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Review of Recommender Systems for Learners in Mobile Social/Collaborative Learning

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ABSTRACT

Social/collaborative learning is a learning procedure that is student-centred and involves a task-based and activity-based approach that collaboratively provides several advantages such as: communication, interpersonal and social co-operation, sharing, caring, openness, creativity, management, practicality, responsibility, involvement and participation. Social and collaborative learning improves pedagogy and are very important aspects of education. Inclusion of social and collaborative learning needs to be considered as a priority in all educational modes. Mobile learning, a new flexible learning landscape is currently being adopted worldwide in both academia and industry. The inclusion of social/collaborative learning in mobile learning is of utmost and vital importance due to its benefits and contributing factors to education/learning efficiency and sustainability. The inclusion of social /collaborative leaning in mobile learning requires the effective management of social activities/data used in learning. Mobile social activities/data involving: non-textual/multimedia (voice/audio and video) and textual that are used by learners and teachers in mobile learning can be extremely large and disorganised with some of the data being educationally irrelevant to the mobile learning process. How educationally relevant mobile social activities/data are realized, structured and managed as well as the filtering of relevant social learning activities/data in mobile learning for learners is a critical issue and needs to be tackled. This paper surveys relevant literature, and proposes recommender systems that can be implemented in mobile social/collaborative learning to solve problems involving the recommendation of relevant social data and learning materials for learners.

Keywords: *Mobile Learning, Collaborative Learning, Social Learning, Recommender Systems*

1. INTRODUCTION & BACKGROUND OF THE STUDY

Modern developments in the field of Information and Communication Technologies (ICTs), specifically mobile computing technologies have lead to a renewed interest among educators in using mobile devices. Current mobile devices such as Mobile phones, Smartphones and Personal Digital Assistants (PDAs) run on Operating Systems such as Windows Mobile, Android or Symbian. These systems have many of the features of desktop computers with access to broadband internet networks as tools for teaching and learning. Location and time independent characteristics of mobile media devices have a distinctive place in the next generation of learning environments [1]. In the last decade, the fast proliferation of mobile devices in our society, especially mobile phones, offered great opportunities for ubiquitous learning (learning everywhere). A survey from Pew Internet and American life project in 2009 states that about 32% of Americans have used a cell phone or Smartphone to access the internet for emailing, instant-messaging, or information-seeking. This is an increase from 2007 where the number was 11% [2]. It is evident and can be realized that the number of mobile internet usage with Smartphones and other mobile technologies has increased rapidly.

The continuous use of ICTs is leading to changes in the activities of teaching and learning. Generally, traditional teaching methods have numerous drawbacks. One of them is the fact that very often students attend a course, take notes and leave without any collaboration in the classroom due to circumstances such as lack lecture of time or the non realization of the importance of social/collaborative learning. There is a saying that “knowledge which is shared is better”. Social/collaborative learning tries to solve this ineffectiveness. It is an educational method in which students work together in small groups towards a common goal [3, 4]. The teacher acts as a coach, mentor or facilitator of the learning process. The successful achievement of the common goal is shared among all group members. The students take initiative and responsibility for learning. They actively learn by doing, by practice, by experience. Social/collaborative learning is a student-centred, task-based, activity-based learning approach that provides several advantages to the student. It assists the student to enhance the following skills: Communication, Interpersonal, Cooperation, Sharing and Caring, Openness, Flexibility and Adaptability, Knowledge Retention, Higher-order and Critical Thinking, Creativity Management, Practicality, Responsibility, Trustworthiness and Dependability, Involvement, Engagement and Participation, Commitment and Persistency, Motivation, Confidence and Self-efficacy [5].

Students work together on a task, exchange their views, experiences and opinions, discuss and negotiate strategies, actions and results. They assist, explain, teach, understand, review and influence each other. By developing a learning community, they combine the special abilities of everyone to achieve a common goal [5].

Mobile learning, a new flexible learning landscape is currently being adopted worldwide by both academia and industry. The inclusion of social and collaborative learning

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in mobile learning is of utmost and vital importance due to its benefits and contributing factors to education/learning efficiency and sustainability [5]. Overwhelming and enormous social data/activities of learners in mobile learning is a challenge which should be tackled and solved by recommender systems and this is the primary focus of this research.

Recommender systems generally fall into three categories:

Collaborative Filtering Systems which compute recommendations by examining users' preferences on items based on similarities of other users of the same group [12].

Content-Based Systems which compute recommendations from the semantic content of items [13] and

Knowledge-Based Systems where recommendations rely on the knowledge about the domain, the users and pre-established heuristics [10].

Collaborative Filtering and Content-Based Filtering Systems are sometimes combined to form ***Hybrid Filtering Systems*** which solve problems such as cold-start in collaborative filtering techniques [25].

This paper is structured and organized as follows: after the Introduction, Section 2 Reviews the Problems and Open Issues. Section 3 discusses the Research Objectives of the paper. Section 4 elaborates on the Literature Review. Section 5 elaborates on the Research Methodology of the paper and Section 6 presents a Discussion of the paper. The paper is finally concluded with proposed future work in Section 7.

2. REVIEW OF PROBLEMS & OPEN ISSUES

Mobile learning occurs ubiquitously with mobile learners usually not present at the same location. Collaborative and social inclusion of learners in mobile learning requires an effective collaborative and social system. A good approach to social/collaborative learning is group formation and participation as well as mobile social learning community building. Mobile learners have to form social and collaborative groups in order to enhance teaching and learning. Social/collaborative learning is usually realized in a mobile learning scenario when mobile devices are used for social activities/data involving: voice/audio, video and text amongst mobile learners. An important aspect of social learning is the management of social activities/data (textual and non-textual). Mobile social data used by learners in mobile learning can be extremely large and difficult to store in a mobile device. Textual or non-textual social data/activities which are usually inevitably overloaded for a mobile learner require the need of suitable techniques and algorithms to filter the most important and relevant information for the leaner in accordance to his/her particular interests and preferences. A great amount of social data/activities results in poor attention and inappropriate time used in accessing reliable and relevant learning data, which are priorities in any learning activity. In order to reduce time and effort mobile social learners go through to access relevant information for learning, mobile social learners should have the opportunity of using a system that has automated filtering techniques to choose recommended relevant social activities/data. Recommendation of appropriate social learning contents involving of both multimedia as well as text will improve and support social and collaborative inclusion in mobile learning.

Information filtering in mobile social learning must also consider human factors in information production and communication processes, in particular, the interests, preferences, and behavioral characteristics of learners. Rapid increase of learning materials and learning resources, either offline or online, has made it is quite difficult to find suitable materials based on learner’s need [15]. Recommender systems help learners find the appropriate learning materials in which they would need to learn.

Personalized Recommendations for students/learners involving issues such as programme/course registration and choices, Lecturer/Supervisor choices as well as learning materials and resources should also be developed in a mobile learning application to help the learners make appropriate educational choices in accordance to their interests and preferences.

Recommender Systems that can make recommendations for mobile learners’ interests and preferences based on similar interests and preferences of other learners in a group or mobile social learning community should be developed.

3. RESEARCH OBJECTIVES

The main objectives of this research paper are:

a. To analyse which recommender systems can be used to educationally realize, manage and support relevant mobile social activities/data (textual and non-textual/multimedia content) in a mobile learning application?
b. To analyse what has to be done so that effectively filtered relevant social learning data/activities of users (learners) can be recommended for efficient collaboration in a mobile learning application?

4. LITERATURE REVIEW

4.1 Personalized Recommendations (Recommender Systems)

Recent research shows that Personalized Recommendations (Recommender Systems) will be very beneficial in areas such as e-commerce, e-learning and m-learning [6]. There is a lot of research in the area of recommender systems dating back from the mid nineteen nineties (1990s). There are two main recommender systems: Content-Based Recommenders (using Content-Based filtering

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techniques) and Collaborative (Social) Recommenders (using Collaborative Filtering techniques) [7].

Content-Based Recommenders analyse features of the content in the set and match them to the features of the user (e.g. preferences, interests) based on a user model developed by analysing the previous actions of the user [7]. Content-Based Recommenders apply information about individual users or items. They propose similar items to what the users preferred in the past [6]. It is sometimes impossible to capture the knowledge about the user's preference to recommend items to them. This causes an overspecialization problem in which recommendations use items which the user already knows or is familiar with [8, 9].

Collaborative or Social Recommender Systems, which is the most well known type of recommender systems work by statistically correlating users based on their previous choices. Collaborative recommendations base assumptions that people who have behaved similarly in the past will continue to do so. Collaborative or social recommender systems suggest contents rated highly by a user, to similar users who have not seen the contents yet. Collaborative or social recommender systems are wildly used to recommend books, movies and other shopping items in e-commerce websites. Collaborative or Social Recommender Systems try to propose the items which users with similar tastes and preferences liked in the past. The problems of cold-start and rating sparsity are present in this approach and are potential drawbacks [10]. The collaborative filtering technique used in collaborative recommenders needs to know about the tastes and interests of a user, therefore recommendations cannot be made without the user's previous ratings [6]. More recently, recommender systems have been applied in Social Network Sites (SNSs) [7].

Another recommender system is the Knowledge-Based Recommender System. The knowledge-based approach aggregates knowledge about the users and items, then apply the knowledge gained to make/generate recommendations [6, 10]. Knowledge-Based Recommenders do not attempt to build long term generalizations about their users, but rather prefer to generate a recommendation based on matching between user's needs, preferences and the set of items available [9]. Knowledge-Based Recommenders ask questions relating to how special items can meet a special user's need through knowledge. This technique exploits deep knowledge about the domain in question and determines the best solution for the user's need. When using the Knowledge-Based approach, the relationship between the user's need and recommended items can be explicitly modelled in the underlying knowledge base [11]. Knowledge-Based Recommender Systems need the expertise of Knowledge Engineering [10]. The main problem of this approach is gathering of knowledge and knowledge acquisition. Knowledge-Based Recommenders need to employ three types of knowledge; knowledge about users, knowledge about the items and knowledge about the matching of items between the items and user's need. The user profile plays a very important role in knowledge-Based recommender systems. Knowledge-Based Recommender Systems unlike content-based and collaborative recommenders do not have the cold-start, sparsity and overspecialization problems [15].

4.2 Related Work

In [14] discussions are presented on how the development and diffusion of compact and portable mobile devices, have given users the ability to use multimedia content such as music and movie on personal mobile devices, anytime and anywhere. However, even with the rapid development of mobile device technology, it is still not easy to search multimedia content or manage large volumes of content in a mobile device with limited resources. To resolve these problems, an approach for recommending content on the server-side is one of the popular solutions. However, the recommendation in a server also leads to some problems like the scalability for a lot of users and the management of personal information. Therefore, [14] defines a personal content manager which acts between content providers (server) and mobile devices and proposes a method for recommending multimedia content in the personal content manager. For the recommendation based on user's personal characteristic and preference, [14] adopts and applies the DISC model which is verified in psychology field for classifying user's behaviour pattern. The proposed recommendation method in [14] also includes an algorithm for reflecting dynamic environmental context. Through the implementation and evaluation of a prototype system, [14] shows that the proposed method has an acceptable performance for multimedia content recommendation.

In [15] discussions and elaborations are given on how the rapid increase of learning materials and learning resources, either offline or online is making it quite difficult for learners to find suitable materials based on their needs. Recommender Systems help learners find the appropriate learning materials in which they need to learn. Further discussions in [15] include personalized recommendation systems in e-learning and comparison of recommendation techniques. There are two concepts which are mainly discussed in [15]. Discussions are firstly made about learners requirements and secondly about the personalized recommendation technique for a particular requirement. The recommendations in [15] aims to recommend to the leaner, some materials based on the leaner's need. By using semantic relationship between learning materials and the learner's need, the system can select suitable materials as a recommendation to the learner. The knowledge-based recommendation system is proposed in [15] for future work.

In [16] due to the development of Information Technology in Physical Education (PE) teaching, discussions are presented on the urgency of how to provide students with personalized Physical Education (PE) course to conform to increasing personalized demands of contemporary college students. [16] starts with an analysis of college students, demands for PE classes and introducing ideas and technology

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about personalized recommendations. Furthermore, functions and processes of the personalized recommendation system for PE courses at universities are analysed. Finally a system application architecture was designed in [16].

In [17] discussions are presented on the very importance of assigning proper articles to individual students for training their reading ability in English courses. This study in [17] proposes an innovative approach for developing reading material recommendation systems by eliciting domain knowledge from multiple experts. An experiment was conducted to evaluate the performance of the approach; moreover, a comparison on the existing approaches is given to show the advantages of applying the innovative approach. The study in [17] successfully developed the expert system for ESL English reading recommendation by the opinions and domain knowledge from the English teaching experts.

In [18] a presentation is made on how finding similar e-learners in a distributed and open e- learning environment and helping them to learn collaboratively is becoming one of the urgent challenges of personalized e-learning services. Literature shows that current e-learner community building approaches are generated from qualitative studies of small-sized learner-centered classrooms which may need the teacher's participation. However, the findings might not apply to large classes in distributed learning environments, which make teachers face hundreds of e-learners in each class. In such situations, teachers also find it impossible to analyze the learning behaviors of each e-learner and divide them into different learning communities accurately. [18] addresses this problem in the adaptive e-learner community self-organizing point of view. Considering both the feature vector of learning resources and a learner's rating value on each resource, [18] firstly defines the learning interest feature vector to model the learner's behavior. Based on this accurate learning interest feature representation method, an innovative e-learner community self-organizing algorithm, called IFV- SORC, is proposed in [18]. Experimental results in [18] show that their proposed algorithm exhibits good community organizing efficiency and scalability.

According to personalized service in a teaching system, [19] proposes curriculum resources personalized recommendation algorithm based on semantic web technology. Firstly, in [19] a collection of curriculum resources of interests in terms of the user evaluation and user browsing behavior is done. Based on the relationship between the concepts in the domain ontology, calculation is done on the semantic similarity between core concepts of different user evaluation. Finally according to the similarity, a decision is made in accordance of the similarity of user preferences/interests and that of nearest neighbors with similar interests, in order to achieve learning resource personalized recommendations. Through the combination of ontology model of “compile theory “course knowledge, [19] design and implement a personalized learning recommendation system.

In [7] a discussion is given on how users of Social Networking Sites (SNSs) like Facebook, MySpace, LinkedIn, or Twitter, are often overwhelmed by the huge amount of social data (friends’ updates and other activities). In [7] a proposal of using machine learning techniques to learn preferences of users and generate personalized recommendations is done. To generate personalized recommendations, four different machine learning techniques on previously rated activities and friends for activities that may be interesting to each user are proposed. In [7] different non-textual and textual features are used to represent activities. The evaluation results in [7] show that good performance can be achieved when both non-textual and textual features are used, thus helping users deal with cognitive overload.

5. RESEARCH METHODOLOGY

A review of relevant literature in accordance to the objectives of this paper were explored and adopted in order to solicit the right information needed for the analysis. In solving the problems elaborated in Section 2, this paper proposes usage of appropriate and relevant techniques for personalized recommendations for mobile social learners. Table 1 below shows a comparison of recommender systems:

Table 1: Comparison of Recommender Systems, Source: [15]

Recommender System	Advantage	Disadvantages	Requirements	Technical Aspects
Collaborative Filtering	No domain knowledge is required	Cold-start problem. Sparsity problem. Insensitive to preference change.	Need to a set of users. Need to large of historical data set.	Easy to create and use. Makes recommend actions based on the past interests of that user.
Content-Based Filtering	No domain knowledge is required	Overspecialization problem	Need to knowledge about user’s presences.	Considers the preferences of a single learner
Knowledge-Based	Sensitive to preference change. Does not need to be initialized with a database of user preferences	Knowledge acquisition	Well understanding from the product domain	Need to knowledge engineering

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6. DISCUSSION

As elaborated above and with reference to the literature review and table 1, knowledge-based recommender systems don't have problems such as cold-start and overspecialization as with Collaborative Filtering and Content-Based Filtering respectively. Considering the collaborative filtering technique, the system needs to know about the taste of user, so recommendations can't be done without the user's previous ratings, which creates the cold-start problem [24].

As discussed above, content-based filtering technique relies on the analysis of the content of the items to generate recommendations. An item is recommended to the active user if its content similarity with the other items that a user has liked, is high. For example, a user who has liked some items about "electronics" will be recommended to some items related to this area [24].

Content-based filtering does not suffer from the cold-start problem. Indeed, a new item can be recommended to any user since the analysis of its content can be performed. However, as elaborated in table 1, content-based filtering has one main weakness: it suffers from overspecialization of its recommendations, also called novelty problem. The recommended items are similar or identical to those appreciated by the user before. Thus, the other items with a different content are neglected and are never integrated in recommendation lists suggested to this user [24].

The analysis of the content of items can help to bridge the gap from existing items to new items, by inferring similarities among them. In the context of solving the cold-start problem, content-based and collaborative filtering are often combined resulting in hybrid recommender systems [25]. In these hybrid systems, the content-based algorithm aims at facing the cold-start problem, while the collaborative filtering algorithm guarantees the introduction of novel recommendations [24].

Another approach called, Ontology-Based Filtering [24] has also been suggested as a solution to the cold-start problem of Collaborative Filtering [6]. Ontologies are used to automatically build knowledge bases and extract semantic profiles of items [22]. Semantic similarities between items can thus be computed. Two examples of ontology-based recommender systems are Quickstep-Foxtrot (recommending research papers) [23] and Entree (recommending restaurants) [9].

7. CONCLUSION & FUTURE WORK

7.1 Conclusion

Social and collaborative inclusion in mobile learning as elaborated in this paper is of vital importance and must be implemented in order to sustain and achieve educational (learning and teaching) goals. However, mobile social data/activities (online or offline) can be extremely too large for relevant learner requirements and also too voluminous be stored in mobile devices. Since collaborative and social learning is an important aspect of this paper, collaborative filtering techniques have to be combined with other techniques to avoid problems such as cold-start.

Through relevant literature review, this paper proposed a hybrid (combination of content-based and collaborative filtering techniques) and an ontology-based (combination of knowledge-based and collaborative filtering techniques) recommender systems that can be used to solve these problems.

7.2 Future Work

Future works in relation to this paper are as follows:

- In order to solve the problem of how educationally relevant mobile social activities/data (textual and non-textual/multimedia) can be realized, structured and managed in a mobile learning application, research on how to use machine learning techniques to learn interests and preferences of learners or to use the DISC model to classify user's learning behaviour pattern in terms of interests and preferences in order to generate personalized recommendation algorithms of social data/activities (contents) for mobile social learners has to be conducted. The personal recommendations of a mobile social learner can further be used for effective collaboration among other mobile social learners in the same group of the mobile learning community through a hybrid recommender system.
- To develop personalized recommendation algorithms to aid mobile social learners intelligently choose programmes, courses and lecturers/supervisors based on their interests and preferences requires a knowledge-based recommender system that has a domain of learners' interest and preferences.

In order to ensure collaborative recommendations in mobile learning, this paper proposes an ontology-based recommender system which basically combines collaborative filtering and knowledge- based recommender systems for future research. The knowledge base in ontology-based recommender systems is built through ontologies and extracted semantic profiles of learners. In this way, learners with similar interests and preferences can collaborate and choose the same educational and learning categories [24].

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