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Goal-Driven Process Navigation for Individualized Learning Activities in Ubiquitous Networking and IoT Environments

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Abstract: In the study, we propose an integrated adaptive framework to support and facilitate individualized learning through sharing the successful process of learning activities based on similar learning patterns in the ubiquitous learning environments empowered by Internet of Things (IoT). This framework is based on a dynamic Bayesian network that gradually adapts to a target student's needs and information access behaviours. By analysing the log data of learning activities and extracting students' learning patterns, our analysis results show that most of students often use their preferred learning patterns in their learning activities, and the learning achievement is affected by the learning process. Based on these findings, we try to optimise the process of learning activities using the extracted learning patterns, infer the learning goal of target students, and provide a goal-driven navigation of individualized learning process according to the similarity of the extracted learning patterns.

Keywords: goal-driven process navigation; learning activity; learning action sequence; learning process; learning pattern
Categories: H.3.1, H.3.3, H.3.5, L.2.0, L.2.1

1 Introduction

Two Chinese idioms can be used to describe the relation of learning process and result. One is "getting twice the result with half the effort," and another is "getting half the result with twice the effort." A lot of studies indicated that different learning process led to different results in students' learning activities [King, 47; Chen, 08; Chen, 09a]. It is assumed that if the learning process of students is applicable to be regulated and navigated with a suitable principle, more efficient and better results can be expected.

In order to help students to improve their learning efficiency, we propose an integrated approach to optimise learning process. In this study, students are assumed to be divided into two groups: one is called reference student group, in which students

have the successful experience in previous learning processes, and another is called target student group, who are the lower-performing students than the reference student group. With our proposed approach, we extract learning patterns of both reference student group and target student group based on their log data, and infer the target students' learning goals by analysing their current learning actions that are defined as an operating unit in a learning activity, and comparing their learning processes with the reference students whose learning patterns are similar to the target students. Moreover, according to the analysis results of reference student group, those learning actions which may be more suitable to the target student will be chosen as his/her next learning action in the optimised learning process navigations to accomplish a specific learning goal.

Based on these, the working flow can be described as follows. At the first step, students' learning patterns are extracted from the access log data using the clustering method. Then, the reference student group can be built for a target student by comparing the similar learning patterns at the second step. At the third step, a Bayesian network of learning actions is created from the reference student group according to the posterior probability of learning actions, which could be viewed as a set of choices for the target student as his/her next learning action during the learning process navigation. In addition, the selection of the target student from the learning action choice set is regarded as a feedback, which is used for the *Gradual Adaptation Model* (GAM) proposed in our previous study [Chen, 2009b] to improve the recommendation results. In this study, the system architecture for goal-driven process navigation is further developed based on a ubiquitous learning environment empowered by Internet of Things (IoT), so that context data, such as location, situation, can be collected and analysed, which consequently enhance the GAM and the proposed system as well. Our proposed approach provides a goal-driven navigation of optimised learning process to students, and this solution does not only consider the relation of learning contents, but also take into account of the individual difference of students. Therefore, it can be expected to help students to know what need to learn, and furthermore, let them apperceive how to learn.

The rest of this paper is organized as follows. Section 2 is an overview of previous work related to individualized or personalized learning. The concept of learning activity and activity course model are introduced in Section 3. In Section 4, we describe the concept of goal-driven process navigation for individualized learning activities. The architecture and implementation of a prototype system are introduced in Section 5. Section 6 discusses the experiment analysis result based on our proposed approach. Finally, Section 7 concludes this study and highlights future works.

2 Related Works

Currently, individualized or personalized learning is a focus in e-learning research field. The research can be roughly divided into two categories: learning content and learning method.

In the learning content category, a variety of researches focused on how to create and reuse the learning contents, e.g., navigation systems [Zhang, 2011]. The ACETS project started from 2002 in UK to investigate on how the RLO (reusable learning object) could help teachers and their teaching. According to the report of Sweet et al.,

the RLOs can be reorganized for a new learning goal [Sweet, 2010]. This result indicates that a learning action can be designed as a reusable and re-organisable object.

In the learning method category, more and more researchers have paid attentions to the learning style. Liu et al. pointed out that the students of different learning styles chose different learning contents, and their learning styles affected the learning process [Liu, 1994]. Some of the researches were based on the Felder–Silverman learning dimension model that came from psychology, and described learning styles as five pairs of preferred learning style: sensory/intuitive, visual/auditory, inductive/deductive, active/reflective, and sequential/global by analysing learning styles questionnaire [Felder, 1988]. Grafter et al. thought a more accurate and detailed description of the five dimensions could be used to improve personalized learning [Graf, 2006; Graf, 2007]. The study of Halstead et al. showed that the difference of their learning styles between engineering students were small and did not appear to depend on the level of study [Halstead, 2003]. On the other hand, the finding of Huang et al. indicated that there was little relation between the assignment score and the learning style score [Huang, 2007]. These researches show that although Felder-Silverman learning dimension model could not describe learning style adequately, the following points are true and important

1) There exist different learning styles among different students;
2) Some of the students have similar learning styles;
3) Students of different learning styles whose learning processes are different.

When using a Learning Activity Management System (LAMS), Levy et al. found that some relationships existed between the processes and contents in knowledge-creation [Levy, 2009]. Lin et al. presented an object-oriented learning activity system [Lin, 2009], in which a learning activity was divided into learning contents, test items, and learning services. According to the result of test items, learning services could be provided to students with learning contents. The key point of their study is the learning sequence. In addition, the learning path was studied by Pirrone et al. [Pirrone, 2005], Chen [Chen, 2008; Chen, 2009a], and Fazlollahtabar et al. [Fazlollahtabar, 2009]. The similar point of these studies is generating a personalized learning path for students by their proposed approaches. In fact, these researches did not pay enough attention to the individual differences of students, but focused much on the relation between learning contents.

On the other hand, as an integrative solution, process mining can be considered as an approach between computational intelligence and data mining, and process modelling and analysis [Aalst, 2011] [Zhang, 2009]. The techniques of process mining have been widely used to discover and analyse business processes based on raw event data, in which there are three types: discovery, conformance and enhancement [Aalst, 2012]. The major feature of process mining is to use the event logs to discover, monitor and improve processes based on facts rather than fiction. In this study, we try to mine, optimise and navigate the learning process in an integrated way.

In recent years, the research and application of the IoT has gained widespread attention in a variety of areas including u-learning, integrated learning support in ubiquitous networking environments [Zhang, 2011]. As is well known, the basic idea of the IoT is the thing-to-thing interconnected internet, in which everything or every object having a unique address is able to interact and cooperate with each other to

reach common goals through sensors or other devices [Atzori, 2010]. In a sense, the IoT can be represented as an extensible learning environment, which could bring tangibility to the learning process, and combine physicality and virtuality [Garreta-Domingo, 2010]. Many studies based on the IoT are on-going. Cube-U is an initial prototype that explores the combination of the IoT and e-learning, which is aimed to enhance the learning experience [Garreta-Domingo, 2011]. Although e-learning based on IoT is in its infancy, some of studies have been demonstrated to be effective. The results of Ming et al. denoted that e-learning based on the IoT environment could better support the communication and interaction [Ming, 2008]. The study of Zhao et al. indicated their approach could improve the learning experience in the ubiquitous learning environments [Zhao, 2011].

Based on our overview and observation on the related works discussed above, we recognise that it is not easy to measure a learning style either by a psychological method or a technological approach. In this study, we propose an integrated adaptive framework to support and facilitate individualized learning through sharing the successful process of learning activities based on similar learning patterns in the ubiquitous learning environments empowered by the IoT. We try to record the learning process log during the interaction of students with the learning system, and then, extract learning patterns from a learning process by using of a clustering method. Furthermore, by finding out the relations among learning contents and individual differences of students in a learning process, our proposed solution can be expected to build a bridge between tangible knowledge and intangible knowledge, which can help students to apperceive intangible knowledge such as how to learn.

3 Learning Activity and Activity Course Model

In this section, we describe the definition of learning activity and architecture of activity course [Chen, 2010].

3.1 Learning Activity and Activity Course

A learning activity is defined as an educational process or procedure intended to stimulate learning through actual experience. On the other hand, a learning action is defined as an operating unit of learning activity. In order to achieve a learning goal, a series of learning actions are arranged in sequence according to the learning principle. Figure 1 shows the architecture of Activity Course. It consists of Knowledge, Resource, Activity and Portfolio. Students need to use media and complete operation according to the requirement of learning actions and their sequence. To learn a concept is regarded as a goal, which can be completed by a series of different learning actions.

The course is the component of the curriculum, and can be regarded as a sequence of the students' needs and experiences. As a curriculum, it could be divided into four layers or facets, each of which shows a specific facet of a curriculum. These four layers of a course are described as follows:

- **The knowledge layer** contains the learning concepts of the course, which comes from the domain knowledge. The sequence of the knowledge map can give the direction of connecting the resource to support the course implementation.

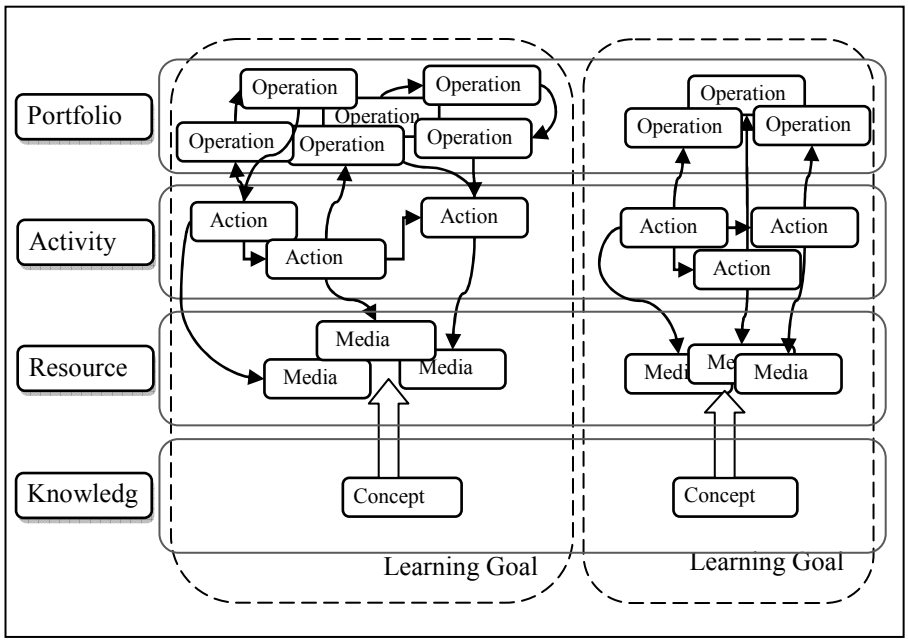

Figure 1: The architecture of the activity course

- **The resource layer** represents the resource to support the transmission of the knowledge, which is the resource base for a teacher to generate a course, namely the media of the knowledge.
- **The activity layer** is the core part for the practice of the learning and teaching activity, which is always designed by the teacher and followed by the students. In this paper, we focus on learning activity, but not on teaching activity. In order to help students to accomplish the learning of concept, a series of learning actions are designed by teacher with a specific sequence. Each learning action relates to a special learning resource and learning operation. The activity is mostly determined with one's different value judgment.
- **The portfolio layer** consists of the student's outcome such as a report or discussion record in a forum with timestamp from the learning operation. It also includes the assessment and even the material generated in the learning activity. These materials are traditionally used to give the assessment of the student.

In order to achieve a learning goal, a student can conduct the learning activities that are provided by an activity course, and the four layers can be used to support activity course so as to help students improve learning effectiveness.

3.2 Activity Course Model

A learning process can be regarded as a learning activity or a series of learning activities with a specific sequence. A learning activity can be divided into a series of learning actions, and a learning action can be further divided into a series of operations. All of the activities, actions and operations are organized with a specific sequence. In a normal LAMS (Learning Activity Management System), a learning activity is designed for realizing a learning motive. As shown in Figure. 2, we give a conceptual view for activity course model. In this figure, a learning activity is used to achieve a corresponding learning motive, a learning action is used to achieve a corresponding learning goal, and a learning operation is done based on the learning situation of the student. Learning situation is regarded as an indicator to describe learning operation. When a student is in a learning situation, he/she can do the corresponding learning operation.

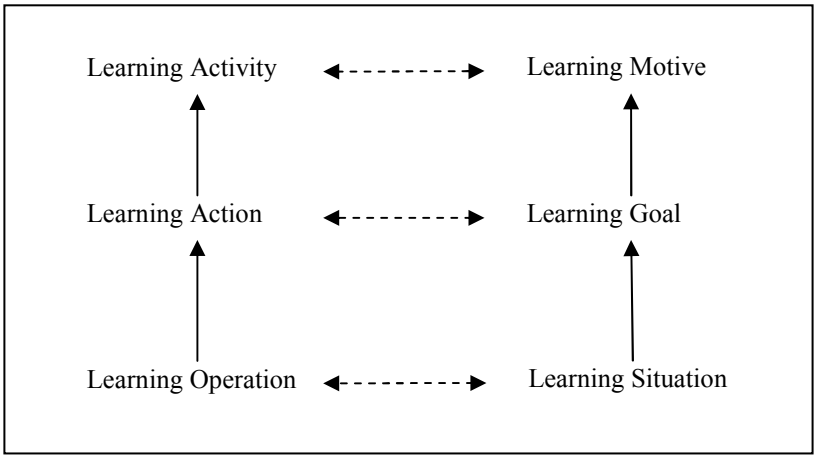

Figure 2: Conceptual view of the activity course model

In this model, the learning motive is used to describe what a learner wants to learn, and it may correspond to one or plural learning goals. A learning activity is paired with a learning motive. It consists of a series of learning actions that a leaner may engage in. A learning action contains a series of specific practical operations. It guides the learner what he or she needs to do at what time. For example, it can remind an English learner to memorize new words in early morning, to learn English grammar in the morning, and to do exercise in the afternoon. Furthermore, for the learning action of memorizing, transcribing and reciting new words are the detailed learning operations in the learning action.

As described in the above, learning activities are regarded as a learning process with a specific purpose and sequence. Learning actions belong to a corresponding learning activity. Both a learning activity and the related learning actions can be utilized to extract information on user contexts to create the user model (specifically the user profile and group profile if available). They are recorded based on the activity

course model as a kind of metadata, which can be used to detect learners' needs, and to extract successful experience as well. The learning activity contains a sequence of learning actions, and the sequence includes metadata, such as time, actors and contents, etc. For example, from viewing lecture video and uploading homework to reviewing the log is a time sequence in a course. Finally, the learning content is paired with the learning operation. On the other hand, by comparing the ongoing learning process with the reference group, we can infer the learning goal of a target student. Therefore, this mechanism can be used to detect students' learning goal, and navigate the next learning operation to target students.

4 Concept of Goal-Driven Process Navigation

In this section, after describing basic concepts about the learning process, we introduce the concept of goal-driven process navigation for individualized learning activities.

4.1 Purposeful Learning Process

Purposeful learning is activity-based in terms of students applying what they learn through completing assignments or specific tasks related to the assignment [Kenedy, 2008]. In this study, a learning operation is an operating unit. A learning action consists of a series of operations, and a learning activity consists of a series of learning actions that constitute a purposeful learning process with a certain sequence and time span [Chen, 2010]. Therefore, a learning activity can be regarded as a purposeful learning process. A standard learning process is given out in a learning activity for a learning goal, and it can be used by students with a free sequence.

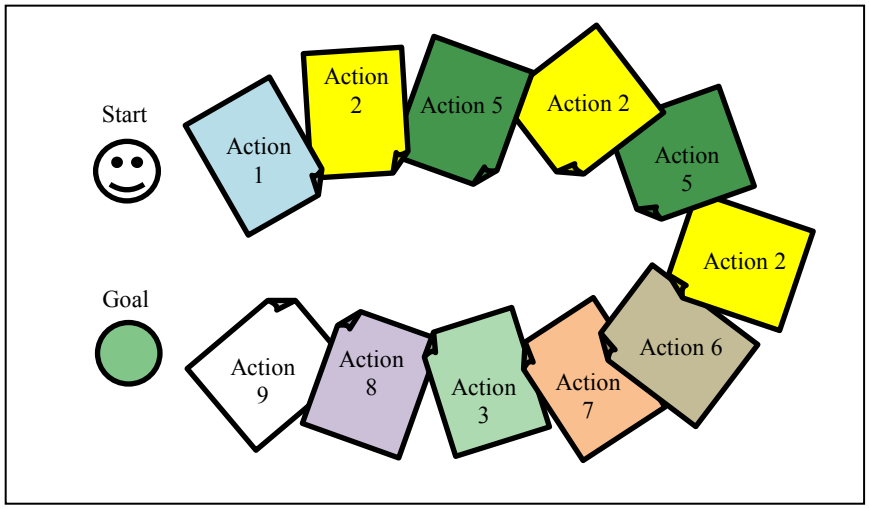

Figure 3: An example of learning action process

Figure 3 shows an example of how a student takes actions for a learning activity. In this example, the standard learning process consists of Learning Action 1, Learning Action 2, …, Learning Action 9 in a certain sequence. A student can do it with a customized sequence. For example, Learning Action 2 is taken three times, and Learning Action 5 is taken two times.

In order to assess a learning process, we can design a quiz at the end of each learning activity. The performance of the quiz is used to describe the effect of the learning process on a student. In a whole learning process, each learning action may have different contribution to the performance of the quiz, and the access times of learning actions are regarded as a weight for calculating their contribution. The detail of contribution will be discussed in the next section.

4.2 Goal-Driven Process Navigation

For a learning process, a different input can lead to a different output. In order to help students to obtain their expectant output, we need to regulate the learning process, and make it to fit to a target student. The goal-driven learning process optimisation approach is used to solve the problem.

Rosenblueth et al. thought that active behaviour may be subdivided into purposeless and purposeful classes, and the purposeful behaviour means that it can direct to the attainment of a goal while the purposeless behaviour cannot direct to the goal [Rosenblueth, 1943]. In this study, by analysing learning actions of students, we can infer their purpose by mining the log data of other students who have similar learning patterns. And then, we can recommend a set of potential next learning

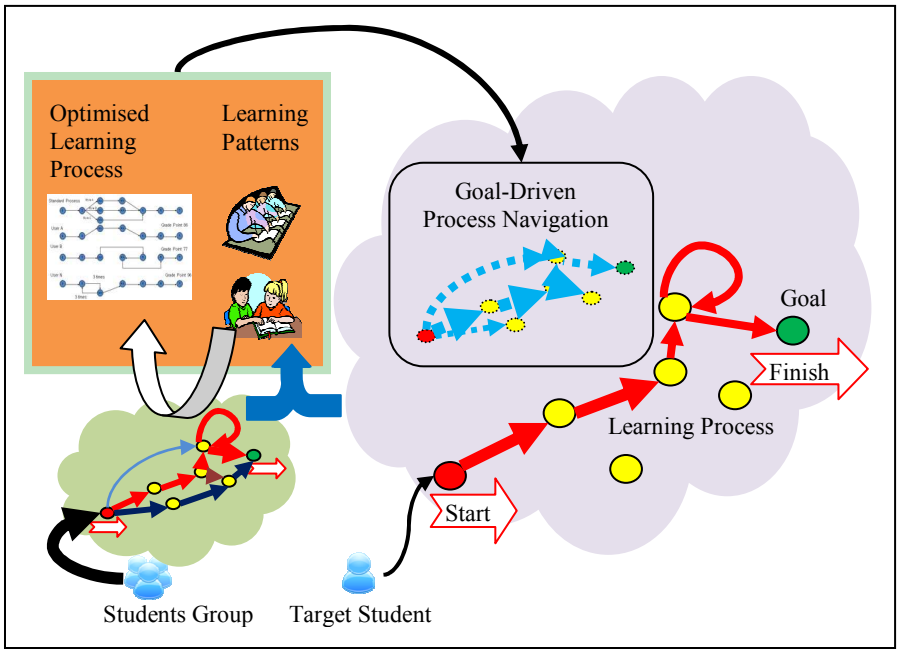

Figure 4: Illustration of goal-driven process navigation

actions to them. After the student selected one of the recommended learning actions, this selection can be further used to predict next learning behaviour. Hence, we call our approach as goal-driven learning process navigation.

As shown in Figure 4, learning patterns of students are extracted by clustering at first. Based on the similarity of learning patterns and the level of experience, a reference student group is extracted for a target student. After the target student started a learning process, his/her current learning action is used to detect his/her learning goal. Based on the collaborative filtering algorithm, a Bayesian network is built. Using the learning process log data of reference students group, the posterior probabilities of next learning actions are calculated, and then a set of choices for next learning actions are delivered to the target student by descending order of posterior probability. After the target student selects the next learning action, new choices will be delivered to him/her till the target student accomplishes the learning process.

5 System Architecture

In this section, the system architecture, its major functional modules, and an integrated algorithm are introduced and described.

5.1 Overview

As shown in Figure 5, the system of goal-driven process navigation consists of User Interface, Situation/Context Analyser (SCA), User Profile Creator (UPC), Learning Pattern Analyser (LPA), Learning Process Optimiser (LPO) and Gradual Adaptation Recommender (GAR), in addition to Learning Activity Management System (LAMS) and Search Engine (SE) [Chen, 2009b]. A specialized User Interface is designed for goal-driven process navigation, which can be used to receive the access behaviours data including location data such as GPS information of students. The SCA is used to analyse the location data transmitted by User Interface, and save the extracted situation/context metadata to the database of Access Logs. The UPC is used to create user profiles that are used to analyse learning patterns. Students can access the goal-driven process navigation, and Learning Activity Management System (LAMS) and Search Engine (SE) as well through the User Interface. All of access logs are recorded into the database of Access Logs.

Moreover, the LPA is used to extract learning patterns of students. By analysing access logs and the standard learning process of LAMS, the extracted learning patterns are recorded into the database of Learning Patterns. The LPO is used to optimise the learning process from the reference student group for a target student. According to the similarity of learning patterns, a series of learning actions that have high contribution for the learning performance are extracted from the reference group. Furthermore, the GAR, as one of the core modules in this system, is used to re-rank the recommended learning actions. According to the selection of the target student, it adapts to the learning transition of the target student gradually, and makes the recommended learning process more suitable for the target student. The details of these three modules are introduced in the next sub-sections.

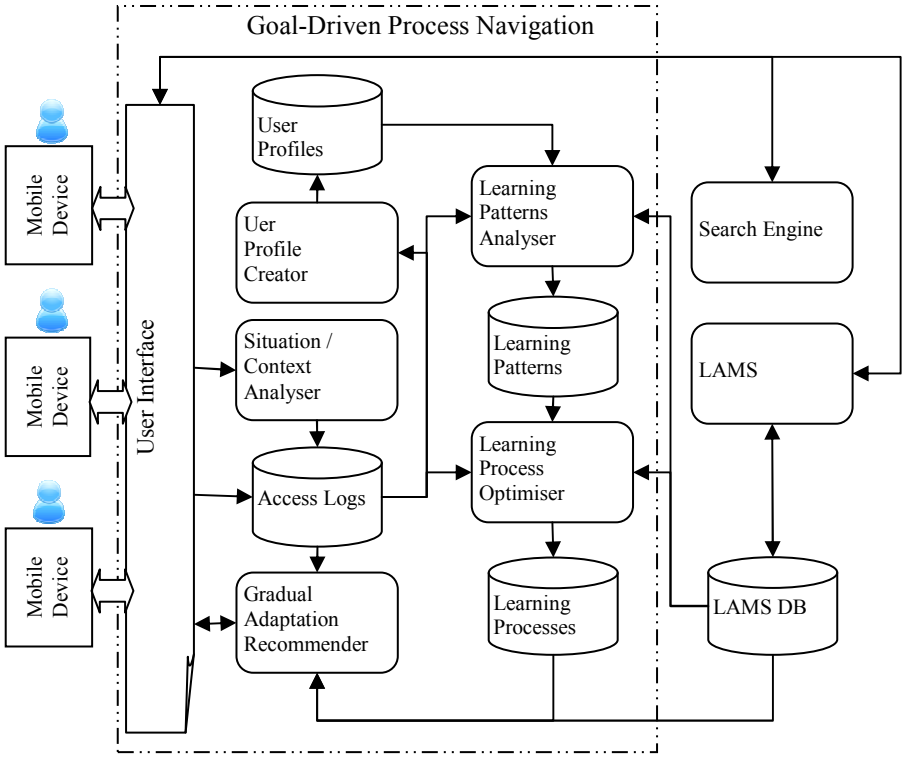

Figure 5: System architecture of goal-driven process navigation

5.2 Learning Patterns Analyser

We extract a data set from the learning activity log data to describe students in a learning activity, that is, $L = \{A_i, D_i, W_i, T_i, P_i\}$, where A_i denotes a learning action ID; D_i denotes the distance between the standard learning action and the actual learning actions of students; W_i denotes the access day of a week; T_i denotes the access time; P_i denotes the access situation. We can obtain A_i from the action ID, obtain D_i by comparing the standard learning action and the actual learning action, obtain W_i, T_i from the action time, and obtain P_i from the action service. The detail will be discussed in Section 5.5. Moreover, we assume that there exist k learning patterns among n students $S = \{s_1, s_2, \ldots, s_n\}$, and there exist m learning actions for a student in a learning activity. Using K-means clustering, we can obtain k clusters. The pattern tendency of a student can be estimated by the distribution of his/her learning actions in the clusters. The algorithm is shown in Figure 6.

In this algorithm, we divide all of data sets into k clusters at the first step. The second step is calculating new centroids in each cluster. The third step is resetting data into the nearest cluster according to the shortest distance that is from data to the new centroids. This process will be repeated till no data can be reset. The proposed algorithm is based on K-means. By this algorithm, we can obtain the clusters of

learning patterns.

LearningPatternClustering()

Input: student profile $S = \{s_1, s_2, \ldots, s_n\}$
Output: centroids g[k]

1. Initialize cluster
   For data set S, we need to extract k clusters, set initial centroid g = $\{\overline{g_1}, \overline{g_2}, \ldots, \overline{g_k}\}$ from S randomly, and set $G = \{G_1, G_2, \ldots, G_k\}$ from S randomly, where $k < n$;

2. Clustering
   2.1. find the new centroids of each cluster $G_1, G_2, \ldots, G_k$
   for (i = 1; i<k; i ++) {
   for (j = 1; j < number of data in G_i; j ++) {

$$Dis_j = \sum_{i=1}^{k} \sum_{s_j \in G_j} || s_j - \overline{g_i} ||^2 \text{ , where } \overline{g_i} \text{ is the current centroid in } G_i.$$

   }
   if (Dis_j is argmin) {
   set s_j into g[k], where $s_j \in G_i$, s_j is new centroid of G_j
   }
   }
   2.2. reset data set to the nearest cluster
   for (j = 1; j < n; j ++) {
   for (i = 1; i<k; i ++) {

$$Dis_j = \sum_{i=1}^{k} \sum_{s_j \in G_i} || s_j - \overline{g_i} ||^2 \text{ , where } \overline{g_i} \text{ is the current centroid in } G_i.$$

   }
   if (Dis_j is the nearest to new centroid in G_i) then set s_j to G_i
   }
   2.3. Do 2.1 and 2.2 till no data can be reset.
3. Return g[k]

Figure 6: Algorithm for pattern clustering

5.3 Learning Process Optimiser

Based on the results calculated by the LPA, we can obtain some students groups that belong to the same cluster with the target student. It means that a target student is possible to belong to more than one group. By moving out the students who do not have high performance, the reference groups are created for a target student.

In this study, we consider the contribution of learning actions for the learning performance. The basic idea is that a more frequently used learning action is considered to have more effect to students. Therefore, the access number of a learning

action is used as a parameter to estimate the weight of a learning action. We use Formulas (1) and (2) to describe the contribution of a learning action.

$$Contribution(lact_j \rightarrow s_i) = \frac{\| lact_j \|}{\sum_{j=1} \| lact_j \|} \times GP_i \qquad (1)$$

Formula (1) denotes the contribution of learning action $lact_j$ to student s_i. Here, GP_i is the grade point that the student s_i obtained in a learning activity, $\|lact_j\|$ is the times of action $lact_j$ used by student s_i and $\sum \| lact_j \|$ is the total times of learning actions taken by student s_i in a learning activity.

$$Contribution(lact_j) = \frac{\sum_{i=1} Contribution(lact_j \rightarrow s_i)}{\sum_{i=1} \sum_{j=1} Contribution(lact_j \rightarrow s_i)} \qquad (2)$$

Formula (2) denotes the contribution of learning action $lact_j$ to all students. Here, the numerator of the formula denotes the total contributions of action $lact_j$ taken by all students and the denominator denotes the total contributions of all actions taken by all students.

Using these two formulas, the contribution of learning actions can be calculated. And then, the learning action which has higher contribution is extracted. Of course, there is a possibility that the access number of a learning action has deviation. We expect using the average access number can avoid this problem. It means that when we calculate the value of contribution, if the access number is bigger than the average access number, this reference student's data will be moved out.

5.4 Gradual Adaptation Recommender

The GAR is used to detect and adapt students' learning transition gradually, and then generate the learning process navigation for students. A Bayesian network is created in the GAR.

As shown in Figure 7, the dotted lines denote a standard learning process, and the solid lines denote an actual learning process used by students. Thickness of the line denotes the utilization rate. The thinner line means that its application rate is smaller than the thicker line. Here, we assume there are k learning patterns $G = \{G_1, G_2, \ldots, G_k\}$ for students. $A = \{A_1, A_2, \ldots, A_n\}$ are the learning actions' access number of the reference group students. In detail, A_1 denotes the access number of Learning Action 1 after the current learning action of a target student. Then, Formula (3) is used to calculate the posterior probability.

$$P(H = h \mid T = t) = \frac{P(H = h)P(T = t \mid H = h)}{P(T = t)} \qquad (3)$$

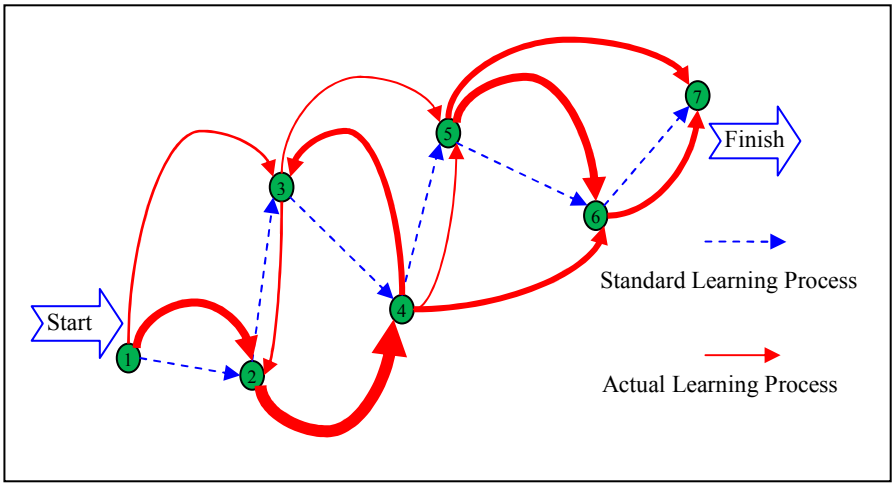

Figure 7: An example of learning process navigation

In Formula (3), $P(H=h \mid T=t)$ denotes a posterior probability, and $P(H = h)$ denotes a prior probability. When we want to calculate the posterior probability of learning pattern G_i and learning action A_j is selected, Formula (3) can be changed to Formula (4).

$$P(H=G_i \mid T=A_j)=\frac{P(H=G_i)P(T=A_j \mid H=G_i)}{P(T=A_j)} \qquad (4)$$

Since the prior probability can be obtained from the reference group, Formula (4) can be further expressed as Formula (5).

$$P(H = G_i \mid T = A_j) = \frac{\frac{1}{\| G \|} \times \frac{A_{A_j \in G_i\ j}}{\sum A_j}}{\frac{\sum_{A_j \in G_i} A_j}{\sum A_j}} \qquad (5)$$

In Formula (5), $\|G\|$ denotes the number of learning patterns. Based on Formula (5), we can calculate the posterior probability of a target student who belongs to learning pattern G_i, and selects learning action A_j. After the posterior probability of learning action is calculated, the results are recommended to the target student by the descending order of posterior probability.

After the target student selects a learning action, the system is then repeated with the above process: calculates the posterior probability of next learning action, and deliveries the results to the target student.

5.5 User Profile Based on Learning Activities

In order to help student to achieve a learning goal effectively, we need to design a learning activity for the student. Because of the diversity, the student may achieve the learning goal along the design or progress in his/her own favorite pace. When a student uses the proposed system, the access data will be saved as access logs.

The learning activity is modeled as follows. Each learning activity consists of a series of learning actions with a sequence, and a learning action is composed of six elements (partly optional) described as follows.

- Time: when the access starts and ends
- Actor: who is using the learning system
- Content: which content is accessed
- Service: which service is chosen
- Operation: a concrete realization procedure
- Situation: learning status and location of students

The basic data structure is shown in Figure 8, and its elements are described as the bullet points. Specifically, the service represents a system component of the LAMS, which is used by students. For example, a BBS search service provided by the LAMS, which can help students to search the history of BBS in the LAMS. The situation includes learning status and location data of students. Here, the learning location is a geographical concept, for example, learning in a classroom or on a train. The learning status indicates the environment characteristics of places, for example, learning in a static environment or in a moving environment. It is conceivable that the multimedia learning content of text, audio and video is suitable for being used in the classroom or at home, and the learning content of audio is more suitable for being used while riding on a bicycle. Student's access logs are recorded, and used to create

```
<activity>
   <action id="c">
      <time />
      <actor />
      <content />
      <service />
      <operation />
      <situation />
   </action>
   <action id ="a" />
      …
   < action id ="x" />
</activity>
```

Figure 8: Data structure

user profiles. In these profiles, the data such as which action is accessed by which sequence, when and how long it was taken, can be used to describe the past learning activities of a student.

6 Experiment Evaluation

A prototype system for experimental evaluation has been built within the Moodle system, a learning content management system. We designed an activity course that consists of 15 learning activities corresponding to 15 weeks. Every learning activity begins on Monday, and ends on Sunday. A quiz is prepared at the end of each standard learning activity. Learning process logs of more than 30 students' were used to infer the successful learning activity, in which the grade point is set to be higher than 8 points in a quiz (full is 10). By analysing the log data, three most frequently used learning patterns are extracted, which are described as follows.

- Pattern 1:
  a) visiting forum/discussion (F),
  b) viewing learning content (C),
  c) viewing/doing quiz (Q).
- Pattern 2:
  a) viewing learning content (C),
  b) viewing/doing quiz (Q),
  c) visiting forum/discussion (F).
- Pattern 3:
  a) viewing/doing quiz (Q),
  b) viewing learning content (C),
  c) visiting forum/discussion (F).

The patterns mentioned above indicate that the actual learning processes of students are different. Figure 9 shows the distribution of students' learning patterns. The different colour indicates that most students have plural patterns in the whole

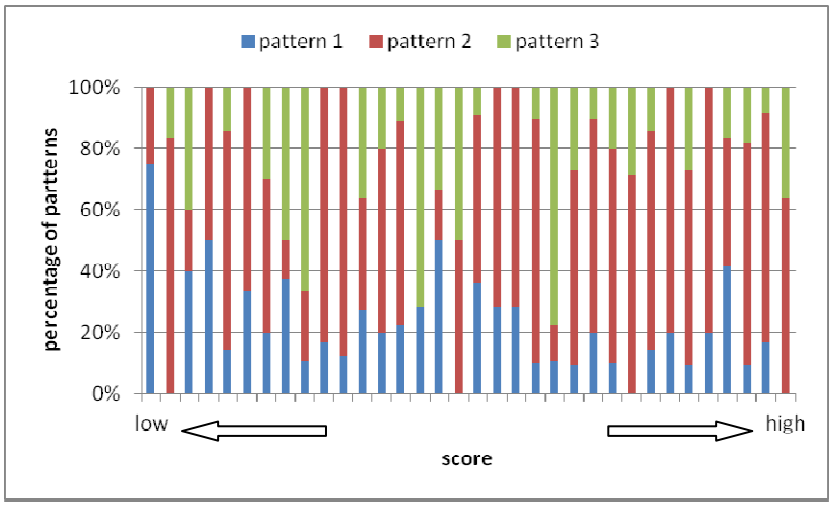

Figure 9: Distribution of *learning patterns*

semester, but most of them have their main patterns or priority patterns. Therefore, we can recommend next learning actions according to the percentage of patterns for learning process navigation. If a student does not select the recommended learning action that is based on his/her learning pattern, our proposed navigation will increase

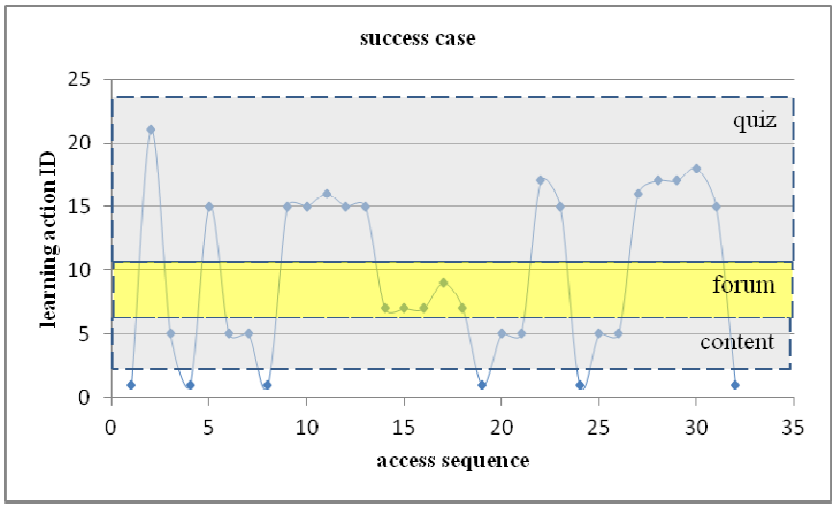

Figure 10: Success case

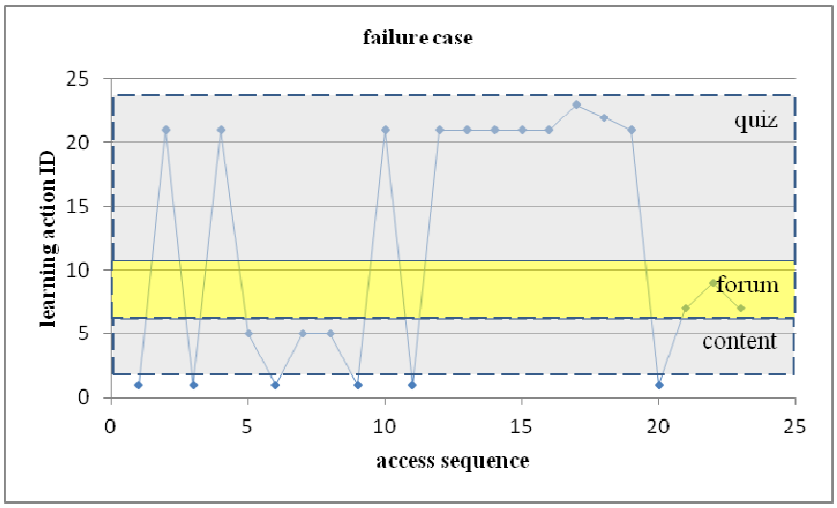

Figure 11: Failure case

the recommending weight of his/her second learning pattern.

The analysis result proved that the learning achievement can be affected by the learning process. Figure 10 shows a success case of learning process, in which high grade point was obtained by the student, where the student started viewing/doing a quiz (Q), and then viewed the learning content (C). After repeating these actions for some times, the student moved to the forum (F), and then returned to do learning actions C and Q. At last, this student obtained a high score at the end of the learning activity. On the other hand, Figure 11 shows a failure case of another student's

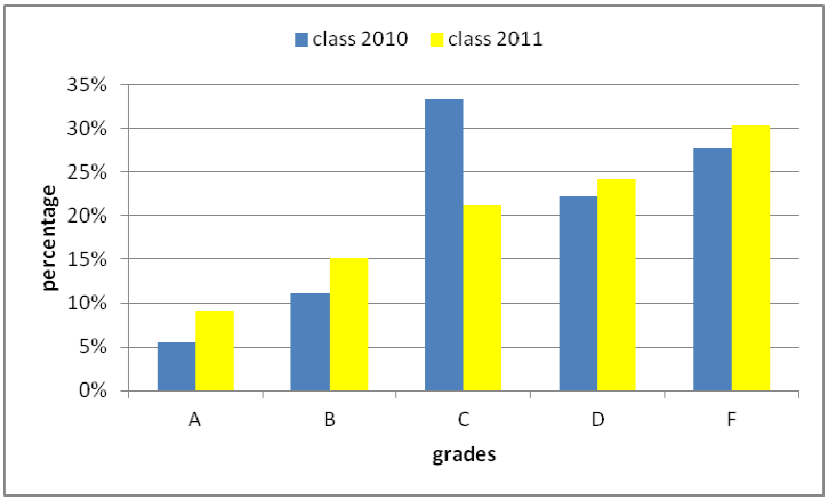

Figure 12: Distribution of *grades*

learning process, in which the student obtained a low grade point. This student also started viewing/doing quiz (Q), but almost did not visit forum (F). The score of this student is low in this learning activity. Comparing these two students, the results indicate that using forum and attending discussion in an appropriate time can improve the learning performance.

Finally, we compared the final achievements of students of two classes that took the course in 2010, in which our proposed system was not used, and 2011, in which our proposed system was adopted. The result is shown in Figure 12, where A, B, C, D, and F in the horizontal axis represent the grades (A is the highest, and F denotes failure), and the vertical axis represents the percentage of each grade. In Figure 12, the grades of Class 2011 are higher than Class 2010 for A, B, D and F, and lower than for C. The reason for the result is that the grade point of a successful learning activity was set as 8 points, which implies that more target students succeeded in improving their learning performance (more A and B grades) with the help of recommendation and navigation from the prototype system. On the other hand, those students whose usual learning achievements were much lower than 8 seem to be unable to match the recommendation and navigation, which results in more D and F grades. This problem can be expected to be solved by using a variable aimed achievement (not a fixed one, like 8 point in the prototype system).

The results discussed above indicate that our proposed approach and prototype system can be used to improve individualized learning. With the improvement of the proposed system and algorithm, more detailed and precise learning patterns are expected to be extracted, so that more successful and satisfactory learning experience can be shared with each other.

7 Conclusion

In this study, we have proposed an integrated adaptive framework for individualized goal-driven learning process recommendation and navigation in the ubiquitous learning environments. In this paper, we have described the concept of learning activity and our vision on goal-driven learning process navigation for individualized learning activities. We have introduced the activity course model based on the well-known activity theory, in which the learning goal of a target student can be inferred by comparing the learning processes of the target student with his/her reference student group of similar learning patterns. To show the effectiveness of our proposed framework and approach, we have described the system architecture and its core functional modules, and data structure. Finally, we have shown the experimental evaluation and analysis result, which was based on the prototype system.

The major features and contributions of our work can be summarised as follows. Firstly, our proposed framework is based on a dynamic Bayesian network that gradually adapts to a target student's needs and information access behaviours. Secondly, an improved Gradual Adaptation Recommender with an integrated algorithm for extracting learning patterns has been adopted in the proposed system. Thirdly, a set of measures and formulas have been introduced and defined to make the navigated learning process optimised, by using the extracted learning patterns. Our proposed framework and system can be expected to help students to improve their learning performance in ubiquitous learning environments empowered by IoT.

As for the future work, we will improve the adaptation mechanism and algorithm to make them fit to all levels of students, based on the experimental evaluation result. We will further investigate the application domain that can fully utilise the advantages of ubiquitous networking and IoT environments.

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