Journal of Universal Computer Science, vol. 22, no. 10 (2016), 1380-1397
submitted: 29/12/15, accepted: 27/9/16, appeared: 1/10/16 © J.UCS

Context-aware and Personalization Method based on Ubiquitous Learning Analytics

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Abstract: In the past decades, ubiquitous learning (u-learning) has been the focus of attention in educational research across the world. Majority of u-learning systems have been constructed using ubiquitous technologies such as RFID tags and cards, wireless communication, mobile phones, and wearable computers. There is also a growing recognition that it can be improved by utilizing ubiquitous learning logs collected by the u-learning system to enhance and increase the interactions among a learner, contexts, and context-based knowledge. One of the issues of analytics based on u-learning is how to detect or mine learning logs collected by u-learning systems. Moreover, it is necessary to evaluate whether the recommendations detected by analysis are appropriate in terms of learning levels, contexts and learners' preference. To tackle the issues, we developed a system that could recommend useful learning logs at the right place in the right time in accordance with personalization of learners. An experiment was conducted to evaluate the system's performance and the recommendations' usefulness for learning. In the evaluation experiment, we found important criteria for recommending in the real-world language learning. In addition, the participants were able to increase their learning opportunities by our recommendation method.

Keywords: Ubiquitous Learning, Context-aware Learning, Spatio-temporal Data Mining, Association Analysis, Ubiquitous Learning Analytics
Categories: D.2.11, D.2.12, D.2.13

1 Introduction

The wide range of available mobile and communications technologies serves as a role in extending the use of mobile or tablet devices for different objectives instead of functioning as a phone only to make calls and send text messages. The technological facilitation has encouraged educators to utilize mobile technologies in a formal or an informal setting as instructional tools for learning. Thanks to evaluation of these mobile technologies, ubiquitous learning (u-learning) enables learners to interact with learning objects in the real-world by using ubiquitous technologies such as RFID tags [Ogata & Yano, 04], QR-codes [Hwang, 14], and wireless communication [Yin et al., 10]. In particular, u-learning can engage learners in experiential and situated learning anytime and anywhere without constrain or limitation of place and time. Unlike Learning Management System (LMS) such as Moodle and Blackboard, the learning data collected by u-learning systems include contextual data such as locations and times in an informal setting. The key benefits of these systems are that it is provided with personalized experiences in real-world situations and that learners' behaviour is detected and recorded for providing them with adaptive feedback and support.

[Aljohani & Davis, 12] and [Ogata et al., 14b] described learning analytics called Ubiquitous Learning Analytics (ULA) for analyzing and visualizing enormous learning data including contextual information. The value or contribution of ULA is discussed by considering two possible kinds of interactions. The first is the interaction between learners and their contexts, referred to as Learners-to-Context Interaction. The second is the interaction between learners and context-based knowledge or word, referred to as Learner-to-Context-Based Learning Materials Interaction. They suggested that the use of learners' contextual data could enhance the interaction among learners, mobile devices, and learning environments. In addition, analyzing and visualizing contextual data has a potential for improving knowledge of the patterns of learners' interactions with their contexts [Ogata et al., 15].

One of the issues of ULA is how to visualize, analyze, detect and recommend learner-to-context and learner-to-context-based knowledge interaction. To solve these issues, [Mouri et al., 14], [Mouri et al., 15a] and [Weyers et al., 16] proposed an innovative visualization and analysis system for connecting relationships of Ubiquitous Learning Logs (ULLs). In this study, ULL is defined as a digital record of what learners have learned in their daily life. For example, in the fields of language learning, when learners visits the supermarket and McDonald's, they face a Japanese-English situation such as "フライドポテト(French fries)". Then, they learn the word "french fries" in the learning places and save what they have learned as ULL. In this study, the learner's activity is defined as "learning".

However, the objective of the studies of [Mouri et al., 14], [Mouri et al., 15a] and [Weyers et al., 16] was visualization of the collected data. They did not analyze nor mine their data. Therefore, it is yet to be realized to recommend appropriate ULLs in accordance with learners' personal characteristics (e.g. age, gender, native language, and learning level) and contexts by utilizing ULLs accumulated in u-learning system. To realize them, it is important to find their learning patterns from the collected ULLs. For example, if there were learning patterns such as "many learners learn tofu right after learning the word natto (a traditional Japanese food made from fermented soybeans)," the relationships between natto and tofu are collocational. It is necessary to explore data mining approaches to detect such collocational relationships. Moreover, it is necessary to evaluate whether the recommendations detected by various analysis are appropriate in terms of learning levels, contexts, and learners' preference [Ferguson, 12] [Buckingham & Ferguson, 12].

We developed a system that could recommend useful learning logs at the right place in the right time. The rest of this paper is constructed as follows. Section 2 introduces context-aware u-learning and certain studies on previous recommendation methods based on spatio-temporal data mining. Section 3 describes a ubiquitous learning system called SCROLL. Section 4 describes how to detect or mine useful learning logs based on association analysis and implementation of recommendation system. Section 5 describes the evaluation experiment. Finally, Section 6 describes the conclusion and future works.

2 Related Works

2.1 Context-Aware U-learning and Language Learning

In the past decade, the rapid advancement of wireless communication networks and the popularity of mobile devices have enabled people to access digital resources and interact with computer systems without limitation of either place or time. Researchers call such learning approach as mobile learning (m-learning), which utilizes mobile and wireless technologies [Hwang, 14] [Zurita et al., 15] [Baloian et al., 15]. The development of sensing technologies such as RFID-tags, QR-codes, and GPS, has enabled learning systems to detect contexts [Hsu et al., 11] [Lai et al., 13] [Lee et al., 14]. [Hwang et al., 11] call such learning approach as context-aware ubiquitous learning (u-learning) which employs mobile, wireless communication and sensing technologies to enable learners to interact with real-world and digital world objects. [Ogata et al., 04] proposed a ubiquitous language learning system called TANGO. The system allows learners to learn the object in the real world by using RFID tags. For example, when a learner reads the RFID tag attached to the learning object, the system provides the meaning and how to read and write the word of the learning object. Learners can also remember the word of real objects in the contexts. The touching is expected to promote an establishment of the learners‘ memory. In the evaluation experiment of [Ogata et al., 04], they reported that it is useful to learn both the pronunciation and spelling of the real object. Therefore, many researchers have shifted from m-learning to context-aware u-learning.

The objective of majority of context-aware u-learning systems is to provide personalized or adaptive learning support based on learners' preferences, learning skills, and contexts of learners. In this study, "context" means locations or places and time information. For example, [Hwang et al., 11] developed a context-aware u-learning system with the attached RFID tag to the plants. Application domain of their studies is nature science. When a learner arrives in front of a target plant with RFID tag, the system asks him questions about the plant's feature, such as its truck, shape, and color using RFID reader. This enables learners to understand deeply the relationships between knowledge about the plant and the place where they learned it. In addition to their studies, [Hsieh et al., 2011] developed an adaptive learning system for guiding students to observe and learn butterflies in a butterfly garden based on their learning styles. It can be seen that applying adaptive or personalized learning techniques to real-world learning scenarios has become an important and challenging issue of technology-enhanced learning.

Majority of u-learning systems are prepared the learning materials and contents in a ubiquitous learning environment by teachers in advance. For example, when an educator prepares a learning content in a ubiquitous learning environment, the learning scenarios and tasks such as "observing butterflies in a context" and "learning the plant's feature in a context" are decided by the educator. Meanwhile, [Ogata, 11] developed a u-learning system called SCROLL (System for Capturing and Reminding of Learning Logs) to support international students who aim to learn Japanese language and Japanese learners who aim to learn English language in an informal setting. Unlike the system developed by [Hwang et al., 11], learners can freely upload words that they learned in their daily lives to the system and share with other users. That means that it is not necessary to prepare learning contents by educators as they can share their learning contents. In the SCROLL studies, [Li et al., 13] reported a context-aware u-learning utilizing SCROLL. For example, when an international student uploads a new word at a certain place to the system, their system reminds him of the word when he visits the same place again. According to the initial evaluation experiment of [Li et al., 13], they reported that the system was effective in recalling past learning words that the students have learned. However, their system merely provides adaptive learning logs based on a learner's own context, especially location information. One of the objectives of ULA is to increase the students' learning opportunities and providing useful learning logs in the right place in the right time by analyzing not only the learner's own logs but also other learners' logs.

To this end, this study first describes how to detect or mine the relationships among learners' age, gender, and learning level, words and contexts in Section 4. Previous spatio-temporal data mining methods are introduced in Section 4. Then how to detect or mine useful learning logs from the ULLs is also elaborated.

2.2 Recommendation Method Based on Spatio-temporal Data Mining

Researchers concerned with spatio-temporal data mining problems proposed appropriate analysis approaches to reveal relationships between objects in time and space [Rao et al., 11] [Rao et al., 12]. The researchers mainly analyze data to predict disaster, weather, and animal actions. For example, a hurricane occurs in a disaster. It occurs in different places at various times. This means the relationships among object (hurricane) on spatial (different places) and temporal (various times) dimension. By analyzing the relationships on spatial and temporal dimension, there is a possibility that it is able to predict whether occurring when and where. To reveal cause-and-effect links behind the disaster, researchers explored spatio-temporal data mining approaches. They discovered the relationships between disaster and location to prevent tsunami floods by predicting landing places.

Little attention has been paid, thus far, to spatio-temporal data mining even in the educational fields, especially, u-learning and m-learning. According to [Liu et al., 14], they described that it is important to memorize the word with location or place in the real world language learning. For example, if an international student learns "*natto*" at the supermarket, there is a possibility that other learners had already learned it at a different location or place such as convenience stores and restaurants and uploaded it into the u-learning system. By detecting or mining relationships between the word and contexts, it is possible to find learning patterns or rules such as "natto-supermarket, natto-restaurants". On the basis of the detected learning patterns or rules, our system could recommend useful ULLs in accordance with their language skill and contexts.

To achieve the recommendations, this study focuses on association analysis proposed by [Agrawal, 93]. Association analysis is one of the popular analysis methods to detect or mine relationships between certain parameters of complex learning data. For example, [Behrouz, 04] found association rules by grouping students who are enrolled in an online education system called LON-CAPA based on parameters such as Grade Point Average (GPA), age, and gender. In their studies, if there were students who had scores between 3.0 and 3.5 in GPA, the system informed them of the most likeliness of their passing the course based on the detected association rules.

This study defines the basic terms regarding association analysis as follows: Transaction means a unit of work performed in a database. Association rule means a rule detected by association analysis. Item-set means set of binary attribute. Support is an indication of how frequently the item-set appears in the database. That means that support is the relative frequency of transactions that contain X and Y (X and Y are item sets). Confidence is an indication of how often the rule has been found to be true. The mathematical definition of the term support and confidence is as follows: Support $(X \rightarrow Y)$ = support(X+Y), and Confidence $(X \rightarrow Y)$ = support(X+Y) / support(X).

In Section 3, this study introduces the design of SCROLL and data used to detect learning patterns or rules.

3 SCROLL

3.1 System Design

As described in Section 2, this study utilizes ULLs accumulated in the database by SCROLL. To simplify the process of capturing learners' learning experiences, SCROLL provides an easy-to-use interface. It adopts an approach to share contents with other users based on a Log-Organize-Recall-Evaluate (LORE) model proposed by [Ogata et al., 11].

SCROLL is designed to support all these learning processes to facilitate learning. How the system supports each learning process is described as below:

1. Log: International students studying in Japan are likely to face certain problems with Japanese words such as how to read, write and pronounce them in their daily lives. They can save what they have learned with photo, location (latitude and longitude), learning place and date and time of creation as a ULL as shown in Figure 1.
2. Organize: When a learner adds a new ULL, the system compares it with his past ULL and those of other users, categorize the ULL and shows him related ULLs. By showing the ULL with information on when and where they learned it, past and current learning can be linked and their knowledge will be reorganized and reinforced [Uosaki et al., 15a].
3. Recall: Learners are likely to forget what they have learned before. It is necessary to support recalling their past ULLs. During this learning process, the

system support learners to recall what they have learned by using quiz and Time-Map function [Mouri et al., 14].

4. Evaluate: It is important to recognize what and how the learner has learned by analyzing the past ULLs, so that he or she can improve what and how to learn in the future. [Mouri et al., 14] and [Mouri et al., 15b] developed innovative visualization system that implemented Time-Map and network graph based graph theory to support this learning process. The system helps learners to memorize the relationships between two words in various contexts using visual cues. For example, if the learner learns word natto at the supermarket, the system automatically provides the results regarding the relationships among natto and other words by analyzing past learning logs.

SCROLL is a client-server application, which runs on different platforms including iPhone and android devices, PC and general mobile phones. The server sides run on Ubuntu 12.04.2 and the system is programmed in Java, Spring MVC and Mybatis. The database on the server side consists of two main parts:

1. User Management Database: It contains all learners' personal information such as their name, age, gender, native language, Japanese Language Proficiency Test (JLPT) [JLPT], and email address.
2. Learning Log Database: It contains information on what, how and when they learned in their daily lives such as word, place, location, and time of creation including photo, audio, video, and tags.

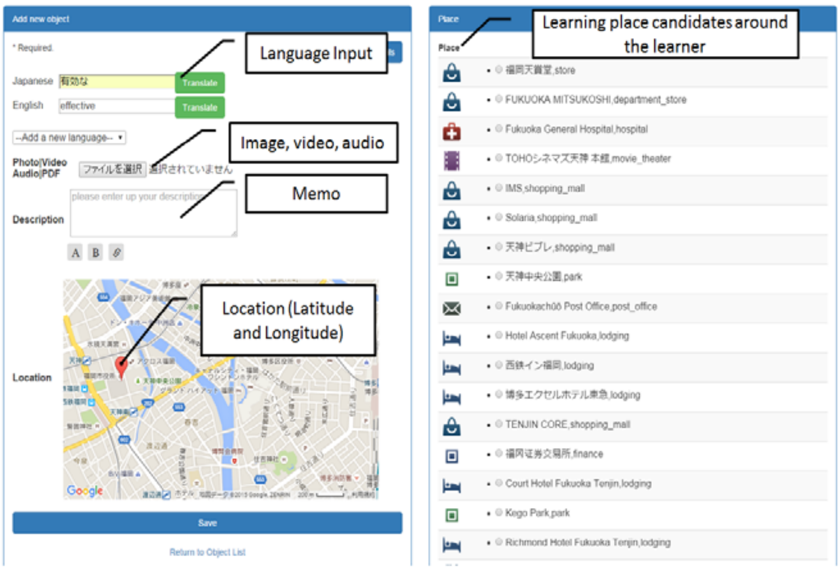

Figure 1: An example of adding a ULL

3.2 Types of Data Accumulated in SCROLL and Their Categorization

Thus, far SCROLL includes not only the data collected in one or two evaluation experiment but also those collected by a number of research studies for a long period of SCROLL project (2011-2015) [Ogata et al., 14a], [Uosaki et al., 15b], and [Lkhagvasuren et al., 16]. During the evaluation experiments conducted by these studies, learners uploaded several ULLs to the system as shown in Table 1.

Attribute	**Description**	**Total**
Word	Word that they have learned {e.g. natto, tofu, passbook}	28335
User	Author name (nickname in SCROLL) {e.g. Liu, Liam, James}	1742
Native Language	Learners' native language {e.g. Japanese, Chinese, English, French}	36
Place	Place where the learning took place {e.g. university, supermarket, bank}	30
Time	Time when the learning took place {e.g. Morning, Summer, Spring}	7

Table 1: Data in SCROLL

Category	**Criteria**
Morning	From am 6:00 to am 9:59
Daytime	From am 10:00 to pm 4:59
Night	From pm 5:00 to am 5:59
Spring	From March to May
Summer	From June to August
Fall	From September to November
Winter	From December to February

Table 2: Criteria for categorizing ULL

There are 28335 ULLs, 1742 users, 36 kinds of native language, 30 kinds of places and 7 kinds of times. Attribute "Word" means words that users have learned. Attribute "User" include collected data such as learners' gender, age, language level into pre-existing database in SCROLL as described section 3.1. Attribute "Native Language" means their mother language (The number of each native language learner saved in SCROLL is Afrikaans:1, Albanian:3, Arabic:7, Armenian:7, Azerbaijani:2, Basque:2, Belarusian:2, Bengali:1, Cherokee:1, Chinese:177, Czech:1, Danish:3, Dutch:15, English:819, Esperanto:1, Estonian:1, Finnish:1, French:62, German:32, Greek:1, Hindi:2, Hungarian:1, Icelandic:1, Indonesian:6, Japanese:439, Khmer:1, Korean:21, Malay:4, Kyrgyz:1, Marathi:1, Mongolian:37, Norwegian:1, Polish:2, Portuguese:5, Romanian:1, Russian:8, Serbian:2, Spanish:13, Swedish:9, Tagalog:4, Tami:2, Thai:13, Turkish:1, and Vietnamese:28). Attribute "Place" means the place where they have learned (The number of each place saved in SCROLL is barkery:10, bank:16, bar:16, bus station:31, café:96, convenience store:55, electronics store:36, fire station:5, gas station:22, hardware store:3, library:90, museum:7, movie theatre:2, park:113, pet store:11, pharmacy:22, post office:19, restaurant:251, train station:158, shopping mall:27, clothing store:27, church:3, laundy:7, jewelry store:2, lawyer:65, city hall:272, university:1306, supermarket:35, and transit station:4). When analyzing time information, it is important to categorize them efficiently to detect or mine useful learning patterns or rules for learning. Therefore, we divide time information to several categories excluding numerical data. Criteria for categorizing the information were established as shown in Table 2. The following are reasons for categories.

- For example, when categorizing time information to "morning", we might be able to detect or mine words that learners have frequently learned in all learning logs. Therefore, we define the different criteria for category "time".

4 Context-aware and Personalization Method

4.1 LKPTE Model

To recommend appropriate ULLs at the right place in the right time to an individual learner, this paper propose an analysis model called Learner-knowledge-Place-Time-Experience (LKPTE) based on parameters shown in Table 3 proposed by [Mouri et al, 15c]. Using this model, the recommendation system can find the regularities between learners and ULLs. Table 3 shows parameters of the LKPTE model.

Learners' parameter L (Who) shows their gender (L_g), age (L_a), native language (L_n), and JLPT level (L_l). Using these parameters, the system can detect other learners similar to themselves.

Knowledge parameter K (What) shows the level of words (K_l) decided by JLPT. N5 and N4 of JLPT level measure the ability to understand basic Japanese. N3, N2 and N1 measure the ability to understand Japanese used in everyday situations, and in a variety of circumstances to a certain degree. Therefore, K_l is important parameter to realize appropriate recommendations in accordance with language skill of each learner.

Parameter P (Where) shows location (P_l) and place name (P_n). [Mouri et al., 15c] measured the distance between learners and place, knowledge and place, and time and place based on cosine similarity. For example, there is a possibility that ULLs in the same location contain different place names such as university and restaurant. Moreover, there is a possibility that the same place names contain different location. Parameter P distinguishes ULLs in different contexts, so that the system can detect learner' contexts in the real world and ULLs in the database. Unlike cosine similarity of previous work by [Mouri et al, 15c], our analysis approach is used association analysis to recommend ULLs in accordance with learner' contexts. Therefore, it is expected that the recommendation system can detect appropriate ULL in accordance with their contexts.

Parameter T (When) shows the season (T_s) and time of learning (T_f).For example, six learners have learned "morning glory" in the morning whereas two learners have learned it in the daytime. It indicates that most morning glories bloom in the morning, but there are certain varieties that bloom during the daytime. Our system is able to detect relationships between knowledge and time, and notify those who learned it in the morning that there exist ones that bloom in the daytime. In this way, learners can deepen their knowledge of “morning glory” through other learners’ experiences.

Parameter E (How) shows direct experiences (E_d) and indirect experiences (Ei). Direct experience (E_d) denotes experiences gained directly by themselves. Indirect experience (E_i) denotes experiences gained through others. Learners can save others’ experiences as indirect experience by “relogging”, which is among the functions of SCROLL. According to [Kolb, 84], it is important to have a direct experience. By revealing the relationships between direct experiences and indirect experiences, the system prompts learners to change from observers to doers by engaging in a task-based learning [Mouri et al., 13].

Parameter	Details
L_g (Who)	Gender of learners
L_a (Who)	Age of learners
L_n (Who)	Native language of learners (e.g. English, Chinese)
L_l (Who)	Level of learners (e.g. Japanese Language Proficiency Test)
K_l (What)	Level of Knowledge (e.g. word level based on Japanese Language Proficiency Test)
P_l (Where)	Location of place (e.g. latitude, longitude)
P_n (Where)	Name of place (e.g. university, museum)
T_s (When)	Seasons (spring, summer, fall, winter)
T_f (When)	Time of day (morning, daytime, night)
E_d (How)	Direct experience
E_i (How)	Indirect experience

Table 3: LKPTE model

Item-set include these parameters. By using these parameters with association analysis, the system detects or mines association rules with useful ULLs in accordance with their current personalization and contexts. In section 4.2, this paper describes how association analysis detects or mines regularities among ULLs.

4.2 How to Detect or Mine Regularities among ULLs

This study uses association analysis with an apriori algorithm to detect learning patterns of all learners in SCROLL similar to the learner based on LKPTE parameters. The analysis conducted had the following criteria [Mouri et al., 15d].

- Support ≧0.01, Confidence ≧0.05, The number of detected association rules is 1,000, Attributes {gender, age, native language, level of learners, word level, word class, place, season, time of day, experience type}

The purpose of setting a value is to exclude such association rules as happen only one or two times out of whole data. To detect many association rules as far as possible, this study defines the support and confidence values more than 0.01 and 0.05, respectively. Table 4 shows certain sample of items of ULLs. This study analyses to detect association rules are based on items in Table 4.

TID	**Item set {gender, age, native language, level of learners, word level, word class, place, season, time of day, experience type}**
1	{man, twenties, Chinese, n2, natto, n1, supermarket, summer, daytime, direct experience}
2	{woman, twenties, Mongolian, n5, apple, n5, supermarket, spring, night, direct experience}
3	{man, thirties, Mongolian, n4, buy, n5, shopping mall, winter, daytime, indirect experience}

Table 4: The part of item of ULLs

Asscoiation rules	**Confidence**
1. Word=fan && Place= university (5) → Native Language = Japanese (5)	1.0
2. Word = fan && Season = Summer (4) → Native Language = Japanese (4)	1.0
3. Native language = Chinese && Day of time = daytime && place = restaurant (8) → Word = ramen (6)	0.75
4. Gender = man Age = twenties && Day of time = daytime && place = park (3) → Word = basketball (2)	0.66

Table 5: The part of the detected association rules

Table 5 shows certain examples of the detected association rules. Rule 1 shows that left-hand-side is that word is “fan” and place is “university”, and right-hand-side is that native language is “Japanese”. This means that Japanese learners are likely to learn the word “fan” at the university. Similarly, Rule 2 shows that left-hand-side is that word is “fan” and season is “summer”, and right-hand-side is that native language is “Japanese”. This means that Japanese learners are likely to learn word “fan” in the summer. This means that this association rules frequently occur as the confidence value of both rule 1 and rule 2 is 1.0. From these association rules, one can find that Japanese learners preferred to learn the word “fan” at the university in the summer. Our system recommends appropriate ULLs based on these association rules. For example, when a Japanese learner is at the university in the summer, the system will recommend word “fan” as an appropriate ULL to the learner.

Rule 3 shows left-hand-side is that native language is “Chinese”, day of time is “daytime” and place is “restaurant”, whereas right-hand-side is that word is “ramen”. This means that Chinese learners are likely to learn at the restaurant in the daytime. In comparison with rule 1 or 2, the confidence value of rule 3 decreases as well as the confidence value of rule 4. It is necessary to evaluate whether the association rules recommended by association analysis are appropriate in certain aspects for learners. For example, when a Chinese learner is at the restaurant in the daytime based on rule 3, the system will recommend the word "ramen" as an appropriate ULL to the learner.

4.3 Recommendation Interface Based on Association Analysis

To find ULLs by place information, it is necessary to get the learners' current location or place information where they are studying. As shown in Figure 2, the green marker on the map of the interface shows learner' current positions, and the red marker shows the name of learning place around the learner. Using the interface, learners can get their location or place information.

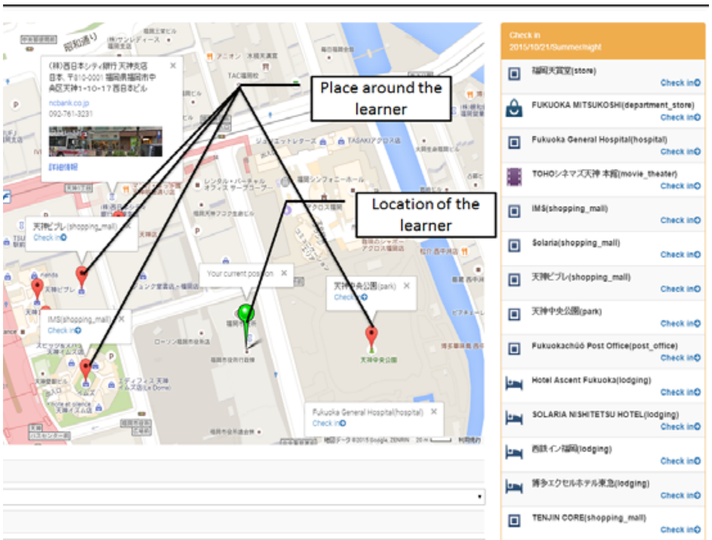

Figure 2: Interface of checking in learners' current location and place

Figure 3 (left) shows an interface with recommendations that are calculated based on LKPTE model. It consists of the following components:

- Association rules: With an understanding of association rules, learners can predict their next learning steps. For example, if international students are at the restaurant in the daytime, the system will recommend a word (case in the Figure 3 is "ramen") related to them based on association analysis and rules. The recommended word is linked with other ULLs as shown in Figure 3 (right). By viewing these links of hypertext references, learners can understand how other learners learned the word in what kind of places and what kind of occasions.

- Evaluation of recommendation: To evaluate whether association rules recommended by the system are appropriate for learners, they will be asked questions such as appropriateness of the word level and the contexts, and interest of the content of the recommendation. In Section 5, this study evaluates whether these recommendations were appropriate in terms of their learning level, context, and interest.

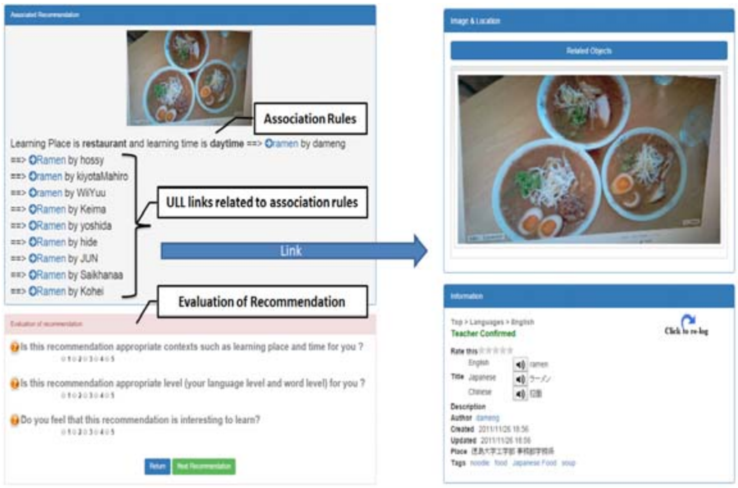

Figure 3: Recommendation interface based on association analysis

5 Evaluation

5.1 Experiment Design and Subject

Twelve international students who were studying at the University of Tokushima and Kyushu University in Japan participated in the evaluation experiments. They were from China and Mongolia aged between 23 and 31. Their length of stay in Japan ranged from one month to five years, and their JLPT levels were from 1 to 3 including level-unknown. The students were divided into two groups: Group A (experimental group) and Group B (control group). Each group comprised three Chinese students and three Mongolian students. Tables 6 and 7 show the details of each student of Group A and B, respectively. This study divided them into two groups as fairly as possible based on each student's age, gender, length of stay, and JLPT level.

Student	**Age**	**Gender**	**JLPT**	**Nationality**	
A	24	Male	N1	Chinese	
B	24	Male	N2	Chinese	
C	25	Female	N3	Chinese	
D	23	Male	-	Mongolia	
E	25	Female	-	Mongolia	
F	26	Female	-	Mongolia	

Table 6: Detail of Group A

Student	Age	Gender	JLPT	Nationality	
A	25	Male	N2	Chinese	
B	23	Male	N2	Chinese	
C	24	Male	N2	Chinese	
D	31	Female	-	Mongolia	
E	28	Female	-	Mongolia	
F	27	Female	-	Mongolia	

Table 7: Detail of Group B

5.2 Experimental Procedure

Group A learned the words in their daily life using SCROLL with the recommendation system for one week. Group B learned the words in their daily life without the recommendation system for one week. Both groups used their own smartphone (iPhone or Android device) by which they saved their ULLs in a formal and an informal setting anytime and anywhere. The mobile devices used in the evaluation experiment were four iPhone 4s, five iPhone 5s, and three Samsung Galaxy Note 3s.

The evaluation experiment was designed to evaluate whether the system can increase the number of ULLs that the participants uploaded to the system during the evaluation period. As described in section 4.3, the system can recommend useful ULLs based on detected association rules. During the evaluation experiment, the participants evaluated the system every time they received recommendations based on association analysis by answering three five-point questions (Best: 5, Worst: 1) as shown in Table 8.

Question
1. Is the recommendation an appropriate level for you? (i.e., if the word of the recommendation is too difficult or easy, you select 1 or 2)
2. Is the recommendation an appropriate context for you? (i.e., when you are at the supermarket, you select 4 or 5 if the system recommends appropriate ULL in accordance with the learning place such as natto and tofu)
3. Do you feel that this recommendation is interesting to learn?

Table 8: Question of evaluation of recommendation

5.3 Results and Discussion

To examine the increase of the number of uploaded ULLs by the recommendation system, the number of uploaded ULLs of Group A was compared with that of Group B after the phase using ANOVA statistical methods. Table 9 shows the number of ULL that participants uploaded during the experiment. When a participant uploads a recommended ULL, this implies that the recommended word is learned by the participant. In total, Group A and B participants uploaded to the system 176 and 88 ULLs, respectively. As indicated, the p-value is smaller than 0.05, indicating that there is a significant difference between the results of the two groups. This means that the recommendation could increase the number of ULLs that the participants uploaded to the system.

Group	Number of ULLs	Mean	SD	p-value
Group A	176	29.3	5.15	.0004
Group B	88	14.6	3.94	

Table 9: The number of the uploaded ULLs

Table 10 shows Group A students' feedback of the ULLs recommended by the system. "Mean/SD (Q1)" in Table 10 shows whether the recommendations were appropriate language level for the learner. "Mean/SD (Q2)" shows whether the recommendations were appropriate contexts for the learner. "Mean/SD (Q3)" shows whether the recommendations were interesting for the learner.

	Criteria	**Mean/SD(Q1)**	**Mean/SD(Q2)**	**Mean/SD(Q3)**	**p-value**
1	0.9 < conf ≦1.0	3.42/1.01	3.81/0.87	3.87/0.85	
2	0.8 < conf ≦0.9	3.43/0.54	3.72//0.8	3.53/0.82	.0000 *
3	0.7 < conf ≦0.8	2.12/1.64	2.31/1.54	2.53/1.11	
4	0.6 < conf ≦0.7	2.43/1.13	2.22/1.45	2.34/1.08	

Table 10: Evaluation of recommendations based on association analysis

Table 11 shows the recommendation and response number with respect to four ranges of the confidence value in Table 10. In total, they learned and responded 48 ULLs with association rules after receiving 375 recommendations. The mean scores shown in Table 10 represent that of three five-point-questionnaires in Table 8. As shown in Table 10 and 11, when the confidence value is more than 0.8, the response rates and mean score are far higher than when it is less than 0.8. In addition, when comparing criteria 2 with 3, the response rate and mean scores dramatically decrease in criteria 3. About one in eight recommendations was uploaded by the participants. When the confidence value is less than 0.8, majority of the participants did not prefer the recommendations as the recommended ULLs are not appropriate in terms of "Mean/SD (Q1)", "Mean/SD (Q2)" and "Mean/SD (Q3)". From the results, we considered that the confidence value more than 0.8 is important to recommend appropriate ULLs.

Therefore, this study considers that the recommendations were appropriate in terms of their learning level, contexts, and preferences when the confidence value was more than 0.8 as "Mean/SD (Q1)", "Mean/SD (Q2)" and "Mean/SD (Q3)" were relatively higher and the response rate dramatically increases.

This study analysed the relationships between criteria 2 and 3 using ANOVA statistical methods. The p-value was smaller than 0.05 indicating that there is a significant difference between the two recommendation criteria. Thus, an important criterion was found for recommending appropriate association rules with ULLs for language learners in the real-world.

In addition, regression analysis was used to quantify the strength of the relationship between mean scores and confidence value. The x-axis represents confidence values from 0.6 to 1.0. The y-axis represents "Mean/SD (Q1)", "Mean/SD (Q2)" and "Mean/SD (Q3)" shown in Table 10. A pattern in the data indicates a positive correlation between the two variables. The correlation coefficient of "Mean/SD (Q1)", "Mean/SD (Q2)" and "Mean/SD (Q3)" are 0.44, 0.47 and 0.51, respectively. Their correlation coefficients indicate moderate positive correlation. Although the correlation coefficient was not so high as expected, the correlation was high enough. We considered that it is necessary to take account into enough number of recommendations. Therefore, our next evaluation is being more carefully planned.

	Recommendation number	**Response number**	**Response rate**
1	24	10	41.6 %
2	48	16	33.3 %
3	231	14	6.06%
4	72	8	11.1%

Table 11: Recommendation number and response number

6 Conclusions and Future Work

This study described a ubiquitous learning system called SCROLL and how to detect or mine learning logs collected by SCROLL. This study tackled to solve one of issues of Ubiquitous Learning Analytics. The issue is how we detect or mine learning logs including contextual data in order to recommend appropriate ULL at the right place in the right time. By using association analysis, this study was able to detect or mine useful learning patterns or rules. By recommending the detected association rules, this study evaluated whether the recommendation calculated by association analysis are appropriate in terms of their level, contexts and preferences for learners and whether the system increases the learners' learning opportunities.

The u-learning of the first generation enabled learner to learn given learning materials in an appropriate context. The u-learning of the second-generation enabled learners to save what they have learned as learning logs and share with each other by using SCROLL. This study considers the paradigm of u-learning of third-generation. We believe that analyzing and mining learning logs lead to enhancing learning effect and increasing learning opportunities.

According to the initial evaluation experiment, the system was able to increase the learners' learning opportunities as described in section 5.3. When comparing Group A with Group B in the evaluation experiment, the learning opportunities increased about two times. Moreover, international students were found to have preferred to learn association rules with ULLs if the confidence value is more than 0.8. In the future, the use of evaluation of the system will continue, and not only life-long learning but also other mobile learning domains, e.g. Computer Supported Collaborative Learning (CSCL) and Seamless learning will be applied. Our future work includes long-term evaluations with enough number of participants more than 100.

Acknowledgements

This part of this research was supported by the Grant-in-Aid for Scientific Research No.16H06304, No.25282059, No.26560122, No.25540091, No.16J05548 and No.26350319 from the Ministry of Education, Culture, Sports, Science and Technology (MEXT) in Japan. The research results have been partly achieved by "Research and Development on Fundamental and Utilization Technologies for Social Big Data" (178A03), the Commissioned Research of National Institute of Information and Communications Technology (NICT), Japan.

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