A M-Learning Content Recommendation Service by Exploiting Mobile Social Interactions

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Abstract—With the rapid development of the Internet and the popularization of mobile devices, participating in a mobile community becomes a part of daily life. This study aims the influence impact of social interactions on mobile learning communities. With m-learning content recommendation services developed from mobile devices and mobile network techniques, learners can generate the learning stickiness by active participation and two-way interaction within a mobile learning community. Individual learning content is able to be recommended according to the behavioral characteristics of the response message of individual learners in the community, and other browsers not of this community are attracted to participate in the learning content with the proposed recommendation service. Finally, as the degree of devotion to the community and learning time increases, the learners' willingness to continue learning increases. The experiment results and analysis show that individualized learning content recommendation results in better learning effect. In addition, the proposed service proved that the experiment results can be easily extended to handle the recommended learning content for learners' time-varying interests.

Index Terms—M-learning, content recommendation service, mobile social community, social interactions

1 Introduction

With increasing computer and network technologies, social network sites (SNSs), such as Facebook, and Plurk, Twitter, become an online virtual community formed by a group of people with the same interests and activities, where users can intercommunicate using the network. Many SNSs provide multiple interactive modes for users, such as chat, messaging, video and file sharing, blogs, discussion groups, etc. [1], [2], [3]. According to statistical data, people now spend more than 20 minutes on Facebook on average per day. The situation illustrates the usage rate of SNSs is very high. Therefore, as styles of learning and education gradually evolve, SNSs have entered educational circles, where they have become popular. At present, the learning behaviors developed from SNSs shows three main trends: (1) information discovery is changing; (2) how we share is changing; (3) social sites have become social webs.

"Information discovery is changing", meaning a learner's friend can instantly and actively assist in searching and solving the problems of the learner. For example, when a question is raised in Facebook, anyone who sees the message can instantly reply. Therefore, the traditional learning behavior pattern of searching for answers on the Internet or in books is changing [4].

"How we share is changing", means that when a learner wants to share important information with others, they need not send individual e-mails as in the past. The information can be shared easily and rapidly with the energy of a virtual learning community, thus, more high social energies can be shared. For example, when releasing new homework, using the sharing function will transfer information to all learners of the same virtual learning community [10].

"Social sites to social web", means that a learner can use SNSs to view which websites other learners have browsed. For example, when a new theme is issued to a SNS, and the friends of a learner browsed this theme, the learner can learn of the new theme from real-time dynamic messaging. Consequently, more learners of this learning community enter the learning website of this theme, thus, promoting interaction between students and learning websites [11].

In a SNS, friends may have a common interest, work environment, or come from the same school, any slight relevancy can be a reason for making friends in a network. Therefore, a normal phenomenon in SNSs is that a user can have hundreds of friends or friend links, as it is easier to build friend links in a virtual network than in real life [12], [13], [30], [31]. However, such virtual learning communities, with massive amounts of information create huge data volumes everyday, as learners must occasionally spend extra time finding information regarding their interests.

Regarding of mobile social interaction, it refers to learners could share information and content each other to build social relationships [43]. Learners interests and favors could be analyzed by characteristics of shared content and information. The information with reference value is able to be used for learning services to recommend content to learners accurately. In the recent years, various mobile social interaction technologies were adopted to connect learners, content

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and resources to create context-rich learning environments, and novel learning services were designed that lead learners could share personal data and knowledge to achieve collaborative learning activities, even recommend learning partners to learners with the same interests [5], [6], [50]. In that case, most previous studies placed emphasis on collaborative recommendations for information regarding interests or preferences similar to that of other learners via learners social interactions [7], [8], [9], [14]. While the recommended items found by such a method have high isomorphism with the original preferences of the learner, three factors are neglected: 1) the learner is more curious about friends items of interest than the items recommended by the recommender system; 2) the learner will change interests and preferences with time and learning environment changes; 3) the learner's latent learning direction and interest are initiated as popular subjects rise.

Therefore, this study does not place emphasis on using similarity as a unique consideration in complex interpersonal networks with numerous target users, but focuses on multi-aspect social network analysis to determine friends with highly correlated interests with the target users, taken from great friend links. Such recommended items are no longer limited to similar users, but to recommend the interesting items to target users from other non-similar in interpersonal networks through social interactions. Such a recommendation mode better enables target users to receive more diversified knowledge sharing through interpersonal networks.

2 Background and Theory-Guided Research

2.1 Activity Theory—Situated Learning Theory

Situated learning is a learning style proposed by Prof. Jean Lave of the University of California, Berkeley, and independent researcher Etienne Wenger [24]. According to the situated learning theory, learning is not only a psychological process of individual meaning construction, but also a social, practical, and different resource mediated participation process [25], [26]. The meaning of knowledge and the learners' own consciousness and roles are derived from interactions between learners and learning situations. Therefore, the creation of a learning situation aims to regress the learners' status and role consciousness, life experience and cognitive tasks to overcome lacks of traditional school learning [27], [28].

According to the situated cognition theory, the meaning of situated teaching is that a teacher can design diversified teaching situations according to the different learning characteristics of learners, and intellectual and perceptual knowledge learning is obtained by participating in learning [19], [20], [49]. In other words, situated teaching centers on learners, where the learners are in the teaching situation, and participate in mobile learning, exploration, and feedback. The purpose is to allow learners interact in diverse environments, and adapt themselves to develop and build their own knowledge meaningfully [47]. In short, the concept of situated learning is to receive learning in actual or simulated situations, where students can apply the learned knowledge more efficiently to real life through interactions between learners and situations. The situated learning theory has three teaching styles: cognitive apprenticeship, learning community, and anchored instruction [21], [22], [23]. The teaching style adopted in this study is learning community, which is a sort of cultural situation. In this situation, each individual not only actively studies, but also bears responsibility for their learning, and the collective learning of all, through the mutual support of interpersonal interactions. The learning community has the following basic elements:

1) The teaching situation must be based on actual tasks; thereby, students can create connections between abstract scientific concepts and application in real world.
2) The students must develop the interdependence of group cooperation in order to promote interdependence by idea sharing, discussions, and disputation.
3) The students and teachers must discuss and negotiate mutual ideas and comprehension.
4) The students and teachers must share ideas and thoughts in public in order to assist the students to explore and correct their concepts and comprehension.
5) The students must cooperate with experts outside classroom.
6) To jointly bear the responsibility of learning and teaching, all members (including teachers and students) must actively participate in "teaching" and "learning" activities.

2.2 Social Presence—Mobile Social Community

There are many definitions of traditional communities. Stern et al. indicated "the community is a place where people build relationships; it is a dynamic, continuous, and non-rigid construction process" [15]. Teng et al. thought "The community is a social organism formed based on free will, such as emotion, habit, memory, mentality, or consanguinity" [32]. Gray briefly indicated "the community is the assembly of a group of people". The opinions of most scholars on community are sorted to be brief, a community is "a group of people assembled for mutual exchange of interest in a specific region. The members of this group trust each other, and have the sense of belonging and identity" [33]. Redfern and Naughton indicated that the nature of community could be divided into Geographical Community and Relation-related Community. The Geographical Community refers to the population established in the same region. The Relation-related Community is built on intangible qualities of interpersonal relationships, interests, or ambitions, and is free from the restriction of geographic area [34]. However, with the development of the Internet and breached time and space limits, the Internet connects virtual community emerges accordingly. Garrett and Ryan defined virtual community as "an interactive space built on the Internet by a group of community members aiming at common and specific subjects". The nature of a virtual community is relatively similar to the aforesaid Relation-related Community; they have the natures of interaction, sharing, exchange, and sense of belonging. The only difference is that they can contact other members without in-person contact [35]. The concept of a mobile community is integrated with the element of mobile equipment, further enhancing the convenience of community communication. Prykop and Heitmann indicated "the Mobile Community is formed of independent regional groups, it is held by clear common interest, and social interaction is undertaken through mobile channels" [36]. Although a mobile community is regarded as an extension of a virtual community, there are actually some differences between them:

1) A mobile community can be undertaken by mobile equipment: the mobile community provides service via various mobile hand-held devices. In short, the interface of mobile community extends from computer to mobile hand-held devices [37], [38].
2) The mobile community can provide new communication services based on the application of a mobile network: Beale and Lonsdale indicated that, due to the characteristics of mobile technology, Mobile Community service can provide some communication services that cannot be implemented in a network. For example, the users are provided with real-time information of their area [39].
3) The mobile community and virtual community have different operating modes: compared with a virtual community, the interaction among mobile community members is subtler. Although they have not met each other in-person, their interactive relationship can be deepened by the characteristics of mobile equipments. Prykop and Heitmann thought that mobile equipment has four characteristics, including location awareness, ubiquity, identification, and immediacy [36].

2.3 Constructivism—Personal Learning Content

As e-learning is learner-oriented, personal learning content has been an inevitable development trend [48]. We can find that many m-Learning integrated application platforms, including Learning Management System (LMS), have tried to integrate personal elements into systems. However, most current e-learning systems lay particular stress on learning content production, storage, management, delivery, and presentation, as well as on the personal management functions of learner data, class authorization, and learning progress tracking. Learners' learning behavior benefit analysis is lacking here.

If all e-learning materials (including authentication, attribute, and category data) and learner data (including basic data, learning courses, and course benefit) can be built in a unified database, we can use data mining technology for statistical analysis of the massive learning behavior information according to the model of personal service recommender system [40], [41], [42].

After extensive learner behavior analysis, the recommender system can recommend teaching materials and courses meeting the personal needs of learners. Personalized recommendations recommend teaching materials and courses meeting the learners' needs according to preference, and learning benefits according to the group similar learners' needs, common interests, and common experiences. Based on long-term behavior data accumulation, personalized recommendation will become increasingly accurate. On the other hand, in the research area of e-learning, how to increase the reusability of different forms of learning resources (e.g., webpage, learning object, video animation, etc.) is very important .

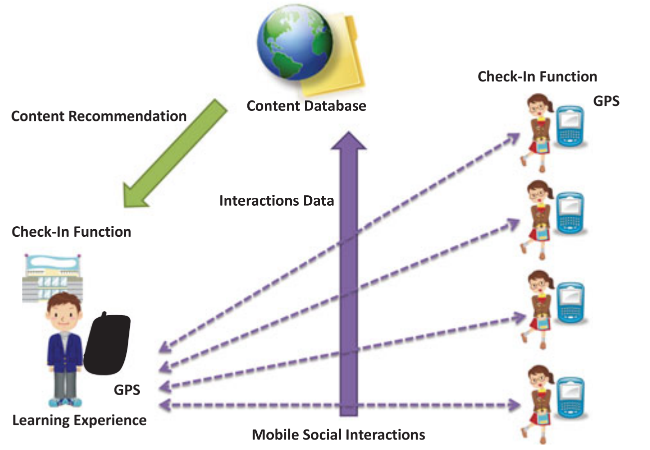

Fig. 1. Architecture of M-learning content recommendation service.

3 Service Design and Architecture

In order to attain the purpose of research, this study developed a set of m-learning content recommendation services by exploiting mobile social interactions. The entire M-learning content recommendation service contains a mobile learning community function, GPS function, mobile network function, and punch function, as well as a student database, learning object database, and learning process database. Fig. 1 shows the architecture of m-learning content recommendation service.

In a learning environment, a learner uses a mobile carrier to observe learning objects in a real-time environment and punches the learning point, uses the photo or file upload function in the service system to upload the data of the learning object to the system, and uses the mobile learning community function to release posted messages to the learner's friends, thus, interesting the learner's friends in viewing the data of the learning object. This service system displays different dynamic prompts according to the degree of interaction between the learner and friends. For example, if the interactive relationship has high correlation, any action in the community will be reported by the system, such as releasing a learning object, liking a learning subject, giving an opinion on a learning subject, etc. The knowledge is automatically organized and constructed by the observations and interactions between the learner and mobile learning community friends, thus, assisting in initiating the learner's interest in learning, while personal knowledge is gradually constructed. Thus, the learner can rethink existing knowledge, while observing the interactions of the mobile learning community. In the course of observation, the constructed knowledge varies due to the different learning effects of learners.

3.1 Infrastructure for Mobile Social Interactions

The rapid development of the Internet means there are numerous open resources, which present another discussed subject, namely, the "Information Overload" of the Internet. People search for required resources in a network with the assistance of search engines. Compared with search engines, the recommender system actively provides learners with required information. The recommender system can recommend potential information, services, or products required by learners, and according to learners' interests, preferences, behaviors, or other needs [16], [17], [18]. The computing process of a recommender system is divided into three major phases, as follows: 1) To extract learners' profile, e.g., interests, purchase lists, bookmarks, favorites, preferences, etc. 2) The collected learner information is analyzed and appropriate recommended items are generated, e.g., similarity calculation. 3) To appropriately modify the recommender system according to the learners' satisfaction with recommended information. The extraction of a learner's profile can be classified into two modes:

(1) *Active mode*. The learner actively provides personal information, or the system requires the learner to provide personal preference information directly to the system for calculation. For example, Huang et al. required a social learner to score Trust in friends, and set the recommender system to recommend higher trust in a collection of friends to the learner [44]. Although the active data acquisition mode can obtain accurate analytic information directly from the learner, the fact that it requires the learner to provide information is likely to cause discomfort for the learner;

(2) *Passive mode*. The required analytic information is collected from the learner's behavior. For example, probable learning content of the future are recommended according to the historical mobile social interactions of the learner [45], [46]. However, the purpose of this study is to seek multiple recommended content, as based on factors other than similarity. Therefore, in addition to the similarity calculation, this study uses various indices to evaluate the degree of correlation between each learner and a target learner, and seeks the learning content of other learners highly correlated with the target learner in the interpersonal network extended from the target learner. Afterwards, the recommendation is calculated according to the recent interest of the target learner and the learning content.

This study is divided into two phases: (1) social network strength analysis of target learner; (2) to determine the learning content of the recent preferences of the target learner considering time factors.

3.1.1 Mobile Learning Community Strength Analysis Phase

The score of correlation between target learner and each learner is calculated. The recommender system mostly uses titles or learning content for similarity calculation to determine similar learners in the past; whereas, the number of common friends in the existing community platform of Facebook or Twitter becomes a base of recommended friends in social networks. Therefore, this study adopts this concept in order to discover the person or favorite learning content, which is probably dissimilar to the target learner, but interesting to the target learner. The consideration of popularity evaluates the value of following the learner. If popularity is high, likely meaning the learner is a famous person or the

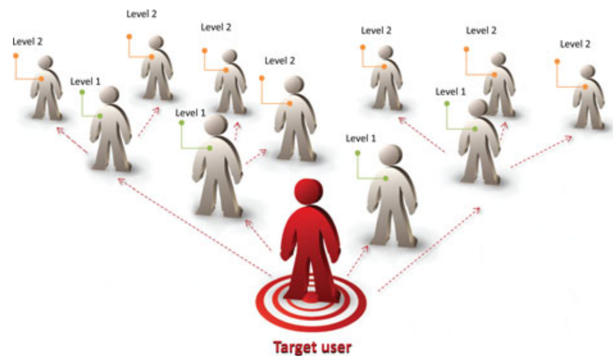

Fig. 2. Concept of mobile learning community strength analysis.

learner's learning content can interest numerous people, this person is likely followed by multiple learners. Fig. 2 shows the concept of mobile learning community strength analysis and the index equations of (1) to (3) are, as follows:

$$ELCS(\alpha,\beta) = \sum_{l\in L} \frac{F_{\alpha,l} * F_{\beta,l}}{\sqrt{F_{\alpha,l}^2} * \sqrt{F_{\beta,l}^2}}, \quad (1)$$

l:Specific M-Learning Content

L:Set of M-Learning Content

$F_{\alpha,l}$:M-Learning Frequency of Learner α to Learned Content l

$F_{\beta,l}$:M-Learning Frequency of Learner β to Learned Content l

$$Common\ Friend = \frac{Number\ of\ Common\ Friends}{Number\ of\ Target\ Learner\ Friends} \quad (2)$$

$$Popularity = Number\ of\ Target\ Learner's\ Followers. \quad (3)$$

The various index values in Eqs. (1)-(3) are derived from the data of different references. Eq. (1) is used to calculate m-learning content-based similarity, Eq. (2) is the measurement mode for number of common friends, and Eq. (3) is designed as the popularity measurement mode. In order to calculate the weights of the various values, and to avoid a too large or too small eigenvalue influencing overall data accuracy, the normalization calculation of Eq. (4) is conducted to make the various attribute values fall within [0, 1]. The computing mode is that each index minus minimum value of the index is divided by the maximum minus minimum value of the index. Weights are divided into three parts by the M-learning content-based similarity, mobile social interactions (number of common friends, number of friends' responses) and popularity. Finally, the normalized index is given different weights, according to Eq. (5), to determine the final score, and the interpersonal network of higher correlation with the target learner is sorted after ordering:

$$X'(i) = \frac{X(i) - Min(X(i))}{Max(X(i)) - Min(X(i))}, \quad (4)$$

$X'(i)$: Normalized Attribute

$$\begin{aligned} &RelevanceScore \\ &\quad = (Weights * ELCS(\alpha, \beta)) + (Weights * Common\ Friend) \\ &\qquad + (Weights * Mutual\ Follow) + (Weights * Popularity). \end{aligned} \tag{5}$$

The social network strength relevancy score computing mode consists of Steps 1 to 3: Step1, Eqs. (1) and (3) are implemented to evaluate the network strength of various learners and target learner. Step 2, the value obtained from Step 1 is normalized by Eq. (4). Step 3, the normalized value is substituted in Eq. (5) to calculate total score.

3.1.2 Build Interest Profiles According to the Recommendation of the Target Learner: Strengthen Recent Interest

Learners may have different preferences for learning in different periods. Considering the accuracy of a recommender system, this study determines recently preferred learning content, according to the learning situation of learners in the recent period. Marked frequency and time weights are considered in this phase. The frequency of using the learning content of a learner can be regarded as a preference for the content. The higher the frequency, the higher the preference of learners for the learning content. The closer the time point of using the learning content to the present, the higher the time weight, and the farther the time point of using the learning content to the present, the lower the time weight, according to equations (6) and (7). Finally, the two indices of Eqs. (6) and (7) are integrated to determine the preference score (PS) of learners for each learning content in a specific period, as expressed in Eq. (8):

$$\begin{aligned} &Time\ Weight \\ &\quad = 1 - \frac{Number\ of\ Days\ to\ Learn\ Content\ Until\ Now}{Number\ of\ Observation\ Days}, \end{aligned} \tag{6}$$

$$Frequency = \frac{Frequency\ of\ Using\ Content\ in\ the\ Day}{Frequency\ of\ Using\ All\ Content\ in\ a\ Period} \tag{7}$$

$$Content\ Preference\ Score = \sum (Time\ Weight * Frequency). \tag{8}$$

3.1.3 Calculate M-Learning Content Recommendation Weight

The concept of social network analysis is evaluating the impact of independent nodes among the network and discovering the social interaction between the users. In this concept, the trend can be found that the social network analysis is able to be adopted to evaluate the quantitative indicators of interpersonal interaction, whereby potential interactions or potential friends can be discovered. Anyhow, the three basic elements should be considered in social networks. One is $Node$ that represents Actor in the communities, two is $Relationship$ that means connection between Actors and Tie is the behavior strength between Actors. Therefore, naive Bayes classifier was adopted for mobile social interactions analysis. To apply the naive Bayes classifier to the recommendation process of the target learner m, the content is referred to the class m-learning content and all of the learned content in the candidate tag model for learner m, $CCM_w(m) = c_1, c_2, \ldots, c_w$, are used as features. Suppose that there are n class m-learning content, $\text{E} = e_1, e_2, \ldots, e_n$. Given a learned content instance c_j in $CCM_w(m)$ as a set of feature variables, the classifier predicts that $CCM_w(m)$ belongs to the class item having the highest posterior probability conditioned on $CCM_w(m)$. We make a similar naive Bayes assumption that the tags are independent given the items. The posterior probability, as a preference probability $P_{m,k}$ of user m with $CCM_w(m)$ for content e_k is obtained.

Fig. 3. Network and device aware Bayesian network.

The target learner's recent preference tag weight and social network RS are considered, the influence is the RS of the learner having a collection the target learner wants, as expressed by Eq. (9). A higher score represents stronger influence, namely, this item is more probable to be learned by the target learner, and the content preference score of the target learner of this item represents a recent preference of the target learner for the learning content:

$$P_{m,k} = P(e_y | CCM_w(m)). \tag{9}$$

3.2 Mobile Community Learning System Interface

The main menu of this system contains punch and learn, recommended learning, learning process, mobile edition, and login. The learners use portable learning tools, a 3G wireless network, and the punch characteristic of a Mobile Community. The form features are as shown in Figs. 3, 4, and 5.

4 Experimental Results

In order to validate the reference value of the m-learning content recommendation service, as proposed in this study, this experiment randomly selected 60 primary school students as target learners. The total number of Level 1 friends of these learners is 587 through the numbers of mobile social interactions, and the maximum RS with target learners is

Fig. 4. Network and device aware Bayesian network.

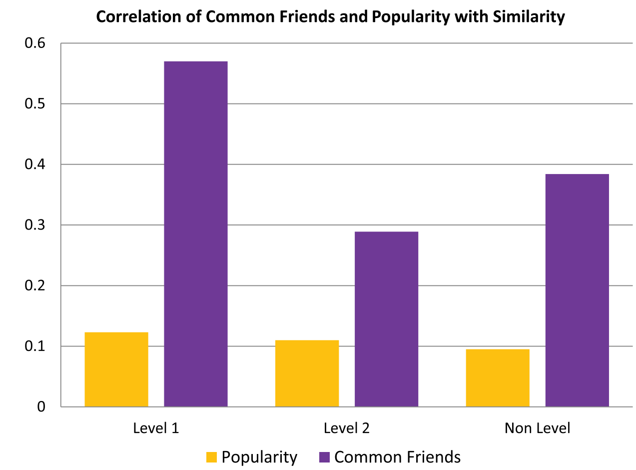

Fig. 6. Correlations of common friends and popularity with similarity.

determined from the 587 persons. Therefore, there are 53 persons of Level 1 extending to higher correlation level (Level 2). There are 2,521 persons at Level 2. The total number of persons of the two levels is 3,108. The following statistical validation is conducted:

1) Statistical analysis results of common friends, popularity, and similarity.

The popularity recommendation is a constantly used recommendation mode, thus, the indices proposed in this study are compared with the popularity recommendation. As shown in Fig. 6, according to the comparison between various levels and non level, the number of common friends is higher correlation is with similarity, rather than popularity. In addition, Fig. 7 shows that two learners following each other have higher similarity, as compared with one-way following.

2) Statistical analysis results of number of target learners' friends and common friends

As shown in Fig. 8, according to the validation of relevance between the number of friends and the number of common friends of 60 learners; when the learners have a larger number of friends, the number of common friends is larger, and the correlation coefficient is 0.602. Fig. 9 shows another case, the larger the number of friends (Level 2) of Level 1 friends of learners, the larger the number of common friends with target learners, and the correlation coefficient is 0.682.

3) Analysis of keywords in recommended content results.

This study evaluates the recommendations for 60 target learners. The first stage of the experiment is presently conducted, the recommendation mode selects one person with a maximum RS from the Level 2 following of the target learners, and the recently recommended learning content is recommended to the target learners.

There are three evaluation modes: (1) to check whether the owner of the learning content to be recommended is already followed by target learners; (2) to check whether the keywords in the learning content to be recommended overlap the first 10 items of frequent learning content or recently used 19 items of the learning content of the target learners; (3) to check whether the keywords in the learning content to be recommended overlap the keywords in recent learning content of the target learners. According to the aforesaid three areas of evaluation comparison from among the 60 target learners, eight persons meet the matching mode (1); four persons meet the matching mode (2); two person meets the matching mode (3); the results show that only three persons have no keyword or content overlap with target learners in such a recommendation mode.

4) Analysis results of content instance selections.

Regarding of content selections, the target learners posts the preferred course instances to his friends through the recommendation service, and the interactions are

Fig. 5. Network and device aware Bayesian network.

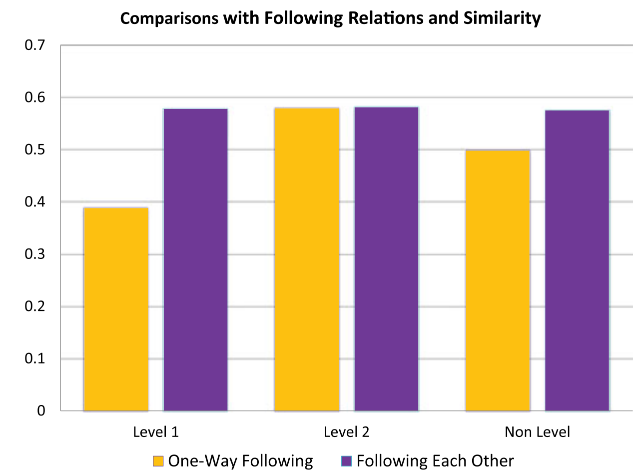

Fig. 7. Comparisons with following relations and similarity.

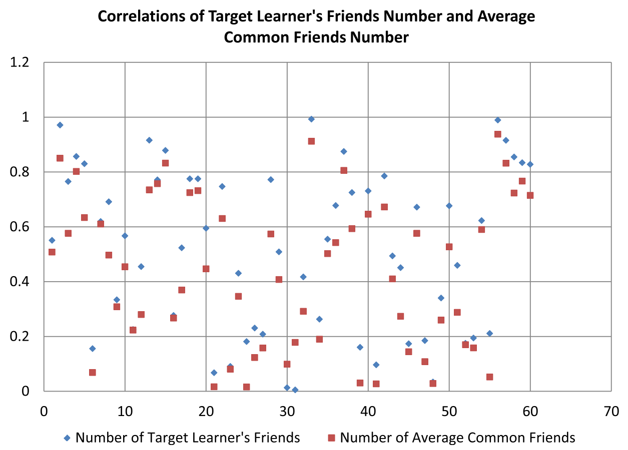

Fig. 8. Correlations of target learner's friends number and average common friends number.

recorded by system once his friends click the content sharing message. The response results collected in this study are shown in Fig. 10. For the specific content instance, the content attract more responses from the Level 1 friends in the beginning stage. It means the level 1 friends are able to sense the novel content posted in the communities immediately. However, the response times of the level 1 friends is limited by the target learner's friends amount, and the response times of level 2 friends arise substantially through the diffusion of the level 1 friends' responses. Furthermore, in Fig. 11, [44] is refereed to compare with the proposed service. In the second part, the learners are able to get the recommended content by social learning networks. All issues the learners can learn only depend on what their friends provide. The condition maybe trends the issues fall in the limited learning areas through a few incentives. And the first part shows that content instance selection proportion that the learners select; the recommendation service provide the content instance lists from their friends and popularity issues to the learners, more than half the content instance selections are from level 1 friends, and 13 percent are referred to the popularity issues that aren't followed by their friends.

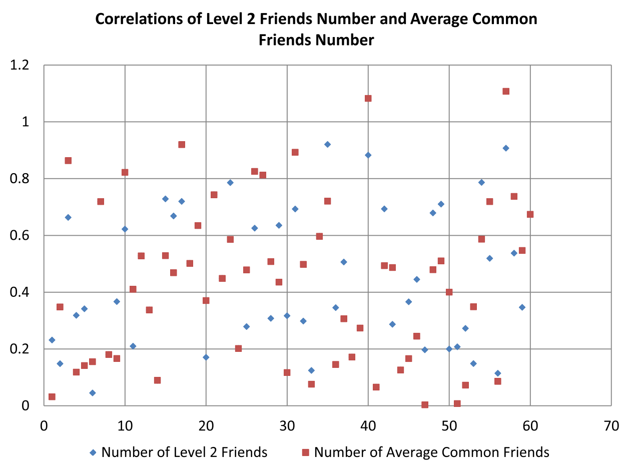

Fig. 9. Correlations of Level 2 friends number and average common friends number.

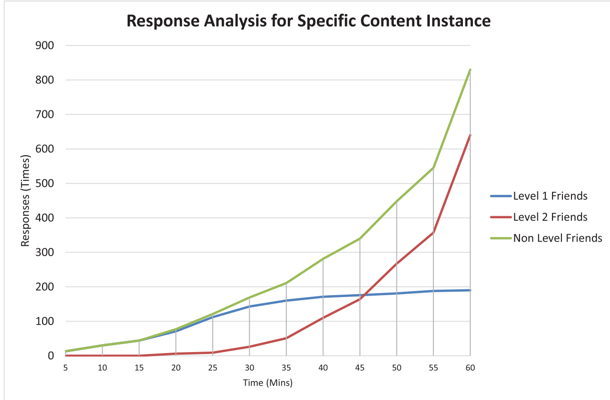

Fig. 10. Response analysis for specific content instance.

5 Conclusions and Future Work

Web 2.0 implements the existence and collective creation of virtual social networks. The platform value of a virtual community is completely co-produced and created by the members, which phenomenon meets service dominant logic, and place emphasis on co-producing and co-creating value during the recommendation learning content service delivery process. Individual learning content is recommended according to the behavioral characteristics of the response message of individual learners in the mobile social community, and other browsers not of this community are attracted to participate in the learning content. In addition, the functions of a mobile social network can be divided into two types, social support, and a reference function. The social support refers to the members' physiological, psychological, tools, or material assistance to others, which allows individuals to respond to pressure and adapt to the environment. In terms of three mobile social networks, the friendship network has the strongest social support. On the contrary, the reference function means the members obtain messages, resources, and knowledge from a mobile social network. The reference function is especially applicable to information and advice networks, due to consultation, emotion, and information.

The aforesaid analytical data can validate several findings in a mobile social interactions: (1) the number of common friends is positively related to similarity; (2) the larger the number of friends, the larger the number of common friends; (3) recent learning content is recommended according to the RS proposed in this study, there are 73.3 percent (40 of 60 persons) having interest overlap with target

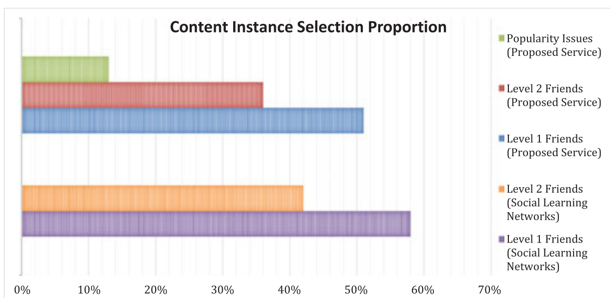

Fig. 11. Content instance selection proportion.

learners. Compared with previous similarity calculation-based learning content recommendation services, the aforesaid findings have the following advantages: (1) if the target learners have not learned any content, they still have recommended items according to the social network score; (2) the number of common friends and followers can be used as filter indices of the recommendation service. The larger the number of friends, the larger the reference value of the number of common friends; (3) recent interest recommendation meets the learners' needs.

This study has the following research limitations and suggestions, as the learners of the mobile social community are of various age-brackets, this study adopted convenience sampling, there may be biased error in inference. Therefore, in order to increase the representativeness of samples, the number of samples, and the diversity of sample sources, shall be increased. In addition, there is a substantial difference between a mobile social community and a traditional community, there is a group in the network world. They only browse the content provided by other community members, and seldom or never participate in community activities. They merely browse webpages as spectators, and probably do not contribute to the co-production process of the network. Second, mobile social networks have more than one purpose in general, thus, it is difficult to distinguish the exact purposes, and findings are not always applicable to explain all types of virtual communities. It is suggested to finely and precisely classify the question items developed. Later scholars can use structured and quantitative social network analysis, actual quantitative data and qualitative interviews, matrices, and graphs to present the results in order that the relationships among learners of a mobile social community are closer to practical situations. Besides being a social network, the ties can influence the interactions and behaviors of learners. According to the strength of weak ties of sociologist, a weak tie can transfer messages between two groups, and provide people with resources outside their life circle. A strong tie connects two groups with the same characteristic, provides emotional support and social integration, and transfers important information, thus, it is likely to form a closed cluster relationship. Therefore, a weak tie is more effective than a strong tie on information transfer. Future studies can conduct further discussions.

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