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Article

Digital Teaching Design and Implementation Strategies for Plant Landscape Courses in Colleges and Universities in Smart Education Environments

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Abstract: As a core course in horticulture-related majors, plant landscape courses play an important role in the cultivation of horticultural professionals. To address issues such as insufficient knowledge point connections in plant landscape course teaching under smart education environments, this paper constructs a plant landscape course knowledge graph and, based on this, builds a plant landscape course resource recommendation model using knowledge graphs and convolutional neural networks. Using a feature extraction module, feature vectors representing course attributes and user attributes are extracted, and higher-order aggregation between vectors is performed from multiple perspectives to achieve more precise plant landscape course resource recommendations for users. A digital teaching practice for plant landscape courses was conducted at a university in Y City, T Province. Among the experimental class students who applied this model for digital teaching, only one student had a teaching satisfaction score below 60, significantly fewer than in the control class. After the experiment, the average score of the experimental class students reached 101.18 points, which was 13.46 points higher than that of the control class, proving that the model proposed in this paper has a positive promotional effect on student learning in plant landscape course teaching.

Keywords: plant landscape course; knowledge graph; convolutional neural network; course resource recommendation

1. Introduction

Plants, as one of the four essential elements of landscape architecture, are a crucial component of landscape design [1]. Plant landscape planning and design is a highly practical and applied course that requires students to master foundational theories in horticulture, dendrology, landscape drafting, and landscape design, and then integrate these theories into practical applications. It is also an important pathway for cultivating high-quality, application-oriented talent [2-4]. The course consists of two parts: theoretical instruction and practical training, emphasizing the integrated application of theoretical knowledge and practical skills [5]. Theoretical instruction combines classroom lectures with interactive scenarios, requiring students to use theoretical knowledge in horticulture, arboriculture, and landscape planning and design as a foundation to build their own knowledge systems and mind maps. They must understand and master the ingenious combination of plants with other landscape elements, the creation of plant community landscapes, and plant landscaping techniques at different scales, such as different types of green spaces, plant landscaping techniques at different scales, summarize the principles and methods of plant landscape planning and design, and lay the foundation for future studies in landscape engineering, landscape construction management, plant cultivation, and maintenance management [6-8].

With the rapid development of information technology, the landscape industry is undergoing profound changes. From landscape planning and design, construction management, to post-construction maintenance and operation, the application of digital technology is becoming increasingly widespread [9]. Technologies such as Geographic Information Systems (GIS), Building Information Modeling (BIM), Virtual Reality (VR), and Augmented Reality (AR) have already demonstrated significant roles in the landscape field, transforming traditional work methods and processes [10-12]. Given this, landscape companies are increasingly in urgent need of composite talents who possess both landscape professional knowledge and digital skills to enhance the company's competitiveness and innovation capabilities [13-14]. For university plant landscape courses, how to adapt talent cultivation to the development of the times and achieve effective and precise alignment with the talent needs of landscape architecture companies has become a core issue that needs to be addressed in the development of this major [15].

In the era of educational reform, the digital upgrade of university landscape architecture majors is not only a vivid embodiment of the integration of information technology and education but also injects new vitality and momentum into professional education and teaching. Literature [16] explores the use of digital twin technology as an innovative teaching aid in landscape architecture courses and has achieved significant results in the landscape architecture program. Literature [17] utilizes deep neural networks (DNN) and deep learning (DL) to create a virtual reality-based landscape, aiming to enhance usability and efficiency. This approach provides direction for the reconstruction of virtual and physical teaching spaces, improvements in smart teaching methods, and reforms in information-based education. Literature [18] explores the application of computer virtual reality technology in plant landscape teaching in higher education institutions and uses SketchUp virtual modeling software to complete virtual modeling of buildings, vegetation, and other landscapes to assist in landscape design. Literature [19] explores how digital technology can assist landscape designers in completing the entire digital workflow from concept to physical prototype or final project components, providing new environments, new spaces, and new connotations for smart teaching and learning practices in higher education.

This paper constructs a knowledge graph for plant landscape courses through four stages: data acquisition, ontology construction, knowledge fusion and processing, and quality assessment. Based on the knowledge graph, a convolutional neural network is combined to construct a resource recommendation model for plant landscape courses. The feature extraction module extracts and converts user historical interaction information and course domain feature information into embedding vectors, which are then integrated into the embedding representations of users and courses. Additionally, the semantic information from the knowledge graph is utilized to further uncover the hidden features of users and courses. The KGCNN algorithm transmits different information to adjacent nodes, thereby better modeling the relationship between user interests and course resource features. The performance of the KGCNN algorithm is evaluated from aspects such as the effectiveness of recommendation paths and learner satisfaction. Taking first-year students majoring in horticulture at a university in Y City, T Province, as the research subjects, experimental and control classes are set up to conduct digital teaching practices for plant landscape courses, exploring the effectiveness of the knowledge graph-based plant landscape course resource recommendation model constructed in this paper in digital teaching.

2. Construction of a knowledge map for university plant landscape courses

Plant landscape courses are core courses in horticulture-related majors. In the context of smart education, university plant landscape courses are increasingly revealing teaching issues such as a lack of effective connections between knowledge points and insufficient guidance on the seasonal changes in landscape form and beauty. To address the challenges faced by university plant landscape courses, this chapter will construct a knowledge map for university plant landscape courses, providing a foundation for the subsequent research on course recommendation algorithms based on the plant landscape course knowledge map [20].

2.1. Principles of Knowledge Mapping Construction for Plant Landscape Courses

Ontologies are composed through conceptual models, formalization, sharing and clarification, referring to the formal description of a shared conceptual model in a particular domain. The knowledge of ontology is utilized to present the target knowledge logical relationship to the ontology model of the course resource can describe the knowledge points of the resource. Since the knowledge points are different, the learning resources are also different. Creating knowledge mapping entities based on knowledge points exists in a number of different representation languages that can be used in plant landscape courses in higher education.

2.1.1. Extraction of entities

Taking the entities in the curriculum knowledge map as knowledge points, it can be implemented in the process of analyzing the concepts in the teaching resources by means of entity-based extraction.The article utilizes web crawlers to extract and process the learning resources, where the keywords are the word frequency TF values in the text inverse frequency IDF:

$$TF_i = \frac{n_{ij}}{\sum_k n_{kj}} \tag{1}$$

$$IDF_i = \log \frac{|D|}{1+|\{j : t_i \in d_i\}|} \tag{2}$$

$$TF-IDF = \frac{TF_i \cdot \log = \left(\frac{|N|}{1+|\{j : t_i \in d_j\}|} \right)}{\sqrt{\sum_{j=1}^{n} \left[TF_i \cdot \log = \left(\frac{|N|}{1+|\{j : t_i \in d_j\}|} \right) \right]^2}} \tag{3}$$

In Eqs. (1)~(3) n_{ij} is the word frequency of the lexical item t_i in the learning resource d_j, IDF is the total number of documents in the course learning resource, and |NI is the number of lexical items in the learning resource.

2.1.2. Extraction of relationships

This step enables problems such as semantic linking between entities to be solved, Word2Vec uses training to map words and phrases into K-dimensional entity vectors, and then uses the distance between individual words to make a judgment on semantic similarity, and also creates hierarchical relationship trees.Define the relationship of knowledge points with actual requirements.

2.1.3. Ontology construction

For the article, a plantscape course in the landscape architecture program was chosen to create an ontology using the Protege tool.

2.2. Knowledge Mapping Process for Plant Landscape Course Construction

The knowledge map of the plant landscape course is shown in Figure 1, and its construction process is divided into four stages: data acquisition, ontology construction, knowledge fusion processing and quality assessment.

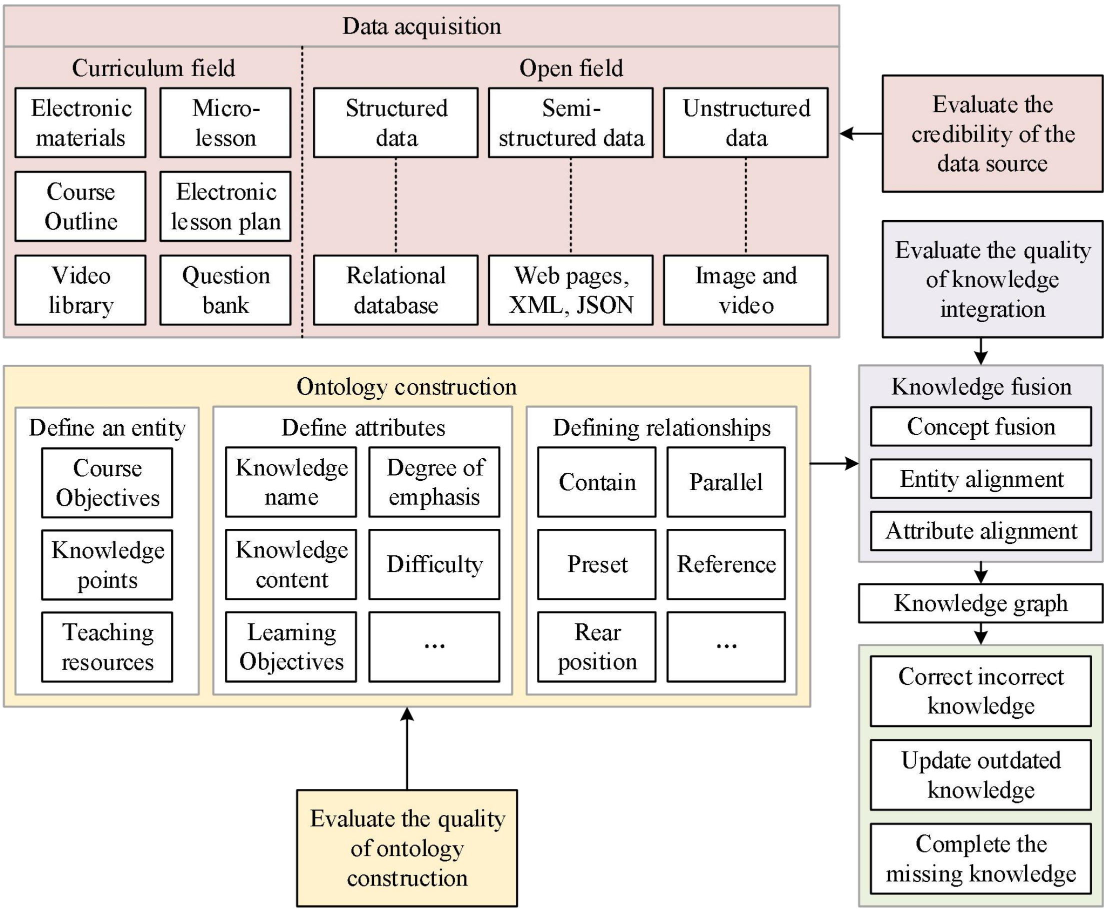


Figure 1. Knowledge map of plant landscape course.

1) Data Acquisition

Data acquisition is the basis for the construction of knowledge map of plant landscape course.The data sources in this paper mainly include two aspects: on the one hand, they come from the course domain to ensure the accuracy and authority of the knowledge points, including the course syllabus, electronic textbooks and lesson plans, microclasses, video libraries, test banks, etc.; on the other hand, they come from the open domain to ensure the richness and comprehensiveness of the knowledge points.

2) Ontology construction

Constructing ontology is a bridge connecting course data acquisition and knowledge integration, which mainly includes defining entities, such as knowledge points and concepts; defining attributes, such as degree of focus and difficulty; and defining relationships, such as predecessor and successor.At this stage, the ontology of basic computer courses is extracted according to the professional cultivation program, including the ontology of course objectives, the ontology of knowledge points, and the ontology of teaching resources.The course objective ontology describes the objectives of basic computer courses, guides the selection of teaching content and the introduction of course resources; under the premise of completing the syllabus, the teaching content is selected scientifically and reasonably according to the knowledge ontology; the teaching resources ontology realizes the close cooperation between classroom knowledge and underclass preparation and consolidation.

3) Knowledge integration

Different data sources may use different ontology construction strategies, which often leads to duplication and conflict of knowledge content, and therefore must be based on a unified standard specification for handling knowledge data from different sources.Knowledge fusion can effectively integrate, disambiguate, fine-tune and update knowledge information from different data sources, including conceptual fusion, entity alignment and attribute alignment.

4) Quality Assessment

Quality assessment is carried out throughout the whole cycle of the knowledge map of plant landscape course, which is used to assess the credibility of data sources before construction, to control the quality of knowledge extraction and fusion processing during the construction process, and to find and correct the wrong knowledge, update the outdated knowledge, and make up for the missing knowledge after the construction process, which determines the validity and value of the knowledge map.

3. A Knowledge Graph-based Model for Recommending Resources in Plantscape Courses

In this chapter, the recommendation model of NGCF and its network framework will be introduced, and the algorithmic framework of the proposed algorithm for recommending plant landscape course resources based on knowledge graph and convolutional neural network and the process of the KGCNN model will be presented for the deficiencies in the current course recommendation model [21].

3.1. NGCF Recommendation Model

3.1.1. NGCF Network Framework Analysis

NGCF is a graph neural network recommendation algorithm, this algorithm still uses the idea of collaborative filtering, and tries to capture the higher-order connectivity information in the user interaction graph when NGCF models the embedding of the user, which essentially still incorporates the preference features of other users related to the user into the recommended user.

After the NGCF algorithm generates the corresponding vectors of users and items to be recommended, the vectors of users and items to be recommended are supplemented with information through multi-layer information aggregation and propagation.At the same time, the algorithm saves the vectors generated by each layer of information aggregation, and at the end of the process, the vectors of users and items to be recommended are spliced with the information generated by the corresponding intermediate aggregation layer, and finally the user's interest in the course to be recommended is obtained through the inner-product algorithm.

3.1.2. NGCF aggregation layer

The embedding vector of the user is denoted as e_{u_k} , and the embedding vector of the project is denoted as e_{i_m} , where $e_{uk} \in R^d, e_{i_m} \in R^d$ and d denotes the embedding vector'sdimension.Then the embedding vectors E_u of the user group and the embedding vectors E_i of the to-be-item group can be expressed using the following equations, respectively:

$$E_u = e_{u_0}, e_{u_1}, \cdots, e_{u_k} \tag{4}$$

$$E_i = e_{i_0}, e_{i_1}, \cdots, e_{i_m} \tag{5}$$

Where E_u, E_i are all the same dimension vectors.

Multi-layer information aggregation is required for user and item information aggregation, and NGCF uses a GCN-like information aggregation method to aggregate user embedding vectors and item embedding vectors in multiple ways.Define p^n as the n th layer of aggregation vector, and its aggregation formula is as follows:

$$p^n = \frac{1}{\sqrt{(|N_u||N_i|)}}(W_1 p_i^{n-1} + W_2(p_u^{n-1} \odot p_i^{n-1})) \tag{6}$$

where p_i^{n-1}, p_u^{n-1} are the embedding vectors of items and users in the $n-1$th aggregation layer, W_1 and W_2 are the corresponding weight parameters, and $\frac{1}{\sqrt{(|N_u||N_i|)}}$ is theLaplace paradigm.The vector representation of the end user $e_{u_k}^n$ is formulated as follows:

$$e_{u_k}^n = f_{relu}(W_1 e_{u_k}^{n-1} + \sum_{e_i \in I_u} p^n) \tag{7}$$

where $f_{relu}(\cdot)$ is the nonlinearization function, $e_{u_k}^{n-1}$ is the embedding vector expression of user u_k in the $n-1$th embedding layer, and I_u represents the set of items that have interaction with user u . By aggregating as above, the algorithm aggregates the collaboration information between the item vectors

e_{u_i} and the user vectors e_{u_k}. After n layers of information propagation and aggregation, the algorithm obtains the final user embedding vector expression and the embedding vector expression of the project, which are formulated as follows:

$$e_{u_k}^n = e_{u_k}^0 \| e_{u_k}^1 \cdots \| e_{u_k}^n \tag{8}$$

$$e_{u_i}^n = e_{u_i}^0 \| e_{u_i}^1 \cdots \| e_{u_i}^n \tag{9}$$

Where $\|$ represents the concat operation, which takes the connection of each layer of embedding expression as the final user and item embedding vector expression, which preserves the information of each layer of embedding layer aggregation to a larger extent.The algorithm predicts the user's rating of the course to be recommended by computing the inner product of $e_{u_k}^n$ and $e_{u_i}^n$ with the following prediction formula:

$$\hat{y}_{NGCF}(u,i) = (e_{u_k}^n)^T e_{u_i}^n \tag{10}$$

3.2. Algorithm for recommending resources for plant landscape courses

In this paper, we propose a feature extraction module based on Convolutional Neural Networks and Knowledge Graph, this module utilizes the powerful feature extraction capability of CNNs to extract implicit features of courses and users.After extracting the corresponding course and user features, the embedded expressions of users and courses in the recommendation algorithm are fused, and a more multi-dimensional information aggregation approach is used to further mine the hidden features of users and courses using the semantic information of the knowledge graph to more accurately model the features of the users and courses and improve the performance of the course recommendation algorithm.

3.2.1. KGCNN algorithmic framework

In order to better mine the deep information hidden in the user interaction history, this paper proposes a course recommendation algorithm based on knowledge graph and convolutional neural network.This algorithm uses the CNN-based feature extraction module proposed in this paper to deeply mine the information related to videos, knowledge points, and course domains to which the knowledge points belong in the history of user interactions, and uses the feature extraction module to extract feature vectors representing course attributes as well as feature vectors representing user attributes to supplement the original vectors of the user and the course, and at the same time performs the higher-order vector aggregation from more angles, thus obtaining a more accurate embedded vector representation of the user and the course.aggregation, thus obtaining a more accurate representation of the embedded vectors of users and courses.The overall framework of the KGCNN model proposed in this paper is shown in Fig. 2.

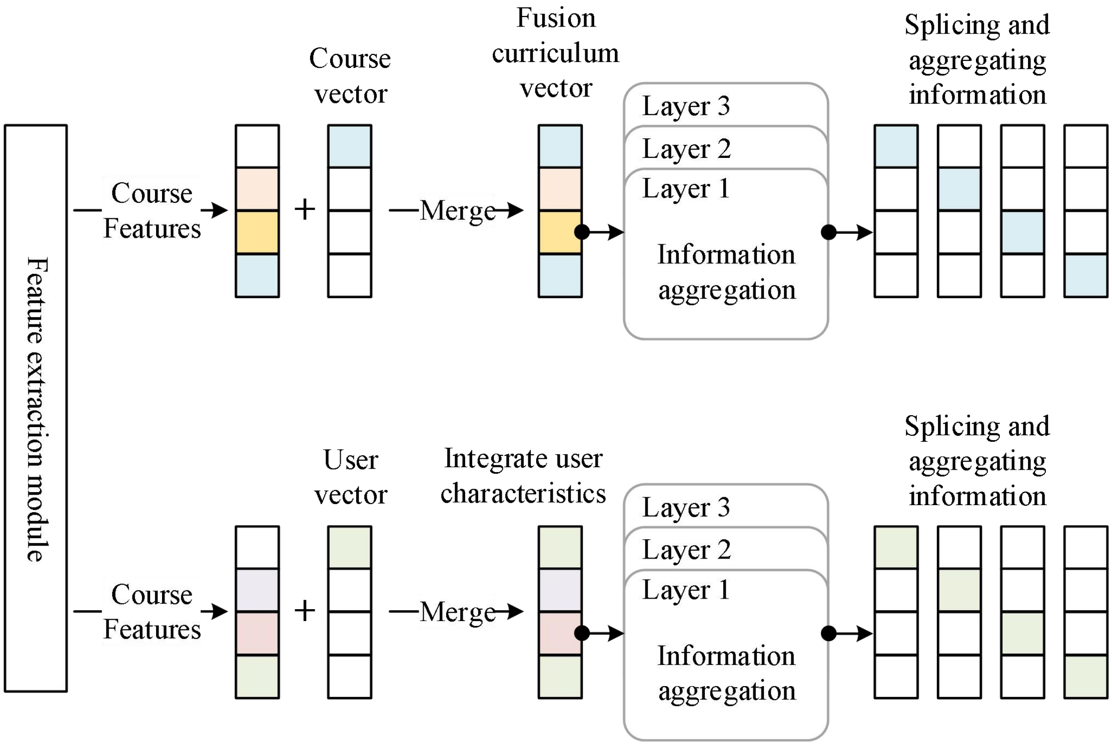


Figure 2. Overall framework of the KGCNN algorithm.

As shown in the above figure, the algorithm, after updating the embedding vectors of users and courses using the feature extraction module, performs message aggregation as well as link propagation along the links in the knowledge graph, and then uses multiple layers of embedding vectors to fuse them to obtain higher-order information, and finally splices the embedding vectors of the users and courses obtained from each layer to obtain the final embedding vectors of the users and courses, and finally splices the embedding vectors of the users and courses to obtain the final embedding vectors of the users and courses.vectors are inner product to get the recommendation result for the user to treat the recommended courses.

3.2.2. Convolution-based feature extraction module

Deep Neural Networks are widely used in various fields due to their powerful learning as well as fitting capabilities.Generally, the convolutional layer in CNN can be used to extract image features and the corresponding convolutional layer can also be used as input to extract features of vectors.In this paper, we propose a feature extraction module based on convolutional neural network, this module is designed for extracting course and user features.

The feature extraction module uses TransR to obtain embedded representations of the user and the corresponding course, video, knowledge point, domain, teacher, school and many other attributes.The feature extraction module receives as input the corresponding embedding vectors from the knowledge graph containing the corresponding video, knowledge point, and domain vectors of the course, and the output of the module is a fixed-size embedding vector representation of the course. For user-specific feature extraction, the module only uses the video vectors that the user has interacted with as input to the module.

3.2.3. KGCNN aggregation layer

Inspired by the KGAT algorithm, the information aggregation layer used in this paper uses a fusion of multiple aggregation approaches [22]. Define the set of embedding vectors for users as e_u, the set of embedding vectors for courses as e_i, and p_e as the splicing of the user vectors and course vectors, which is formulated as follows:

$$p_e = e_u \,||\, e_i \tag{11}$$

where $||$ is a splice-by-line operation. Define p_e^n as the n th layer aggregation vector of the information aggregation layer, where only neighbor nodes are aggregated in each aggregation, where the information aggregation formula is as follows:

$$p_e^n = f_{relu}(f_u(p_e^{n-1} + p_s^{n-1}) + f_u(p_e^{n-1} \odot p_s^{n-1})) \tag{12}$$

where $\odot$ is the inner product operation, $f_{relu}(\cdot)$ is a nonlinear function, and p_e^{n-1} and p_s^{n-1} are related to the $n-1$th layer of aggregation vectors, where $f_u(\cdot)$ is given by the following formula:

$$f_u(x) = wx + b \tag{13}$$

where w is the weight parameter and b is the corresponding bias.The corresponding p_s^n formula is as follows:

$$p_s^n = A * p_e^n \tag{14}$$

Where A is the record of the user's interaction with the course, the information fusion between different entities is realized by left-multiplying the interaction matrix A by the entity vector p_e^n, and p_e^0 is the corresponding initial p_e vector, which is formulated as follows:

$$p_e^0 = ((e_u + \alpha e_u^{cnn}) \,||\, (e_i + \beta e_i^{cnn})) \tag{15}$$

Where e_u^{cnn} and e_i^{cnn} are the representations of feature vectors extracted by the CNN-based feature extraction module for users and courses, respectively, and α and β are the corresponding weight parameters, and the algorithms in this paper, α and β, are both 0.4.

3.2.4. KGCNN loss function

BPR loss is a loss function used for recommender systems, which is based on the Bayesian Personalized Ranking (BPR) model.The BPR loss is used in KGCNN algorithm as the optimization objective of the algorithm, which is formulated as follows:

$$Loss_{BPR} = \sum_{(u,i,j)\in O} -\ln \sigma(\hat{y}_{ui} - \hat{y}_{uj}) + \lambda \,||\, \theta \,||^2 \tag{16}$$

where (u,i,j) is two sets of training data, i is the course that user u has actually interacted with, j is the course that the user has not interacted with, $\hat{y}_{ui}$ is the prediction score of the corresponding user u for course i, and $||\, \theta \,||^2$ is the regularization term, which in general prevents the model from being toofitting.

3.3. Experimental results and analysis

In this section, experiments will be designed to evaluate whether the KGCNN algorithm in this paper more accurately captures learners' preference to complete the recommendation of a plantscape course.This experiment will be evaluated in terms of recommendation path effectiveness,learner satisfaction and so on.

3.3.1. Data sets and evaluation indicators

The datasets used in this experiment are MovieLens-1M, Last.FM, and Course, where MovieLens-1M is a typical dense dataset and Last.FM is a sparse dataset.In this paper, AUC and F1 are used as evaluation metrics, AUC is the area under the ROC curve, which indicates the probability that the predicted positive scenario is ahead of the negative scenario.The larger the AUC is, the better the model is.F1 can be regarded as the mean value of the model's precision and recall, and the larger the F1 value is, the better the model is.

3.3.2. Analysis of experimental results

1) Algorithm performance evaluation

The experimental comparison results of the KGCNN algorithm in this paper with the comparative algorithms such as CNN, NGCF and SKGCN are specifically shown in Table 1.It is known through the experimental data.In the three datasets of MovieLens-1M, Last.FM, and Course, the AUC values of this paper's KGCNN algorithm are 0.925, 0.851, and 0.826 correspondingly, and the F1 values are 0.875, 0.758, and 0.739 respectively, which are the highest among all algorithms.Obviously, for both dense and sparse data, the performance of the KGCNN algorithm in this paper is the best, with higher AUC and F1 values compared to other algorithms.

Table 1. Experimental comparison results.

Model	MovieLens-1M		Last.FM		Course	
	AUC	F1	AUC	F1	AUC	F1
CNN	0.872	0.79	0.827	0.743	0.808	0.712
KGCN	0.901	0.785	0.793	0.703	0.818	0.718
SKGCN	0.865	0.837	0.791	0.724	0.785	0.723
KGCNN	0.925	0.875	0.851	0.758	0.826	0.739

2) Satisfaction Assessment of Recommendation Effect

In order to assess learners' satisfaction with the course resources recommended by this paper's Plant Landscape Course Resource Recommendation Model, a questionnaire was used to collect 30 learners' subjective ratings of the recommendation effect.A Likert scale was used to quantify learners' satisfaction.The total score of the ratings is 5, where 5 represents very satisfied; 4 represents satisfied; 3 represents average; 2 represents dissatisfied; and 1 represents very dissatisfied.The distribution of learners' satisfaction scores is specifically shown in Figure 3.It can be seen that the distribution of learners' recommendation effect ratings is in the 3 to 5 point range, and there is no rating in the 1 to 2 point range.There are 15 and 11 students with ratings of 4 and 5, which together account for 86.67%.This proves that the plant landscape course resource recommendation model in this paper can provide learners with satisfactory recommendation results.

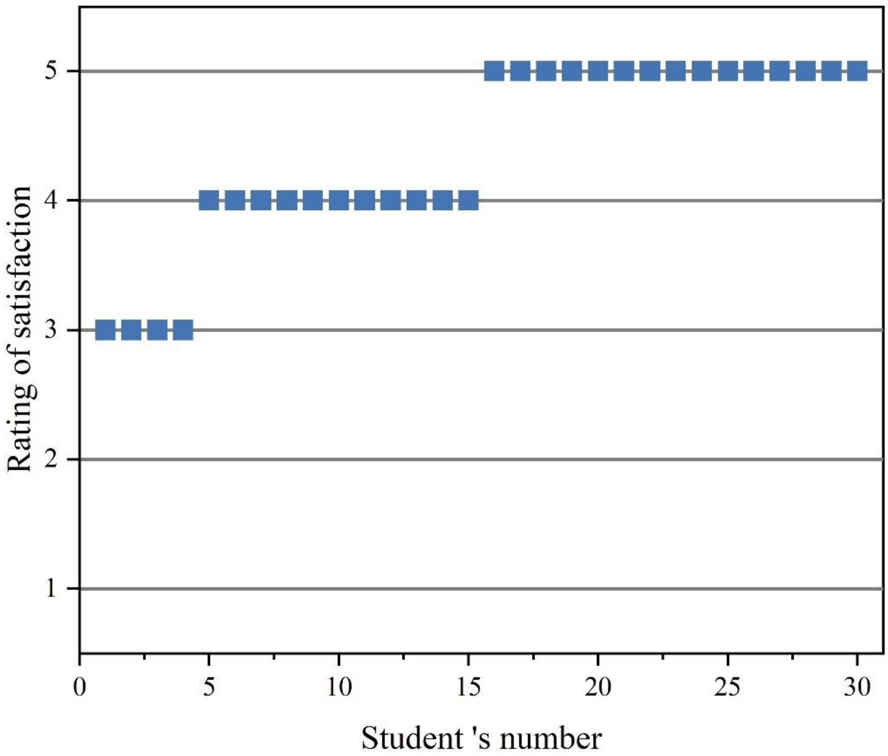


Figure 3. Learner 's rating results.

4. Digital Teaching Practices in Plant Landscape Courses

In this chapter, the proposed knowledge graph-based plant landscape course resource recommendation model will be applied to carry out digital teaching practice of plant landscape course within a university in Y city, T province.

4.1. Experimental design

4.1.1. Purpose of the experiment

The purpose of this experiment is to apply the knowledge graph-based plant landscape course resource recommendation model proposed in this paper to the teaching of plant landscape courses in colleges and universities, so as to verify the effectiveness of the plant landscape course resource recommendation model in this paper, and to explore the practical effects of digital plant landscape course teaching in combination with the plant landscape course resource recommendation model in this paper.

4.1.2. Experimental Objects

This experiment was carried out in a university in Y city of T province,the selected experimental subjects are students of two classes in the first year of horticulture program.The students of the two classes have similar levels of achievement in the plant landscape course,and the original teaching mode is basically the same.On this basis, the experimental class and the control class will be determined separately, and the number of students in each class will be 50.The experimental class will carry out digital teaching by applying this paper's knowledge graph-based plant landscape course resource recommendation model, while the control class will maintain the original teaching mode.

4.1.3. Experimental variables

The experimental variables for this experiment are:

1) Independent variables

The independent variable of this experiment junior high school mathematics teaching model, divided into two levels of independent variables, one is the digital teaching model implemented in the experimental class applying this paper's knowledge graph-based plant landscape curriculum resource recommendation model, and the other is the original teaching model implemented in the control class.

2) Dependent variable

The dependent variables of this experiment are the changes in students' academic performance and teaching satisfaction.

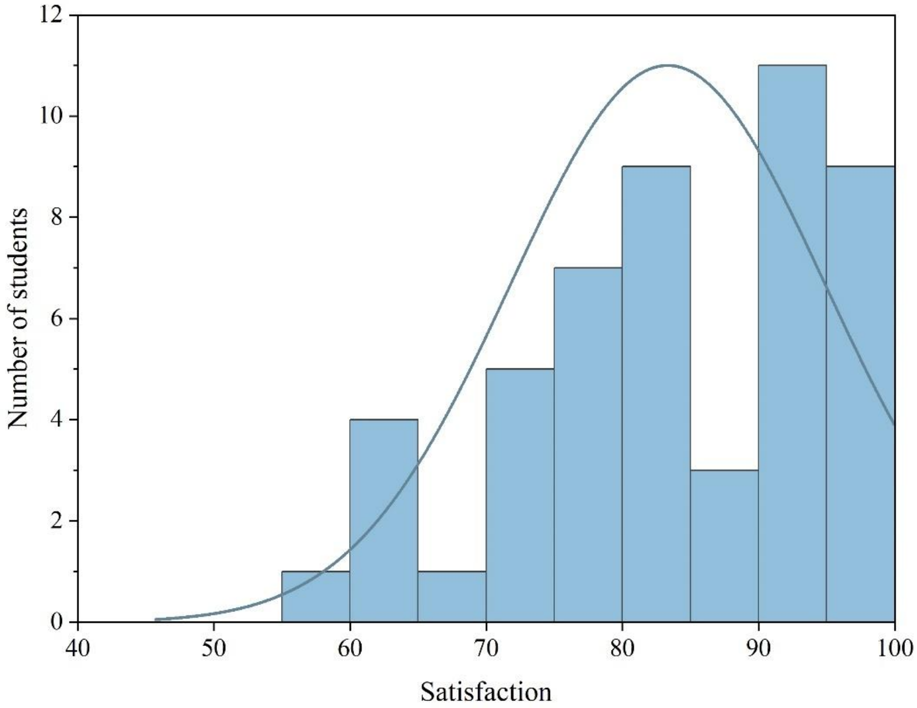
3) Control of interfering variables

The experimental class and the control class were selected as similar as possible; the teacher of the experimental class and the control class was the same teacher; when conducting the experiment, the teacher would not tell the students of the experimental class that the experiment was being conducted, but only told them that the teaching mode would be adjusted to avoid increasing their psychological burden; the teaching progress of the experimental class and the control class was the same and the teaching content was the same; and the test set of the experimental class was the same; the test set of the experimental class was the same; the test set of the experimental class was the same; and the test set of the experimental class was the same.The difficulty level of the test papers will be controlled to ensure that the difficulty level of the test papers is comparable.

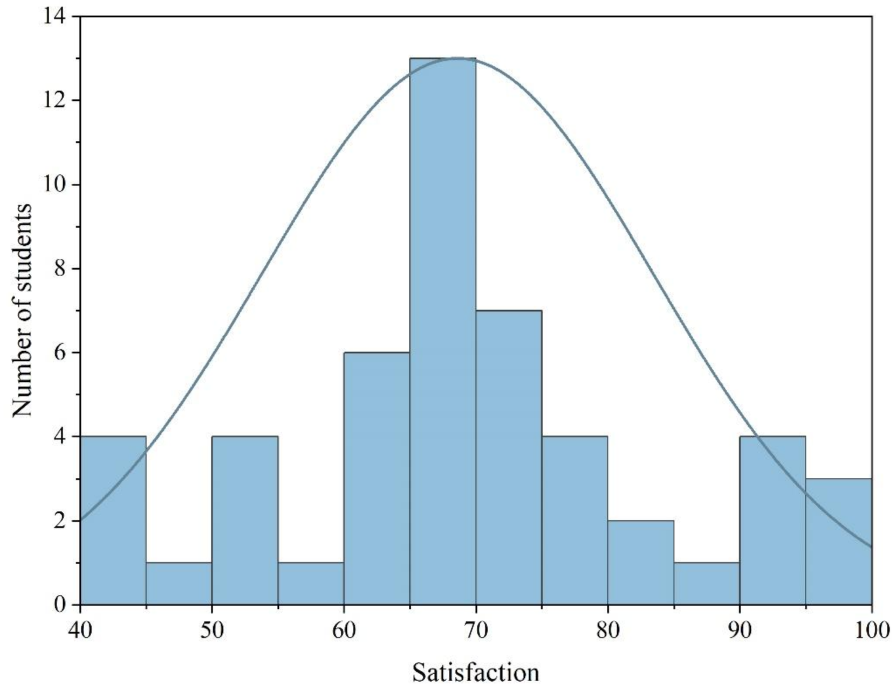
4.2. Analysis of experimental results

4.2.1. Analysis of Teaching Satisfaction

After the data collection and statistics, the point distribution graphs of students' satisfaction in the experimental class and the control class were obtained as shown in Fig. 4, with graphs (a) and (b) corresponding to the experimental class and the control class, respectively.As a whole, it can be seen that most of the students in the experimental class have a satisfaction level above 60, and only one student has a satisfaction level below 60, while the number of students in the control class who have a satisfaction level below 60 is 10, which is much more than that of the experimental class.This indicates that the application of this paper's knowledge graph-based plant landscape course resource recommendation model for digital teaching in the experimental class can better cater to students' learning needs in general, and students can better master the knowledge points of the plant landscape course.



(a) Experimental class



(b) Control class

Figure 4. Student satisfaction distribution.

Classroom interestingness is an important factor in promoting students' interest in learning. Classroom interestingness was categorized into four score intervals of [0,60], [60,80], [80,90], and [90,100], which corresponded to an interestingness rating of very interesting, interesting, average, and not interesting.The results of the experimental and control class students' fun ratings of the course are specifically shown in Figure 5.About 93.33% of the students in the experimental class thought that the lectures of the plant landscape course during the experiment were interesting.In contrast, only 26.67% of the students in the control class class thought that the course delivery was interesting, and as many as 40% of the students thought that it was not interesting.

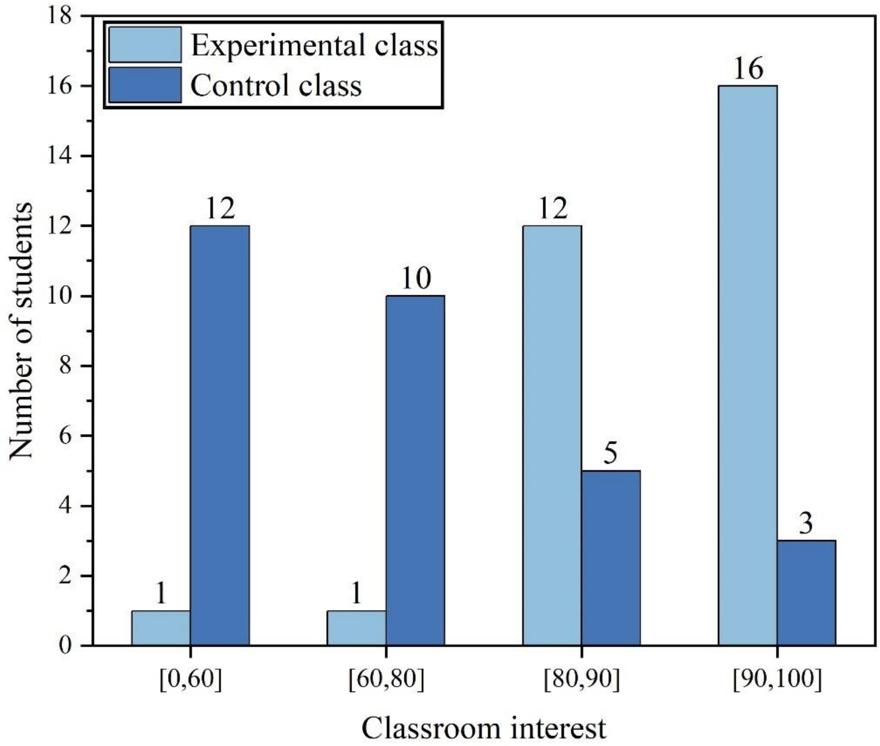


Figure 5. Classroom interesting statistics.

Whether the teaching content is mastered or not is an important indication for evaluating the effectiveness of a teaching mode, so this study investigates the statistics for the learners in the satisfaction of content mastery in the data statistical analysis. The content mastery satisfaction of students in the experimental class and the control class is shown in Figure 6.It can be seen that the content mastery satisfaction scores of the students in the experimental class were mainly concentrated in the interval of [80,100], while the students in the control class were mainly concentrated in the interval of [60,80].Obviously, after applying this paper's knowledge graph-based plant landscape course resource recommendation model to carry out digital teaching in the experimental class, the students have a more adequate mastery and learning of the teaching content, and their performance is better than that of the control class.

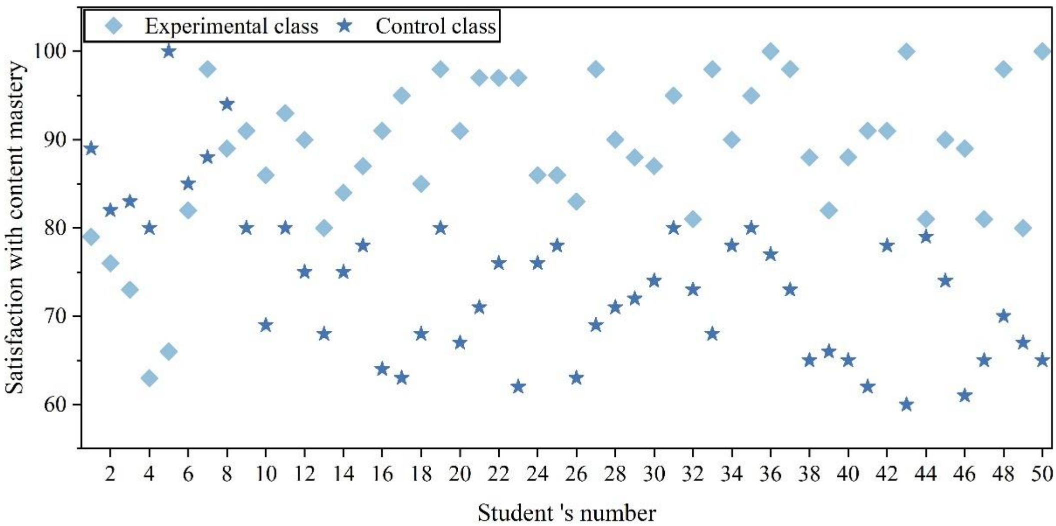
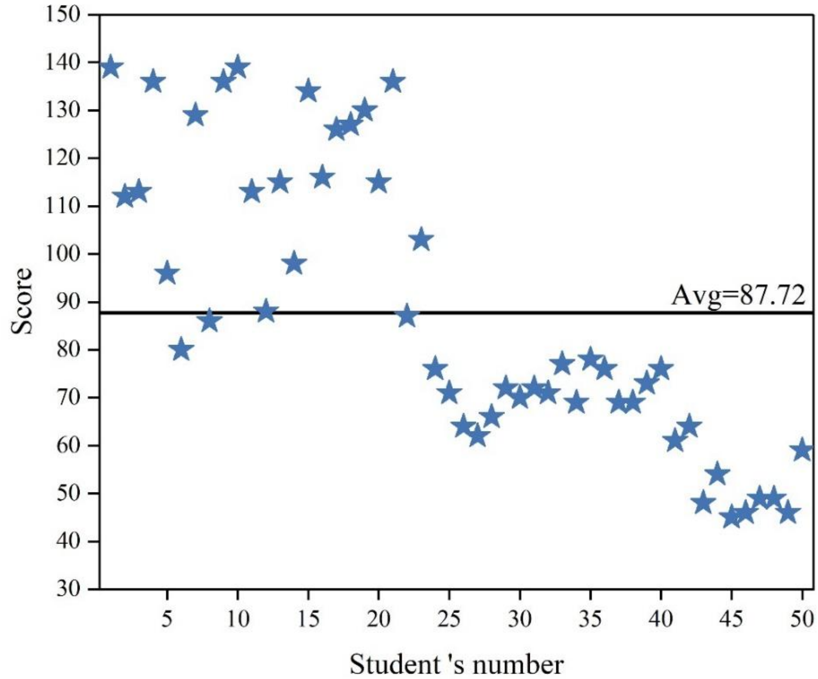


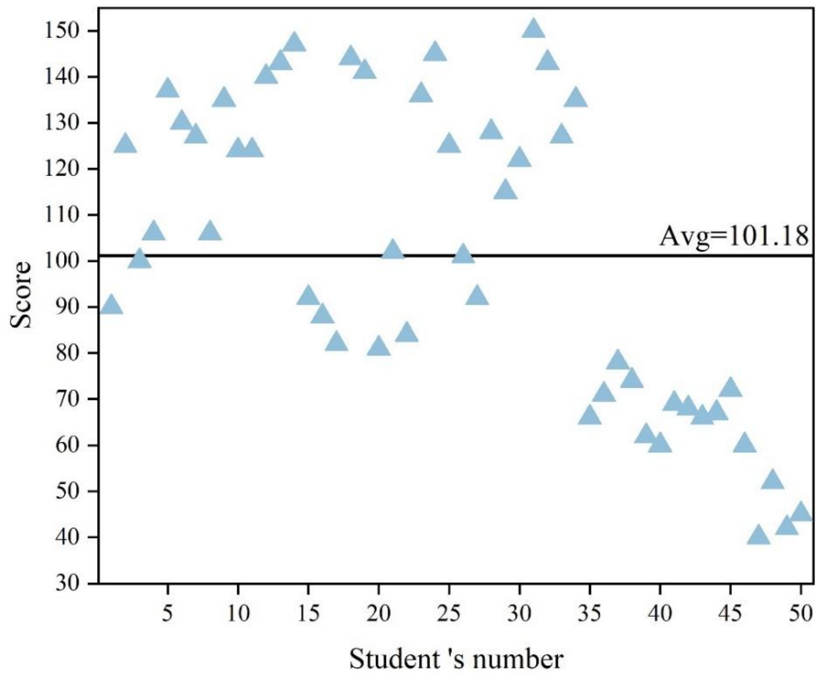
Figure 6. Satisfaction with content mastery.

4.2.2. Analysis of student performance

Learner achievement performance can intuitively reflect the teaching effect.In this study, the test scores of the experimental class and the control class in the plant landscape course at the end of the experiment were compared, and the distribution of students' performance in each class is specifically shown in Figure 7.Figures (a) and (b) correspond to the control class and the experimental class.As can be seen from the figures, the overall distribution of students' grades in the control class is lower.With a total score of 150 points, the average score of the students in the class is 87.27, and the highest score is also below 140 points.In contrast, students in the experimental class were significantly higher than the control class, with an average score of 101.18, 13.46 points higher than the control class.



(a) Experimental class



(b) Control class

Figure 7. Score distribution.

The test scores of the experimental class and the control class students after the experiment were subjected to independent samples t-test, and the results of the test are specifically shown in Table 2.The difference in mean values between the two groups is significant, Sig = 0.037<0.05, indicating that the two groups are not in variance and are significantly different.The independent samples t-test yielded T = -12.623 with a significant two-tailed value of P = 0.001<0.05, so the difference between the test scores of the experimental class and the control class was statistically significant.This indicates that applying the knowledge graph-based plant landscape course resource recommendation model proposed in this paper to the plant landscape course in colleges and universities, and carrying out digital teaching can effectively improve the students' performance in the plant landscape course, and play a positive role in the students' course learning.

Table 2. Independent samples test.

-	Levene's test for equality of variances		Hest for equality of means			Mean difference	95% confidence inteival of difference	
	F	Sig	T	Df	Sig.(two-tailed)		Lower	Upper
Equal variances assumed	4.268	0.037	-12.623	25	0.001	-56.256	-65.148	-47.426
Equal variances not assumed			-10.774	10.533	0.001	-56.256	-67.472	-45.137

5. Conclusion

In this paper, we constructed a knowledge map of plant landscape courses, and on the basis of the knowledge map, combined with the convolutional neural network to propose a resource recommendation model for plant landscape courses.The performance of this paper's course resource recommendation algorithm KGCNN is examined from the aspects of recommendation path effectiveness and learner satisfaction.Comparing with CNN, NGCF and SKGCN, this paper's KGCNN algorithm obtains the highest AUC and F1 values on MovieLens-1M, Last.FM, and Course datasets, with the AUC values of 0.925, 0.851, and 0.826, and the F1 values of 0.875, 0.758, and 0.739, respectively, which indicates that for both dense and sparse data.both dense and sparse data, the KGCNN algorithm in this paper has excellent performance.Learners' satisfaction with the course resources recommended by this paper's plant landscape course resource recommendation model is evaluated.The subjective ratings of 30 learners were collected, and the learners' recommendation effect ratings were distributed in the range of 3 to 5, with the combined percentage of those with ratings of 4 and 5 amounting to 86.67%.This indicates that 86.67% of the learners' satisfaction level is satisfied, very satisfied, and the plant landscape course resource recommendation model in this paper can provide learners with satisfactory recommendation results.

To carry out the digital teaching practice of plant landscape course in a university in Y city, T province, freshmen students majoring in horticulture were selected as the research object, and the experimental class applying the plant landscape course resource recommendation model of this paper for digital teaching and the control class maintaining the original teaching method were set up to explore the effectiveness of the resource recommendation model of this paper's plant landscape course.In terms of teaching satisfaction, only one student in the experimental class had a satisfaction rate of less than 60, while 10 students in the control class had a satisfaction rate of less than 60. 93.33% of the students in the experimental class thought that the teaching of the plants and landscapes course in the experimental process was interesting, while 40% of the students in the control class thought it was not interesting.Moreover, the content mastery satisfaction of the students in the experimental class was mainly concentrated in the interval of [80,100], while the students in the control class were mainly concentrated in the interval of [60,80].Obviously, the teaching satisfaction of students in the experimental class was higher than that of the control class as a whole.In terms of student achievement, the average score of students in the experimental class after the experiment reached 101.18, which was 13.46 points higher than that of the control class.The row independent samples t-test was conducted on the academic performance of the experimental and control classes.The difference between the means of the two groups is significant, Sig = 0.037<0.05, and the variance of the two groups is not significant.T =

-12.623, significant two-tailed value P = 0.001<0.05, proves that the difference between the test scores of the experimental and control classes is statistically significant.In conclusion, applying the value of the knowledge graph-based plant landscape course resource recommendation model proposed in this paper to the teaching of the course can effectively improve the learners' teaching satisfaction and play a positive, positive role in the improvement of students' academic performance.

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