Personalized Learning Path Recommendation Based on Context Awareness

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Abstract: With the rapid integration of computer technology and sensing technology. The rapid development of the mobile Internet, Internet of Things and smart mobile terminals has been promoted. In order to promote the popularization of educational information, the construction of lifelong learning platform provides technical support and guarantee. Although the emergence of search engines helps learners find learning resources quickly and efficiently, it still cannot obtain personalized dynamic learning services. Therefore, in order to adapt to people's individual needs, at the same time reduce the user's search costs. Personalized recommendations have also become one of the research trends in referral services. The semantic matching algorithm calculates the similarity between the context ontology and the ontology of the subject domain, and calculates the knowledge information required by the learner, so as to accurately recommend the personalized learning path. This paper is based on context-aware data inference technology, and infers implicit context information according to context inference rules and constraints, and establishes an adaptive learning path. Finally, the accuracy of the model prediction method for adding scene-aware data proposed in this paper is greatly improved. Collaborative filtering algorithms are caused by data sparsity. The accuracy of mitigating prediction scores has been greatly improved.

1. Introduction

With the rapid development of the economy and the Internet, the diversity of products and services often leaves users lost in the torrent of choice. The growth of nuclear thorns also makes people need to pay more for the information they want [1]. The rich and diverse educational resources in the digital learning environment are the main source of learners' access to knowledge. However, they are also the main cause of learners' cognitive load or learning failure during learning [2-5]. When people get information content, they can easily spread from the target content to a larger amount of data, so they can't get the information they need in time. The problem of information overload has brought us a huge information burden, not only because of the productivity of Internet technology. On the contrary, since the amount of information is large and the productivity is lowered, an information push service mode is generated. According to the personalized needs of users, a recommendation system for users and goods and interaction between users and users is formed, and information that the user may need but is difficult to obtain is pushed [6-9]. Context awareness is considered an enabling technique for ubiquitous computing systems. Situational awareness is used to design innovative user interfaces that are often used as part of ubiquitous wearable computing [10, 11]. The emergence of hybrid search engines has also begun to apply to the Internet [12-14]. Recently, this article has done a lot of work to reduce the distribution of contextual information and to design transparent middleware solutions. These solutions are designed to enable context management and discovery in mobile systems. Therefore, when a learner recommends personalized educational resources based on contextual awareness, contextual information hiding variables are used to express user preferences.

2. Research on Situational Awareness Recommendation Technology

2.1 Content-Based Context-Aware Recommendation

Content-based recommendations are the most basic recommendation method in the recommendation system. This method originally originated in the field of information retrieval, especially in information filtering and text categorization. The user's interest-related description is learned by analyzing the user attribute characteristics of the hierarchical item. Finally, the relevant items most similar to the description of interest are recommended to the user. Content-based context-aware recommendations first predict and mine user requirements, ie, perceive user context information. User context information is primarily a description of the personalized service needs of users in different environments. The user context information is then matched against the recommended resources and services. Finally, the user's actual needs and potential needs are inferred and predicted based on the results, thereby forming user recommendations. The key to implementing this recommendation method is the description of the user attribute characteristics and the calculation of the matching degree. An effective way to describe unstructured projects is to calculate key weights based on TF-IDF, which is widely used in the field of information retrieval. The TF-IDF consists of the product of the word frequency and the reverse frequency of the document. The word frequency is the number of times a keyword appears in a document. The document frequency reciprocal represents the reciprocal of the keyword frequency in all documents, ie the total number of documents. The ratio of the number of documents containing keywords whose product indicates the importance of the keyword in the document. The formula for calculating TF-IDF is as follows:

$$TF-IDF(s,k)=TF(s,k)\times\log\left(\frac{|S|}{DF(k)}\right) \tag{1}$$

2.2 Situational Awareness Recommendation Based on Collaborative Filtering

The suggestion based on the context of collaborative filtering is to accurately mine the potential interests and needs of users from the perspective of the user. There is no need for complex knowledge modeling and classification of users, projects and programs. Save labor and time costs. The advantage of this recommendation method is to extend traditional collaborative filtering to user similarity calculations and model-based context-aware collaborative filtering. And by introducing context information constraints to improve the accuracy of the similarity calculation and the accuracy of the model. The learning process of the model uses existing scoring data to train the optimal user feature matrix U and the project feature matrix M. Once the two matrices are obtained, the user score data can be predicted based on the product of the two. In order to introduce the training process of the model, the user is first provided with a prediction formula for the project score:

$$\hat{r}_{ij}=(u_i)^T m_j \tag{2}$$

The basic idea of context-based collaborative filtering recommendation is that the best way to recommend the correct project for the current user is to first find the set of neighboring users that are closest to the current user's interests. The interest preferences of neighboring users can be used as current users. Recommended basis. The quality of the model directly determines the accuracy of the recommendation.

2.3 Scenario User Preference Extraction

Scenario user preference extraction is a prerequisite for context-aware recommendations. The purpose of contextual user preference extraction is to introduce context information into the user preference model. There are currently two main types of contextual user preference extraction techniques, quantitative analysis and qualitative analysis. The contextual user preferences are converted to numerical scores in a quantified form based on a quantitative analysis method.

Mathematical calculations are performed in conjunction with corresponding preference extraction techniques. Multidimensional vector scoring models and hierarchical models are widely used for quantification of contextual user preferences. This paper is based on context-aware personality learning recommendation algorithm, which extracts contextual user preferences based on quantitative analysis techniques. Unlike quantitative analysis, in order to extract contextual user preferences, qualitative analysis based methods ignore the user's quantitative value of project and attribute preferences from the perspective of logical reasoning and partial ordering models. And the user's deviation between any two items or corresponding attributes is extracted. This method mainly studies the "binary part order relationship" of the project and its attributes under the constraints of the user context.

3. Experiments

The theory of personalized learning that supports this research mainly includes social construction theory. The theory of social construction was formed and developed in the process of the integration of Vigsky's three philosophical thoughts and psychological development theory. It advocates that knowledge originates from the meaning construction of society, and learners should actively interact in the social environment. Social constructivism believes that individuals and society are interrelated. Emphasis on learner learning is mainly done by participating in social practice. Social constructivism points out that learners can gradually acquire knowledge or ideas that were previously unfamiliar with the help of more capable learners. However, not all dialogues and discussions make sense for learning, nor are all web-based learning. Online e-learning should also be guided by social constructivism. Pay attention to the social interaction of students, provide students with a harmonious and independent communication platform, and pay attention to the growth of students' collaborative work.

According to the research needs of the personalized learning path recommendation problem in the online learning community, the corresponding research framework is given. The framework works on the basis that when searching in a state in the domain knowledge domain state space, it will be based on the current learning. The feature data of the model is implemented by an ant colony algorithm to determine the next search direction. This process can be repeated until the search reaches the leaf nodes in the state space so that the online learning community can be obtained. The personalized learning path for a particular learner function is shown in Figure 1.

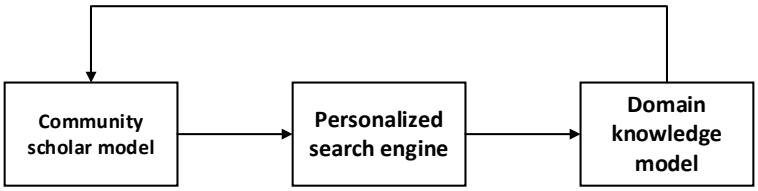

Figure 1. Personalized learning path recommendation workshop framework

As shown in Figure 1, the personalized learning path recommendation research framework consists of a personalized learner model based on an online learning community. The personalized learner model describes the learner's characteristic information and reflects the learner's learning progress from the side. Building an actionable and sensible personalized learner model helps the system to mine the associations between various learning-related data in educational big data. Finally, according to the different learning characteristics of learners at different stages of learning. Different learning pathways that suit their needs and goals have inspired their interest and enthusiasm for learning. The role of the domain knowledge model is to describe learning resources or objects in a structured way. The personality recommendation engine is the core component of the personalized learning path recommendation and is the carrier of the personalized learning path recommendation algorithm. Its role is to calculate a personalized learning activity plan or plan suitable for the learner based on the learning characteristics and personality characteristics of the individual learner described in the learner model.

4. Discussion

4.1 Accuracy Analysis of Various Recommendation Algorithms under Different Data Sparse Degrees

To test the predictive accuracy of context-aware personalized learning recommendation systems, the system combines the adaptive weights of the two recommended components with two recommended components. The performance of the content model recommendation algorithm and the collaborative filtering recommendation algorithm, we designed two experimental parts. The first is to compare the accuracy of the RBNL recommendation method with scene information hidden variables and the recommendation method without scene information. The second is to set the size of the training set, that is, artificially simulate the number of user scoring data in different periods of system operation, and adopt the adaptive weighted recommendation algorithm, RBNL model recommendation algorithm and collaborative filtering recommendation. The change in data size can effectively reflect the problems encountered in the actual recommendation algorithm, so the evaluation results are more valuable. Using the Movie Lens dataset, the predictions of the RBNL model prediction algorithm can be compared to the hidden variables of context information and traditional collaborative filtering using lateral differences. At the same time, vertical feedback can be used to evaluate the feedback of various recommendation algorithms for sparsity problems through RMSE errors under different data sparsity. The experimental results are shown in Table 1.

Table 1. Accuracy of various recommendation algorithms under different data sparsity levels

Training set percentage (%)	Model recommendation algorithm	Collaborative filtering recommendation algorithm	Content recommendation algorithm
0.2	1.0246	1.0647	1.1508
0.4	1.0264	1.0578	1.1084
0.6	1.0056	1.0587	1.0784
0.8	0.9719	1.0414	1.0354

4.2 Comparison of MAE Values of Different Users with the Same Number of Neighbors

Firstly, the BIC score under the Bayesian network construction algorithm based on scene features is considered. The BIC score can reflect the degree of fit between the scene feature addition mechanism and the user score data. The BIC score is used to evaluate the addition of the scene feature Bayeux. Compare the validity of the network model with the general fractional Bayesian model. In order to better illustrate the improvement of the algorithm recommendation accuracy, the random sample user is selected to compare the average absolute error. The neighbor number is set to 10, and the experimental result is shown in Figure 2.

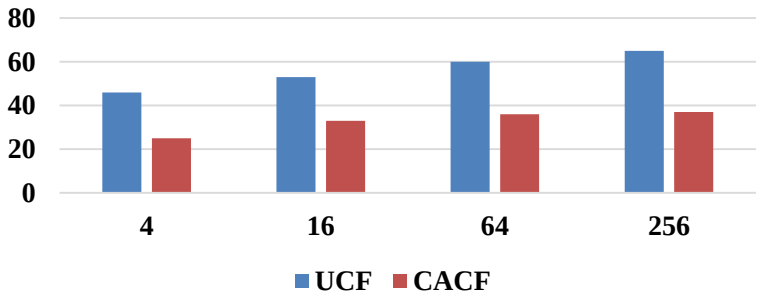

Figure 2. Comparison of MAE values for different users with the same number of neighbors

It can be seen from the data results shown in Figure 2 that the MAE values displayed by random users under different algorithms are significantly different. The general trend is that the improved user personality learning recommendation recommendation method considering the situation information is superior to the traditional collaborative filtering algorithm. Delivery to some extent further illustrates that the improved model algorithm is more accurate in terms of recommendation

quality. Therefore, after adding the situation information, the Bayesian network model is more suitable for scoring data.

5. Conclusion

Traditional recommendation behavior relies too much on the user's behavioral records to mine potential user preferences. Despite the constant application of advanced technology for improvement, it ignores the subject of user interaction with the system. User interests and needs will vary with the environment and time. The user's subjective conditions will affect the accuracy of the recommendation to some extent. Therefore, this paper constructs a personalized learning recommendation prediction model that comprehensively considers context information, user basic information and historical personality learning behavior. And enhance the user interaction process by calculating the degree of influence of multi-dimensional information on user preferences. The average absolute error and accuracy are chosen as the evaluation indicators. By setting the number of different neighbors of the same user and the same random user value, this paper proposes a personalized recommendation method for user learning based on comprehensive multi-faceted information of scenario analysis. The results show that the improved method is superior to the traditional user-based collaborative filtering method. Therefore, the application of the personalized recommendation method based on scene analysis can provide a reference for the network learning service provider to optimize the personalized recommendation service.

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