Learning Path Construction Based on Association Link Network

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Abstract. Nowadays the Internet virtually serves as a library for people to quickly retrieve information (Web resources) on what they want to learn. Reusing Web resources to form learning resources offers a way for rapid construction of self-pace or even formal courses. This requires identifying suitable Web resources and organizing such resources into proper sequences for delivery. However, getting these done is challenging, as they need to determine a set of Web resources properties, including the relevance, importance and complexity of Web resources to students as well as the relationships among Web resources, which are not trivial to be done automatically. Particularly each student has different needs. To address the above problems, we present a learning path generation method based on the Association Link Network (ALN), which works out Web resources properties by exploiting the association among Web resources. Our experiments show that the proposed method can generate good quality learning paths and help improve student learning.

Keywords: Learning Path, Association Link Network, Learning Resources.

1 Introduction

Learning resources (LRs) refer to materials that help students learn and understand certain knowledge. Such LRs can be constructed by different types of media, including text, audio, and video. Typically, producing LRs is very time consuming. With the availability of the Internet, such situation may be improved, as information covering a huge variety of ready-made knowledge, namely Web resources, is made available. Examples of Web resources include materials from Wikipedia, BBC, Reuters, etc. Reusing such resources may help teachers significantly reduce their time on producing LRs and may also facilitate the generation of self-pace courses. However, Web resources may be loosely connected without any well-defined structure or relationship, and may also be redundant. It is not trivial to transform Web resources into LRs, as relationships among LRs are required to be well defined and LRs should be arranged to deliver in a proper order for students to study.

Identifying relevant LRs is essential to learning path [11] generation. Existing work determine such a relevancy by matching student specific requirements, including topics to learn, learning preferences or constraints [4, 3] against the characteristics of LRs, which can be maintained by a list of attributes, such as related topic and difficulty level, or additionally by a structure that defines how LRs are related among each other [9]. Learning path generation methods aim at arranging selected LRs into a proper sequence for delivering to students, such that they can learn effectively in terms of minimizing the cognitive workload. Basic work [4], only considers attributes associated with each LR, such as its related topic. More advanced works [5, 2] consider the structure among LRs which facilitates them to model the cognitive relationships among LRs. Such relationships are fundamental to learning effectiveness. However, structures among LRs are not trivial to build. Existing work considers using predefined structures [5] or generating LR structures based on pre-test results [2], which involves significant human effort.

We present a learning path (LP) generation method based on the Association Link Network (ALN) [6, 8]. It discovers knowledge structure among Web resources based on association, allowing teachers to reuse Web resources forming LRs automatically. Our main contributions include:

1. We apply ALN to transform Web resources into well-structured LRs, where their pedagogical attributes, including knowledge domain, importance and complexity, can be automatically determined. This allows us to construct a teacher knowledge model (TKM) for a course and generate adaptive LP to each student. A student knowledge model (SKM) is also included to monitor student learning progress.
2. We model learning paths by a set of three different ALNs, namely LR, topic and keyword based ALNs. This modeling allows students to perceive the relationships among LRs through different abstraction levels, which can help students minimize their cognitive workload during the learning process.

This paper is organized as follows. Section 2 discusses related works. Section 3 and 4 respectively explain the construction of the teacher knowledge model and adaptive learning paths. Section 5 shows some results and Section 6 concludes this paper.

2 Related Work

To support students learning effectively, relevant LRs should be identified and delivered in a proper sequence based on student needs and knowledge background. [4] proposes using Web resources as LRs without requiring teachers to create LRs. Suitable Web resources are selected based on certain student specific criteria, including topics to study, learning preferences and learning constraints, e.g. available study time. [3] also allows students to search LRs for learning. However, the method in addition performs a query rewriting based on student profiles, which describe student learning preferences and learning performance (which indicate student knowledge level), such that students only need to focus on what they want to learn and the system will take care of the suitability of every LR, which matches the student searching criteria. [9] proposes a more comprehensive modeling of LRs, where each of them is designed to associate with a concept, a knowledge type (verbal information or intellectual skills), and a knowledge level. LRs are connected based on concept relationships, where teachers manually define prerequisite among concepts. However, such relationships are not fine enough to support arranging individual LRs in a proper sequence for delivery. [1] characterizes LRs based on subjects and organizes LRs by ontology-based subject relations, including part of, prerequisite, and weaker prerequisite relations. They form the basis for both determining the delivery sequence of LRs and selecting suitable LRs according to the student preferred subjects. However, subject information is too coarse that each subject is associated with many LRs, making precise learning path hard to be generated.

Given that LRs are properly modeled, a learning path generation algorithm can be used to deliver LRs for students to learn. [4] allows students to submit queries for selecting suitable LRs. The selected LRs will then be ordered by the topics and the instructional methods that they belong to, respectively. As structures of LRs and relationships among LRs, which are critical to the control of student cognitive workload in learning, are not considered, learning effectiveness cannot be guaranteed. [5] models the structure among LRs based on a hierarchy of topics, which are defined by the ACM Computing Curricula 2001 for Computer Science. The method initially generates all possible learning paths that match the student goal. It then selects the most suitable one for a student to follow by considering the student cognitive characteristics and learning preferences. Although the relationship among LRs is essentially constructed manually, learning effectiveness is better addressed. [2] models the relationships among LRs based on an ontology-based concept map, which is generated by running a genetic algorithm on a set of student pre-test results. The method successfully works out the prior and posterior knowledge relationships of LRs, such that LRs can be delivered based on their difficulty levels and concept relationships to reduce student cognitive workloads during the learning process. However, the results do not necessary reflect the semantic relationships among LRs and may not be applicable to other groups of students who have not taken part in the pre-tests.

3 The Teacher Knowledge Model

The Association Link Network (ALN) [6, 8] is designed to automatically establish relations among Web resources, which may be loosely connected without well-defined relations. ALN defines relations among Web resources by analyzing the keywords contained in Web resources. Such relations are referred as associations, which link up Web resources as an ALN to describe the semantic relationships of Web resources, and turn Web resources into LRs. In our work, we further exploit such associations to automatically formulate key attributes of LRs, including their importance and complexity, which are fundamental to learning path (LP) generation. The LPs are exacted from the whole set of 3 different ALNs, namely LR, topic and keyword, to help students perceive LRs together with their multiple levels of relationships. By following such learning paths, the cognitive workload of a student on learning can be greatly reduced. To set up a measure for evaluating student learning progress, we define the set of three ALNs that links up all available LRs of a course as the teacher knowledge model (TKM). We also maintain a student knowledge model (SKM) (Ref. Section 4) to describe student learning progress. SKM comprises the system recommended LP and the part of the LP that a student has finished studying, together with all relevant LRs. SKM also comprises a student profile, indicating the student's knowledge levels and preferred topics.

Technically, the foundation of ALN is the association of keywords, where there exists an association link between two keywords if these keywords appear in the same paragraph. To facilitate the formulation of LRs and learning paths, we extract the most important keywords identified from a set of LRs as topics, where the association link between two topics are inherited from that between the corresponding keywords. The topics are used as a means to determine whether any two knowledge concepts are related. In contrast to a topic, a keyword only indicates a certain aspect of a piece of knowledge concept. On the other hand, there exists an association link between two LRs if some keywords contained in the two LRs are associated with each other. As an ALN represents a network linking a set of nodes $\{c_1, c_2, \cdots, c_n\}$ by their association, where n is the number of nodes. Mathematically, an ALN is represented by a matrix of association weights aw_{mn}, where each formulates the association relation between a cause node c_m and an effect node c_n. It is defined as follows:

$$ALN = \begin{pmatrix} aw_{11} & \dots & aw_{1n} \\ \vdots & \ddots & \vdots \\ aw_{m1} & \dots & aw_{mn} \end{pmatrix} \tag{1}$$

Particularly, LRs, topics and keywords are all modeled by ALNs. An ALN can be incrementally constructed by adding or removing nodes. When a new node is added to an ALN, we need to check such a node against all existing nodes in the ALN, identifying whether the nodes are relevant and computing the association weights between the newly added node and each of the relevant existing nodes in the ALN. When removing a node, all association links induced by the node will be removed. This incremental property makes adding new Web resources to form new LRs to or removing LRs from a course easily. We now depict the details of the construction of the three different ALNs in our system.

To turn a set of Web resources into LRs, we initially extract their keywords and construct the association links among the keywords by Eq. 2;

$$aw_{ij} = P\left(k_j | k_i\right) = \left(\sum_{k=1}^{n} b_{ir}\right)/n \tag{2}$$

where aw_{ij} is the association weight from a cause keyword k_i to an effect keyword k_j, k_i is associated to k_j when they appear in the same paragraph [6]. An association weight, which is calculated as $P\left(k_j | k_i\right)$, indicates the probability of the occurrence of a cause keyword k_i leads to an effect keyword k_j in the same paragraph at the same time. b_{ir} is the probability of the occurrence of a cause keyword k_i in the r^{th} sentence leads to the occurrence of an effect keyword k_j in the same sentence. n is the number of sentences in the paragraph p_m. We apply TFIDF Direct Document Frequency of Domain (TDDF) [7] to extract domain keywords from a set of Web resources, where keywords are texts that appear in a good number of Web resources, i.e. the document frequency is higher than a threshold. The associated relation is determined by $A \xrightarrow{\alpha} B$, meaning that if node *A* is chosen from an ALN, node *B* will also be chosen with the probability α.

We then extract and link up topics from the LRs. Topics refer to the most important keywords, which have the highest numbers of association links than the other keywords, meaning that they can represent the most important information of a set of LRs. In our experiments, we select the top 20% of keywords forming the topics. Pedagogically, topics model the knowledge concepts covered by the LRs, while keywords are associated to a topic as its key attributes, which help explain why certain knowledge concepts are related to some others. This modeling is much comprehensive than existing work, as they only associate LRs based on topics.

To construct LRs for a course, we follow the knowledge domain (i.e. a set of topics) of the course and select relevant Web resources that match the knowledge domain, turning such resources into LRs. We have conducted experiments on our method using 1085 Web resources about health information from www.reuters.com/news/health. We do not create LRs for similar Web resources in order to avoid students spending time on learning similar content repeatedly. We check Web resource similarity based on their keywords and association links. In the implementation, we pick the first selected item of such Web resources to create a LR and stop creating further LRs for any Web resource that has a high similarity. Fig. 1 shows part of the keyword ALN that we have created, where each node represents a keyword, and each edge, namely an association link, represents the existence of an association between two nodes. The importance of a node is directly proportional to the number of association links connecting to it. Note that the edges showing in the figure do not imply any association weight.

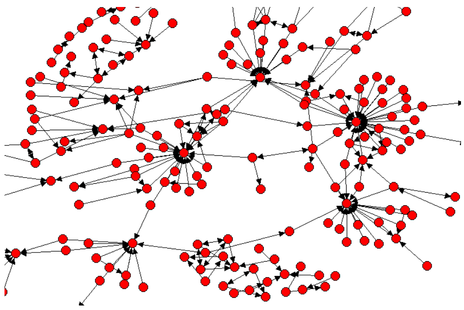


Fig. 1. An illustration of a keyword-based ALN.

TKM formulates the overall knowledge structure of a course based on topic, keyword and LR ALNs. [10] shows that formulating concepts into a knowledge map, which is a graph having concepts as nodes and they are connected by links that model the relationships between two concepts, can significantly improve student understanding, particularly when comparing with studying through LRs collated by a simple Webpage browse-based structure. Our ALN based knowledge structure is similar to a knowledge map. Instead of having freestyle labeling to formulate the relationship (i.e. the link) between two concepts, we use association weight to model quantifiable relationships among concepts. In addition, we have three different types of ALNs representing different abstraction levels of a set of concepts, i.e. topics, keywords and LR ALNs, where the relationships among such ALNs are also explicitly defined, i.e. given a node in an ALN, the corresponding nodes in the other two ALNs are well-defined. This implies that it is easy to retrieve LRs based on student-preferred topics and the knowledge structure for a set of LRs.

The ALN structure also allows us to automatically compute the complexity and the importance of each LR, avoiding instructors or course designers to manually define such attributes, which is extremely time consuming when there are a massive number of LRs to deal with. More specifically:

- We compute the complexity of a LR, which can be used to match student knowledge level, based on the algebraic complexity of human cognition that associates with the complexity of both keywords and association links of the LR *X* as follows:

$$\lambda^T = \sum_{K=0}^{D-1} W_k \cdot \lambda_X^k \tag{3}$$

  where λ_X^T is the text complexity of LR *X* in terms of keywords, *D* is the number of keywords in LR *X*. λ_X^k is the number of degree-k association, i.e. the number of keywords having k association links connected to LR *X*, which indicates the complexity of association link. W_k is the number of keywords having degree-*k* association, which indicates the complexity of keywords. A LR is low in complexity if it has low number of association links while such links are of low degrees.
- The number of association links indicates the number of relationships existing between a node and its connected nodes. The association weight indicates how strong a node is related to another one. We therefore use the association weight and the number of association links to indicate the importance of a node.

4 Student Knowledge Model and Personalized Learning Path

Student Knowledge Model (SKM) formulates the student learning progress. It comprises a dynamically generated personalized LP and a set of student characteristics. A personalized LP is technically a subset of the TKM. Student characteristics that we consider include knowledge background, knowledge level, and preferred knowledge concepts, which are learned topics, performance on such learned topics, and topics that a student is interested or can effectively learn, respectively. The algorithm for personalized LP generation is as follows:

1. **Initialization:** Based on the topic ALN of TKM, we determine the starting point of a personalized LP according to the initial knowledge of a student, i.e. the topics learned. If such information does not exist, we consider the topics, where their complexity match the student's knowledge level, and select the most important one as the starting point. This ensures the most suitable and fundamental knowledge is selected for a student to start learning. We compute the complexity of a topic by considering the average complexity of all LRs associated with the topic as follows:

$$D_T(x) = \frac{1}{N}\sum_{p=1}^{n} \lambda^T\left(LR_p\right) \qquad (4)$$

where $D_T(x)$ represents the complexity of topic x, and $\lambda^T\left(LR_p\right)$ is the complexity of LR p (ref. Eq. 3).

2. **Incremental LP Generation:** Based on the current node of a LP, we incrementally generate the next node of the LP by identifying a suitable one from the set of direct connected nodes according to the topic ALN of TKM. The selection is based on two criteria: the *complexity* and the *importance* of the topic. The complexity of the topic should match the student's knowledge level. If there are more than one node meeting the complexity criteria, we then select the node with the highest importance $I_{S_i}(x)$, which is formulated by the summation of association weights where student preference on a topic is considered as in Eq. 5:

$$I_{S_i}(x) = \sum_{j=1}^{n} aw_{xj}(x) \cdot P_{S_i}(x) \qquad (5)$$

where I_{S_i} represents the importance of topic x for student i, $aw_{xj}(x)$ represents the association weight between topic x and topic j, and $P_{S_i}(x)$ represents student i's preference degree on topic x.

3. **LR Selection:** Based on the LR ALN of TKM, we select a set of LRs, where their associated topics match with the selected topic by step 2. As shown in Eq. 6 and 7, a student specific LR p will be identified by matching the complexity $\lambda^T\left(LR_p\right)$of the LR with the knowledge level KL_{S_i} of the student.

$$LRs = \left\{p \middle| \left\|\lambda^T\left(LR_p\right) - KL_{S_i}\right\| < 0.1KL_{S_i}\right\} \qquad (6)$$

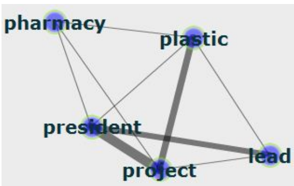
$$D_{S_i}(x) = \lambda^T\left(LR_p\right)/P_{S_i}(x) \qquad (7)$$

LP Progression and Alternative LP: After a student successfully studying a LR, we update the SKM by indicating the student has finished such a LR and the associated keywords. Our system will then go back to step 2 again for incremental LP generation. If a student fails the corresponding assessment, it is likely that the student lacks the knowledge of some aspects of the topic about the LR. To deal with such a learning problem, we adjust the LP by redirecting the student to learn an alternative LR, which is the most important unlearned prerequisite node of the failed LR as defined in the LR ALN of the TKM, before coming back to learn the failed LR. Such an alternation may be carried out repeatedly on the rest of the unlearned prerequisite node of the failed LR if necessary.

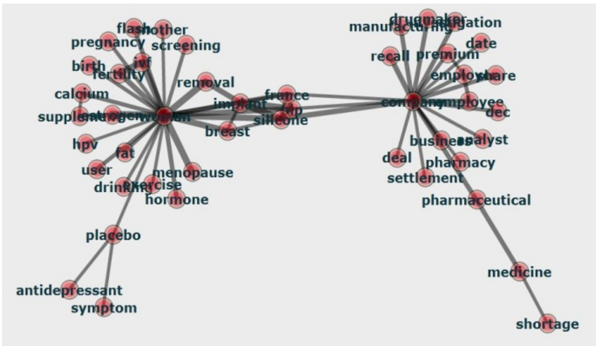
4. **Learning Performance:** A student i has finished learning a course when there is no more LR to follow. The student learning performance D_i can be computed by the difference between the real performance SKM_i (i.e. the finished LP) and the expected performance LP_i defined by the recommended LP as stored in the TKM:

$$D_i = \|SKM_i - LP_i\| \qquad (8)$$

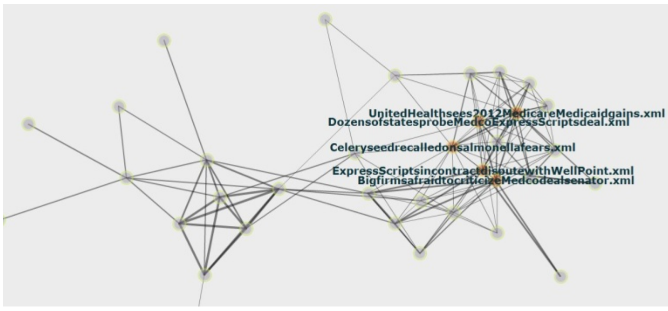
where D_i evaluates whether the student has a good learning performance at the end his learning. The student has a better learning performance if SKM_i is closer toLP_i. Fig. 2 shows an example of a system recommended LP formed by a set of three different ALNs for a student. Fig. 2(a) depicts the topic ALN that comprises 5 topics, forming the topic level of the LP (i.e. project → president → pharmacy → plastic → lead), where the edge thickness indicates the association weight. The corresponding keyword ALN and LR ALN are respectively shown in Fig. 2(b) and 2(c). The highlighted LRs as shown in Fig. 2(c) are the recommended LRs that match the student knowledge level. Since there are associations among LRs through sharing keywords, a student showing interest in a LR may also interest in its associated LR. A student can also gain understanding in a LR through its associated LRs. Our three different ALNs provide such associations and therefore help improve student learning.



(**a**) System generated topic ALN.



(**b**) The corresponding keyword ALN.



(**c**) The corresponding LR ALN, representing the system generated LP for a student.

Fig. 2. The three different ALN's that constitute the system recommended learning path.

5 Evaluation

5.1 Comparison based on LP Importance

In this experiment, we compare the quality of manually generated LPs with system recommended ones based on the LP importance, which is evaluated by summing up the importance of the nodes that constitute a LP. Ten teachers are asked to manually construct LPs that comprise 5 nodes (i.e. topics) according to the topic ALN. Such a construction should fulfill two requirements: 1) the selected topics should connect with each other, and 2) should be important to students. Such requirements also govern how the recommended LP generated by our system. Results show that the LP importance of our generated LP is higher than the teacher generated ones. To determine whether the comprehensiveness of the ALN structures will affect the quality of LP generation, we conduct experiments using three different resolutions of the TKM by changing the number of association links constituted the topic ALN. Particularly, we use topic ALNs having 196 links, 271 links and 360 links, which correspond to 20%, 50%, and 80% of the total association links, forming the low, middle and high resolutions of TKM, respectively. Table 1 depicts the details of the LPs constructed by both the teachers and our system based on the middle resolution of TKM. As shown in the table, although some of the teacher selected topics are the same as the ones recommended by our system, indicating that teachers are able to pick some important topics, the LP importance of their constructed learning paths are lower than the system recommended one.

Table 1. Topics in the selected learning path in Middle resolution

	Topic 1	**Topic 2**	**Topic 3**	**Topic 4**	**Topic 5**	**Importance**
Teacher 1	FDA	Roche	**Avastin**	Stent	Patient	9.6
Teacher 2	Antidepressant	Vaccine	FDA	Avastin	**Drug**	15.2
Teacher 3	Cancer	Risk	Analyst	**Company**	Childhood	12.8
Teacher 4	Patient	Staff	Pneumonia	**Drug**	Analyst	17.0
Teacher 5	Researcher	Implant	**Company**	Calcium	Cancer	9.2
Teacher 6	**Company**	Calcium	HPY	Supplement	France	11.2
Teacher 7	FDA	Pneumonia	Dialysis	Antidepressant	Treatment	12.2
Teacher 8	Cancer	Implant	Test	Screening	Prostate	7.2
Teacher 9	Analyst	**Pharmaceutical**	Medicine	**Company**	Premium	11.2
Teacher 10	Antidepressant	Patent	Pneumonia	Analyst	Staff	15.8
System	Drug	Company	Avastin	Pharmaceutical	Shortage	27.2

Fig. 3 compares the LP importance of the learning paths generated by the teachers and our system when different resolutions of the TKM are made available. In the figure, the left y-axis shows the LP importance and is referred by the histogram, while the right y-axis shows the LP importance ratio of the teacher generated LPs w.r.t. the system recommended one and is referred by the polylines. We group the results by the resolutions of the TKM. It is found that no matter which resolution of the TKM is made available, our system still produces learning paths with a higher LP importance than the teacher generated ones. The upper and the lower polylines respectively show the maximum and the average LP importance ratios of the teacher generated learning paths. They indicate the quality of the learning paths generated by the teachers w.r.t. to the system recommended ones. On the other hand, when the resolution of the TKM increases, the generated LPs both by the teachers and our system also increase in the

LP importance. It is because when richer course domain information is made available, i.e. more association links forming the TKM, a better decision can be made on the LP construction. However, as teachers are generally overwhelmed by the massive number of LRs and association links, they tend to construct learning paths based on partial information from the TKM. As a result, their produced learning paths are of lower LP importance.

5.2 Comparison on Student Learning Performance

We conducted experiments on comparing student learning performance based on the teacher generated learning paths and the system recommended one. We have invited 10 postgraduate students in computer science to participate the experiments. The students have different learning abilities, which perform differently when studying the same LR. We randomly divide the students into two even groups. The 1st group of students performs learning based on the teacher constructed LPs, while the 2nd group of students learn by the system recommended LP. All students are given 50 minutes for studying the contents (contains 5 LRs) provided the LPs and take the same examination with 25 questions, which assess their understanding. Results show that students using the system generated LP perform better and have more stable performance.

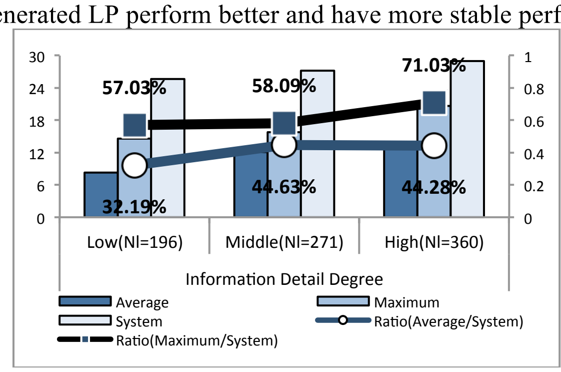


Fig. 3. Comparison of the importance of manually selected and system recommended LP in topic layer

Better performance: We compare the learning performance between two student groups by one sample t-test based on the differences in their performance variances:

$$t = \frac{\bar{x}-\mu_0}{s/\sqrt{n}} \tag{9}$$

where $\bar{x}$ is the average of the differences in the learning performance variances between the two student groups after studying n LRs, μ_0 is the population mean of the null hypothesis, and s is the standard deviation of the samples. Assume the null hypothesis is that two student groups have the same learning performance on the same LRs. So $\mu_0 = 0$. The t-value is 2.3181 which is larger than the threshold of the t-value 2.1319 when the p-value is set to 0.05. It means the null hypothesis is rejected, i.e. the performance of the two student groups is significantly different. We then compare the detailed learning performance of the two student groups based on each

LR. As shown in Fig. 4, students studying using the system recommended LP generally perform better. In average, they got 60.8% in the examination, while the students studying through teacher generated LPs got 51.2% only. Note that y-axis shows the scales of the learning performance, while x-axis shows the indices of individual LRs. Although students using the system recommended LP perform less well in LRs P462 and P193, performance of both student groups in such LRs are still quite similar.

Stable performance: We test if the students in each group can have similar learning performance σ_i^2 on the same LR i by analyzing their performance variances (ref. Eq. 10). The results are shown in Fig. 5, where the y-axis indicates the performance variances.

$$\sigma_i^2 = \frac{1}{m} \cdot \sum_{j=1}^{m} \left(x_{ij} - \bar{x}_i\right)^2 \tag{10}$$

where $\bar{x}_i$ is the average performance on LR i, x_{ij} is the performance on LR j of student x_j, and m is the number of students. If different students show similar performance on the same LR, their performance variances will be low. We refer this as stable performance. For instance, if all students have the same performance on the same LR, the performance variance will be equal to 0, and their performance is the most stable. In contrast, if half of the students got very high marks and the other half got very low marks, their performance is described as unstable, where the performance variance can approach to 6 according to Eq. 10.

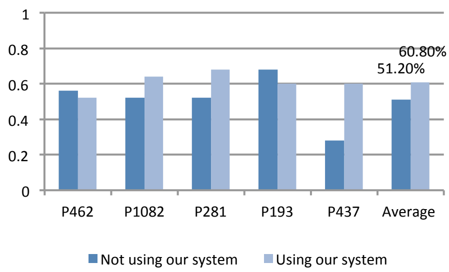


Fig. 4. Learning performance

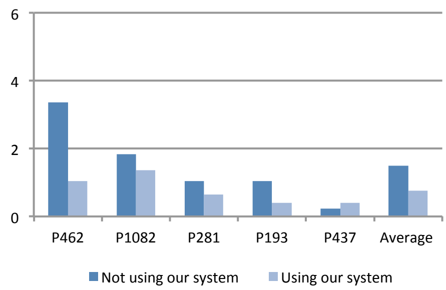


Fig. 5. Stability of learning performance.

As shown in Fig. 5, although students studying through teacher generated LPs (Group 1) perform slightly better on LRs P462 and P193 than those studying by the system recommended LP (Group 2), the performance of group 1 students is quite unstable, i.e. students perform quite differently in the same LR. Overall, group 2 students generally have more stable performance than group 1 students. However, for LR P437, group 1 student has more stable performance as they have consistently low performance in such a LR. Our experiments indicate that by using the system recommended LP, even student coming with different learning abilities can be trained to perform better in learning. In addition, the entire cohort will have a more stable performance.

6 Conclusion and Future Work

In this paper, we have presented an ALN-based LP construction method. We construct multi-level of abstractions of LRs through association, allowing a knowledge map like learning path to be derived. Such a learning path structure can help students learn more effectively. The ALN-based association structure also allows important parameters of LRs, such as their complexity and importance, to be derived. This offers sufficient information for automatic construction of pedagogically meaningful LPs. This feature is particularly critical when a massive amount of Web resources are considered to be transformed as LRs for students to learn. Our experiments show that our method offers better and much stable student learning performance. In practice, as Web resources obtained from different providers may have very different presentations and inconsistent contents. As a future work, we will investigate methods to address such presentation and consistency problems to allow students to learn more smoothly with Web resources constructed learning materials.

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