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Development of Personalized Learning Resources Recommendation System Based on Knowledge Graph

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Abstract

This study focuses on how to efficiently and accurately recommend personalized learning resources for users when they are in the face of massive learning resources. A recommendation system is developed with software engineering methods. Knowledge graph technology is integrated in the system; curriculum knowledge graphs are constructed to solve the problems of semi-structured data storage and knowledge fragmentation. Two kinds of recommendation methods are adopted to achieve the goal of learners' personalized learning, one is Euclidean distance recommendation algorithm based on user behavior graph library, the other is learning mode recommendation algorithm and sequential mode recommendation algorithm based on user session library. The recommendation system maintains the interpret-ability and the accuracy of recommendation based on user historical behavior data; and realizes recommendation based on user session library in the context of lacking users' historical data.

Keywords:
Knowledge graph
Personalized recommendation
Session system.

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1. Introduction

Online learning has become a main learning style. However, learners often encounter problems such as network trek, cognitive overload, knowledge fragmentation and so on when they learning from massive resources in the Internet. The problems greatly affect learners' interest and learning efficiency. Therefore, how to recommend personalized learning resources has become a key issue in current online education.

Research on personalized recommendation algorithms is recommendation algorithms based on content filtering and recommendation algorithms based on user filtering. The former determines the recommended content based on the "user-resource" relationship (Hongwei & Guangwei, 2009); The latter determines the recommended content based on the "user-user" relationship (Hui, 2020). Most recommendation systems adopting the above algorithms store data using relational databases (Wei & Bing, 2020). The efficiency and response performance of the connection query will inevitably decrease when the scale of the system is too large with a large number of tables. In addition, the above algorithms rely on the users' historical data (Rong

& Hongtao, 2020), so it cannot meet the requirements of making a reliable recommendation for users in the absence of historical data.

The knowledge graph describes all online learning resource entities and their associated relationships in the form of triples {subject, relationship, object}(Xiaolan & Zhijian, 2018). It provides a good, standardized, semantic-level description standard for online learning resources, which solves the problems of resources unified store and integration cased by heterogeneous descriptions, resource redundancy and inconsistent label semantics in traditional learning resources management. At the same time, it automatically establishes semantic-level knowledge associations for massive learning resource entities, and develops connection among various educational knowledge points through accurate semantics.

This study aims to develop a personalized learning resources recommendation system using software engineering methods. This research uses a graph database to store data based on knowledge graph theory and combines with a session system to improve efficiency and reduce dependency on historical data.

2. Basic Architecture of the Recommendation System

The core functions of the system include constructing and visually displaying curriculum knowledge graphs, which allows learners to clarify the main learning systems and goals, storing learning resources based on knowledge graphs, and recommending personalized resources for users through relevant recommendation algorithms. The system has three main parts: curriculum knowledge graphs library, user behavior graphs library and a session library. Its basic structure is shown in Figure1.

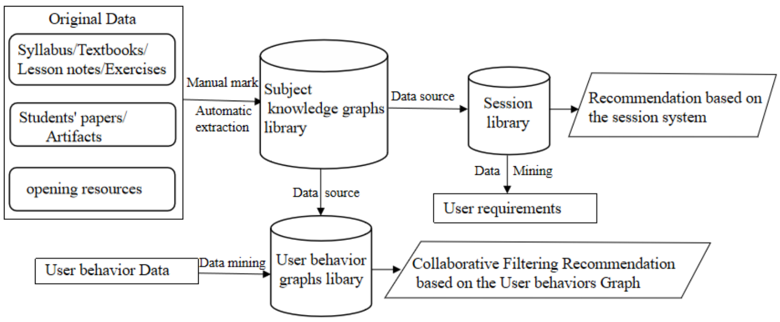

Figure-1. Basic architecture of the recommendation system.

2.1. Construction of Curriculum Knowledge Graphs

Construction of curriculum knowledge graphs is divided into three steps: knowledge extraction, entity recognition, and relationship extraction. Knowledge extraction is mainly to extract structured data and semi-structured data; Entity recognition uses the LSTM model (Xiyu & Qimai, 2018) based on deep learning to identify entities. Relationship extraction uses ACE relational data extraction model (Shaoheng, Donghao, & Lulu, 2015) based on deep learning. The original data comes from resources in educational field such as syllabus, textbooks, exercises, artifacts etc, and also comes from opening resources such as Encyclopedia, and China University MOOC. A example of a curriculum knowledge graph is shown as Figure 2.

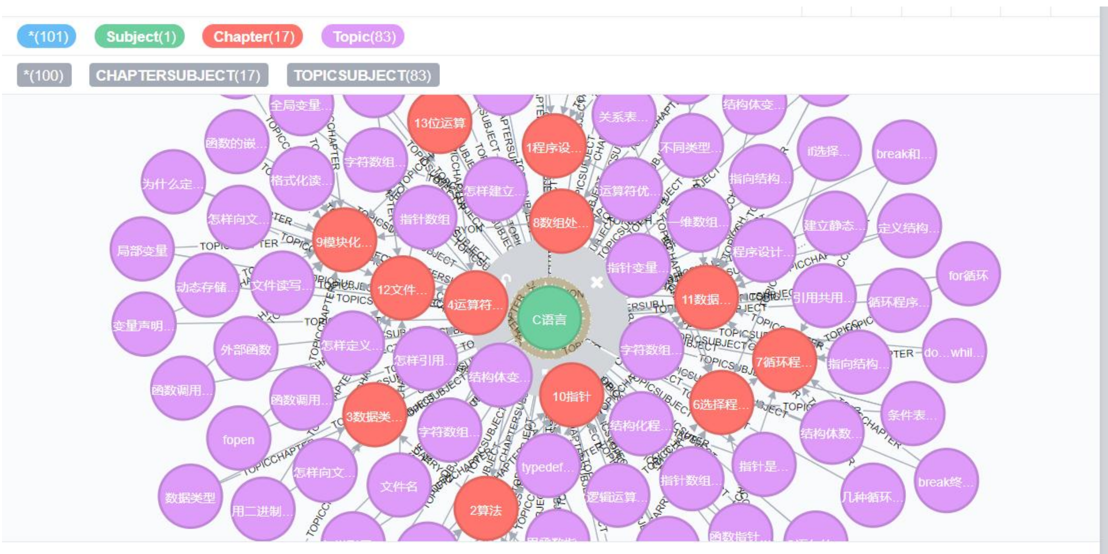

Figure-2. A knowledge graph in C Language.

2.2. Construction of User Behavior Graphs

There are two types of user behavior graphs in this study. One type is constructed as user-behavior-project user behavior graphs through extracting historical data (browsing, favorites, ratings, likes, etc.) of user interaction with the project. The other type is constructed as user-behavior-project user behavior graphs through extracting historical data of user-user interaction (follows, comments, etc.)

2.3. The Session Library

Sessions refer to the process of data exchange between a user and an interactive system. There is an accessing rule of session type within a certain period of time when users acquire learning resources in the Internet (Nan, 2019). When users obtain resources, they will present a theme within a certain period of time, and will expand around the theme in a session. Recommendation based on session library can can be modeled as a serializable problems, take users' multiple interaction data as input, predict the content that the user may learn in the next moment through the algorithm, and take the higher priority as the output. The recommendation technology based on sessions can provide reasonable recommendation responses for users in the absence of historical data.

3. Key Recommendation Methods in the System Developing

3.1. Euclidean Distance Recommendation Algorithm Based on user Behavior Library

The recommendation algorithm is shown as Figure 3.

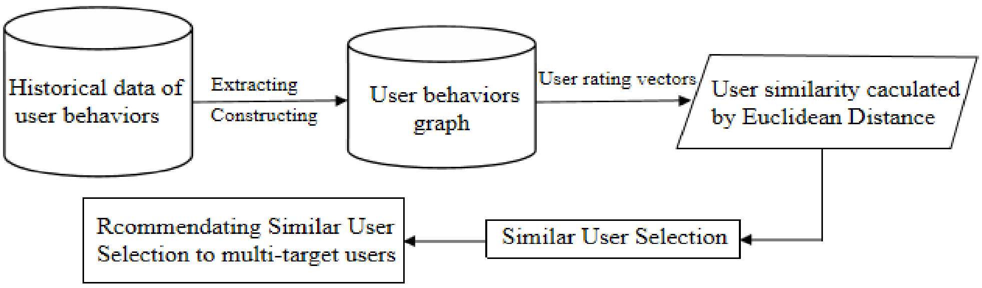

Figure-3. Procedure of Euclidean distance recommendation algorithm based on user behavior library.

Key idea of the Euclidean distance recommendation model is calculating the similarity index according to users' historical rating. It takes resources jointly evaluated by the two users as a dimension to construct a a muti-dimensional space. In the space, it takes the resources jointly evaluated as the horizontal coordinate system X(s1 ,s2,s3,...,sn), and takes scores evaluated resources on a single dimension by users as the vertical ordinate system Y (g1, g2, g3,..., gn), it considers the Euclidean distance Distance (X, Y) between any two positions as the similarity of the two users. The formula for calculating Euclidean distance is given below:

$$\text{Distance(X,Y)}=\sqrt{(s1-g1)^2+(s2-g2)^2+(s3-g3)^2+\ldots+(sn-gn)^2} \quad (1)$$

In the user behavior library, users' preferences are shown in Figure 4. Henry is the target user, user Jerry and Mark have rated resources of "float data" and "function call of function pointer".

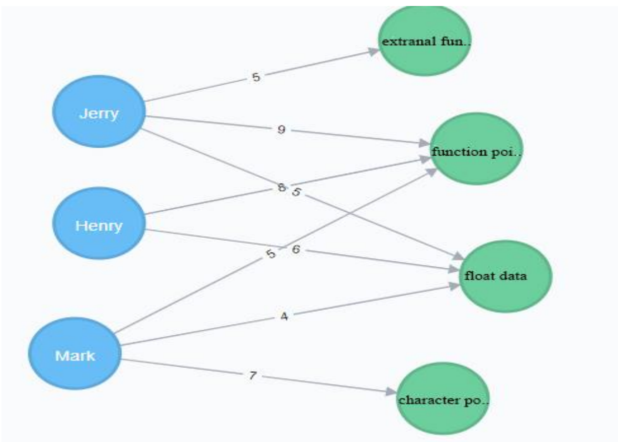

Figure-4. The procedure of Euclidean distance recommendation.

We can get the score vector of the two common resources of "float data" and "function call of function pointer" rated by three users: $\overrightarrow{\langle 8,6\rangle}$ $\overrightarrow{\langle 9,5\rangle}$ $\overrightarrow{\langle 5,4\rangle}$,and we can calculate the similarity index between the target user and similar users:

$$Distance(H,J) = \sqrt{2} \tag{2}$$

$$Distance(H,M) = \sqrt{13} \tag{3}$$

The similarity of users is compared by calculating the Euclidean distance values of multiple sets of data. The user difference is smaller as the value is smaller. If the similarity is higher, then the resources data from similar users will be given a higher order in the recommended candidate set (Liwei & Bitao, 2018). Applying this similarity index calculation to the recommendation system, we can easily obtain the preference list of similar users with high similarity and find the resources that have not been browsed by the target user, and then get the recommendation result as shown in Figure 5.

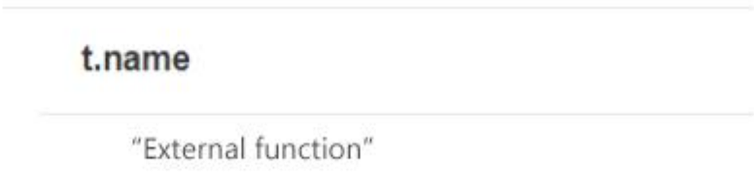

Figure-5. The recommendation result based on the Euclidean distance algorithm.
Source: An interface of the recommendation system developed by our research team.

3.2. Recommendation Method Based on user Session Library Model

The procedure of the recommendation algorithm is shown in Figure 6:

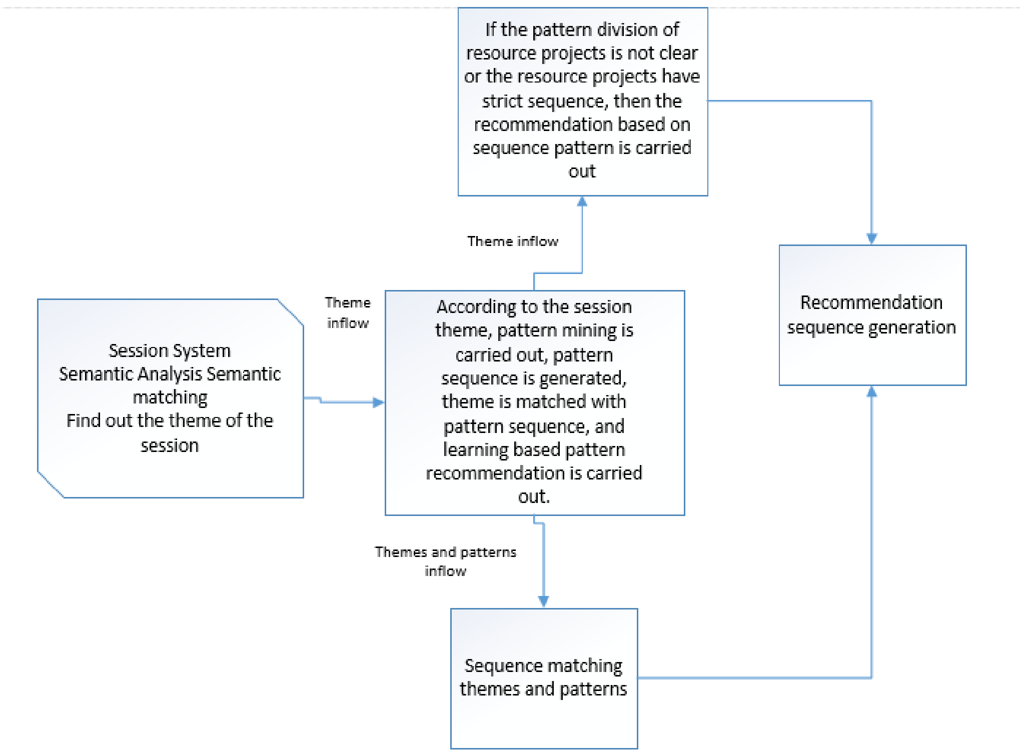

Figure-6. The procedure of the recommendation algorithm based on user session library model.

3.2.1. The Recommendation Method Based on Learning Pattern

The recommendation model based on learning pattern mainly includes three modules: learning pattern mining, topic matching and resource recommendation. Firstly, it mines learning patterns, and then uses learning patterns for continuous recommendation according to the theme.

For example, we get a session in a historical session: "pointer / pointer variable / what is a pointer". We can extract the topic "pointer" through semantic analysis, and then match this learning mode {concept, utilization, Test} in the learning pattern set. Firstly, we provide feedback resource "the concept of pointer variable" to the user, then predict information searched next step by the user, and prepare the candidate resources list for the user as shown as Figure 7.

d2.name	d3.name
"Application of pointer varialbe"	"Pointer varialbe exercises"

Figure-7. The recommendation result based on learning pattern.

3.2.2. The Recommendation Method Based on Sequential Pattern

Sometimes as the division of learning pattern is not clear or cannot be clearly divided in the structure of learning resource graph , we can add precursor and successor relationships for the learning notes in the pattern, or set weights for all relationships around the resource, so that there is a certain order between the nodes. In this way, we can use the sequential pattern to solve the problem, search the successor node or the node with higher weight as the member of the recommendation list.

4. Conclusion

The recommendation of learning resources should not only be efficient, but also consider the appropriateness and knowledge integrity. Based on these goals, this study integrates knowledge graph technology into the personalized resources recommendation system, constructs curriculum knowledge graphs through extracting data from different kinds of resources to avoid knowledge fragmentation. As developing the system, we adopt two kinds of recommendation methods to achieve the goal of learners' personalized learning, one is Euclidean distance recommendation algorithm based on user behavior graph library, the other is learning mode recommendation algorithm and sequential mode recommendation algorithm based on user session library. The next research is to analyze the data in practical application to explore the efficiency and accuracy of the two kinds of recommendation methods in this paper, so as to better provide personalized learning resources for users and improve the effect of online learning.

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