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A Markov-based Recommendation Model for Exploring the Transfer of Learning on the Web

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ABSTRACT

The ability to apply existing knowledge in new situations and settings is clearly a vital skill that all students need to develop. Nowhere is this truer than in the rapidly developing world of Web-based learning, which is characterized by non-sequential courses and the absence of an effective cross-subject guidance system. As a result, questions have arisen about how to best explore and stimulate the transfer of learning from one subject to another in electronically mediated courses of study. In this study, we argue that online learners would benefit from guidance along applicable group-learning paths. This paper proposes use of the learning sequence recommendation system (LSRS) to help learners achieve effective Web-based learning transfer using recommendations based on group-learning paths. We begin with a Markov chain model, which is a probability transition model, to accumulate transition probabilities among learning objects in a course of study. We further employ an entropy-based approach to assist this model in discovering one or more recommended learning paths through the course material. Statistical results showed that the proposed approach can provide students with dependable paths leading to higher achievement levels, both in terms of knowledge acquisition and integration, than those typically attained in more traditional learning environments. Our study also identified benefits for teachers, providing them with ideas and tools needed to design better online courses. Thus, our study points the way to a Web-based learning transfer model that enables teachers to refine the quality of their instruction and equips students with the tools to enhance the breadth and depth of their education.

Keyword

Groups-learning paths, Transfer of learning, Markov chain model, Individual learning, Entropy.

Introduction

Recent advances in network bandwidth availability have increased use of Web-based education. In Web-based educational settings, information and communication technology (ICT) provides access to various resources, such as audio recordings, videos, images, and text. ICT has therefore had a dramatic impact on both learning processes and outcomes. For learners, the need for large amounts of information is increasing. However, not every learner can effectively organize and choose between these learning resources. A good learning management system (LMS) should provide learners with guidance that will assist them to make the best choices in their management of the available resources. Therefore, the selection of learning contents and recommended learning sequences have been recognized as two of the most interesting research topics in Web-based learning systems (Chen *et al*., 2005; Tseng *et al*., 2007).

Sharable Content Object Reference Model (SCORM) a model of web-based learning content and sequence standards, was proposed in 1997 at the 4th International forum on research and technology advances in digital libraries. This model was not innovative, but combined many existing international standards, such as the Content Packaging, Simple Sequencing (IMS, 2003), and LOM (IEEE LTSC, 2002). According to SCORM, learning contents, such as multimedia, images, slides or others learning objects, can be packaged and organized based on the SCORM standards to form a learning sequence. Notably, the SCORM-based learning sequence (ADL, 2004) offered a way to string several learning objects together and design instructions easily. In spite of the digital content learning sequence specifications instituted by SCORM, the pedagogical meaning of a learning sequence also needs to be recognized in e-Learning environments.

Generally speaking, the goals of education are not only the transfer of skills and knowledge in one context, but also the transfer and application of those skills and knowledge to other contexts. “Transfer of learning”, which refers to the expansion and generalization of learning outcomes, is one major criterion of learning efficacy. The theory of

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transfer of learning was introduced by Thorndike and Woodworth (Thorndike & Woodworth, 1901). They explored similarities in the features of transfer of learning in different contexts. The theory asserted that effective transfer of learning depends on identical elements shared between the learning task and the transfer task. Several studies (De Corte, 2003; Haskell, 2001; Richman-Hirsch, 2001) have noted that transfer of learning is fundamental to learning because it generally aspires to impact on contexts quite different from the context of learning (Perkins & Salomon, 1992). In Web-based learning settings, however, there are two limitations that obstruct the transfer of learning. First, there is no guide to assist learners to conduct cross-subject transfer of learning in a Web-based learning environment. Second, while considerable attention has been paid in the past to research issues related to Web-based course design (Chan *et al*., 2006; Chen *et al*., 2005; Kabassi & Virvou, 2003; Zhu, 2007), the designer seldom takes the transfer of learning into consideration during the process of course design. Therefore, learning transfer is a significant issue for educators to take into consideration during the course-designing process for Web-based learning environments.

As noted before, transfer of learning is the process whereby skills learned in one situation or under one set of conditions are demonstrated in a different situation or under a different set of condition (Borich & Tombari, 1995). However, since transfer effects are not concrete, how to achieve and evaluate transfer of online learning is a challenging issue. In this study, we argue that transfer of online learning can be effectively achieved from group-learning sequences. Intrinsically, a learning sequence which describes a learner moves from one context to another is a concrete presentation of transfer of learning. Herein, constructing a learning sequence can be regarded as the process of completing a set of several learning transfers. Thus, developing an ideal learning sequence may help to trigger the transfer of learning. On these grounds, the purpose of this paper is to explore the idea that certain learning sequences could trigger transfer of Web-based learning. By developing a learning sequence recommendation system, the present study proposes the idea of applying an online learning sequence to trigger the transfer of Web-based learning.

This study proposes that the best way to deal with learning transfer exploration is by analyzing group-learning experiences in the field of intelligent tutoring systems (ITS). In this study, the group-learning experience is the sequence pattern from the different subjects' (contexts) learning. The proposed system, the Learning Sequence Recommendation System (LSRS), analyzes group-learning experiences to predict and provide a personal learning list for each learner by tracking others' learning patterns regarding certain topics. This will provide learners opportunities to improve their transfer of learning. For example, some learners have studied the course "Management Information System: MIS", and then moved on to enroll the course "Data Structure". It is clear that both courses are in different domains. Since both courses are not closely correlated in terms of course continuity, it's difficult to achieve the integration in learning and the transfer of learning. So far as this problem is concerned, LSRS will provide a relationship, which is represented as the same concept across the two different domain subjects.

In this paper, we propose a novel learning mechanism by using the Markov chain model to analyze the prediction of time-series recommendation problems. The Markov chain model is the simplest mathematical model for random phenomena evolving in time and it has been widely used in sequence prediction and navigation analysis (Heller *et al*., 2004; Rajapakse & Ho, 2005; Sarukkai, 2000; Tian *et al*., 2000). However, few studies have used the Markov chain model to predict the recommended learning sequence. Using this model, this study focuses on exploring dependable group patterns. The outcome of the Markov chain model can also illustrate the structure of the learning sequences. These explored learning sequences have strengths that may be reinforced by the responses of the learners, which provide the LMS with suitable recommendations as to which sequences facilitate effective and efficient learning.

Additionally, using ranking techniques, we can also record learners' feedback for sorting group learning paths. We propose an entropy-based approach to automatically compute the average entropy value of each predicted learning sequence and estimate its quality as well. Consequently, the system provides a re-ranked recommendation list for the learner to create an adaptive learning sequence recommendation, which then provides him/her with the guidance of learning transfer.

The main goal of this paper is to investigate the impacts of group-learning patterns on the transfer of learning via a proposed learning system that has ability to provide each learner with an adaptive learning sequence list. As mentioned earlier, the following two research questions in web-based learning settings need to be answered:

- Could online learners achieve appropriate transfer of learning by recommended learning sequences?

- Could recommended learning sequences provide an e-Learning course designer with guidance or suggestions to design online courses, which should possess effects of transfer of learning?

The next section describes the mathematical methodology used in this study to examine group-learning patterns. The recommendation prediction mechanism is also proposed, which uses an entropy-based approach to re-rank the recommended results to accommodate each learner with an appropriate sequence list. An illustrated example is given to explain the recommendation process in the following section. After that, the developed learning sequence recommendation system (LSRS) description and the diagrams of manipulation are displayed. The evaluations are then presented, with a thorough description of the participants in the research and of the instruments and procedures used. Finally, the results are discussed and the conclusions are drawn.

The proposed model for predicting and recommending dynamic learning sequences

In this section, we first describe the multi-subject learning sequencing model that has been adopted to define the sequencing model in our study. Then, we detail the learning sequences prediction and recommendation mechanisms in subsections.

Multi-Subject Learning Sequencing Model

The concept-mapping technique is usually applied to show the structure of a specific knowledge field. It uses a graphic representation of the knowledge base so that learners can easily see the entire learning structure at a glance. So far, many studies that discussed concept-mapping only focused on a single subject or domain (Chen *et al*., 2008; Hsu & Hsieh, 2005; Tseng *et al*., 2007). However, a general learning process requires learners to go through several subjects to achieve a learning goal. For example, if a learner needs to learn the "Markov Chain Model", he or she should possess prerequisite knowledge about subjects "Direct graph", "Probability and Statistics", "Engineering Mathematics", and "Discrete Mathematics" (Figure 1). Hence, a learning map associated with several subjects has the capability of clearly presenting the entire learning process. From Figure 1, it is evident that some courses or learning objects are connected to each other, so a learner can recognize and follow the appropriate learning sequence.

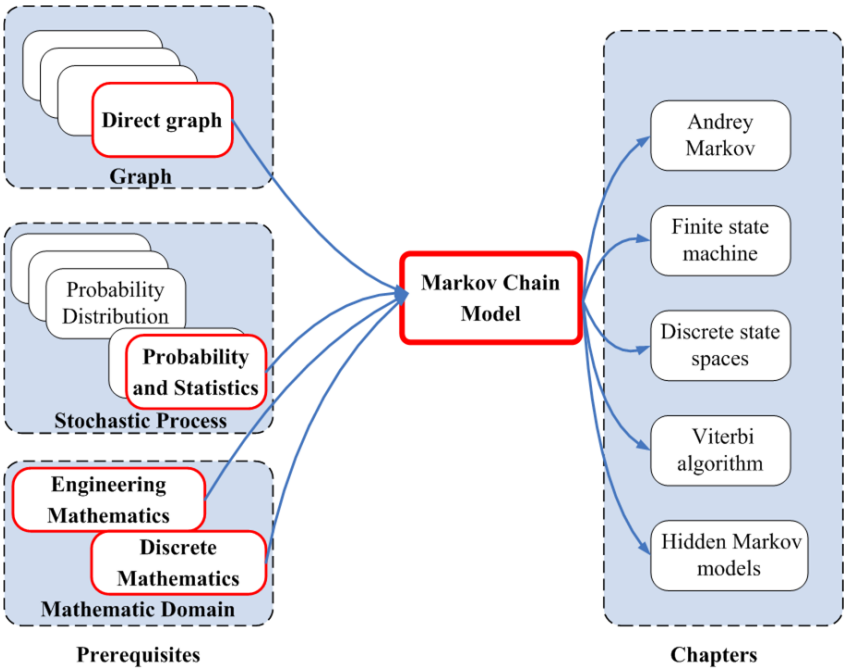


Figure 1. A number of prerequisites and chapters for a course on the "Markov Chain Model"

We observe that nowadays many students cannot apply what they have learned, or are learning to existing problems or contexts, and many students cannot appreciate the applicability of their reading materials. That is to say that the transfer of learning seems not to be effectively present among students. Through the multi-subject learning sequencing model, learners can clearly recognize the relationships between several courses and see how to apply what they are learning to other fields or courses. In addition, by seeing the connections between the subject being studied and the subjects in which they experienced the most success, they are better informed in choosing other related subjects to study in the future.

Definition

The application of the Markov chain model in a learning system has the advantage that the likelihood of the group-learning patterns is simply a product derived from the collective likelihoods of individual instances. It can provide learners in need of assistance with several learning sequences that are based on actual learners' experiences, and in accordance with group-learning patterns. In a Web-Based learning environment, an LO is first used by individual learners as a learning course related to a topic or issue. LOs are placed in a learning repository and the learners' profiles are recorded in a transaction database. Thus, we can retrieve the learning data of each learner, which can be viewed as a learning sequence. Moreover, we give a definition that an LO, denoted as o_i, belongs to the record of a learner, and each learner produces their own learning sequence $< o_1, ..., o_n >$ during the learning process for learning a specific concept. Furthermore, the dynamic learning sequence can be formally defined as:

Definition 1: Dynamic Learning Sequence (DLS)

Let O be a set of LOs from a learning repository. Given a set of LOs $X = \{x_1, x_2, ..., x_m\}, x_i \in O, 1 \le i \le m$, then the learning sequence at time t is denoted as $LS_t = x_1 \rightarrow x_2 \rightarrow x_3 \rightarrow ... \rightarrow x_i$, and the end is $x_i \rightarrow x_l$ at the time $t+1$, where $1 \le i \le l$.

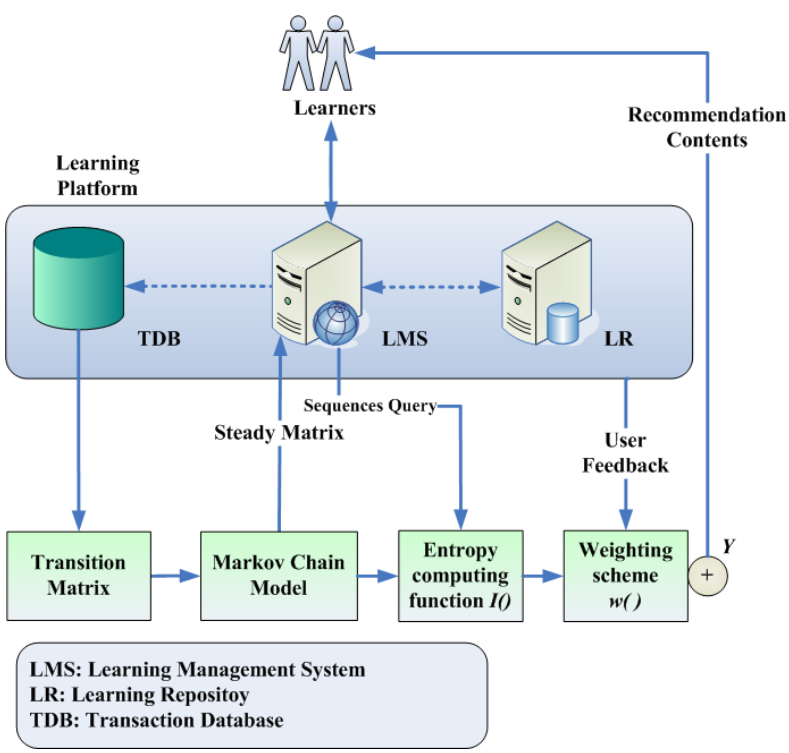


Figure 2. The methodology of the proposed learning mechanism

Analysis of sequences prediction mechanism

First, we illustrate the learning mechanism, which is useful for the learning platform. All of the learning activities of learners on the platform can be monitored and dealt with as a transaction database, and a transition matrix expresses all of the sequences of learners from there. Thus, the matrix can be seen as a base set of states, which accumulates the probability of each node (as an LO) using the Markov chain model. We utilize the model to provide the predicted learning sequences. Additionally, by using an entropy-based approach, we turn ranked learning sequences into recommendation lists, which will be described in a later section. For individual learning, a weighting scheme is utilized to determine the final recommended sequences. We ask learners to write down opinions for feedback in order to adjust the weight values of the recommended sequences and reorder them by using a combination sort function. The methodology of the proposed learning mechanism is shown in Figure 2.

Transition Matrix

The learning sequence of each learner is obtained from the learning objects that reside in the learning corpus. Next, the sequences of all learners are used to form a transaction dataset. To signify the LS of each learner, we give an n-dimensional matrix A including transition probabilities from the transaction dataset, which is positive and non-irreducible. The transition matrix is shown in Figure 3.

$$\begin{array}{cc} & \overbrace{\begin{array}{ccccc} a & b & c & \cdots & n \end{array}}^{\textbf{Learner LO in next period}} \\ \textbf{Learner LO in current period} \left\{ \begin{array}{l} \textit{from a} \\ \textit{from b} \\ \textit{from c} \\ \cdot \\ \cdot \\ \textit{from n} \end{array} \right. & \begin{bmatrix} 0 & p_{ab} & p_{ac} & \cdots & p_{an} \\ p_{ba} & 0 & p_{bc} & \cdots & \\ p_{ca} & p_{cb} & 0 & \cdots & \\ \cdots & & & 0 & \\ p_{na} & & & \cdots & 0 \end{bmatrix} = A \end{array}$$

Figure 3. States transition matrix

In Figure 3, the P_{ij} is the transition probability from one state to the next state. Notably, in the matrix *A*, the diagonal elements all are zero, that is, there is no self-loop in the graph.

Markov Chain Model

The state spaces of LS are a case of the Markov chain model, which is to say, a chain of random LOs in which each subsequent LO depends only on the current LO. Thus, by estimating the learning process of the *k*-th learner from their learning profiles $X^k = \{x_0, x_1, ..., x_n\}$, we can obtain sequences of different lengths in state *i*. All learners have their own learning sequence, which is shown as follows :

$$x_0^{(1)} \to x_1^{(1)} \to x_2^{(1)} \to \ldots \to x_m^{(1)}$$

$$\ldots$$

$$x_0^{(k)} \to x_2^{(k)} \to x_3^{(k)} \to \ldots \to x_n^{(k)}$$

If a learning sequence includes duplicate learning objects, it belongs to a repetitive learning, otherwise, it is held by a progressive learning.

If the current state is i and the next state is j, the transition probability is represented as $p_{ij} = \Pr\{x_{t+1} = j \mid x_t = i\},\ t \in Z^+$, where $p_{ij} \geq 0\ and\ \sum_{j=1}^{n} p_{ij} = 1, i = 1, 2, ..., n$. According to the Chapman-Kolmogorov equations (Gross & Harris, 1998), which are shown as formula (1), we can easily find the matrix $P^{(n)}$ formed by the elements $p_{ij}^{(n)}$.

$p_{ij}^{(n)} = \Pr\{X_{n+m} = j \mid X_m = i\},\ and\ \ p_{ij}^{(n+m)} = \sum_{k=0}^{\infty} p_{ik}^{(n)} p_{kj}^{(m)}$	(1)

According to equation (1), the matrix $P^{(n)}$ can be conducted as multiplying the matrix *P* by itself *n* times. That is, $P^{(n)} = P \cdot P \cdots P = P^n$.

Stability of the learning sequence

In order to discuss the stability of the learning sequence, we need to consider the long-term behavior of Markov chains. This means that we need to find the steady-state probabilities of the Markov Chain after a long period of time. Therefore, we first consider a discrete Markov chain, which is ergodic and represented as equation (2).

$\lim_{n \to \infty} p_{ij}^{n} = \pi_j,\ \forall i, j \geq 0$	(2)

where π_j is the steady state distribution. Also, it is independent of initial probability distribution and exists uniquely with the state. In order to verify whether the transition achieves equilibrium, π_j can be checked using equations (3) and (4).

$\pi_j = \sum_{i \in S} \pi_i p_{ij},\ j \geq 0$	(3)
$\pi e = 1$	(4)

where π_i stands for the initial probability that $X_0 = i$. Equation (3) indicates that if the transition approaches the steady state, the distributions will not change repeatedly. Equation (4) is a vector notation where $\pi = (\pi_0, \pi_1, ...)$ represents the limiting probability vector and *e* is a matrix whose elements all equal one. It implies a boundary condition (i.e. $\sum_j \pi_j = 1$).

Adaptive model of learners' feedback

After each learning process, learners will give feedback information to the LMS. According to the given feedback, the adaptive model will enhance the choosing probability of the learning sequence. This model provides a weight for each learning sequence. By changing these weights, the rank of learning sequences will also change. From Figure 4, $\Upsilon = f(S_1, S_2, ..., S_n \mid \Phi)$, where *f* function is a combining function that sorts the weighted learning sequences, S_i represents the *i*th learning sequence and Φ is the set of weights, $w_1, w_2, ..., w_n$. If the feedback from the learner is positive, the weight of the learning sequence is increased, and vice versa.

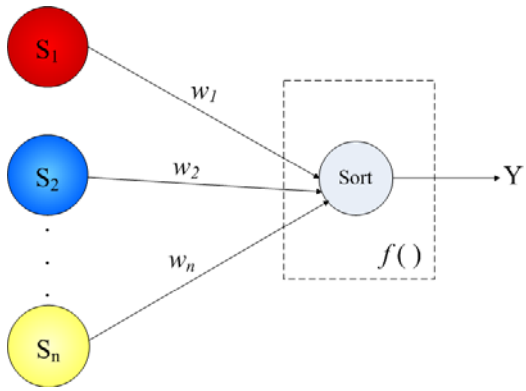


Figure 4. The sorting of learning sequences

The advantage of the adaptive model is that the rank of learning sequences not only follows the training data, but it is also evaluated by feedback from other learners.

The entropy-based approach for learning sequence recommendation

Having obtained the steady probability transition matrix, one has also acquired several steady learning sequences. In this subsection, we propose an entropy-based approach for sorting these group learning sequences so that they can be substantiated as dependable learning recommendations for learners.

Since a learning sequence consists of a few learning objects, the links among learning objects are important clues for determining the significance of the sequence. Therefore, it is necessary to design an approach to discover the most informative learning sequences. First of all, Shannon's information entropy (Cover & Thomas, 1991) is applied to calculate the link entropy based on the above-mentioned steady state matrix. According to the definition of entropy, it can be expressed as $-K\sum_{i=1}^{n} p_i \log p_i$, where K is a positive constant which is set to one in this study. p_i is probability of *i*th event and n is the number of events. To calculate the average information within a learning sequence, the equation is expressed as follows:

$$E(LS_i) = (-\sum_{j=1}^{n} p_j \log p_j)/n \quad (5)$$

where p_j is the probability from one LO to another, which can be obtained from the above-mentioned steady transition matrix, and n is the number of links within a learning sequence. According to the definition of entropy, the most informative learning sequence should have the least entropy value. Therefore, the equation used to evaluate the amount of information of learning sequence I_{LS_i} is used to define and represented as follows:

$$I_{LS_i} = 1 - E(LS_i) \quad (6)$$

After calculating the average information amounts of the learning sequences, the adaptive model is applied to extract more informative learning sequences based on learners' feedback. As mentioned in section 2.3, every learning sequence has a given weight that is regulated by learners' feedback. The feedback is either positive or negative and determines whether the weight value is increased or decreased. The combination function is utilized to sort the every weighted entropy set $\{w_1 I_{LS_1}, w_2 I_{LS_2}, ..., w_n I_{LS_n}\}$. Afterwards, LMS will recommend the re-ranked list to the learners. Through the repeated feedback process, a more precise learning sequence list will be provided to the learners.

An Illustrative Example

We now present an example that demonstrates how we can find the steady state probability distribution. For simplicities sake, we present four learning objects, a, b, c and d, with 400 learners in this learning process. Table 1 shows the initial state and the first state shifting.

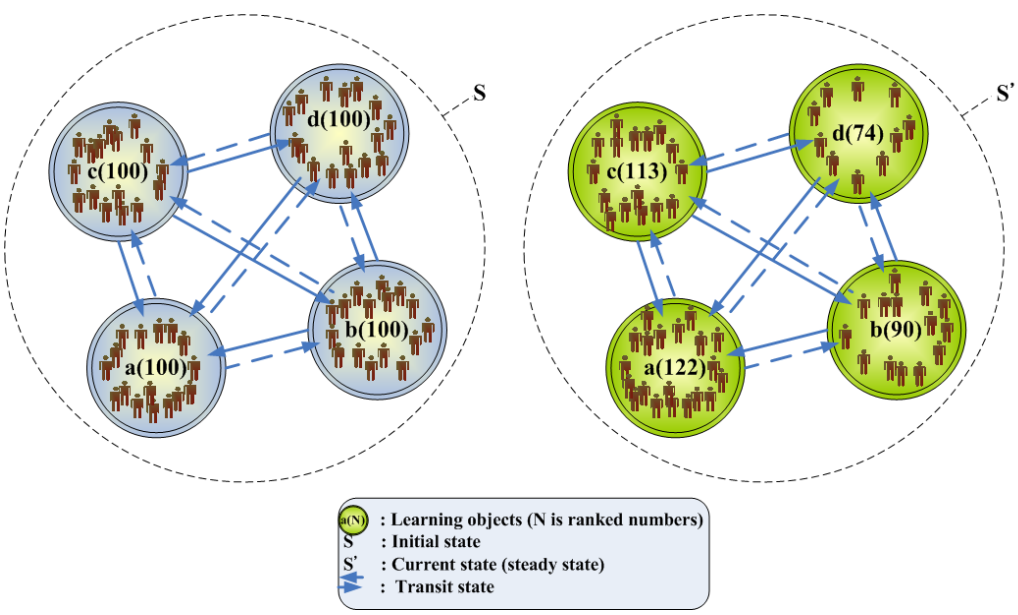
Table 1. Shift of learners among the learning objects

Learning Objects(Learners before shifts)	Learning objects shifts								Learners after shifts
	To *a*	To *b*	To *c*	To *d*	From *a*	From *b*	From *c*	From *d*	
a (100)	0	40	40	20	0	40	60	25	125
b (100)	40	0	30	30	40	0	20	25	85
c (100)	60	20	0	20	40	30	0	50	120
d (100)	25	25	50	0	20	30	20	0	70
total (400)									400

In the initial state, each learning object has 100 learners. After one shift we assume that the learners will not stay at the same learning object and, as a result, the number of learners staying at the same object is indicated by zero. To find out the number of learners at each learning object, the matrix is transposed and the sum of each row is calculated. After the first shift, the number of learners staying at the learning objects *b* and *d* decreases, while that of learners staying at *a* and *c* increases. As time passes, the transition will approach equilibrium. In Table 2, we can observe the transition process gradually going to steady state.

Table 2. Approaching a steady state

Learning Objects	State							
	0	1	2	3	4	5	6	7
a	100	125	110	98	105	115	122	122
b	100	85	95	100	94	85	90	90
c	100	120	110	103	110	111	113	113
d	100	70	85	99	87	80	74	74



(a) Learning objects interlink each other within the state S	(b) Learning objects interlink each other within the steady state S'

Figure 5. The instance of the probability transition matrix of learning objects trends towards to a steady state.

The figures 5a and 5b illustrate the transient and steady states respectively. In Figure 5(a), the number of learners is mapped to state 5 (described in Table 2) while Figure 5(b) is mapped to the above-mentioned states 6 and 7. Before state 6, the number of learners is in a transient state, since the number of learners in any one learning object will vary. The number of learners, however, reaches equilibrium after state 6, implying that the amounts of inflow and outflow between two learning objects are the same. It also demonstrates that the learning process has achieved a steady state.

From the steady state table (see Table 2), the steady state distributions can be computed as $\pi_a = 0.305$ $(=122/400)$, $\pi_b = 0.225$, $\pi_c = 0.283$ and $\pi_d = 0.185$. As the transition approaches a steady state, we can also compute the steady probability transition matrix. Table 3 shows the first shift in transition probability, and the summary of each row satisfies the constraint $\sum_j p_{ij} = 1$.

Table 3. Probability Transition Matrix at first shift

Learning Object	To *a*	To *b*	To *c*	To *d*	$\sum_j p_{ij}$
a	0	40/100=0.4	40/100=0.4	20/100=0.2	1.0
b	40/100=0.4	0	30/100=0.3	30/100=0.3	1.0
c	60/100=0.6	20/100=0.2	0	20/100=0.2	1.0
d	25/100=0.25	25/100=0.25	50/100=0.5	0	1.0

By the same procedure, the remaining transition probabilities can be calculated. Hence, we can obtain the steady probability transition matrix, which is able to assist in the prediction of the learning sequence associated with a new learner. The steady probability transition matrix can be obtained from the following table.

Table 4. Steady Probability Transition Matrix

Learning Object	To *a*	To *b*	To *c*	To *d*	$\sum_j p_{ij}$
a	0	0.45	0.28	0.26	1.0
b	0.304	0	0.376	0.31	1.0
c	0.731	0.124	0	0.14	1.0
d	0.165	0.226	0.609	0	1.0

The user can then give source and destination LOs so that the system can provide the recommendation list. In this example, if the user sets LOs *a* and *d* as source and destination respectively, the system will calculate the average entropies associated with the learning sequences from *a* to *d*. Table 5 shows learning sequences and their average entropy values, which are calculated according to the steady transition probabilities in Table 4. For instance, the average entropy of sequence *a→b→c→d* can be computed by the entropy equation (Eq. 5).

$$E(LS_1) = \frac{(-0.45 * \log 0.45) + (-0.376 * \log 0.376) + (-0.14 * \log 0.14)}{3} = 0.81$$

Table 5. The average entropy of each learning sequence

a→b→c→d	0.81	a→c→b→d	0.61	a→b→d	0.639	a→c→d	0.654	a→d	0.505

Finally, equation (6) is used to calculate the information amount in each learning sequence. Furthermore, the adaptive model is employed to evaluate the effect of the learners' feedback on the recommended sequences. In this example, the weights are all initially set to 0.5. Therefore, the ranked recommendation list can be obtained shown as Table 6 (e.g. The weighted information amount of the sequence *a→d* is computed as 0.5*(1-0.505) = 0.248, where 0.505 is the average entropy of the sequence).

Table 6. The ranked learning sequences with weighted information amount

Re-ranked learning sequences	Weighted Information amount
$a \rightarrow d$	0.248
$a \rightarrow c \rightarrow b \rightarrow d$	0.195
$a \rightarrow b \rightarrow d$	0.181
$a \rightarrow c \rightarrow d$	0.173
$a \rightarrow b \rightarrow c \rightarrow d$	0.095

It can be shown that the more information a learning sequence has, the more weighted information amount value becomes. It must be noted that the provided learning sequences present the progressive learning type; that is, repetitive learning information is eliminated from the recommendation list.

System Development

Our proposed system was incorporated in a learning portal run by lecturers to create learning contents and manage course processes, as well as to offer learners a useful learning sequence suited to their current individual learning status. These courses are based on the specifications of SCORM; that is, the contents are packaged into learning objects by specific authoring tools and reorganized into the course structure as related to a topic. The learning process is comprised of system portal logging, learning sequencing exploration, and the delivery of suitable learning objects; after which, the metadata is generated. This is be demonstrated in the following subsections.

Learning interface

First, we launched a learning portal for a dynamic learning sequences model, which provides a personalized learning interface for learners. After registration, learners enter this system using their user identity and password. The portal offers learners a set of comprehensive learning services such as personal information, a personal directory, course lists, and reference lists. When learners' lists are available, they can study each course by clicking the courses' hyperlink. Figure 6 presents an example of the layout of a learning course. It is noteworthy that each course was produced using the standardized course generation process (Huang *et al*., 2008). Hence, each course in our learning platform corresponds with the SCORM standard. Several multimedia file types, such as streaming video and audio files, Macromedia Flash files, and Microsoft PowerPoint files are included within a designed e-learning course.

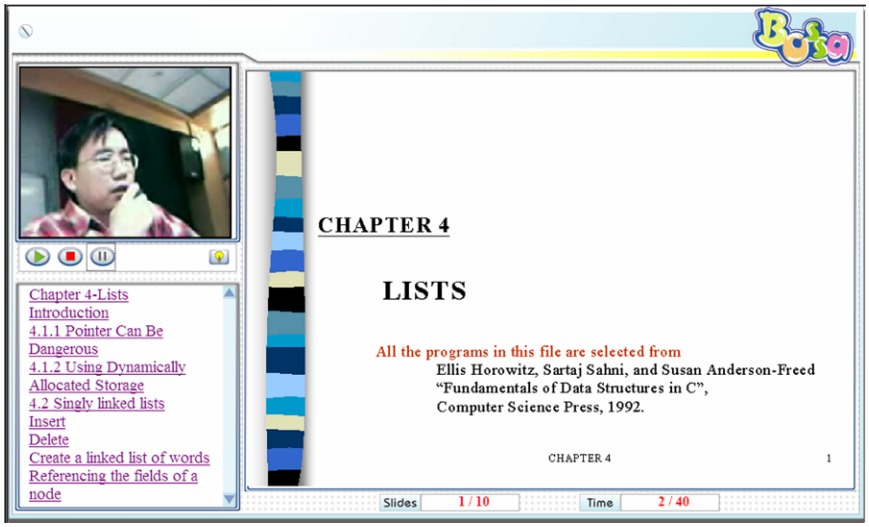


Figure 6. The layout of a course presentation

Learning sequence recommendation system (LSRS)

From the portal login page, learners can proceed to the learning sequencing exploration. As shown in Figure 7, the interface of LSRS consists of three operation areas: the source subject inputting area is located in the upper-left side, the presentation area for recommended subjects and the concurring concept list is located on the left side, and the active area, which represents recommended learning sequences, is located on the right side of the window.

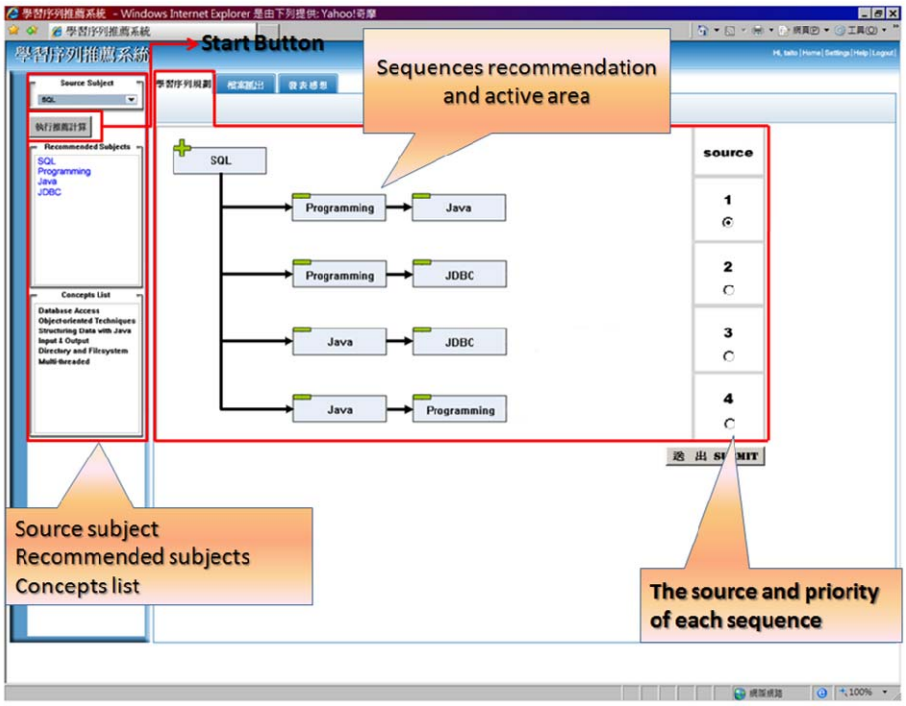


Figure 7. Annotated screenshot of the learning sequence recommendation system

The source subject specifies the source course of the learning sequences. After inputting the source subject and pressing the Start Button, the system will provide recommended learning sequences. A recommended list displays all subjects contained in the recommended sequences. For example, if the recommended sequences contain four topics, SQL, Programming, Java, and JDBC (like that shown in Figure 7), the learner selects a prerequisite topic, SQL, as the starting point. Using information gained by tracking the groups' learning (i.e. learning sequences), the learner acquires a recommended sequence list that consists of these four topics. At this time, the learner clearly sees the relationship between the recommended subjects and the source subject and chooses these subjects for study.

The concurring concepts are shown in the concept list while the learner selects one of recommended subjects. These concepts are very useful for learners in finding the same concepts shared between two subjects, which is the main concern in transfer of learning. This is to say that the system applies the concept list to help learners find the relations between two subjects for achieving transfer of online learning. However, the system does not point out the locations of shared concepts in the learning object. The goal is to train learners to carefully find out where the shared concepts located in and narrowly learn them. This is also a part of whole learning process. Recall our earlier example, in which a learner gets a recommended list, he can see the concurring concepts after selecting a subject 'SQL'. When he selects another subject 'Java', he finds a concurring, concept 'Database Access', shared between the two subjects. At this time, he needs to ascertain and learn the relationship between the learning objects.

Moreover, the most important information is shown in the largest field, which is called the active area for the presentation of learning sequences. It represents some of the successive paths, which were calculated by the above-mentioned process and are listed from top to bottom. The learners can easily see the inferred learning sequences after the start button has been pressed. The source subject drawn in the active area is denoted as the root. A number is also given to each sequence, which stands for the priority of the recommended sequences. Of course, the learner could re-

select different source subjects according to their own needs or interests. In the active area, the learners can also click expansion and contraction symbols to expand or condense the sequences.

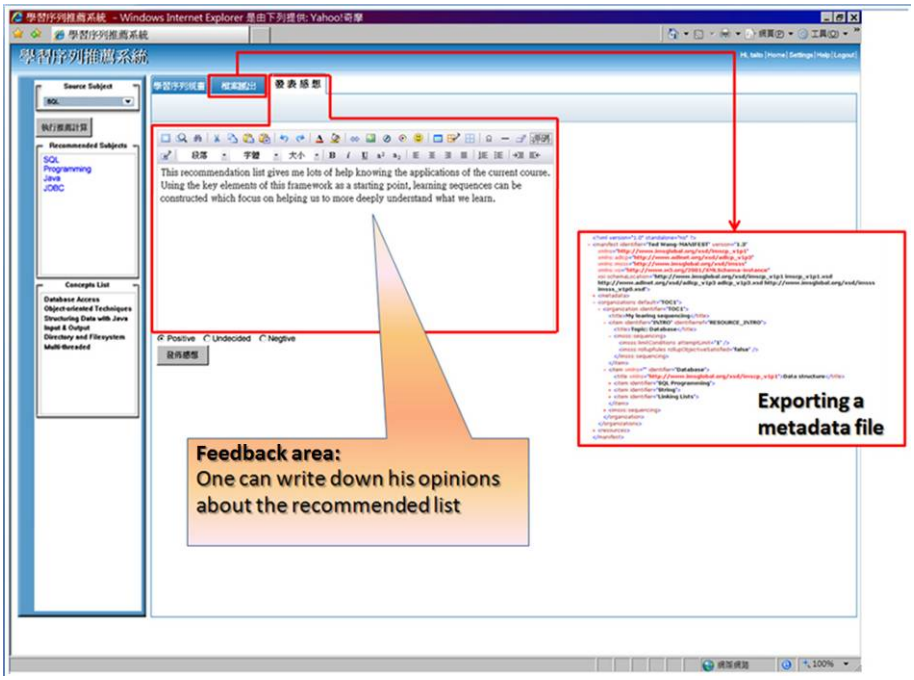


Figure 8. The annotated screenshot of feedback and a metadata exporting utilities

In addition, after the learning process, learners can express their own opinions regarding the recommended results and give the feedback to the system, using one of three rating options: positive, negative, or undecided. Figure 8 demonstrates a feedback-giving example. In this manner, the score of the learning sequence can be recalculated, which is beneficial for recommendation to other learners. For further enhancing the transfer of learning between specific two subjects, any new relationship found from their own studying could also be recorded in the feedback area. The recommendation result metadata is exportable in XML format (see Figure 8) so that it may be imported into other SCORM-based learning platforms. The main benefits of the metadata focus on two points: operational efficiencies of the learning portal, including reuse and curriculum analysis, and interoperability of course materials among different learning portals.

In essence, this work establishes explicit guidelines for group paths to ensure that learning objectives are met and to ensure that the learners' honesty and integrity are protected by the transparency of the process. Besides outlining such learning sequences, the learners can use the recommendations to manage their learning plan, to guide their study of how to fit course material into the "bigger picture" of real world applications and implications, and to generally widen and deepen the quality of their learning.

Research Methodology

Research Design

The purpose of the learning sequence recommendation system is to assist learners to achieve effective transfer of learning in web-based learning settings. As noted above, since learning transfer is a crucial educational concern, and Web-based learning is often non-sequential, guiding online learners to achieve effective transfer of learning is an important research problem. With the aid of LSRS, this study needed to investigate whether valuable learning sequences are beneficial for transfer of learning, and to further assist transfer of learning even if there is no guide in Web-based learning settings.

In this study, forty subjects were monitored while using the Web-based learning system (personal learning portal site) during the 2005 fall semester. Each experiment participant was asked to complete three courses during the semester, and each course lasted for six weeks. That is to say total learning process on the Web lasted for 18 weeks. To estimate the effectiveness of LSRS in assisting learners to achieve transfer of learning with regard to Web-based learning, a randomized subject control group design was used. The participants were randomly assigned into the experimental group and control group respectively, after they submitted registrations on the learning system. The only dissimilarity between the two groups is that the experimental group learners were given recommended learning sequences along with their corresponding primary concepts via LSRS. In other words, the second and the third subjects that the experimental group learners studied were decided by LSRS, while control group learners followed their inclinations to choose three subjects without concept suggestions. To evaluate the learning outcome and the usability of the LSRS, a post-test was conducted in both groups after the 18th week. The post-test consisted of the evaluation examination and the questionnaire introduced in the instrument section.

Participants

The experiment was performed in one large university in Taiwan, and the target population was comprised of 113 college sophomore students and 23 teachers. 76 of the student participants were male and 37 were female. The reason for choosing sophomore students is that they are in the process of learning a number of fundamental courses, which are the foundations of higher-tier, more specialized courses and fields of knowledge. 57 students served as the experimental group, which studied online learning courses and were asked to follow the learning sequences recommended by LSRS throughout the experiment period. The other students (56 persons) served as the control group, which was exposed to the same online learning environment as the experimental group, without the aid of LSRS.

Instruments

In this section, we evaluate the effectiveness of the proposed models and the usability of the learning sequence recommendation system. In order to evaluate the effectiveness and impact of using LSRS, and its assistance to course designers for designing online courses, two different research instruments were devised, one for learners and one for course designers. The following two subsections introduce these research instruments in more detail.

Evaluation system

This section describes how we measured the transfer of learning after the whole learning process was complete. The devised evaluation system (see Figure 9) was used to evaluate whether the effective transfer of learning of learners who used the LSRS was achieved in the web-based learning setting. The instructions section explains how the system is used. There are three more sections in the evaluation system including a subject selection section, a concept selection section, and an explanation section. In part 1, learners chose the three subjects that they had studied during the experiment. Next, in part 2, the most important or impressive concepts associated with each course were chosen. Finally, learners had to explain the reason why they chose these concepts and whether relationships exist among these concepts. Each learner's results were evaluated by four teachers, who were all experts with regards to their respective subjects. To avoid the experimenter effect, the scorers were not told which group participants belonged to. Teachers graded with regard to learners' responses in the explanation section. Students' responses included three sections, solidity, relation, and rationality. The solidity section described the completeness of the description given regarding the chosen concepts; the relation section measured whether a relationship existed between the chosen concepts; and the rationality section indicated the accuracy of the explanation given regarding the chosen concepts. As mentioned before, the evaluation system was conducted after an 18 week learning period and the evaluation process lasted for two weeks.

Questionnaire

In order to evaluate the usability of LSRS for learners, and its effect on course design for teachers, two semi-open ended questionnaires were devised. In addition to the questionnaires a Likert-type scale was adopted to measure

learners' and teachers' degree of satisfaction, ranging from strongly approve to strongly oppose. Each response was assigned a corresponding score as follows: 5 for strongly approve, 4 for approve, 3 for neutral, 2 for oppose, and 1 for strongly oppose. The participants were required to write down the reason for their choice, with a two hundred word limit, so that we could gain a better understanding of what students received from, and how they felt about their interactions with, the system. Tables 8 and 9 respectively show the questions and results of the semi-open ended questionnaires.

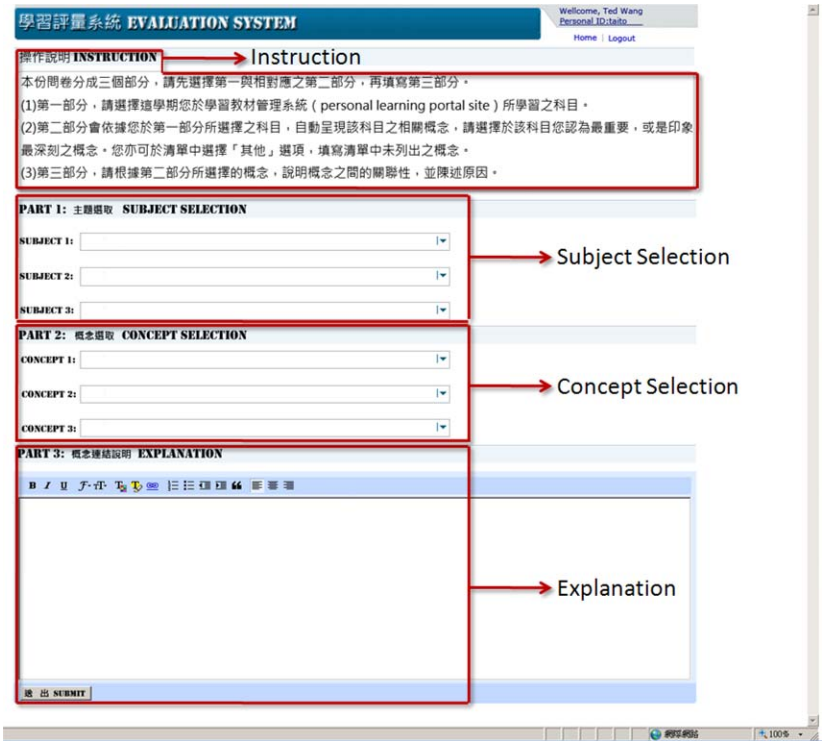


Figure 9. Screenshot of devised evaluation system

Regarding teachers, question 1 in Table 8 evaluates whether or not LSRS can provide effective learning transfer for teaching in the Web-based learning environment. In question 2, we assess whether the recommended learning sequences constructed knowledge of the subjects from the teachers' perspective. Then, in the third question, we assessed whether or not teachers referred to the learning transfer information for designing future courses. Finally, according to the results assessed in the evaluation system, the teachers told us whether or not LSRS enhanced students' transfer of learning.

For the learners, the first two questions in Table 9 assess the usability of the proposed system, which includes the clearness and understandability of the user interface interaction and the learning sequences. The third question evaluates whether or not the learning sequences provided by LSRS rendered the connections between the existing knowledge and new subjects, and the fourth question evaluates whether or not the recommended learning sequences offered a macro view, similar to a learning map, during the curriculum learning process.

Results and discussion

We first compared the evaluation scores of the two groups, which each comprise three independent scores, solidity, relation, and rationality. As mentioned above, according to the results from the evaluation system, a group of four teachers who are experts in the subjects graded the scores. An independent-sample *t*-test was conducted to detect any significant difference between the two groups. The next part of the analysis used the questionnaires to examine the potential of LSRS to promote learning transfer and curriculum design. We then analyzed the perceptions of the experimental group learners toward the usefulness of LSRS. Finally, we separated our findings regarding learning transfer by gender.

The potential for LSRS to promote learning transfer and curriculum design

As shown in Table 7, data analysis of the evaluation scores with independent-samples *t*-testswere almost all statistically significant (Evaluation score: $t(111)= -9.588^*$, $p < 0.05$; relativeness: $t(111)= -13.308^*$, $p < 0.05$; rationality: $t(111)= -11.360^*$, $p < 0.05$), except for the solidity score ($t(111)= .274$, $p = .785$).

Table 7. Learners' performance on evaluation sytem

Score	Group	N	Mean	t
Evaluation score	Control	56	65.82	-9.588*
	Experimental	57	75.09	
Solidity	Control	56	77.46	.274
	Experimental	57	77.00	
Relativeness	Control	56	69.59	-13.308*
	Experimental	57	84.37	
Rationality	Control	56	59.98	-11.360*
	Experimental	57	74.25	

* $P< 0.05$

On further investigation we find that the experimental group gets a higher score in the relation aspect ($M_{\exp}$ =84.37; $M_{control}$ =69.59). The results may be explained by the assistance of LSRS. Since the recommended learning sequences possess high public acceptance and the structural characteristic, they can assist learners to recognize relationships between subjects. Hence, experimental group learners had the ability to choose courses with more correct relationships than control group learners. In addition, the experimental group also attained higher scores in the rationality aspect ($M_{\exp}$ =74.25; $M_{control}$ =59.98), which implies that the metacognition of experimental group learners could be reinforced. Since the clear connections between subjects facilitated learners in giving more attention to these connected concepts, learners were able to accurately and reasonably describe the connections between the chosen concepts.

According to the hierarchy of cognition ability, recognition is easier than description or lucubration. Additionally, describing contents in one's own words presents a process of elaboration in information processing. Therefore, learners could not clearly describe the meaning of subject connections unless they were certain that there was substantial meaning in the subject connections. The statistic significance on rationality aspect supports this claim that LSRS assists learners in exploring the meaning of the subject connections. However, it is worth noting that the experimental group attained higher scores in the relation aspect than in the rationality aspect (84.37 vs. 74.25). This may imply that the system needs to provide more explicit information instead of only providing implicit connection information. More detailed discussions will be presented after the questionnaire results are shown.

As for the solidity aspect, the results revealed that there was no significant difference between two groups. A partial explanation for this may lie in the fact that the experiment adopted the random assignment method and that this aspect mainly focuses on the completeness of description of concepts for one single subject. Therefore, there is almost no effect on the variance of the solidity score between both groups, which also matches our expectations.

Despite the fact that the statistical data supplies positive evidence to support the LSRS's potential in promoting learners' learning transfer in the Web-based learning environment, the results evaluated from questionnaires provide more meaningful information and explanations of participants' perceptions. The results of two semi-open questionnaires render partial explanations of the statistical results, as shown in Table 8 and Table 9.

70% of the teachers agreed that the recommended learning sequences actually facilitate transfer of learning in a Web-based environment (Question 1, Table 8). They admitted to the limitations of Web-based learning mentioned in the introduction, including the absence of cross-subject guiders and neglect of learning transfer during the course-design process. They expressed the view that that LSRS provides connections between each pair of subjects, which usually have identical elements or similar concepts. Hence, 65% of them thought that students could track the related elements among different courses (Question 4, Table 8). However, few teachers agreed that LSRS provided the

knowledge structure that connects the subjects (Question 2, Table 8). The reason they pointed out is the deficiency of helpful information, which is able to construct the knowledge structure within a curriculum. Also, they signified that LSRS should provide the substantial meaning behind recommended learning sequences rather than only provide the concepts that are similar between each pair of subjects. Thus, the transfer of learning would perform well after taking the meaning of learning sequences into account. Other than that, over half of teachers decided to take the learning transfer into consideration during future course-design, but some of them thought that the situation should depend on the features of the subjects (Question 3, Table 8). The opposite teachers believed that some subjects possess very high levels of independence from, rather than connections with, other subjects. Therefore, from the teachers' perspective, LSRS would be better if it provided more meaningful learning sequences, which should depend on the different features of each subject.

Table 8. The research questions to teachers and their responses

	Teachers' Choices			
Question	Strongly approve & approve (%)	Neutral (%)	Oppose & Strongly oppose (%)	Mean
(1) The LSRS made teaching for learning transfer possible in the Web-based learning environment.	70	26	4	4.0
(2) The LSRS appropriately illustrated the knowledge structure of the subjects.	26	31	43	2.7
(3) I will take the suggestions provided from LSRS into consideration while I am designing the courses for the next semester.	57	4	39	3.3
(4) With the system's assistance, students can track the related learning elements (concepts) among different subjects.	65	31	4	3.9

Table 9. The research questions to learners and their responses

	Learners' Choices			
Question	Strongly approve & approve (%)	Neutral (%)	Oppose & Strongly oppose (%)	Mean
(1) My interaction with LSRS was clear and understandable.	88	10	2	4.3
(2) The learning sequences provided by LSRS rendered an understandable relation between each of the two subjects.	51	5	44	3.1
(3) The learning sequences introduced by LSRS effectively helped me to explore a new subject or knowledge domain.	61	30	9	3.8
(4) During this semester, LSRS provides a macro view of the curriculum which consists of three subjects chosen.	44	30	26	3.3

The results indicate that 61% of learners gave positive views of the recommended learning sequences, which can help them explore a new subject (Question 3, Table 9). Some of them expressed the view that they had no idea how to choose the most useful subjects, while the fact that only three subjects can be chosen was stipulated in advance. Herein, LSRS provided them a few directions to help them choose the subjects and connect their existing knowledge from previous subjects with a new subjects or knowledge domain. However, 9% of students expressed the opinion that the learning sequences only displayed the connections between each pair of subjects rather than explaining how to actually apply the learned knowledge or skills to the next subject. The results also corresponded with the statistical findings mentioned earlier, which were regarded as a limitation of LSRS. Other than that, 44% expressed positive views about the assistance of LSRS for enhancing their cognition in a semester curriculum (Question 4, Table 9).

They pointed out that LSRS helped them to choose a coherent curriculum. Despite the fact that nearly 50% of students gladly accepted the curriculums recommended by LSRS, 26% of students were still not predisposed to choosing the curriculums arranged in advance. They expressed the idea that the subjects within the recommended learning sequences were usually found in the similar domain, while regarding subjects from different domains, LSRS seemed not to offer a macro view of the curriculum. The most important finding from this result suggests that LSRS should improve its recommendation ability for cross-domain subjects. According to above mentioned limitations, additional research focusing on these aspects would be of great interest and value in understanding the role of cross-domain subjects and their influence on transfer of learning.

The usability of LSRS for experimental group learners

The responses to questions 1 and 2 (see Table 9) summarize the results obtained for evaluation of the perceived usability of LSRS, and the clearness and understandability of the learning sequences. Opinions extracted from questions 1 and 2 in the semi-open ended questionnaire denoted how the learner perceived the system user interface and the objects display presented in LSRS. 88% of learners responded that the LSRS user interface is very friendly and that the system is easy to use (Question 1, Table 9). Additionally, 51% of learners expressed the positive views about the clear display of the learning sequences while 44% of learners disagreed on this point (Question 2, Table 9). The mixed results imply that the system can still be greatly improved. Some of the opposite learners expressed that, although LSRS provides a clear display of learning sequences and the connections among subjects, the presented learning sequences should include more information about the linking relations, such as which textbooks have caused the relations or related assessments between two subjects. In this regard, more research is needed on the effects of more displayed information toward effective transfer of learning.

The LSRS's effectiveness for learners of different genders

Gender based differences in learning and behavior have long been recognized as an important issue on educational research (Herring, 1994; Scanlon, 2000; Weinman & Cain 1999). Furthermore, the importance of investigating whether or not gender differences exist in web-based learning settings is also reported in the literature (Garland & Martin, 2005; Lee & Tsai, 2004; McSporran & Young, 2001). However, the findings of these studies have been mixed. In this study, an independent-sample t-test was conducted to examine whether or not differences in learning transfer related to gender exist in the web-based learning environment. The results revealed no significant difference between males and females. Perhaps future research could examine different samples from different learning domains, and provide more detailed results, which may differentiate these views from one another.

Overall, the above evaluations reflect positively on our efforts since most respondents gave positive feedback regardless of whether they were teachers or learners. Both positive and negative feedback gives us more information to analyze so that we can offer more precise levels of individualization for each user in the future.

Conclusion

When effective group patterns are successfully applied, the likelihood of positive learning achievement and students' satisfaction with group activities is significantly increased. Alternatively, when students encounter obstacles and feel frustrated because they do not use the experienced group-learning patterns for assistance, or do not believe that continued searching the available material is useful, web based learning can become a cause of stress, and its benefits to users are reduced. Therefore, it is all the more important for teachers to have a well planned learning sequence in hand when designing a course and ensure it leads learners to achieve transfer of learning.

In this paper, we have proposed a dependable learning sequence recommendation system. By employing the Markov chain model and an entropy-based approach, we discovered learning sequences and formed a recommended learning map that allowed learners to set their own learning pace in Web-based educational settings. The proposed approach successfully discovered applicable learning sequences so that learners could avoid redundant or otherwise ineffective learning behaviors.

From the evaluation results, we found that the use of the learning sequence by learners was able to significantly promote their learning transfer, a fact that has several important pedagogical implications.

For teachers, the system offers learning sequencing support by providing good recommendations and constructing a learning picture that is able to clarify the learning objectives for students. The evaluation results showed that most lecturers responded positively to the use of the system for their teaching, as it allowed them to effectively utilize the limited time they had available for student assistance. In the future, we will make an effort to provide sufficient learning objects to allow instructors to create more meaningful learning maps.

For learners, applicable learning sequences can be dynamically generated to target individual learners. Learning sequences inferred by the Markov chain model can narrow down and focus the whole learning process. The results revealed that there was not only a statistic significant difference in evaluating learning effectiveness; but that the learners also felt that they received benefits from the experienced learning sequences. Therefore, such learning recommendations in particular, may reduce the workload involved in searching for and accessing information, and lead to the development of better time management skills in a professional context. In addition, it is important to emphasize that the method of investigation is not without problems. Although we have measured whether learners acquired the essential elements of learning transfer, the detailed cognition and knowledge transfer processes seem not indicated from the results of the present study. We are hopeful that future research will provide more detailed results which may clearly reveal the transfer process of knowledge during students' learning.

By observing patterns of group learning, the possible pitfalls in terms of student perceptions of the worth of the learning sequences become clear, and it is obviously important that efforts should be directed towards the provision of high quality materials, rather than the provision of large quantities of material.

We also may expand to a number of unanticipated nodes (or paths) for a subject, which means that the provision of learners' selection would need to be carefully arranged so that all individual learners would be assured of some viable opportunities for extra learning over their course of study. Therefore, we will weight up the options for these recommended learning sequences and deploy the proposed system to the real-world learning environment found in our university e-learning system. Then, we believe much more research work is still needed to investigate for the scalability, performance, and fault-tolerance of the system.

Given a system capable of exploiting learning patterns in e-Learning settings, statistical heuristics might provide a default track to groups' paths. To promote learning, we will hopefully find more detailed and precise criteria to accommodate their needs, and then provide a foundation upon which an even more intelligent and responsive system can be built.

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