

Research Article

Research on Online Learners' Course Recommendation System Based on Knowledge Atlas in Smart Education Cloud Platform

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At present, there are still some problems in the application of recommendation algorithm in course, such as data sparseness, lack of knowledge logical relationship, and lack of explanation. Therefore, in this paper, the recommendation system of course for online learners based on knowledge map is implemented where different functional modules are designed, and the recommendation model is optimized based on the loss function. In addition, a recommendation algorithm is designed, which selects the data set, tests the algorithm based on knowledge map, and mainly evaluates the performance from the rate of click-through predicted evaluation, accuracy rate, and recall rate. The results show that the overall performance of online learner course recommendation system based on knowledge is excellent.

1. Introduction

With the rapid development of information technology, Internet has been widely used in our society. We enjoy the convenience brought by information, but also have to face the problem of overload information. For the information consumers who do not have a clear demand, in the face of massive and complex data, it is difficult to quickly get information that they are interested in or valuable to themselves. For another major information producer, even if they produce high-quality content, it is difficult to accurately push it to the target audience [1, 2]. In order to solve this contradiction, major Internet companies select recommendation system as the tool which completes the task of connecting users and information. While helping users obtain valuable information efficiently, it also makes the information present to the target users more accurately, so as to achieve a win-win situation between information consumers and information producers.

There are two conditions for successful application of personalized recommendation [3, 4]: one is information overload; second, the needs are not clear or it is difficult to

accurately describe with keywords; otherwise, users can directly find the items of interest through the search engine. In the recommendation system, collaborative filtering algorithm is one of the most important recommendation algorithms. Collaborative filtering algorithm is based on the principle of "people clustered by kind, and things classed by group," which does not rely on specific knowledge and is easy to expand in engineering. Therefore, it has become the focus of many experts and scholars. However, the recommendation algorithms based on collaborative filtering are faced with the problems of cold start, data sparsity, and computational complexity, which become the bottleneck of collaborative filtering methods [5–7].

In recent years, knowledge mapping has become one of the main sources of knowledge for semantic search, knowledge answering, and other tasks [8]. Knowledge map contains various types of entities and semantic relations between entities. Therefore, it is introduced into personalized recommendation, which can alleviate the problem of cold start, find the potential relationship between recommended items, and improve the accuracy and diversity of recommendations [9, 10].

At present, there is a demand for recommendation of online learners' course, and knowledge map can effectively improve the effect of traditional personalized recommendation algorithm; this paper studies the recommendation technology of online learners' course based on knowledge map, designs a recommendation system based on knowledge map, and recommends online learning courses with high accuracy that meet users' preferences.

In this paper, the development of recommendation system based on knowledge map has important practical significance: First, it analyzes users' behavior actively and recommends courses that users are interested in, which improves their engagement and experience. Second, online learners' courses can be recommended for users through analyzing their behavior, which can increase the consumption of users, and greatly increases the company's profit margin.

2. Overview of Knowledge Map

Knowledge map is an interdisciplinary subject which intuitively shows the complex field of modern science and technology knowledge through data mining, information processing, and knowledge measurement with visual images. It is based on science of science, involving applied mathematics, information science, computer science and many other disciplines. It also includes broad prospects for research and development and application. As a new research field, the related technology and standards of knowledge mapping are not fully mature, so the concept definition of knowledge mapping is still developing and changing. The application of knowledge mapping is very extensive, mainly in the following aspects [11, 12]: scientific research, social problem solving, semantic search, deep answer, and intelligent recommendation. The knowledge map is integrated by recommendation system where the project entity attributes are given, and semantic analysis, knowledge mining, and logical reasoning are supported. The relationship between projects can be completed from the perspective of association relationship and hierarchical structure between entities, and expressed as graph model. Combined with traditional recommendation mechanism and algorithm, accurate and intelligent recommendation can be realized.

Knowledge map can provide rich information and prior knowledge for various fields, and reinforcement learning method has strong exploration ability and independent learning ability. Knowledge map based on reinforcement learning can reduce the interference of noisy data, automatically select high-quality sample data, better understand the environment, and provide reliable interpretation, which has been applied in many fields. The combination of deep learning and knowledge map can be divided into two categories in terms of combination methods [13]. One is to model the actual problem as a knowledge graph containing multiple node types and relationship types, and reinforcement learning explores learning strategies on the knowledge map. The other is to introduce knowledge map as external information into the reinforcement learning framework to guide the exploration process of reinforcement learning.

3. Design of Recommendation Algorithm of Online Learners' Course

When collaborative filtering is used in traditional personalized recommendation technology, the performance will be reduced due to the sparsity of interaction matrix, and there are problems of cold start for new items and new users. However, the content-based recommendation algorithm attaches importance to the information of the item itself and ignores the user's behavior, which often leads to the low accuracy of the algorithm. At present, the most representative and large-scale use of information is knowledge map. It can describe various events, characters, and their relationships in the real world. In essence, it is a semantic network composed of "nodes - edges.". The technical process of knowledge map is shown in Figure 1.

Knowledge modeling is an important link in the construction of knowledge mapping system, which is used to express the relationship between knowledge itself and knowledge, and the model needs to update the knowledge of the model constantly. There are many ways to model knowledge map, such as the same data. Therefore, for different industries, it is necessary to develop appropriate methods of knowledge modeling, which can accurately establish the association between data and improve the speed of operation. Knowledge extraction refers to the process of extracting knowledge from data of different channels and classifications and storing knowledge in the knowledge map [14]. After knowledge extraction, we get the entity's relationship, attributes, and other information, but the logical relationship between information is chaotic and its structure is incomplete, as well as the information extracted from knowledge may be full of redundant and wrong information. Through integration of knowledge, we can integrate this information. After knowledge extraction and knowledge integration, we get many facts, but they are not knowledge actually. After knowledge processing, we can get a structured knowledge system and the purpose is to make computers have reasoning thinking like the human brain.

3.1. Design of Recommendation Model of Course for Online Learners. In this paper, the advantages of knowledge map are used to mine information, which can help online learners to improve the performance of recommendation tasks. An algorithm that integrates knowledge map and recommendation module is proposed, —(Knowledge Graph Movie Recommendation Model, KGMRM). This model is a generalized framework based on recommendation algorithm, which can be applied to common recommendation requirements [15]. This recommendation model is a multi-task learning model, which uses knowledge map to improve the quality of recommendation. The knowledge map and the recommendation module are connected by a cross-region, which can learn the interaction between the items in the recommendation module and the entities. In addition, it also enables the knowledge map and recommendation module to discover and use hidden features each other. As shown in Figure 2, the online learner course recommendation model of knowledge mapping is composed of three parts:

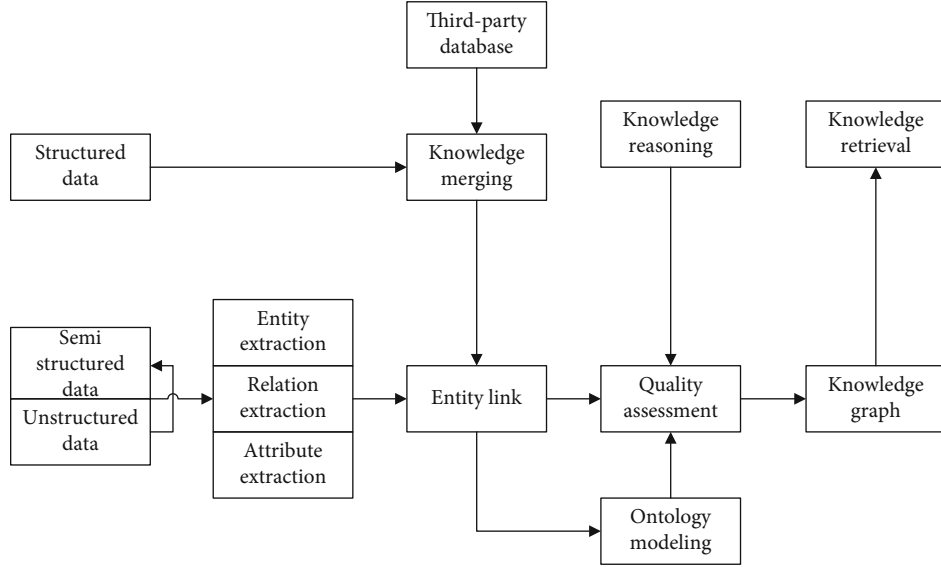


FIGURE 1: Technical process of building knowledge map.

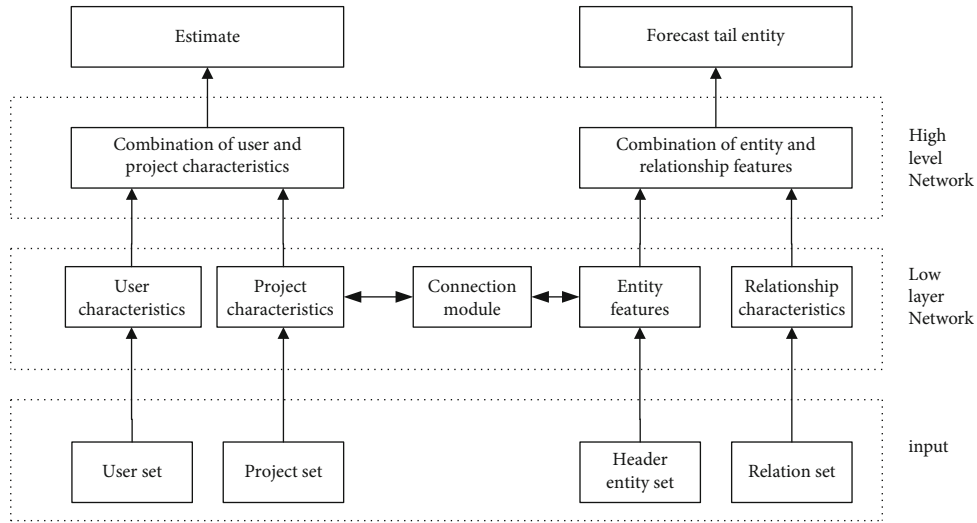


FIGURE 2: The recommendation model based on knowledge map.

recommendation module, knowledge embedding module, and connection module.

3.1.1. Recommendation Module. Because items in the recommendation system can correspond to the entity of the embedded module, that is, they can describe the same object, the connection module can realize the interaction between the project and the entity. Each layer has interaction between project and entity, and each layer corresponds to a connection module. For the interaction of the first layer, project V and entity e , assume that $v \in R^n$, $e \in R^n$, an interactive feature matrix of entity and project is constructed from their potential features

$$H_l = v_l e_l^T \begin{pmatrix} v_l^1 e_l^1 & \cdots & v_l^1 e_l^n \\ \vdots & \ddots & \vdots \\ v_l^n e_l^1 & \cdots & v_l^n e_l^n \end{pmatrix}. \quad (1)$$

Among them, $H_l \in R^{n \times n}$ represents the cross-feature matrix, and N is the size of the hidden layer. In the interactive feature matrix, each item is combined with the associated entity, so all feature interactions are modeled. The concept of cross-network in DCN network structure is used to construct the cross-module.

DCN, with full name of Deep & Cross Network, is a model for Ad Click prediction proposed by Google and Stanford University in 2017.

DCN is very efficient in learning combination features of specific order, it does not need feature engineering, and the additional complexity introduced is very small. First, Embedding and Stacking layer, then parallel Cross Network and Deep Network, finally Combination Layer, which combines the results of cross-network and deep network to get output.

The cross-network of DCN network structure is to construct feature crossover [16]. It can cross-combine the

features of the first layer and then transfer them to the $l + 1$ layer. The function of the cross-network is not only to make feature combination but also to maintain the original characteristics. Its formula is as follows:

$$x_{i+1} = x_0 x_i^T w_i + b_i + x_i. \quad (2)$$

Among them, x_0 is input, x_i and x_{i+1} are the output of the first layer and the $l + 1$ layer, and $w_i, b_i \in R^n$ is the weight and bias parameters of the 1st layer.

Therefore, in the connection module of this paper, the cross-feature matrix is mapped into their potential representation space, and the feature vectors of items and entities in the next layer are obtained, as shown in the formula:

$$\begin{aligned} v_{l+1} &= e_l v_l^T w_l^1 + v_l + b_l^1, \\ e_{l+1} &= v_l e_l^T w_l^2 + e_l + b_l^2. \end{aligned} \quad (3)$$

Among them, w_i and b_i are the trainable weight and deviation, which may be different. Due to the weight vector, the feature matrix changes from $R^{n \times n}$ back to the feature space. R^n , then the eigenvector transfer of the connection module can be expressed as the formula:

$$[v_{l+1}, e_{l+1}] = H(v_l, e_l). \quad (4)$$

However, the connection module can only be used in the lower level of the online learner course recommendation model of knowledge map, and the recommendation module and knowledge embedding module are still independent in the upper level, that is, users and projects are connected, while entities and relationships are also connected. The input of recommendation module is user feature vector u and item feature v . For the user feature vector u , a multilayer neural network $M(x)$ with k layers is used to extract the potential features of each layer, as shown in the formula:

$$\begin{aligned} u &= M^K(u), \\ M(x) &= f(Wx + b), \end{aligned} \quad (5)$$

where w is the weight (also called connection coefficient), b is the deviation, and f is the activation function.

In that low-level network, for item v , the feature extracted from k connected modules are used, and the results are shown in the formula:

$$v = H^K(v, e)[v]. \quad (6)$$

The meaning of the above expression is to extract the features of project v from the related entity set of project v .

The user's implicit feature u and item feature v obtained from the lower layer network above are transferred to the higher layer network. They are directly combined by the inner product function F , and finally by the activation of function. σ , the probability of users' satisfaction of goods

(y'_{uv}) is predicted, which is shown as follows:

$$y'_{uv} = \sigma(f(u_K, v_K)). \quad (7)$$

3.1.2. Module of Knowledge Embedding. Knowledge map can be embedded to interpretable recommendation, establish user-item knowledge map, obtain the embedding of each user, item, entity, and relationship by studying the map, and recommend to users by finding the most similar items under the relationship of "purchase." Explanatory can be generated by finding the shortest path of users and items on the knowledge map. In some special cases, the recommended explanation is not generated by the recommendation model but is generated after the item is recommended by the causal inversion model.

The function of this module is to embed entities and relationships into a continuous vector space and keep its structure. Knowledge map embedding technology can be divided into two types. The first is translation distance model, such as the Trans E model. For each triplet (h, r, t) , the Trans E model translates it into embedding vector. The head entity vector h and the relation r are embedded in the same space. The translation invariance of word vectors is used to keep the structure between them, while the ultimate goal is that the vector obtained by the translation of H and R is similar to the tail entity vector t . The second is semantic matching model, which mainly judges the relationship of things through the potential semantics and relationships of entities.

In the recommendation model, a deep semantic matching architecture is selected [17]. For triples (h, r, t) , firstly, the connection module and multilayer neural network are used to deal with the relationship between the head entity vector h and the vector space r , respectively, and then, the Z -layer neural network $M(x)$ is used to connect their potential features to get the predicted tail node vector. t' , see formula:

$$\begin{aligned} h &= H^K(v, h)[e], \\ r &= M^K(r), \\ t' &= M^Z(h, r). \end{aligned} \quad (8)$$

Among them, t' is the prediction vector of the tail node t . Finally, the function F is used to calculate the predicted tail entity node and the real tail entity node, and get the score of the triple, so that the model can optimize this score, as shown in the formula:

$$\text{score}(h, r, t) = f(t', t). \quad (9)$$

3.2. Optimization of Model Based on Loss Function. The important components of knowledge map include four parts: entity, attribute, relationship, and network diagram [18, 19]. Among them, entities and attributes are node sets of the network graph, and the relationships constitute the edges of the network graph. Entities need to have unique

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Input: Interaction matrix H of the recommendation module, and embedding knowledge map G.
Output: prediction function f(u,v|u,v,h,r)
1: Initialize parameters
2: for does not meet the stop condition do:
3: // Recommend the task part
4: for loop t times do:
5, Extract a small number of positive and negative samples from the interaction matrix H;
6. Extract a small number of samples from items related to entities;
7. Update the parameters in function f by gradient descent method.
8: end for
9:// Knowledge map is embedded in task
10: Extract a small number of triples from input g;
11. Extract a small number of samples from the entities related to the project;
12. Update the parameters in function f by gradient descent method.
13: end for

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ALGORITHM 1

identification, attributes are a description of the intrinsic characteristics of entities, and relationships are used to connect entities and attributes, describe the relationship, and finally form a network diagram. This network map is the knowledge map, which can retain the original semantic information of the article. On one hand, the recommendation system has the problem of cold start for new users, and it can be used as auxiliary information for its recommendation; on the other hand, knowledge map can break the shortcoming of high similarity of content recommended by traditional recommendation system, thus making the recommendation of the system more accurate and diverse.

The recommendation module, the knowledge map embedding module, and the connection module together constitute the recommendation model of course for online learners. The loss function of the model is as follows, and the model is optimized through the loss function:

$$L = L_{RS} + L_{KG} + L_R = \sum J(y'_{uv}, y_{uv}) - \lambda_1 \left(\sum \text{score}(h, r, t) - \sum \text{score}(h', r, t') \right) + \lambda_2 \|W\|_2^2, \quad (10)$$

where j is the entropy function. The recommended module loss of the first term is λ_1 and λ_2 . The second term is the knowledge embedded module loss, and the third term is the regular term that can prevent over-fitting, which is a balance parameter.

3.3. Training and Analysis of Model. In this paper, a small batch gradient descent method is used to update the parameters. There are two kinds of gradient descent algorithms in the past: the first one is batch gradient descent, that is, after traversing all data, calculating the loss function, and the gradient of parameters through the function, a new gradient is obtained. The second type is random gradient descent, that is, the loss function is calculated for each data, and then calculate the gradient and get new parameters. Because all data samples are cycled through in the former method, it costs a lot and can only be learned offline. The second method is

TABLE 1: Data set statistics.

Edition	Number of users	Number of labels	Number of scores	Sparsity
100K	945	0	10million	93.63%
1M	6040	0	100 million	95.53%
10M	71565	95580	1000 million	98.60%
20M	138490	465560	2000 million	99.46%

fast because of the small sample size, but it may form a local optimal solution that is just very close to the optimal solution.

The small batch gradient method, as a compromise method of the above two kinds, has both their advantages, that is, the data is divided into multiple samples, and a small number of samples are selected in each cycle, so that the calculation is small, and for a group of data in the samples, the gradient descent direction is jointly determined, which increases the accuracy.

The training process of the recommendation model is as follows:

4. Experimental Analysis of Recommendation Algorithm of Course for Online Learners

4.1. Data Sources. The experimental data in this paper comes from the data set of MOOC Network. The data set contains three files: user information, online learner course information, and user rating information on online learner courses. According to the difference of data collection time and data volume, it can be divided into four versions: 100K, 1M, 10M, and 20M data sets, the specific differences of which are shown in Table 1.

Although 10M and 20M have a larger amount of data, they lack demographic data (age, gender, occupation, zip code) and add the label of user's personal online learner interest. In order to ensure the basic demographic data, Movie Lens_1M data set is selected.

TABLE 2: Confusion matrix.

	Positive sample	Negative sample
The forecast is positive	TP (real case)	FP (false positive case)
The forecast is negative	FN (false positive case)	TN (real case)

TABLE 3: Results of evaluation in predicted click rate of different models.

Model	AUC	Accuracy
CKE model	0.833	0.756
DKN model	0.712	0.678
Kgmm model	0.890	0.818

Based on the data set _1M, the knowledge map of online learner's curriculum domain is constructed. After the process of knowledge map and extraction, the experimental data in this chapter are regarded as the rating data of 6040 users on 3625 online learner courses, and the related knowledge of online learner courses, including 3625 entities of online learner course and 13884 role entities, 44 publishers and 19 entities of online learner course type.

4.2. Experimental Scheme. Data sets are all display feedback. Firstly, they are returned into implicit feedback. Because the score is from 1 to 5, the threshold value is set to 4, and if the user likes the items, it is represented by the number 1. In this paper, an online learner course with no score is sampled for each user, which is marked as the number 0. Then, a knowledge map triplet is constructed from the data set, in which the item and entity use the same ID. Finally, the data set is divided into training set, verification set, and test set, and the ratio of them is 6:2:2 in turn.

To verify the performance of KGMRM model, the following models in the experiment is compared:

- (1) CKE model: Collaborative Knowledge Base Embedding is a model that adds text or graph data from knowledge base to recommendation system to improve recommendation accuracy. In this experiment, the embedding dimension of users and projects is 64, and that of entities is 32
- (2) DKN model: Deep Knowledge-Aware Network is a model that combines knowledge map entity embedding with neural network for recommendation. In this experiment, the online learner course name is used as the text input of DKN network, and the entity embedding dimension is 64

Each experimental model was repeated three times and the model on the verification set is optimized to get hyperparameters.

4.3. Indicators of Evaluation. There are two indicators used to evaluate the performance of the model [20]:

- (1) Prediction and evaluation of click rate. The trained model is applied to the test set, and the effect of click-through rate (CTR) is evaluated by AUC and Accuracy. The larger the AUC value, the better the classification effect. AUC is the area of the part of the curve ROC below the coordinate axis. ROC curve is drawn by TPR (True Positive Rate) and FPR (False Positive Rate) on the coordinate axis. In the classification problem, the threshold is set as m , when the prediction score presents $n > m$, it is called the sample prediction positive; otherwise, it is called the sample prediction negative, so we can get a confusion matrix, as shown in Table 2

Let TPR be the true positive rate and FPR be the false positive case rate. Then, get the calculation formulas of both, as shown in the formula:

$$\begin{aligned} \text{TPR} &= \frac{\text{TP}}{\text{TP} + \text{FN}}, \\ \text{FPR} &= \frac{\text{FP}}{\text{FP} + \text{TN}}. \end{aligned} \quad (11)$$

ROC curve can be drawn according to the above formula, and then AUC can be calculated.

Accuracy is calculated by using the proportion of correctly classified items in the total items, as shown in the formula:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}. \quad (12)$$

- (2) Select the precision and recall of the first K items after sorting to evaluate the performance of recommendation

The accuracy is shown in the formula:

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \quad (13)$$

Recall rate:

$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \quad (14)$$

4.4. Analysis of Experimental Results. Kgmm, CKE, and DKN models are run on the data set to obtain their respective AUC and ACC. The comparison is shown in Table 3.

According to Table 3, the AUC of KGMRM model proposed in this paper is 6.2% and 20.1% higher than CKE

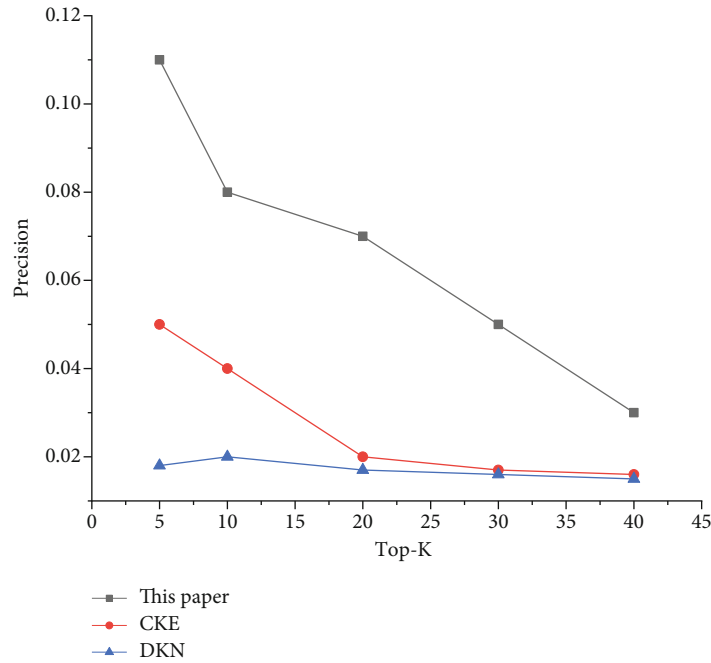


FIGURE 3: Prediction results of precision in different models.

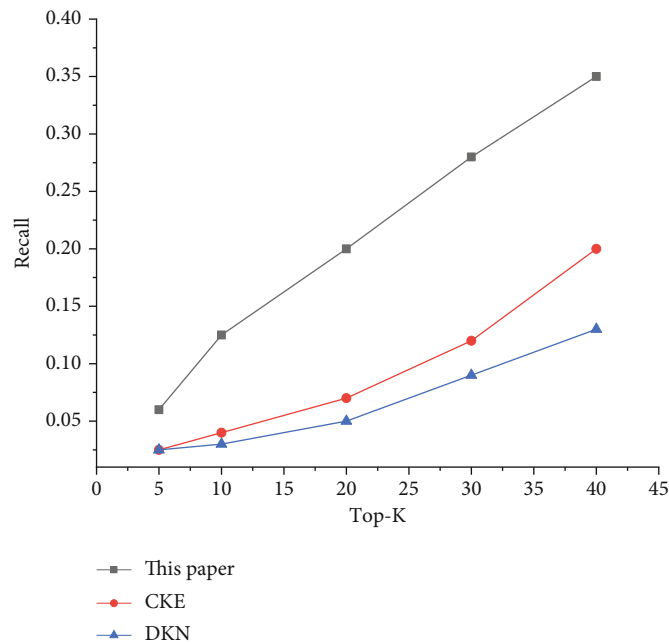


FIGURE 4: Prediction results of recall in different models.

model and DKN model, and the accuracy rate of KGMRM model is 15.05% higher than CKE model and DKN model in average. It can be seen that the effect of KGMRM classification is very good, and the prediction accuracy is higher than the commonly used models.

Under the condition of recommending K items list, the results of each model are calculated according to the formula of precision and recall, as shown in Figures 3 and 4.

According to Figure 4, the KGMRM model proposed in this paper is superior to the other two models in terms

of accuracy and recall rate, and has obvious advantages. DKN model is at the bottom of the experimental results of accuracy and recall, and there is a significant gap between the results of AUC and accuracy compared with the other two models, because DKN is suitable for text analysis, while the names of course in the data set are relatively short.

Based on the comparison results of the models above, the KGMRM model proposed in this paper can advance the implementation of online learners' course

recommendation, and the overall performance is good, with obvious advantages.

5. Conclusion

In this paper, the recommendation system of course for online learners is designed, combined with the advantages and disadvantages of the current recommendation algorithm, the recommendation based on knowledge map is proposed, and it is applied to online learner course recommendation. In addition, the construction of the recommendation system based on knowledge map is completed, which embeds knowledge map to improve the quality of recommendation. Moreover, it can learn the interaction between the items in the recommendation module and the entities in the knowledge map. It also enables the knowledge map and the recommendation module to jointly explore implicit characteristics each other, so as to realize recommendation of course for online learners. Through the design and experiment of online learners' course algorithm based on knowledge map, which can advance the implementation of the function of recommendation, the overall performance is excellent.

Data Availability

The data set can be accessed upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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