SOCIAL APPRAISAL SUPPORT FOR POINT-OF-INTEREST VISITING DECISION-MAKING

Complete Research

Lien Fa, Lin, University of Kao Yuan, Kaohsiung, Taiwan, R.O.C, lienfa0704@gmail.com

Yung Ming, Li, University of National Chiao Tung, Hsinchu, Taiwan, R.O.C,
yml@mail.nctu.edu.tw

Abstract

As neighborhood and city exploration is one of the major themes in many location-based social network services, it is vital to provide Point-of-Interest (POI) recommendations to users. With a fast growing number of mobile users and POIs within such services, it is important to adopt efficient techniques so as to provide precise POI recommendations. Owing to the strong participation of knowledgeable users, a social networking service can be seen as a large number of experts who support the decisions of online users. People make decisions based on their personal preferences, but they also rely strongly on the opinions of others, especially close friends or influential people. The "location" where the decision-making takes place is also equally important in affecting user behaviour. In this paper, we propose a social decision support mechanism that integrates the methodologies and techniques of social network analysis, geographic distance analysis, and local expert analysis to achieve social decision support for mobile users. We aim to discover the POIs to which a mobile user is likely to go. With this proposed mechanism, online users can efficiently reduce their decision-making processes and reduce the risk of visiting an unsuitable POI.

Keywords: Mobile Intelligence, POI, Social Influence, Social Decision Support.

1   Introduction

According to the report from IDC (2013), over 57.4% of the US population uses smartphone, and, 222.4 million smartphones will be shipped to users in 2017, accounting for 68.7% of the US population. Mobile devices such as smartphones and tablets have been so popularised that they have become indispensable in daily life (Kanlan, 2012). Along with the emergence of social media, location-based services (LBS) and mobile devices, John Doerr (2013) proposed a concept named SoLoMo (Social-Local-Mobile), combining social networking services (e.g. Facebook, Twitter and Foursquare) with mobile phone platform and positioning services to become a new paradigm in mobile commerce. With the huge potential of growth in the location-based e-commerce, many new business applications have been inspired by the concept of mixing mobile and social media. For example, marketers can explore potential customers by analysing their behaviour on social network platforms and in current locations to make personalised recommendations of points of interest (POIs), coupons or advertisements (Li and Du, 2012) through the mobile channel in order to increase business opportunities.

The increasing availability of location-position technology enables people to add a location dimension to existing online social networks. The dimension of location brings social network back to reality, bridging the gap between the online social networking service (online) and physical world (offline). For example, in Flickr, users can upload location-tagged photos; using Foursquare, users can share their present location on a website (such as) for organizing a group activity in the real world; GeoLife (Chen et al., 2013) records travel routes with GPS trajectories to share travel experiences in an online community, including local search, maps, lists, real-time updates, the development QR codes, coupons, and corporate images capture capabilities (as in Google Place). This kind of location-driven social structures is known as location-based social network (LBSN) (Zheng 2009). The main purpose of recommendation systems are developed by online vendors for sales improvement. Nevertheless, online users have begun to doubt official advertising/recommendations (Lewis and Bridger, 2000) and turn relied on the opinions and social appraisal support from their close friends. Social support is one of the important functions of social networks (House 1981); however, methodologies for implement social support mechanisms on social media have not been widely discussed. From the perspective of customers' view, it is beneficial to design an appropriate appraisal system that can analyze collective opinions to support their decision-making process.

In a city tour scenario, for example, making decisions about where to go next sometimes is a pressure. The pressure increases when tourist faces a large number of choices and have insufficient information; seeking social support thus becomes a useful manner to alleviate the problem. However, the mental pressure might not alleviate but can even increase if the support provided is not what the requester wished to receive (Ziegler and Lausen, 2004). With a rapidly growing number of users and POIs within such services, it is essential to adopt efficient techniques to provide accurate POI appraisal. Three main research questions are studied in this paper:

(1) How can the social relationship between the support requester and decision supporters be identified? Because closer friends might understand our preferences, habits, and needs better, their appraisals should be more reliable than those of others.

(2) How can the supporters of suitable decisions be analysed and consolidated? To find the suitable supporters from the friend network of a requester, the degree of expertise on the selected POI category of the requester, the trustiness level with the requester, and the local degree of expertise have to be analysed.

(3) How can a decision consensus on the alternative ranking be obtained? Each support requester has individual preferences regarding the POI's alternative decision criteria. It is thus effective and

essential to rank the alternatives appropriately by consensually considering personal preferences and collecting supporters' evaluations.

In this paper, we propose a social appraisal support mechanism (SASM) that integrates the methodologies and techniques of social network analysis (SNA), geographic distance analysis, and local expert analysis to achieve social decision support for mobile users. Through the proposed mechanism, online users can efficiently reduce their decision-making processes and reduce the risk of visiting an unsuitable POI.

The remaining sections are organized as follows. Section 2 discusses the related literature. In Section 3, the research model will be demonstrated, and the experiments will be presented in Section 4. The experiment results and evaluation are discussed in Section 5. Finally, Section 6 concludes this study and presents the directions of future research.

2 Related work

2.1 Social Support Mechanism

Social support is generally defined as help from others when people face a difficult life event. Social support refers to the assistance available from other people who are part of a social network. In a city tour scenario, for example, making decisions about where to go next sometimes is a pressure. The pressure increases when a tourist faces a large number of choices and has insufficient information; seeking social support thus becomes a useful way to alleviate the problem. Recently, social appraisal has been widely used due to the popularity of social network analysis. For example, much research has been conducted in the field of electronic commerce, such as that on information filtering and spreading (Liu et al., 2009). Social decision making is the process that takes every individual's local decisions and generates a collective response. The social decision support system (SDSS) idea was first introduced in (Turoff et al., 2002) as a computer supported group decision making system. A social decision support system (SDSS) allows users in a network-based environment to form a decision group and participate in a collaborative decision making process.

Although a large amount of research has been undertaken on information filtering and dissemination for increasing business opportunities on the part of firms, few systems have been developed for the social support of users' in their online behaviour. Thus, the aim of the current paper is to develop mobile appraisal support for suggestions involving POI for tourist support.

2.2 Social Influence and Decision Making

The growth and popularity of social media such as Twitter and Facebook has become a powerful tool for marketers to promote their products and for consumers to share their opinions. People often look at social media sites to seek the reviews of others when making a purchase or decision, and therefore, social influence is a vital factor in the group decision making process. Much research (e.g. Sinha and Swearingen, 2001), leverages online social media to understand target customers and consider social recommendations with social influence more suitable than traditional recommendations. Identifying the closeness of social relationships and social interactions is a crucial component to effectively leverage social influence.

Social influence can be classified into two types: informational and normative (Deutsch and Gerard, 1995). Informational influence is the propensity to refer to other people's opinions, and normative influence is the desire to participate in similar behaviours to those around you. Both of these influence types are highly correlated to the decision making behaviour of individuals. Sinha and Swearingen (2001) find that consumers are more likely to consider recommendations from people they know and

trust, such as family members and friends. Thus, many researchers take social influence as a factor in decision-making systems. In this study, we investigate the impact of social influence in the suggestion of POI alternatives by considering friend influences along with crowd influence.

2.3 Spatial Economics

Spatial economics is concerned with the allocation of (scarce) resources over space and the location of economic activity. Economists model how scarce resources are allocated among alternatives. Economists apply a range of mathematical techniques to location problem. A successfully economic model rationalizes a broadly observed choice pattern, or, provides insight into how specified exogenous changes affect choices (Kilkenny and Thisse 1999). In general, customers are willing to visit the POI whose location is close and most convenient to reach. Transportation convenience is one of the important factors affecting a customer's purchase intention. If the transportation convenience is greater, more people will be attracted to visit (checked-ins) the POI. On the contrary, if the transportation convenience is smaller, the number of checked-ins and comments will decrease. The "location" where the decision-making takes place is also equally important in affecting user behaviour. In this study, we investigate the impact of social influence in the suggestion of POI alternatives by considering friend influences along with crowd influence.

3 The Model

A successful location-based e-commerce service emphasises the economic benefit that the platform can bring from the online world to the real world. With the help of the smart phone, customers can now instantly obtain all the information they need, from nearby sales information to which friend have been to which POIs. To match the objective of make a POI decision suggestion for the mobile user, several techniques are required. The main components considered in the social appraisal support mechanism (SASM) consist of the POI alternatives constructing module, the social supporters discovering module, and the POI candidate choosing. The system framework is depicted in Figure 1.
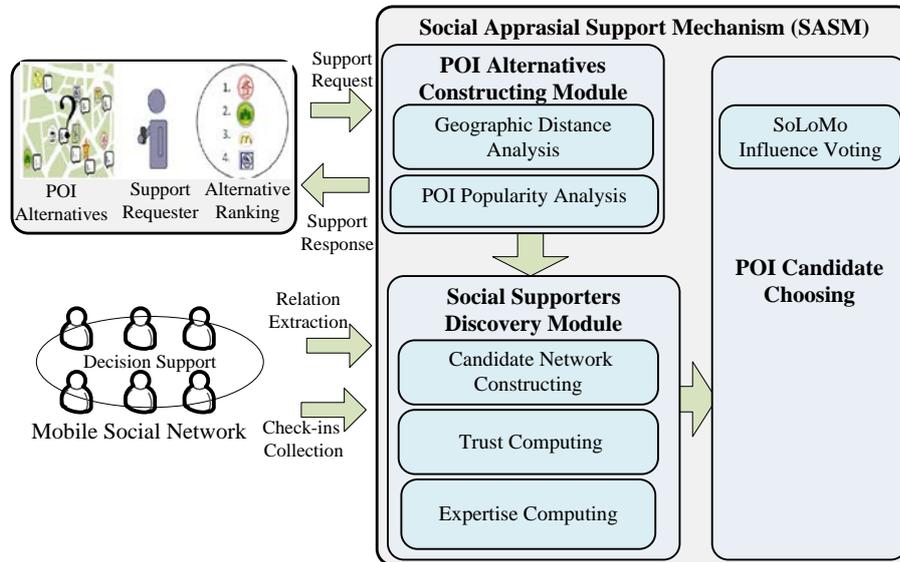

Figure 1. System framework of mobile social advertising

3.1 POI Alternatives Construction Module

The proposed mechanism provides an instant service to help people making a decision about the next POI to visit, so it is important when utilising the context data to be aware of the people around. If this mechanism suggests someone far away from the mobile user, they may not want to visit the POI due to the distance, even with a strong preference for the target POI. On the other hand, if they are near the POI, then they can go there at once. In this module, we take (1) user location and (2) user selected POI categories as the context. The module uses the locations of users detected by mobile devices to find the POI candidates which the mobile user will visit next, near the mobile user. As well as the distance and preference (POI category selected by user) factors, people behave according to the influences of others. In this research, we take friend influence and crowd influence factors as representing social influence to calculate the popularity of the POIs. According to the popularity factor of the POIs, we can select the top-N POIs with high popularity as alternatives for social supporters to make a decision for more users.

3.1.1 Geographic Distance Module

To make a POI suggestion to a requester, we first need to identify the qualified set of POIs according to the POI category that the requester selected and the geographic distance between the POI and the requester. The candidate set of the OPIs for requester u is represented as

$$C(u) = \{ poi \mid Category(u) \parallel Loc(u) - Loc(poi) \mid < d \}, \tag{1}$$

where d is the maximal distance acceptable to requester u.

3.1.2 POI Popularity Analysis

As well as the distance and the preference (POI category selected by requester) factor, people are very likely to behave according to the influence of others. Social influence can be distinguished into two types: informational and normative (Deutsch and Gerard, 1995). Informative influence means the propensity to refer other user's opinion, and normative influence is the desire to make similar behaviors with the user around (Amblee and Bui, 2011). Both types of social influence highly affect the purchasing behavior (Phang et al., 2013). In this proposed social appraisal support system, we consider the social influence from two aspects: structure (friend) influence and population (crowd) influence when modeling the social influence. Wasserman and Faust (1994) indicate that a person with more connections (e.g., friends and interaction) is more important and influential than another with fewer connections. The stronger the tie strength between two people, the deeper the relation they have. That is, they might understand each other's preference, habits, and needs.

Friend Influence: When making a decision, we tend to ask for suggestions from our friends and will be influenced by their opinions. Similarly, a user tends to like or visit a POI that their friends also like. The more "likes" made by a user's close friends on a POI, the higher the attractiveness of the POI to the user. The social influence of friends can be quantified as:

$$FI(u, p) = \alpha \times FS(f, u) + \beta \times \sum_{p \in C(u)} CT(f, p) + \gamma \times \sum_{p \in C(u)} LT(f, p), \tag{2}$$

where $FS(f,u)$ represents the friend strength of friend f for the user u, $CT(f,p)$ denotes the number of times friend f has been checked-in at POI p, and $LT(f,p)$ is the number of "likes" received on the check-in or comments posted by friend f. Friend strength is measured by the number of out-links a friend has, plus the number of mutual friends of the user and their friend. The formula is expressed as:

$$FS(f, u) = OL(f) + N_{mf}(f, u), \tag{3}$$

where $OL(f)$ means the out-link connection of friend f in a social network platform, and $N_{mf}(f,u)$ is the number of mutual friends between user u and friend f. Kiss and Bichler (2008) indicated out-degree centrality performs better in influencer identification. An information seeker in online media follows

other users' information regularly. Thus, a people with a higher out-degree could infer that he/she might be an information seeker so that he/she could give helpful POI appraisal according to preferences, habits, and needs observed from other professionals.

   Crowd Influence: People make decisions not only based on the opinions of their close friend, but also based on the opinions of the general public. If POI is visited or tagged "like" by many people, this POI should be properly interesting to a user who is seeking POI to visit. In this research, we evaluate the general public's opinions in terms of overall check-in counts and numbers of "like" in a POI to measure the crowd influence on a POI. It is formula as follows:

$$CI(p) = w \times \sum_{i=1}^{N} check-ins(i,p) + (1-w) \times \sum_{i=1}^{N} like(i,p) \tag{4}$$

where *check-ins(i,p)* represents the number of user *i* check in at POI *p*, *like(i,p)* denotes the number of like of user *i's* tags on POI *p*, and *N* is the number of participants. *w* is a tuning parameter ranging with [0,1].

   Once we have both internal and external influence calculated, we can obtain the final social influence as the equation below:

$$SI(u,p) = \alpha \times FI(u,p) + (1-\alpha) \times CI(p), \tag{5}$$

where $SI(u,p)$ means the social influence score for the POI from the perspective of user *u*. α is a tuning parameter ranging with [0,1]. We also use min-max normalisation in Formula (6) for both friend and crowd influence before we aggregate them. After the aggregation, we normalise again so that the value will remain between 0 and 1.

$$Norm(v_i) = \frac{V_i - V_{min}}{V_{max} - V_{min}}, \tag{6}$$

where V_i is the value that needs to be normalised, V_i and V_{max} represent the minimum and maximum values of all data respectively.

3.2   Social Supporters Discovering Module

Users visit various kinds of POIs according to their preference. Identifying preference from users is an important marketing skill for finding the target POIs in which users are interested. If people have strong interest in some POI categories, they are likely to have high familiarity with and expertise on the POI categories. The purpose of this analysis is to find a social supporter's preferences and infer the expertise influence of a social supporter. The measurement of this analysis is denoted as the SE score which represents the expertise of a social supporter in some POI categories.

3.2.1   Supporter Candidate Network Constructing

We construct a social supporters' candidate network based on the requester. This module will discover the friends of the requester to expand the network first. Any user who interacted with the requester in the recent three months will be used to expand the network from the requester. The network will expand repeatedly from these users also according to who interacted with them in the same period of time. After expanding, the network constructed from the requester will have a structure with three layers. This network needs shrinking further to be the final candidate network, in order to ensure the trustworthiness of the decision supporters. Thus, the candidate supporters must have visited these POI alternatives before.

3.2.2   Social Support Trust Computing

In order to measure the influential degree of a social supporter to the requester, the degree of trust between the requester and all their social supporters has to be evaluated, since social influence is

associated with trust (Jing and Xie, 2011). Social interaction may stimulate trust and perceived trustworthiness (Tsai and Ghoshail, 1998). Zingler and Golbeck (2007) claims that trust should be derived from user similarity and trust is the basis of social interaction. It would be reasonable to measure trust value by using similarity and interaction. Inspired by the above researches, our work followed similar formulation and proposed social similarity and social interaction to be the replacement of trust value. Therefore, in this sub module, we compute the social similarity (SS) and social interaction (SA) between a typical requester and each of his/her social supporters as the requester's trust value to each of his/her social supporter. The trustworthiness between requester r and his/her supporter s is computed as formula (7).

$$TR(r, s) = SS(r, s) + SA(r, s) \tag{7}$$

An individual's check-ins history in the physical place implies his/her interests or behaviours (Zheng et al., 2009). Accordingly, users who share similar check-ins are likely to have common interests and behaviour. In this research, the similarity between requester r and his/her social supporter s is computed as the numbers of intersection between their checked-in histories. Jaccard index was used here:

$$SS(r, s) = \left| \frac{\Theta_{CI}(s) \cap \Theta_{CI}(r)}{\Theta_{CI}(s) \cup \Theta_{CI}(r)} \right|, \tag{8}$$

where $\Theta_{CI}(r)$ represents the set of total checked-ins of user r.

Besides, the social interaction between requester r and supporter s is measured by activities related to information sharing. For example, on Facebook, friends usually post their own status, share photos or comments on friends' status. Hence, we defined the social interaction as follows:

$$SA(r, s) = \begin{cases} 0 & \text{if } IA(r,s) = 0, \\ \dfrac{IA(r, s)}{\sum\limits_{s=1}^{N} IA(r, s)} & \text{otherwise.} \end{cases} \tag{9}$$

Where $IA(r,s)$ denotes the number of interaction between requester r and supporter s. N is the number of supporters

3.3 Social Expertise Analysis

3.3.1 Domain Expertise Analysis

Expertise characterisation (EC) was devised to measure the relative expertise level of individual members within a decision group. If people have high interest in some POIs, they probably have strong familiarity with and expertise on the POI. To represent the expertise in different levels quantitatively, it is defined based on the number of POIs which belong to the same POI category as the selected POI category of the requester a supporter has visited. Therefore, the normalised expertise level of supporter s can be formulated as:

$$DE(s, p) = \frac{vc(s, p)}{\sum\limits_{i=1}^{N} vc(i, p)} \tag{10}$$

where $vc(s,p)$ is the number of POIs visited by supporters which falls into the same POI category with POI p.

3.3.2 Local Expertise Analysis

With users' locations, we can find the local experts who have richer knowledge about POI than others. Their experiences, e.g., the POIs where they have been, are more accountable and valuable for visiting. For example, local experts are more likely to know about the high-quality restaurants than some

tourists (Zheng et al., 2009) The location data is obtained directly from the user profile recorded in the mobile social network platform to discover the customers who live or have ever lived in the city where the POI is located. The location information of a supporter, such as company address and current city in which they live, can be obtained from their profile. To measure the local expertise degree of the supporter, the company address has to be provided for computation. When the data is missing, the candidate supporters are requested to fill this information when they first join the experiment. Another approach to handle this problem is to define the address as the average position of check-ins with the most check-ins. The local expertise degree of supporter s is represented as $SE(s)= [company(s),city(s)]$. If POI p is located in city $Loc(p)$, the local expertise score for supporter s with respect to POI p is measured as Formula (11).

$$LE(s, p) = \begin{cases} 1 \text{ if } company(s) = Loc(p) \text{ and } city(s) = loc(p) \\ a \text{ if } company(s) = Loc(p) \text{ and } city(s) \neq loc(p) \\ b \text{ if } company(s) \neq Loc(p) \text{ and } city(s) = loc(p) \\ 0 \text{ if } company(s) \neq Loc(p) \text{ and } city(s) \neq loc(p) \end{cases}, \tag{11}$$

where $0 \leq a, b < 1$. In this research, we set $a=b=0.5$. Finally, we combine the domain expertize degree (*DE*) and local expertize degree (*LE*) to evaluate the expertize degree of supporters on a POI. The expertise degree of supporter on POI is formulated as:

$$ED(s, p) = \alpha \times DE(s, p) + (1 - \alpha) \times LE(s, p), \tag{12}$$

where α is a tuning parameter ranging with [0,1].

3.4 POI Candidate Suggestion

3.4.1 SoLoMo Influence Voting

In a traditional majority voting system, all members of the decision group people are treated equally. For example, a decision group with N members votes on whether to suggest a certain POI p. Assume the sum of total voting is 1, and every member can *vote v(i)* (agree/disagree) with (1, 0) . The POI p with the maximal voting value will be suggested.

$$\underset{p \in C(u)}{Max} \sum_{i=1}^{N} \frac{v(i, p)}{N}, \tag{13}$$

In this study, the voting evaluation mechanism was improved by introducing truth and expertise degree of social supporter as the weight of voting. The SoLoMo influence is defined as follows:

$$SoLoMo(r,s,p) = \alpha \times TR(r,s) + (1 - \alpha) \times ED(s, p) \tag{14}$$

where α is a tuning parameter ranging with [0,1]. The consensus weight of the ith support depends on the SoLoMo influence of the member's strength relative to other members of the group. The stronger that member's influence is to other members' influences, the more weight that member is given in defining the group consensus. Thus, the normalized voting power of the ith supporter on POI p is defined by:

$$w(i, p) = \frac{SoLoMo(r,i,p)}{\sum_{s=1}^{N} SoLoMo(r,s,p)}, \tag{15}$$

so the POI p will be recommended if:

$$\sum_{i=1}^{N} v(i, p) \times w(i, p) > 0.5 \tag{16}$$

3.5 Experiment Design

In this section, we describe the experimental processes designed to evaluate the proposed model. The aim of our model is to suggest the most suitable POI for a mobile user to visit. We chose to use one of the most popular social network platforms, Facebook as our data source. Data descriptions of the experiments are outlined in Table 1. Our experiments were conducted using three popular landmarks in Southern Taiwan: the Dream Mall, Love River and Liuohe Tourist Night Market. Each of these locations contains rich data related to the location categories that our model is designed for. All the collection data was divided into entertainment, food, shopping, and recreation categories. To evaluate our model, we also collected social data and context data. Data descriptions of the experiments are shown in Table 1. At first, users are selected at random using the snow ball sampling (Ann et al, 2007), we invited nine users who were willing to authorise us to collect their social information and agreed to provide their check-in history to support the experiments. We request their help in inviting their friends and requesting their friends help to invite friend-of-friends. Finally, after filtering out those users who were not willing to join in our experiment, there were 87 users in the experiment (male 47% and female 53%), 4,465 points of check-in information and 107 unique POIs. A total of 100 decisions for the next POI that the requester should visit are evaluated. A typical decision support request contains five alternatives, and an average of eight decision supporters' reply to a request within their options.

Statistics of the experiment data	
Number of invited participants	87
Age	22-41
Gender	Male:47% Female:53%
Number of check in	4,465
Number of POIs	107
Number of social decision support requests	100
Average number of decision supporters per request	7
Decision alternatives for per request	5

Table 1. Data descriptions of the experiment

Check-in Data Collection: Check-in data is the important resource for preference discovery. In order to collect check-in data, we developed a Facebook application to collect all participants' check-in data once they authorised the application by logging in. Using the Facebook Graph API and FQL (Facebook Query Language) features, we collected a total number of 4,465 check-ins from the 87 participants on Facebook. FQL enables you to use a SQL-style interface to query the data exposed by the Graph API. Each check-in contains the geographical data of the location visited, and the name of the location.

POI Data Collection: The locations collected from the context rating data were also used to form the location data source. Specifically, we selected locations within 1000 meters of the three landmarks chosen for our experiments. Location information includes the POI name, POI category, POI location.

These collected POIs were classified into one of four categories: entertainment, shopping, food, and recreation. Our experimental POI database contained 107 unique POIs that we collected. Originally, before pre-processing we collected 158 locations; however after data cleaning we removed those were located too far from the target landmarks (within 1000 meters of the three landmarks), or received less than 100 "likes". The data is collected during 2014/04/10~2014/08/16.

In the experiments, we asked participants to recall their original decision-making processes and report the POI they visited, and whether the POI visiting decision was satisfactory. The procedures for a requester to solicit decision support from their friend network so as to suggest a suitable POI to visit is detailed as follows.

(1) The support requester initiates a request message with a selected POI category. For example, the requester at Dream Mall selected the Food category.

(2) The agent would automatically generate suitable top-N POI alternatives according to the requester's current location and the POI category the requester selected.

(3) According to the POI alternatives generated, the agent constructs the supporter candidate network, computing the social supporters' trust, and social expertise analysis to discover suitable social supporters for decision.

(4) Those selected social supporters receive the request message and reply opinion.

(5) The agent responds to the results of the decision analysis. The received feedback is consolidated by the proposed mechanism to rank the POI alternatives.

The time interval system setting for supporters to response is thirty minutes. If there is no response, the requester can change the setting under different location zone with different population of current situation.

4   Results and Evaluations

The effectiveness of social decision support is determined by the requester's subjective judgment (Gurung, 2006), the results suggested by the proposed mechanism should be compared with the support requester's self-evaluation. The detailed evaluation rules are listed in Table 2. There are two major evaluation rules to judge the effectiveness of the social support mechanism.

		Requester evaluation	
		Satisfied	Unsatisfied
System suggestion	Visit	RSS	1-WSA
	Not Visit	1-RSS	WSA

Table 2. Evaluation Metrics Table

(1)   Suggest that the requester visit the POI they are satisfied with. If the support requester feels satisfied with the POI and the SASM also suggests visiting it (i.e. it is ranked in the top score by the system), the mark "RSS," which means right social support is made.

$$RSS = \frac{|S \cap R|}{|S|},$$
(16)

where S stands for the set of satisfactory POIs visited and R for the set of POIs suggested for visiting.

(2)   Do not suggest that the user visit a POI they are dissatisfied with. If the support requester feels dissatisfied with the POI and the SASM does not suggest visiting it, a mark "WSA" is given, which means that wrong social support is avoided:

$$WSA = \frac{|\bar{S} - R|}{|\bar{S}|},$$
(17)

where $\bar{S}$ stands for the set of unsatisfactory POI visited. Finally, the overall successful support (noted as accuracy rate) is measured as:

$$SS = \frac{\left|S \cap R\right| + \left|\overline{S} - R\right|}{\left|S\right| + \left|\overline{S}\right|},$$
(18)

We constructed and compared the results of experiments with three decision approaches: the proposed Social Appraisal Support Mechanism (SASM), the majority voting method, the five-star rating method, and the random selection method. The majority voting method was one of the baseline social support methods allowing users to aggregate friends' opinions. In this approach support requesters are asked to issue their social support requests and then decision supporters vote directly for which alternative is most suitable without criteria and evaluations. The five-star rating method is one of the baseline product evaluation methods for gathering the collective opinions of public users. In this approach, decision supporters are requested to reply with their opinions using a five-star scale for each alternative. The random selection method is used to simulate the scenario that there is no social support mechanism. In this approach, participants do not know which POI is the most suitable and choose one to visit randomly. In the experiments, we asked participants to recall their original decision-making processes and report the POI they visited, and whether the POI visiting decision was satisfactory. Each participant is requested to issue 2 decision problems to decision support group, one for majority voting and the other for 5-star weighting. Each experiment last for 3 weeks. When the decision problem was presented to decision support group, members of decision group were asked to vote (first round) or 5-star weighting (second round) on the alternative POIs. Figure 2 indicates that the proposed mechanism is more effective than the other baseline social support methods. The measures "RSS" and "RSA" respectively indicate that the support requester indeed visits the most suitable POI, and that the support requester indeed avoids visiting an unsuitable POI. The result of the two-paired sample t-test is shown in Table 3. At the 95% significant level, all the test results show that the proposed SASM approach significantly outperforms the other approaches.

As we can see, the performance of our proposed SASM is better than that of the other approaches. The SASM, majority voting method, and five-star rating method perform better than the random approach. This finding indicates that soliciting social support from a social network is helpful for supporting requester POI visiting. Second, both the SASM and the majority voting method aim to provide suggestion support for support requesters, but the majority voting method does not consider the relative importance of decision supporters. This finding shows that considering social trust and the degree of social expertise could improve the SASM. Third, the result of the five-star rating method is similar to that of the voting method. According to the visiting purpose, the requester would like to visit the most suitable POI. A decision supporter provides the highest star to POI to indicate that they feel the POI is the most appropriate. Similarly, they will vote for the most suitable POI by using the voting method.
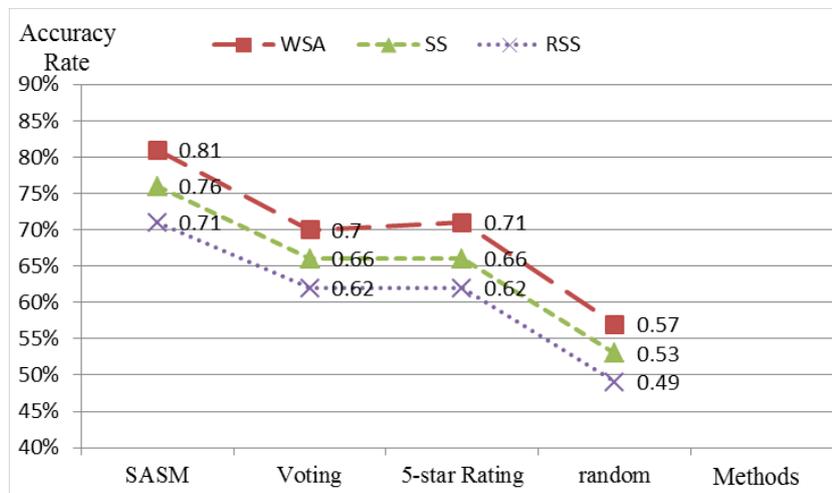
Figure 2 Accuracy rates of different methods

Paired Group		Mean	Std. Deviation	Std. Error Mean	t	Sig. (2-tailed)
SASM V.S.	Voting	0.0801	0.0807526	0.0080352	9.969	0.000
	5-star	0.1001	0.077311	0.0076927	13.012	0.000
	random	0.2401	0.0949157	0.0094445	25.422	0.000

Table 3. Statistical verification of the decision analysis results with different methods

5 Conclusion and Future Works

In this paper, to promoting location-based commerce service, social network analysis skills were used to profile individual users within mobile online social networks. A POI alternative constructing method was also proposed to generate suitable POI alternatives for use in decision-making. From the perspective of system innovation, this research proposes a new social appraisal mechanism to improve the effectiveness of the POI visiting decision-making process. From the perspective of methodology, the proposed framework appropriately considers that the factors of personal preference analysis, social influence analysis, geographic influence, local expertise analysis, and adaptive majority voting successfully introduced decision process theory and social psychology into the development of the LBNS application. This study also extended the concept of decision support system development so as to utilise LBNS platform. From the viewpoint of practice, this study demonstrated a feasible way to develop a social network-based decision support system together with the related techniques for the purpose of POI visiting decision-making. There are several limitations and future studies connected to this thesis. First, we analysed users clicking the "Like" button to determine the user's social information. In the future, a user's comments could be further considered to help determine the user's preference. By using the text mining and semantic analysis techniques, customer preferences can be identified more clearly on social websites. Second, we adopt the concept claims by Zingler and Golbeck (2007) that trust should be derived from user similarity and trust is the basis of social interaction. Hence, it is reasonable to measure trust value by using similarity and interaction. However, this is a simplistic view of truth. We will address this issue to consider more social factors to evaluate the truth. Lastly, from a business point of view there is an increasing essential to infer and act upon information from large-volume media, such as Facebook and Twitter. However, social media is abundance of inaccurate and false information. To ensure the validity of social media data, how to effective deal with the inaccurate and false information is an interesting issue and can be a desirable future study.

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