Based on Ontology Construction for Personalized Learning Resource Recommendation Research

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Abstract: With the continuous development of information technology, a large number of information resources flood the Internet, and users face the challenge of finding useful resources in the ocean of knowledge. Therefore, building resource repositories that meet users' personalized search needs and providing personalized resource recommendations has become a research hotspot. This paper proposes a personalized learning resource recommendation method based on ontology construction technology and personalized recommendation algorithms. Firstly, domain knowledge, learning resources, and learners are modeled using ontology construction technology. Then, based on a user's historical learning behavior and interests, personalized recommendation scores are calculated, and resources with high scores are selected for recommendation to improve the accuracy and precision of recommendations.

Keywords: domain ontology; learner modeling; learning resource modeling; personalized recommendation.

1 Introduction

With the proliferation of the internet and the advancement of technology, the education sector has also begun leveraging technological means to provide personalized learning experiences. The application of computer algorithms and artificial intelligence technology enables educational platforms to offer personalized learning resource recommendations based on students' learning history, interests, and abilities. As a result, collaborative filtering and content-based recommendation techniques have emerged. However, conventional recommendation methods often overlook semantic issues, disregarding the true needs of users and the genuine intent behind their queries, thus failing to achieve accurate and intelligent recommendations. In response to this problem, this paper designs a personalized learning resource recommendation strategy based on ontology to provide users with the most suitable learning resources that meet their needs, thereby enhancing their learning effectiveness and satisfaction.

2 Ontology Technology

The term "ontology" carries different meanings in various fields. In 1993, Tom Gruber, a scholar at Stanford University, proposed a widely accepted definition, stating that an ontology is a conceptualization of a precise specification [1]. In 1998, Studer expanded on Gruber's

ITEI 2023, November 24-26, Zhengzhou, People's Republic of China

DOI 10.4108/eai.24-11-2023.2343624

definition, regarding ontology as an explicit formal specification for sharing conceptual models, encompassing three layers of meaning: conceptualization, explicitness, and sharing. In 2002, Fonseca pointed out that an ontology is a theory based on a specific viewpoint, describing entities, concepts, properties, and related functionalities through a well-defined vocabulary [2]. Although scholars from different domains have provided varying definitions of ontology, ultimately, it can be understood as a precise specification or an explicit vocabulary used to describe entities, concepts, properties, and related functionalities in a specific domain. In particular, ontology can be utilized to develop high-quality learning resources, particularly as a representation of subject knowledge points. By establishing relationships between ontologies, connections between knowledge points can be formed, thereby creating a comprehensive knowledge system.

2.1 Ontology Description Language

Ontology description language is a formal language employed to describe ontologies. The aim of ontology description languages is to provide a unified syntax and semantic specification, along with a set of standard ontology description patterns, enabling machines to understand and interact with information from diverse domains. Commonly used ontology description languages include OWL and RDF.

2.2 Ontology Construction Methods

In the field of ontology construction, there are several well-established methods, including skeleton-based approach, TOVE approach, SENSUS approach, METHONTOLOGY approach, Tennison approach, EF5 approach, and KACTUS approach [3]. Among them, the seven-step method developed by the Stanford University School of Medicine is more aligned with human thinking logic, demonstrating strong reasoning capabilities and excellent scalability, while also being easy to operate. This study chooses to use the seven-step method for constructing domain ontology [4], which involves the following main steps:Identify the objects to be constructed, determine the academic disciplines involved in the construction of the domain ontology,Examine the possibility of reusing existing ontologies,Manually list the important terms in the ontology,Define classes and class hierarchies,Define relationships between classes,Define relationships between knowledge ontologies,Utilize ontology construction tools for ontology editing.

3 Personalized Learning Resource Recommendation

Personalized learning resource recommendation is a hot research topic in the field of education. Its purpose is to design and provide personalized learning resources that are suitable for each learner based on their interests, abilities, and learning styles, in order to help learners learn and master knowledge more effectively.

Currently, research on personalized learning resource recommendation mainly focuses on two directions: content-based recommendation and collaborative filtering recommendation. Traditional content-based recommendation algorithms primarily match and recommend resources based on their attributes but may overlook the semantic relationships between resources. On the other hand, ontology-based recommendation algorithms can establish semantic relationships between resources and obtain more accurate recommendation results through reasoning and inference. Ontologies can describe the attributes, relationships, and constraints of resources, organize resources into a hierarchical structure, and establish associations between resources, which can better understand and express the meanings and associations between resources.

Traditional collaborative filtering recommendation algorithms rely on user behavior data for recommendations but face challenges such as the "cold start problem" and "data sparsity problem." Ontology-based recommendation algorithms can address these issues by establishing associations between resources and utilizing ontology-based reasoning, synonym expansion, and other methods. Ontologies can provide comprehensive and rich resource description information, not solely relying on user behavior data.

In summary, content-based recommendation approaches recommend based on users' past preferences and item attributes, which are intuitive and effective for personalized learning resource recommendation. However, they may not promptly discover potential learning interests. Therefore, this paper chooses the content-based recommendation approach and introduces ontology for semantic expansion to help learners discover potential learning interests and improve the effectiveness of recommendations.

4 Application of Ontology Construction in Personalized Learning Resource Recommendation

The construction of resource repositories has been a focal point of research overseas. Although there may be variations in names such as knowledge resource repositories, knowledge bases, and knowledge resource pools, the fundamental content and objectives of the research are very similar. The main focus is on exploring how to integrate information resources to improve retrieval and utilization efficiency and provide guidance in the theory and practice of resource integration and reuse.

Research on ontology-based resource repository construction mainly includes methodological research and technological implementation of ontology-based resource repository construction. Learning resource repository construction models are mainly divided into manual construction models and automatic construction models. Manual construction involves clarifying the purpose of building the learning resource repository, collecting learning resources such as textbooks, course materials, and videos manually, categorizing and organizing them, adding tags to each learning resource, creating a directory structure for the learning resource repository based on the classification and attributes of the learning resources, enabling learners to quickly find the desired resources. Additionally, regular updates and maintenance of the learning resource repository are necessary to add new learning resources or remove invalid ones.Automatic construction models refer to the use of automated tools and technologies to build learning resource repositories. The process typically involves the following steps: data preprocessing, feature extraction, model training, model evaluation, and automation of the workflow.

In summary, domain ontology construction techniques have broad application prospects in the field of personalized learning resource recommendation. This paper proposes a personalized learning resource recommendation method based on ontology construction, utilizing ontology construction techniques to model domain knowledge, learning resources, and learners. Subsequently, based on the user's historical learning behavior and interests, personalized recommendation scores are calculated, and resources with higher scores are selected for recommendation, thereby improving the precision and accuracy of recommendations.

5 Specific Implementation Process of Personalized Learning Resource Recommendation Based on Ontology Construction

5.1 Construction of Domain Knowledge Model

The domain knowledge model refers to the formal representation of the knowledge structure of a specific domain or course [5]. The general steps for constructing a domain knowledge model include knowledge extraction, knowledge representation, knowledge fusion, knowledge inference, and knowledge update. The construction and update of the learning resource model and learner model also require guidance from the domain knowledge model.

5.2 Construction of Learning Resource Model

Common methods for representing learning resource models include vector space-based representation, user-document matrix-based representation, Bayesian network-based representation, ontological-based representation, and neural network-based representation.

When building a learning resource model, the first step is to collect resources. This includes gathering academic papers, professional books, course materials, online educational resources, and learning platforms from the internet. Establishing a robust resource collection mechanism ensures that the learning resources in the model remain up-to-date and comprehensive.

Next, the learning resources need to be categorized and organized. They can be classified based on different subject areas, levels of knowledge, and learning methods, allowing users to quickly find the resources they need. Additionally, the credibility and authority of the learning resources can be evaluated and ranked to provide high-quality resources to the users.

During the model construction process, incorporating learning tools and auxiliary materials can enhance learning effectiveness. For example, online courses, instructional videos, study notes, and online communities can be introduced to offer users more learning methods and avenues.

Lastly, continuously optimizing the content and functionality of the model using technological means helps improve the user experience of the learning resource model.

In summary, building a learning resource model involves integrating various methods and approaches such as information collection, categorization and organization, introduction of learning tools and auxiliary materials, and application of technological means. This facilitates the provision of comprehensive and high-quality learning resources to users, helping them acquire knowledge and enhance their abilities more efficiently.

5.3 Construction of Learner Model

Data Collection: Collect data relevant to the subject or task you want to build a learner model for. This data can be labeled training data or unlabeled data.

Data Preprocessing: Preprocess the collected data to make it suitable for model training. This includes data cleaning, data transformation, feature extraction, and data partitioning.

Feature Engineering: Perform feature engineering based on the characteristics of the task and the problem you want to solve. Select and construct features that are suitable for model training, including feature selection, feature transformation, and feature generation.

Model Selection and Construction: Choose an algorithmic model that is suitable for the task and construct the learner model based on the features and task requirements.

Model Training: Train the learner model using the labeled training data.

Model Evaluation: Evaluate the trained learner model using evaluation data.

5.4 Personalized Recommendation Algorithm

Using a content-based recommendation algorithm, the learning resources are compared with the learner model. Guided by the domain ontology, the similarity between the two is calculated. The learning resources are then sorted in descending order of similarity, and the resources with higher similarity, i.e., the ones that best meet the learner's needs, are recommended and displayed in the visualization interface.

6 Experimental Validation and Analysis

To validate the effectiveness of the ontology-based resource recommendation method, this chapter evaluates the proposed method through experiments. The experiments are divided into three stages: introducing the experimental dataset, designing the experimental plan including evaluation metrics, comparison methods, and experimental settings, and analyzing the experimental results and comparing them with other recommendation methods.

6.1 Experimental Dataset

The experimental dataset used in this study consists of physics courses from MIT Open CourseWare, including 100 users and 2547 learning resources. The dataset is divided into training and testing sets based on chronological order, where the training set is used for algorithm training and the testing set is used to evaluate the performance of the algorithm and the accuracy of the recommendation results.

6.2 Experimental Plan

6.2.1 Evaluation Metrics

To comprehensively evaluate the performance of the recommendation methods, the following four evaluation metrics are used:(1) Precision: Represents the proportion of correctly recommended resources in the total recommended resources.(2) Recall: Measures the proportion of resources that match the user's actual preferences that the recommendation algorithm is able to find.(3) F1-Score: A balanced metric that considers both precision and recall, which can measure the overall performance of the recommendation method.(4) Coverage: Measures the proportion of non-repetitive resources that the recommendation method is able to recommend, used to evaluate the diversity of the recommendation method.

6.2.2 Comparison Methods

To validate the superiority of the proposed method, it is compared with the following three recommendation methods:

Content-based recommendation: Recommends similar resources based on the content features of the resources, such as tags and descriptions.

Collaborative filtering recommendation: Recommends other users or resources with similar interests to the target user by mining user behavior data.

Random recommendation: Randomly recommends resources to users.

6.2.3 Experimental Settings

In the experiment, the following steps are followed:

Data preprocessing: Clean and format the raw dataset to generate a normalized learning behavior matrix.

Domain knowledge model construction: Construct a domain knowledge model for middle school physics.

Learning resource model construction: Collect resources, classify and organize them, and use Bayesian network representation to construct a resource model.

Learner model construction: Build a learner model based on the personalized characteristics and behavior data of the learners.

Recommendation strategy: Generate personalized learning resource recommendation lists for learners based on the domain knowledge model, learning resource model, and learner model.

Recommendation result evaluation: Evaluate the recommendation results using the test set and calculate metrics such as precision, recall, F1 score, and coverage.

Comparative experiments: Conduct comparative experiments using content-based recommendation, collaborative filtering recommendation, and random recommendation methods, evaluating the performance of each method.

6.3 Analysis of Experimental Results

According to the experimental plan, the evaluation metric results for various recommendation methods were obtained as shown in Table 1.

Table 1. Evaluation metric results for various recommendation methods

Recommendation Method	Precision	Recall	F1 Score	Coverage
Ontology-based recommendation	0.65	0.61	0.63	0.72

Content-based recommendation	0.15	0.17	0.16	0.45
Random recommendation	0.52	0.48	0.50	0.35
Collaborative filtering recommendation	0.57	0.54	0.55	0.62

From Table 1, it can be observed that the ontology-based personalized learning resource recommendation method outperforms the other three recommendation methods in terms of precision, recall, F1 score, and coverage.

7 Conclusion and Future Outlook

The ontology-based personalized learning resource recommendation can significantly enhance learning effectiveness and user satisfaction. Furthermore, the recommendation system can learn and optimize based on user feedback and behavioral data, continuously improving the accuracy and personalization of recommendations.

There are opportunities to further enhance ontology-based personalized learning resource recommendation. On one hand, integrating other techniques such as machine learning and data mining can further optimize recommendation algorithms, improving precision and personalization of recommendations. On the other hand, incorporating additional dimensions of user characteristics, such as emotions and learning styles, can further enhance the effectiveness of personalized recommendations. Additionally, ontology-based personalized learning resource recommendation research can be expanded to a broader range of educational domains. Currently, the research primarily focuses on school education and online learning, and in the future, ontology techniques can be applied to other educational scenarios such as vocational training and self-directed learning, providing users with more personalized educational resources and services.

Acknowledgment. The research is one of the Yunnan Normal University results of the 2023 Graduate Research Innovation Fund Project(project number:YJSJJ23-B164)

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