SS(i,j) = Sim_{cf}(i,j) + Sim_{cc}(i,j) .$$

4.2 Marketing Intelligence System

In this section, we describe the proposed marketing intelligence system framework in detail. For the convenience, we use the term "query" to represent the name of entity that the end users want to know about. A query could be a keyword, such as a brand name or a product name. The goal of framework is to indentify relevant trendy topics for a user's query and obtain a representative score of customer opinions on microblog towards the targeted topics. For example, when the user queries system with "google", the system should find out topic terms such as "gmail", "google map" and provide scores toward these topics. Figure 5 displays the main modules and procedures of our proposed system.

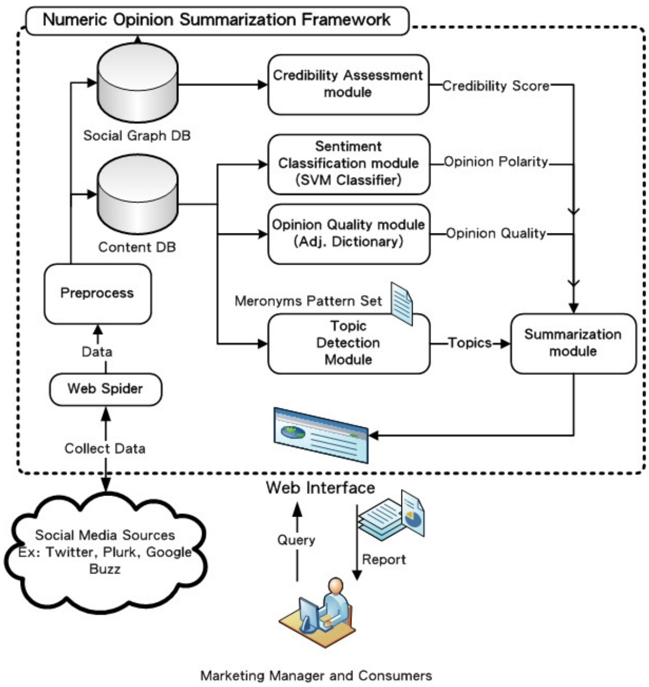

Figure 5. Architecture of Numeric Opinion Summarization Framework

The major task of the relevant topics detection module is to assign a tendency score of being a relevant topic to each term appeared in the opinion set of a given query. We define Q as a set of queries and O is the set of opinions the system has collected. $q \in Q$ as a query given by end users, $O_q \subset O$ which represents a set of opinions in which a query q is mentioned. T is defined as the set of nouns/phrases which appears in opinion set O and $t, \in T$ is a distinct term in T. The Topic Tendency Score (TTS) of a term t on a query q, t_q, is calculated as:

$$TTS_{t_q} = TF_{t_q} \times IDF_t^q \times MPP_{t_q} ,$$

where TF_{t_q} is the frequency of term t in opinion set O_q and IDF_t^Q is the inverse document frequency of term t in opinion set O. Specifically,

$$TF_{t,q} = \text{number of occurrences of term } t \text{ in opinion set } O_q .$$

$$IDF_t^q = \log\left(\frac{|O|}{\left|\{O_q : t \in O_q\}\right|}\right), O_q \subset O .$$

The consideration of TF and IDF is based on the assumption that relevant topic terms of a specific query q should appear often in O_q and should be less frequent across O. The last factor, MPP_{t_q}, stands for the portion that a term appears with a pattern, which is in the predefined set of meronym patterns, P, with which people express meronym and hyponym relation. To improve precision of topic detection, we utilize the meronym pattern matching method [24] in the module. For example, a post

"Battery of iPhone is not good." matches meronym pattern "PART of ENTITY". "Battery" matches token PART while "iPhone" matches token ENTITY in the meronym pattern. With these evidences, we could gain confidence that "battery" is a part of "iPhone" and also a discussed topic of "iPhone". MPP_{t_q} is calculated as equation (4).

$$MPP_{t_q} = \frac{\text{number of occurrences of } t \text{ in } O_q \text{ with patten in } P}{TF_{t_q}}.$$

For each query q, we calculate TTS for each term t_q and rank the terms by their TTS. With the TTS-ranked terms, we select top k terms as the relevant topics TPq for further summarization processes.

Since the ultimate goal of our system is to provide numeric scores for opinions, we have to propose an approach converting the format of an opinion from text to a numeric value. In the framework, Semantic score evaluation module identifies the polarity and quality of opinions and combines them as a Semantic Score (SS) for final opinion aggregation.

Generally, a larger portion of emotional words will be used in the sentences by users when people are expressing their own feelings, relative to the description of objective information. Hence, we define Opinion Quality (OQ) of a post o as the average emotional and sentimental words density in all sentences in post o which mentions topic t. To evaluate the quality level of opinions, we prepare a subjective word set, which includes emotional and sentimental words via word set expansion with WordNet. We define a seed set of subjective words suggested in advance [27] and then query WordNet for synonyms and antonyms recursively for word set expanding. Once we have the subjective word set, Φ, the opinion quality for a post o related to a topic t , OQo,t, is formulated as:

$$OQ_{o,t} = \left(\sum_{s \in S_t^o} \frac{|U_s \cap \Phi|}{|U_s|} \right) / |S_t^o|,$$

where U_s = the set of unigrams pertained in sentence s,

S_t^o = the set of sentences in opinion o which mentions topic t.

In the sentiment classification module, a SVM model is trained and used for opinion polarity classification. Upon SVM feature selection, we test various features shown in Table 1. Unigrams and bigrams are distinct one-word and two-word tokens sliced from the opinion text. All of these features are counted in a presence-based binary value, {0,1}. "1" stands for appearance of the feature while "0" stands for absence in a post.

Table 1 Feature set used for testing SVM classification performance

Feature	Unigram	Bigram	Unigram+ bigram	Subjective Word Set
Frequency or presence?	Presence	Presence	Presence	Presence

We collected data from Twitter which was queried with two kinds of emoticons: returned posts with ":)" are labeled with "+1", which stands for positive polarity and posts with ":(" are labeled with "-1", which means negative polarity. We found that about 87% posts are labeled correctly.Than, we adopt a grid search [11] to find out best combination of parameters c and γ for the SVM with Radial Basis Function (RBF) kernel. With the trained SVM, polarity of opinion o, $polarity_o = \{-1, +1\}$, which stand for positive and negative sentiment respectively, is predicted.

Finally, with derived quality and polarity of the opinions towards a topic t, we calculate the semantic score SS as:

$SS_{o,t} = polarity_0 \times OQ_{o,t}$, where $SS_{o,t} \in [-1,1]$

Notice that opinion quality OQ could be used to alleviate inability of SVM classifier to filtering out neutral opinions.

Credibility score evaluation module is designed to measure Credibility Score (CS), which reflects credibility of an opinion expresser. To measure the credibility of a user, we calculate the user's follower-follwee ratio (Number of the user's followers over number of users followed by the user). A user with relatively more followers will obtain higher source credibility since most of users tend to follow the users who provide fair and informative content. Assume there are N users in the social network SN. SN can be represented as a $N \times N$ adjacent square matrix. If user i follows user j then SNi,j=1, otherwise SNi,j=0. Note that SN is asymmetric. The source credibility score of user i, f_i^{SN}, is defined as:

$$f_i^{SN} = \min\left(\frac{\sum_{j \neq i}^{N} SN_{j,i}}{\sum_{i \neq j}^{N} SN_{i,j}}, 1\right).$$

Besides, reposts frequency should be an adequate proxy for measuring the quality of posts from the users. In most microblog platforms, users could repost posts from the others with no modification and comments added. Since users could not add any personal opinions to the reposted posts, it is believed that highly agreement shown between the posts and the users repost them. Therefore, the repost rate of a user's posts could be used as a measure of the content credibility. We define content credibility score of user i in a time period TP as:

$$r_i^{TP} = \frac{\text{number of posts reposted of user } i \text{ in time period } TP}{\text{number of posts of user } i \text{ in time period } TP}.$$

Finally, the credibility score of user i is the geometric mean of source credibility score f_i^{SN} and content credibility r_i^{TP} as shown as:

$CS_i = \sqrt{f_i^{SN} \times r_i^{TP}}$.

Notice that some interested parties (e.g. a company promoting its products or attacking its opponent's products) in the micro-blogging sphere may attempt affect the analysis. To prevent the improper abuse of credibility, the users with exceptional high credibility could further be identified

The final score for a topic t with respect to a query q is formulated as:

$$Score_{t,q} = \frac{\sum_{o \in O_{q,t}} \left(SS_{o,t} \times CS_i^{SN,TP} \right)}{\sum_{o \in O_{q,t}} \left(\left| SS_{o,t} \right| \times CS_i^{SN,TP} \right)},$$

where $O_{q,t}$ is the set of opinions mentioning topic t for a given query q and user i is the expresser of an opinion o.

4.3 Social Support Mechanisms Design

In this section, we consider three different phenomenon of product purchasing decision process scenarios. According the properties of each scenario, we design different social support mechanism. The process of different mechanisms design is shown in detailed as follows.

4.3.1 Social Support Mechanism in Micro-blogosphere

The proposed model is comprised of three main elements: companionship analysis, collective opinions modeling, and decision analysis. The purpose of the companionship analysis is to identify importance weight of each decision maker based on the companionship between the originator and the decision maker. We apply the two-mode social network analysis to derive the importance weights of various decision makers. Figure 6 briefly presents the concept and the architecture of our system model.

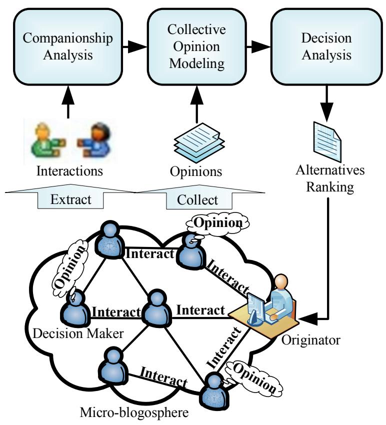

Figure 6: Decision Making Support System

The 2-mode network is built for companionship analysis and the elements of the 2-mode network are listed as follows.

- The user set is a set of users having interaction with the originator.
- The micro-blogging message set is a set of messages posted by users in the user set.
- The relation measurements are measured by posting and replying a message.

In the 2-mode network structure, a decision maker with a greater degree of the companionship will be given a greater degree of importance weight. Namely, their opinions might be trustable for the originator.The obtained user weight would be normalized by linear normalization as follows:

$$\lambda_k = \frac{RM_k}{\sum_{i\in\Theta} RM_i}, \sum \lambda_k = 1,$$

where Θ denotes the set of decision makers included in the user set, RM_k denotes the relation measurement value of the decision maker k, and λ_k denotes the importance weight of the decision maker k.

The main purpose of the collective opinion modeling is to obtain the collective decision table (D) according to the rated decision table by the decision makers. Suppose that the originator releases m alternatives (A), n criteria (C) and there are k decision makers who evaluate each alternative with respect to various criteria. Considering the limited expertise of decision makers about the problem domain, they are expected to answer “Good (G)” or “Bad (B)” or “Unknown (U)” to the question whether alternative A_i satisfies criterion C_j. We use G_{ij} and B_{ij} to respectively denote the decision maker set of who answer “Good” and “Bad” for the alternative A_i with respect to the criterion C_j. After the alternative evaluation, there are k decision tables

$$D^k = \left[d_{ij}^k\right]_{m\times n}, \text{ where } d_{ij}^k \in (G,B,U)$$

to be collected and transformed into a collective decision table taking the form of intuitionistic fuzzy values

$$D = \left[d_{ij}\right]_{m\times n}.$$

In this study, the characteristics of the alternatives d_{ij} are represented by the IFS as:

$$d_{ij} = \left\{< \mu_{A_i}(C_j), v_{A_i}(C_j) > \mid C_j \in C\right\}, i = 1,2,...,m,$$

where $\mu_{A_i}(C_j)$ and $v_{A_i}(C_j)$ indicate the degree of the alternative A_i satisfies and does not satisfy the criterion C_j respectively. We denote that

$$\mu_{A_i}(C_j) = \sum_{k\in G_{ij}} \lambda_k, \mu(C_j) \in [0,1] \quad \text{and} \quad v_{A_i}(C_j) = \sum_{k\in B_{ij}} \lambda_k, v(C_j) \in [0,1]$$

for calculating these two degrees. Note that, $\mu_{A_i}(C_j) + v_{A_i}(C_j) \in [0,1]$ and the third intuitionistic index $\pi_{A_i}(C_j) = 1 - \mu_{A_j}(C_j) - v_{A_j}(C_j)$ is used to evaluate the level of hesitation. That is, the larger value of $\pi_{A_i}(C_j)$ which means the higher hesitation margin of the decision makers about the alternative A_i with respect to the criterion C_j.

After having the intuitionistic fuzzy decision matrix, decision analysis is next applied to derive the final collective decision and provides an alternatives ranking list for supporting the originator. The procedure of TOPSIS calculation for decision analysis is described as follows:

Step 1. Obtain the criteria weight set.

The originator could give their criteria weight set (w) or just use the default equal weighting. If the originator does not set the criteria weight, then each criterion weight in w are all equal to 1. For each $d_{ij} \in \mathrm{IFS}$, the $d_{ij}w_{C_j}$ is defined as follows [6]:

$$d_{ij}w_{C_j} = \left\{ < 1-(1-\mu_{A_i}(C_j))^{w_{C_j}}, (v(C_j))^{w_{C_j}} > \right\}$$

Step 2. Determine intuitionistic fuzzy positive ideal solution (IFPIS) and intuitionistic fuzzy negative ideal solution (IFNIS).

The calculation of the IFPIS (A^+) and IFNIS (A^-) in this step is respectively defined as follows:

$A^+ = \left\{ \max_i \mu_{ij}(C_j), \min_i v(C_j) \right\}$, and $A^- = \left\{ \min_i \mu_{ij}(C_j), \max_i v(C_j) \right\}$.

Step 3. Calculate the distance between alternative and IFPIS and between alternative and IFNIS.

Refer to Szmidt and Kacprzyk [25], the following measurement definitions will be used to determine the Euclidean distance. The $\mathrm{ED}(A_i, A^+)$ and $\mathrm{ED}(A_i, A^-)$ respectively denote the Euclidean distance between alternative A_i and IFPIS A^+ and between alternative A_i and IFPIS A^-.

$$\mathrm{ED}(A_i, A^+) = \sqrt{\sum_{j=1}^{m} \left[\left(\mu_{A_i}(C_j) - \mu_{A^+}(C_j)\right)^2 + \left(v_{A_i}(C_j) - v_{A^+}(C_j)\right)^2 + \left(\pi_{A_i}(C_j) - \pi_{A^+}(C_j)\right)^2 \right]}$$

$$\mathrm{ED}(A_i, A^-) = \sqrt{\sum_{j=1}^{m} \left[\left(\mu_{A_i}(C_j) - \mu_{A^-}(C_j)\right)^2 + \left(v_{A_i}(C_j) - v_{A^-}(C_j)\right)^2 + \left(\pi_{A_i}(C_j) - \pi_{A^-}(C_j)\right)^2 \right]}$$

Step 4. Calculate the relative closeness coefficient (CC) and rank the preference order of all alternatives.

The relative closeness coefficient of each alternative with respect to the intuitionistic fuzzy ideal solutions is calculated as:

$$CC_{A_i} = \frac{\mathrm{ED}(A_i, A^-)}{\mathrm{ED}(A_i, A^+) + \mathrm{ED}(A_i, A^-)},$$

where $CC_{A_i} \in [0,1], i = 1,2,...,m$.

Hence, the ranking list of all the alternatives can be determined according to the descending order of closeness coefficient values. Finally, the alternative with the highest-ranking order is the most preferred alternative.

4.3.2 Building Social Decision Support Mechanisms with Friend Networks

The proposed model using social network analysis along with regression model, fuzzy Delphi and fuzzy AHP methods as tools, designs a social network based decision support system with better effectiveness. Our requirements for this model are governed by the objective of designing a system to support decision processes on social network. Typically, a group decision process includes choosing the experts, determining the evaluation criteria, aggregating experts' criteria and suggesting alternatives. For more vivid picture of the study, Figure 7 served as the research paradigm. In the following, we describe our important system modules in detail.

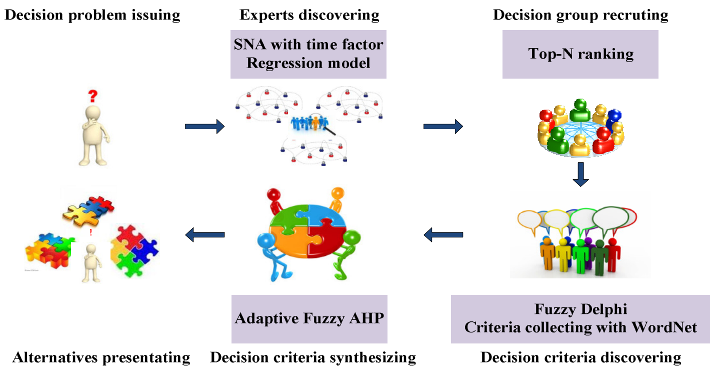

Figure 7. System flow

In our model we choose closeness from three commonly used centrality metrics to be one of our first expert selection factors.

Closeness centrality is defined as the total distance of a user from all other users, and can be formulated as [37]:

$$C_c(p_i) = 1 / \sum_{j=1}^{n} d\left(p_i, p_j\right)$$

where n is the number of users and $d(p_i, p_j)$ is the distance between decision maker i and his friend j.

Betweenness centrality tracks the number of geodesic paths through the entire social network, which pass through the concept whose influence is measured. It is an approximation of its influence on the discussion in general [37]. Besides, betweenness centrality best measures which members, in a set of members, are viewed most frequently as a leader, than other social network analysis measures [39]. The betweenness centrality evaluates the capability of interactions between two friends and is defined as [40]:

$$C_B(i) = \left(\sum_{i \neq j \neq l} g_{jl}(i) \right) / G_{jl}$$

where G_{jl} is the number of the shortest paths linking two friends (i, j) and $g_{jl}(i)$ is the number of shortest paths linking the two nodes (j,l) containing node i.

However, even two people are close friends; friendship may evaporate as time goes by if they do not interact frequently. To measure how the friendship changes within a time period, we define an evaporation function to be a new factor of evaluating friendship among friends. The evaporation function is formulated as:

$$\tau_{ij}^{t+1} = (1-\rho_{ij}^{t})\tau_{ij}^{t} + \vartriangle\tau_{ij}^{t}$$

where:

τ_{ij}^{t} : friendship deposited for friend

ρ_{ij}^{t} : friendship evaporation coefficient,

$$\rho_{ij}^{t} = \frac{\overline{L^t} - L_{ij}^{t}}{S_t / \sqrt{N_t}}$$

$\vartriangle\tau_{ij}^{t}$: amount of friendship changed in time t,

$$\vartriangle\tau_{ij}^{t} = \begin{cases} Q / L_{ij}^{t} & \text{if interaction exists between } (i, j) \\ 0 & \text{otherwise} \end{cases}$$ where:

$\overline{L^t}$: average number of interaction over time periods

L_{ij}^{t} : count of mutual interaction of (i, j) in time t

S_t : standard deviation of interaction between (i, j)

N_t : number of time periods used to calculate $\overline{L^t}$

Q : difference between L_{ij}^{t} and L_{ij}^{t-1}, i.e., $L_{ij}^{t} - L_{ij}^{t-1}$

Regression analysis is a tool for the investigation of relationships between variables, and its major use is prediction or forecasting [38]. Usually, the investigator seeks to ascertain the causal effect of one variable upon another. To explore the friendship between friends, we assemble data on the underlying variables of interest (in our work, closeness, betweenness and evaporation) and employ regression to estimate the quantitative effect of these three variables upon friendship. In our work, we use the following regression model to estimate the friendship between decision maker i and friend j in time t:

$$F_{ij}^{t} = \beta_0 + \beta_1 C_c(p_i) + \beta_2 C_b(p_i) + \beta_3 \tau_{ij}^{t} + \varepsilon_{ij}$$

where β_0 , β_1 , β_2 and β_3 are parameters, ε_{ij} is error term, and $E(\varepsilon_{ij}) = 0$, $Var(\varepsilon_{ij}) = \sigma^2$, $Cov(\varepsilon_{ij}, \varepsilon_{ik}) = 0$.

After the regression model is build, we can use this to measure decision maker's friend and select required decision group. In our system, we select top-N friends by ranking their friendship and form the decision group.

Our study used FDM for the screening of alternate factors [42]. Using the fuzzy theory could solve the fuzziness of common understanding of experts, and the efficiency and quality of questionnaires could be improved. In our work, we followed typical FDM process to implement our system, but made further improvement. To implement FDM, we have to collect opinions of decision group first. However, traditional questionnaire survey for criteria collecting is time consuming, so we design an online criteria-collecting module to do the job. To maintain basic requirement of Delphi method, during the process, individual opinions are unknown to others.

After collecting all the opinions, we calculated the value of triangular fuzzy number of all factors and discovered the significance triangular fuzzy number of factors. By using simple center of gravity method to defuzzify, the fuzzy weight of each opinion can be converted to definite value. Finally proper opinions can be screened out as decision criteria from numerous factors by predefined threshold value.

In determining evaluation criteria phase, our system has screened the important factors conforming to a decision problem through FDM investigating experts' criteria to set up the hierarchy architecture. Here we modify typical FAHP to calculate the weights of individual criteria of a decision problem. Hsu and Chen [41] proposed a fuzzy similarity aggregation method (SAM), in which similarities between experts were collated and fuzzy numbers assigned directly to each expert to determine the agreement degree between them. Taking the degree of importance of each expert into consideration, we modified the original weighting method as below. In [41], the average agreement degree of expert E_j is given by

$$A(E_j) = \frac{1}{n-1}\sum_{\substack{k=1 \\ k \neq j}}^{n} S_{jk}$$

where S_{jk} is the agreement degree, and n is the number of experts. Besides, RAD_j is the relative agreement degree of expert E_j, which is formulated as:

$$RAD_j = \frac{A(E_j)}{\sum_{k=1}^{n} A(E_k)}$$

The relative importance of experts is formulated as:

$$w_j = \frac{r_j}{\sum_{k=1}^{n} r_k}$$

Meanwhile, the consensus degree coefficient of expert $E_j, j = 1,2,...n$ is defined as:

$$CDC_j = \gamma_j \bullet w_j + (1-\gamma_j) \bullet RAD_j$$

where $0 \le \gamma_j \le 1$. In our work, we improve the calculation of relative importance of experts (w_j) and consensus degree coefficient of expert (CDC_j) to capture the spirit of social network.

For w_j, in the original definition the weight of the most important expert is 1, that is, $r_j = 1$. Then the *k*th expert is compared with the most important expert, and a relative weight r_k is assigned. Since the decision group was selected based on friendship F'_{ij}, in our design the expert with highest friendship index is considered to be the most important expert with $r_j = 1$, for all other experts, $r_k = F'_{ik} / F'_{ij}$. Therefore, we can reformulate the relative importance of experts as

$$w_j = \frac{F'_{ij}}{\sum_{j=1}^{n} F'_{ij}}, \ j = 1, 2, ..., n$$

4.3.3 Designing a social support mechanism for online consumer purchase decision making

Based on Simon's decision process, our system supports the decision-makers with necessary functions in every stage. Our requirements for this system are governed by the objective of designing a system to support product purchasing decision processes on social network. For more vivid picture of the study, Figure 8 served as the research paradigm. In the following, we describe our important system modules in detail.

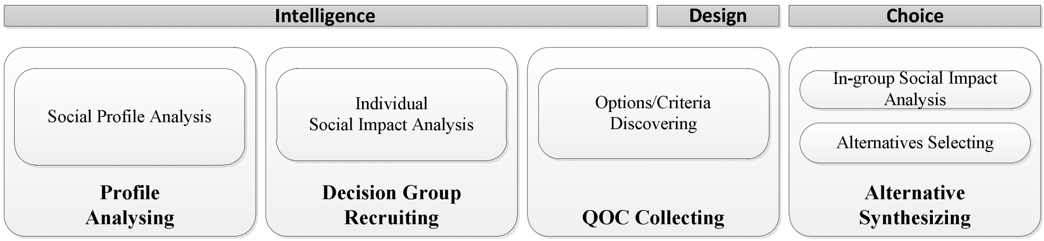

Figure 8. System framework

As social network analysis is used to analyse complex networks [44], in our model we choose closeness and betweenness from three commonly used centrality metrics to be characteristics of system users. Closeness is used to measure the immediacy in social impact [49]. Closeness centrality is defined as the total distance of a user from all other users, and can be formulated as [46]:

$$C_C(p_i) = 1 / \sum_{j=1}^{N} d\left(p_i, p_j\right)$$

where N is the number of users and $d(p_i, p_j)$ is the distance between decision maker i and his friend j. Individuals who are higher in betweenness are considered to hold greater power in the network [47]. Betweenness centrality tracks the number of geodesic paths through the entire social network, and it is an approximation of influence [44]. Besides, betweenness centrality best measures which members, in a set of members, are viewed most frequently as a leader, than other social network analysis measures. The betweenness centrality is defined as [46]:

$$C_B(i) = \sum_{i \neq j \neq l} g_{jl}(i) / G_{jl}$$

where G_{jl} is the number of the shortest paths linking two friends (i, j) and $g_{jl}(i)$ is the number of shortest paths linking the two nodes (j,l) containing node i.

Out-degree refers to the attribute that can present an initiative action from a user. The higher the number of out-degrees, the more motivation a user has to interact with others. When a target user posts comments or sends links to others, they make links of this type. Out-degree centrality is defined as [46]:

$$C_D(p_i) = \sum_{j=1}^{N} a(p_i, p_j)$$

where $a(p_i, p_j) = 1$ if and only if p_i and p_j are connected. Otherwise, $a(p_i, p_j) = 0$.

Social similarity (SS) and social interaction (IA) are two important factors for analysing friendship. Compared with social similarity, social interaction is a more dynamic relation that contains all kinds of people's actions [45], and these actions can reveal social closeness. In our research, we used these two factors to define social relation. Social relation (SR) is defined as:

$$SR_{ij} = SS_{ij} + IA_{ij}$$

In our research we use the number of friends in common to measure social similarity, that is:

$$SS_{ij} = \frac{\{Friend\ of\ i\} \cap \{Friend\ of\ j\}}{\{Friend\ of\ i\} \cup \{Friend\ of\ j\}}$$

Besides, the social interaction between i and j is measured by the activities related to information sharing. For example, friends usually post their own status, share photos or comment on friends' status on Facebook. Therefore, the social interaction is defined as:

$$IA_{ij} = \frac{Total\ Interactions\ between\ i\ and\ j}{Total\ Interactions\ between\ i\ and\ All\ Friends}$$

In our work, we use social impact to be the selection factor of decision group members. Social impact was governed by social forces, psychosocial law and multiplication versus division of impact [48]. Social forces law states that social impact is affected by strength (S), immediacy (I) and number of people (N), and

$$I_i = f\left(SIN\right)$$

The greater the number of sources of social impact in a social situation, the greater the impact would be. In our research, by applying the result from social profile analysis, the social impact of i is defined as:

$$I_i = \sum_{j=1}^{N}\left(C_{B(i)} * SR_{ij}\right) * C_C(p_i) * C_D(p_i)$$

Information retrieval (IR) deals data where information items cannot be precisely defined. Since the discussion process contains various free-typing texts, we used IR methods to collect the options. A Part-Of-Speech Tagger (POS Tagger) reads text and assigns parts of speech to each word, such as noun, verb and adjective. In our system framework, we adopted POS tagger developed by Stanford University to identify POS.

The tagged nouns were considered to be options from decision group members. WordNet is a large lexical database in which nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets are interlinked by means of conceptual-semantic and lexical relations. To measure the semantic similarity between two synsets, we use hyponym/hypernym (or *is-a* relations).

After the similarity is computed, the options are then presented to decision group by using QOC schema. Then the group members are asked to describe the criteria behind the options proposed. The same technique is used to collect the criteria during the discussion of criteria. At the end of this process, a complete QOC diagram can be obtained.

After the decision group members are selected, the decision support process starts. During the alternatives design phase, they can propose their own options related criteria. However, the group members are likely to impact each other. Some members may be persuaded and concur on others' options. Suppose the decision group consists of N members. Each of them can have opposite attitude on a certain criteria proposed by other members. Denote the attitude of member p as $\alpha_p = \pm 1, p = 1, 2, ..., N$. Member p agree with the criteria if $\alpha_p = 1$, and vice versa. Members can influence each other, and each of them is characterised by self-confidence $\beta_p > 0$, which is the strength of his/her influence and the confidence about his/her own criteria/options. Member p and q have social distance d_{pq}. The change of attitude is determined by the in-group social impact exerted on every member:

$$GSI_p = -\beta_p - \alpha_p - \sum_{q=1, q\neq p}^{N} \frac{\beta_q \alpha_p \alpha_q}{g(d_{pq})}$$

Member p will change his/her own attitude if $GSI_p > 0$, or maintain his/her attitude otherwise.

At the final stage, the final alternatives shown to the decision-maker is synthesized based on QOC and in-group social impact. In QOC schema, an option can have positive and negative assessment about. By evaluating the in-group social impact, we can count the number of decision members who support or concur in a certain criteria.

For a criterion, if the number of positive assessment exceeds that of negative assessment, then the negative assessment link is removed. The option with the largest number of positive assessment is then selected as final suggested alternative to decision-maker. The complete process is shown in Figure 9.

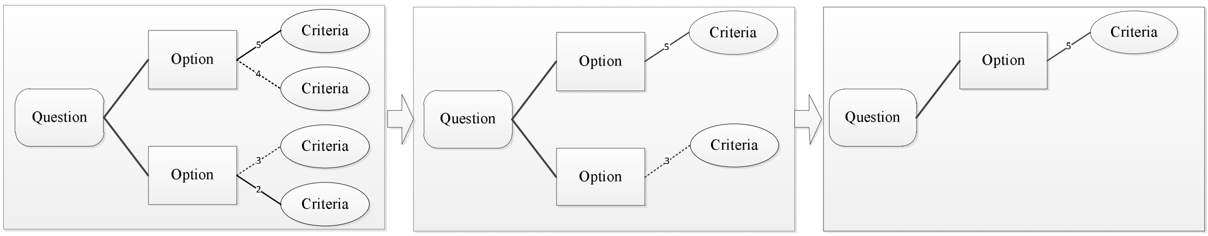

Figure 9. Alternatives selecting process

5. Conclusion

The contributions and managerial implications of social diffusion mechanism are summarized as follows. Firstly, from the perspective of system innovation, while marketing on social media has become increasingly popular, little research has discussed a diffusion mechanism to study the online advertisements on social media.

Secondly, from the perspective of methodology, we not only consider the static factors (individual preference and link structure of relationship), but also dynamic factors (social activeness, social interactions, and social similarity) in the evaluation of nodes' propagation capabilities to identify the people who can spread the adverting messages widely.

Thirdly, from the perspective of performance, better click-through rate reflects that our mechanism can raise the visibility of advertising information. A higher repost rate indicates a higher exposure of the advertising and reveals that users are interested in the advertisement when shared by friends and are willing to share it with others.

It also proves that our system can reduce the risk of spamming friends and improve resonance among users. Our proposed mechanism can widely extend the spreading coverage of advertisements and improve the resonance of advertisements.

Lastly, from the perspective of practice, our empirical experiments show that social advertising is particularly effective in marketing goods and services such as movies/TV, music, games, sports, and outdoor pursuits. The proposed diffusion mechanism provides the advertisement sponsors with a powerful vehicle to conduct advertising diffusion campaigns successfully.

The contributions of market intelligence system are summarized as follows. On the theoretic aspects, first, as microblog posts are less structural than traditional blog articles or documents, we provide good precision on topic detection in microblogs by combining the refined meronym patterns and term frequency information.

Second, the performance of SVM as a sentiment classifier for microblogs is justified although the opinions text of microblogs is limited to be short. Another noteworthy part is our survey reveals it is applicable to use emoticon as a proxy for sentiment expressed, which allow us to feasibly quantify a huge number of opinion expressed in microblogs.

Third, as the microblog message can be disseminated quickly over the social networks of users, in order to detect and avoid the spamming problem, we develop a model, considering the social network structure and interactions activities, to quantify the credibility of an expresser. On the managerial aspects, with the proposed system, the marketers could learn what topics are interesting and concerned by the customers in real-time and cost-efficient. And the sentiments towards these topics can be easily traced with time. The marketers could effectively comprehend the change of customers' attitude by different time period and specific campaigns or events.

Furthermore, the proposed system prevents the information used for making marketing decisions from interfering by incredible information source and irrelevant opinions.

The contributions of social support mechanisms design are summarized as follows. First, the contribution of the "*Social Support Mechanism in Micro-blogosphere*" is a social decision support mechanism composes with social network analysis (SNA), intuitionistic fuzzy set (IFS) and technique for order preference by similarity to ideal solution (TOPSIS) has proposed in this paper.

In SNA we form the post and response interaction as the two-mode network data, and obtain the strength of social relationship for analyzing the companionship between originator and decision makers.

IFS is mainly used to model the completely unknown or incompletely known opinions from micro-blogosphere. For achieving the social appraisal support for originators, TOPSIS was applied to obtain the final alternative rank list.

Through this proposed social appraisal support mechanism, the originators could put their whole social network as their own experts group. Additionally, the proposed mechanism successfully speeds up the decision process and provides appropriate models processing the incomplete opinions from online social network.

Second, the research results of the "Building Social Decision Support Mechanisms with Friend Networks" are that we introduced time factor into social network analysis.

By using regression a friendship index calculation model is proposed and served as our tool to predict friendship between two users in specific time period. By equipping FDM with online decision criteria mechanism, timeconsuming problem of conventional Delphi method was solved. Furthermore, an adoptive SAM was also suggested to further improve the application of FAHP on social network related research.

An empirical study further proved the feasibility and effectiveness of our work.

Finally, the contributions of the "Designing a social support mechanism for online consumer purchase decision making" are that we introduced social impact theory into the design of social decision support mechanism. QOC representation schema was used to describe the design logic of decision alternatives.

From the viewpoint of academic contribution, by using social impact theory a decision group selection mechanism and consensus making within decision group were proposed and served as our tools to select adequate members to support decision-making process.

By equipping decision support mechanism with proper design rationale representation schema a product purchasing decision problem can be understood clearly by decision members, and various discussion records can be easily communicated and assessed.

An empirical study further proved the feasibility and effectiveness of our work. Our research successfully introduced the social impact theory and design rationale into the development of social network-based decision support mechanism. Besides, we also extended the concept of decision support system development to utilize social network platforms.

From the viewpoint of practice, we showed a feasible way to develop a social network-based decision support system together with the related techniques for product purchasing decision problems. By dividing the system framework into modules, those who are interested in developing such kind of applications can further improve the system by plugging in new modules as needed.

Reference

[1] Bagherjeiran A., Parekh R., Combining Behavioral and Social Network Data for Online Advertising, In Proceedings of the 2008 IEEE International Conference on Data Mining Workshops, Pisa, Italy, 2008, 837-846.

[2] Berendt B., and Navigli R., Finding your way through blogspace: Using semantics for cross-domain blog analysis. In Proceedings of the AAAI Spring Symposium 2006 (AAAIS) on Computational Approaches to Analyzing Weblogs, Palo Alto, CA, 2006, 1-8.

[3] Biichner A.G., and. Mulvenna M.D, Discovering Internet Marketing Intelligence through Online Analytical Web Usage Mining. SIGMOD Record 27, 1998, 54-61.

[4] Caverlee J., Liu L., and Webb, S., The SocialTrust framework for trusted socialinformation management: Architecture and algorithms. Information Sciences, 180, 1, 2010, 95-112

[5] Cha M., Haddadi H., Benevenuto F., and Gummadi K.P., Measuring User Influence in Twitter: The Million Follower Fallacy. In Proceedings of the 4th International Conference on Weblogs and Social Media, Washington, 2010.

[6] De S.K., Biswas R., and Roy A.R., Some operations on intuitionistic fuzzy sets. Fuzzy Sets and Systems, 114, 2000, 477-484.

[7] Dinev T., Hu Q., and Yayla A., Is there an on-Line Advertisers' Dilemma? A Study of Click Fraud in the Pay-Per-Click Model. International Journal of Electronic Commerce 13, 2, 2008, 29-60.

[8] Hearst M., Direction-Based Text Interpretation as an Information Access Refinement. Text-Based Intelligent Systems. Lawrence Erlbaum Associates, 1992, 257-274.

[9] House, J. S., Work Stress and Social Support. Reading, Mass: Addison-Wesley, 1981.

[10] Hu, Y. C. Classification performance evaluation of single-layer perceptron with Choquet integral-based TOPSIS. Applied Intelligence, 29, 3, 2008, 204-215.

[11] Hsu C., Chang C., and Lin C., A Practical Guide to Support Vector Classification Citeseer, Taipei. 2003.

[12] Hu N., Bose I., Gao Y., and Liu L., Manipulation in digital word-of-mouth: A reality check for book reviews. Decision Support Systems. 50, 3, 2011, 22-30.

[13] Jansen B.J., Zhang M., Sobel K., and Chowdury A., Twitter Power: Tweets as Electronic Word of Mouth. J. Am. Soc. Inf. Sci. Technol. 60, 2009, 2169-2188.

[14] Kuo, M.S., Tzeng, G.H., and Huang, W.C., Group decision-making based on concepts of ideal and anti-ideal points in a fuzzy environment. Mathematical and Computer Modelling, 45, 3-4, 2007, 324-339.

[15] Kim Y., Kim M., and Kim K., Factors Influencing the Adoption of Social Media in the Perspective of Information Needs, In Proceedings of the iConference 2010.
[16] Kimura M., Saito K., and Nakano R., Extracting influential nodes for information diffusion on a social network. In Proceedings of the 22nd national conference on artificial intelligence, Menlo Park, CA, 1371-1376.
[17] Kimura M., Saito K., Nakano R., and Motoda H., Finding Influential Nodes in a Social Network from Information Diffusion. Social Computing and Behavioral Modeling, 2009, 1-8.
[18] Kleinberg J.M., Authoritative Sources in a Hyperlinked Environment. J. ACM 46, 1999, 604-632.
[19] Li Y.M., and Chen C.W., A synthetical approach for blog recommendation: Combining trust, social relation, and semantic analysis. Expert Systems with Applications 36, 3, 2009, 6536-6547.
[20] Liu D.R., and Shih Y.Y., Integrating AHP and data mining for product recommendation based on customer lifetime value. Information and Management 42, 3, 2005, 387-400.
[21] Liu, H.W., and Wang, G.J., Multi-criteria decision-making methods based on intuitionistic fuzzy sets. European Journal of Operational Research, 179, 2007, 220–233.
[22] Saaty T.L., The Analytic Network Process: Decision Making With Dependence and Feedback RWS Publication, Pittsburgh, 2001.
[23] Scaffidi C., Bierhoff K., Chang E., Felker M., Ng H., and Jin C., Red Opal: Product-Feature Scoring from Reviews. In 8th ACM Conference on Electronic Commerce ACM New York, NY, USA, 2007, 182-191.
[24] Sundblad H., Automatic Acquisition of Hyponyms and Meronyms from Question Corpora. In ECAI 2002 Workshop on Machine Learning and Natural Language Processing for Ontology Engineering (OLT'2002) Citeseer, Lyon, France. 2002.
[25] Szmidt, E., and Kacprzyk, J., Distances between intuitionistic fuzzy sets. Fuzzy sets and Systems, 114, 2000, 505-518.
[26] Tatemura J., Virtual Reviewers for Collaborative Exploration of Movie Reviews. In Proceedings of the 5th international conference on Intelligent user interfaces, New Orleans, Louisiana, United States2000 ACM. 2000.
[27] Twitter.Com Twitter 101 - Case Study: Best Buy's Twlpforce.
[28] Ulicnya B., Baclawskia K., and Magnusb A., New Metrics for Blog Mining. In SPIE Defense & Security Symposium, Orlando, FL. 2007.
[29] Wang J.C., and Chiu C.C., Recommending trusted online auction sellers using social network analysis. Expert Systems with Applications 34, 3, 2008,

1666-1679.

[30] Wang K., Wang E.T.G., and Farn C.K., Influence of Web Advertising Strategies, Consumer Goal-Directedness, and Consumer Involvement on Web Advertising Effectiveness. International Journal of Electronic Commerce 13, 4, 2009, 67-96.

[31] Wathen C., and Burkell J., Believe It or Not: Factors Influencing Credibility on the Web. Journal of the American Society for Information Science and Technology 53, 2002, 134-144.

[32] Wasko M., and Faraj S., Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. Mis Quarterly 29, 2005, 35-57.

[33] Wen C., Tan B.C.Y., and Chang K.T.T., Advertising Effectiveness on Social Network Sites: An Investigation of Tie Strength, Endorser Expertise and Product Type on Consumer Purchase Intention. In proceedings of the International Conference on Information Systems (ICIS), Phoenix, Arizona, United States, 2009, 15-18.

[34] Wikipedia, Multicast, URL: [yayahttp://en.wikipedia.org/wiki/Multicast], Accessed: 09/28/2010.

[35] Wright S., and Calof J.L., The Quest for Competitive, Business and Marketing Intelligence. European Journal of Marketing 40, 2006, 453-465.

[36] Xia R., Zong C.Q., and Li S., Ensemble of feature sets and classification algorithms for sentiment classification. Information Sciences, 191, 6, 2010, 1138-1152

[37] L. Chi, C.W. Holsapple and C. Srinivasan, “Competitive Dynamics in Electronic Networks: A Model and the Case of Interorganizational Systems”, International Journal of Electronic Commerce, 2007, 11(3), pp. 7-49.

[38] J. B. Copas, "Regression, prediction and shrinkage", Journal of the Royal Statistical Society, 1983, 45(3), pp. 311-354.

[39] L.C. Freeman, “A Set of Measures of Centrality Based on Betweenness”, Sociometry, 1977, 40(1), pp. 35-41.

[40] L.C. Freeman, “Centrality in Social Networks Conceptual Clarification”, Social networks”, 1979, 1(3), pp. 215-239.

[41] H.M. Hsu and C.T. Chen, “Aggregation of Fuzzy Opinions under Group Decision Making”, Fuzzy Sets and Systems, 1996, 79(3), pp. 279-285.

[42] Y.L. Hsu, C.H. Lee and V.B. Kreng, “The Application of Fuzzy Delphi Method and Fuzzy Ahp in Lubricant Regenerative Technology Selection”, Expert Systems with Applications, 2010, 37(1), pp. 419-425.

[43] F.M. Krienen, P.C. Tu and R.L. Buckner, “Clan Mentality: Evidence That the Medial Prefrontal Cortex Responds to Close Others”, The Journal of

Neuroscience, 2010, 30(41), pp. 13906-13915
[44] Chi, L., Holsapple, C. W., & Srinivasan, C. (2007). Competitive dynamics in electronic networks: A model and the case of interorganizational systems. *International Journal of Electronic Commerce*, 11(3), 7-49.
[45] De Meo, P., Nocera, A., Terracina, G., & Ursino, D. (2010). Recommendation of similar users, resources and social networks in a Social Internetworking Scenario. *Information Sciences*. 181(7), 1285–1305.
[46] Freeman, L. C. (1979). Centrality in social networks conceptual clarification. *Social Networks*, 1(3), 215-239.
[47] Killeya-Jones, L. A., Nakajima, R. and Costanzo, P. R. (2007). Peer standing and substance use in early-adolescent grade-level networks: a short-term longitudinal study. *Prevention Science*, 8(1), 11-23.
[48] Latane, B. (1981). The psychology of social impact. *American Psychologist*, 36(4), 343.
[49] Rashotte, L. (2007). *Social Influence*,1st Edition, Blackwell Publishing, Malden, MA.

計畫成果自評

本計畫工作目前已經順利完成，其主要核心為資訊擴散模型以及市場趨勢監測方法之建構與分析。本專題計畫目前完成項目與計畫初預期項目之情形如下：

1 廣泛文獻探討與理論方法研究

我們已發表(或審查中)了 9 篇研討會論文以及 4 篇期刊論文分別在「研究背景」與「相關文獻」都有這些內容之記載。領域涵蓋「社會網路分析」、「資訊散播」、「病毒式行銷」、「資訊萃取」、「社會網路運算」、「信譽評量」等。本研究先從技術層面，在既有與建立之社會網路運算基礎服務平台，找出潛藏在網際網路之中的人類社會結構，並據以發展人類社會實際互動的各項應用。基於這些工作，我們得以建立社群散播模型（social diffusion mechanism）以及行銷智慧系統（marketing intelligence system）。另外，我們也發現社群決策支援機制在電子商務上的優缺點，以作為未來進一步分析與探討的基石。

2 社群網路廣告之研究

會議論文[1, 6]以及期刊論文[1] 主要研究如何發展資訊散佈機制以協助在社群網站中有效的進行線上廣告或重要以及緊急資訊傳遞的用途。社群媒體近年來迅速崛起，儼然已成為主要的訊息傳播平台。近年來，許多公司皆曾試圖利用社

群媒體進行的廣告推廣，以期能將產品訊息提供給適當的社群使用者，藉此開發潛在客戶。能否在社群媒體成功的傳播訊息，除了社會成本的考量外，內容的相關性和使用者之間親密的社會關係佔有相當程度的關鍵。在本文所提出的機制中，我們考慮到社群使用者的喜好因素，在社群網路中的影響力和本身的傳播能力與強度，為有意在微網誌中進行線上廣告的廣告商們提供了代言人選擇和散播路徑建議。我們的實驗結果證實，此模型可以為廣告商提供合適的人選和散播方式，至使目標廣告能不斷擴散，從而有效地提高廣告效果。

3　社群網路行銷智慧之研究

會議論文[2]以及期刊論文[2]主在研究如何方能協助企業能有效率的在微網誌平台中進行市場趨勢監測，促使企業能迅速針對市場反應擬定對策。此研究中，我們提出了一個能有效運行的智慧行銷系統，提供了總合分數評量以支援企業決策。本系統中成功結合了趨勢話題檢測、發言情感分類、使用者信譽評估以及分數聚合方法四大項工作，發展出得以監測市場趨勢之系統。根據我們的實驗結果發現，審視聚合微網誌意見確實有助於判讀市場趨勢，且用戶信譽和發文質量皆是必不可少的。本研究中所提出的機制能有效地發現市場情報以支持決策者。

4　社群網路決策支援機制之研究

會議論文[3]以及期刊論文[3, 4]主在研究如何方能協助線上使用者能有效率的利用微網誌平台的特性進行推薦或決策支援，藉以達到縮短並加速決策過程的效果。此研究中，我們提出了一個能有效運行的社群決策支援機制，提供了總合式的決策支援分析以支援使用者進行決策。本機制中成功結合了友誼交情分析、共識意見搜集以及決策分析方法三大項工作，發展出得以支援決策的機制。根據我們的實驗結果發現，本機制可以成功地吸納社群媒介中朋友們的意見，加速使用者的決策過程，協助做出購買決策。會議論文[7] 透過引入設計理論基礎和社會影響理論於系統開發，利用資訊技術作為工具對消費者的購買決策問題設計一個社交網路為基礎的決策支持系統框架。QOC 架構是用來描述找出產品可能的替代品的推理過程。此外，在社交網路上的社會影響力是用來選擇決策小組成員和針對特定的選項或標準來衡量其改變決策成員的態度的效果。透過實證的研究證明，我們所提出的架構比目前基準方法有更好的表現。會議論文[9]主要探討社會網路的朋友如何協助朋友進行購買決策。我們利用社會網絡分析以及回歸模型，Fuzzy Delphi 和 Fuzzy 層次分析方法當成工具，設計開發了一種基於社會網絡具有更好效果的決策支持系統。

5　其他經濟分析研究

會議論文[4, 5, 8] 是計畫研究期間內進行有關網路經濟分析的研究，會議論文4主要在探討目前網路最熱門Download 以及 Streaming兩種不同的 Video分享機制，針對市場中的定價問題進行分析。我們研究當這兩種分享機制內容頻道的

供應商，是相同公司或兩個獨立的公司的情況下，不同的技術與市場因素對於發展商業策略的影響。會議論文 5 討論最熱門的網路電話 VoIP 的問題。雖然 VoIP 在兩端電腦是免費的，VoIP 服務提供商從所謂的 phone-in 與 phone-out 賺取利潤。VoIP 服務與傳統的公共交換電話網絡（PSTN）的服務相比，具有較低的充電速率的優點。然而，這也導致通話的穩定度與品質的不確定性和安全風險的問題。此篇論文，利用博弈論模型進行經濟分析，我們分析市場的 VoIP 到 PSTN 服務行業的互動和規定的最優定價策略。而會議論文 8 則對最近迅速出現的雲端計算服務中，商業軟體外包模式的成為以服務為導向的模式。從經濟的角度來看，相較於軟體需要巨大的前期開發成本和持續維護的努力，依據需求多寡付費的特點讓雲端計算有顯著的優勢。但是，企業可能面對的問題是外部各方的公共雲端計算服務有潛在的安全性風險。在此論文中，我們使用了博弈理論模型對於根據需求多寡付費以及根據建置成本與維護合約計價的不同商業模式進行定價策略分析。我們發現，計算服務的價格和收入顯著地受到計算服務平台的市場結構和技術參數所影響。我們的分析結果提供對企業有用的管理意涵，以及提供 IT 外包計算服務市場的經營策略。

目前本專題研究成員將整理研究成果，並將最後成果投稿國際期刊。本研究團隊在經濟分析上的傑出部份是我們認為能夠大幅超越過去資訊管理領域在網路服務品質研究上的優勢，同時也是本研究室核心，並且是全球資訊管理學界頂尖學府如MIT、CMU目前專注的領域。因此，如受到獎勵資助的研究時程能得以延伸，我們相信能夠做出更創新、突破的研究。

附錄

已發表國際會議論文

1. "A Diffusion Mechanism for Online Advertising Service over Social Media", Li, Y.-M., Y.-L. Shiu, *Proc. 4th International Workshop on Architectures, Concepts and Technologies for Service Oriented Computing* (ACT4SOC 2010), Athens, Greece, July, 2010.
2. "Deriving Marketing Intelligence over Microblogs", Li, Y.-M., T.-Y. Li, *Proc. 44th Hawaii International Conference on System Science* (HICSS-44), Kauai, Hawaii, USA, January, 2011.
3. “Social Support Mechanism in Micro-blogosphere”, Li, Y.-M., C.-Y, Lai, 13th International Conference on Electronic Commerce (ICEC 2011),Liverpool, UK, August.
4. “Business Modeling for Online Video Services: Download vs. Streaming”, Li, Y.-M., L.-F. Lin, 13th International Conference on Electronic Commerce (ICEC 2011), Paper 48, Liverpool, UK, August, 2011.
5. “VoIP Pricing in Competing Markets”, Li, Y.-M., S.-W. Chu, 13th International

Conference on Electronic Commerce (ICEC 2011), Paper 49, Liverpool, UK, August, 2011, forthcoming .

6. “Evaluating Disseminators for Time-Critical Information Diffusion on Social Networks”, Li, Y.-M., L.-F. Lin Proc. International Conference on E-Business (ICE-B 2012), p. 251-260 Rome, Italy, July, 2012.
7. “Designing a Social Support Mechanism for Online Consumer Purchase Decision Making”, Li, Y.-M., Y.-L. Lee, Proc. 16h Pacific Asia Conference on Information Systems (PACIS 2012), Ho Chi Minh City, Vietnam, July, 2012.
8. “Analyzing The Pricing Models for Outsourcing Computing Service”, Li, Y.-M., C.-L. Chou,, Proc. 16h Pacific Asia Conference on Information Systems (PACIS 2012), Ho Chi Minh City, Vietnam, July, 2012.
9. “Building Social Decision Support Mechanisms with Friend Networks”, Li, Y.-M., Yi-Lin Lee, Proc. 45th Hawaii International Conference on System Science (HICSS-45), Maui, Hawaii, USA, January, 2012.

已發表或修改中期刊論文

1. "A Diffusion Mechanism for Social Advertising over Microblogs, Li, Y.-M., Y.-L. Shiu, submitted to *Decision Support Systems*, forthcoming, 2012 (SCI)
2. "Deriving Market Intelligence from Microblogs", Li, Y.-M., T.-Y. Li, submitted to *Decision Support Systems*, 2011.
3. “A Social Recommender Mechanism for E-Commerce: Combining Similarity, Trust, and Relationship,” with J.- D. Wu and C.-Y., Lai, submitted to *Decision Support Systems*, under revision.
4. “A Social Appraisal Mechanism for Online Purchase Decision Support in the Micro- Blogosphere” with C.-Y., Lai , submitted to *Decision Support Systems*, under revision.

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