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A Model for *e*-Learning Using Adaptive Navigation

Yihjia Tsai

Department of Computer Science and Information Engineering
Tamkang University
Tamsui, Taiwan 251, R.O.C.
E-mail : u6191488@mail.cs.tku.edu.tw

Abstract

In the area of *e*-learning environment, there are many researches in adaptive learning. Adaptive learning means that providing adaptive service or content according to different users. The major issues of adaptive learning are adaptive navigation and adaptive content presentation and we focus on adaptive navigation. Although there have already been many models or systems for adaptive navigation they either make dynamic navigation based on assuming adaption exists or are too complexity that could be less flexible. Therefore we develop a new model and use Bayesian Network and concept-based learning to make adaptive efficacy.

Key Words: adaptive learning system, Bayesian Network, e-learning, adaptive navigation

1 Introduction

In the area of e-learning environment, similar change of mind set is also taking place. Pedagogically, a one-to-one instruction provides the best learning environment for the learner. However, practically due to the consideration of teaching personnel resources and time, it is seldom that one can create such ideal learning environment. Two significant advantages of online learning: the paradigm of learning any time and anywhere, and the ability to deliver personalized contents. One of the main goals of student modeling in educational hypermedia is student guidance. Students have learning goals and previous knowledge, which should be reflected by the learning material for adapting the contents.

There are many researches in adaptive learning. The adaptive learning means that providing adaptive. The adaptive learning means that providing adaptive service or content according to different users. The major issues of adaptive learning are adaptive navigation and adaptive content presentation and we focus on adaptive navigation. Although there have already been many models or systems for adaptive navigation [2–8] they either make dynamic navigation based on assuming adaption exists or are too complexity that could be less flexible. Therefore we develop a new model and use Bayesian Network and concept-based learning to make adaptive efficacy.

2 Concept-based Learning

Concept is the basic unit knowledge and knowledge is the presentation of concepts. Thus learning behavior is humans trying to understand concepts or how to organize them.

When the course material is organized in small conceptual units (Figure 1) and every course is based on these object, learners only learn once for every concepts. In other words, if a course has some concepts that learner has already known, learner doesn't learn the same thing in the course.

3 User Profile Model

In the *e*-learning, learners study in the hyperspace[1] like navigation. Brusilovsky [1] refers to the pur-

[1] WWW or Internet

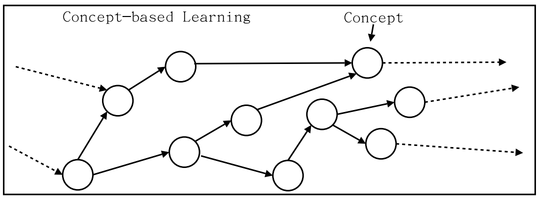

Figure 1: Concept-based Learning

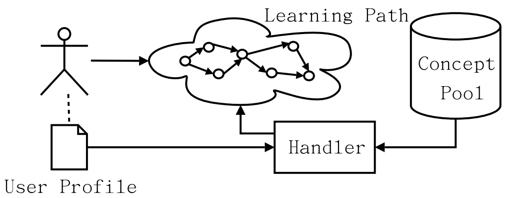

Figure 2: The Concept of adaptive Navigation

poses of adaptive navigation as follows:

- local or global guidance: Helping users find the shortest learning path.
- local or global orientation support: Local orientation support helps users to understand where there are in the hyperspace and global orientation support helps users to understand the structure of the hyperspace.

Learners have their own learning paths because different learning experience and characteristic and we store these attributes into a formatted structure called user profile. According to different user profiles, we can generate different adaptive learning paths and that is called adaptive navigation (Figure 2).

In user profile, the important part is how to describe the known concepts. According to concept-based learning, concept is encapsulated into a basic unit. In other hand, the cognition of concept have different understanding degree but not only be known or unknown. We define a *knowledge vector* that includes the known concepts of learner u and every concept in *knowledge vector* has a attribute λ to describe how much does the learner u understand it. There we call λ proficiency parameter and its value is between 0 to 1. The definition of knowledge vector is as follows.

$$KV(u) = \{\lambda_1, \lambda_2, \cdots, \lambda_n\} \qquad (0 \leq \lambda \leq 1)$$

The popular and best way to evaluate the value of λ is a test. When a learner finishes a concept, there will a test to evaluate how much does he understand. In general, the tests we often do are based on classical test theory. However, our objective is a adaptive model and if we use classical test theory , we will get biased estimate because some congenital defects. Thus we use item response theory (IRT) to estimate the value of λ and choose the popular *three-parameter logistic model* in the paper. The definition of three-parameter logistic model as follows:

$$P_i(\theta) = c_i + \frac{1 - c_i}{1 + e^{-1.702a_i(\theta - b_i)}}$$

- $P_i(\theta)$: the probability that a user with ability θ answers item i correctly.
- b_i: the difficulty parameter.
- a_i: the discrimination parameter.
- c_i: pseudo-chance parameter that means the probability of user guess item i correctly.

By using three-parameter logistic model, we can evaluate the ability θ of learner. Then we can use some ways to transfer θ to λ.

3.1 The Estimate of λ

When a learner finish a test, there is a response pattern like this:

$$(U_1, U_2, \cdots, U_i, \cdots, U_n)$$

U_i means the answer is correct or wrong of item i and its value is 1 (correct answer) or 0 (wrong answer). We define the likelihood function for response pattern as follows.

$$\begin{aligned}
&L(U_1, U_2, \cdots, U_i, \cdots, U_n|\theta) \\
&= P(U_1|\theta)P(U_2|\theta)\cdots P(_i|\theta)\cdots P(U_n|\theta) \\
&= \prod_{i=1}^{n} P(U_i|\theta) \\
&= \prod_{i=1}^{n} P(U_i|\theta)^{U_i}(1 - P(U_i|\theta))^{1-U_i} \\
&= \prod_{i=1}^{n} P_i^{U_i} Q_i^{1-U_i}
\end{aligned}$$

where $P_i = P(U_i|\theta), Q_i = 1 - P(U_1|\theta)$

The value of the likelihood function may be very small because the value of probability between 0 to 1. Thus we transfer it to nature log form.

$$\ln L(U_1, U_2, \cdots, U_i, \cdots, U_n|\theta) = \sum_{i=1}^{n}(U_i \ln P_i + (1-U_i)\ln(1-P_i))$$

Then, the ability θ is the maximum likelihood estimate (MLE) of the nature log likelihood function.

In other hand, the expect grades of a test is

$$E(X) = \sum_{i=1}^{n} P_i(\theta)G_i$$

where G_i is the grades of item i. Now, we can transfer θ to λ by using the equation below.

$$\lambda = \frac{\sum_{i=1}^{n} P_i(\theta)G_i}{\sum_{i=1}^{n} G_i}$$

4 Adaptive Navigation Support

The generation of learning path has two phases. The first phase generate a generic learning path by teachers or professionals. It is based on concept-based learning and Bayesian Network. Bayesian Network is a powerful knowledge representation and reasoning tool under conditions of uncertainty. It is a directed acyclic graph (DAG) with a conditional probability distribution for each node.

For example, figure 3 is the part of the course "The Introduction to Network Programming" with three level degree .

In the example, node $A \rightarrow$ node B means that B is based on A. For example, "connection" is based on "TCP" and "UDP" and learner must finish "TCP" and "UDP" firstly if he want to learn "connection". In other hand, every node has a conditional probability table. According to conditional probability table , if a learner has level 2 for "MAC", we can infer he may have level 2 for "ARP/RARP" because the maximum probability. Therefore, in the second phase, it infer the level of unknown concepts according to the level of known concepts in the knowledge vector. When every unknown concept's level has been inferred, comparing the level of all concepts with learning objective. The learning objective means that a learner

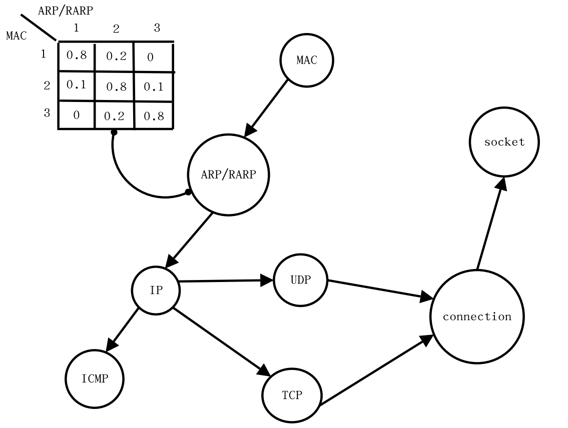

Figure 3: The Introduction to Network Programming

expects what level does he reach for all concepts in a course. If the level of concept is greater then learning objective that means he isn't necessary to learn it and it will be removed from the Bayesian Network.

4.1 Level Degree

In our model, we must classify every concept in Bayesian Network but the value λ in knowledge vector is continuous. Thus we define *level degree* to translate λ to *level.* Every course has its owned *level degree* because flexibility and exactness.

$$\text{concept level} = \lfloor \lambda \times (\text{course level degree}) \rfloor$$

5 The Model Construction

The model can be divided into three layers — "concept", "relation", "user view". Concept layer is a pool used to store the content of concept and every concept is a basic unit of knowledge, describes a self-contained, and independent idea. Relation layer describes the relationship between concepts and generic learning path and it means generic learning path is just generated in this later. Finally, learners will see their adaptive learning paths in user view layer (Figure 4).

The construction has four phases:

- *draft*: The professional (or teacher) gives a generic learning path.

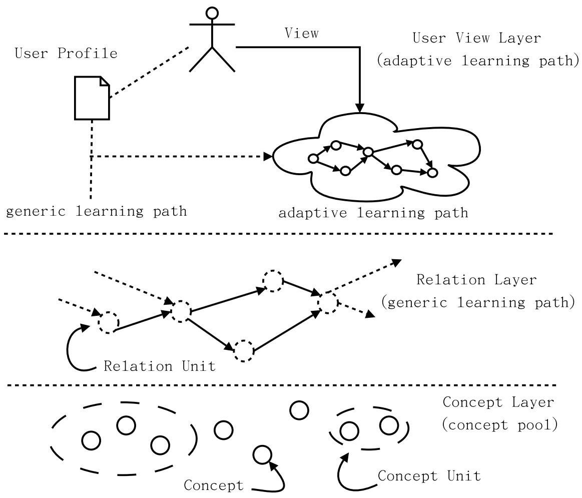

Figure 4: The model in three layers

- *inference*: According to user profile, it infers the level of unknown concepts in the generic learning path.
- *remove*: If any concept's level is less then learning objective, remove it.
- *rebuild*: After removing concepts, there are some fail edges in the learning path. Then, correct or remove them.

5.1 The Pseudo Algorithm

1: Initiate a empty set U.
2: Initiate a graph $G(V, E)$
  where $V = \{$ all nodes of a concept set $\}$,
  $E = \{\}$.
3: **for all** node $v_i \in V$ **do**
4:   Initiate a ordered set
    $P = \{$All require nodes of $v_i\}$.
5:   **if** P isn't empty **then**
6:     Put all pair of nodes (p_i, v_i)
      into E where $p_i \in P$.
7:   **end if**
8: **end for**
9: Use the **LS algorithm** to set states
  of nodes.
10: **for all** $v_i \in V$ **do**
11:   Initiate a empty ordered set R.
12:   **if** the level of $v_i >$ learning objective
    then
13:     Put v_i into U.
14:     **for all** (v_i, v_j)
      where $v_j \in V$, $(v_i, v_j) \in E$ **do**
15:       Put them into R and
        remove them from E.
16:     **end for**
17:     Initiate a empty set E'.
18:     **for all** pair $(v_m, v_n) \in R$ **do**
19:       **for all** pair $(v_x, v_y) \in E$ **do**
20:         **if** $v_y = v_m$ **then**
21:           Put (v_x, v_n) into E'.
22:         **else**
23:           Put (v_x, v_y) into E'.
24:         **end if**
25:       **end for**
26:     **end for**
27:     $E = E'$
28:   **end if**
29: **end for**
30: Generate a new graph $G'(V - U, E)$.

- **Step 1**: Initiate a empty set U to store the nodes that will be removed.
- **Step 2–8**: Declare a graph $G(V, E)$ and transfer a course (generic learning path) to a graph.
- **Step 9**: Use "LS algorithm[2] [9]" to infer the level of the unknown concepts
- **Step 10 –29**: Look up every node.
  - *Step 11 – 13*: Find the level of node greater than learning objective and put it into U. That means this concept doesn't to be learn.
  - *Step 14 – 16*: Find all child nodes of the removed node.
  - *Step 17 – 26*: Find all parent nodes of the removed node and add directed edge from every parent node to every child node.
  - *Step 27*: Remove the edges between the removed mode and its parent and child nodes.
- **Step 30:** Finally, generate a graph $G'(V - U, E)$ that is a adaptive learning path.

[2]LS is short for Lauritzen and Spiegelhalter and it is an inference algorithm that determines the probabilities of node states with or without evidence (instantiated) nodes.

6 Conclusion and Future Work

How to make adaption is the important issue in this area. There are many researches but there are no easy, flexible, and extendable ways. We use Bayesian Network to implement adaption and combine it with *link hiding* to make adaptive navigation. In our model, there can be added more attributes (user characteristics) and use Bayesian Network to do inference. In other hand, the model is based on concept object that means you can adapt learning object model in concept layer. The learning object model can be developed by yourself or use other existed models like SCORM (Share Content Object Reference Model).

In the future, our model can be combine with the other issue — *adaptive content presentation* to extend a complete adaptive learning model. Adaptive content presentation means that providing adaptive content according to different users. We can providing adaptive content according *learning objective*, *concept level* or other user characteristics which are defined in our model. That means we can combine our model with adaptive content presentation model without changing our model because the content is encapsulated into a basic unit (concept object).

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