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Research on the Generation and Recommendation Algorithm of Civics Teaching Content for Engineering Management Course Based on Knowledge Graph and Machine Learning

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ABSTRACT

Curriculum Civics refers to the integration of Civics elements into the teaching of professional courses, so that courses other than Civics courses can also play the role of Civics teaching. In this paper, we study a knowledge mapping-based content generation technology for teaching course Civics and Politics, so that the knowledge of Civics and Politics courses can be integrated and visualized. The knowledge points, concepts, definitions and other information of the course Civics and Politics are extracted in the form of Civics and Politics knowledge triples. Through the extraction of the knowledge entity of curriculum Civics and politics, the relationship between semi-structured data and unstructured data is extracted to realize the integration of knowledge and content generation. After achieving content generation, the generated content is personalized through a deep reinforcement learning recommendation algorithm based on diversity optimization. Taking the two courses of Engineering Cost Management and Engineering Economics in the engineering management specialty as an example, it is found that the proposed knowledge graph construction method has an accuracy rate of 96.2%, which is able to effectively establish the knowledge association between the civic elements and the elements of professional knowledge, and realize the mining and generation of the civic elements. Meanwhile, the DDRL-Base recommendation algorithm achieves the optimum in accuracy, recall and F1 value indexes, and optimizes the problems such as cold start and sparse data in resource matrix, which improves the effect of recommending the Civics and Politics teaching content of the course.

Keywords: knowledge graph, knowledge triad, reinforcement learning, DDRL-Base, curriculum civics and politics

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1. Introduction

Engineering management is an important application-oriented specialty, involving the planning, design, construction, supervision and operation of engineering projects, which is one of the important disciplines to cultivate professionals in the field of engineering. With the development of society and economic growth, the demand for engineering management professionals is also increasing [1-4]. In the curriculum of engineering management majors, the Civics course is often neglected or marginalized, and many schools do not pay enough attention to the teaching of Civics course in engineering management majors, and there are even the problems of lagging behind in the teaching content and methods, which are difficult to attract students [5-8].

Engineering management is a field involving multidisciplinary knowledge, aiming to cultivate students to become engineering management talents with solid professional foundation and high humanistic literacy [9-10]. As an important part of students' ideological and moral quality education, the ideological and political courses play an indispensable role in students' growth and success. Therefore, as future practitioners in the field of engineering, engineering management students [11-13], in addition to professional technical knowledge and practical ability, they also need to have a good moral quality and sense of social responsibility. Strengthening the teaching of Civics and Political Science courses in engineering management majors, cultivating students' sense of social responsibility, cultural literacy and humanistic spirit are of great significance for improving students' comprehensive quality and future career development [14-17].

On the basis of the subject ontology knowledge of the engineering management course, Neo4j graph database is utilized to construct a knowledge map of the course's civics and politics, and the process involves the extraction and fusion of knowledge, as well as the establishment of relationships between knowledge and the generation of content. The interaction between student users and the recommendation algorithm is modeled as a Markov decision-making process, and on the basis of the reinforcement learning algorithm, combined with the teaching content recommendation task scenario of the course Civics and Politics, the key information is extracted from the interaction data through the state representation model, and transformed into vector representations that can be processed by the reinforcement learning intelligences, and a Deep Reinforcement Learning Recommendation for Diversity Optimization of Teaching Content Recommendation (DDRL) algorithm is proposed. -Base) algorithm. Finally, taking “Engineering Cost Management” and “Engineering Economics” in engineering management professional courses as research objects, the course civic knowledge maps of the two professional courses are constructed, and the effect of DDRL-Base recommendation is examined.

2. Technologies for the generation of content for the teaching of Civics in the curriculum

2.1. *Knowledge Mapping of Curriculum Civics*

The establishment of a knowledge map of Civics for engineering management-oriented professional courses involves several processes, such as ontology establishment, knowledge extraction, knowledge generation, and the implementation of a visualization system. This topic is based on the characteristics of the topic of Civic and Political Science and the design principle of knowledge graph, and gradually build a visualization system based on knowledge graph. The construction process of the course Civics and Politics knowledge graph is shown in Figure 1 [18].

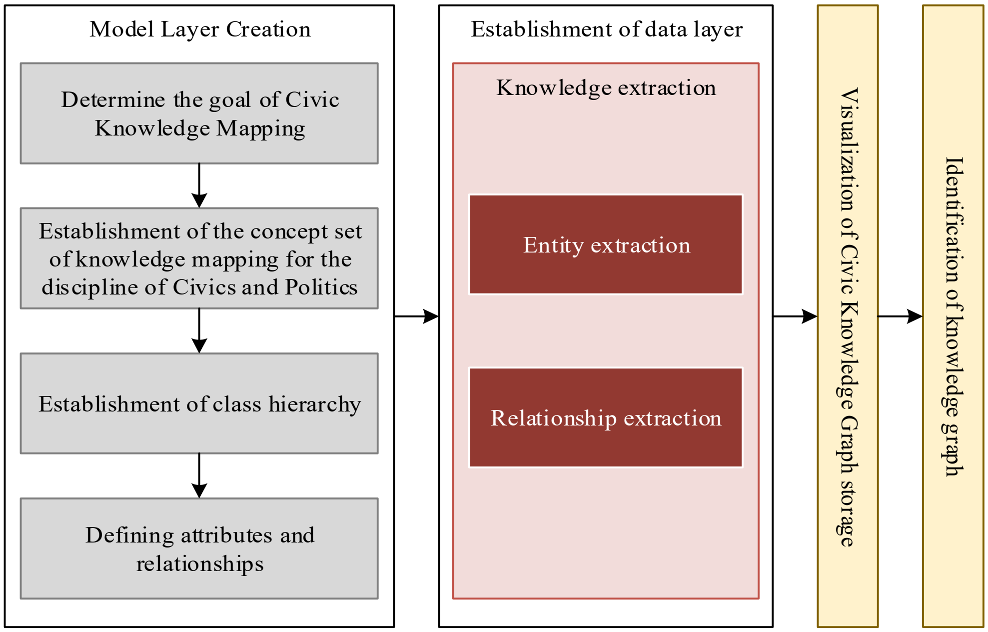

Fig. 1. Knowledge graph construction process of ideological and political courses

2.2. Establishment of the Civics Ontology of the Curriculum

2.2.1. Ontology Description Language. In order to establish the standard, two ontology description formats, RDF and OWL, were finalized.RDF is an ontology description language based on the XML language, which is composed of a point representing a resource and an arc representing the resource.It can be used to inscribe connections between resources and is suitable for expressing complex relationships. RDFS based on RDF is a way to describe the hierarchy of classes, attributes, etc., but it does not fully express the resources. To solve this problem, OWL appears as an improved RDFS ontology description language.

OWL is an object-oriented development language based on classes, individuals, and attributes, and provides users with three seed languages, OWL Lite, OWL DL, and OWL Full, to satisfy the needs of users for a wide range of applications.The vocabulary of OWL contains a lot of information, which makes it more versatile and interpretive. Overall, OWL provides a rich mechanism for describing classes and attributes to more accurately describe information resources.

2.2.2. Ontology construction tools. Protégé was chosen for this paperThis paper has chosen an object-oriented generator tool for the development of domain ontologies.Protégé is a Java language-based software specially designed for creating and editing ontologies, with many features that other tools do not have.Protégé is an object-oriented generator that allows you to create and edit your own ontologies:

1) Intuitive, allowing the use of a graphical interface.

2) Extensibility, with support for plug-ins and so on. Users can easily use it to develop classes, instances, and relations of ontologies, and visualize the hierarchical structure of ontologies through the OntoGraf plug-in.

3) Protégé also provides editing and management functions for RDFS and OWL.

2.3. Curriculum Civics Knowledge Extraction

Entity recognition of curriculum civics knowledge is a kind of named entity recognition task based on Chinese language classification, due to the complicated and polysemous characteristics of curriculum civics knowledge itself. Therefore, named entity recognition of curriculum civics has many technical difficulties that need to be broken through compared to other fields.

The area of research in this paper involves extracting Civics knowledge triples from semi-structured and unstructured data to build a knowledge graph. The construction of a knowledge graph requires the extraction of knowledge triples from preprocessed data. This process is usually divided into four steps:

1) Use entity recognition techniques to extract domain entity names contained in the text.
2) Relationship extraction techniques are used to extract the relationships between entities.
3) Perform knowledge fusion on the extracted entity-relationship triples.
4) Store the acquired knowledge triples into the appropriate database.

2.4. Integration of Civic and Political Knowledge in the Curriculum

This session uses a two-layer filtering approach for the fusion of course Civic Knowledge as shown in Figure 2. In the fusion process, each entity needs to go through two rounds of filtering. Each round of filtering sets a threshold σ_1 and a threshold σ_2. At each stage, the entities are scored for similarity. When the similarity between the two is greater than threshold σ_1, they are considered as the same entity and are fused. If the similarity score of both is less than threshold σ_2, it means that they are not the same entity and have different meanings, which need to be further determined. Between thresholds σ_1 and σ_2, or if there is a loss of objects during the determination, the next filtering step is required. The first filtering uses a characterization based on a string of entity names.

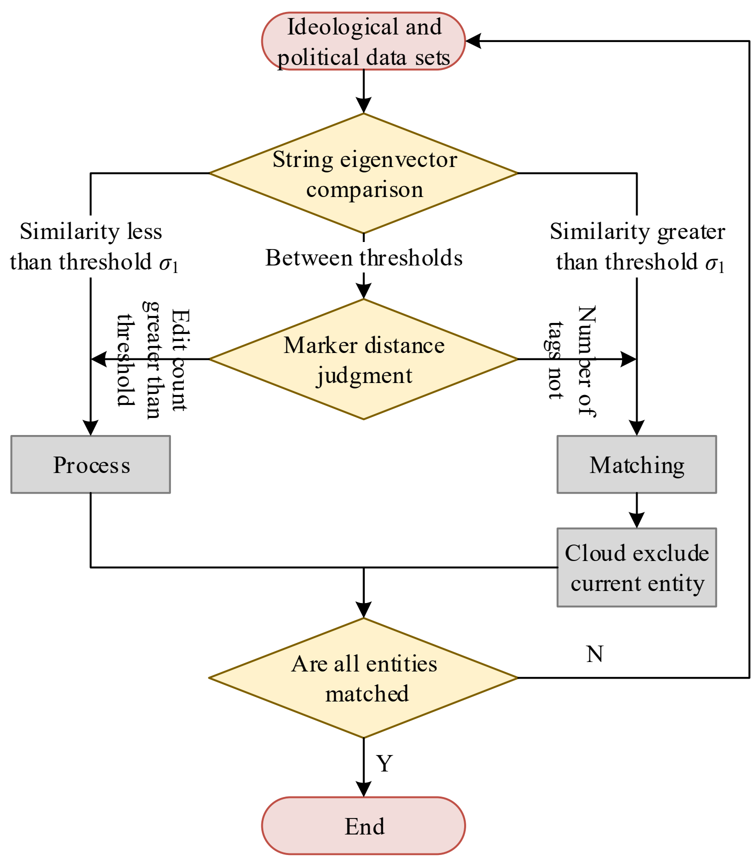

Fig. 2. Course ideological and political knowledge fusion process

On this basis, vector graphs of ideological and political entity names were extracted using the Word2Vec model, and then these vector graphs were analyzed by cosine similarity analysis. The second round of filtering was judged by the method of edit distance.

2.5. *Curriculum Civics Knowledge Generation*

Knowledge generation for knowledge mapping refers to generating a knowledge triad obtained after the process of entity identification, relationship extraction and knowledge fusion in the computer for query and use. The knowledge generation method of Curriculum Civics Knowledge Graph needs to meet the following requirements:

1) Scalability With the continuous growth of the knowledge base, a scalable storage method is needed to support more data and queries.

2) Flexibility. The generation approach needs to be flexible enough to meet the needs of a variety of queries and applications, such as querying information about the relevant attributes, relationships, and text of an entity.

3) Efficient. The generation method needs to be efficient enough to support real-time queries and applications, such as supporting complex queries and aggregation operations.

4) Reliability. The generation method needs to be reliable enough in order to ensure data integrity and security, for example, to support operations such as data backup and recovery.

In this paper, we have chosen Neo4j graph database as the knowledge generation method for curriculum Civics, Neo4j is a graph database management system specialized in generating and processing graphically structured data. Its advantages are its ability to handle highly correlated and complex structured data, its ease of use and functionality, and its ability to easily connect to Web frameworks.

3. Algorithm for recommending content for teaching Civics in courses

3.1. *Markov Decision Making*

Markov Decision Process (MDP) is the most fundamental model of machine learning, which is generally applied to sequential processes with Markovian properties. A Markov decision process is a well-designed model that embodies the nature of the interaction between an intelligent and its environment and on which rigorous mathematical operations and logical reasoning can be performed [19]. A complete Markov decision process needs to contain the following five elements:

1) The state space S. Is the set containing all the states of the current environment, which can be discrete or continuous depending on the environment.

2) The action space A. Is the set containing all executable actions of the intelligence in the current environment.

3) Reward R. Which is the feedback obtained by the intelligent body, is usually the positive or negative feedback harvested by the intelligent body for making action A in the current state S.

4) The transfer probability P. Denotes the probability that the environment state is transferred from the current state S to the next state S' when the intelligent body makes an action A for the environment state S.

5) Discount factor $\gamma \in (0,1]$. Is used to balance the delayed reward and immediate reward faced by the intelligent body, the closer the value is to 0, the more the intelligent body will tend to get the immediate reward.

Reinforcement learning records the interaction process between the intelligent body and the environment forms a typical data stream, also known as reinforcement learning interaction experience, with the formula:

$$S_1, A_1, R_1, S_2, A_2, R_2 \dots \tag{1}$$

The goal of the reinforcement learning intelligences is to maximize the cumulative rewards (or payoffs) obtained, and the cumulative rewards are denoted as:

$$G_t = E_\pi \left[R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \dots \right] \tag{2}$$

where π denotes the current action strategy of the intelligent body $\pi : S \times A \to [0,1]$ and t is the moment of interaction. The state value can be obtained from the cumulative rewards, which represents the cumulative rewards that the intelligent body can obtain by interacting according to the action strategy π from the current moment. The state value is denoted as:

$$V_\pi(s) = E_\pi\left[R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \ldots \middle| S_t = s\right] \tag{3}$$

In this paper, the interaction between the student user and the process of recommending the content of the course's Civics teaching is modeled as a Markov decision-making process, thus enabling the application of reinforcement learning to the recommendation task.

3.2. Recommendation Algorithms for Diversity Optimization

In this subsection, a deep reinforcement learning recommendation algorithm based on diversity optimization (DDRL-Base) will be introduced, which is based on the classical Markov Decision Process (MDP), combined with the recommendation task scenarios, designs and implements a state representation model and a decision model, and improves the diversity of the recommendation results by optimizing and improving the loss function.

3.2.1. State representation model design. The state representation model has an important role for intelligences in reinforcement learning, and for the course Civics teaching content recommendation task in this paper, the state representation model can provide the intelligences with dimensional compression, context modeling and generalization capabilities to extract key information from the interaction data and transform it into vector representations that can be processed by the reinforcement learning intelligences. The state representation model designed in this paper consists of a data preprocessing layer, an action embedding layer, a reward coding layer and a recurrent neural network, and the model structure is shown in Figure 3. The input interaction sequences are first pre-processed to separate the action records from the reward records to form action sequence $A_0, A_1, \ldots, A_{t-1}$ and reward sequence $R_0, R_1, \ldots, R_{t-1}$. The action sequences and reward sequences are then input to the action embedding layer and reward coding layer, which are used to convert the action and reward information into vector representations, respectively.

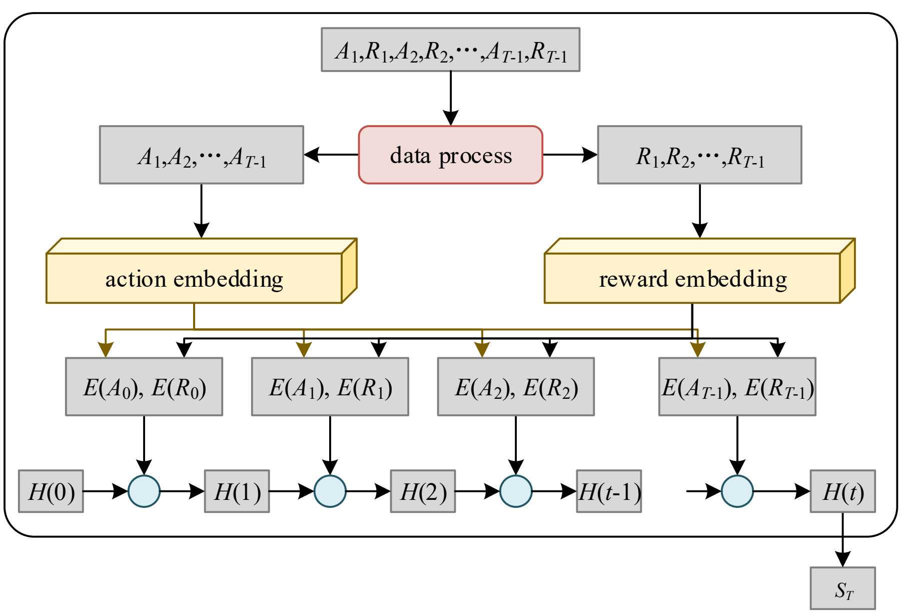

Fig. 3. The state represents the model structure

The action embedding layer maps each push action to a k-dimensional vector in the embedding space, and the principle of its realization is public as:

$$E(A_i) = E_{k\times num\_items} \cdot O_{A_i}, i \in [0, num\_items] \quad (4)$$

where O_{A_i} is a one-dimensional vector of length num_items, the element at position A_i^{th} inside it is 1, and the rest of the elements are 0.

The reward coding layer chooses one-hot coding to map the reward values into a l-dimensional vector of uniform length, which is realized as follows:

$$E(R_i) = onehot\left(l - floor\left(\frac{l^*(b-r)}{b-a}\right), l\right), i \in [0, num\_rewards] \quad (5)$$

where l is the encoded dimension and the length of the output vector, $floor(x)$ serves to round x down to the largest integer whose result is not greater than x, and $(a,b]$ is the range of values of the reward R, for the l-dimensional vector output by $onehot(i,l)$, where the value of the position of i^{th} is 1 and the rest of the positions are 0.

3.2.2. Decision modeling. In order to realize the personalized recommendation of course Civics teaching content while making the recommendation results have a certain degree of random perturbation, the decision model designed in this paper does not directly generate specific course Civics teaching content, but rather calculates the sampling probability of the recommendation corresponding to each action in the current action space. Subsequently, based on the sampling probability output from the decision model, the recommended actions in the action space can be selected for random sampling, to get a list of candidate items of length k, and finally after sorting and screening to get the final recommended items, the structure of the decision model is shown in Figure 4.

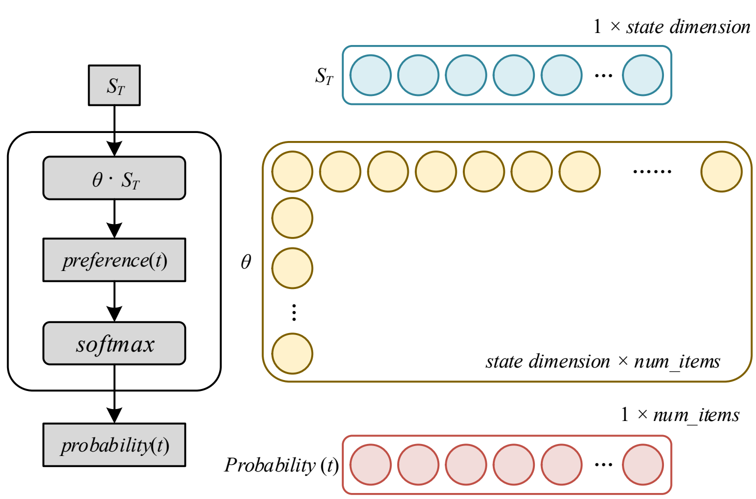

Fig. 4. Decision model structure diagram

The first fully connected layer contains a number of nodes equal to the number of recommendable items, and the preference vector h_t of candidate recommended items can be computed based on the input S_t. The principle of implementation is:

$$h_t = \Theta_{mum\_items\times d} \cdot S_t \quad (6)$$

where Θ is the weight matrix, d is the length of the environment state representation vector S_t, and the element in h_t represents the preference value of the intelligent body to select the item in the current state S_t.

The second fully connected layer is the soft-max activation function, which is responsible for mapping the previously obtained item preference vector h_t to the action probability P_t, which is implemented as follows:

$$P_t = \frac{e^{h_t}}{\sum_{i=1}^{num\_items} e^{h_i}}, i \in [1, num\_items] \tag{7}$$

In order to improve the learning efficiency, the loss function and parameter update are formulated as:

$$\begin{aligned} \theta_{t+1} &\leftarrow \theta_t + \alpha\left(R_t + \gamma \hat{v}_w\left(S_{t+1}\right) - \hat{v}_w\left(S_t\right)\right)\nabla_\theta \ln \pi_\theta\left(S_t, A_t\right) \\ w_{t+1} &\leftarrow w_t + \beta\left(R_t + \gamma \hat{v}_w\left(S_{t+1}\right) - \hat{v}_w\left(S_t\right)\right)\nabla_w \hat{v}_w\left(S_t\right) \end{aligned} \tag{8}$$

where π is the current policy network of the intelligent, $\hat{v}$ is the predicted state value in the current S_t environment state, and R_t is the reward obtained by the intelligent in the interaction sequence.

In machine learning, the concept of cross-entropy is usually introduced to optimally adjust the loss function, which indicates the uncertainty of the model prediction results. The higher the entropy value, the higher the uncertainty of the model's prediction result, so it is usually necessary to minimize the entropy value of the model to achieve higher accuracy [20].

4. Analysis of the effect of generating and recommending content for teaching Civics on the curriculum

4.1. *Analysis of the Effectiveness of Generating Content for Teaching Civics in Courses*

In this paper, we take the two courses of Engineering Cost Management and Engineering Economics in engineering management as an example to realize the application of entity-relationship joint extraction algorithm and HyperKA entity alignment algorithm in knowledge mapping of curriculum Civics and Politics domain. Firstly, the entity and relationship requirements in the knowledge extraction stage are defined according to the different data sources, and different methods are adopted to realize the extraction of ternary groups. Then the knowledge storage and visualization are carried out to finally complete the construction of the knowledge graph of curriculum Civics and Politics.

4.1.1. Data sources. This paper takes Engineering Cost Management and Engineering Economics in engineering management as the research object to construct the course civics knowledge graph, whose main data sources are literature and book materials, and the webpage content as the auxiliary resources is obtained by crawling through the crawler technology. The constructed professional course knowledge graph is denoted as KG1, and the course Civics knowledge graph is denoted as KG2 with the course Civics literature as the main data source.

The main data source of KG1 is the professional book information, which is constructed using the top-down approach, adopting the ontology hierarchy, which defines the ontology hierarchy of the content of the professional courses as knowledge system, knowledge tree, knowledge module, and knowledge point from top to bottom, and realizes the ontology construction using Protégé.

The main source of data for KG2 is the literature, which is searched in China Knowledge Network with the keywords “engineering cost or course ideology” and “economics or course ideology”, and the search results are 351 papers, removing the records with low relevance, and obtaining 285 papers in total. The search results were 351 papers, and 285 papers were obtained by removing the records with low relevance. Other webpages were searched by keywords, including Zhihu, the inside pages of Civic Government in Colleges and Universities, the Ideological and Political Work Network of National Colleges and Universities, and other official media webpages.

4.1.2. Generating results displays. Screening about 5000 sentences in the corpus that are more related to the knowledge of curriculum Civics and Politics, totaling about 400,000 words, the vector map of the names of the Civics and Politics entities was extracted using the Word2Vec model to realize the extraction of entity relationships. After extracting the entities of the elements of curriculum ideology and politics, Python was used to conduct a word search in Baidu Encyclopedia to obtain information as supplementary information about their attributes and attribute values.

After obtaining the relationship triples and attribute triples under various relationships, due to different data sources, different naming conventions and other reasons, there are some unreasonable situations in the obtained triples, such as, "love of country and love of family" and "family and national sentiment", For example, "love the country and love the family" and "family sentiment", "abide by the rules" and "abide by the rules", etc., which express the same semantics but have different expressions. In this paper, the entity alignment algorithm, using deep learning technology to realize the knowledge fusion of the knowledge graph, and finally get the knowledge graph of the two professional courses "Engineering Cost Management" and "Engineering Economics" in the engineering management profession, and the knowledge graph of the two professional courses "Engineering Cost Management" and "Engineering Economics", and the statistical information of the data KG is shown in Table 1. It contains 65 types of entities, 43,352 entities and 31 pairs of relationship types.

Table 1. Statistical information of knowledge graph

Statistical item	KG
Entity type	65
Number of entities	43352
Relation type	31
Relational quantity	73691

The generated partial relationship triad information is shown in Table 2. Among them, the first column is the entity ID, the second column is the entity name, and the third column is the entity type (ET1~ET65) totaling 65 types, and ET1 and ET2 shown in the table are the two types with the largest number of entity types representing the Civics Element and Course Knowledge Points respectively. The fourth and fifth columns refer to the main entity ID and guest entity ID respectively, which together with the entity ID form a triad. The sixth column refers to the relationship type of the triad.

Table 2. Partial relational triplet information generated by knowledge graph

Entity ID	Entity name	Entity type	Master entity ID	Guest entity ID	Relation type
e1	Unremittingly	ET1	e132	e3837	Precursor
...	...	...	...	...	...
e256	Modesty and caution	ET1	e221	e2489	Parallel
e257	Fair and fair	ET1	e6	e5053	Inherit
e258	Explore innovation	ET1	e572	e6632	Inherit
e259	Follow the rules	ET1	e6128	e932	Parallel
e260	Cooperative consciousness	ET1	e1294	e357	Precursor

e261	Modesty and caution	ET1	e16	e468	Inherit
e262	Patriotic feelings	ET1	e114	e19592	Parallel
e263	Project Management	ET2	e183	e26328	Precursor
e264	Safety training	ET2	e13921	e1525	Inherit
e265	Safety control	ET2	e1362	e120	Precursor
e266	Quality Control	ET2	e4456	e5021	Parallel
e267	Engineering coordination	ET2	e6838	e2251	Inherit
e268	Quality supervision	ET2	e666	e2489	Precursor
...	...	...	...	...	...
e43352	Schedule control	ET2	e7322	e37	Inherit

4.1.3. Knowledge graph visualization. After importing the entities and relational data of the knowledge graph KG of the professional course Civics of Engineering Cost Management and Engineering Economics constructed in this paper into the graph database Neo4j, the knowledge graph is visualized using Cypher query statements. Figure 5 is a partial display of the knowledge graph of course Civics, in which blue nodes indicate professional course knowledge entities, including course knowledge system, knowledge tree, knowledge modules, and knowledge point entities, and red nodes indicate Civics elements, and brown color indicates Civics materials, and Civics elements are distributed among professional course knowledge entities.

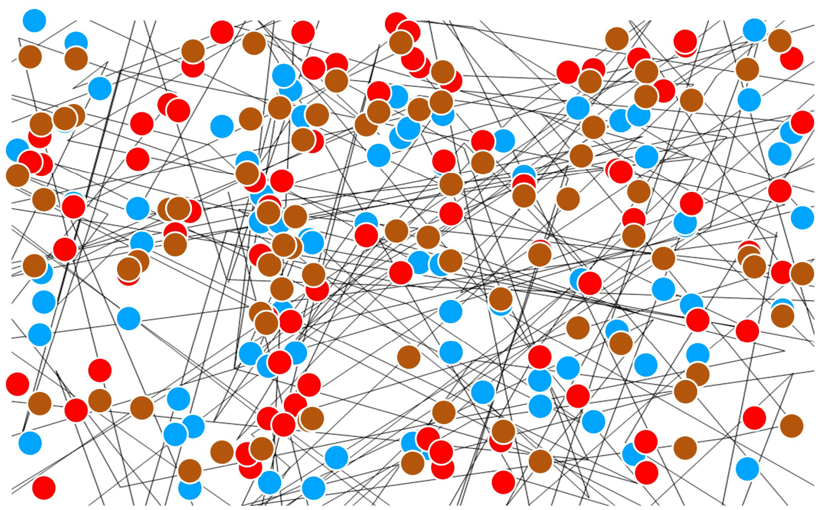

Fig. 5. Visual display of curriculum ideological and political knowledge map

Figure 6 demonstrates an example of interconnecting knowledge elements such as knowledge system, tree, module, knowledge point and Civic elements such as Civic knowledge and Civic material by relationship in the knowledge graph. The red nodes in the figure indicate the Civics elements, indicating that the constructed domain knowledge graph can effectively mine the Civics elements in the curriculum, and also realize the association between the nodes under the knowledge system through the Civics elements.

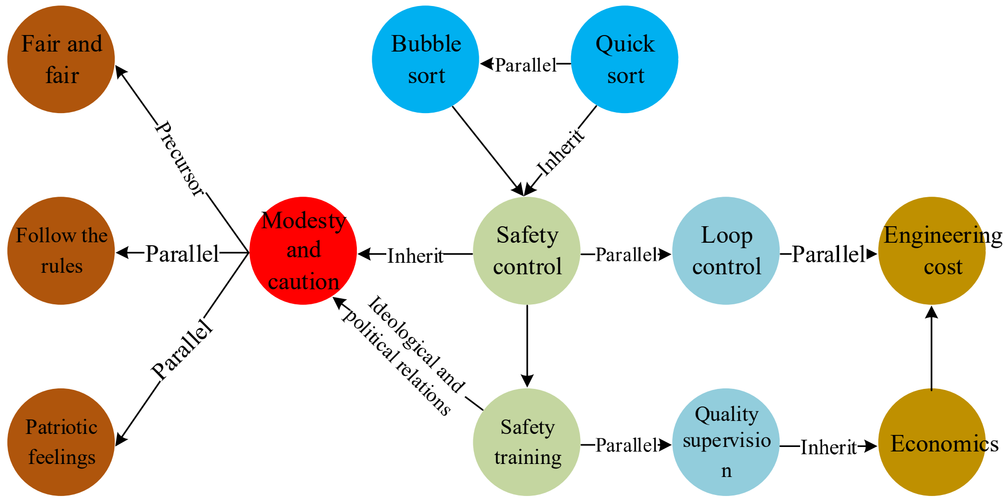

Fig. 6. A case study of curriculum ideological and political knowledge map

The definition of the Civics element entity and the Civics relationship where the text is located is in the attribute list (attribute, attribute value) as ("literature", "specific description"), 30% of which are randomly selected for manual judgment to verify the correctness of the entity, and after the verification is calculated that its correct rate is 96.2%, establishing the knowledge association between Civic and Political elements and professional knowledge elements, and realizing the mining and generation of Civic and Political elements.

4.2. Analysis of the effect of the recommended content of the course's Civics teaching

4.2.1. Experimental setup. The computer CPU used for the test experiments of the Recommendation for Diversity Optimization (DDRL-Base) algorithm is Intel Core(TM) i5-1135G7 at 2.40GHz,16GB of RAM, and the operating system is a 64-bit windows 10. The source code is implemented in a development environment combining Pycharm and Anaconda, using the python language in the TensorFlows framework. The version of Python used is 3.6, the version of TensorFlows is 1.12.0 and the version of MySQL database connected to the system is 5.7.30.

The dataset used for the experiment is divided into two parts, the data of students' basic attributes and behaviors come from the online teaching platform of School X, and the Civics resources come from the contents of the course Civics generated by Knowledge Graph KG of Civics of Engineering Cost Management and Engineering Economics professional courses constructed in the previous section.There are 7,875 students' users' data in the teaching platform of X, among which the number of engineering majors is 1,231 students. The data of two courses, Engineering Cost Management and Engineering Economics, and 312 student users were randomly selected for experiments. These experimental data include basic attributes such as students' names, ages, affiliated colleges and majors, and behavioral data such as cumulative video viewing progress, cumulative task completion progress, video viewing time (min) on the same day, and the number of times of chapter study on the same day. Since there is no course preference tag set in the teaching platform, and students' preferences change over time. Therefore, a questionnaire is set up in the recommendation algorithm and course preference labels are collected from each student every two weeks. In order to train the model and validate the effectiveness of the model, 90% of the data from the dataset is randomly selected as training samples and the rest of the data is used as test samples.

4.2.2. Test results. In order to compare the recommendation results derived from the original recommendation algorithm with the improved hybrid recommendation algorithm. Three sets of experiments are designed here:

Experiment I compares the effect of the value of weight α for the similarity calculation of the two algorithms Collaborative Filtering and Content Based Recommendation in DDRL-Base recommendation algorithm on the recommendation results.

Experiment II compares the MAE values of four algorithms User-CF (user-based collaborative filtering algorithm), Item-CF (item-based collaborative filtering algorithm), Content-Base (content-based recommendation algorithm), and DDRL-Base (diversity-optimized recommendation algorithm) with different number of recommendation lists, i.e., K-value, in terms of prediction accuracy.

Experiment III compares the accuracy, recall and F1 values of the four algorithms in terms of recommendation accuracy, so as to analyze the recommendation effect of the recommendation algorithms.

1) Experiment I. Taking the DDRL-Base recommendation algorithm as an example, the MAE value of the hybrid recommendation derived from the ratio of the similarity of collaborative filtering algorithm to the similarity weight of content-based recommendation α is taken in four cases, namely, the number of recommendation lists with K values of 10, 20, 40, and 80, respectively, and is used to determine under what circumstances the error of the hybrid recommendation algorithm is minimized, so that an optimal solution can be provided for the comparison of results of the different algorithms in the subsequent process. -MAE values of Base recommendation algorithm are shown in Fig. 7, where the horizontal coordinate is the similarity weight α and the vertical coordinate is the MAE value. According to the comparison results of Experiment 1, when the number of recommendation lists is the same, the MAE value shows a decreasing state with the increase of similarity weight α, and the MAE value reaches the minimum when α is 0.6. It can be concluded that, with a fixed number of recommendation lists, the error value is minimized when the similarity of the improved collaborative filtering and the content-based similarity in the similarity calculation session of DDRL-Base have the same weight.

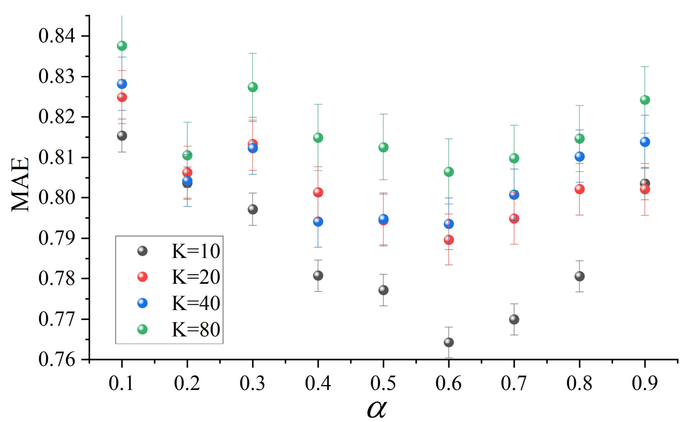

Fig. 7. MAE of different similarity weights

2) Experiment 2. Based on Experiment I, the similarity weight α is set to 0.6 to compare the prediction accuracy effects of user-based collaborative filtering (User-CF), item-based collaborative filtering (Item-CF), content-based recommendation (Content-Base) and diversity optimization recommendation (DDRL-Base), and the final result of the MAE value comparison is shown in Figure 8. Where the vertical coordinate is the MAE value of the predicted score, and the horizontal coordinate is the value of the number of recommendation lists K, which is taken to increase from 10 to 90, with a growth interval of 10. It can be seen that, as the number of recommendation lists for the content of the course Civics, K, continues to increase, the MAE value decreases, and the MAE value

decreases to the lowest when K = 20, and then the MAE value increases incrementally with the increase of the K value, and it can be found that, when the number of recommendation lists is around 20, the error of predicting the rating is the most, and the length of the recommendation list can be set to 10, making the recommendation effect optimal. It can also be found that when the value of K is 20, at this time the MAE value of the DDRL-Base algorithm proposed in this paper is the lowest at 0.7396. It shows that when the value of K is fixed, the recommendation effect of the DDRL-Base algorithm is higher than that of other algorithms.

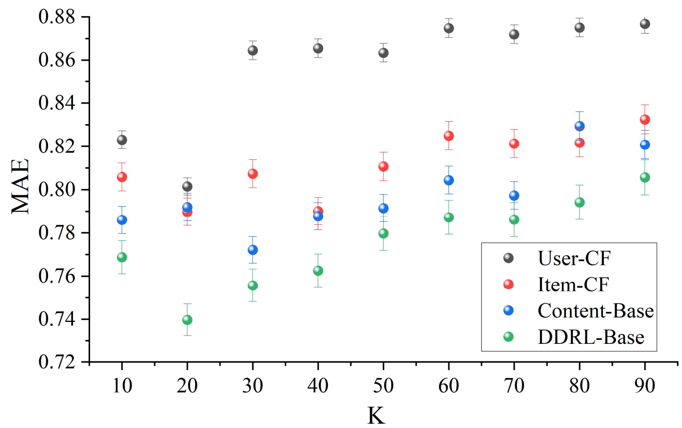

Fig. 8. MAE comparison of different recommendation algorithms

3) Experiment three. Through the analysis of Experiment 1 and Experiment 2, in Experiment 3, the number of recommended lists of course Civics content K value is set to 20, the mixed similarity weight α is set to 0.6, and under the condition of the lowest MAE value, the accuracy rate, the recall rate and the size of the F1 value of the four algorithms are calculated to analyze the effect of different recommendation algorithms on the recommendation precision, and the resulting comparative results of the accuracy rate, the recall rate and the F1 value are shown in Figure 9. From the comparison results, it can be seen that the accuracy rate of DDRL-Base algorithm compared with the other three algorithms is improved by 0.158, 0.122, 0.074, the recall rate is improved by 0.141, 0.107, 0.068, and the F1 value is improved by 0.15, 0.104, 0.084, respectively.It can be seen that the algorithm introduces the collaborative filtering similarity computation of state representation model and Markov decision model design to optimize the problems of cold start and resource matrix data sparsity. It is higher than the other three algorithms in the three indexes of recommendation accuracy, and it can be concluded from the combined prediction accuracy indexes of Experiment 1 and Experiment 2 that the DDRL-Base algorithm has improved the effect of recommending the contents of the course Civics and Politics teaching.

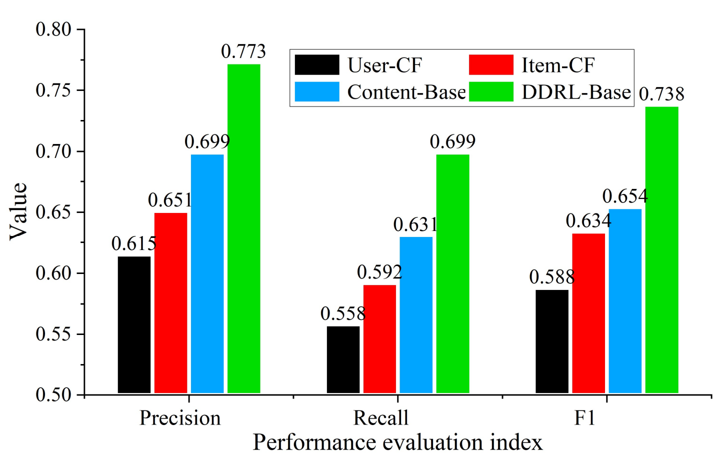

Fig. 9. Comparison of recommendation accuracy indicators of four algorithms

5. Conclusion

With the development of society and the progress of science and technology, the subject settings and curriculum systems of colleges and universities are becoming more and more rich and diverse, and intelligence has become the trend of future development. In this paper, by constructing the knowledge map of curriculum civic politics, the related knowledge is logically reorganized, the correlation and hierarchy between the knowledge are enhanced, and the generation of curriculum civic politics content is realized through the visual query and text query functions of the knowledge map. And with the help of personalized recommendation algorithm, the generated content is accurately recommended to the student users, which finally serves the construction of curriculum Civics.

Through the DDRL-Base recommendation algorithm, the corresponding resources of curriculum Civics are pushed to students for learning. Experimental comparisons with four traditional recommendation algorithms were carried out with the actual data of the teaching platform of School X. The results show that the DDRL-Base recommendation algorithm is able to effectively realize personalized recommendation of Civic and Political resources according to the user's preferred courses, trigger students' interest in learning Civic and Political resources, and effectively solve the whole process of cultivation under the concept of "three-whole cultivation" which is difficult to be realized in the traditional teaching.

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