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Article

Intelligent Application of Knowledge Graph Construction and Course Management in Open Education Platforms

Ling Zhu *

Yulin Open University, Yulin, Shaanxi, 719000, China; zhuling710410@sina.com

Abstract: The application of open education platforms in the field of education has positive significance, which helps to optimize course implementation and promote the research and development of online teaching and adult education. The platform can be based on multimodal knowledge graph to construct the co-occurrence network map of adult education keywords. Based on the statistical high-frequency keywords, it is found that the current adult education mainly focuses on educational technology, followed by more attention to information technology, television and radio universities, and educational resources. The platform is able to use knowledge mapping to personalize course recommendations based on learners' knowledge when making course recommendations. The feasibility and effectiveness of the method is proved by validating it on Amazon open dataset and self-built dataset. Finally, it is verified through practical teaching that the course management model based on the open education platform is well received by teachers and students, and the average passing rate of students' courses reaches 85.87%. The open education platform can effectively improve the quality of talent training and meet the needs of intelligent management of courses.

Keywords: open education platform; multimodal knowledge graph; course recommendation strategy; course management

1. Introduction

Under the background of the rapid development of education informatization in the new era, the transformation of education mode led by big data and "Internet+" mode has given rise to the changes and innovations in education mode and the way of using education resources, nowadays, education informatization has become a public consensus, and has greatly changed the way of the public to obtain education resources and receive education. Education platform has become an important way for the public to acquire, utilize and share knowledge [1-3]. The huge open education market provides students with all the former educational resources and opportunities, and the gradual development of the shift of education to digitalization has not only changed the way of people's learning, but also changed the way of teachers' teaching [4]. Taking MOOC (Massive Open Online Course) as an example, it has become the most mainstream form of learning in digital education because of its advantage of breaking through the time and space limitations of traditional education [5-7]. However, although MOOC teaching can ensure the continuity and safety of teaching [8], it is significantly different from traditional courses, which may affect the learning effect of students [9]. For example, students' low and persistent attention span, difficulty in comprehending course material, and low course engagement suggest that despite the abundance of OERs, they are not used effectively [10].

In addition, the current mainstream teaching method in open education is that teachers deliver lectures through sequentially structured PowerPoint. This approach allows students to quickly access the main content and concepts of the course to a certain extent, but it is not very helpful for learners to recognize the complex relationships between concepts and may lead to confusing knowledge structures [11]. In addition, due to the lack of further interactive guidance from teachers during the learning process



on open education platforms, students are likely to fall into the misunderstanding of mechanical rote memorization of knowledge points, leading to a loose and confusing knowledge system [12-13]. For example, the inability to express complex knowledge structures and the possibility that learners may construct false hierarchical knowledge that is not intended by the teacher will reduce the learning effect of students. Therefore, how to integrate and organize these open educational resources and data to better facilitate the development of smart education has become a research hotspot for scholars from all walks of life.

Knowledge graph, as a semantic network, has great advantages in knowledge organization and balancing educational resources, which can enhance the interpretability of the model and reveal the relationship between the knowledge in graph form to visualize the resources and knowledge. Knowledge graphs not only make waves in the general field knowledge graphs, while gradually expanding to other fields such as education [14]. In recent years, educational knowledge graph has gradually become a hot research topic, with the gradual deepening of the research on smart education, the research on knowledge graph for the field of education is also increasing day by day, and various types of educational knowledge graphs have also emerged [15]. The construction of knowledge graph of educational resources can complete the effective management and efficient utilization of open educational resources, help to crack the many problems brought about by the use of educational resources, so that open educational resources can be better shared and applied [16-17].

Knowledge mapping, also known as scientific knowledge mapping, is able to visualize the structural relationships and developmental processes of scientific knowledge in graphical representations, and its object of study is scientific knowledge, so knowledge mapping belongs to the category of scientometrics [18]. Knowledge mapping was first applied in the field of scientific research, which is able to visualize scientific knowledge, and its research results are relatively large. Börner et al. (2003) argued that knowledge visualization aims to reveal the field of scientific communication reflected in scientific literature and the citation paths woven by individual scientists in publications, and that it can provide techniques for multidisciplinary and rapidly evolving fields of study, such as dimensionality reduction techniques that thereby visualizing abstract non-spatial bibliographic data [19]. Shi and Weninger (2018) proposed a new Knowledge Graph Completion (KGC) model that learns the embedding of entity names and parts of their textual descriptions to connect invisible entities to the knowledge graph, and the results indicated that the model is useful in open world knowledge graph refinement task [20]. Meissner and Köbis (2020) argued that school teachers' lectures can only benefit some of their students and are not effective for individual learning, so they proposed a technique for semi-automatically analyzing course material and supplementing the teacher's knowledge graph, and gave example pedagogical approaches as well as potential for future applications [21].

In recent years, many domain-specific knowledge graph studies have appeared, and the same knowledge graph research boom has also been set off in the education field. Educational knowledge mapping can aggregate multiple, heterogeneous, and massive educational resources into knowledge after schematization and standardization, and the semantic relationship between the knowledge supports the intelligent recommendation of educational resources, so that users can get the knowledge they need quickly and accurately. Chung and Kim (2012), among others, constructed an educational knowledge mapping using the course ontology, the syllabus ontology, and the main body ontology as the ontology model and embedded it into an e-learning support system, aiming to improve the students' learning in e-learning. , and embedded it into an e-learning support system, aiming to improve the learning effect of students in online learning [22]. Sun et al. (2016) acquired and analyzed the entities and entity relationships contained in the educational knowledge system, and constructed the visualization and analysis platform, EduVis, in which they designed and implemented a Web-based event network layout exploring the topology in detail, based on the timeline of the Web browsing time information event layout, click tracking path, record user's click history and help users to backtrack [23]. Evans and Jeong's (2023) study found that students' knowledge comprehension and memorization abilities improved significantly when they used knowledge mapping for learning, and furthermore, it was found that knowledge mapping, as a learning activity, improves students' ability to face challenges with confidence to cope successfully, thus promoting more persistence and effortful learning, as well as more meaning construction and relational reasoning [24].

The application of knowledge mapping in the field of education has led to the emergence of different concepts such as disciplinary knowledge mapping and educational knowledge mapping, but their essence is to use knowledge mapping to model knowledge in the field of education [25]. Subject knowledge mapping can construct the association between knowledge and knowledge from the massive and disorderly knowledge information, so as to reconstruct the knowledge system according to the requirements of the subject, and provide powerful support for teachers' intelligent teaching and students' personalized learning [26-27]. Chen et al. (2018) developed a K12EduKG system to automatically

construct the knowledge map of K-12 education topics, which utilizes heterogeneous domain-specific educational data, extracting educational concepts and identifying highly educationally significant implicit relationships, and constructing a knowledge map illustrated with the subject of mathematics as an example [28]. In the same year, Chi et al. (2018) proposed a scientific publication management model based on knowledge graphs and data analytics for integrating scientific metadata, which can improve the retrieval efficiency of scientific publications, reduce the difficulty of learning scientific domains, and encourage the utilization of disciplinary resources in various domains [29]. Su and Zhang (2020) proposed a deep learning-based automatic construction of an educational domain knowledge mapping approach, which realizes automatic identification of subject knowledge points and knowledge map construction by integrating multi-source data and utilizing deep learning techniques [30]. Zouri and Ferworn (2021) proposed a knowledge ontology-based approach for mapping higher education courses, which focuses on the creation of core course ontologies that can support effective knowledge representation and shared reuse, and for specific course implementation cases to validate its good results [31].

The development of smart education is a general trend, by vigorously developing the smart education market brings the problem of efficient organization and utilization of huge educational resources, it requires new forms of knowledge organization to solve, so many scholars and experts will turn the research focus on the construction and study of knowledge graphs [32]. Zhang et al. (2016) used the TransR method to extract the structural representations in the nodes and relationships, and used the stacked denoising autoencoder and stacked convolutional autoencoder to extract textual representations and visual representations of items, and finally, joint learning of collaboratively filtered latent representations and semantic representations of items in the knowledge base as a means of constructing a collaborative knowledge graph embedding model (CKE) [33]. Rizun (2019) argues that Knowledge Management (KM) is one of the most important activities in almost all organizations, yet knowledge mapping is a technology that can facilitate and enhance the KM process in universities, and by constructing a knowledge map, students and teachers can personalize the courses they are interested in and personalize education in universities [34]. Zheng et al. (2019) defined an ontology for basic education, divided the knowledge graph into three subgraphs, and then used an unsupervised approach to extract conceptual instances from the textbook and the existing knowledge base and relationship instances, and obtained four different learning resources to aid learning [35]. Li et al. (2019) proposed a collaborative learning model, RCoLM, which differs from previous knowledge-aware recommendation approaches by focusing on combining relationship-awareness and collaborative learning, utilizing user-item interactions in recommendation to complete the knowledge graph, and unifying the two tasks of recommendation and knowledge graph complementation into a joint model to achieve mutual enhancement [36]. Ji et al. (2021) focused on investigating how to extract rich knowledge information, including entities, relationships and attributes, from educational texts using natural language processing techniques in order to construct a rich and multidimensional educational knowledge graph [37].

Open education platforms have important research significance in constructing course knowledge graphs and providing quality course management. In this paper, we take the construction of adult education course knowledge graph as an example, based on DeepKE framework, we complete the entity extraction of conceptual knowledge data so as to generate link anchors for multimodal data. Label the entity relationships according to the entity relationship text dataset. Load the entity relationship set into DeepKE training to generate entity relationship extraction model. Based on the collected data, keyword co-occurrence network mapping is constructed. In the course intelligent management, to calculate the relevance of topics and knowledge points, the difficulty of the topics, and recommend personalized courses for learners. The open education platform has positive application value in helping teachers teach courses, promoting learners' personal development, and promoting open education.

2. Educational support functions of the open education platform

2.1. Promoting open education

The open education movement based on the concept of “open sharing” has been an important trend in the development of global education. From open courseware (OCW) to massively open online courses (MOOC), open education has advanced from pure resource sharing to the innovation of curriculum and teaching mode. In the current environment of cloud computing and big data, artificial intelligence development, in the future, open education will further develop from the dimension of focusing on resources and courses to the dimension of paying more attention to collaboration and research, and from open resources and open courses to the direction of open data, open projects and open science.

At present, more and more resources, projects and researches choose to be released on the open education platform for open source sharing, and rely on the good collaboration mechanism of the open

education platform to obtain benign and rapid development. Open education should pay attention to the application and research of socialized collaboration systems, build educational open data resources, strengthen the application of educational open projects, and promote the open sharing of educational science [38].

2.2. Support big data-based learning analytics research

Knowledge graph is an important support for the application of artificial intelligence technology. The in-depth integration of knowledge graph technology with various industries is the basis of application, and it is also a key issue that needs to be solved in the field of educational artificial intelligence. The current construction of knowledge graph in the field of education is still very immature, in which the problem of educational data is a major bottleneck restricting the construction of knowledge graph. At the same time, not only static knowledge but also dynamic knowledge is needed in the application of domain knowledge, and the center of gravity of knowledge representation and knowledge acquisition will pay more and more attention to dynamic knowledge. The development of open education platform makes it an important dynamic information network data source, whose data are novel and fast-growing, and contain rich specialized information, such as all kinds of specialized documents, courseware, research papers, self-reported documents, WiKi and so on. These rich structured data provide new data sources and ways to carry out the construction of educational knowledge graph and educational big data research and learning analysis.

2.3. Provision of a quality course management platform

In terms of teaching teachers' courses, the Open Education Platform provides a high-quality course management platform, the features of which include:

(1) A convenient way of sharing resources, which makes it easy to distribute course-related materials to learners.

(2) In terms of the assignment mechanism, it assigns collection assignments by automatically creating a student repository and monitors the completion of student assignments at any time.

(3) Providing timely feedback, it is suitable for teaching aids for courses of various scales. The resource richness and collaborative flexibility of open education platforms provide good conditions for online classroom teaching and can better support future social collaborative learning environments.

3. Construction of course knowledge map

The open education platform designed in this study focuses on open education for adult education. The research hotspots of open education are summarized by counting the keywords of 3506 documents.

3.1. Knowledge model definition

The traditional Knowledge Graph (KG) [39] is defined as a directed graph based on relation triples and attribute triples:

$$KG = \{\varepsilon, R, A, V, T_r, T_a\} \quad (1)$$

$$T_r = \varepsilon * R * \varepsilon \quad (2)$$

$$T_a = \varepsilon * A * V \quad (3)$$

Eq. (2) represents relationship = {head entity, relationship, tail entity} ternary.

Eq. (3) represents attribute = {entity, attribute, attribute value} ternary.

Multimodal Knowledge Graph (MMKG) [40] has two main definitions: multimodal data as specific attribute values of entities or concepts and multimodal data as entities in a knowledge graph.

In constructing the curriculum knowledge graph, entities were categorized into algorithms, structures, related terms, and speech, and relationships were categorized into containment, antecedent, same, sibling, correlation, and association relationships. The adoption is to use multimodal data as entities in the knowledge graph.

The modalities involved in the open education platform include multi-source video, text, and audio, and if multimodal data are used as entities in the knowledge graph, then data fusion will be complicated and it is difficult to complete the training of the fusion model in a single space, which makes it difficult to support the task of flexible teaching assistance with multimodal data:

$$MMKG = \{\varepsilon, R, A, V_x, T_r, T_a\} \quad (4)$$

$$T_r = \varepsilon * R * \varepsilon, T_a = \varepsilon * A * V \quad (5)$$

$$V_x \in \{V_{audio}, V_{video}, V_{PPT}, V_{Academic_sentiment}\} \quad (6)$$

Eq. (6) indicates that the set of graph attributes contains multi-source audio, video and text data.

The biggest advantage of using multimodal data as entities in the knowledge graph with unified spatial encoding is on intelligent search, which can accomplish multimodal intelligent search applications. However, the open education platform does not focus on the application of intelligent search, so the multimodal knowledge graph is constructed by using equation (6) to take the multimodal data as the specific attribute value method of entities or concepts.

According to the platform application characteristics, the knowledge entities are categorized into four types: algorithms, structures, concept terms and formulas. Relationships are categorized into containment, antecedent, same, brother and related. Attributes are categorized into fine-grained multi-source audio and video, student learning and question bank data.

3.2. Text Data Acquisition and Preprocessing

The knowledge graph constructed based on course text mainly involves natural language processing related techniques. Construct entity-relationship dataset through course text data acquisition and preprocessing. The collected course text data is preprocessed, and in the open education platform, knowledge extraction needs to complete the identification of “entities” and “relationships”, so it is necessary to complete the preprocessing of named entity identification and relationship extraction.

(1) Named entity recognition dataset preprocessing

Named entity recognition dataset construction is mainly divided into two important steps: each statement in the text is cut into line-by-line and word-by-word formats, and entity BIO data labeling is completed. Then the unlabeled text is made up, and finally the acquired data are built into a training set, validation set and test set with the organization in the ratio of 5:3:2.

(2) Pre-processing of Relational Extraction Dataset

Relationship extraction is based on the entity dataset, the entities and the starting serial numbers of the entities in the named entity recognition dataset are extracted, the sentences with only two entities in a sentence are filtered out, and the relationship labeling is completed manually.

3.3. Knowledge extraction

One of the approaches to knowledge extraction is carried out in a pipelined manner, i.e., entity extraction and relationship extraction are performed in steps. Firstly, named entity recognition technique is utilized to extract entities, and then the relationships between these entities are identified, which in turn generates ternary groups. The textual knowledge point triad extraction process is shown in Figure 1. The raw corpus is formed into DeepKE standard training corpus format after data preprocessing. Before model training, the framework provided by DeepKE is used to configure the model into a transformer model, which is used to complete the ternary extraction task, and after the model is configured, the labeled training corpus is loaded into DeepKE to start model training. Constructing a knowledge graph can also be done by first constructing a simple knowledge graph using the already labeled triples in the training corpus. In the inference process, more triples in the corpus will be extracted, and the knowledge graph will be enriched gradually. That is, in the construction process of knowledge graph is used in the training set labeled ternary information, the training corpus labeled ternary in the data preprocessing time through the function in the DataMarking class to complete.

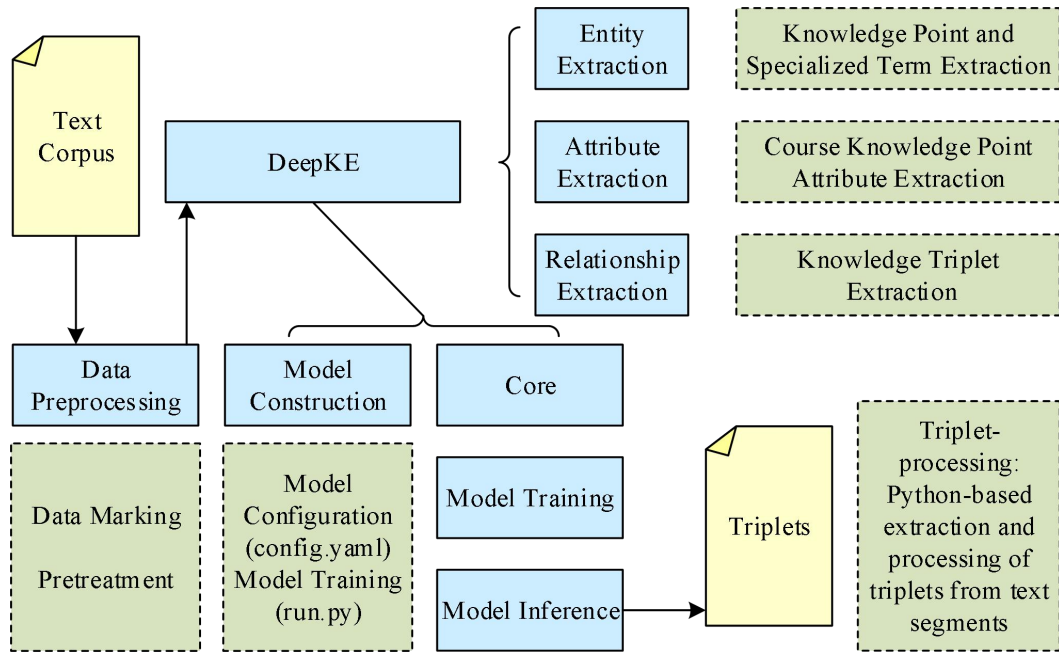


Figure 1. The process of extracting the text knowledge.

The original corpus of this paper is realized in two steps: firstly, the start and end indexes of the head and tail entities in the original corpus are put into a tuple, and the index ids of the relations are put into a list, and then preprocessing is carried out to extract and process the contents of the labeled index ids, and then finally the training format of "bubbling sort is a simple exchange sort containing, exchange sort, 0, bubbling sort 10" training format. With DeepKE's built-in Transform model training, the relevant concepts in the data structure are categorized into four entity classes: STR, ORG, LOC, and FOR.

3.4. Adult Education Curriculum Knowledge Mapping Construction

3.4.1. High-frequency keyword statistics

Firstly, the Bicom2 software was used to analyze the bibliographic information of 3,506 valid documents, extract keyword data, and standardize the keywords. Keywords with similar or identical meanings were merged, such as "MOOC", "xMOOC", "MOOCs", and "Massive Open Online Courses" being uniformly referred to as "MOOC". The terms "teaching quality" and "teaching effect" are collectively referred to as "teaching effect". Secondly, keywords with no practical significance, such as "research", "strategy", "thinking", etc., were eliminated, and a total of 5,805 valid keywords were obtained.

According to the calculation of Price's formula, it is known that the frequency of high-frequency keywords is greater than or equal to 35 times, totaling 36, which is not enough to reflect the hotspots in the field of adult education. When the research sample is small, 45% of the cumulative percentage of keywords can be selected as the high-frequency threshold. When the research sample is larger, 20% of the cumulative percentage can be selected as the high-frequency threshold. In order to make the keywords more representative and able to reflect the research hotspots in the field of adult education more specifically, combined with the cumulative percentage of the keywords, this paper identifies the keywords with a frequency greater than or equal to 35 times as high-frequency keywords, totaling 20. The frequency of occurrence of the 20 high-frequency keywords is shown in Table 1. The cumulative frequency percentage of occurrence is 57.28%.

Table 1. Frequency of high frequency keywords.

Ranking	Key words	Frequency	Ranking	Key words	Frequency
1	Education technology	1805	11	Education informationization	56
2	Information technology	223	12	agro-engineering	53

3	Television and broadcasting university	191	13	Online learning	52
4	Education resources	136	14	Lifelong education	51
5	Remote teaching	92	15	Learning support service	42
6	library	91	16	Higher education	41
7	Network education	90	17	Web course	40
8	Remote learning	86	18	Network teaching	39
9	Learning process	85	19	Teaching media	37
10	Open University	80	20	Teaching model	35

3.4.2. Keyword co-occurrence network analysis

The keyword co-occurrence matrix data of 20 high-frequency keywords in the field of adult education were imported into Ucinet6, and the keyword co-occurrence network mapping constructed by importing the file into NetDraw after data conversion is shown in Figure 2. Each node in the graph represents a keyword, and the larger the node proves that the keyword co-occurs with other keywords more often. The thicker the connecting line, the closer the connection between keywords. As can be seen from the graph, all nodes are linked and there are no isolated nodes. Educational technology is the core of the research conducted. This is followed by Information Technology, Television and Radio Universities, Educational Resources. The connecting lines between higher education, online courses, online teaching, teaching media, and teaching modes are thicker and closely connected, which are the focus of adult open education.

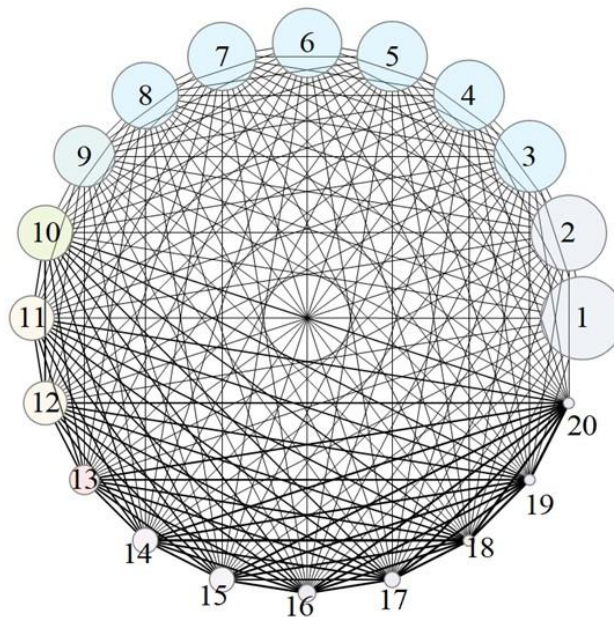


Figure 2. Key words common network map.

4. Knowledge graph-based personalized course recommendation

In the open education platform, which provides a high-quality course management program, personalized course recommendation is particularly important in the course management process. The program can help learners acquire appropriate course resources and make their learning more directional. In order to recommend personalized learning courses for different learners, reduce blind repetitive learning of mastered knowledge as well as the neglect of knowledge blind spots, the platform carries out personalized learning path recommendation based on knowledge mapping [41]. In order to effectively recommend knowledge points that meet the learner's current learning ability and the appropriate level of

difficulty, the platform defines an evaluation function F_i for the learner's mastery of knowledge points. The learner's mastery of a knowledge point is calculated based on the test papers completed by the learner in the learning platform. Each test paper consists of a number of questions, and each question is associated with a number of knowledge points. By calculating the relevance of the questions to the knowledge points, the difficulty of the questions, and developing a question extraction strategy to obtain an evaluation of the learner's mastery of each knowledge point. Finally, the mastered knowledge points are labeled in Neo4J, which stores the knowledge graph, and then the breadth-first search algorithm is used to search for the next layer of knowledge points, which are used as the knowledge points to be learned in the next stage to recommend courses for the learners.

4.1. Definition of topic relevance and topic difficulty

(1) Relevance

The degree of relevance represents the degree of association between the knowledge points and the questions. Since the number of knowledge points examined is different in different questions, one or more knowledge points may be examined. Therefore, we define the number of knowledge points it contains for each question in the question bank, the number is N , and the degree of association of each associated knowledge point i with the question j is P_{ij} , and we specify that the sum of the degrees of association of the knowledge points in the question is 1, i.e.:

$$\sum_{i=1}^N P_{ij} = 1 \quad (7)$$

(2) Difficulty

The difficulty of a topic depends on the difficulty of the knowledge points contained in the topic and the relevance of the topic to the knowledge points. In the database, we have labeled each knowledge point with a corresponding difficulty coefficient value, and the difficulty of the knowledge points can be divided into five grades: easy, basic, mid-range, difficult, and grand finale, with corresponding difficulty coefficient values of $v = \{0.2, 0.4, 0.6, 0.8, 1.0\}$. The difficulty V of each question is calculated by summing the product of the difficulty of the knowledge point it contains and the relevance of this knowledge point to the question, i.e.:

$$V = \sum_{i=1}^N p_{ij} \times v_i \quad (8)$$

where p_{ij} is the relevance of knowledge point i to the topic j and v_i is the value of the difficulty coefficient of knowledge point i .

4.2. Topic Extraction Strategy

In order to ensure that the questions produced have a suitable degree of differentiation, the system, each time a question is produced for the learner, it is in the question bank associated with the knowledge points that the learner has learned to select test questions, each set of test paper question extraction algorithm mainly examines two points:

(1) The total value of the difficulty of the test paper conforms to the set target S_v :

$$S_v = \sum_{k=1}^p V_k \quad (9)$$

where p denotes the number of questions and V denotes the difficulty of each question.

(2) The correlation between the difficulty and the number of questions conforms to the characteristics of normal distribution.

Taking the difficulty of the questions as the X -axis and the number of questions as the Y -axis, make sure that the distribution of the questions in each paper conforms to the normal distribution, and make sure that the standard deviation of the difficulty, SD , takes a value between 6-9, i.e. $6 \leq SD \leq 9$.

4.3. Evaluation of Knowledge Mastery and Extension Strategies

Based on the above methodology test questions are taken for the learners and their mastery of the knowledge points is evaluated after their completion. Assume that in each set of test questions, the number of questions associated with a certain knowledge point is M , defining that a correct answer to a question earns 1 point and an incorrect answer earns 0 points. Then the learner's mastery evaluation function F_i for knowledge point i is:

$$F_i = \sum_{j=1}^M p_{ij} \times f \quad (10)$$

where p_{ij} is the relevance of knowledge point i to the topic j and f takes the value of 1 or 0:

$$f = \begin{cases} 1 & \text{Answer correct} \\ 0 & \text{Answer incorrect} \end{cases} \quad (11)$$

For those that meet the requirements of knowledge point mastery, it means that this knowledge point has been mastered, and the mastered knowledge point will be labeled in the Neo4J database stored in the knowledge graph, and then the next step is to use the graph breadth-first search to find the next stage of the knowledge point to be learned, and select the next level of knowledge point to continue learning.

4.4. Experiments and analysis of results

Since the current open education course knowledge graph dataset currently does not have the user's historical learning footprint, in order to validate the effectiveness of the course recommendation model based on knowledge graph fusion, this paper selects the Amazon book dataset, which exists a consistent data structure with the open education course knowledge graph dataset as the validation dataset, which, like the current scenario, can constitute a complete knowledge graph, containing a large number of node sequences, while nodes exist introductions about the nodes. Therefore, this dataset can be utilized to verify the validity and reasonableness of the model. Since a large number of node sequences already exist in the Amazon book dataset, the process of randomly wandering to obtain node sequences can be omitted on the Amazon book dataset.

The Amazon dataset contains user IDs, book IDs, ratings and reviews, etc. Due to the large amount of data and the fact that some of the data have some missing content, this paper selects 100,000 pieces of data with complete content from this dataset as the experimental dataset. Among them, 80% is used as the training dataset, 10% is used as the validation dataset, and 10% is used as the test dataset. To verify the feasibility and accuracy of the recommendation method. The evaluation metrics are proposed to use Precision, Recall, and F1 as evaluation metrics. The specific calculations are as follows:

Define TP as the number of nodes whose recommendation results hit and FP as the number of nodes whose recommendation results did not hit. Thus there is the precision rate:

$$Precision = \frac{TP}{TP + FP} \quad (12)$$

Define FN as the number of nodes that should have been hit by the recommendation result but were not, hence there is a recall:

$$Recall = \frac{TP}{TP + FN} \quad (13)$$

The F1 index is calculated as:

$$F1 = \frac{2 \cdot PRE \cdot REC}{PRE + REC} \quad (14)$$

In this paper, in order to verify the difference in effect between different models and the effectiveness of this model, the personalized learning path recommendation method based on knowledge graph is compared with Bert, Node2Vec, and GCN models, respectively. The Bert pre-training model embeds text summaries in the knowledge and relies on this feature to achieve the recommendation. The Node2Vec model embeds the knowledge graph graph only through the Node2Vec model and utilizes the node vector results for recommendation. The GCN graph embedding model is trained on the user-knowledge bipartite graph against which vector representations of user and knowledge entities can be obtained separately. The final experimental results obtained are shown in Fig. 3. Through the experiment, it is found that the course recommendation method based on knowledge graph is effective, and its Precision, Recall and F1 are 0.82, 0.79 and 0.81 respectively, which are higher than the evaluation indexes of other

methods.

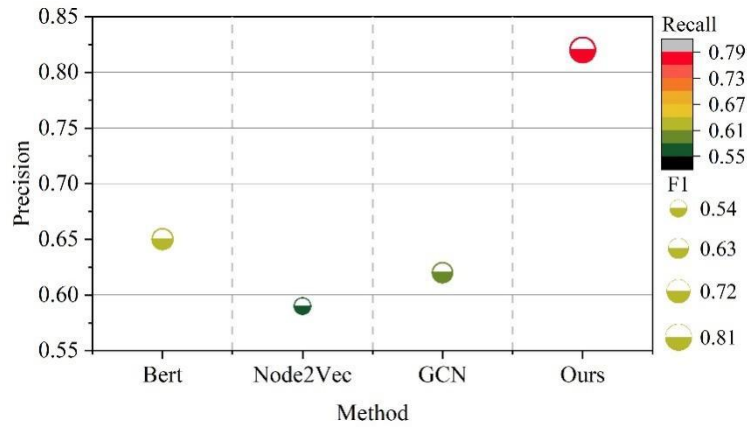


Figure 3. Book data aggregation.

In order to further validate the effectiveness of the knowledge graph based course recommendation method, this paper collects the learning paths of 763 users, obtains the records of users' interactions with learning resources such as courses, knowledge points, exercises, etc. as well as their ratings of their mastery of these learning resources, from which it builds its own dataset, which ultimately contains 75,635 pieces of data. Again 80% of this is used as a training dataset, 10% as a validation dataset and 10% as a test dataset. The result of the run on the self-built dataset is shown in Fig. 4. The recommendation accuracy of this paper's method is 13%, 22% and 10% higher than Bert, Node2Vec and GCN respectively, which shows that this paper's method is able to utilize knowledge graph for course recommendation based on learners' knowledge.

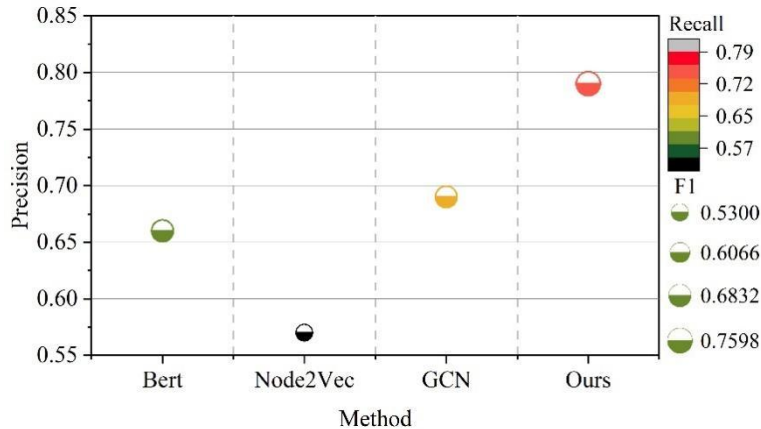


Figure 4. Self-built data aggregation fruit.

4.5. Analysis of the Effectiveness of Intelligent Management of Courses

This article takes the adult open education platform of S University as an example to complete the integration of the experimental systems of 25 existing courses such as "Computer Network", "Electrical and Electronic Technology", and "Construction Management". The practical teaching of courses for adult education has been moved online, and students conduct course experiments through this experimental platform. In 2024, based on the characteristics of the courses and the number of students enrolling in them, The school chose "Linux Eight courses, namely "Network System Management" (C1), "Introduction to E-commerce" (C2), "Networking Technology" (C3), "Construction Project Management" (C4), "Basic Knowledge of Engineering Cost" (C5), "Legal Practice" (C6), "Local Government Performance Evaluation" (C7), and "Skill Experiment - Position Accounting" (C8), will be piloted. A sampling survey was conducted among teachers and students, and the survey results are shown in Figure 5. The average pass rates of the 8 courses and the proportions of students, tutors and teaching administrators who were satisfied with the course management were 85.87%, 85.25%, 85.48% and 83.98% respectively. The teaching model of adult education based on the open education platform has

received high praise from teachers and students and meets the current needs of teaching assistance for adult education courses.

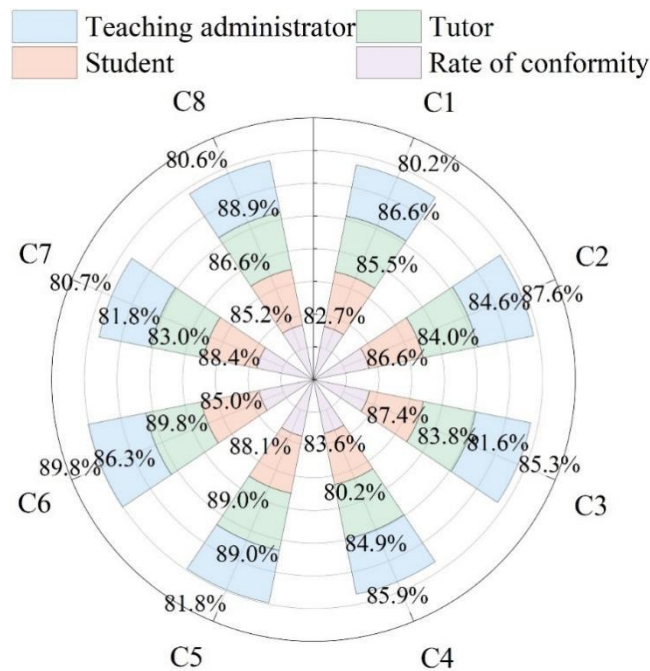


Figure 5. Survey statistics.

5. Conclusion

The study explores the construction of knowledge graph and intelligent management of courses in open education platform. Taking adult education as an example, it is found by constructing the keyword co-occurrence network mapping of adult education that adult education mainly focuses on educational technology, followed by focusing on the research of information technology, television and radio universities, and educational resources. The platform adopts personalized course recommendation based on knowledge graph in the intelligent management of courses, which is able to recommend courses according to the learners' mastery of knowledge, as the method performs well in Precision, Recall, and F1 evaluation indexes compared with Bert, Node2Vec, and GCN. The platform is able to ensure that the course pass rate of learners is above 85% in the process of practical teaching, while students, tutors and teaching administrators are more satisfied with the use of the platform. The application of open education platform in the field of education will have a positive significance for us to explore the online education mode, in-depth research on new technology teaching, and grasp the direction of the development of education technology.

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