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Learning Analytics to Share and Reuse Authentic Learning Experiences in a Seamless Learning Environment

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ABSTRACT: Authentic learning experiences are considered to be a rich source for learning foreign vocabulary. Prevalent learning theories support the idea of learning from others' authentic experiences. This study aims at developing a learning analytics solution to deliver the right authentic learning contents created by one learner to others in a seamless learning environment. Therefore, a conceptual framework is proposed to close the loops in the missing components of the current learning analytics framework. Data is captured and recorded centrally via a context-aware ubiquitous learning system which is a key component of a learning analytics framework. k-Nearest Neighbor (kNN) based profiling is used to measure the similarity of learners' profiles. Authentic learning contents are shared and reused through re-logging function. This paper also discusses how two previously developed tools, namely learning log navigator and a three-layer architecture for mapping learners' knowledge-level, are adapted to enhance the performance of the conceptual framework.

Keywords: Authentic learning experiences, informal learning, learning analytics, seamless learning, share and reuse, ubiquitous logs, vocabulary learning.

1 INTRODUCTION

Authentic learning is referred to real life learning. According to Steve Revington, this kind of learning style encourages students to create a tangible and useful product to be shared with their world (Revington, 2016). In language learning, the idea of using authentic learning materials to teach foreign vocabulary has a long history. Authentic learning materials considered to be a rich source of target language input (Duda & Tyne, 2010). In Glimore's viewpoint, authentic materials and authenticity in foreign language learning opposes contrived materials of traditional textbooks which typically display a meager and frequently distorted sample of the target language while authentic materials offer a much richer source of input for learners (Gilmore, 2007). Tomlinson's viewpoint (Tomlinson, 2008) is equally severe. He claimed that various English language teaching materials, particularly global course-books currently make a significant contribution to the failure of many learners of English to acquire even basic competence in English and to the failure of most of them to develop the ability to use it successfully. Therefore, exposure to authentic language learning contents is crucial for language development, particularly for foreign vocabulary. However, the debate over the role of authenticity, as well as what it means to be authentic, has become increasingly sophisticated and complex over the

years and now embraces research from a wide variety of fields including discourse and conversational analysis, pragmatics, cross-cultural studies, sociolinguistics, ethnology, second language acquisition, cognitive and social psychology, learner autonomy, information and communication technology, motivation research and materials development (Gilmore, 2007).

While authentic learning experiences are crucial in foreign vocabulary learning, how ubiquitous and sensing technologies facilitate in it? During the twentieth century, massive development of sensing technologies made it possible to attain contextual information, such as people, date, precise time, location, theme etc. regarding the learners' usage of various ubiquitous technologies, for example, lifelong camera, multi-touch interface, Wi-Fi, RFID, GPS, wearable smart tracker, and Bluetooth. Using such functions, learners authentic learning experiences can be tracked and recorded. For instance, an international student, upon experiencing a culturally authentic content, records it in the system with its context information (memo), picture/video/voice-data, together with its textual information. Ubiquitous functionalities automatically track the learning experiences can be captured. Now the questions arise, how this vast amount of educational big data to be dealt to improve next-generation education? Also, can learning analytics provide solutions to sharing and reusing those captured authentic learning experiences (i.e. logs) among a community of language learners having similar learning interest in the right time and place?

The present study aimed at discovering a ubiquitous dataset to innovate a learning analytics solution for sharing and reusing authentic learning contents in a seamless learning environment. The contributions of this paper are- to begin with, an authentic learning experience is defined. We defined an authentic experience is comprised of the word, it's representative picture/video/voice-data, contextual information (i.e. memo), and translation data together with the time (when) and location (where) information. These parameters are must for a content to be treated as an authentic learning experience. These authentic learning experiences are collected using a context-aware ubiquitous language learning system (Ogata et al., 2011) that supports both formal and informal learning seamlessly. After that, a conceptual framework is proposed for putting the missing components together to close the loops (i.e. learning analytics cycle) in their learning analytics framework (Flanagan & Ogata, 2018). The conceptual framework is to impliment Kolb's experimental learning theory(Kolb, 2014) using learning analytics. Finally, an extended objective of this work is to establish a personalized learning path to optimize vocabulary learning. Moreover, this study also aimed to increase foreign language learners' motivation and engagement with location-based learning system.

2 LEARN FROM OTHERS EXPEREINCES: KOLB'S VIEWPOINT AND LEARNING ANALYTICS CYCLES

Kolb's experimental learning theory is a renown learning theory which is widely recognized and accepted not just for language learning but to for learning-focused curriculum development and instructional design (Kolb, 2014). In light of the increasingly competitive and complex learning environments, Kolb's experimental learning theory has been used to carry out many studies over the last two decades. Kolb's experimental learning theory comprises of four phases, each of which involves using different processes to acquire and use information and skills. The four phases are

Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC), and Active Experimentation (AE). In CE stage of learning, learners actively experience an activity in real-life or in the classroom. The RO happens when the learner consciously reflects back on that experience. In the AC stage, learners attempt to conceptualize a theory or model of what is observed. Finally, in the AE stage, learners try to plan how to test a model or theory or plan for a forthcoming experience. The assumption of Kolb's learning theory, later simplified by Knutson (Knutson, 2003a) as- we seldom learn from experience unless we assess the experience, assigning our own meaning in terms of our own goals, aims, ambitions, and expectations. From these processes come the insights, the discoveries, and understanding. The pieces fall into place, and the experience takes on added meaning in relation to other experiences.

In relation to Kolb's theory, Doug Clow's idea is a great example for learning analytics practice on a base of established learning theory. Doug Clow (Clow, 2012) has shown how learning analytics cycles overlap with Kolb's theory. In his viewpoint, the learning analytics cycle begins with learners (Phase 1 in Fig.3) of formal and informal learning. The next step to it is, to generate and capture of data (Phase 2 in Fig.3) about or by the learners. For example, demographic, login, clickstream, location etc. about a potential learner. Some of it can be generated automatically while some require a large multidisciplinary team to expend significant effort. The third step is the processing of this data into metrics or analytics (Phase 3 in Fig.3), which provide some insight (Phase 4 in Fig.3) into the learning process. Phase 4 includes visualizations, dashboards, personalized feedback tools where the comparisons of outcome can be measured. We yield this conclusion that, in order to implement a learning theory at an individual level, learning analytics cycles can facilitate by providing information on learners' activities, conception, and actions which, in future leads to propose rich feedback or intervention mechanism.

This paper aimed at closing the loops in the current learning analytics framework (Flanagan & Ogata, 2018). Precisely speaking, in the current setup, elements of the first two phases learners (which is the Phase 1) and dataset (Phase 2) exist. However, the analytics (Phase 3) and interventions (Phase 4) do not exist. Therefore, with this study, we aimed at establishing the relationship between the phases to close the loops.

3 PREVIOUS WORKS TO SUPPORT THE CONCEPTUAL FRAMEWORK

3.1 Location-based sharing

Learning Log Navigator (hereafter LLN), an analytics tool is developed as a function of the system to analyze authentic learning experiences. LLN aims to automatically provide appropriate learning experiences in accordance with the individual learner (Mouri, Ogata, & Liu, 2014). In the LLN system, sharing authentic learning contents happens in three conditions (shown in Fig.1). LLN's analytics first records concrete experiences in the system, and then using location data, it guides learners to the authentic learning environment. Next, when learners reflect on themselves based on reflective observation, the system provides experiences that others learners have learned in the authentic learning environment. Finally, it supports conceptualizing from concrete experiences by recommendation and analysis of learning logs. LLN system recommends authentic learning contents that were created in the nearest location of a learner's current location. This calculation is based on the latitude and longitude information of a learner. The number of contents to be recommended, which is 10, is controlled by the system. If the number of the recommended task is too much; learners will be confused because it is difficult for learners to select the most accurate one (Mouri, Ogata, & Liu, 2014). If a learner wishes to browse more contents, he/she needs to change his/her learning location (that is, to extend the limit of distance). Learners can learn tasks using the mobile device through these whole flow (Mouri, Ogata, & Liu, 2014).



Figure 1: Authentic learning experiences sharing using LLN

3.2 A three-layer architecture

To support LLN, a three-layer architecture (visualized in Fig.2) is developed that identifies learners and knowledge or knowledge and location by using network graph. This architecture visualization can be widened by linking one's own learning logs to the knowledge learned by doing tasks (Mouri, Ogata, Uosaki, & Liu, 2014). The architecture is defined as a three-layer architecture where the upper layer contains each author in order to confirm position of own or other learners, the intermediate layer contains the knowledge that learners learned, and the lowest layer contains data such as location and time (Mouri, Ogata, Uosaki, et al., 2014). In order to realize spatiotemporal visualization of our learning logs, nodes on the intermediate layer are linked to the nodes on the lowest layer (Mouri, Ogata, Uosaki, et al., 2014).



Figure 2: Authentic learning experiences sharing using LLN (Mouri, Ogata, Uosaki, et al., 2014)

4 LEARNING ANALYTICS FOR SHARING AND REUSING CONTENTS

4.1 A Conceptual Framework: Design

Doug Clow's paper has shown that learning analytics cycles overlap with the four phases of Kolb's experimental learning theory. Which mean, learning analytics cycles can be utilized to implement this theory. Based on that, a conceptual framework is proposed based on learning analytics cycle for sharing and reusing authentic learning experiences in a seamless learning environment. The system is a key research component of our learning analytics framework where learners get the opportunity to learn in various learning environments regardless of place or time. The framework is designed in the way that it provides an interface between integrated production and research systems to allow user authentication, information, and learning analytics results to be seamlessly transferred between systems (Flanagan & Ogata, 2018). As stated earlier, at present, Phase 1(users) and Phase 2 (dataset) exit without having any analytic connection. Therefore, with the proposed conceptual framework, this study aimed at closing the loop for missing parts of the learning analytics cycle. Fig.3 shows the conceptual framework that is proposed to support this study. This study is carried out precisely for Phase 3 (analytics) and Phase 4 (interventions).



Figure 3: The proposed conceptual framework for closing the loop

4.2 Implement the Framework: Phase-by-Phase

4.2.1 System-used for capturing authentic learning experiences

This present study defines an authentic experience as it comprised of the word, it's representative picture/video/voice-data, contextual information (i.e. memo), and translation data together with the time (when) and location (where) information. These parameters are must for a content to be treated as an authentic learning experience. Foreign language learners' authentic learning experiences are captured as concrete experiences using a context-aware ubiquitous language learning system that offers seamless learning of multiple foreign languages. The system is based on LORE (Log-Organize-Recall-Evaluate) model by which intends to automatically extract meaningful knowledge from past learning experiences so that that information can serve as the guide for future learning (Ogata et al., 2011). The ubiquitous functionalities of the system are capable of recording learners' concrete experiences (such as the geolocation information, vocabulary knowledge, quiz, learning context, contextual image information etc.) as ubiquitous learning logs into its learning record store (LRS)(Hasnine et al., 2018). Learners' activities in the system are recorded precisely in the LRS as xAPI (Experience API) statements. The system also captures various educational big data through its five key features namely, authentic learning logs capturing, lifelogging, share and reuse logs, automatic quiz generation based on past learning logs, and an e-Book reader. Most of the logs are created for either Japanese or English language's vocabulary learning. A learning log-tracking dashboard, shown in Fig.3, is developed where learners can track their formal (eBook-based learning activities) and informal (real-life) learning activities. A time-map is also developed for chronological tracking of

learning contents with learning location and time. This client-server application runs on different platforms including Android mobile phones, PC and general mobile phones (Hasnine, 2018).

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	ch yeah, thanks!	Condition

Figure 4: An authentic learning log (on left) and seamless activity tracking function (on right)

4.2.2 Phase 2 (Dataset)

Data is collected primarily from learners of foreign languages, tourists, and international students looking for jobs in Japan. As of now, over 30000 learning logs and over 400000 quiz logs are captured using the system from over 1700 learners from over thirty-nationalities (Ogata et al., 2018). The dataset contains vocabulary Information (words that a learner wishes to learn in a specific context), learner profile Information (such as, name, age, gender, education etc.), cultural Information (information about nationality, social interaction level etc.), study place-time-location (Geo-locational information, place-details, and study time etc.), past Knowledge: Vocabulary that learners have previously acquired (i.e. learning history), and contextual Image Information(unique image features (color, shape, object etc.) that may describe the learning context and/or the word itself. Note that, not all of those logs are counted to be authentic learning experiences. It can be reported that, the majority of learners in the system have registered themselves as Chinese, English and Japanese languages as their default languages.

4.2.3 Phase 3 (Analytics)

kNN (K-Nearest Neighbor) is a renowned machine learning algorithm that can find clusters of similar learners based on common properties, and make predictions using the average features of top-k nearest neighbors. kNN is an intuitive and easy-to-implement algorithm. This algorithm is used to develop partner-matching, Facebook's friend-matching and friend-suggestion, Amazon's interest-based book recommendation etc. Aiming to find learners from one's neighborhood having similar demography, we looked at a learner's neighborhood and measured the similarity in profiles. This technique is adapted to improve the matching accuracy and efficiency. In order to run the kNN

algorithm, a metrics with certain parameters are required. Hence, a metrics is formed for profile matching using kNN algorithm. Table 1 briefly summarized the metrics.

Value	Description
User id	Universally Unique Identifier (UUID) of a user
Age	Age of a user
Nationality	Nationality of a user
Target language(s)	Language(s) that a learner registered as language(s) of interest
Past knowledge	Vocabulary that learners have previously acquired (i.e. the learning history)
Knowledge level	Current knowledge level in a target language. For instance, JLPT3 refers to a learner's Japanese language level as intermediate
Learning location	Latitude and longitude data of a learner's learning locations
Time	Time of each session
Learning context	The context that a learner created an authentic learning experience
Image	Image that is uploaded by the learner in the process of capturing a log
Video	Video that is uploaded by the learner in the process of capturing a log

Note that, a log containing either image and/or video clip is treated as an authentic learning experience. We plan to integrate this analysis with our previous developments. As stated earlier, previously we developed two tools namely, LLN system and the three-layer architecture. These tools are used for determining the right person to deliver the right content by analyzing the current learning location and level of knowledge.

4.2.4 Phase 4 (Intervention): Analytics Dashboard and Re-log Function

Re-log function (located on the top-right corner in Fig.4(left)) is developed for reusing and sharing of an authentic learning experience. This function enables a learner to reuse an authentic learning material created by other learner in the system. A prototype dashboard is underway as an intervention which is the first step to an analytics dashboard. In this dashboard, learners will be able to interact with his/her peers of similar interest in foreign language learning.

5 CONCLUSION

The assumption of Kolb's learning theory is that we seldom learn from experience unless we assess the experience, assigning our own meaning in terms of our own goals, aims, ambitions, and expectations. From these processes come the insights, the discoveries, and understanding. The pieces fall into place, and the experience takes on added meaning in relation to other experiences (Knutson, 2003b). From this viewpoint of Kolb's theory, this research initiated to contribute to the learning analytics research community by proposing an analytic method for sharing and reusing one learner's authentic learning experiences among others when learning foreign vocabulary in a seamless learning environment. A conceptual framework is proposed to connect the missing components of our learning analytics framework. With this conceptual framework, this study aimed at connecting learning analytics phases, namely learners (Phase 1), dataset (Phase 2), analytics (Phase 3) and interventions (Phase 4). For profiling, kNN-based profile matching algorithm used. In order to enhance the performance of the model, two previously developed analytics tools namely, Learning Log Navigator (LLN) was developed that can analyze learners' authentic learning experiences based on learning location, and a three-layer architecture to map a leaner with his/her knowledge and learning location, are adapted.

For future works, an experiment is designed to evaluate the proposed framework. The experiment is aimed to find answers to the research questions- First, the right way to deliver the right content at the right time and place; Second, find out the right learner to whom an authentic learning experience can be shared; Third, establish personalized learning path to optimize vocabulary learning. Moreover, the experiment will analyze whether learners' engagement with the system and motivation is increased. Two groups of subjects are planned to recruit for this experiment. One of which is tourists visiting in the city. And, another group is the combination of international students studying Japanese and Japanese students learning the Spanish language. The experiment is designed to guide international students to experience real-life Japanese learning activities by the word they learned either in class or out of the class.

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