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A Cross-Curriculum Video Recommendation Algorithm Based on a Video-Associated Knowledge Map

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ABSTRACT Learning resource recommendation, such as curriculum video recommendation, is an effective way to reduce cognitive overload in online learning. The existing curriculum video recommendation systems are generally limited to one course, ignoring the knowledge correlation between courses. In this work, we propose a two-stage cross-curriculum video recommendation algorithm that considers both the learners' implicit feedback and the knowledge association between course videos. First, we use collaborative filtering to generate a video seed set, which is based on the learner's implicit video feedback, such as video learning frequencies, video learning duration, and video pausing and dragging frequencies. Second, we construct a cross-curriculum video-associated knowledge map and use a random walk algorithm to measure the relevance of the course videos. The relevance is based on each video seed as a starting node and is extended to a video subgraph. Then, several cross-curricular video-oriented subgraphs are recommended for the learners. The experimental results indicate that our cross-curriculum video recommendation algorithm performs better than the traditional collaborative filtering-based recommendation algorithms in terms of accuracy, recall rate and knowledge relevance.

INDEX TERMS Online learning, Collaborative filtering, Video-associated knowledge map, Curriculum video recommendation

I. INTRODUCTION

RECENTLY, with the increasing growth in the number of learning resources in online learning, it is quite challenging to find suitable resources to meet learners' different demands [1][2]. Learning resource recommendation is an effective way to reduce the cognitive load when massive learning resources are available [3][4][5]. From the granularity of the recommended resources, research on learning resource recommendation has been divided into curriculum-level recommendation, video-level recommendation and knowledge-level recommendation. Dwivedi [4] classified learners based on the learners' profiles and learning logs and then adopted association rule mining to recommend curriculums for learning groups. Li [2] collected the learner's rating on the course and made course recommendations based on a collaborative filtering algorithm, which solved the cold start problem of new courses based on the similarity of the course content. Tarus J K [5] and Gulzar Z [6] constructed a course ontology and retrieved the course in the ontology for the learners. Jia [7] analyzed the interactive data of learners in the forum to mine associations between learners and then recommended videos to the learner based on the learners' association. Tam V [8] presented an explicit semantic analysis, then enhanced the ontology analysis through concept clustering, and applied an optimizer to find an optimal learning path of involved concepts or modules. Zhu [9] proposed a multi-constraint learning path recommendation algorithm based on a knowledge map. The recommended learning path is generated by considering the combination of the domain knowledge structure and the cognitive structure of the learners.

In summary, the existing learning resource recommendation algorithms often ignore the relevance between learning resources in cross-curriculum scenarios. As is known, this relevance exists not only within the curriculum but also in a number of courses in similar specialties. On the other hand, the result of the recommendation is mainly based on a resource list, which weakens the knowledge association between the learning resources, such as curriculum videos.

This study selects the curriculum video as the recommended object. From two aspects of the learner's learning log and curriculum resources that rely on the Distance Learning College (DLC) of our university, a two-stage cross-curriculum video recommendation algorithm based on a video-associated knowledge map (named CCVR) is proposed that considers both the implicit learning features of the user and the knowledge relevance between the course videos. The main contributions of this paper are as follows.

First, the recommended video seed set is obtained based on implicit learning feature extraction from the learner's point of view. Through the analysis of the learner's log data, implicit features such as video learning frequency, video learning duration, video pausing and dragging frequency and the learning behavior of the courseware (PPT) are mined. A learner's video preference model is built, and then the recommended video seed set is generated by a collaborative filtering algorithm based on the proposed implicit features.

Second, to show the degree of relevance between the curriculum videos, the recommended video seed set is expanded to generate a video recommendation subgraph. From the perspective of learning resources, the knowledge map of the multicourses is integrated to construct a video-associated knowledge map that represents the degree of relevance between the curriculum videos. In addition, the degree of relevance is measured by a random walk algorithm. Based on the video-associated knowledge map, each video seed is extended to generate a video subgraph. This provides the learners with video recommendations that conform to their implicit learning preferences and knowledge relevance.

In the experiment, we selected 224 course videos, 53,491 video learning logs and 140,122 courseware learning logs as experimental datasets. A video-associated knowledge map, which contains 973 knowledge elements and 224 course videos, is constructed. The user-based collaborative filtering recommendation algorithms Times-CF and Dur-CF are used as benchmarks. By comparison of the accuracy rate, recall rate and the degree of relevance between the curriculum videos, the experimental results show that the proposed cross-curriculum video recommendation algorithm improves the performance indexes compared with those of the benchmarks.

The rest of the paper is organized as follows. Section 2 presents the relevant research on video recommendation in online learning. Section 3 gives a framework of the cross-curriculum video recommendation algorithm based on a video-associated knowledge map (CCVR), which includes the video preference modeling of learners based on implicit feedback and the construction of a video-associated knowledge map. Section 4 explains the specific implementation process of the three major steps of the CCVR algorithm. Section 5 presents the experimental results and analysis.

II. RELATED WORKS

Online video recommender systems help users find videos suitable for their preferences. The current methods of video recommendation mainly include collaborative filtering-based video recommendation and content-based video recommendation.

A. VIDEO RECOMMENDATION BASED ON COLLABORATIVE FILTERING

Collaborative filtering is considered the most popular technology in recommendation systems [10], which provides users with similar items of interest to the users. The collection of user preferences is the basis for the CF algorithm. User preferences are divided into explicit feedback and implicit feedback [11]. Chen [12] constructed an interaction vector between learners and videos based on the behavior of learners watching and collecting videos and measured the similarity between the learners with interactive vectors, thus created a video recommendation system based on collaborative filtering. I Y Choi [13] proposed a recommendation procedure using changes in the users' facial expressions captured every moment. The proposed procedure addresses a user's preference changes often as observed while the user watches a video. J Zhang [14] proposed an AP-based context-aware (APCA) recommendation scheme in addition to the traditional factor-based CF algorithm by utilizing the information of access points. Yildirim [15] proposed a new memory-based collaborative filtering algorithm. The adopted idea in this study is that the more similar the user's preferences are, the more similar the products that are chosen. Ding J [16] used a multiple linear regression model to fit the user's preferences to the video so that the user's preferences can be automatically calculated by analyzing a series of user behaviors toward the video without requiring the user's rating action.

Due to the lack of explicit scoring data on the online learning platform [17], an increasing number of collaborative filtering-based curriculum video recommendation systems collect user preferences with implicit feedback [18,19], such as video viewing length and video viewing times. However, they often neglect the learners' behaviors of video pausing and dragging, which also reflect the learner's preferences toward the video. In addition, the existing research often ignores the analysis of the courseware learning behavior, which can also reflect the learner's preferences toward the curriculum content.

B. CONTENT-BASED VIDEO RECOMMENDATION

Although the collaborative filtering algorithm is widely used, it still suffers from data scarcity, scalability, and cold start, which seriously restrict the recommendation quality. Content-based recommendation is a common method to solve the cold start problem. The core idea of content-based recommendation is to recommend a similar project to the user based on an analysis of the content of the recommended project [20,21]. This depends on the content extraction from the curriculum video.

Ling Xiong [22] proposed a label-based video recommendation method that provided learning video recommendations to learners by constructing a learners' interest model by labeling the watched video. Tsai K H [23] used an ontology to describe learning resources such as videos and then recommended videos for the learners. Content-based curriculum video recommendation often uses labels and ontologies to describe the video but largely ignores the knowledge correlation between the videos. Cui L [24] proposed a novel video recommendation algorithm based on a combination of video content and social networks. It consists of the trust friends computing model and the video's quality evaluation model. Liang J S [25] proposed a collaborative filtering recommendation system based on video content detection. The gradient description is adopted to compute the main motion direction and scale of the space-time interest points; then, a gradient vector matrix is constructed for each video sequence. Li Y [26] proposed a content-based video recommendation approach by taking advantage of deep convolutional neural networks to alleviate the cold start problem. Deldjoo Y [27] proposed a content-based recommender system that encompasses a technique to automatically analyze video content and to extract a set of representative stylistic features (lighting, color, and motion) grounded in existing approaches of applied media theory. Lee J [28] modeled recommendation as a video content-based similarity learning problem, and employed learned deep video embedding that are trained to predict video relationships identified by a co-watch-based system. G Wu [29] presented an approach for video recommendation based on session progress prediction and incorporating the context. C Bhatt [30] described a system for video recommendation that combines topic-based video representation with sequential pattern mining of intertopic relationships. There are also some video recommendations based on deep learning, they used it to model auxiliary information, such as the video content or user feature information.

In summary, content-based video recommendation often uses labels and ontologies to describe the video but largely ignores the knowledge correlation between the curriculum videos. Therefore, this paper constructs a cross-curriculum video-associated knowledge map and then provides learners with several cross-curriculum video subgraphs, which not only satisfy their learning preferences but also take into account the knowledge associated with the video.

III. RESEARCH FRAMEWORK

A cross-curriculum video recommendation framework based on a video-associated knowledge map is shown in Fig. 1.

The framework is divided into three parts: construction of the video seed set, calculation of the degree of relevance between the curriculum videos and generation of the video-oriented subgraph recommendation. First, the implicit feedback features of the learners' video preference can be mined from the learner's log, and then the video seed set is obtained by using the collaborative filtering recommendation based on implicit feedback. Second, drawing on the concept of a heterogeneous information network, a cross-curricular video-associated knowledge map is built to calculate the degree of relevance between the curriculum videos. Third, the recommended video-oriented subgraph is provided, which extends the video seed set according to the degree of relevance between the curriculum videos. In this section, we present the learner's video preference model based on implicit feedback and the related definitions in the video-associated knowledge map construction process.

A. VIDEO PREFERENCE MODELING FOR LEARNERS BASED ON IMPLICIT FEEDBACK

This section uses the online learning platform of the DLC as an example to analyze the learning logs and mine the implicit feedback features of learners. We filter three video learning behaviors from the 88 online learning behaviors, which include video learning frequency, video learning duration, and video learning pausing and dragging.

- Definition 1: preference of the video learning frequency
  The ratio of the learner's video learning frequency to the maximum frequencies by a single learner is shown in (1):

$$p_f(u_i, vl_k) = \frac{frequency(u_i, vl_k)}{\max\limits_{1 \le j \le N} frequency(u_j, vl_k)} \tag{1}$$

  where vl_k represents video k, $frequency(u_i, vl_k)$ represents the learning frequencies of u_i watching vl_k, and $p_f(u_i, vl_k) \in [0, 1]$ is the preference of video learning frequencies.
- Definition 2: preference of the video learning duration
  The ratio of the learner's video learning duration to the video's original duration is shown in (2):

$$p_d(u_i, vl_k) = \begin{cases} \frac{duration(u_i, vl_k)}{3 * dur_{vl_k}}, & \frac{duration(u_i, vl_k)}{dur_{vl_k}} \le 3 \\ 1, & \frac{duration(u_i, vl_k)}{dur_{vl_k}} > 3 \end{cases} \tag{2}$$

  where $duration(u_i, vl_k)$ represents the learning duration of u_i watching vl_k, dur_{vl_k} represents the video's original duration, and $p_d(u_i, vl_k) \in [0, 1]$ is the preference of the video learning duration.
  With reference to the definition of the single effective learning duration [31], this paper considers that the learner has effectively learned this video if the video

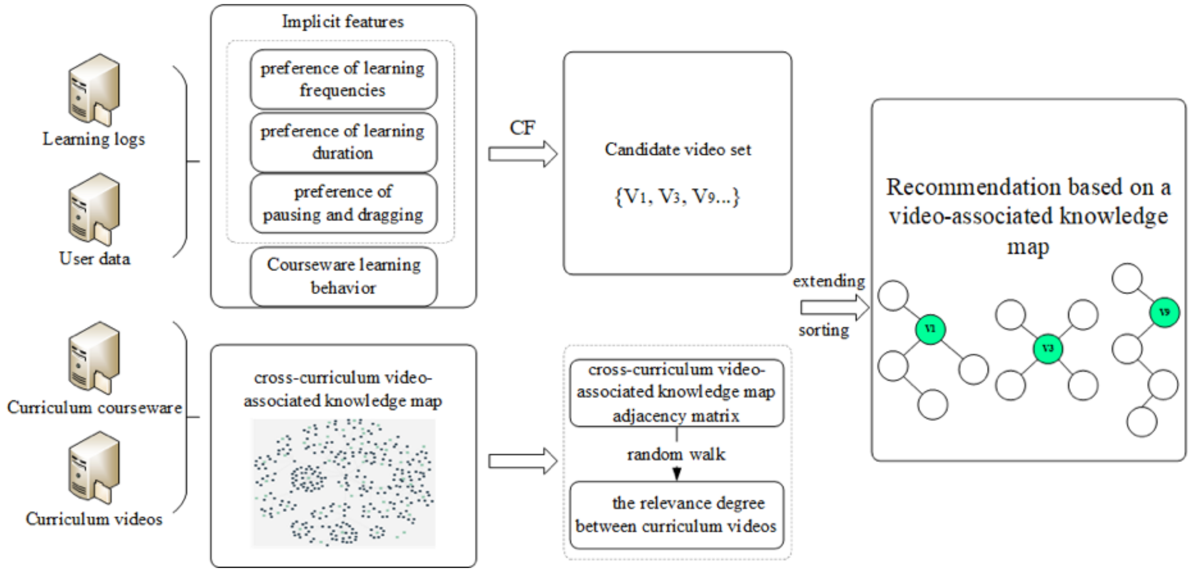

FIGURE 1. Research framework

learning duration is 3 times longer than the video's original duration.

- Definition 3: preference of the video pausing and dragging frequency The ratio of the learner's video pausing and dragging frequency to the maximum frequencies by a single learner is shown in (3):

$$p_{pd}(u_i, vl_k) = \frac{pause(u_i, vl_k) + drag(u_i, vl_k)}{\max\limits_{1 \le j \le N}(pause(u_j, vl_k) + drag(u_j, vl_k))} \tag{3}$$

where $pause(u_i, vl_k)$ represents the frequency of u_i pausing the vl_k, $drag(u_i, vl_k)$ represents the dragging frequency, and $p_{pd}(u_i, vl_k) \in [0, 1]$ is the preference of the video pausing and dragging frequencies.

B. CONSTRUCTING THE CROSS-CURRICULUM VIDEO-ASSOCIATED KNOWLEDGE MAP

Research on the internal relevance of the curriculum videos is not limited to a single curriculum but extended to cross-curriculum videos. For example, we explored the relevance between the videos of several relevant curriculums in the same semester. Therefore, this section constructs a cross-curriculum video-associated knowledge map as the basis for the cross-curriculum video recommendation.

1) The relevance between the cross-curriculum videos

For most online curriculum videos, there is a many-to-many relevance between the video and knowledge units[32], which include the following three typical relevance relationships between curriculum videos among several related curriculums, especially during the same semester:

1) Within a certain curriculum, the knowledge unit ku_i exists in both videos vl_a and vl_b, which is defined as KV^2.
2) Within a certain curriculum, there is a learning dependency between the knowledge unit ku_j contained in video vl_c and the knowledge unit ku_k contained in vl_d, which is defined as KK_{inner}.
3) Among different courses, there is an association relevance between the knowledge units ku_l contained in video vl_e and ku_m contained in vl_f, which is defined as KK_{cross}.

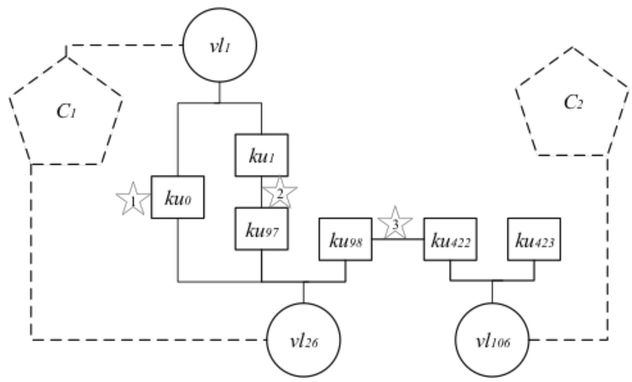

FIGURE 2. Three types of relevance between curriculum videos

Fig. 2 presents an example to illustrate the three types of relevance between curriculum videos:

As shown in Fig. 2, C_1 and C_2 in the dotted box represent two different curriculums. The symbols 1, 2 and 3 correspond to the above three typical relevance between curriculum videos.

[2]Simplify the spelling of KU and VL, where V represents curriculum video, K represents knowledge unit.

2) Cross-Curriculum Video-Associated Knowledge Map ($CCVKM$)

The metapath in the heterogeneous information network [33,34] is a path that links two types of objects defined on the network pattern. The metapath not only describes the semantic relevance between objects but also can extract feature information between objects. Referring to the concept of heterogeneous information networks, the above three types of relevance can be viewed as three types of meta-path: VKV, $VKKV_{inner}$, and $VKKV_{cross}$. We use keyword matching and semantic analysis to define the nodes of the cross-curriculum video-associated knowledge map as knowledge elements KU and curriculum videos VL. There are three kinds of edges, which include the learning dependency between the knowledge elements in the curriculum KK_{inner}, the relevance between the cross-curriculum-videos KK_{cross} and the association relevance between the curriculum videos and knowledge elements KV.

The cross-curriculum video-associated knowledge map can be defined as:

$$CCVKM = \{V, E\} \tag{4}$$

where $V = \{v_p | p = 1, ..., N_p\}$ represents node sets in $CCVKM$, including KU, VL and N_p, which represents all nodes; $E = \{e_{pq}\} = \{(v_p, v_q) | 0 < p, q \leq N_p\}$ represents the edges sets in $CCVKM$, including three types: KK_{inner}, KK_{cross}, KV, where $e_{pq} = (v_p, v_q)$ is the edge from the node p to the node q.

Fig. 3 shows the visualization of a cross-curriculum video-associated knowledge map with three curriculums in the fourth semester of computer science in DLC, Operating System Principle, Principles of Computer Network and Java Language. As shown in Fig. 3, the dots represent the knowledge unit KU, the boxes represent the curriculum video VL, and the different colors represent the different curriculums. There are 973 knowledge units and 224 curriculum videos, KK_{inner} has 1033 edges, KK_{cross} has 108 edges, and KV has 1070 edges.

FIGURE 3. $CCVKM$ of three professional curriculums

IV. A CROSS-CURRICULUM VIDEO RECOMMENDATION ALGORITHM BASED ON A VIDEO-ASSOCIATED KNOWLEDGE MAP

As seen in Fig. 1, the cross-curriculum video recommendation algorithm based on a video-associated knowledge map is divided into three steps. The following will introduce these step by step.

A. CONSTRUCTING THE VIDEO SEED SET

To recommend the video-oriented subgraph for learners, we need to construct a video seed set and then take each video seed as the starting node to construct a video-oriented subgraph recommendation. Next, we will introduce the construction of the video seed set.

1) Constructing a rating matrix based on implicit feedback

According to the learner's video preference model in 3.1, the learners' preferences for the video learning frequencies, video learning duration and video pausing and dragging frequencies are weighted as the learners' rating for the videos, which is shown in (5):

$$p(u_i, vl_k) = \alpha * p_f(u_i, vl_k) + \beta * p_d(u_i, vl_k) + \gamma * p_{pd}(u_i, vl_k) \tag{5}$$

For a given learner and a given course, using (5) to calculate the score of the course video by all learners, the score matrix can be formed as the basis for the similarity calculation of learners and the construction of the recommended list. In this paper, a total of 67 different combinations (α, β, γ) were tested under the ratio of integer, and it was concluded that the recommendation accuracy was the highest when the value was (1,5,4).

2) Calculating the learners' similarity

Learner similarity is measured in two parts: video learning similarity and courseware learning similarity. Courseware is another important method of learning other than video. The smaller the difference in total learning times of learners' courseware, the higher the similarity of learners' learning behaviors. Based on the differences in the learning times for the courseware, this paper defines the similarity of the learners' courseware learning behavior, which is shown in (6):

$$sim_{cw}(u_i,u_j)=\begin{cases}1, & |CT(u_i,u_j)|=0\\ \frac{1}{|CT(u_i,u_j)|}, & 0<|CT(u_i,u_j)|<T\\ 0, & |CT(u_i,u_j)|=T\\ \frac{1}{|CT(u_i,u_j)|-T}-1, & |CT(u_i,u_j)|>T\end{cases} \tag{6}$$

where CT represents the difference between the courseware learning frequencies of u_i and u_j and T is the threshold of the difference between the two learners' courseware learning frequencies.

The learners' similarity is calculated by combining the Pearson [10] correlation coefficient and the similarity of the learners' courseware learning behavior, which is shown in (7):

$$sim(u_i,u_j)=\xi * sim_{pearson}(u_i,u_j)+\eta * sim_{cw}(u_i,u_j) \tag{7}$$

where $sim_{pearson}(u_i,u_j)$ represents the rating vectors' Pearson correlation coefficient of u_i and u_j.

3) Calculating the video seed set

In this paper, we calculate the video seed set by using collaborative filtering based on implicit feedback. The prediction of a learner's rating for one specific video is shown in (8):

$$p_{prediction}(u_i,vl_k)=\sum_{u_j\in neighbor(u_i)} sim(u_i,u_j)*p(u_j,vl_k) \tag{8}$$

where $p_{prediction}(u_i,vl_k)$ represents the prediction rating of u_i for video k. The video seed set generation algorithm is shown in Table 1. The algorithm complexity is $O(n^2)$.

B. CALCULATING THE DEGREE OF RELEVANCE BETWEEN CURRICULUM VIDEOS

As mentioned in section 3.2, $CCVKM$ contains three typical types of relevance between curriculum videos, which are VKV, $VKKV_{inner}$ and $VKKV_{cross}$. In this paper, we define the degree of relevance to represent the correlation between the curriculum videos in $CCVKM$. The degree of relevance matrix of the videos will be used to generate the video-oriented subgraph recommendation in the next section.

Fouss $et\ al.$ [35] proposed a Markov-chain-based node similarity calculation method for a weighted graph. They defined a random walk through the nodes by assigning a transition probability to each link. When the number of paths connecting two nodes was more or the length of the path was smaller, the correlation between the two nodes was closer. This can be used to calculate the degree of relevance between the curriculum videos. In their paper, the average commute time was defined as the average number of steps that a random walker starting in state $i \neq j$ takes to enter state j for the first time and return to i.

First, we build the adjacency matrix of $CCVKM$. The adjacency matrix is symmetric because the $CCVKM$ we

TABLE 1. The video seed set generation algorithm

```
Input: learnerId
  K, Number of neighbors
  N, Recommended videos
Output: videoSeeds, recommended video seed set
for i < learnerNum do: // i = 0; learnerNum represents the total
                       //number of learners;
                       //Calculating the learner's rating matrix
   for j < videoNum do: // j = 0;videoNum represents the total
                        //number of curriculum videos
      p = calLearnersPreference(i, j, α, β, γ) // go to (5)
      preferenceMartrix[i][j] = p
      j++
   end for
   i++
end for
for l < learnerNum do //l = 0; Calculating learners' similarity
   sim = calLearnersSim(l, learnerId, ξ, η) //go to (7)
   simArr.add(sim)
   l++
end for
simLearners = getKNeighbors(simArr, K)
                       //Selecting neighbor learners
for m < videoNum do:   //Calculating recommended results
   pred = calPrediction(preferenceMartrix, simLearners, m)
   pArr.add(pred)
end for
for aVideo in learnedVideos do:
               //eliminating videos that have been effectively learned
   totalTlen = countTotalTlen(aVideo)
   if effectiveLearned(totalTlen, videosDur)
      learnedVideos.remove(aVideo)
   end if
end for
videoSeeds = getTopN(pArr, learnedVideos, N)
 //selecting from the candidate videos list using the TOP-N principle
return {rec}
```

construct is an undirected graph. Assume that the $CCVKM$ consists of n nodes, and then the adjacency matrix A is defined as follows:

$$A=[a_{ij}]_{n*n} \tag{9}$$

$$a_{ij}=\begin{cases}w_{ij}, & if\ node\ i\ is\ connected\ to\ node\ j\\ 0, & otherwise\end{cases} \tag{10}$$

where w_{ij} represents the weight between node i and node j. In this paper, we set the weights of KK_{inner}, KK_{cross} and KV all equal to one.

Second, the calculation of the average commute time, denoted as $avgCT(i,j)$, is shown in (11):

$$avgCT(i,j)=V_G(l_{ii}^{+}+l_{jj}^{+}-2l_{ij}^{+}) \tag{11}$$

where $V_G = \sum_{k=1}^{n} d_{kk}$, $d_{ii} = \sum_{j=1}^{n} a_{ij}$, l_{ii}^{+}, l_{jj}^{+}, l_{ij}^{+} are the members of the Moore-Penrose pseudoinverse of the symmetric Laplacian matrix of the graph, denoted as $\boldsymbol{L}^{+}$.

According to the definition of the average commute time, the larger $avgCT(i,j)$ is, the smaller the similarity between the two nodes. Theoretically, as the scale of the graph increases infinitely, the range of $avgCT(i,j)$ is $[0,+\infty)$.

TABLE 2. Example of the degree of relevance for the curriculum videos

	videos of one-dimensional array	videos of multi-dimensional array	videos of character array
videos of one-dimensional array	1.0	0.6459	0.4096
videos of multidimensional array	0.6459	1.0	0.2938
videos of character array	0.4096	0.2938	1.0

Finally, based on the average commute time $avgCT(i, j)$, we propose the formula for the degree of relevance between the curriculum videos $r(vl_i, vl_j)$ as (12):

$$r(vl_i, vl_j) = 1 - \frac{avgCT(i, j)}{\max(avgCT(i, j))} \tag{12}$$

where $\max(avgCT(i, j))$ represents the max value of all the curriculum videos' $avgCT(i, j)$. The range of $r(vl_i, vl_j)$ is $[0, 1]$. The greater the value of $r(vl_i, vl_j)$ is, the greater the relevance between vl_i and vl_j.

We calculate the degree of relevance for the 224 curriculum videos of the $CCVKM$ in Fig. 3. Table 2 shows an example of the degree of relevance of the three curriculum videos for the $Java\ Language$ course.

C. GENERATING A CROSS-CURRICULUM VIDEO-ORIENTED SUBGRAPH

The video-oriented subgraph consists of two parts. One part is the video seed, and the other part is the extended videos that have knowledge relevance with the video seed. The cross-curriculum video recommendation algorithm based on a video-associated knowledge map algorithm is shown in Table 3.

As shown in Table 3, $visited$ is defined to store the nodes that have been visited, and $selectedNodes$ and $selectedEdges$ are defined to store the nodes and edges that have been added to the video-oriented subgraph recommendation (denoted as $subGraph$). For each video in the video seed set, the procedure used to generate $subGraph$ is as follows: first a certain seed node is added to $selectedNodes$. Second, when the number of nodes in $selectedNodes$ is less than N, the following operations are executed cyclically: For each node in the current $selectedNodes$, find the node that has the highest degree of relevance with it. Then, select the node with highest degree of relevance, and add it to $selectedNodes$ and visited; meanwhile, the relevant edge is added to the $selectedEdges$. Finally, generate a video-oriented subgraph with the $selectedNodes$ and $selectedEdge$, and then add it to $recVideosSubgraphs$.

V. EXPERIMENT

This section describes our experiment, its dataset, the performance index and the results. Two user-based collaborative filtering algorithms Times-CF and Dur-CF are used as benchmarks. Times-CF takes $p_d(u_i, vl_k)$ to construct its rating matrix, while Dur-CF takes $p_f(u_i, vl_k)$ to construct its rating matrix. In addition to the accuracy rate and recall rate, the knowledge relevance of the recommendation results is verified.

TABLE 3. The cross-curriculum video recommendation algorithm

```
Input: learnerId
videoSeeds represents the video seed set
CCMV represents the adjacency matrix of the video-associated knowledge map
N represents the size of the video-oriented subgraph
Output: recVideosSubgraphs represents the video-oriented subgraph set
for aVideo in videoSeeds do:
    visited = {{}}  // visited represents nodes that have been visited
    selectedNodes = {} //nodes that have been added to video-oriented
                       //subgraph
    selectedEdges = {} //edges that have been added to video-oriented
                       //subgraph
    selectedNodes.add(aVideo)
    setVisited(visited, aVideo)
    while selectedNodes.size() < N
        (node1, node2) = findMaxRelatedNodes(selectedNodes)
        selectedNodes.addNode(node2)
        selectedEdges.addEdge(node1, node2)
        setVisited(visited, node2)
    end while
    subGraph = genSubG(CCMV, selectedNodes, selectedEdges)
               //Single video-oriented subgraph
    recVideosSubgraphs.add(subGraph)
               //the video-oriented subgraph set
end for
return recVideosSubgraphs
```

TABLE 4. Log format

Fieldname	Sample	Field meaning
LOGID	30528972	Log number
PLATFORMID	2	Platform number
OPERATEID	76	Operation number
COURSEID	148	Curriculum number
OPERATETIME	2014-11-16 14:29:53.0	Operation time
STUDENTCODE	106980011203****	Student id
TLEN	89	Operation duration
TITLEID	25445729	Title number
TITLE	CPU	Title content

A. DATASET OF THE EXPERIMENT

Three curriculums (Operating System Principles, Principles of Computer Networks and Java Language) from the computer science and technology program of the DLC are selected. There are 224 curriculum videos, 53,491 video learning logs and 140,122 courseware learning logs. We divide the video learning logs into five parts, of which the first four serve as training sets and the remaining one serves as a test set. The learning log format is shown in Table 4.

B. EVALUATION INDICATOR

The following is the definition of the three evaluation indicators: accuracy rate, recall rate and knowledge relevance.

1) Accuracy rate

$$P_{u_i} = \frac{|rec(u_i) \cap real(u_i)|}{|rec(u_i)|} \tag{13}$$

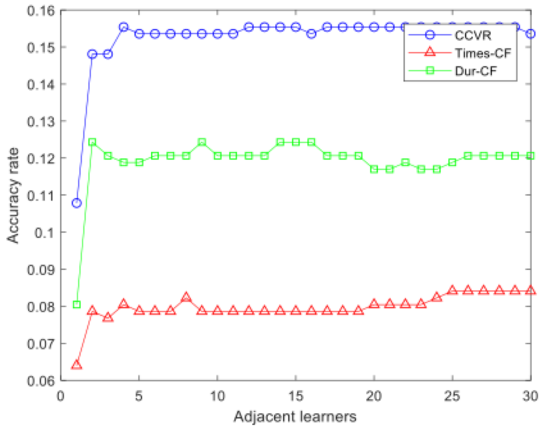

FIGURE 4. The accuracy rate under different K values when $N = 3$

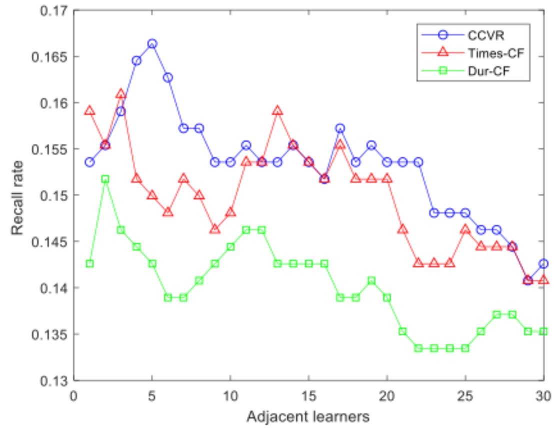

FIGURE 5. The recall rate under different K values when $N = 3$

2) Recall rate

$$R_{u_i} = \frac{|rec(u_i) \cap real(u_i)|}{|real(u_i)|} \quad (14)$$

where $rec(u_i)$ represents the video list recommended to u_i and $real(u_i)$ represents the video list that u_i has actually learned. As shown in Table 1, $rec(u_i)$ is the video seed set.

3) Knowledge relevance
Based on the degree of relevance between the curriculum videos, we propose knowledge relevance (KR), which is used to describe the degree of knowledge relevance between the recommended videos. The specific calculation is the average of the degree of relevance of all pairs of videos in the recommendation list, which is shown in (15).

$$KR = \frac{\sum r(vl_i, vl_j)}{n} \quad (15)$$

The range of KR is [0, 1]. The larger the value is, the greater the degree of knowledge relevance of the recommended videos.

C. EXPERIMENT RESULTS AND ANALYSIS

We evaluate the evaluation indicator of our proposed algorithm CCVR with the two benchmarks Times-CF and Dur-CF.

1) Accuracy rate & recall rate
Based on the training sets, by adjusting the number of adjacent learners K and recommended videos N, we generate the video seed set for all the learners via the video seed set generation algorithm. Meanwhile, we generate the recommended video list for all the learners via Times-CF and Dur-CF and then evaluate the accuracy rate and recall rate of the three algorithms. The experimental results are shown in Fig. 4, Fig. 5, Fig. 6 and Fig. 7.

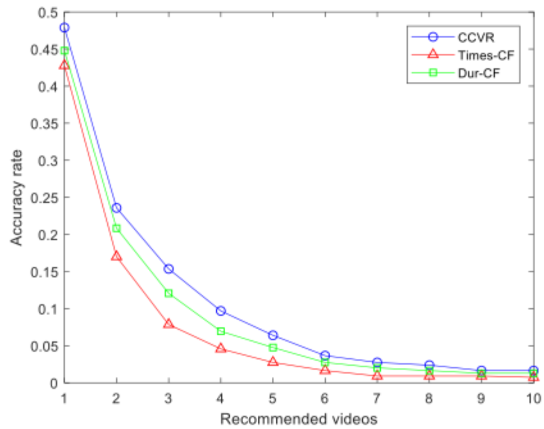

FIGURE 6. The accuracy rate under different N values when $K = 10$

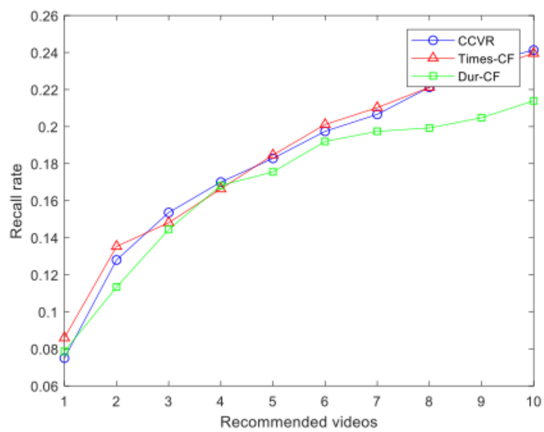

FIGURE 7. The recall rate under different N values when $K = 10$

As shown in the above four figures, our algorithm outperforms Times-CF and Dur-CF in accuracy rate and recall rate in most cases due to the learners' behavior

TABLE 5. The knowledge relevance KR under different N values

number of recommended videos / knowledge relevance	$N=2$	$N=3$	$N=4$	$N=5$
CCVR	0.8523	0.8317	0.8217	0.8011
Times-CF	0.7112	0.7066	0.6979	0.6953
Dur-CF	0.7280	0.7176	0.7126	0.7070

of video pausing and dragging.

2) Knowledge relevance
For a given learner, first, we set $K = 10$, adjust N from 2 to 5, and then generate the video seed set $videoSeed$ for the target learner via the video seed set generation algorithm. Second, for each video in the video seed set, we use the algorithm in Table 3 to generate the $subgraph$ that has a scale N, and then we can calculate KR. The experimental results are shown in Table 5.
As shown in Table 5, the CCVR algorithm extends the video seed set and generates the video-oriented subgraph recommendation that takes into account the knowledge relevance, which improves the knowledge relevance among the recommended videos and is more conducive to the learners' mastery of knowledge.

VI. CONCLUSION

Recently, the field of online learning has developed rapidly, and an increasing number of studies have recommended system-related technologies to solve the cognitive overload of learners in the face of massive learning resources. This paper focused on the cross-curriculum video recommendation for online learning. From the two perspectives of the learners and the learning resources, this paper analyzes the learning log of the learners and the learning resources of the course video and courseware, on the basis of which a cross-curriculum video recommendation algorithm based on a video-associated knowledge map was proposed. The recommendation algorithm, which considers the learner's learning preferences, integrates the knowledge associated with the video and aims to provide a cross-curriculum video recommendation for the learners. The algorithm is mainly divided into three steps, which include video seed set construction, course video correlation calculation and cross-curriculum video subgraph generation. The performance of the proposed algorithm is verified. For cold-start user recommendation, we will consider recommending directly based on knowledge map. Next, we will optimize the computation of the video correlation in the videos-associated knowledge map by adjusting the weight of three different types of edges, then evaluate the impact on the degree of curriculum video correlation, and select a reasonable weight ratio to optimally measure the degree of knowledge correlation between the course videos.

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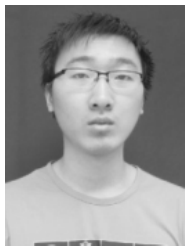

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