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Learning as Construction of Personalized Cognitive Structures

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Abstract

Among the many factors that influence learning efficiency, the cognitive structure of learners is the most important. In order to solve common problems in online learning systems, this article puts forward a new approach to build knowledge as an individualized cognitive structure. Firstly, the formal subject knowledge structure is defined, and then we enrich it through attribute extensions so that it meets personalized and dynamic learning needs. Secondly, we subdivide the personalized cognitive structure hierarchically for the sake of learning efficiency. Finally, we propose a method to measure the learning dynamics between concept nodes; that enable the online learning system to calculate the learning expectation about the new knowledge point in the light of the learner's current cognitive level. Thus, the system can introduce the appropriate next learning objective for learners and improve the adequacy of future online learning.

Keywords: *online learning; cognitive structure; personalized; objective push*

1. Introduction

Personalization in an educational context needs a certain understanding of the learner as well as of the targets that are important to learning. Personalized learning refers to adopting learner and appropriate learning objectives and content according to their personality, preferences, abilities, needs, knowledge and experience, and specific learning scenarios.

Many traditional online learning systems were dominated by content service and piling up lots of audiovisual materials. People have to spend a lot of energy to adapt and use these systems and which lead to lack of learning efficiency and the high dropout rate. An excellent system should be on learners and actively provide intelligent and personalized services to reduce unnecessary learning burden. Therefore, people try to build a personalized and intelligent online learning system, and the key issue is to explicitly express and analyze the learner's learning situation. In addition, with the progress of learning, the learner's situation is always changing, which requires the learning system to be real-time and dynamic.

In this field, the NIST's high-tech research project began investing heavily in 1998 to fund personalized learning systems, aimed at seeking more flexible and evaluative teaching techniques to improve the quality of online learning. There were some famous personalization systems established one after another, including 4MAT, INSPIRE, 3DE, ELM-ART and so on [1, 2, 3, 4]. These systems attempted to come up with useful learning guidance, but the results are modest due to the lack of real-time quantitative analysis.

Education by means of the e-learning method is becoming more and more popular nowadays and a rapid development of information technologies makes traditional, static websites used for online education being replaced by interactive, intelligent portals [5]. Goltz presents some research results conducted among students learning English in a blended learning form [6]. Janssen argues that in order to achieve comparability and exchangeability a uniform and meaningful way to describe learning paths towards attainment of learning outcomes is needed [7]. Vasilyeva focus on the problem of feedback adaptation in web-based learning systems [8]. Brooks argue for a more flexible approach to both defining and associating metadata with learning objects [9].

There are many factors that affect learning efficiency. Constructivism believes that people's cognitive structure is the most important among the factors that affect learning. Cognitive structure is the content and organization of learners' knowledge and it is the reference framework for people to perceive and process external information and perform reasoning activities. Learning is the process of establishing various connections between old and new knowledge. With the constructivism learning theory, this paper constructs learners' personalized cognitive structure (PCS) as the basis of the online learning system, and puts forward corresponding application methods, so that the online learning system can actively propose many appropriate advices for learners and finally improve learning efficiency.

2. Formalization and structure of PCS

People often have so much prior knowledge that the data are too large to represent a complete cognitive structure. Considering that when people study a new topic, they are always confined to the scope of the discipline in which the new knowledge is located, the cognitive structure of learners should be constructed according to the kinds of disciplines, which can effectively reduce system burden and improve operational efficiency.

Usually a discipline consists of chapters; each chapter contains several knowledge nodes, and the context between knowledge prescribes an instructional sequence, which should be in line with people's cognitive repertoire. In most of the instructional theories it is, a gradual sequential process order from before to after, from easy to hard, from basic to advanced.

Definition 1. A Meta-knowledge point is one that cannot be further divided.

Definition 2. Compound knowledge points. A knowledge point made up of related knowledge points.

For example, in physics, mass, distance and time are meta-knowledge points, while force is a compound knowledge point related to mass and acceleration, and energy is a compound knowledge point composed of mass and velocity. In this article, the meta knowledge points and compound knowledge points are collectively referred to as knowledge points.

Definition 3. Predecessor relationship. Assume that $\sum$ represents all knowledge points of the discipline. Given $c_i \in \sum$, $c_j \in \sum$, an ordered pair $<c_i,c_j>$ means that you need to learn c_i before learning c_j. If there is $c_k \in \sum$, so that both $<c_i,c_k>$ and $<c_k,c_j>$ satisfy the ordered pair relation, the pair $<c_i,c_j>$ is denoted relation R_{GC}, or it is denoted relation R_{PC}.

Definition 4. Given a set of knowledge points $c \subseteq \sum$, if $\forall c_i \in C$, $\exists c_j \in \sum$, $<c_i,c_j> \in R_{GC}$ is satisfied, the C is called Predecessor Set of c_j. If $<c_i,c_j> \in R_{PC}$, the C is called 1-level predecessor set and denoted as 1_ P(c_j), otherwise C is called k-level predecessor set and denoted as k_ P(cj), where k is the shortest path length from c_i to c_j.

As knowledge points and its relation, cognitive structure is essentially a directed graph representation of knowledge, in which knowledge point is the node and the relation is the edge of the directed graph. In the form of a directed graph, the knowledge points and the interrelationship in the learner's cognitive structure are represented and defined as follows:

Definition 5. An Ordered Knowledge Map (OKM) is an acyclic digraph G (N, E, R), where N is the set of nodes which represents knowledge points; E is the set of directed edges which represents ordered relation between points; R is a sequence of direct relationships

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between knowledge points, representing the path of learning.

On the one hand, the discipline knowledge structure is very stable and will not change greatly along a short time. This stability is fortunate for domain experts to construct the ordered knowledge map. On the other hand, with the progress of learning, learners' cognitive structure is constantly changing, so that the static discipline knowledge structure cannot keep up with the dynamic changes of the learning situation. Therefore, the node and the relationship between nodes in the OKM should be redefined through attribute extension, so that it can construct the dynamic cognitive structure in line with the personalized requirements.

Definition 6. Personalized Cognitive Structure (PCS) is a framework based on the OKM of the discipline, by adding attributes to the nodes and relationship between nodes. It includes:

- name of node
- cognitive objective
- exercise and test
- answers and scoring criteria
- score
- threshold of allowed access
- threshold of allowed passing
- label of relationship
- extent of influence

Where the attribute "cognitive objective" means that the tasks in the field of cognition are divided into six levels in Bloom's taxonomy: knowledge, understanding, application, analysis, synthesis and evaluation. In this way, the nodes are classified so that the online learning system can make a mark to the cognitive level that learners should reach about a certain knowledge point, which can be set according to the outline of discipline. the attribute "extent of influence" refers to the extent to which learners' mastery of the predecessor knowledge points will affect their learning of their successor points.

There is no cycle in PCS because of ordered relationships between points. The following two problems need to be dealt with when constructing the PCS for each individual learner in the online learning system.

3. Layering of personalized cognitive structures

The process of learning should conform to people's cognitive rules, that is, orderly from easy to difficult and making progress step by step. Each node and its' predecessors in PCS should be in different layers, and each node always points to its' successor. In order to ensure the consistency of pointing between nodes, it is necessary to perform the node layering algorithm, and which is very important for our next work.

The process of learning should be compatible to people's cognitive rule, that is, ordered from easy to difficult and making progress step by step. Each node and its' predecessors in PCS should be in different layers, and each node always points to its' successor. In order to ensure the consistency of pointing between nodes, it is necessary to perform the node layering algorithm, and which is very important for our next work.

A personalized cognitive structure is essentially a hierarchically directed acyclic graph (DAG) that is represented:

Definition 7. Given a DAG *G=(V,E)*, it is defined as *n-layered directed graph* IFF (if and only if):

(1) $V = L_1 \cup L_2 \cup ... \cup L_n \qquad \left(L_i \cap L_j = \varnothing, i \neq j\right)$

(2) For each $(u,v) \in E$, if $u \in L_i, v \in L_j$, $i < j$.

Where n is the height of the layered graph, and the width of layer V_k is defined as $w(V_k) = \sum_{v \in V_k} w_v$ so that the width of a layered digraph is $w = \max_{1 \le k \le n} w(V_k)$.

There are three classic algorithms that have been widely used for graph layering: the longest-path layering (LPL), the Coffman-Graham algorithm and the network simplex algorithm (NSA) [10].

The longest path algorithm ensures the minimum height. The Coffman-Graham Algorithm tries to minimize the height with width at most w. The network simplex algorithm attempts to the fewest dummy nodes which are Introduced into graph when

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layering. Which one is proper should be assessed by comparing with measurement results.

Thousands of DAGs generated randomly were used as material for algorithm testing. Every algorithm has its own advantages, as shown in table 1.

Table 1 Comparison of node layering algorithm

Compare items	LPL	Coffman-Graham	NSA
height constraint	yes	yes	no
width constraint	none	good	no
Height × width	normal	weak	excellent
dummy nodes	weak	normal	excellent
runtime	very fast	fast	fast

The performance of the three algorithms was illustrated in Figure 1 in terms of the number of dummy nodes.

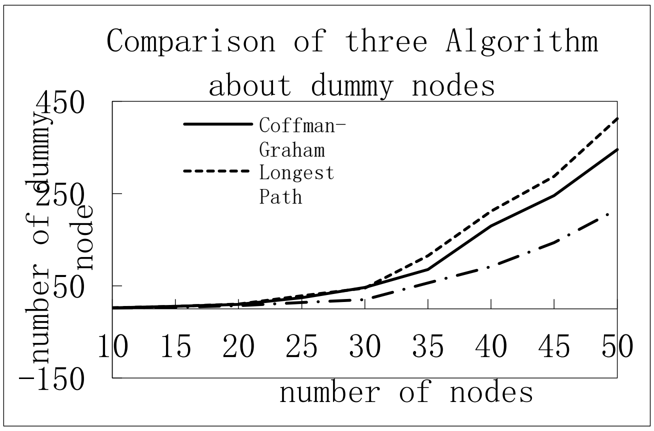

Figure. 1 Dummy nodes introduced by the 3 algorithms

In Figure 2, three algorithms were compared in terms of readability. As a result, the Simplex method maintains a very compact appearance although there is no direct mechanism to control the dimensions.

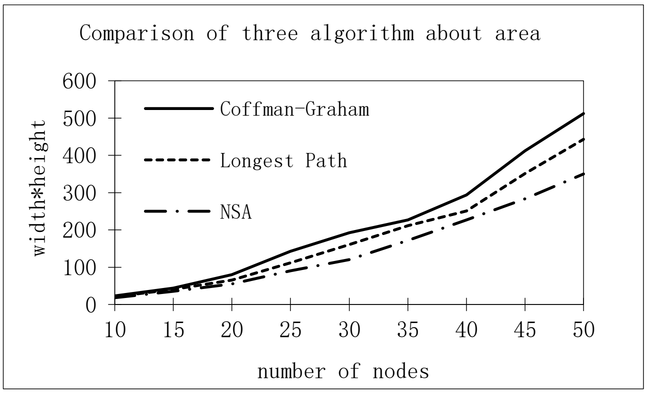

Figure. 2 width × height computed by the 3 algorithms

In terms of running time, LPL algorithm is the fastest, which can be finished in linear limit by using depth-first search, and its average complexity of is $O(|V|)$. The complexity of Coffman-Graham algorithm is $O(|V|^2)$ in the worst case. The NSA needs exponential time in the worst case, but it has not been proven that the average running time is not polynomial [11]. Overall, with the NSA algorithm the layout of nodes is the most reasonable and has a good appearance.

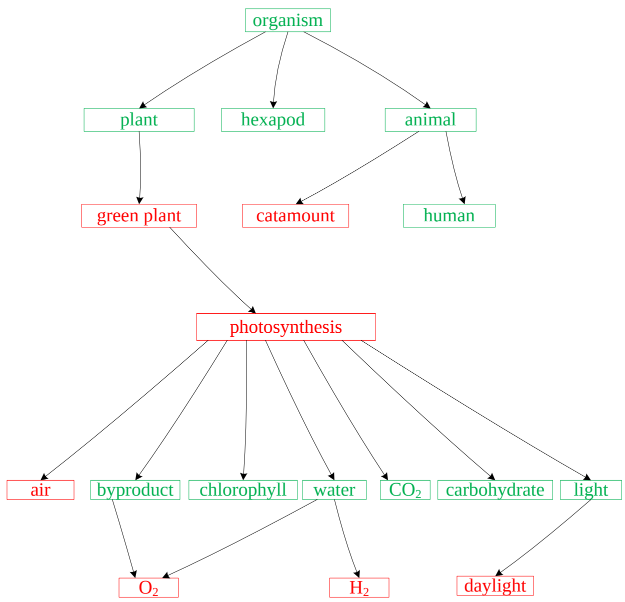

Figure. 3 PCS with the theme of photosynthesis

The online system updates the PCS data in real time according to the learning process and presents it to learners in the form of a hierarchical graph. As shown in Figure 3, graph layering is carried out with NSA in

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the PCS with the theme of "photosynthesis". The green node indicates the knowledge points that have been learned, and the red node represents no passing the test.

4. Active push of next learning objectives

After constructing and layering the PCS, the online learning system can predict the learner's appropriate learning objectives and actively push out according to the following methods.

Definition 8. Learning expectations: It refers to the possibility of understanding and mastering new knowledge points under the normal learning situation based on the learner's current cognitive structure.

The nodes of PCS can be divided into three disjoint zones depending on whether the expectation is greater than the threshold of allowed access. One is the zone of nodes under learnability, one is the zone of nodes within learnability, and the other is the zone of nodes beyond learnability [12].

In order to calculate the learning expectations and perform the partition of PCS, it is necessary to measure the influence of knowledge points that have been learned on that has not been yet. This influence has two main parts. One is the hierarchical information of knowledge points in PCS, i.e. the predecessor relationship between points. Usually the direct predecessor node has a greater influence than the indirect one, and this part of influence can be measure. This part of the impact can refer to the calculation method of semantic relevance based on hierarchy [13,14,15]. The other is the intensity of the connection between knowledge points. Constructivism believes that the learning is the process of establishing various connections between the learned and the unlearned and different predecessor knowledge points have different correlation intensity for the same knowledge points. For example, when learning the knowledge point of "motion and force", if only the hierarchical information is considered, there would be no difference between direct predecessors' "acceleration" and "mass". But actually, for the learning “motion and force", "acceleration" is more important than "mass", because the former has a stronger correlation.

According to the definition of PCS, each knowledge point has the attribute of "cognitive objective", which is divided into six levels. From a cognitive point of view, these levels indicate the knowledge point’s different cognitive load for learners. The higher the level, the more cognitive labour required.

Definition 10. load(c_i). It refers to the cognitive load of the knowledge point c_i, and assigns an integer value of 1 to 6 according to the level of "cognitive objective" of knowledge points.

In the example mentioned above the cognitive objective of “acceleration” is “synthesis”, then load (“acceleration”) = 5, and the cognitive objective of “mass” is “application”, then load (“mass”) = 3. Obviously it takes more cognitive labour to learn "acceleration" than to "mass". Thus "acceleration" has a greater influence on the "motion and force".

Definition 11. In a PCS G(V, E, R), $c_i \in V, c_j \in V$, if c_i is the k-level predecessor of c_j, the set $A_{i,j}$ is:

$$A_{i,j} = \sum_{n=1}^{k} \{\text{n-level predecessor of } c_j\}$$

Actually Ai, j is the set of all of the prerequisite knowledge points within the process of study from c_i to c_j.

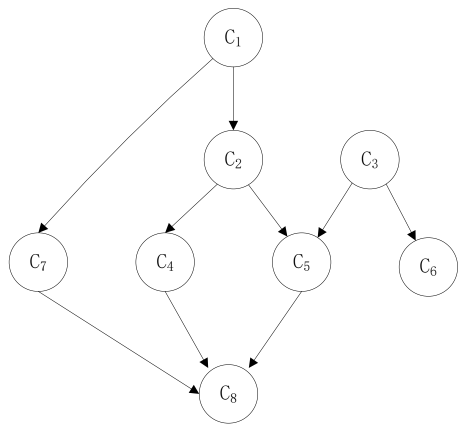

Figure. 4 An example of PCS for measuring connection

As shown in Fig. 4, $C_{1,8} = C_{2,8} = \{c_1, c_2, c_3, c_4, c_5, c_7\}$.

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Then the intensity of connection between the two nodes is calculated by Formula 1:

$$con(c_i,c_j)=\begin{cases}\dfrac{load(c_i)}{\sum_{t_{i,j}\in C_{i,j}} load(t_{i,j})}, & \text{if } <c_i,c_j>\in(R_{PC}\cup R_{GC}),\\ 0, & \text{else}\end{cases} \quad (1)$$

Where $\sum_{t_{i,j}\in C_{i,j}} load(t_{i,j})$ is the total amount of cognitive labor required from c_i to c_j. Given *load(C₁) = 2*, *load(C₂) = load(C₇) = load(C₃) = 3*, *load(C₅) = load(C₆) = 4, load(C₄) =load(C₈) = 5*, the matrix M of the intensity of connection of PCS shown in figure 4 is (where the connection on itself is defined as 1):

$$M=\begin{bmatrix} 1 & 1 & 0 & 0.4 & 0.25 & 0 & 1 & 0.1\\ 0 & 1 & 0 & 1 & 0.5 & 0 & 0 & 0.15\\ 0 & 0 & 1 & 0 & 0.5 & 1 & 0 & 0.15\\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0.4167\\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0.3333\\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0.25\\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Depending on both the hierarchical information and the intensity of connection between nodes, formula 2 is proposed to measure the learning influence between any knowledge points and its predecessors.

$$inf_{pcs}(c_i,c_j)=\frac{(1+con(c_i,c_j))\times depth(\mathrm{DCP})}{depth(c_i)+depth(c_j)} \quad (2)$$

Where depth(c) is the depth of node c in PCS, DCP (Deepest Common Predecessor) means that for the two nodes c_i and c_j in the PCS, the node closest to the bottom of all the common predecessor nodes. Then, for PCS as shown in Figure 4, the matrix M' of measuring learning influence between nodes is:

$$M'=\begin{bmatrix} 1 & 0.8 & 0.2 & 0.4667 & 0.4167 & 0.1667 & 0.6667 & 0.3143\\ 0.4 & 1 & 0.1667 & 0.8571 & 0.6429 & 0.1429 & 0.2857 & 0.4312\\ 0.2 & 0.1667 & 1 & 0.1429 & 0.6429 & 0.8571 & 0.1429 & 0.4312\\ 0.3333 & 0.4286 & 0.1429 & 1 & 0.375 & 0.125 & 0.25 & 0.6297\\ 0.3333 & 0.4286 & 0.4286 & 0.375 & 1 & 0.375 & 0.25 & 0.5926\\ 0.1667 & 0.1429 & 0.4286 & 0.125 & 0.375 & 1 & 0.125 & 0.1111\\ 0.3333 & 0.2857 & 0.1429 & 0.25 & 0.25 & 0.125 & 1 & 0.5556\\ 0.2857 & 0.375 & 0.375 & 0.4444 & 0.4444 & 0.1111 & 0.4444 & 1 \end{bmatrix}$$

Then for the new knowledge point, Formula 3 is proposed to calculate the learning expectation on the basis of Formula 2.

$$D_k=\frac{1}{inf_{k\_num}}\times\sum_{i=1}^{n}\left(inf_{pcs}(c_i,c_j)\times s_i\right) \quad (3)$$

Where $inf_{k\_num}=\sum_{i=1}^{n} inf_{pcs}(c_i,c_k)$, n is the number of predecessors of nodes c_k, c_i is any predecessor node of c_k. s_i is the score of the learner's knowledge points obtained through the test.

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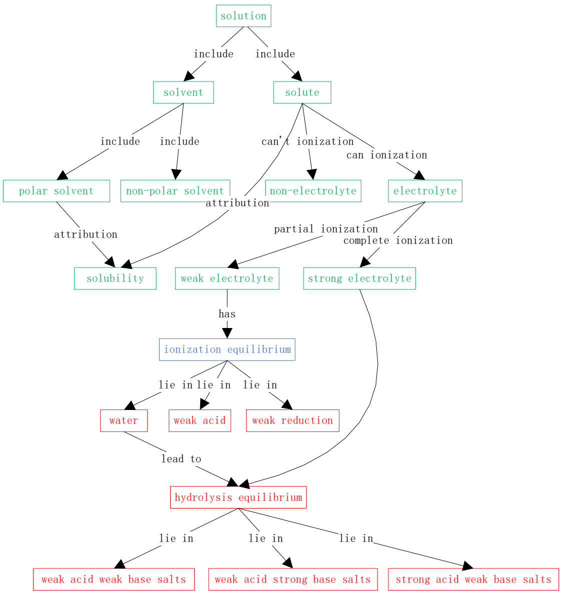

C_name	Score	Expectation	Zone
solution	81	......	under
solvent	75	......	under
solute	75	......	under
polar solvent	73	......	under
non-polar sol	73	......	under
non-electroly	73	......	under
electrolyte	73	......	under
solubility	70	......	under
strong electr	71	......	under
weak electro	71	......	under
ionization eq	68	73.237	within
water	66	71.006	within
weak acid	66	71.006	within
weak reducti	66	71.006	within
hydrolysis eq	64	70.925	within
weak acid w	61	68.675	beyond
weak acid st	61	68.675	beyond

Figure. 5 Learning expectation of nodes and its correlative data

If the expectation of a node is greater than the presented threshold of allowed access, it will be placed into the zone-within-learnability, otherwise into the zone-beyond-learn-ability. The setting of threshold depends on the situation, for example it can be set lower in a relaxed learning environment.

The experimental results are shown in Figure 5. This is a cognitive structure of a learner with the theme of "solution", in which the knowledge points that have been learned are marked as green. The learnable threshold of each knowledge point is set as 70. The learning expectation of the knowledge point "ionization equilibrium" in the figure is greater than the threshold, which means that it's a new knowledge point that you can learn right now, and marked blue. Those below the learnable threshold are marked in red to indicate the new knowledge points that are not currently suitable for learning.

5. Conclusion

As the most important factor of learning efficiency, personalized cognitive structure is the basis for our online learning system to provide learning objective push service. With the analysis of knowledge points as well as the relation between them, this paper defines the discipline knowledge order map as the stable knowledge framework for learners. Because the static KOM cannot keep up with the dynamic changes of the learning situation, attribute extension is carried out. Then a real-time updated, personalized cognitive structure that matches the learner's cognitive level is constructed.

In order to be in line with the learning process, the personalized cognitive structure is layered, and perfect hierarchical information plays an important role in measuring the of learning influence between knowledge points. In terms of the application of personalized cognitive structure we propose a method to measure the learning influence between nodes in PCS, which enable the online learning system to calculate the learning expectation of the new knowledge point according to the learner's current cognitive level. So as to the system can push the appropriate next learning objective for learners and improve the efficiency of online learning.

Another note: Figure 3 and Figure 5 were automatically drawn by the knowledge visualization editing software developed by ourselves.

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