Recommendation Method of Nursing Teaching Resources in Geriatric Internal Medicine Based on Internet of Things Technology

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Abstract. When many learning websites recommend course resources, the correlation between recommended resources and target resources is not very good, which leads to the low correlation between recommended courses and target resources. This paper designs a method of elderly nursing teaching resources recommendation based on Internet of things technology. Integrate interactive data and model data to browse course feature data. The correlation between recommended resources and target resources is compared, and the correlation between browsing function data and recommended resources is calculated. According to the degree of feature association, the weight of recommended resources is calculated. Through the weight set sorting, with the help of Internet of things technology to rearrange the recommended order of curriculum resources, complete the design of elderly nursing teaching resources recommendation method based on Internet of things technology. Through experimental analysis: the highest correlation between recommended courses and target resources is 72%. The results show that the method is more perfect.

Keywords: Internet of Things technology · Geriatric internal medicine nursing · Curriculum resource recommendation · Recommendation order

1 Introduction

Digital learning of Internet of things has become an important way of distance education and learning [1]. The network teaching resources are also growing rapidly. The overload of information brings many challenges to teaching organizers and learners. They have to spend a lot of time and energy to screen out the resources that meet their needs. And the Internet of things technology is an effective way to solve this problem [2]. It has been widely used in the business field and has achieved remarkable results by recommending the information and commodities of interest to users according to the characteristics of users' interest and historical behaviors. The pre oral recommendation system has also been applied to e-learning environment. It can help teaching organizers and learners to effectively reduce the burden of information overload and improve the efficiency of work learning. However, it is difficult to apply the recommendation methods

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and systems directly to business field in e-learning, because the teaching and learning process is more complex than the business system, and is subject to the user's knowledge level and teaching The influence of the task of oral standard and the characteristics of the subject. With the development of Internet of things technology and the improvement of people's living standard [3].

In the related research, the common resource recommendation methods include personalized learning resource recommendation method based on 3D feature co domination and online learning resource recommendation method based on ontology and recurrent neural network. Among them, the personalized learning resource recommendation method based on Collaborative domination of three-dimensional features improves the matching relationship between learners and online learning resources, establishes the Personalized Learning Resource Recommendation Model Based on Collaborative domination of three-dimensional features, and describes it parametrically; Secondly, a binary particle swarm optimization algorithm based on fuzzy control of Gaussian membership function (fcbpso) is designed to solve the objective function of the recommended model; Finally, five groups of comparative experiments are conducted to verify the good performance of the proposed method. This method designs reasonable indicators in recommendation, but it has the problem of less resources. In the online learning resource recommendation method based on ontology and recurrent neural network, this method uses ontology method to model and represent the domain knowledge of learners and learning resources, and uses recurrent neural network to mine learners' learning mode to get the final resource recommendation list. This method has high recommendation accuracy, but poor linkage.

The cause and spectrum of diseases have changed greatly, which also led to the progress of medical science and technology and the change of medical mode. It also poses new challenges to nursing work. It requires that the nursing work should change the patients from the whole concept of biology, psychology and society, from the simple disease nursing mode to the "people-oriented" nursing mode; from the individual nursing of patients to group nursing; Let the patient produce the concept of changing from passive nursing to active disease prevention [4]. Of course, with the change of disease spectrum and aging of population, the cooperation and exchange in Internet of things technology and nursing are expanding day by day. Diversified community care services, such as family care, hospice care, day ward. These all put forward higher requirements for nursing, requiring the development of nursing work to specialization and specialization, and the nurses' theoretical study, self-study ability, active change of nursing service mode and the concept of nursing education.

2 The Design of the Recommended Method of Nursing Teaching Resources for the Elderly

2.1 The Collection and Browsing Course Characteristic Data of Internet of Things Technology

The data collection of course features mainly includes the collection of interactive data between online layer and users and the construction of model, including teacher behavior record, teacher model, course model and resource model. Teacher behavior record is used to record various operations of teachers on the system platform. Based on the Internet of things technology, it provides data basis for personalized recommendation. According to the behavior objects of teachers, teachers' behavior records can be divided into resource behavior records, teaching task records and label behavior records [5]. The operation behavior of resources includes downloading, scoring, collecting and browsing; teaching task record refers to the teacher's teaching design and lesson preparation in the process of UI interaction; tag behavior record refers to the teacher's operation of recommended resource tags, including selection, modification, deletion and addition [6]. The course model is used to represent the relationship between courses and the content characteristics of each lesson [7]. It is composed of curriculum relationship and curriculum label based on Internet of things technology. Use resources related to the course. Describes the state sequence of a data set, each of which depends on the first and finite states. Therefore, the Internet of things technology is used to express the characteristic relationship between courses, that is, the course prepared by teachers in the next state is only related to the current position of the course. By using the state transformation relationship of Internet of things technology, teachers' position in the course structure can be predicted when they log in to the system again, so as to collect relevant resources more accurately, as shown in Fig. 1.

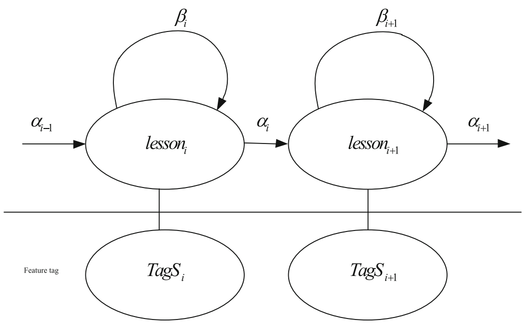

Fig. 1. Course characteristic data

In the figure, αi is the number of course nodes, which represents the probability from lessoni state to lessoni+ 1, βi represents the probability from lessonI to lessoni, αi + βi = 1, α0 = 0. The curriculum label is used to represent the content characteristics of each class. It is represented by vector space model, and the formula is as follows:

$$TagS_i = \left\{ tag_k : w_k \middle| 1 \le k \le N_t, \sum_{k=1}^{N_t} w_k = 1 \right\} \tag{1}$$

where tagk is the k tag, Wk is its weight, and Nt is the number of tag sets. The initialization and adaptive adjustment of tag sets are completed by the course tag adjustment module in the offline layer. It mainly describes the resource owner's description of the resource, including resource title, resource keyword, resource description and resource type (such as picture, video, audio, document, etc.); it represents the content characteristics of the resource, expressed by VSM. the formula is as follows:

$$TagS_i = \left\{ tag_k : w_k \middle| 1 \le k \le N_i, \sum_k^{N_i} w_k = 1 \right\} \tag{2}$$

Among them, Nt is the number of label sets, initialization and adjustment process, which is completed by the resource tag adjustment module of offline layer, and consists of static and dynamic curriculum attributes. Record the necessary information filled in by users during registration, such as user name, registration mailbox, etc., and record the position of teachers in the curriculum model and dynamically track the user's context. Analyze and process data of data layer, initialize and adjust the model, and calculate the relevance or similarity between curriculum and resources, resources and resources based on content and user behavior data, and provide data support for mixed recommendation algorithm of online layer [8]. The course label adjustment module initializes and adjusts the curriculum label in the curriculum model, which makes the curriculum label more accurately and comprehensively represent the content characteristics of the course. The module is composed of the crawler module and the text analysis module. The course name is used as the query word by Internet technology, simulating the search process and crawling the relevant web content. The paper analyzes the Internet of things technology module uses word frequency reverse file frequency algorithm to analyze the web page content obtained by the web crawler, or extract the content characteristics of teaching task record in the data layer, so as to realize the adjustment of course label [9]. In the course of course label initialization, the extracted content features are directly regarded as curriculum tags; in the course of course label adjustment, the content features are obtained by analyzing the teaching task records, and the common words and tags with low weight are removed by the method of unified training. Through the potential semantic analysis method, the curriculum label matrix is constructed, the eigenvector of the matrix is solved by matrix decomposition method, and the feature vector is analyzed by distance measurement method, and the adjacent neighbor of the label is solved to expand the curriculum label set and dynamically adjust the course label, so as to improve the course label, as shown in Fig. 2.

The resource label adjustment module initializes and adjusts the resource label in the clinical nursing resource model. Different from the adjustment of course label, due to the differences in the types of resources (including video, pictures, documents, audio, etc.), it is impossible to analyze the content of resources based on DF algorithm. Meanwhile, the description text of static attribute of clinical nursing is relatively short [10]; therefore, in the initialization process, the static attributes of resources are analyzed by using file frequency Internet of things technology, common words are filtered and keywords are extracted as label sets. The weight of the label obtained by nursing name, clinical key words and nursing description is different. The process of resource label adjustment is similar to the course label adjustment process. According to the teacher's feedback behavior to the resource label, the resource label set is optimized by statistics and potential semantic analysis. The course resource relevance training calculation module and resource similarity training module are based on the curriculum content characteristics (curriculum tags) and resource content features (resource tags), and calculate the similarity between curriculum and resources, resources and resources respectively according to

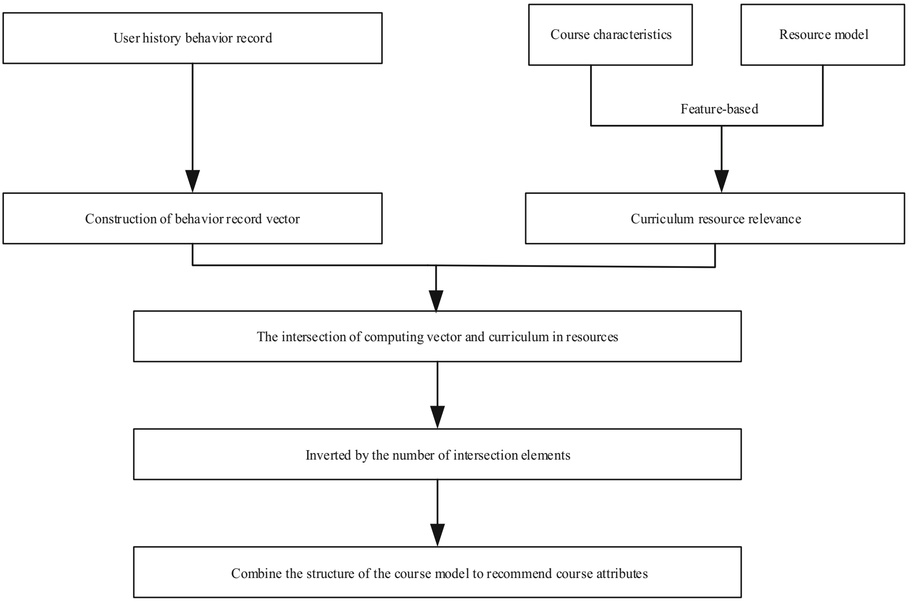

Fig. 2. Reasoning of course resource characteristics

similarity measurement and k-nearest neighbor algorithm, and establish the relationship between curriculum and resources, resources and resources. The resource association degree calculation module analyzes the teacher's resource behavior record and transforms it into the "shopping basket" problem. It transforms the resources of each login operation into the user's purchase record, mining by association rules, and training the correlation between resources. Teacher model reasoning, based on the teacher's behavior record of resources in the system, and combined with the results of the calculation of curriculum resource relevance, infers the current position of the context in the curriculum model, thus completes the collection of the whole browsing course feature data, and then forms the comparison between the feature data and the recommended resources, and then determines the correlation value between the two.

2.2 The Correlation Degree Between Browsing Feature Data and Recommended Resources

According to the obtained browsing course feature data, the correlation degree of feature data is compared, and the problem of course recommendation is abstracted and formalized as follows: given the learner learning data on the learning website of geriatric medical nursing teaching course, we get a set of M learners L = {l1, l2, …, lM} and a set of N courses C = {c1, c2, …, cN}. The interaction matrix between learners and courses can be obtained from the records of course selection, which is recorded as R ∈ RM × N. The interaction matrix Y = {yic | l ∈ L, c ∈ C} is defined by the learner's course selection behavior:

$$y_{lc} = \begin{cases} 1, \text{Learners chose the course} \\ 0, \text{other} \end{cases} \tag{3}$$

ylc = 1 means that learner 1 has selected course c, otherwise ylc = 0. As a supplement to the recommendation information, we also have a knowledge map G = (E, R), E and R represent the set of entities and relationships in knowledge map G. Each data in knowledge map G is composed of triples (h, r, t). h, r and t represent the header entity, relationship and tail entity of the triples respectively, where h ∈ E, r ∈ R, t ∈ E. For example, triples mean that the invention of C language originated in BCPL. In the course recommendation scenario, a course c ∈ C consists of a word sequence, namely C = (W1, W2, W3,…), for example, "Python development simple Crawler" = (Python, development, simplicity, crawler). Each of these words may correspond to an entity e ∈ E in the knowledge map G. For example, Python and crawler in the course Python development simple crawler correspond to entities python (computer programming language) and web crawler, respectively. Based on the interaction matrix Y between learners and curriculum and curriculum knowledge map G. The goal of the recommendation algorithm is to estimate one on one course for the elderly medical care course learner who has not previously chosen. What is the possibility of choosing a course. That is, through the model, a prediction function is trained to turn y = F(l,c | θ, Y, G), where y represents the probability of selecting C from the course selected by the learner 1 of the elderly medical nursing course predicted by the model, and theta represents the parameters related to function F. According to the comparison of the target feature data and the resource feature data, the paper finds out whether there are other target feature data between them. According to the recommendation algorithm of knowledge map enhancement, the compactness between the two is calculated. The resource feature and target feature direction quantization module are shown in Fig. 3.

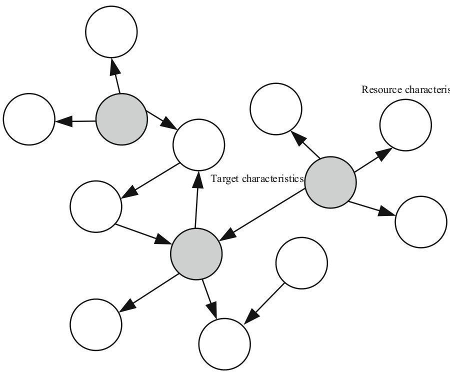

Fig. 3. Recommended data target feature orientation module

Based on this, the vector module compactness of target feature and resource feature is calculated. The sparse feature vectors of nursing course learners and courses in geriatric medicine were used as input, and transformed into dense vector representation through full connection layer. The deep feature learning module takes the embedding of learners and courses as the input, as shown in Fig. 4.

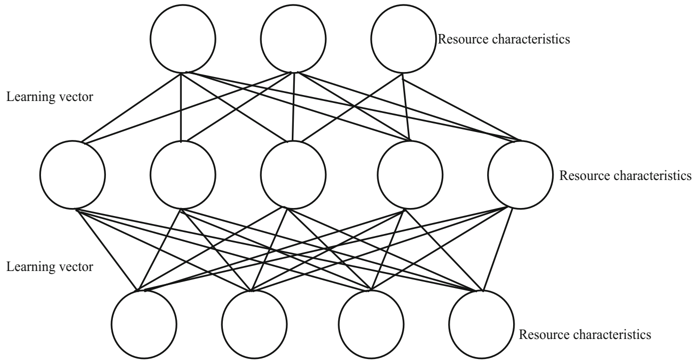

Fig. 4. Vectorized feature input

The deep perception mechanism is used to mine the characteristics of learners and courses, and the nonlinear characteristics of learners and courses are obtained. The knowledge map feature learning module can extract features based on the idea of multi-layer relationship diffusion. While learning the vector representation of entities and relationships in the knowledge map, we also learn the linear feature representation of learners and courses. Connect the prediction module, connect the vectors from the deep collaborative filtering module and the knowledge map feature learning module, and then normalize them to get the recommended prediction value. Thus, the correlation degree between browsing feature data and recommendation resources is calculated.

2.3 The Recommended Resources are Weighted According to the Feature Association Degree

The calculated correlation degree value is used as the activation coefficient in the MLP module to perform the weight assignment of the feature correlation degree. The number of MLP layers can be adjusted according to the experimental requirements, and the number of neurons is halved layer by layer. Use LM to denote the hidden vector of the learner in the MLP module, and CM to denote the hidden vector of the course in the MLP module. Each output layer of MLP is expressed as, the input of the module is also the learner vector and the course vector obtained by the input and vectorization module. Through the learning and training of this module, we can get the entity set contained in the hidden vector LR of the learner in the Ripple module and the hidden vector CRo of the course in the Ripple module as E1 = {e1, e2,…, eu}. The entity set E1 is regarded as the seed set of the knowledge graph. Just like throwing a stone into the water and splashing layers of ripples, the seed entity will spread outward along the correlation r in the knowledge map, forming a circle of "water waves". The set of triples involved in each wave of water, that is, the set of triples with a distance of k from the seed set is called the set of water waves bang (k = 1, 2, 3,…, H). The water wave set will interact with the course word segmentation entity for multiple iterations, so as to obtain the learner's degree of love (or interest preference) for the course. Combining all these preference values can get the user's characteristic LR. The relationship weight Pi from course name to course participle can be calculated by the following formula:

$$P_i = \left(C_R^T R_i h_i\right) = \frac{\exp\left(C_R^T R_i h_i\right)}{\sum_{(h,r,e) \in Co_i} \exp\left(C_R^T Rh\right)} \tag{4}$$

Among them, i is the data set, c is the feature data of the course, R is the recommended learning feature, h is the feature interaction matrix, and T is the parameter obey average value. According to this, the process of assigning the recommended resource weight to the feature relevance is completed.

2.4 Combine Recommendation Weights to Arrange the Recommendation Order of Course Resources

According to the weight value of the above-mentioned feature association degree, the recommended resources are arranged in order. In the knowledge graph feature learning module of the original model, the Internet of Things technology is used to carry out the feature ranking method of multi-layer relationship diffusion. The core idea is to use the multi-layer relationship that seed entities diffuse in the knowledge graph to find the user's interest characteristics. Especially for the related entities of the superimposed part of the layer caused by the "splashing ripples" of seeds, a phenomenon similar to "interference enhancement" in physics will occur. This strengthening phenomenon caused by multiple "hits" and the use of co-occurrence networks to find hot spots and preferences are shown in Fig. 5.

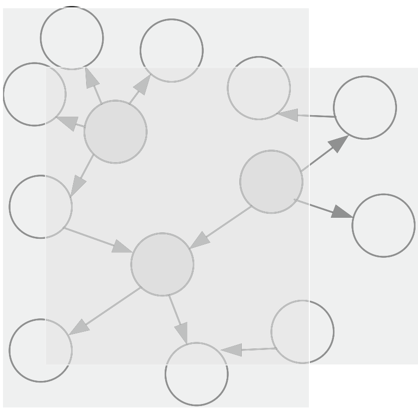

Fig. 5. The feature weights of recommended resources and courses are overlapped and added

The overlapping and shaded part in the figure is the co-reality network Co-net, which contains the course entity (the dark part) and the course word segmentation entity (the light part). For the training of the co-reality network and the determination of the weights of the edges, we adopt the same method as the knowledge graph training. The common reality network information is analogous to the knowledge graph triplet information, and the relationship is assigned to the two types of "technical participle" and "non-technical participle", which can form (course name, technical participle, technical entity) and Course name, non-technical participle, non-technical entity) triples, the set of triples is called Col. Among them, the loss function of the algorithm includes the loss value of the learner-course interaction matrix, the loss value of the learning knowledge graph and the common reality network, and the regular term to prevent overfitting of training. In the specific training process, we used stochastic gradient descent (SGD) to optimize the parameters. At the same time, during the training process, we added negative samples to the learner's course selection records and knowledge graph data to improve the efficiency of training, and the number of negative samples and positive samples remained the same. By optimizing the loss function, the model will use the backpropagation algorithm to update the relevant parameters and characteristics of the model. So far, the design of the recommended method for the elderly internal medicine nursing teaching curriculum resources based on the Internet of Things technology is completed.

3 Experiment Analysis

Analyze the comparative experiments of traditional method 1, traditional method 2 and the recommendation method design of elderly internal medicine nursing teaching curriculum resources based on Internet of things technology, compare the relevance of recommended courses and target resources, so as to confirm the better recommendation method.

3.1 Experiment Preparation

The data crawling and cleaning in this research, and the realization of the model are all realized by writing code in Python language. The model uses Tensorflow as the basis of algorithm implementation. The main hardware and software configuration of the experiment is shown in the following table (Table 1):

Table 1. Basic values of experimental configuration

Experimental configuration	Parameters table
CPU	I52200U
RAM	8192MB
Existing	5400
System operating system	4182MB
Python version	3.4.6
Tensorflow	1.14

The course selection experiment data used in this article is taken from a certain geriatric internal medicine nursing course website, which includes learner selection record data, auxiliary information of all selected courses (course name, course category, course difficulty, etc.), and learner-related information. The final crawled data set situation is shown in Table 2:

Table 2. Basic parameters of experimental data

Data set	Group A	Group B	Group C
Number of courses	943	833	941
Number of learners	73773	52415	67453
Number of interactions	4116285	3015389	443792
Course auxiliary information	Category, name, instructor	Name, teacher	Classification name
Auxiliary information for learners	Name, study time, online time, search preference	Study time, online time	Search preferences, study time

According to the accuracy estimation of the scoring matrix of the experimental data parameters, predict the relevance of the recommendation task and the target resource, and use Accuracy to evaluate the final effect of the model recommendation. Accuracy represents the percentage of the correct number of samples in the test set that the model classifies to the total number of samples. Generally speaking, it is the ratio of the number of samples that classify positive samples into positive samples and negative samples into negative samples to the total samples. In the prediction task, the value of the correlation degree can be calculated by the following formula: target correlation degree recommended resource feature data set/target resource feature data set.

3.2 Experimental Result

Figure 6 shows the correlation between the recommended courses and target resources of the traditional method 1, traditional method 2 and the Internet of Things-based elderly internal medicine nursing teaching curriculum resource recommendation method.

According to the data in the figure, the correlation degree between the recommended courses and target resources in the traditional method 1 is up to 63%. As the number of recommended courses increases, the correlation degree gradually decreases, and the correlation degree between the recommended courses and target resources is as low as 33%. The traditional method 2 recommends courses and the target resources have a maximum relevance of 65%, and the minimum decrease of relevance is 30%. Based on the Internet of Things technology, the relevance of the recommended courses and target resources of the recommended methods for the elderly internal medicine nursing teaching curriculum resources is 72%, and the relevance is reduced to 51%. Therefore, it is better to recommend the resources of nursing teaching courses for the elderly based on the Internet of Things technology.

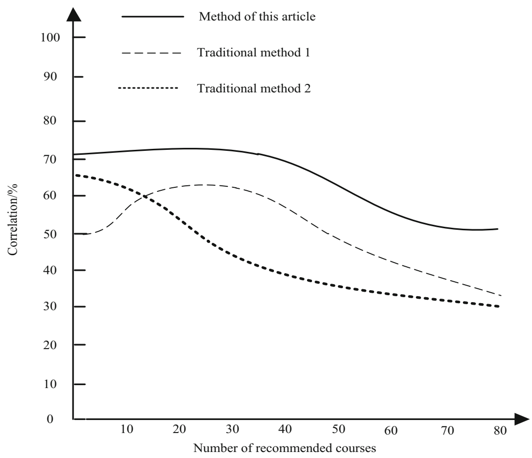

Fig. 6. The degree of relevance between recommended courses and target resources

4 Conclusion

Through the research of this article, the relevance of recommended courses for geriatric internal medicine nursing has been improved, and the accuracy of recommended course resources has been improved. In the future, in the learning part of the common reality network, in order to better integrate the common reality network with the original knowledge map, it should use the hit frequency or reference other models to train and generate, so that the weight of the target feature can be optimized, and the accuracy of the recommendation can be improved. rate.

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