1-1-2016

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Keywords

learning, path, systems, adaptation, online

Disciplines

Engineering | Science and Technology Studies

Publication Details

Muhammad, A., Zhou, Q., Beydoun, G., Xu, D. & Shen, J. (2016). Learning path adaptation in online learning systems. 2016 IEEE 20th International Conference on Computer Supported Cooperative Work in Design (CSCWD) (pp. 421-426). United States: IEEE.

Learning Path Adaptation in Online Learning Systems

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***Abstract*—Learning path in online learning systems refers to a sequence of learning objects which are designated to help the students in improving their knowledge or skill in particular subjects or degree courses. In this paper, we review the recent research on learning path adaptation to pursue two goals, first is to organize and analyze the parameter of adaptation in learning path; the second is to discuss the challenges in implementing learning path adaptation. The survey covers the state of the art and aims at providing a comprehensive introduction to the learning path adaptation for researchers and practitioners.**

Keywords—learning path, learning path adaptation, personalized e-learning, adaptive online learning system

I. INTRODUCTION

An adaptation of the online learning system has been researched extensively over the last decade in the various models. The purpose of adaptation is to optimize the relationship between the learning requirement and course content, hence, the learning outcome could be obtained with minimum time and interaction expended on a course [1]. Several types of adaptation, such as adaptation based on students' characteristics , learning style , and context history , are widely discussed in the literature and in several surveys [2-5].

In this paper, we investigate the adaptation based on learning resources (learning objects) and links between them, i.e., the learning path [3, 6]. A learning path is defined as a *sequence* of learning tasks or activities which are designated to assist the student in improving their knowledge or skill in the particular subject [7]. The purpose of sequencing learning path is to provide learners with the most suitable individual learning object to learn according to the learner characteristics.

As an example, let us take two students John and Julia which are interested in learning Web Programming using a tutorial available from the online learning resources in their school. John has the basic foundation in algorithms, but he is interested in furthering his learning to programming. Meanwhile, Julia is a first year student without any prior relevant knowledge. John and Julia can have different learning paths to achieve the set proficiency target in web programming. Julia will likely require a longer learning path than John's learning path. It would be more appropriate to individualize their learning path to match their prior knowledge. This is the essence of adaptation of learning path based on the content, to enable students to reach their learning objectives quicker and matching their individualized learning path to their background and knowledge. Sequencing the components in a learning path accommodates the students and prepares the relevant knowledge units or learning activities required.

Providing an optimal learning path tailoring to the context of the learners is a crucial issue in online learning adaptation. An optimal learning path could reduce the student's cognitive overload and disorientation; consequently, this process would improve the student learning outcome and efficiency of the adaptation in the online learning systems [8, 9].

This paper presents a survey of learning path adaptation efforts in the web-based educational system from 2008 up to 2015. The survey highlights the significance of adopting a

learning path in the web-based educational system, such as e-learning, intelligent tutoring system, or virtual learning environment. Moreover, the challenges and approach on the adapting learning path are also highlights. We believe that the survey of learning path adaptation is a very significant issue for improving the research in online learning system.

The next section will first discuss problems identified from literature when determining suitable learning paths for students. Several approaches to solving learning path problem in online learning will then be discussed.

II. Learning Path Adaptation

In order to understand and analyze the adaptation of learning path in e-learning, this section first reviews the concept, process, problem formulation of learning paths, and several approaches to solving learning path problem.

A. Conceptualizing Learning Path

The concept of learning path adaptation is developed from the field of adaptive hypermedia and depend on complex conceptual models, which is usually driven by sequencing rules produced in the courseware [10]. In order to generate automatic learning path construction, knowledge elements are used to build a learning path and arrange them in proper sequence [7]. The choice and sequence of knowledge elements can be determined by several characteristics of the student, for instance by their learning styles, preferences, abilities or by some constraints, such prerequisites of the course and length of study. A learning path generation algorithm searches the best possible match between each student on one hand; and the learning objects or pedagogical requirements on the other hand.

This research continues to expand along with the need for personalizing learning online. Indeed, personalized online learning precisely targets at finding the best learning materials and optimizing the learning path [11]. The main challenge faced in this area is combining the wide diversity among the individuals with the specific characteristic of the learning objects. These include the consideration of learning style, cognitive style, learning goal [11, 12], as well as the domain model, knowledge structure, and curriculum [12, 13]. The challenging continues as the nature of online learning environment that constantly changing as learning resources are being introduced/removed and the learning experience is constantly evolving. Though a lot of novel ideas in this area have been proposed in recent years [10, 14, 15], learning path construction is still having some challenges worth for studying.

Recommending suitable learning path is practically applied in online learning and could enhance learning quality. In [16], the authors propose an artificial intelligence technique to find suitable learning paths based on students' learning styles. The results of their experiment have shown that learning in suitable learning paths could improve students' learning results and saves learning time. This result is in line with previously published studies [7, 17, 18], which have indicated that learning path adaptivity has successfully guided learner to get satisfactory assessment results.

B. Adaptation Process

Learning path adaptation involves several processes. In paper [19], the author illustrates five-step scheme to personalized learning object in e-learning (Fig.1). These steps could illustrate the process of adapting the learning path on online learning system:

1. *Metadata labeling formulation*. This process is usually specified when creating learning objects (LO). A learning object is a resource, digital or non-digital, that can be used and re-used to support the learning in the environment [11, 20]. To address personalization, we need to describe at least three specifications: the platform for the LO, the information about the learner's profile and the relationships among learning objects.

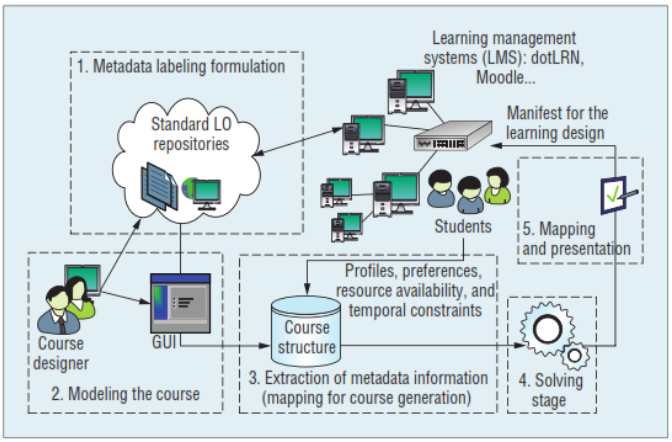

Fig. 1. The schema for personalized learning [19]

2. *Modeling the course*. The course in e-learning is initially designed same for all users. In this stage, the LOs is enhanced to adapt the students' profiles. For instance, the creator could extend the metadata record by tailoring student's learning style classification. However, the compatibility and coherence between learning objects need to be considered before making any adjustment.

3. *Extraction of metadata information*. The main process at this stage is mapping the LO metadata information and automatically build the course structure through adaptation aspects. Some literature modeled the mapping process using constraint satisfaction problem [10, 21] while others use mathematical models [7, 22]. The course is then created by mapping the learning objects with student information.

4. *Solving stage*. The result of solving stage is a tailored learning design (learning path) or a sequence of learning objects that suit students' preferences.

5. *Mapping and presentation*. This process is to translate the calculated learning design into a standard language for learning management system (LMS). The process will generate a document according to learning design and the student could navigate through the contents.

C. Problem Formulation

The main objective in learning path adaptation is to minimize the path or route of individual learning. The literature has revealed several ways to formulate problem in learning path adaptation (Fig. 2).

The first way is to formulate learning path as *traveling salesman problem* (TSP) with multiple agents [23, 24]. In TSP, each agent seeks to minimize the path of their own traveling course, while discovering the location between different agents at each time step. The same way in the learning path adaptation, during minimizing each time phase of students attending learning objects, each student attempts a personal learning path by minimizing the relevance loss between consecutive learning objects along the path.

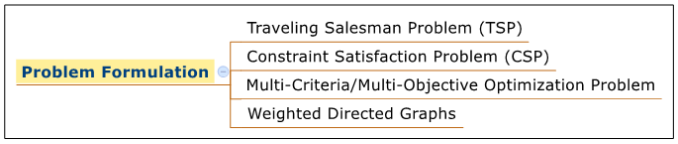

Fig. 2. The schema for personalized learning

The common method to formulate learning path problem in literature is to formulate as a *constraint satisfaction problem* (CSP) [10, 19, 21, 25]. Constraint satisfaction problem consists of a set of precedence constraints (rules) and objective criteria. The problem in CSP is defined as the state of the variable definition. The solution space of the problem comprises all possible sequences and the objective function is to minimize or maximized the penalty function designed to evaluate the sequencing [25]. According to de-Marcos [10], sequencing learning object to adapt learning path can be modeled as a PermutCSP. A PermutCSP is a CSP in which all solution are the permutation of a given tuple.

Since a single objective with several constraints may not adequately represent the problem, we may need to formulate the problem with more than one objective. Therefore, several authors [15, 17] propose *multi-criteria/multi-objective optimization* problem to solve learning path adaptation. The concern in multi-objective optimization problem is to satisfy multiple objectives simultaneously. For instance, in [17] the author attempted to generate adaptively the learning object sequence by formulating the evaluation viewpoint for sequencing as a multi-objective optimization problem. The conditions that must be satisfied are concept relation, prerequisite satisfaction, difficulty level. In [15], the author formulates curriculum optimization problem that asks to minimize four objective function according to: (1) whether the learning concepts meets the expected learning target, (2) the difficulty of the e-learning material matches a learner's ability, (3) the limitation of learning time, and (4) the balance of the weight of learning concepts.

The problem in learning path could also be formulated as *weighted directed graphs* [7, 14, 22, 26], where each node represents a course unit. Domain knowledge and learning goal is represented by learning path graph. In order to adapt the optimal learning path, [26] proposes a two-step:

- Determining the least minimum cost matrix between each pair of courses.
- Finding and constructing an ideal learning path for each learner.

Then the optimal learning path for individual learner constructs a context based on the minimum cost of course learning unit and relevant personal information.

D. Approaches to Learning Path Problem

Once the learning path model has been formulated, the methods to build the approach are chosen according to the problem. Many works in the literature proposed evolutionary algorithm, such as Genetic Algorithm [8, 11], Particle Swarm Optimization [10, 15], or Ant Colony Optimization [25, 27], to solve learning path adaptation based on Constraint Satisfaction Problem [28]. Among this method, ant colony optimization is the most used to solve the learning path problem [28].

Ant colony optimization is initially a system based on a colony of agents which simulate the natural behavior of ants in order to solve optimization problems [27]. In the perspective of learning path, individual learner is typically modeled as an ant, while the sequence of course is modeled as arcs between nodes [28]. Furthermore, ants or learners try to find the shortest path from their nest to the food source, which in this case is pedagogical objective, in a reasonable time. Pheromones along the route (arcs) are represented as weights, which can be defined based on various parameters. Although the research has shown that ant colony optimization could sequence the learning path successfully, however, in the reality there is no guarantee that it will strengthen the learning process. In this case, even though the ants do not mind revisiting the same place, however, according to Benabdellah et al. [29] in practice the learners may complain and get bored if the same unit is represented twice.

Although the above is a very promising approach to solve the learning path optimization problems, however, the intelligent evolutionary algorithm proposed computationally intensive. The problem of learning path optimization is NP-hard problem, hence only computationally efficient methods can realistically be deployed. The author [9] proposed the Forward Greedy algorithm to improve efficiency. In paper [21], the author proposes the hill climbing (HC) heuristic to find optimal learning paths for a group or individual learner. The proposed algorithm will iterate to apply either crossover and mutation operators until the solution is converged or the maximum number of generations is exceeded.

Using domain modeling to support path optimization is not new. Several authors propose learning path graph [14, 22, 26], concept map [30], and ontology [18, 31]. Specifically, the use of graph theory is not new in e-learning, however, there has been no formal model for discussing learning path problems based on graph theory. The works in the paper [21, 29] defined a formal model for discussing learning path problems based on graph theory. The authors propose to address the problem of learning design recommendation in large repositories by reducing the problem space, then using a greedy algorithm. Although this approach is not optimal, however, this method

could be computationally improved by local and global optimization.

III. Parameter Adaptation

The process of adapting a learning path relies heavily on the parameters of the context. However, this research is very complex due to various parameters involved in the adaptation process that causes the decision will become more complicated [21, 32]. From the literature, the level of adaptation in learning path may be divided into three domains (Fig. 3): learning object, learner, and pedagogical.

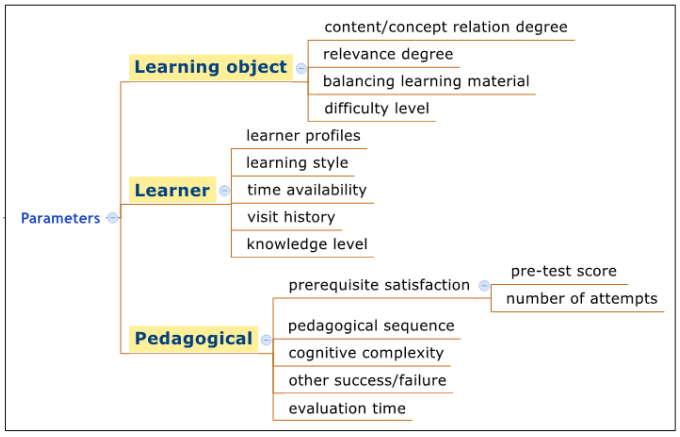

Fig. 3 Parameters adaptation in learning path

A. Learning Objects

A learning path could be personalized based on the context of learning objects. The main idea of the use of learning objects in e-learning is to support reusability. The common procedure for supporting reusability is by developing educational content into small chunks, so that it can be reused in various learning environments. To support reusability, learning objects have to be annotated with metadata. The parameters of adaptation based on learning object can be classified in several ways, according to content/concept relation degree, relevant degree between learning object, balancing learning material, and difficulty level.

The learning object modules may not be closely related to each other in the online learning system, therefore, Tam et al. investigate the concept relation degree of the learning objects in the curriculum [21]. More detail in their paper, Tam et al. propose the integration of semantic analysis, concept clustering, and evolutionary algorithm with hill-climbing heuristic to propose an optimal learning path for learners. The results of their experiment indicate a better performance than a shortest-path approach in providing learning path.

Another parameter being identified in learning object as suggested by Hwang et al. [23] and Acampora et al. [20] is the relevance degree between learning objects that match the learner knowledge. Since there are usually many objectives for learners in the online learning system, it is difficult for them to determine the suitable learning path without guidance. In order to assist the learners to absorb new concepts based on the relevant concepts they already know, it is important to adapt the learning path that relevant with their existing knowledge.

In contrast to relevance degree, Chu et al. [15] investigate the balance of the weight of learning concepts in online learning. Considering the balance learning concepts, it will provide adaptation with the difficulty level of learning materials that meet individual learning target.

B. Learner

Most adaptive online learning systems consider the learner parameters to customize learning content. The adaptation of learning material is performed by considering several parameters as follow: learner preferences and background, learning style, learning time availability, history, and knowledge level. Based on these characteristics the online learning system will determine the appropriate learning path for each learner.

Learner profile is one of the most widely used parameters in adapting learning system. It can be described directly by learner themselves or identified from the learners' behavior patterns [3, 33]. Several parameters which can be applied in learning profiles are age, educational background, gender, language, preferences, or goals [4, 14, 33]. Learning path can also be adopted based on students' learning style. The learning style is generally described as the way people learn [33]. The learning style of the learner can be identified by using the behavior pattern of each individual [3]. In the adaptive learning system, the most preferred learning style is Felder-Silverman, then followed by Kolb and VAK [5].

Several authors [9, 34] also suggest using the limitation of learning time (affordable time) of a learner as a parameter. Since a learner's ability and attention affect individual learning time, the expected learning time for each learner is different. Ballera et al. [32] use exam/study performance and review performance of the learner as a parameter.

Another learner adaptation is based on their knowledge level. Knowledge level or student ability is also common in learning path adaptation [15]. Some literature implemented Bloom's taxonomy to classify student's ability [7, 25] while another using pre-test result to pattern learner prior knowledge [15]. Another parameter as suggested by [23, 32, 34] is the relevance of the number of visiting the same learning objects.

C. Pedagogical

The adaptation based on pedagogical preferences is also needed in the adaptive learning path, in order to organize learning path in a comprehensive way. The pedagogical models preferred by each learner may be different from other learners. To satisfy the need of the learners and improve the quality of adaptive learning, the following pedagogical preferences are needed to be considered: prerequisite satisfaction, pedagogical sequence, cognitive complexity, others learners success/failure, and evaluation time.

Prerequisite is performed to infer learner's background and decide the pedagogical model for them. In general, the adaptive learning system can infer prerequisite from pretest score or the number of attempts [16, 29, 30].

Another pedagogical parameter in adaptive learning path as explored by Tam et al. [21] is the pedagogical sequences which can be represented by a set of reference prior/posterior rules. In their paper [25], Dharsini et al. propose to use the difficulty level in pedagogic materials. Several authors [9, 14, 22] adopt learning path sequence from other learners success/failure path and the time they spend during the courses.

IV. Challenges in Learning Path Adaptation

Although some significant works have been made towards the direction of learning path adaptation, much research needs to be conducted to fully adapt the learning path in online learning systems. This section of the paper highlights several areas where much work remains.

A. Implementation

Although an adaptive learning path will improve learning efficiency in the online learning system, however implementing learning path activities in a real-world situation are quite different, especially when included it in the LMS. For instance, it is possible to adopt learning styles and learner profiles, however, it is tricky when including these parameters in LMS [35]. It will require taking into account both the type of each learning task and the opinion of an expert to assess the students' learning styles. It also needs to map types of learning styles with the types of tasks to decide which combinations are better.

Another instance of the challenge is related to the number of learners, which actually affects the students' learning achievements significantly. Some researcher [23] suggested to given consideration to the real-world learning objects and the number of students who visit the same learning objects. In learning path adaptation, this approached is called as social sequencing [28]. As each learning object represents different concepts to be learned, it is difficult for the students to determine the learning path for visiting the target objects without any guidance. Hence, the solution in social sequencing will incorporate the experiences of other similar learners. However, if the learning path from social sequencing is not well arranged, the learners might fail to understand the relationships among those learning objects. This will likely cause the disorientation in the learning process.

B. Competency

The second type of challenge comes from the need to achieve competency from learning path adaptation. Competency is defined as a measurable ability of an actor to perform a necessary action in context to achieve a specific outcome [14]. Competencies such as prerequisites and learning outcomes are dealt with in meta-data definitions [25]. By defining a competency as a learning object outcome and as the prerequisite for another learning object, then a constraint between the two learning objects might be established so that the first one must precede the next learning object in a valid sequence [10]. The definitions of metadata description are attached to learning objects, and within those definitions, references to competencies are included (prerequisites and learning outcomes).

C. Curriculum

One of the goals of the study in the online learning system is to allow learners study in their own way. Although the learning is being personalized, however the curriculum is still needed to drive the direction of the learning. The adaptive learning path is expected to be one of the ways to achieve the curriculum [12]. Therefore, further investigation in analyzing and mining the data from the interaction of the learner with the online learning system is essentially needed. The more relevant information on the models, the better adaptation and personalization will be.

D. Dynamic Sequencing

Another challenge in adapting a learning path is how to resolve the expanding learning objects that available in the system as compared with the learning objects that can be found on the internet. For example, if there is a condition when a subject requested by a learner is not sufficiently addressed in the existing system. Then it is better if the system could identify the set of criteria to be used for searching the new suitable materials from the internet and provide an appropriate learning path based on learner's profile in the system. Further investigation and experimentation in this dynamic sequencing would be worthwhile.

E. Optimization

A great deal of previous research into learning path has focused on optimization problem. Survey papers by [28, 36] offer probably the most comprehensive study related to optimization personal learning path using evolutionary computing approaches. Many works based on soft computing techniques has been developed to achieve an adaptive learning path. It would be interesting that further studies be undertaken in exploring soft computing techniques to provide adaptive learning path with the new massive (MOOCs) and seamless online learning environment.

V. Summary and Conclusion

Constructing and optimizing Learning paths is a key issue in personalized online learning systems. This paper reviews the important related research issues. The issues can be categorized in a number of layers of abstractions that are instructive: issues related to the main concept and integrating all other the issues involved, issues related to the construction and optimization process, issues related the problem formulation and knowledge representation involved in adapting the learning path in the online learning system. Several approaches to each of those category of issues were discussed. Specifically, we also provided our analysis along the following domain dimensions: the learning target, the learner, and the pedagogy. Although significant progress has been made in along all dimensions and categories of issues, there is clearly much work needed in this area. We highlighted the following: lack of workbenches to validate many of the concepts, areas lacking in problem formulation (competency and curricula), and in dynamic sequencing and optimization.

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