A Framework for Context-Aware Recommendation in Mobile Social Learning

Nana Yaw Asabere

Computer Science Department
Accra Polytechnic, Greater Accra Region, Ghana

Received 07 January 2013; accepted 31 January 2013

Abstract
Quite recently the involvement and incorporation of context-aware recommender systems in different commercial disciplines as well as the Technology Enhanced Learning (TEL) community has gained the need for extensive research. Traditional recommender systems such as collaborative filtering, content-based filtering and their hybridizations apply users and items to generate recommendations. However, the incorporation and modeling of contextual information in a recommendation prediction will improve and make recommendations more accurate and efficient for a user. With a focus of contextual information, this paper discusses and elaborates on a framework for the recommendation of learning resources to learners in a mobile social learning community.

Keywords: Context-Awareness. Mobile Devices. Mobile Social Learning. Recommendation

INTRODUCTION
Mobile Social Learning is an educational mode/discipline that involves the use of mobile devices such as mobile phones, smartphones and Personal Digital Assistants (PDAs) for collaborative teaching and learning activities. Sharing and socializing between learners in a mobile environment enhances teaching and learning and has proved to be beneficial in terms of accuracy, efficiency and effectiveness in most educational modes. In mobile social learning, sharing and socializing activities can take place anywhere (ubiquitously) and anytime due to the portability of mobile devices and proliferation of the internet and broadband wireless networks.

Mobile social learners have different cognitive abilities and also have different learning interests and preferences, making learning resource recommendations necessary, relevant and important in mobile social learning. Different learning groups within a mobile social learning community have different learning interests and preferences. Furthermore mobile social learners within the same learning group need to collaboratively recommend similar learning resources to each other, in order to share learning knowledge and help each other achieve their learning goals [1].

Recent extensive researches in recommender systems have suggested the involvement and incorporation of context-aware recommender systems in different commercial disciplines and Technology Enhanced Learning (TEL). Traditional recommender systems such as collaborative filtering, content-based filtering and their hybridizations apply users and items to generate recommendations. However, the modeling and incorporation of contextual information in a recommendation process generates more accurate recommendations and has attracted a lot of interest in the research community of recommender systems [1][2]. The use of explicit and implicit procedures to obtain the interest of users in order to recommend items to them may not be sufficient to predict or generate recommendation resources for users in certain mobile computing circumstances.

Therefore, in a mobile social learning community it is necessary to model and integrate contextual information such as location, physical conditions, time and social relations in the recommendation process to improve generated recommendations for mobile social learners. To corroborate the above scenarios, this paper focuses on discussing the various contexts which can be modeled and incorporated in a mobile social learning community and elaborate on how each of these contexts are important in the recommendation of learning resources for mobile social learners in different circumstances.

The rest of the paper is as follows: Section II discusses the Background of Mobile Social Learning and Recommendation. Section III presents a Contextual Framework for Recommendation in Mobile Social Learning. The paper is finally concluded in Section IV.
BACKGROUND OF MOBILE SOCIAL LEARNING AND RECOMMENDATION

Mobile Social Learning aims to develop socio-technical innovations that will support and enhance collaborative learning and teaching practices through the use of modern mobile devices. Collaborative Filtering (CF) Recommenders retrieve relevant learning resources for learners by matching similar interests of the active learner and other learners within the same mobile social learning domain/community. Content-Based Filtering (CBF) Recommenders retrieve relevant learning resources for learners by matching similar interests of the active learner to his/her past learning resource interests within the same mobile social learning domain/community. By combining CF and CBF, Hybrid Recommenders improve the disadvantages and inconsistencies in both CF and CBF recommenders. Other notable traditional recommender systems include Knowledge-Based, Demographic and Utility [3][4]. Context-Aware Recommenders, which is the focus of this paper, retrieve relevant learning resources for learners through applicable context sensors such as mobile computing, location and time within the mobile social learning domain/community.

A. Idiosyncrasies of Recommendation in Mobile Social Learning

Since the 1990s, the field of Recommender Systems have been studied and well established in research and applications. Major E-Commerce websites such as Amazon and search engines such as Google have incorporated recommender systems in their services in order to achieve personalization of results for users. Recommendation algorithms which are used for commercial activities such as using Amazon are not directly transferable for usage in mobile social learning. In mobile social learning, recommendation technologies require specific characteristics in order to generate efficient and accurate learning resource recommendations for mobile social learners [1].

The main difference in commercial recommendation and recommendation in mobile social learning is that the philosophy of education allows each learner to have his/her own: methods, paths, processes, tools and collaborations. Personalization of mobile social learners through recommendations must be done at a very extreme extent. Certain factors pertaining to the user needs to be considered when generating personalized recommendations for mobile social learners. In addition to recommending learning resources to the active learner based on similar learning resource interests of other learners, recommenders for mobile social learning must also take note of factors such as cognitive abilities of the learner, emotional mood of the learner, environment, timing, location and accessible resources [1][5].

Different learning activities take place in learning environments that are composed of several tools and systems. For instance, a Mobile Learning Management Systems (mLMS) as a concept of mobile social learning environments, provides access to learning resources and collaborative activities, the provision of learning resources by a mLMS may not be enough for both mobile social learners and teachers, therefore learners may require additional tools such as Adaptive Learning Environments (ALEs) and Personal Learning Environments (PLEs) to improve collaboration [11][13]-[15]. ALEs provide support to personalized access to learning materials and PLEs allow learners to compile tools they want to address in a learning scenario or challenge. Therefore a combination of a mLMS incorporated with ALEs and/or PLEs improves learning efficiencies, effectiveness, collaboration and recommendation. The differences in pedagogical approaches in both formal and informal learning processes/settings have made recommendation requirements and current learning situations complex. For instance, a Recommendation System for a mobile social learning community will have to organize and generate recommendations of interests of both mobile social learners and teachers as users. There is therefore the need for a massive amount of data of users (teachers and learners) activities contexts and interests in a mobile social learning community in order to facilitate and generate precise and exact recommendations with a higher focus on learners since they need more resources to learn.

B. Context-Aware Recommender Systems in Mobile Social Learning

As discussed above, traditional recommender systems generate recommendations by the user of two (2) main entities i.e. users and items normally referred to as 2 Dimensional (2D) recommendations. Mobile Social Learning recommendations have characteristic intricacies that may not fit well through the use of the traditional 2D recommendation processes. For effective recommendations in mobile social learning, resource interests of both teachers and learners constituting user learning resource interests and items as well as the new research focus on context are important. Without incorporation of contextual information in the recommendation process of mobile social learning, contextual sensors such as location, time and physical conditions can’t be used to improve and generate accurate recommendations for mobile social learners and teachers. An initial research work on context-aware recommender systems has been done by Adomavicius and Tuzhilin [2]. The authors extended the traditional 2D recommendation approach to support the additional attributes of incorporating contextual information for effective recommendations to be generated. Contextual information is usually acquired or obtained through three (3) procedures/methods namely: explicit, implicit and inferred.

- **Explicit**: Contextual information can be captured or acquired explicitly from the learner or teacher within the mobile social learning community. Explicit user interests, ratings and context relies on manual input from mobile social learners and teachers though a module such as a resource rating module.
- **Implicit**: Implicit procedure/methods of capturing or acquiring contextual information involve sensor and observable feedback from the environment. For example acquisition of the current location of the mobile social learner and the characteristics of the mobile computing device he/she is using.
Inferred: Another procedure to obtain contextual information is to infer by analyzing how mobile social learners and teachers interactions use their tools and resources in order to estimate their current task and activities. According to Verbert et al. [1], different paradigms such as context-driven querying and search and contextual preference elicitation and estimation have been proposed to incorporate contextual information in a recommendation process. The context-driven querying and search approach uses contextual information to search or query a certain repository of resources (e.g. archaeological sites) and presents the best matching resources (e.g., nearby archaeological sites that are currently around a particular location) to mobile social learners and teachers. The contextual preference elicitation and estimation which is a more recent trend in context-aware recommender systems, attempts to model and learn contextual user (mobile social learner and teacher) preferences by using data records such as user, item ratings and context. Therefore, through ratings, each record captures how much a user (mobile social learner) is interested in a particular learning resource in a specific context (e.g. time and location).

Three (3) different algorithm approaches, namely: contextual modeling, contextual post-filtering and contextual pre-filtering have been identified for dealing with contextual information interests and preferences. The contextual modeling methodology uses contextual information directly in the recommendation process as an explicit predictor of a rating of an item (e.g. physical conditions of a mobile social learner). The contextual pre-filtering methodology uses contextual information to filter the dataset before applying traditional 2D (users and items) recommender systems such as CF and CBF to generate recommendations. The contextual post-filtering methodology uses contextual information to filter the entire dataset after gaining recommendation results though traditional 2D recommender systems such as CF and CBF. Both contextual pre-filtering and post-filtering methodologies use 2D recommender systems to generate final recommendations for users (mobile social learners and teachers) while the contextual modeling methodology uses multidimensional recommendation algorithms [1][2].

Some contextual recommender systems that have been developed using the above algorithms and paradigms in various mobile social learning environments are depicted below:

Cui and Bull [6] discussed how to support the mobile language learner using a handheld computer. They introduced TenseITS, a language learning environment that adapts to the interaction to the individual learner’s understanding, as represented in a learner model constructed during the interaction. TenseITS also adapts according to contextual features of the learner’s location that may affect their ability to study.

Chen et al. [7], proposed and developed a Learning Companion Recommendation system (LCRS) on the social networking site, Facebook. The developed LCRS supports mobile collaborative learning. LCRS collects friends’ profile data automatically according to their learning needs, such as interests and professional abilities. Zhu et al. [8] presented a user-centric system, called iScope, for personal image management sharing on mobile devices. The iScope system uses multimodality clustering of both content and context information for efficient image management and search, and online techniques for predicting images of interest.

Broisin et al. [9] used location and tracking as context and presented a solution for recommending documents to students according to their current activity that is tracked in terms of semantic annotations associated to the accessed resources.

Yin et al. [10] proposed a system to address and contribute to the challenge of location in a mobile social learning environment based on hypothesis that involved asking for help from others. These hypotheses were: 1) the closer people are, the easier it is to get help; 2) the more simple things are, the more it is easier to get help with them.

Yau and Moy [11] introduced a novel Context-aware and adaptive learning schedule framework which makes use of a learning schedule to support the students' daily routines, adapts the activities to the student's learning styles and then selects the appropriate activity for the learner based on their current learning context.

C. Context Sensors in Mobile Social Learning

The definition of context has experienced an evolution in the research area of context-aware computing, but still suffers from either generality or incompleteness. According to Zimmermann et al. [12], many authors define context by example and enumerate context elements like location, identity, time, temperature, noise, as well as the beliefs, desires, commitments, and intentions of the human. Zimmermann et al. [12] introduced two extensions to available context definitions that provides a natural understanding of this concept to users of context-aware applications and facilitates the engineering of this concept for software developers of such applications. Dourish [16] defines context to have a dual origin: (1) technical and (2) social science based. From a technical perspective, there is the need to define context in a more specific way as an operational term [12]. From a social science based perspective, Dourish [16] contends that context can be described a feature of interaction rather than reflecting a certain situation or setting. Verbert et al. [1] discussed that computing, location, time, physical conditions, activity, social relations and user are applicable types of contexts in different learning settings involved with technology.

- **User Context**: User context describes the profile of the user, ratings of the user and social situation of the user.
- **Computing Context**: Computing context involves communication bandwidth and cost, network connectivity and nearby computing resources such as printers, scanners and workstations.
- **Location Context**: Location context describes where (which place) the user can be found at a particular time.
- **Time Context**: Time context describes the date and time information such as minute, hours, days, weeks etc. of the current situation.
- **Physical Conditions**: The physical context involves what is currently going on in a particular location and
environment, e.g. noise levels, traffic conditions, weather, temperature, heat and lighting.

- **Activity**: The activity context reflects the actions and tasks of a user.
- **Social Relations**: Social relations context involves the relationship, connections, social associations, social affinity and social affiliations between two or more users.

### A Contextual Framework for Recommendation in Mobile Social Learning

In order to generate and obtain accurate and precise recommendations for learners and teachers in mobile social learning, there is the need to define, acquire and model context in a specific way to suit the environment and mobile social learning community. To this extent, this paper introduces a simple classification framework of context information that is relevant to context-aware applications in mobile social learning. The framework was constructed by analyzing existing context definitions and their relevance to mobile social learning. We initially discuss how different contexts that are applicable in mobile social learning can be sensed or acquired and introduce each context associated with mobile social learning in a framework shown in figure 2.

#### A. Mobile Computing Context

Mobile computing context has been researched extensively by the mobile research community, including researchers in mobile learning [17][18]. Mobile computing characteristics include:

- **Mobile Device Hardware**: This comprises input and output capabilities and the type of the mobile device. Input such as the capability and durability of keypads and output such as screen size (big or small) of the mobile device are important for efficient recommendation in mobile social learning. The storage/memory capacity (high or low) of mobile devices as well as processor speed (high or low) have to also be considered when generating recommendations in mobile social learning.

- **Mobile Device Software**: The learning resources in mobile social learning should be supported by certain mobile softwares such Application Program Interfaces (APIs) and Operating Systems (OSs) for effective delivery of recommendations in the mobile device.

- **Mobile Network Technologies**: This is made up of the available network technologies such as 3G, Wi-Fi and the maximum and available bandwidth for effective transmission and communication. There should be reliable mobile network technologies in order to generate effective and accurate recommendations for mobile social learners.

Obtaining and using the right mobile computing context is necessary to support intelligent interfaces that can be used to select or recommend suitable learning resources for the mobile device that are used in mobile social learning. Computing context can usually be sensed through a Hyper Text Transfer Protocol (HTTP) request by transmitting identifier information about the mobile device. The HTTP uses the identifier information to retrieve relevant mobile device information from a repository of device profiles. In a case where by there is no information about the mobile device, information such as screen size, battery life and CPU speed of the mobile device are sometimes captured through a request [1].

#### B. User (Mobile Social Learner) Context

Models for learners have been extensively researched in educational adaptive hypermedia, educational user modeling and philosophy research areas. Intelligent tutoring systems (ITS) implicitly build a model of the individual learner’s knowledge, difficulties and misconceptions, as they interact with the system. According to Cui and Bull [6], this learner model can be associated with a model of the target domain to enable suitable tutorial approaches to be inferred by the system, as appropriate for the learner according to the contents of their learner model – i.e., the educational interaction is personalized towards the specific learning needs of the individual student. This paper adopted the main learner characteristic models proposed by [13] and [14] and summarized them as follows:

- **Basic Personal Information of Learner**: The basic personal information of mobile social learners typically includes attributes such as name, gender, age, identification information, contact information, affiliations, profession and educational level.

- **Cognitive Abilities of Mobile Social Learners**: Mobile social learners differ in their preferred ways and cognitive abilities of learning. Some mobile social learners may learn faster and easier with text, others through audio and others through video or through a combination of different media. It is therefore important to seek information about cognitive abilities of mobile social learners in order to generate accurate and effective recommendations for them.

- **Knowledge and Performance Abilities of Mobile Social Learners**: The knowledge and performance levels of different mobile social learners in terms of different learning resources are important factors to be considered for recommendation in mobile social learning. A wrong recommendation may be suggested or predicted for a mobile social learner, if his/her knowledge about a current/topic or course is not known.

- **Learning Interests of Mobile Social Learners**: The learning resource interest of mobile social learners are a priority and very paramount in generating recommendations. Learning resource interests are key characteristics that support personalization in mobile social learning. Usually the learning resources read and rated by the mobile social learning as well as the comments he/she makes about certain learning resources reveals his/her interests pertaining to a particular topic or course.

- **Learning Goals of Mobile Social Learners**: Mobile social learners should have goals pertaining to topics and courses. Learning goals can be classified as long-term or short-term. When the goal classifications of mobile social learners are known, accurate recommendations can be generated for the mobile social learner to that effect.

- **Emotion of Mobile Social Learners**: The emotional mood of mobile social learners is also important for the
generation of recommendations. Mobile social learners should be in the right emotion and frame of mind to receive a recommendation for learning, otherwise the output of generated recommendations will not be effective enough.

Fig.1. Mobile Social Learner Modeling

A shown in figure 1, learning resource interest information about the mobile social learner can be captured either implicitly through user observation or explicitly through user ratings of a particular learning resource and also through registration modules of mobile social learners. For example, the system in Yau and Joy [11] captures information about learning styles. Some other systems such as MOBILearn [17] use the time a mobile learner spends at a particular location to estimate and predict interests. The contextual information of mobile social learners are also captured through explicit and implicit methods described below.

C. Mobile Social Learner Location Context

Depending on a particular circumstance, the location of the mobile social learner is important for generating recommendations. Location context has dominated research on context-aware mobile computing to a large extent. Different location models that capture human-readable and geometric information of objects, persons and devices through Location Based Services (LBS) have been proposed and are available [1]. Some of these proposed and available models include: (i) proximity within a particular space and (ii) communicative ability. In mobile social learning, some of the location contexts that are often referenced by learning applications include outdoor, home and classroom. Location context in mobile social learning can be captured or sensed through Global Positioning System (GPS) and Wireless Fidelity (Wi-Fi). The systems in Cui and Bull [6] called TenseITS, relies on an explicit approach where a mobile learner is asked manually to input his/her location context such as at home, in a bus or train or at the university campus. In Broisin et al. [9], location and tracking contexts are sensed in terms of semantic annotations associated to the accessed resources. SENSIMILE [10] supports recommendation in mobile social learning by using location-based sensing information.

D. Time Context

Time context in mobile social learning includes information such date, days, weeks etc. of various course events within a learning process. Time is often used in conjunction with other contexts such as location, either as a timestamp or time span which indicates the period or which instance a particular context is accessible or relevant for recommendation. For example a mobile social learning activity involving an outdoor game is likely to take place at a particular location in a particular time and such contextual information is relevant for generating a recommendation. Time interval data, such as the available study time of the learner is captured explicitly in Cui and Bull [6]. In Broisin et al. [9], the user profile of the learner is updated as soon as an activity is completed; thus, recommendations provided by the service are up-to-date in real time. In Yau and Joy [11], a learning timetable is presented to learners to enable them enter their schedule explicitly, so that they can use their entered schedule to plan their studies.

E. Physical Condition Context

Physical contexts consisting of noise levels and people nearby are relevant and important when generating recommendations in mobile social learning. Disturbing noises at a particular location by either people nearby, music or any other form doesn’t auger well for a mobile social learning recommendations at that particular time. This will result in poor recommendation output if a recommendation is generated in such physical conditions. An unsuitable temperature, heat or weather will also result in a poor recommendation output for a mobile social learner. Physical conditions are captured explicitly by the user or implicitly by the environment. For example in Cui and Bull [6] and Yin et al. [10], the physical conditions are captured through explicit means from the mobile social learners. In Yau and Joy [11] a microphone is used to acquire the physical conditions at a certain point in time.

F. Mobile Social Learner Activity Context

The activity context of a mobile social learner is defined by his/her actions, tasks and objectives. An example of such a model has been illustrated is the Contextualized Attention Metadata (CAM) illustrated in Broisin et al. [9]. In [9] the actions of the learner can be captured through events of an application within a session and time of related data. Such information is used to analyze and infer information about the current objective, task or topic of interest of the learner. Explicit procedures are mostly used to capture or sense information about activity context in mobile social learning. Such explicit procedures may involve: manual text input or scanning a Radio Frequency Identification (RFID) tag [1].

G. Mobile Social Learner Relations Context

The social relations context of a mobile social learner usually contains information such as his/her friends, neighbours, relatives, co-workers and even enemies. Explicit approaches that are used to sense or capture social relation context usually rely on a manual representation within a group structure or how a corporate environment is organized. Analyzing interactions between different mobile social learners as well as using enrollment data in a mLMS are instances of implicit procedures of sensing social relations context in mobile social learning.

To represent these concepts, an example in accordance to [1][2] is elaborated below. Consider the application for recommending academic videos to mobile social learners, where mobile social learners and academic videos are
described as relations having the following attributes: Academic Video: The set of all the videos that can be recommended; it is defined as Academic Video (Academic-Video-ID, Title, Length, Release Year, Source). Mobile Social Learner: The people to whom academic videos are recommended; it is defined as Mobile Social Learner (Mobile-Social-Learner-ID, Name, Cognitive Ability, Knowledge/Performance, Learning Interest, Learning Goal, Emotions).

Fig. 2. Contextual Framework for Mobile Social Learning

Additionally, the contextual information consists of the following three categories below that are also defined as relations having the following attributes: Mobile Computing Device: The characteristics of the mobile device that will show/broadcast the academic video; it is defined as Mobile Computing Device (Mobile-Device-ID, Name, Screen Size, Battery Power, CPU Speed, RAM Capacity, Hard Disk Capacity, Bandwidth, APIs and Operating Systems). Time: The time when the Academic Video can be or has been watched; it is defined as Time (Date, Day-of-Week, Time-of-Week, Month, Quarter, Year). In such a scenario the attribute Day-of-Week has values Mon, Tue, Wed, Thu, Fri, Sat, Sun, and attribute Time-of-Week has values “Weekday” and “Weekend” or “Morning and Afternoon”. Social Relations: Social Relations represents a person or a group of persons with whom the user can watch the Academic Video. It is defined as Social Relations (Social-Relations-Type), where the attribute Social-Relations-Type has values “alone”, “social affiliations”, “group members”, “social associations” and “others”. Location: The location of the mobile social learner represents where he/she can watch/view the Academic Video. It is defined as Location (outdoor location, home location, classroom location). Physical Conditions: This represents the current environmental situation of the mobile social learner. It is defined as Physical Conditions (heat condition, light condition, noise levels, people nearby). The ratings that are therefore assigned to an academic video by a mobile social learner also depends on where and how the academic video has been watched, with whom, and at what time [1][3]. Figure 2, depicts a framework involving different contextual information that are relevant in mobile social learning as discussed above.

CONCLUSION

This paper discussed, the importance and relevance of incorporating contextual information in a mobile social learning recommendation process. The paper noted that in certain mobile social learning circumstances, contextual information such as time, location and physical conditions are necessary for effective recommendations to mobile social learners and that without such contextual information, recommendation output may be poor. Furthermore the paper introduced a contextual framework for mobile social learning based on the different types of context sensors described in the paper. The development of appropriate recommendation algorithms through a reflection of the contextual framework in this paper will enable the generation and prediction of more precise, effective and trustworthy recommendations in mobile social learning.

REFERENCES


Source of support: Nil; Conflict of interest: None declared