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A Social Approach to High-level Context Generation for Supporting Context-aware M-Learning

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ABSTRACT

In m-learning environments, context-awareness is for wide use where learners' situations are varied, dynamic and unpredictable. We are facing the challenge of requirements of both generality and depth in generating and processing high-level context. In this paper, we present a social approach which exploits social dynamics and social computing for generating high-level context. It is a novel and generic paradigm where the crowds of learners in m-learning environments directly engage in creating contents about high-level context and interactions by social tagging, and these contents and interactions are further explored to discover more implicit and complex high-level contextual information. We present the concept model, the context representation, the context matrix, and the context retrieval method. We evaluate our approach by a social simulation based experiment. The experimental results demonstrate that the context retrieval performance is improved in both the accuracy and the diversity, and validate that the proposed social approach is effective for generating high-level context.

Keywords: mobile learning, context-aware, personalized recommendation, social computing, social tagging

INTRODUCTION

With the increased availability of mobile Internet and the wide use of mobile devices, mobile learning (m-learning) is becoming the future developmental trend in the field of education (Sun & Chang, 2016). Context aware m-learning applications can exploit significant contextual information to capture dynamic nature of the learner's needs and then provide more optimized and personalized items, increasing user satisfaction and facilitating learning achievement (Abech, da Costa, Barbosa, Rigo, & da Rosa Righi, 2016). Context can be divided

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State of the literature

- Context-aware m-learning applications are able to adapt their behaviors to the changing situation with a minimum of human interventions, it is becoming the future developmental trend in the field of education.
- Applying context-aware middleware can free developers from the concern of managing context, and allow them to focus on designing desired application functions and business logic, so it has been the main stream in context aware application.
- How to exploit high-level context information and patterns has become a crucial factor in context-aware middleware. However, current approaches cannot satisfy the need for more general solutions in both generality and depth for wide use of context-aware m-learning applications.

Contribution of this paper to the literature

- We present a social approach which exploits social dynamics and social computing for generating high-level context in m-learning environments.
- We develop a novel social model for generating high-level context which is capable of dynamically defining, retrieving and refining high-level context in terms of sensor data by the crowds of learners.
- We construct a high-level context retrieval technique which comprehensively considers participants social ability, steadiness and relevance of association between low-level context and high-level context. A social simulation based experiment validates the effectiveness of our approach both in accuracy and diversity.

into low-level context and high-level context (Hong, Suh, & Kim, 2009). The former is from external sensors and devices; the latter is the information about users' goals, emotions, activities, etc. Stimulated by the technological evolution, more low-level contextual becomes available through a variety of new sensors in mobile devices. Nevertheless, the high-level context usually could not be directly obtained from these sensors/devices. There is still a major gap that separates the data provided by sensing devices and the high-level contextual interpretation required for m-learning (Martin, Lamsfus, & Alzua-Sorzabal, 2016). To recognize and generate high-level contextual information, statistical, syntactic, and description-based approaches are proposed respectively (Ryoo & Aggarwal, 2009). In most current approaches, high-level context is usually inferred or recognized through predefined models, rules or logics which are provided by a small group of experts (called as expert-predefined approach). As to main drawbacks, these approaches require a complete definition of all possible context dimensions and values, as well as rules and logics of interpreting high-level context in advance. This results in the fact that such approaches are only applied to predictable certain domains and ad-hoc applications. However, in m-learning environments, learners need adaptive and personalized learning objects/services where their situations are varied and dynamic. We are facing unpredictable scenario, expert-predefined approaches involve the following problems:

- For high-level context definition, expert-predefined approaches could not deal well with unpredictable context dimensions and their values of diverse and dynamic context in m-learning environments, for experts can only predefine limited dimensions and values.
- For high-level context obtaining, expert-predefined approaches could not discover lots of implicit and complex high-level context which is not considered in advance. However, the fact is that there are many unpredictable situations in m-learning environments.
- For high-level context management, expert-predefined approaches not only have great difficulty to cope with the change and uncertainty at run-time, but also are unable to adapt to the requirements of adaptive organization and management of massive diverse and dynamic high-level context in m-learning environments.

Consequently, there is a strong need for more general solutions, ready for wide use for developing context-aware m-learning applications. In this paper, we propose a social approach to high-level context generation for supporting context-aware m-learning. Main idea of the proposed approach is to encourage the crowds of learners in m-learning environments to create more contents about high-level context and interactions, and further use these contents and interactions to obtain more new high-level contextual information by social computing. Specifically, we make the following contributions:

- We develop a novel social model for generating high-level context in m-learning environments. The social model is capable of dynamically defining, retrieving and refining high-level context in terms of sensor data, which is contributed by learners.
- We construct a high-level context retrieval technique which comprehensively considers participants social ability, steadiness and relevance of association between low-level context and high-level context.
- We design and implement a social simulation based experiment to evaluate our proposed approach and models. The results validate the effectiveness of our approach.

LITERATURES REVIEW

Many researchers have developed varying contents for learning through context-aware method (Chiang, Zhu, Wang, Cui, & Cai, 2016). Context-aware m-learning applications are able to adapt their behaviors to the changing situation with a minimum of human interventions. In general, three typical approaches have been of much value to developing context-aware applications (Hu, Indulska, & Robinson, 2008):(1) Each application interacts, obtains, processes and uses the context in its own manner; (2) Some libraries/toolkits are added and reused for building context-aware applications; (3) Applications are built upon context-aware middleware. Applying context-aware middleware can free developers from the concern of managing context, and allow them to focus on designing desired application functions and business logic, so the third approach outperforms the other two. In the early stage, the majority of middleware architectures, such as NAMA (Kwon, Choi, & Park, 2005) and SOCAM (Gu, Pung, & Zhang, 2005), adopt a centralized approach and focused on processing individual context. In recent years, many technologies have made breakthroughs, such as Cloud Computing, Big Data Analytics and Social Computing. Some context middleware, such as CoCaMAAL (Forkan, Khalil, & Tari, 2014) achieve multiple benefits from cloud. Social context-aware middleware is proposed to offer social tie inference and group detection services (Liang & Cao, 2015).

To improve the awareness and smartness of context-aware middleware, how to exploit high-level context information and patterns has become a crucial factor. Undoubtedly, ontology has dominated the landscape of abstracting and inferring high-level context(Li, Eckert, Martinez, & Rubio, 2015). As a description-based approach, context ontologies and their properties as well as ontological rules have to be defined and provided in advance by a small group of experts. To overcome these shortcomings, some efforts have been made to extend the ways to providing and defining high-level context. One way is to investigate the use of ‘‘freely-available’’ information, such as query results of Google (Perkowitz, Philipose, Fishkin, & Patterson, 2004) and social media data (Zhu, Blanke, & Tröster, 2016). In these works, supervised machine learning methods are usually employed, which means that some classes (e.g. activity taxonomy, emotion state, etc.) have to be predefined. As the result, the generality of context-aware applications is limited. Another way is to encourage end-users to directly provide and define high-level context or involve in context development, such as Social Context-Aware Browser (Mizzaro & Vassena, 2011) and the CP360 system (Raychoudhury, Shrivastav, Sandha, & Cao, 2015). In these works, end-users directly and explicitly participate in developing or defining context, which means that more complex and implicit high-level context information is not exploited adequately. As the result, the depth of context representations is limited. Consequently, there is still a need for more general solutions satisfying in both the generality of applications and the depth of context representations. Our work is focused on such general solutions.

SOCIAL APPROACH TO HIGH-LEVEL CONTEXT GENERATION

Concept model

The proposed social approach brings a fundamental change in providers and ways of interpreting high-level context. It is built on the social dynamics of social media, and is to exploit social computation to increase context generation effectiveness. In proposed social approach, learners are encouraged to provide and define the high-level context to interpret the data from sensed devices, so a simple way is needed to provide users to facilitate their participations. Social tagging provides users equal rights to freely assign arbitrary keywords (i.e., tags) to various resources, in which users, resources and tags are connected together by tagging or post actions (Pan, He, Zhu, & Fu, 2016). If we take the low-level context and the

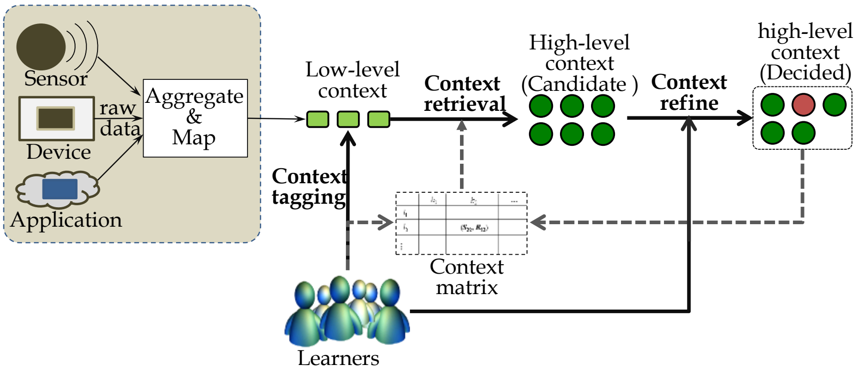

Figure 1. Concept model for social approach generating high-level context

high-level context as resources and tags respectively, the tagging actions done by learners is just similar to generating new information (i.e. tags) about the low-level context. So social tagging is introduced into context-aware m-learning application to generate high-context which is important for personalized objects/services delivery in m-learning environments.

By exploiting social tagging, we integrate context-aware m-learning application main elements and build a concept model of the social approach for generating high-level context, (**Figure 1**). The left dotted box is about the low-level context aggregating and mapping, which has been discussed a lot. To focus on the core of this paper, we put our effort on the right part, i.e., how to exploit social approach to generate high-level context. Context matrix is additional element which is hidden in our model. It represents the associations between low-level context and high-level context. In our model, high-level context is socially generated and discovered by learners themselves through tagging operations:

1. Context tagging: learners explicitly employ tags to represent her high-level contextual information based on her current low-level context. Tags can be every word which is used to better describe the learner's situation, such as "walk", "cat", "happy", etc. As the result, high-level context tags will be directly linked to low-level context ones.
2. Context retrieval: high-level context tags provided by all learners in the community that are considered as the best description of the target learner's actual situation are retrieved in terms of her low-level context. As the result, the current target learner's context could be automatically enriched by the retrieved high-level context tags.
3. Context refinement: learners can remove some high-level context tags providing through the context retrieval process, and/or add new high-level context tags. As the result, the target learner's current context can be represented more accurately.

Context tagging and context refinement are two operations that directly take charge of the interactions between learners and computational devices. Such interactions contribute to

	l_1	l_2	…
h_1			
h_2		**(S_{22}, R_{22})**	
⋮			

Figure 2. Context Matrix

explicitly creating the associations between low-level context and high-level context, which are represented in the context matrix. With more these interactions, the context matrix will describe the associations better. Context retrieval is another operation that is conducted mainly by computing, without direct intervention of learners. However, context retrieval operation is based on context matrix which describes learners' social interaction behaviors. So, through these three operations, the concept model takes advantages of social participation dynamics of the crowds and their aggregated behaviors.

Context representation

In our approach, both low-level context and high-level context are represented as tags, where each tag represents a single contextual information. Since low-level context is automatically generated from sensors or devices, it necessary to provide a formal common structure to represent low-level contextual information. To facilitate interoperability and systematic management of low-level contextual information, a simple ternary structure is designed, i.e., (class: property = value). Here, a class represents a certain context dimension or concept, a property specifies one characteristic of a class, which have a certain value for a given context. The high-level contextual information is introduced to detail the learner's context description. Some examples are: walk, cat, happy, etc. High-level context tags are freely defined and managed by learners without conditions, and their associations to low-level context tags are formed with tagging process.

Context matrix (see **Figure 2**) represents the associations between low-level context tags and high-level context tags. It is used to retrieve the most relevant high-level context tags based on known low-level context tags. Context matrix is built on the basis of learners' social behaviors and their history. In context matrix, each column corresponds to a low-level context tag, and each row corresponds to a high-level context tag. With constantly social tagging the context of the user in m-learning environments, the number of columns and lows in context matrix can continually extended. Each cell in the matrix contains two values:

- S_{ij}: a positive number that defines how steady the association is between the high-level context tag h_i and the low-level context tag l_j.
- R_{ij}: a positive number that defines how much relevant the high-level context tag h_i is for the low-level context tag l_j.

Context retrieval

Context retrieval is to determine the best high-level context tags in a given context, which has been described by certain low-level context tags. The associations between low-level context and high-level context are formed based on social behaviors of learners, so the ability of a learner affects the building of association. Different learners have different ability to tag high-level contextual information. So we introduce participant score C_p, which defines how good a participant is in associating high-level context tags with low-level context tags. Generally, C_p is related to the number of tagging, C_p will increase as more tagging the participant operates. At the same time, the growth rate of C_p is not the same at different tagging stages of the participant. At the initial stage, the participant only performs a small amount of tagging, C_p will get a rapid growth. With more tagging, the growth rate of C_p will be slower, and ultimately tends to 0. So we define C_p as:

$$C_p = \frac{1}{1+e^{-k(N_p-\overline{N_p})}} \tag{1}$$

where k is the growth rate, usually set k=0.5; N_p is the tagging number of the participant p; $\overline{N_p}$ is the average tagging number of all participants. From this definition, we can see $C_p \in (0,1)$, especially, when $N_p=\overline{N_p}$, C_p =0.5.

S_{ij} is used to describe the steadiness of the association between the high-level context tag h_i and the low-level context tag l_j. Obviously, S_{ij} is not a constant. It will increase with the growth of association numbers. In addition, the more tagging ability of the participant (i.e. C_p is greater) makes more contribution to the steadiness. So we define S_{ij} as:

$$S_{ij}(t_{k+1}) = S_{ij}(t_k) + C_p(t_{k+1}) \tag{2}$$

where t_k represents a discrete time instant, t_{k+1} is the subsequent time instant, k=0,1,..., set S_{ij} (t_0)=0. From definition, we see that S_{ij} (t_{k+1}) synthesizes the accumulated steadiness at the last time instant and the user's tagging ability at this time instant.

R_{ij} is used to describe the relevance between the high-level context tag h_i and the low-level context tag l_j, i.e. the strength of the association between h_i and l_j. Similar to the steadiness S_{ij}, the relevance R_{ij} is not a constant, it is related to both the steadiness S_{ij} and the participant ability C_p. So we define R_{ij} as:

$$R_{ij}(t_{k+1}) = R_{ij}(t_k) \times S_{ij}(t_k) + C_p(t_{k+1}) \tag{3}$$

where t_k represents a discrete time instant, t_{k+1} is the subsequent time instant, k=0,1,..., set R_{ij} (t_0)=0.

Context retrieval is to find the best matched high-level context tags based on the low-level context tags which are obtained from sensors and devices in m-learning environments.

Context retrieval works on the context matrix. SinceS_{ij} and R_{ij} in the cell of context matrix are computed, we can process context retrieval. The process is described as follows.

Input: A_L, the set of obtained low-level context tags regarding a given context;

CM, the context matrix;

Output: T_H, the set of the retrieved high-level context tags;

Process:

CT_H = associate(A_L, CM); //get the set of high-level context tags that have been associated with at least one of the low-level context tags in A_L.

for each h_i in CT_H

Rank(h_i) = computeRank(h_i, A_L, CM); //compute the rank value of the high-level context tag h_i.

return T_H = selectTop(CT_H, Rank(h_i)); //select the limited high-level context tags which are ranked at the top and return.

In the above process, the key is to compute the rank value of each considered high-level context tag h_i. The rank value is computed mainly based on the context matrix that represents the associations between high-level context tags and low-level context tags. We define the computation as follow:

$$rank_{h_i} = \frac{N_l}{N_h} \times \sum_{l_j} R_{ij} \tag{4}$$

where $rank_{h_i}$ is the value of the considered high-level context tag h_i; N_l is the total number of obtained low-level context tags, to which the high-level context tag h_i is related; N_h is total number of low-level context tags, to which the high-level context tag h_i has been associated; $\sum_{l_j} R_{ij}$ is to accumulate R_{ij} for each obtained low-level context tags l_j.

EXPERIMENT DESIGN AND IMPLEMENTATION

Measurement of effectiveness of the proposed social approach is to determine how much the retrieved high-level context tags reflect the target learners' real notions. It thus is necessary to compare the retrieval tags with tags about learner's real notions. In information retrieval area, accuracy and recall are usually used to evaluate retrieval effectiveness, so we also use these two measures. As the proposed social approach is a novel way to generating high-level context in m-learning environments, there are no dataset from real applications. To achieve the evaluation, we simulate the social process of generating high-level context tags and create evaluation dataset manually. Experiment design and implementation are introduced as follows.

Step 1: Design low-level context tags

Low-level context is from sensors and devices in m-learning environments. In the experiment, we select time and location context to express the low-level context. The time

Table 1. Designed experimental scenarios

No. of scenarios	Low-level context
1	a.m. weekday, home
2	a.m. weekday, office
3	a.m. weekday, meeting room
4	a.m. weekday, gym
5	p.m. weekday, home
6	p.m. weekday, gym
7	p.m. weekday, park

context includes two values: a.m. weekday and p.m. weekend, and the location context includes five values: home, office, park, meeting room and gym. Then we design seven scenarios based on some combinations of time and location context, as shown in **Table 1**.

Step 2: Design and implement context tagging and context refinement

To simulate context tagging and context refinement, we design two questionnaires. The first one contains seven questions corresponding to seven scenarios designed in Step 1. The respondents are required to freely create more than one word or string of text (i.e., tag) which they think can be used to further describe these scenarios. As respondents can use any tags to describe a given scenario, this process is similar to context tagging in our model (see **Figure 1**). We select eight persons with different occupations to answer the questionnaire, and collect and gather answers of each question. The second questionnaire design is based on the answers of the first one. This questionnaire contains the same seven questions in the first one, but the respondents should select some tags from a provided tags list for each question, instead of freely creating tags in the first questionnaire. The provided tags list is from the answers of the first questionnaire. All tags for one question created by all respondents in the first questionnaire constitute the tags list for the same question in the second questionnaire. The same eight persons take part in answering the second questionnaire. This process is similar to context refinement in our model.

Step 3: Context retrieval implementation

After we have gotten social behaviors of respondents through Step 2, we begin to compute C_p, S_{ij} and R_{ij} in terms of formula (1), (2) and (3) respectively, and then form context matrix. Thus, we get the rank value of considered tags for every respondent in each scenario. According to the rank values, we select Top 5 tags for every scenario of one respondent as the retrieval result, i.e. recommendSet1. To compare with current expert-predefined approach in context retrieval, we also simulate a mode to get the retrieval result. In the above steps, there are no experts involved. However, we consider that an expert is just one of the crowds, whose understanding is based on common knowledge of the crowds. So we can take the most respondents selection as the retrieval results of the expert-predefined approach. To do so, we count the number of tags for every scenario and respondent from the answers of the second questionnaire, and select tags its count in Top 5 as the retrieval result, i.e., recommendSet2.

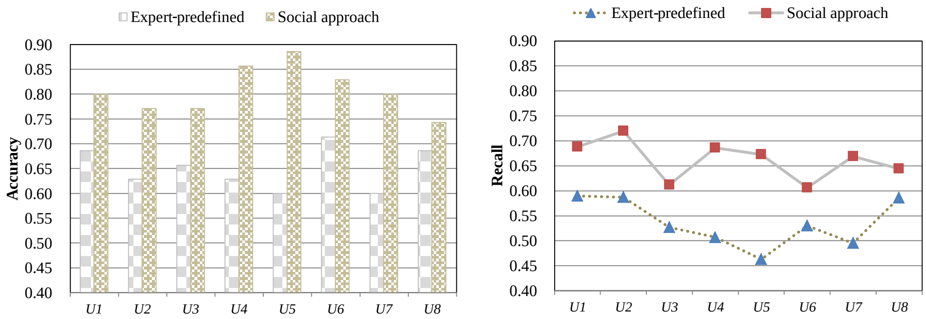

Figure 3. Average accuracy and recall for respondent users

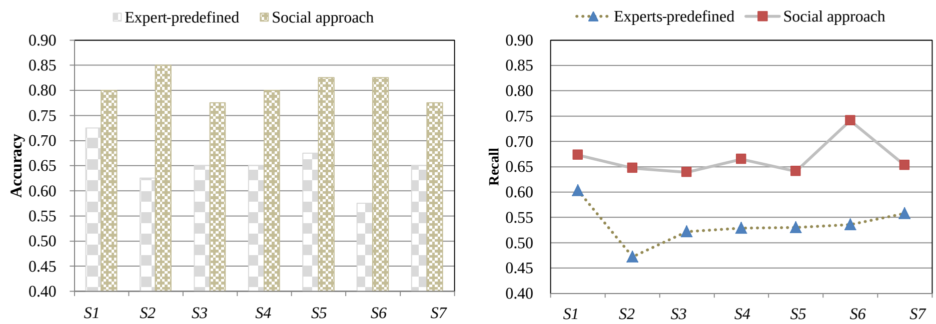

Figure 4. Average accuracy and recall for scenarios

The likeSet of every respondent user in each scenario is the answer of each question in the second questionnaire. From these answers, we find that some respondents only select two tags for some scenario, whereas most select 4-6 tags.

CONCLUSION AND RECOMMENDATION

After conducting the experiment process, we have obtained the dataset for evaluating the accuracy and recall of context retrieval. We calculate two average values of accuracy and recall respectively: one for each respondent user in all scenarios, and another for each scenario of all respondent users. The results are shown in **Figure 3** and **Figure 4** respectively. From figures, we can directly see that the average accuracy and recall both for respondent users and for scenarios based on our social approach are higher than that based on expert-predefined approach. Furthermore, we can observe that the average accuracy is always higher than the average recall both for every user and for each scenario. In addition, the social approach has a greater difference value between accuracy and recall than the expert-predefined approach does. The fact that the accuracy value is higher than its corresponding recall value shows that some elements in recommendSet are not included in likeSet, which means that context retrieval has retrieved some new high-level context tags for a certain respondent user in a given scenario, i.e. context retrieval provides some diversity and novelty. The greater of the difference in values represents more novelty which the social approach provides. Therefore, we can make a conclusion that the context retrieval based on our social approach provides more diversity and novelty of retrieval result than that of the expert-predefined approach. Therefore, the proposed social approach for generating high-level context in m-learning environments is effective.

In this paper we present a social approach for generating high-level context to facilitate interpretation between data from sensors/devices and requirements of personalized recommendation in m-learning environments. It is a novel and generic paradigm for generating high-level context in m-learning environments, where the community of learners engages in defining and providing high-level contextual information through collaboration and participation. We present the concept model, the context representation, the context matrix, and context retrieval. A social simulation based experiment is conducted and the effectiveness of our proposed social approach is verified. Since social approach for generating high-level context is novel, it still needs more efforts to achieve its original purpose. We hope the continuing research on this topic can establish achievements in:

1. Design the business model of our proposed social approach, and develop prototype systems based on real situation backgrounds.
2. Perform a broader and more complex evaluation involved in a fully real world. This will help us understand if the proposed social approach is effective in real world environment.
3. Study the privacy issues which will arose for the reason that the crowds participate in context tagging and context refinement in the social approach.

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