A Knowledge-Based Teaching Resources Recommend Model for Primary and Secondary School Oriented Distance-Education Teaching Platform

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Abstract In distance education systems, the ranked list of resources is very important for learners and teachers to find useful resources effectively. Apart from user's interest, the knowledge point of subject is a crucial factor for education system, especially for primary and secondary school oriented distance education. Much of the previous work are models based on recommender systems, however, these models considered only user's interest, ignoring the crucial impact of subject knowledge. In order to improve the performance of recommender systems, we considered both the subject knowledge and user's interest. To get this target, Latent Knowledge Model (LKM) is adopted. LKM is a knowledge-based and teaching task-oriented model. It enables subject knowledge resources through knowledge tree extended search strategy, and gets personalized resources through user feature mining strategy. LKM is realized on real data sets which are obtained from a popular distance education teaching platform. Recall and precision rate are used to evaluate the performance of our proposed method for resources recommendation tasks. Experimental results show that the LKM captures subject knowledge and personal preferences for resources selection, which yields significant improvement in recommendation accuracy.

Keywords Distance education. Knowledge tree. Extended search. User feature. Recommender system.

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1 Introduction

The concept of distance education has been getting more and more popular during the last half decade. As a result, network educational resources and the number of various network educational platforms have drastically increased. However, the lack of effective organization of the overloaded educational resources brought difficulty to users, especially to teachers in teaching task (such as teaching design, courseware or homework assignment) to get effective resources quickly and accurately. Effective recommender algorithms can separate useful resources from mass of information. Thus, recommender system becomes a very good idea to solve this problem.

Personalized recommendation approaches are firstly proposed and applied in ecommerce area for product purchase. It helps customers find products which they would like to purchase by producing a list of recommended products [1-3]. There are some well-known recommendation techniques [4]: the items are recommended to users based on user's past activities (interest) in content-based recommender system; the items are recommended to users based on people with similar interests liked in the past in collaborative filtering recommender system; the items are recommended to users based on rules that enable precisely the recommended items to those that limiting particular conditions in rule-based recommender system. To improve performance, sometimes these techniques combine together as a hybrid recommendation [5-6]. The system justifications can be obtained from preferences directly expressed by users, or from the customer experience represented by data [7].

However, education resource, especially resource in primary and secondary school oriented distance education, has its own unique characteristics. These unique characteristics can be used in resources management systems or recommendation systems. We summarized these unique characteristics as follows:

1. Education resources are closely related with subject knowledge
2. Education resources have hidden semantic relations, so resources can contact with each other through teaching knowledge nodes
3. Subject knowledge formed a complex and orderly network
4. Knowledge points of certain subject play more important role than teacher's preferences and interests in subject learning, especially in China's primary and secondary school.

In order to help teachers find adequate and useful resources from mass of online teaching resources, we make use of these unique characteristics. In our proposed approach, we considered both the user's interest and subject knowledge. To realize this idea, a knowledge-based teaching task-oriented recommendation model called Latent Knowledge Model (LKM) is proposed. It enables subject knowledge resources through knowledge tree extended search strategy, and gets personalized resources through user feature mining. The LKM achieves significant improvement in recommendation accuracy.

The rest of this paper is organized as follows: a brief literature review in topics related to this paper is given in Section Ⅱ. Section Ⅲ is a core section explaining the composition of LKM which contains the concept of extended search strategy and user feature mining strategy. In SectionⅣ the proposed LKM based recommendation system is introduced, with a discussion on how to get parameters and how to recommend resources. Section Ⅴ gives the recommendation evaluation results. Finally SectionⅥ gives an overall discussion and conclusion, together with directions for future research.

2 Related Works

In recent years, the mainly knowledge-based approach employed in resources recommender system is ontology-based resource management method. In [8], it introduced an ontology-based framework for semantic search of education content in E-learning, and its main idea is that the domain ontology is used to represent the learning materials. The ontology here is composed by a hierarchy of concepts and sub-concepts. However, this method still cannot meet the extended search requirement because of the absence of relationship between resources. In another work [9], the education resources are recommended using the semantic relationship between learning materials and the learner's need. But this recommender model makes the learner's need as the recommend center rather than the teaching goal. As a result, there will have a deviation in the final resources recommendation list. The research purpose in [10] is to study the personalized service of basic data resources integration platform based on ontology, to combine the traditional personalized service technology with ontology, to analyze user's preferences and demands, and then to design a user model based on ontology direct to the features of basic data resources integration platform which includes multiple fields of specialty, multiple information resources and multiple subsystems. This work also focus in user's preferences and demands, ignored the knowledge points hidden in subjects.

Our proposed method, LKM, is different from the aforementioned methods because the relations among resources are organized through knowledge tree. There are three innovation points: extended search, extending depth controllable and large potential of knowledge mining. Apart from enjoying good performance, LKM, also maintains personalized teaching style reflected by user features.

3 Latent Knowledge Model

In this section, we provide the core theories on the problem of education resources recommendation, LKM, which include knowledge-based extended search strategy and user feature mining strategy. We first describe the organization of knowledge tree, and then introduce our knowledge-based extended search work briefly. The user feature mining strategy will be explained later for the integrity of LKM.

3.1 Knowledge Tree Structure

In order to implement knowledge mining among resources, we need to construct knowledge trees which contact education resources with each other. The principle of constructing knowledge tree can be summarized as follows:

1. Knowledge tree is composed of a hierarchy of knowledge nodes and sub knowledge nodes.
2. The hyponymy relation and synonymy relation between knowledge nodes contain parent-child relation and leader-membership relation. The parent-child relation has inherited attribute and the leader-membership relation has reverse inherited attributes.
3. Every knowledge node is composed of several attributes, and each attribute is represented by attribute name and attribute value. These attributes reflect the knowledge points of the current knowledge node.

After the comprehensive and careful investigation of teaching material of Chinese primary and secondary schools, we build our domain knowledge tree for distance education resources. We determined the basic resource knowledge tree organization model—“1+n” knowledge tree structure, which include one basic tree (textbook transverse knowledge tree) and n extended trees (such as subject longitudinal knowledge tree, people tree, events tree, place tree and etc).

The textbook transverse knowledge tree is organized by national textbook classification criteria, takes the “section” as each branch’s terminated note, and makes several attributes to represent the knowledge of this “section”. In a similar way, we obtain our subject longitudinal knowledge tree through summarizing the longitudinal knowledge of certain subject in a period of time. The people tree, events tree and place tree contain the important persons, events and place that referred in textbooks. Figure 1 is a textbook transverse knowledge tree schematic diagram of the text “Qilv • Changzheng”, the attributes of this section are author, background, genre and place.

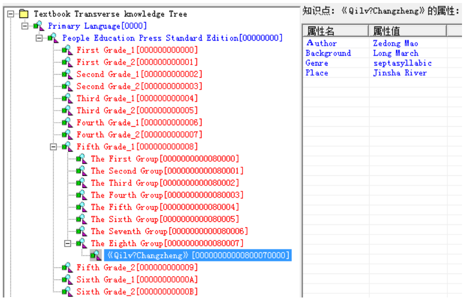

Fig. 1 The textbook transverse knowledge tree schematic diagram of text "Qilv • Changzheng "

3.2 Knowledge-Based Extended Search Strategy

Knowledge-based extended search strategy searched the semantic related attributes of a given teaching task through several knowledge trees. And then the most important resources of this given teaching task can be founded. With the constructed knowledge tree structure, we implement our extended search strategy according to the following steps:

1. Teaching object locate: locate the current teaching object to a certain section of the basic knowledge tree(textbook transverse knowledge tree)
2. Attributes search: search other related attributes of knowledge nodes from several extended knowledge trees through attribute values of the basic knowledge tree
3. Attributes extended search: repeat the above step using the current attribute values until the extending depth meet requirement. It should be pointed out that the depth of extended search can be defined by users, and usually 1-3 times attributes query will offer enough information.
4. Recommended resources list construct: take the searched attribute values as keywords to search the related resources. Different extended depths of researching sources have different weights. Usually, the deeper the search extended, the smaller the weights are.

Assuming the teaching task is courseware design, we implement the strategy on a special object "Qilv • Changzheng": through the attribute of textbook transverse knowledge tree, we get the author of the text "Qilv • Changzheng" is Zedong Mao, and then we can extend to the knowledge node of "Zedong Mao" of the people tree, through which we can obtain more information and resources about "Zedong Mao", such as the attribute about his literary works or the attribute about his achievements. In a similar way, through other attributes of textbook transverse knowledge tree, we can extend to the rest of the five trees and get enough information of this section. Then we take those semantic related attribute values as keywords to search for resources. Figure 2 is the extended search process schematic diagram of section "Qilv • Changzheng".

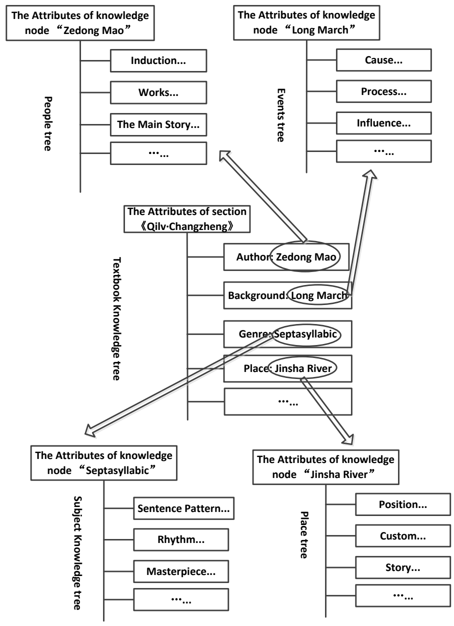

Fig. 2 The extended search process schematic diagram of text "Qilv • Changzheng"

3.3 User Feature Mining Strategy

In teaching platform, each teacher user has individual differences, such as age, gender, address, cognitive level, educational background, hobbies, etc. The teachers in the teaching platform tend to reflect personalized style. User feature mining strategy can help teachers get personalized recommendation to meet each teacher's unique requirement. For this purpose, the user features are represented by a vector space $U_N(\cdot)$ representing N features. Take the features age, gender and address for example, the user features can be described as follows:

$$U_N(\cdot) = U_N(1, 1, 010) \qquad (1)$$

On the above equation, age=1 denotes the user's age below a certain number, gender=1 denotes the user is male and address=010 denotes the user living city is Beijing. Different feature has different affect in the process of recommending, therefore, our user feature mining task is to find the weight of each feature.

The feature weights can be acquired by calculating the distribution of downloading resources. In our strategy, we take the overall variance of resources in each feature as the initial weights firstly. And then the accurate weights are obtained by dataset training using recall and precision rate for resources recommendation tasks. The weights of user features are represented by another vector space $W_N(\cdot) = W_N(a, b, c \dots)$ which will be calculated in the final recommend rank algorithm.

4 Resources Recommendation Using Latent Knowledge Model

In the knowledge-based recommender system, LKM attempt to obtain the top-K resources which reflect both the knowledge points of the current teaching object and teacher's personalized teaching style. In this section, the way to achieve this goal through the proposed recommender system architecture is explained.

4.1 Recommender System Architecture

The inputs of recommender system are depth of extended search and teaching task tag, while the output is recommended resources list. The idea of system can be summarized as follows:

1. Construct the "1+n" knowledge tree structure
2. Implement extended search strategy to obtain related teaching semantic object keywords
3. Generate knowledge-based recommended resources list
4. Implement user feature mining strategy to obtain the user features which reflect teacher's personalized teaching style
5. Generate knowledge-based recommended resources list
6. Generate the final recommended resources list through resources rank algorithm

The Graphical system architecture is presented in figure 3.

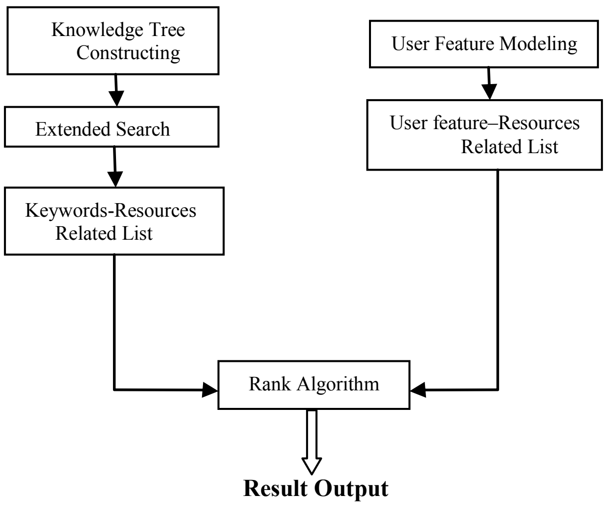

Fig. 3 Graphical recommendation system architecture

4.2 Rank Algorithm

We use the following formula to compute the final recommendation result:

$$L = \sum w_{ki} L_k(i) + \sum w_{uj} L_u(j) \tag{1}$$

On the above equation, L is the final ranked resources recommendation list, $L_k(i)$ and $L_u(j)$ denotes the ranked resources recommendation list obtained from extended search and user feature mining respectively. The index i denotes the recommendation results decided by ith level extended search and the index j denotes the recommendation results decided by jth user feature. Variables w_{ki} and w_{uj} express the weights of each recommendation results. We obtained the final ranked recommendation result by finding the optimal weights.

5 Experiment Results

In this section, the experiment results are reported on two different teaching object data sets collected from the CASIA-HHT Joint Laboratory of Smart Education[2]. The first (small) data set consists of 42 users, 684 resources and 931 tags. The second (big) data set consists of 106 users, 911 resources and 3885 tags. 90% of data for training and 10% for testing, and experiment with 10 times repeat. We choose the user features of age, gender and address for personalized training, and set the extended search depth as two.

Recommendation performances in resources recommendation task are evaluated by precision/recall. Assuming R(u) denotes resources recommended to user u, and T(u) denotes resources tagged by user u, the precision/recall functions are defined as follows:

$$\text{Precision} = \frac{\sum_u |R(u) \cap T(u)|}{\sum_u |R(u)|} \tag{2}$$

$$\text{Recall} = \frac{\sum_u |R(u) \cap T(u)|}{\sum_u |T(u)|} \tag{3}$$

The parameters optimized through training based on recall from small dataset are $w_{k1} = 0.92, w_{k2} = 0.33, w_{u1} = 0.67, w_{u2} = 0.81, w_{u3} = 0.12$, while the pa-

[2] The education resources datasets can be collected from: http://www.910edu.com/reslibsrv/web/index/index.do

rameters optimized through training based on recall from big dataset are $\mathrm{w}_{\mathrm{k}1} = 0.39, \mathrm{w}_{\mathrm{k}2} = 0.11, \mathrm{w}_{\mathrm{u}1} = 0.18, \mathrm{w}_{\mathrm{u}2} = 0.28, \mathrm{w}_{\mathrm{u}3} = 0.04$. We compare the recommendation results between our LKM and DM (which based on simply recommend the top-N resources according to download rate). Table 1 reports the recall values at top-20 and top-100 resources. The results in table 1 clearly show the superiority of LKM approach. Resources recommendation recall values of LKM are consistently higher than those of the DM-based method, up to about 33% in accuracy. Note that except the precision/recall accuracy, LKM approach can also recommend some amazing and unexpected resources which may be very useful to teachers due to the subject knowledge organized in knowledge trees.

Table 1 Recall @ 20 and Recall @ 100 values of LKM and DM for resources recommendation in the two datasets.

Method	Dataset	Recall @20	Recall @ 100
LKM	Small	0.429	0.857
DM	Small	0.286	0.714
LKM	Big	0.667	0.916
DM	Big	0.583	0.833

6 Conclusions and Future Work

In this paper, we introduce our work of a novel knowledge-based personalized teaching resources recommendation method called LKM. The advantage of this approach is the ability to joint subject knowledge and personalized feature. Experiments on real datasets show the effectiveness performance of LKM in both small and big dataset. Note that besides the precision/recall accuracy, LKM approach can also recommend some amazing and unexpected resources which may be very useful to teachers due to the subject knowledge organized in knowledge trees. The recommender model has three innovation points:

1. Extended search: we implement extended search through attributes of these five knowledge trees.
2. Extending depth controllable: the depth of extended search can be defined by users.
3. Large potential of knowledge mining: besides the attributes of knowledge nodes, other features of knowledge tree can also be considered for semantic mining, such as the hyponymy of knowledge nodes.

In the proposed method, a core problem is the organization of knowledge tree. A strong knowledge tree structure may help user find enough and satisfied teaching resources. On the other hand, effective user features play important impact on personalized recommendation. Those two issues are the subjects of our further work.

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