

Improving Automated learning in Mobile Environment

[Samara Banno and Yanyan Yang]

Abstract— *the advance of mobile learning technologies has led to a new research issue in education, that is, the development of educational assessment with personalized learning system supports. In the meantime, it also becomes a challenging issue to evaluate the students learning achievement in mobile environment. In this paper, an integration of student modeling system with dynamic assessment strategy and context recommendations is proposed. This combination is able to guide the student to the proper level of performance by providing him with the necessary hints and learning material recommendations. The theoretical basis of dynamic assessment produce a proper mediation to help learners to apply some necessary principles to independently solve problems and thus learn more, plus provide more accurate individual knowledge estimation. Moreover, proper learning materials are suggested to the students to support their understanding and development of their knowledge level.*

Keywords— *Mobile Learning, Dynamic Assessment, Student Modeling, Recommender System.*

I. Introduction

In the last decade, several studies have addressed the advantages of web-based learning. Various learning methodologies such as assessment and feedback mechanism, learning material recommendation method and educational website evaluation criteria have been presented for enhancing the effectiveness of web-based learning [1]. However, educators have emphasized the importance and necessity of “ubiquitous Learning”, in which students can work without limitations of time and place. Therefore, it has become a challenging issue to access learning digital-world resources via the use of mobile and wireless communication technologies [2]. In such a new learning environment, students are situated in real-world scenarios, accessing the online resources via handheld devices and wireless networks. Such a learning scenario has been called mobile learning [3] or ubiquitous learning [4]. The most essential thing in mobile learning is that it is dynamic, and it can provide online expert and best resources for the students anytime. It helps to remove some of the formality from the learning experience and encourage learners to remain more focused for longer periods. Also, it can automatically adapt to learner’s interest and level through providing personalized system [5].

In improving personalized regulated learning, researches have focused on the educational assessment in which can be an effective strategy in directing the student upon the appropriate learning path. Assessment keeps teachers affording functional feedbacks, and allows students to navigate their own performance by addressing the strength and failure points in their cognitive ability [6]. Besides, it provides students with further dependence on their own feedback for more knowledge improvement [7]. However, researchers have also indicated the difficulty of supporting and approaching learners in such digital environments including the selection of situations that would afford the particular knowledge to be learned [8], the provision of “scaffolding” for learners with different prior knowledge or competence, and managing of teachers learning system to analyse the learning progress of students. Therefore, it has become an important and challenging issue to develop effective and easy-to-follow learning guidance models for mobile systems [9].

To cope with this problem, this paper proposes a dynamic assessment-based approach integrated with student modeling and context recommender system for mobile learning. This approach helps improve students’ learning attitudes and cognitive load of the\from different aspects. Dynamic Assessment differs sharply from the most other forms of assessment in its basis, that fully understanding the learners’ abilities and shifting the focus to the process through which abilities are formed [10]. It is called ‘dynamic’ because of its attempt to assess processes (depends on the student’s state), and the occurrence of teaching within the assessments [11]. However, very limited research and studies have performed the dynamic assessment strategies in the educational environment and specifically within the mobility community. The presented system integrated the concept of dynamic assessment with mobile Student modeling and learning recommendations methodologies, to get more personalized approach scaffolding the student learning process and achieving better knowledge level.

The rest of this paper is organized as follow: Section 2 relates this work to existing approaches. Section 3 describes the presents the overall architecture and its’ basic components, and in section 4 we summarize and point to future work.

II. Related Work

A. Student Modelling

A student model is the base for constructing personalization in computing educational applications. It represents several cognitive issues, such as, analysing the student’s performance, isolating the underlying misconceptions, representing

Samara Banno
University of Portsmouth / School of Engineering-UK

Yanyan Yang
University of Portsmouth/ School of Engineering-UK

students' goals and plans, identifying prior and acquired knowledge, and describing personality characteristics. It is a process of gathering relevant information in order to infer and represent the current cognitive state of the student. Therefore, it is an effective way in making instructional decisions which enables understanding and identification of students' needs [12]. In order to apply the student modelling approach efficiently, some requirements need to be determined, and they are stated as follows:

- **Student Personalisation**

A significant initial stage of constructing a student model is to consider the appropriate students' preferences. The question "what aspects of the student should we model in a specific intelligent tutoring system?" has to be answered when a new student model is built [13]. Such these aspects are implemented in many systems under the title of student profiling, such as [14] and [15] who presented an approach to dynamically update mobile users' profiles so that they can be provided with appropriate services while moving from one location to another.

- **Student Prior Knowledge**

Learners' prior knowledge is considered to be one of the most important factors affecting learning effectiveness and influence learner achievements. Learner will have trouble in learning new information and constructing new understandings when they lack appropriate prior knowledge [16]. Learners with different levels of prior knowledge had different perceptions about the features of learning environment; they need more guidance and assistance to facilitate their learning in a personalized Learning environment [17]. On the other side, several studies have addressed some drawbacks of user modeling, in general. Kobsa [18] made the point that the user modeling components draw mostly on assumptions about the user, which may not necessarily be correct. User modeling therefore inherently involves the risk of misunderstandings. Furthermore, [19] listed similar problems for adaptive assessment, for example the inconsistency in estimating a learner's knowledge level, and a lack in supporting lifelong learning in adaptive assessment systems according to the difficulties in updating rules, content and assessment within these systems. According to what have been highlighted above, the proposed system overcomes the mentioned problems by integrating the dynamic assessment techniques with the user modeling in order to produce more accurate estimation of user knowledge support lifelong learning, through the continues updating of the student performance level in the educational environment.

B. Dynamic Assessment

The development of dynamic assessment was greatly influenced by L.S. Vygotsky whose set the role social context of children's learning and development and ways to improve their level performance level using the adult's assistance. By proposing the theory of the 'Zone of Proximal Development

(ZPD) which describes the difference between the learners performances achieved with and without adults guidance, greater number of opportunities are provided to interact with more competent peers and adults, such as teachers [20].

According to Sternberg [21], there are commonly two formats of dynamic assessment: sandwich format and cake format. Both formats are presented in the form of 'test–teach–retest'. Sandwich format dynamic assessment means that the teaching is held between pre-test and post-test, thus constituting a sandwich-like process. In cake format dynamic assessment, the teaching is a response to examinee's answers to each item. The main difference between the two dynamic assessments' format is that instruction and assessment are separate in sandwich format dynamic assessment but combined in cake format dynamic assessment. Since this research treats assessment as teaching and learning strategy, the main feature of cake format dynamic assessment is the design of successive and proper series of hints. This design is similar to the 'graduated prompt approach' presented by [22]. They start with 'general hints' with little specific information about the solution, and gradually become 'specific hints' 'describes detailed blueprint from which learners can generate the correct answer. This research refers to the 'graduated prompt approach' which is developed by GPAM-WATA and the hints (called instructional prompts (IPs)) provided by its dynamic assessment items [23]. Conducting the dynamic assessment with context aware is presented by Huang who used a decision tree approach to guide the individual students to improve their ability for classifying Host Plants of Butterflies in the physical learning environment. An assessment activity has been conducted in an elementary school to show the positive effect on student performance motivation [24].

Our approach will extend the 'Graduated Prompting Assessment Module of the WATA system (GPAM-WATA) integrated with obtained personalized student's modeling. This integration will provide more accurate personalized performance for each individual, as well as, better approach in enhancing student learning process. According to [25], the 'graduated prompt approach' (presented in GPAM-WATA) emphasizes that when examinees have difficulties solving problems, examiners would help them through mediation (hints). The interaction between examiners and examinees can help examinees discover or apply some principles to independently solve problems and learn more. Therefore, it is expected that IPs may play the role of a teacher in instructing and guiding learners depending on their previous knowledge towards expert performance level. The teaching process will be performed through suggesting the proper learning material depending on the student knowledge level in each stage. The post dynamic test will be performed once again to extract his new level; hence the student profile will keep dynamically updating the new student performance state.

C. Context Recommender System

Recommender systems have been researched extensively since the last decade. Suitable resources are identified from a

potentially overwhelming variety of choices to facilitate both learning and teaching tasks. As learning is taking place in extremely diverse and rich mobile environments, the incorporation of contextual information about the user in the recommendation process has grabbed major interest. Such contextualization is researched as a paradigm for building intelligent systems that can better predict and respond to their behavior and preferences. Most systems suggest learning resources to help students with their learning activities such as [26] and [27]. Additionally, intelligent Tutoring Systems (ITSs) use information about the learner to suggest personalized hints solving a problem [28]. Since mobile learning environment mostly depends on a learner context as a personalized approach of user’s modeling, therefore, from a technical perspective, there is a need to define context in a more specific way as an operational term [29]. The location context of the user is taken into account by several systems. Lehsten et al. [30] detected the location to indicate whether the learner is attending a lecture, if not, a stream of the lecture or other relevant learning resources is recommended, similar work presented by [31] and [32]. User preferences are also captured in different ways, depending on the type of information. CALS [33] and [34] detect information about learning styles explicitly via registration module, which enables the user to select the best matching learning style. Furthermore, user’s interests are modeled implicitly through interactions of the user with the system [32].

The proposed system will handle the issue of context user recommendations through suggesting test items and learning materials depending on the student context (train, library, home or school). The idea behind this is to adapt the location and the learning item complexity depending on the student knowledge level and context. The system will recommend more complex learning material after detecting the place that the student can concentrate, while the less complicated items are suggested in other places like train or university where the student are most likely to be distracted. These locations are explicitly defined previously by the user and the system will detect it implicitly.

III. System Design

This paper presents a Dynamic Recommendations for Student Assessment (DRSA) general prototype for supporting more accurate learning recommendations, and easing the student knowledge level development in mobile learning applications. The proposed architecture consists of two essential patterns: *Automated Learning* side and *mobile student* side as illustrated in Figure1.

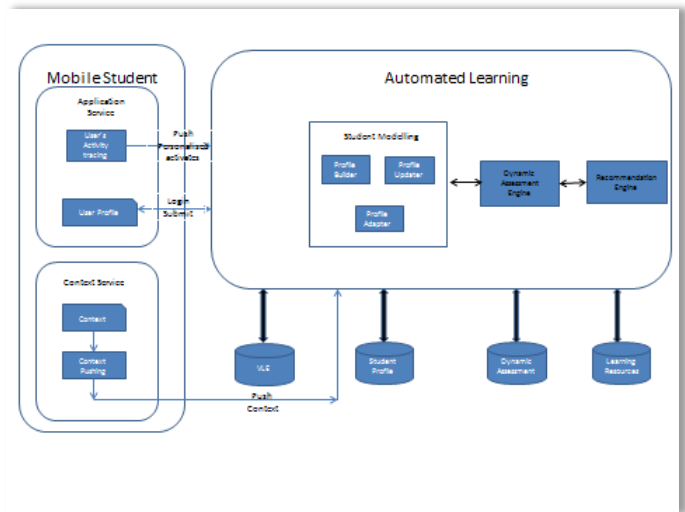


Figure 1: Initial Prototype Architecture

As described in the figure, **Automated Learning Side** contains four major components:

- **The student Modelling Engine:**

It is composed by a range of relevant information about the student using the M-learning environment. Frequently common types of information used in this engine can include the learner knowledge, context information, preferences, learning styles, etc. Generally, according to [35], two main categories are outlined in student modeling: the domain specific information and the domain independent information. The presented approach adopted three components student’s model: *Profile Builder*, *Profile Organizer*, and *Profile Adapter*. These components get the user personalized preferences by accessing student scores in any Virtual Learning Environment (VLE) as described below:

Profile Builder: it is in charge of the creation of two types of profiles in order to carry out the personalization efficiently: Static and Dynamic user profile. Static features, for instance, email, age, tongue language etc., are set before the learning process takes place, and they usually remain unchanged throughout the learning session. While dynamic features, are determined directly from the student’s interactions with the system and updated during learning sessions based on the collected data [36]. Therefore, the challenge is to define the individual dynamic student’s characteristics that constitute the base for the system’s adaptation. These characteristics include knowledge and skills, errors and misconceptions, learning styles and preferences, affective and cognitive factors. Knowledge refers

to the prior knowledge of a student on the knowledge domain as well as her/his current knowledge level. This is usually measured through questionnaires and tests that observed during student's learning process each time the student is dynamically assessed. This observation of the learner during instruction requires the usage of intelligent methods, such as, Bayesian or machine learning methods which keeps the learner knowledge state updated.

Profile Organizer: It is responsible of putting each user (after accessing their profiles) within a cluster of users whose share similar preferences. By gathering the new users with the users groups, the new user (who recently created their profile and do not have yet enough behavioral historical data) can benefit from other users' experiences, and have already some term of knowledge discovery and learning resources recommendations. Some of learner modeling approaches might be used in order to group similar learners into categories, such as, Stereotypes and Overlay methods. Although Stereotypes is powerful in providing considerable information based on basic observations, it does not provide an accurate learner model [38]. Therefore, this method can be applied to obtain the initial student information from VLE profile as the first step of using the application, and then the Overlay model can be used later for each learner's profile individually to reflect the expert-knowledge level of the subject .This method applies the qualitative measure (good-average-poor) that indicates the degree of user's knowledge.

Profile Adapter: Interacts with any external application (VLE) or user to make use of modeling engine by accessing the profile builder. This will help external services subscribed and be notified by the user modeling engine.

To determine the student prior knowledge as explained above, it connects directly with the *Student Profile database* which performs two different types of techniques: Knowledge and Behavioral based [18]. The Knowledge-Based adaptation typically results for data collected through questionnaires and studies of the user (hence the student prior knowledge), with the purpose to produce a set of initial knowledge estimation and classify users in groups and generalizes student characteristics to that group. The Behavioral adaptation results of user monitoring during his dynamic test activity. Hence the Profile Organizer helps the student improving his current

level by providing the suitable questions and hints depending on his knowledge group.

- **Dynamic Assessment Engine:** It follows the GPAM-WATA structure. It gets the assessment questions from the dynamic assessment database, in which it includes all the recommended questions and hints that will be used in assessing the students all the way along to perform the dynamic assessment strategy (pre and post-tests). When learners answer any given item incorrectly for the first time, the system will provide a general hint (IP). If they answer the item incorrectly a second time, they will be given more specific hint (IP), this will be done three times till the student get the right answer. After that, Learners then go on answering other items when either of two conditions is fulfilled: learners still fail to answer correctly after a maximum of three IPs are delivered, or learners answer it correctly. After learners finish the test, meaning there is no item left for them to answer; the proposed system provides information about the items that the learners failed to answer correctly. Furthermore, the student profile will be updated simultaneously with the new student performance level estimation after each test via student modelling agent.
- **Recommendation Engine:** Its task is to suggest all the necessary learning materials stored in *learning resources database* that indicated by the instructor and can be recommended by the system to the user to help him improving his learning knowledge and skills, after been dynamically assessed and determined his current performance level. The proposed (DRSA) system describes an automatic personalization approach for providing learning object recommendations for students in M-learning systems. The term "Learning Object" means any digital educational resource used within the M-learning environment, it is all known formats of digital educational resources i.e. a course, a web page, books. These learning objects are tracked in databases references. Therefore, automatic recommendation of learning objects means generating a list of educational resources (hosted and/or created inside the M-learning platform) in order to guide and support the learners. The recommendation procedure is performed to be able to compute relevant learning resources to recommend for the active learner by applying a number of recommendation strategies, such as collaborative filtering, content-based filtering, and/or hybrid recommendation algorithms. These algorithms use information about users and resources to generate recommendations [39]. To meet the task objectives, the student is required to have the test once again after accessing the recommended learning resources

till he gets the expert level knowledge of his subject. This process will ensure better understanding level of the student besides enhancing his self-learning motivation.

Mobile Student Side:

Consists of two essential layers which are the *application service* and *context service* described as following:

- **Application Service:** responsible for all user interactions with the system including the User Interfaces, contents representation plus tracking the user's activities such as recording new learning items that the user has recently read and save them in the server side by pushing the personalized notifications to the student modeling engine .

- **Context Service:** automatically pushes user changing context to the user profile database by collecting the student real time learning environment. Generally, User Context is defined into three categories (Dey, Abowd, and Salber, 2001):

Computing context, such as, network connectivity, communication costs, and bandwidth.

User context, such as, user profile, location, people nearby and social situation.

Physical context, such as, lighting, noise levels, traffic conditions, and temperature.

The system will record the students' favorite places such as (library, train, home, etc...), then proactively deliver notifications to his mobile device based on user's current status. During the interaction with the user, the recommended test items and learning resources will be delivered to the student based on his current context by adopting the user and physical contexts. More complex items will be suggested based on the place where the student can concentrate, while the less complicated ones are recommended to other places like train or university where the student are most likely to be distracted. These locations are previously stored in the user preferences.

iv. Conclusion

This paper has outlined the general principles of a new approach to perform personalization strategies in m-learning environment. This approach combines digital learning resources and real-world learning contexts for more flexible learning not restricted with time and place. In this study, a dynamic assessment-based learning mechanism is proposed, and a mobile learning environment is developed accordingly. In addition, student modelling approach is integrated with context recommender system. This integration performs better and more accurate determination of student learning ability, provide informal learning any time, and enhance his

knowledge process with proper learning resources recommendations. Currently, the practical implementation of the proposed prototype is being contributed on a specific mobile platform in order to evaluate its efficiency and accuracy on different students' knowledge level.

References

- [1] Liu, Gi-Zen, Zih-Hui Liu, and Gwo-Jen Hwang. "Developing multi-dimensional evaluation criteria for English learning websites with university students and professors." *Computers & Education* 56, 2011, p. 65-79.
- [2] Chu, Hui-Chun, Gwo-Jen Hwang, and Chin-Chung Tsai. "A knowledge engineering approach to developing mindtools for context-aware ubiquitous learning." *Computers & Education* 54, no. 1, 2010, p.289-297.
- [3] Sharples, Mike, Dan Corlett, and Oliver Westmancott. "The design and implementation of a mobile learning resource." *Personal and Ubiquitous Computing* 6, no. 3, 2002, p. 220-234.
- [4] Hwang, Gwo-Jen, Yen-Ru Shi, and Hui-Chun Chu. "A concept map approach to developing collaborative Mindtools for context-aware ubiquitous learning." *British Journal of Educational Technology* 42, no. 5, 2011.
- [5] Attewell, J. "From research and development to mobile learning: Tools for education and training providers and their learners." In 4th World Conference on m-Learning , 2005.
- [6] Bransford, J. D., Brown, A. L., & Cocking, R. R. "How people learn", 2000. M. Young, *The Technical Writer's Handbook*. Mill Valley, CA: University Science, 1989.
- [7] Shepard, L. A. "Using assessment to help students think about learning." Keynote address at the Assessment Training Institute Summer Conference, Portland, OR, 2001.
- [8] Chu, H. C., Hwang, G. J., & Tsai, C. C. "A knowledge engineering approach to developing mind tools for context-aware ubiquitous learning." *Computers & Education*, 54(1), 2010.
- [9] Hwang, G. J., & Chang, H. F. "A formative assessment-based mobile learning approach to improving the learning attitudes and achievements of students." *Computers & Education*, 56(4), 2011.
- [10] Lantolf, J. P., & Poehner, M. E. "Dynamic assessment". In *Encyclopedia of language and education* . Springer US, 2008.
- [11] Haywood, H. C., Brown, A. L., & Wingenfeld, S. "Dynamic approaches to psychoeducational assessment". *School Psychology Review*, 1990.
- [12] Li, N., Cohen, W. W., Koedinger, K. R., Matsuda, N., & Mellon, C. "A Machine Learning Approach for Automatic Student Model Discovery." In EDM, 2011.
- [13] González, C., Burguillo, J. C., & Llamas, M. "A qualitative comparison of techniques for student modeling in intelligent tutoring systems". In *Frontiers in Education Conference, 36th Annual IEEE*, 2006.
- [14] Tuzhilin, A. S. "System and method for dynamic profiling of users in one-to-one applications." U.S. Patent No. 6,236,978. Washington, DC: U.S. Patent and Trademark Office, 2001.
- [15] Ouanaim, M., Harroud, H., Berrado, A., & Boulmalf, M. "Dynamic user profiling approach for services discovery in mobile environments". In *Proceedings of the 6th International Wireless Communications and Mobile Computing Conference , ACM*, 2010.
- [16] Dochy, F. J. R. C. "Prior knowledge and learning." *International encyclopedia of education*, 4698-4702, 1994.
- [17] Mitchell, T. J., Chen, S. Y., & Macredie, R. D. "Hypermedia learning and prior knowledge: domain expertise vs. system expertise." *Journal of Computer Assisted Learning*, 21(1), 2005, 53-64.
- [18] Kobsa, A. "User modelling: Recent work, prospects and hazards." *Human Factors in Information Technology*, 1993.
- [19] Sitthisak, O., Gilbert, L., Davis, H. C., & Gobbi, M. "Adapting health care competencies to a formal competency model." In *Advanced*

- Learning Technologies, Seventh IEEE International Conference on, 2007.
- [20] Vygotsky, L. S. "Mind in society: The development of higher psychological processes". Harvard university press, 1980.
- [21] Grigorenko, Elena L. "Dynamic Assessment and Response to Intervention Two Sides of One Coin." Journal of Learning Disabilities ,2009.
- [22] Campione, J. C., & Brown, A. L. "Linking dynamic assessment with school achievement." In C. S. Lidz (Ed.), Dynamic assessment: An international approach to evaluating learning potential New York: The Guilford Press, 1987.
- [23] Wang. "Web-based dynamic assessment: Taking assessment as teaching and learning strategy for improving students" e-Learning effectiveness, 2010.
- [24] Huang, S. H., Wu, T. T., Chu, H. C., & Hwang, G. J." A decision tree approach to conducting dynamic assessment in a context-aware ubiquitous learning environment. "In Wireless, Mobile, and Ubiquitous Technology in Education, 2008. WMUTE 2008. Fifth IEEE International Conference on . IEEE, 2008.
- [25] Poehner, M. E." Dynamic assessment: A Vygotskian approach to understanding and promoting L2 development." New York: Springer, 2008.
- [26] Tang and G. McCalla. "Smart Recommendation for an Evolving E-Learning System. Proc. Workshop Technologies for Electronic Documents for Supporting Learning." Int'l Conf. Artificial Intelligence in Education (AIED), 2003.
- [27] Garcia-Molina. "Flexible Recommendations in CourseRank On the Move to Meaningful Internet Systems". (OTM '08), Springer, 2008.
- [28] Koedinger and A.T. Corbett. "Cognitive Tutors: Technology Bringing Learning Sciences to the Classroom." The Cambridge Handbook of the Learning Sciences,2006.
- [29] Winograd." Architectures for Context". Human-Computer Interaction, 2001.
- [30] Lehsten, R. Zender, U. Lucke, and D. Tavangarian. "A Service-Oriented Approach Towards Context-aware Mobile Learning Management Systems." Proc. IEEE Eighth Int'l Conf. Pervasive Computing and Comm. Workshops (PERCOM), 2010.
- [31] El-Bishouty, Moushir M., Hiroaki Ogata, and Yoneo Yano. "PERKAM: Personalized knowledge awareness map for computer supported ubiquitous learning." Educational Technology & Society 10, no. 3, 2007.
- [32] Zhou and K. Rechert. "Personalization for Location-Based ELearning." Proc. Int'l Conf. Next Generation Mobile Applications, Services and Technologies (NGMAST '08), 2008.
- [33] Yau and M. Joy. "A Context-Aware and Adaptive Learning Schedule Framework for Supporting Learners' Daily Routines." Proc. Second Int'l Conf. Systems, 2007.
- [34]] Macedo, D. F., dos Santos, A. L., Nogueira, J. M. S., & Pujolle, G. "A knowledge plane for autonomic context-aware wireless mobile ad hoc networks." In Management of Converged Multimedia Networks and Services .Springer Berlin Heidelberg, 2008.
- [35] Brusilovsky, P. "Methods and techniques of adaptive hypermedia." User Modelling and User-Adapted Interaction, 1996.
- [36] Jeremić, Z., Jovanović, J., & Gašević, D. "Student modeling and assessment in intelligent tutoring of software patterns. "Expert Systems with Applications, 2012.
- [37] Cannataro, M. and Pugliese, A. "A survey of architectures for adaptive hypermedia". In Web Dynamics M. Levene and A. Poulouvassilis, 2004.
- [38] Adomavicius, G., & Tuzhilin, A. "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions." Knowledge and Data Engineering, IEEE Transaction,2005.
- [39] Dey, G. Abowd, and D. Salber. "A Conceptual Framework and a Toolkit for Supporting the Rapid Prototyping of Context-Aware Applications. "Human-Computer Interaction, 2001.