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Building an AI-driven interdisciplinary teaching innovation system for two universities

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Abstract The integration of interdisciplinary knowledge in higher education teaching has gradually become an important way to improve teaching quality and innovation ability. This paper proposes a method of designing and realizing the interdisciplinary knowledge integration and teaching innovation system of dual colleges and universities based on artificial intelligence algorithms. The study constructs a multidimensional disciplinary knowledge network through graph convolutional self-encoding model and LDA topic model, and analyzes the knowledge fusion process between dual colleges and universities. The experimental results show that among the 15 themes, the contribution degree of theme 2 “Big Data and Artificial Intelligence Application” is 0.9878, which indicates its important position in the interdisciplinary knowledge integration between dual universities. The point centrality analysis of the knowledge network shows that “interdisciplinary” and “artificial intelligence” are the most influential knowledge nodes. This method not only provides theoretical support for interdisciplinary knowledge integration in dual colleges and universities, but also provides practical basis for teaching innovation in related fields. This paper shows that the integration of interdisciplinary knowledge through artificial intelligence algorithms can effectively promote the quality of teaching and research innovation in universities, and enhance the overall competitiveness of universities.

Index Terms Artificial Intelligence, Interdisciplinary Knowledge Integration, Teaching Innovation, Graph Convolutional Self-Coding, LDA Topic Model, Dual Colleges and Universities

I. Introduction

Interdisciplinary research is a significant feature of today's scientific development and an important research direction, which is an important means to promote contemporary scientific and technological progress and economic and social development, and is also a key link in the implementation of the national innovation-driven strategy [1]. In the context of today's educational reform, the development of disciplinary knowledge fusion has brought new development opportunities and challenges for college teaching [2]. Discipline integration can break the boundaries between disciplines and disciplines, learning and life, realize the integration of disciplines, discipline knowledge and life field, reorganize the teaching content, reconstruct the teaching method, stimulate the learning autonomy and innovation consciousness, and ultimately achieve the goal of educating students for comprehensive development [3]-[6]. The formation of this concept stems from the deep reflection on the differentiation and specialization of the modern knowledge system, recognizing that a single discipline is often incompetent in the face of complex real-world problems, and urgently requiring educators to break the boundaries of the disciplines and explore the teaching path of interdisciplinary integration [7]-[10]. As a result, interdisciplinary knowledge integration teaching is carried out by establishing connections and interactions between different disciplines in order to help learners understand and solve complex problems or phenomena in a more comprehensive and in-depth way [11], [12].

From a practical point of view, although subject integration teaching has its own advantages, it also has inherent core requirements, which leads to certain misunderstandings and bias in the operation of many front-line teachers, and the effect is not as ideal as imagined [13]-[15]. At the same time, the development of information technology deeply affects the change of productivity and the improvement of life style, and the advent of the network era is changing the overall teaching pattern of school, family and society [16], [17]. Therefore, innovative teaching design with information technology will be conducive to realizing the sharing of subject teaching resources, expanding and extending the existing textbook knowledge, helping students to build a complete knowledge system and broaden their knowledge [18]-[20].

The core of this study is to explore how to effectively integrate the disciplinary resources of dual colleges and universities through graph convolutional neural networks and LDA topic models by constructing a framework for AI-driven disciplinary knowledge fusion. In the implementation process, firstly, the topic identification of literature data is carried out through LDA model to extract the core topics of discipline knowledge. Then, the disciplinary knowledge network is constructed based on the graph convolutional self-coding model, and the interdisciplinary knowledge integration of the dual universities is quantitatively assessed by social network analysis method. Finally, the feasibility and effect of the method in dual-university cooperation is verified through experiments, which provides new ideas for education and teaching innovation.

II. A methodology for constructing disciplinary knowledge networks based on graphical convolutional self-encoding models

II. A. Graph Convolutional Neural Networks

Graph Convolutional Neural Network [21] is a text classification method with excellent classification effect, and it is also often used as a kind of base network for other models due to its simple structure and stackable use.

II. A. 1) Generalization of Convolutional Operations

In order to deal with graph data effectively, many attempts have been made to generalize the concept of convolution to relational graph data, and the approaches are broadly categorized into two groups, one of which is based on the properties of the convolution operation and uses other methods to redefine the convolution to fit the relational graph data. The other is to make the traditional convolutional neural network applicable to the processing of relational graph data by constructing a transformation from relational graph data to regular graph data.

II. A. 2) Graph Convolutional Neural Network Model GCN

The GCN model has solid theoretical support for the performance demonstrated by feature extraction of node feature signals in the relational graph. Compared with the computational overhead of GNN's one-time operation of aggregating all the neighboring nodes of each center node with an indefinite number of nodes, the introduction of GCN's computational step for the Laplace matrix further increases the computational burden of this process, which makes it difficult to apply the GCN model directly to large-scale data of the relational graph.

Therefore, the research on GCN model is mainly divided into two directions: to reduce the computational overhead of single training process of GCN model by sampling or other methods, and to construct more effective Laplace matrix for training by utilizing the relational graph.

II. A. 3) GCN modeling principles

The process of feature extraction through specific arithmetic operations. For any node signal x, the operation procedure of spectral filtering can be seen in equation (1).

$$g_\theta * x = U g_\theta U^T x \tag{1}$$

The method of calculating the Laplace matrix is shown in equation (2).

$$L = I_N - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} = U \Lambda U^T \tag{2}$$

The Chebyshev polynomial-based approach proposes that the functional relation $g_\theta(\Lambda)$ can be expanded into the form of a Chebyshev polynomial of order K:

$$g_\theta(\Lambda) \approx \sum_{k=0}^{K} \theta_k T_k \left(\frac{2}{\lambda_{\max}} \Lambda - I_N \right) \tag{3}$$

where $T_k(x)$ represents the k th term of the K th order Chebyshev polynomial, which is defined in equation (4).

$$T_k(x) = 2x T_{k-1}(x) - T_{k-2}(x), \quad T_0(x) = 1, \quad T_1(x) = x \tag{4}$$

and the equations about Chebyshev polynomials, eigenvalue matrix, and eigenvector matrix hold, and the equations are given in equation (5).

$$T_k(U \Lambda U^T) = U T_k(\Lambda) U^T \tag{5}$$

At this point the spectral filtering operation $g_\theta * x$ can be approximated using Chebyshev polynomials to obtain equation (6).

$$g_\theta * x \approx \sum_{k=0}^{K} \theta_k T_k \left(\frac{2}{\lambda_{\max}} L - I_N \right) x \tag{6}$$

The use of Chebyshev polynomials to approximate the spectral filtering operation $g_\theta * x$ ultimately makes the spectral filtering process of the channel signal x no longer involve the operation of matrix multiplication for computing the eigenvector array of the graph Laplacian matrix, which greatly reduces the arithmetic overhead in the spectral filtering process.

By restricting the sense field of the graph convolution operation to all neighboring nodes with a step of 1 from the center node, the Chebyshev polynomial order is 1, and then the spectral filtering operation $g_\theta * x$ can be further simplified to Eq. (7).

$$g_\theta * x \approx \theta_0 x + \theta_1 \left(\frac{2}{\lambda_{\max}} L - I_N \right) x \tag{7}$$

At this point, the spectral filtering process of the signal x is completely determined by the 2 parameters θ_0, θ_1 from the Fourier domain as well as the maximum eigenvalue of the graph Laplace matrix and the matrix $\lambda_{\max}$.

Consider a further transformation of the spectral filtering process for a single channel signal x by first making $\lambda_{\max} \approx 2$ in order to remove the eigenvalue term in Eq. x and expanding it based on the Laplacian matrix to obtain Eq. (8).

$$g_\theta * x \approx \theta_0 x - \theta_1 D^{-\frac{1}{2}} A D^{-\frac{1}{2}} x \tag{8}$$

Using the unique parameter θ instead of the parameters θ_0 and θ_1 in Eq. (8), the spectral filtering process containing only the unique parameter θ is then obtained, see Eq. (9).

$$g_\theta * x \approx \theta \left(I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \right) x \tag{9}$$

Considering that the eigenvalue range of the matrix $I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}}$ is in the range of $[0,2]$, which may cause the gradient explosion or gradient vanishing problem in repeated spectral filtering operations, a similar form of substitution is applied to the $I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}}$ term with a similar form of substitution:

$$I_N + D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \rightarrow \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} \tag{10}$$

$$\tilde{A} = I_N + A, \tilde{D}_{ii} = \sum\nolimits_j \tilde{A}_{ij} \tag{11}$$

Considering the case of spectral filtering with multiple channels and multiple signals, the computational flow of one spectral filtering operation can be expressed as equation (12).

$$g_\theta * x \approx \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} X \theta \tag{12}$$

Based on the above graph convolution operation one can define the operation procedure of graph convolution neural network:

$$X^{(t+1)} = \sigma\left(\tilde{A} X^{(t)} W^{(t)} \right) \tag{13}$$

For any node v_m, the specific computational procedure of aggregation with v_m as the center node during the aggregation operation of single-layer graph convolutional layer is shown in Equation (14).

$$\overline{x}_i^{(t+1)} = \sigma\left(\sum_{v_j \in V_i} \frac{1}{\sqrt{d_{ij} d_{ji}}} \overline{x}_j^{(t)} W^{(t)} \right) \tag{14}$$

II. B.Thematic Modeling LDA

The graph convolutional neural network text categorization method proposed in this paper makes use of the topic model LDA [22] in constructing the graph.

The LDA model considers the parameters in the text-topic probability distribution, i.e., the probability that the text belongs to each topic is unknown in advance but exists with certainty, and therefore constructs a priori Dirichlet distribution for the topic distribution of the text.

The LDA model uses the Delikeray distribution as the form of distribution obeyed by the parameters in both the text-topic probability distribution and the topic-word probability distribution:

$$\sigma \sim Dir(\beta), P(\sigma \mid \beta) = \frac{\Gamma\left(\sum_{i=1}^{d} \beta_i\right)}{\prod_{i=1}^{d} \Gamma(\beta_i)} \prod_{i=1}^{d} \sigma_i^{\beta_i - 1} \tag{15}$$

The goal of the LDA model can be summarized as using the actual occurrence of words in each text to correct the prior Dirichlet probability distribution of the text-topic multinomial distribution for each text and the prior Dirichlet distribution of the topic-word multinomial distribution for each topic on the premise that all the constituent vocabularies of each text are known. Let all the probability distributions and prior probability distribution parameters related to text, topic and word be uniformly denoted as z, and let all the occurrences of words in all the texts in the corpus be denoted as w, then the LDA model actually solves the posterior probability $P(z|w)$. The computational process can be represented by equation (16).

$$P(z|w)=\frac{P(z,w)}{\sum_z P(z,w)} \tag{16}$$

Since the LDA model involves two discrete state spaces of large size where the document-topic variable and the topic-word variable are located, the denominator term in Eq. (16) is difficult to compute, and thus its covariates need to be computed with the help of Gibbs sampling.

Since the $\sum_z P(z,w)$ term is difficult to compute directly, it is necessary to use indirect sampling to estimate the posterior probability $P(z|w)$ and indirectly obtain the parameters θ and σ. The subject assignment of the process of generating word w at a time in the corpus is noted as $\vec{z}$:

$$\vec{z}=\left(z_1,z_2,\cdots,z_m\right) \tag{17}$$

The value z_k of any dimension k of $\vec{z}$ can be regarded as the number of times that the LDA method selects to the k th topic and generates the word w by that topic in the process of constructing the corpus W. At this point $\vec{z}$ can also be regarded as a sample form sampled from $P(z|w)$.

A Markov chain is constructed with $P(z|w)$ as the target probability distribution, with any state $\vec{z}_t$ as the initial state, denoted as $\vec{z}^{(0)}$, and $P(z_k|z_{-k},w)$ as the subject assignments $\vec{z}$ from the states $(z_1,\cdots,z_{k-1},z_k,z_{k+1},\cdots,z_m)$ to state $(z_1,\cdots,z_{k-1},z_{k'},z_{k+1},\cdots,z_m)$ based on the probability of transferring $P(z_k'|z_{-k},w)$ to the initial state $\vec{z}^{(0)}$ by time step for state transfer.

According to the Gibbs sampling method, it is known that the Markov chain constructed with $P(z_k'|z_{-k},w)$ as the state transfer probability is able to converge to the target posterior distribution, therefore, when the preset upper limit of the transfer time-steps t is reached, the state transfers are continued, and the state sequence generated after the continuous sampling threshold s times of the transfers is that the sequence of states $\{\vec{z}^{(t)},\vec{z}^{(t+1)},\cdots,\vec{z}^{(t+s)}\}$ that is, the set of samples sampled according to the posterior probability distribution $P(z|w)$. At this point, the estimated values of the parameters θ and σ can be calculated based on the samples, and then the text-topic probability distribution and topic-word probability distribution based on the corpus can be obtained.

The input of the LDA model is a text-word frequency matrix, and the output is the text-topic probability distribution and topic-word probability distribution, both of which are in discrete form, obtained from the sample estimation of the parameters and further computed. The LDA method uses the perplexity degree to evaluate the model, and the lower the perplexity degree, the better the model is.

II. C.Multi-dimensional disciplinary knowledge network construction methods

II. C. 1) Knowledge unit extraction

(1) Topic

In this paper, we use LDA topic model for topic extraction, firstly, we use natural language processing method to clean the original data set, pre-process it by word splitting and so on, then we use confusion degree to determine the optimal number of topics, set the parameters of the LDA model and run the LDA program, and finally, we summarize the output of the program as a "topic-word" file to get the subject knowledge topics. Finally, the output of the program is summarized in the "topic-word" file, and the subject knowledge topics are obtained.

(2) Keywords

Keywords are the phrases given by the author that can reflect the center and theme of the paper, which are highly condensed and summarized for the content of the literature, and can reflect the research content of the discipline to a greater extent, and the keywords in the scientific literature can be extracted directly from the entries.

(3) Entity

The improved TF-IDF algorithm is utilized to screen the high-frequency words in the corpus, and after lexical annotation, the topN nouns with larger TF-IDF values are selected as the entity set.

$$TF-IDF_{wm}=\frac{TF_{wm}^2+IDF_w}{|m|} \tag{18}$$

$$IDF_w=\log\left(\frac{N}{DF_w+1}\right) \tag{19}$$

In the above equation, w denotes the word, m denotes the document, TF_{wm} denotes the frequency of the word w in the document m, and $|m|$ denotes the number of words contained in the document m.

II. C. 2) Knowledge sub-network construction

Taking the extracted topics, keywords and entities as knowledge nodes, and determining the connecting edges by the similarity degree between the knowledge nodes, the topic sub-network, keyword sub-network and entity sub-network are constructed respectively.

(1) Topic sub-network

The weighted sum of the three indicators of document overlap $(doc_{coincidence})$, topic word similarity $(feature_{sim})$ and keyword similarity $(keywords_{sim})$ is used as a measure of the degree of similarity between topics. The calculation method of each index is as follows:

$$topic_{sim(i,j)} = w_1 doc_{coincidence(i,j)} + w_2 feature_{sim(i,j)} + w_3 keywords_{sim(i,j)} \tag{20}$$

Where $topic_{sim(i,j)}$ denotes the similarity between topic i and topic j, w_i is the weight corresponding to each indicator, and $\sum_{i=1}^{3} w_i = 1$.

1) Document overlap: the more the number of overlapping documents between the topics, the higher the similarity between the topics, calculate the Jaccard coefficient of the subset of documents between different topics that is the degree of document overlap.

$$doc_{coincidence(i,j)} = \frac{num(set_i \cap set_j)}{num(set_i \cup set_j)} \tag{21}$$

In Equation (21), $num(set_i \cap set_j)$ denotes the number of document subsets of topic i and topic j taken as intersection, and $num(set_i \cup set_j)$ denotes the number of document subsets of topic i and topic j taken as concatenation.

2) Theme word similarity: each theme usually selects the topN words with larger probability value as the feature words describing the theme, and the cosine similarity of feature words between themes is used to measure the similarity between theme words. The feature words under all themes are combined, C is the total number of non-repeated feature words, p_i^w indicates the weight of feature word w in the distribution of words of theme i, if theme i does not contain the feature word w, then the value of p_i^w is zero.

$$feature_{sim(i,j)} = \frac{\sum_{m=1}^{C} (p_i^w * p_j^w)}{\sqrt{\sum_{w=1}^{C} {p_i^w}^2} \times \sqrt{\sum_{w=1}^{C} {p_j^w}^2}} \tag{22}$$

3) Keyword similarity: the keywords of the documents in the subset of documents corresponding to the topic are transformed into a vector space model, and the cosine similarity of the keywords is computed, and tf_{ik} denotes the frequency of the k th keyword of topic i.

$$keywords_{sim(i,j)} = \frac{\sum tf_{ik} \times tf_{jk}}{\sqrt{\sum (tf_{ik})^2} \times \sqrt{\sum (tf_{jk})^2}} \tag{23}$$

(2) Keyword sub-network

Statistics of keywords appearing in all the literature, if two keywords appear in the same piece of literature, then these two keywords have a co-occurrence relationship, according to the number of pieces of literature in which the keywords appear at the same time, i.e., the number of co-occurrences to construct the co-word matrix to mine the similarity relationship between the keywords, and the more co-occurrences indicate that the keywords have a higher degree of similarity with each other.

(3) Entity sub-network

The similarity relationship between entities is identified using the LR algorithm, LR is an indicator of truthfulness, defined as the ratio of the maximum value of the likelihood function with constraints to the maximum value of the likelihood function without constraints, where the constraints on the appearance of one entity are whether another entity appears or not, i.e., conditional probability $p(e_1 | e_2)$, which indicates that entity e_1 appears under the condition of the appearance of entity e_2. The probability of occurrence of these two entities, if these two entities frequently occur together i.e., the value of LR is large, then it means that there is a strong association between these two entities. Based on this the LR value of an entity and other entities are calculated and the entity with larger LR value is selected as the similar entity of that entity, thus generating the entity similarity matrix.

$$LR(e_1, e_2) = \frac{p(e_1 | e_2)}{p(e_1 | not\_e_2)} \tag{24}$$

$$p(e_1 \mid e_2) = \frac{p(e_1, e_2)}{p(e_2)} \tag{25}$$

According to the similarity matrix, the topic sub-network, keyword sub-network and entity sub-network are constructed respectively as the knowledge structure map of the 3 dimensions of the disciplinary knowledge network, which lays the foundation for the subsequent network fusion work.

II. C. 3) Knowledge subnetwork convergence

There are the same or similar knowledge nodes in the knowledge sub-networks constructed from different dimensions, such as topics, keywords and entities network nodes may indicate the same technical method, nomenclature or research object. Knowledge network fusion is to integrate the knowledge sub-networks constructed using different rules into a more complete knowledge network, the key is to determine whether two knowledge units in different networks describe the same object, including node alignment and structural fusion of two steps.

(1) Node Alignment

In this chapter, the arbitrary-size network is transformed into a fixed-size network structure, and the algorithm is divided into three steps, and the constructed three knowledge subnetworks are represented as $G = \{G_1, G_2, G_3\}$, and each knowledge subnetwork structure can be represented as $G_P = (V_P, E_P, A_P, X_P)$, V_P represents the set of nodes, E_P represents the set of connected edges, A_P represents the adjacency matrix of the subnetwork G_P, and X_P represents the attribute feature matrix of nodes.

1) Node embedding in d-dimensional vector space

Assuming that any knowledge sub-network G_P contains n nodes, use the node embedding method to map each knowledge unit in the knowledge sub-network to a d dimensional vector space for vectorized representation. The d-dimensional feature vector of the i node in the P subnetwork is denoted as $DB^d_{p,i} = \{vec_1, vec_2, ..., vec_d\}$, and the vectors of all knowledge units are available in the set $R^d = \{R^d_1, R^d_2, ..., R^d_U\}$ indicates that U is the total number of knowledge units.

2) Node clustering to generate template network

Use Kmeans clustering algorithm to cluster the nodes of all sub-networks into C classes, and get C clustering centers by minimizing the objective function $PR^d = \{u^d_1, u^d_2, ..., u^d_C\}$, each clustering center node is represented by a d-dimensional vector, and the C clustering centers form a template network.

$$\arg\min_{\Omega} \sum_{j=1}^{C} \sum_{R^d_i \in C_j} \left\| R^d_i - u^d_j \right\|^2 \tag{26}$$

3) All sub-network structures are aligned with the template network transmission

The distance matrix between each node in each sub-network and the set of nodes of the template network is calculated separately, and the distance matrix between the P knowledge sub-network and the d dimensional node vector of the template network is denoted as D^d_P, and the distance matrix between the sub-network's i th node of the sub-network and the j th node of the template network have Euclidean distances that can be computed by Equation (27).

$$D^d_P(i,j) = \sqrt{\sum_d \left\| DB^d_{p,i} - u^d_j \right\|^2} \tag{27}$$

The alignment matrix C^d_P is expressed as a binary-valued matrix, which can be derived from the distance matrix D^d_P: in the distance matrix D^d_P, if the i row of the j column is the minimum of the i row, then the value of the corresponding position of the alignment matrix is 1, otherwise it is 0.

$$C^d_P(i,j) = \begin{cases} 1 & \text{If } D^d_P(i,j) \text{ is the minimum value in row } i \\ 0 & \text{Others} \end{cases} \tag{28}$$

After obtaining the alignment matrix C^d_P, the adjacency matrix of the first P sub-network to add the self-loop is $\tilde{A}_P$, i.e., $\tilde{A}_P = A + I$, I is the unit matrix, and node attribute feature matrix is X_P, and the calculation of each sub-network after the alignment is performed adjacency matrix $\bar{A}^d_P$ and the identity matrix $\bar{X}^d_P$:

$$\bar{A}^d_P = (C^d_P)^T (\tilde{A}_P)(C^d_P) \tag{29}$$

$$\bar{X}^d_P = (C^d_P)^T X_P \tag{30}$$

(2) Structure fusion

The subnetwork fusion algorithm framework flow is shown in Fig. 1.

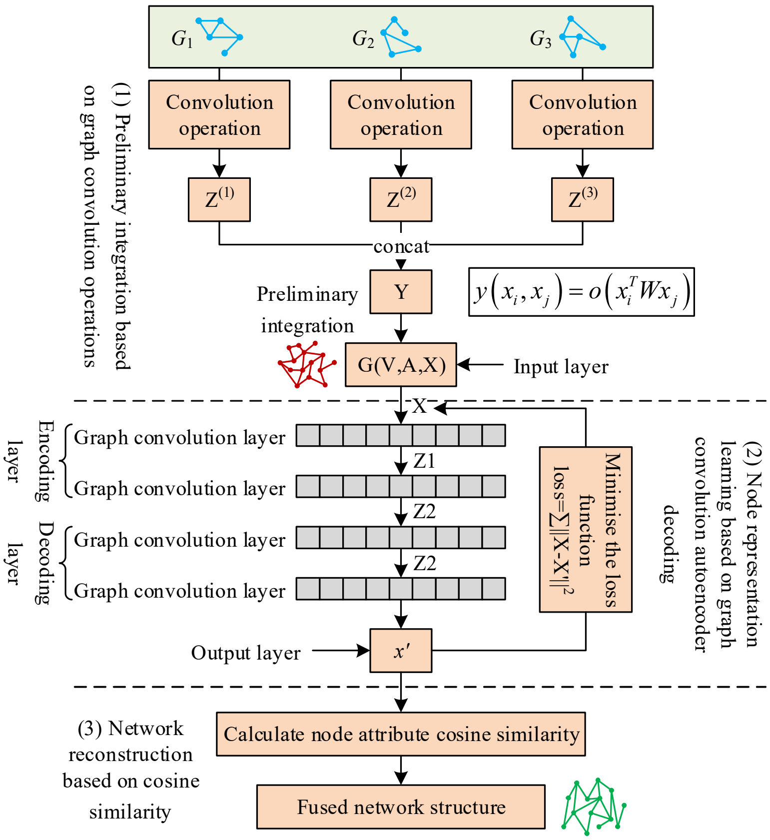

Figure 1: The flowchart of the network fusion algorithm

Transforming the representation learning problem of network node structure information into a representation learning problem of words, this chapter utilizes neural network language models to mine the deep semantic information of network knowledge nodes, and then utilizes attribute similarity to carve the network structure.

II. D. Construction of Interdisciplinary Knowledge Social Networks in Dual Colleges and Universities

II. D. 1) Fundamentals of social network analysis

Social network analysis [23] is a quantitative research tool based on graph theory and statistical methods, in which the disciplines located in the interdisciplinary knowledge social network of dual colleges and universities are regarded as “nodes” in the network, and the trade relations are regarded as “edges”, to reveal the mutual relations and structural characteristics among the nodes in the network. To reveal the relationship between the nodes in the network and their structural characteristics. Commonly used analytical methods in academia include:

1) Network density analysis: used to measure the overall degree of connectivity of the social network, this method reveals the degree of closeness between the nodes of the dual-university interdisciplinary knowledge social network nodes by calculating the ratio between the number of relationships between the nodes and the theoretically possible maximum number of relationships. The value of the density of the dual-university interdisciplinary knowledge social network is $[0,1]$, and the closer the value is to 1, the more closely connected the nodes are. If there are a nodes in the social network, the maximum value of the number of relationships exists is $a(a-1)$, if the number of relationships actually exists is b, the social network density is:

$$D = \frac{2b}{a(a-1)} \tag{31}$$

2) Point-degree centrality analysis: used to assess the influence of nodes in social networks, this method measures the degree of centrality and role of a node in a social network by examining the number of nodes directly connected to other nodes. In this paper, point degree centrality is assigned. If there are a nodes in the social network, the total amount of node x is t and there are directly connected edges to i nodes, the degree of freedom of node x is $\deg(x) = i$, and the weighted point-degree centrality of the interdisciplinary knowledge social network of the dual university is:

$$C_{\deg}(x) = \frac{\deg(x)}{a-1} * t \tag{32}$$

(3) Core-edge analysis: the whole world consists of core, semi-edge and edge regions. The “core-edge” analysis is an ideal structural model that divides the rows and columns of the analyzed data matrix into two categories, with blocks of high density on the main diagonal being core regions and blocks of low density being edge regions. International trade social network related research shows that there is a core-edge structure in the world trading system. This paper adopts correlation analysis method (CORR) to analyze the core-edge of the interdisciplinary knowledge social network matrix of dual universities.

4) Cohesive subgroup analysis: when certain nodes in a social network form a group with similar network location characteristics due to structural equivalence, the group is called a cohesive subgroup.

II. D. 2) Construction of the social network matrix

In this paper, we define matrix A^t as the dual-university interdisciplinary knowledge social network at time point t. In this paper, a^t_{mn} is defined to denote the discipline elements in the matrix A^t of interdisciplinary knowledge social network of dual colleges and universities. According to the corresponding t time point, the interdisciplinary knowledge data of dual colleges and universities are selected.

III. 3. Identification of themes in the field of interdisciplinary knowledge integration in dual universities

III. A. Model training

The optimal values of the three variables in the LDA topic model (hyperparameters α, β, and the number of topics, K) are determined in a Dirichlet distribution.The smaller the value of α the fewer topics will be assigned to each document, whereas the larger the value of α the more topics will be assigned to each document. A smaller value of β will use fewer words to characterize the topics, while a larger value of β will have more words used to characterize the topics, resulting in more similarity between the topics. Because LDA cannot determine the number of topics K on its own, a third hyperparameter, the number of topics the algorithm will detect, must be set when implementing LDA.

When training the LDA topic model, the hyperparameter α for the document topic distribution θ and the hyperparameter β for the topic lexical item probability distribution φ are set to their default values, and α is set to 50/K (K is the number of topics). β is set to 0.02, and the number of topics K is determined by the consistency index.The number of Gibbs sampling iterations is set to 1200.In this study, the top 4 words of the distribution probability in each topic are selected as the topic concept words to express the topic content.The implementation of the LDA model adopts a Python library, Gensim, which is capable of efficiently and automatically extract semantic topics from documents. Figure 2 shows the change of the consistency index value of the themes in the field of interdisciplinary knowledge fusion in dual colleges and universities under different number of themes, with the increase of the number of themes, the consistency index increases and gradually tends to be stable, and finally, when the number of themes is 15, the consistency index is higher and the consistency index region is stable, so the number of themes K of the theme model is set to 15.

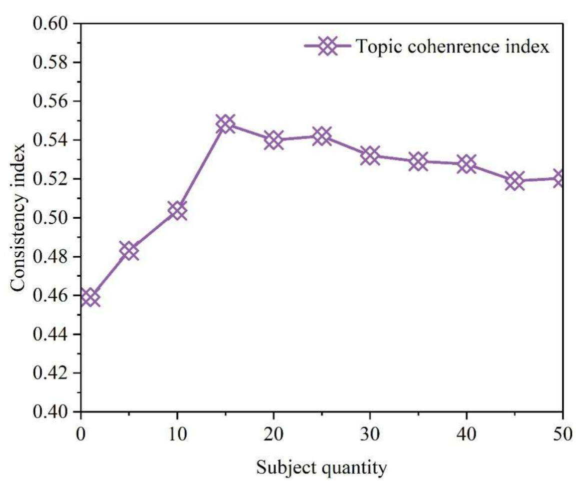

Figure 2: Topic cohenrence index

III. B. Thematic Identity and Thematic Contribution Analysis

The 15 themes of interdisciplinary knowledge integration in dual universities include research on discipline intersection and innovation, and the application of big data and artificial intelligence, etc. The themes of interdisciplinary knowledge integration in dual universities are shown in Table 1. For example, research on the application of big data analysis and artificial intelligence technology in university research and teaching. The theme with the highest theme contribution for interdisciplinary knowledge integration in dual universities is theme 2, “Big Data and Artificial Intelligence Applications”, with a theme contribution of 0.9878, indicating that the theme is highly represented and can effectively characterize the semantic content of the text. The theme with the lowest theme contribution is Theme 1 “Discipline Crossing and Innovative Application”, with a theme contribution of 0.5645, indicating that the representation of this theme is not too good, and cannot fully summarize the semantic content of the text, although discipline crossing and innovative research is the core concept of interdisciplinary research in dual colleges and universities, it is more of a research method and direction, not a specific subject area. The average thematic contribution of each theme of interdisciplinary knowledge integration in dual colleges and universities is 0.8659, indicating that these 15 themes are general enough to characterize the main content of the scientific literature dataset of the discipline.

Table 1: The theme of interdisciplinary knowledge fusion

Subject number	Subject term	Theme mark	Theme contribution
1	Interdisciplinary, innovation, cross-study, fusion	Interdisciplinary and innovation	0.5645
2	Large number according to, artificial intelligence, machine learning, data mining	Large number according to artificial intelligence application	0.9878
3	Biomedical, genetic, disease, health	Biomedical and health science	0.8945
4	New energy, sustainable development, environmental protection, clean energy	New energy and sustainable development	0.9156
5	Materials, nanotechnology, new materials, traditional materials	Materials and engineering	0.9258
6	Economic, social, administrative, large number according to	Economic and social science research	0.9356
7	Intelligent education, online learning, education technology, learning analysis	Intelligent education and learning technology	0.8977
8	Cultural, artistic, digital, cultural heritage	Digitization of culture and art	0.7546
9	Intelligent manufacturing, industrial 4.0, automation, robot	Intelligent manufacturing and industry	0.6589
10	Environmental science, ecology, ecosystem, environmental monitoring	Environmental science and ecology	0.7984
11	Information security, network security, encryption technology, network defense	Information science and network stability	0.9345
12	Social policy, public administration, policy analysis, social governance	Social science and policy research	0.9468
13	Aerospace, space science, satellite technology, aircraft	Aerospace and space science	0.9125
14	Mathematics, computational science, mathematical modeling, algorithm	Mathematics and computational science	0.9369
15	Philosophy, ethics, artificial intelligence ethics, genetic ethics	Interdisciplinary research on philosophy and ethics	0.9244

The number of literatures for each theme is shown in Figure 3, and the popular themes with more than 1,500 literatures in interdisciplinary knowledge fusion in dual colleges and universities are Theme 1, Theme 6, Theme 11, Theme 12, and Theme 14. Which are Interdisciplinarity and Innovation, Research in Economics and Social Sciences, Information Science and Cyber Stability, Social Science and Policy Research, and Mathematics and Computational Science, respectively. The highest number of literature is Interdisciplinarity and Innovation, and the lowest number of literature is Interdisciplinary Studies in Philosophy and Ethics, with 2,568 and 452 literature, respectively.

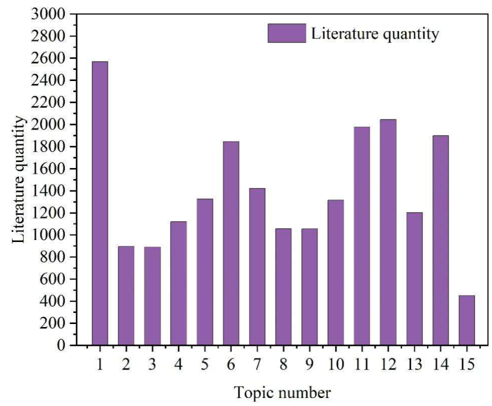

Figure 3: The number of documents on each topic

IV. Characterization of interdisciplinary knowledge integration in bi-university

IV. A. Data acquisition

In this chapter, after the data cleaning, jieba participle finally get the theme words to do the subsequent operation, the final theme words can well represent the interdisciplinary knowledge fusion of dual universities.

IV. B. Social Network Analysis of Interdisciplinary Knowledge Integration in Dual Colleges and Universities

WordCloud library is a word cloud mapping toolkit in Python language environment, which can visualize the high frequency words in text data to form a word cloud map. In a word cloud map, the size of a word usually represents the frequency of its occurrence in the text, which can visually represent the importance of the word. The WordCloud library treats the word cloud as a WordClound object, which can be used to draw an intuitive word cloud map based on the number of times the word occurs in the text and other key parameters. In addition, other parameters of the WordCloud object can be adjusted to customize the appearance of the word cloud, such as setting the color, size, and shape of the word cloud.

Using the processed topic words, the Python code was used to first import the necessary libraries, then create a list of high-frequency topic words and create a WordCloud object, which was used to generate the word cloud. Finally, Matplotlib was used to display the generated word cloud image to visualize the high-frequency topic words of interdisciplinary knowledge fusion in dual-university, and the visual display of high-frequency topic words is shown in Figure 4.

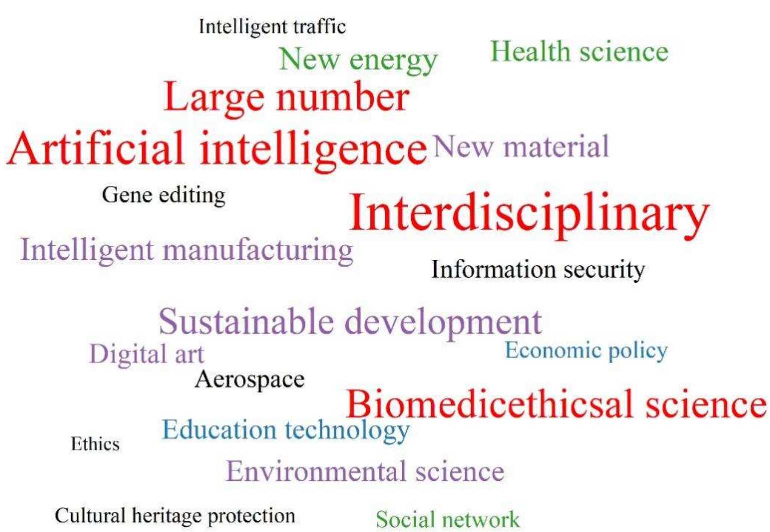

Figure 4: High frequency theme word visualization

By standardizing and cleaning the theme words, 20 theme words with the highest frequency are selected as the high-frequency theme words of interdisciplinary knowledge integration of the dual universities, and with the help of BICOMB software, the obtained high-frequency theme words are generated into the co-occurrence matrix, which characterizes the knowledge integration through the thematic co-occurrence network, so as to get the situation of interdisciplinary knowledge integration of the dual universities, and the high-frequency theme word co-occurrence matrix is shown in Table 2. The degree of association between interdisciplinary and sustainable development is high, and the value of the co-occurrence matrix reaches 4936.

Table 2: Common word matrix (part)

High frequency word	1	2	3	4	5	6	7	8	9	10
1. Interdisciplinary	2868	1937	1355	2264	4936	2172	583	715	1240	1415
2. Artificial intelligence	1937	1674	1126	2698	1309	1053	658	432	499	189
3. Large number	1351	1118	1651	1638	3973	921	534	1227	851	457
4. Biomedical science	2264	2695	1644	1391	1173	436	819	762	466	604
5. Sustainable development	4931	1308	3971	1176	1196	443	315	575	452	175
6. Intelligent manufacturing	2169	1055	921	431	444	1070	193	282	596	649
7. New material	573	674	539	816	314	194	952	597	477	186
8. New energy	711	432	1222	768	567	289	593	940	1128	254
9. Health science	1246	493	847	458	451	582	477	1131	891	505
10. Environmental science	1405	195	456	599	185	650	195	258	508	869

The NetDraw drawing function provided in Ucinet 6.0 is used to present the co-occurrence matrix of high-frequency topic words, and the three indexes of point degree centrality, proximity centrality, and mediation centrality of the nodes are also counted, and the results of the index measurements are shown in Table 3.

Point centrality can measure the importance of a topic word in the social network relationship, and from the values, it can be seen that the topic words with higher point centrality are interdisciplinarity, artificial intelligence, sustainable development, and intelligent manufacturing, which indicates that these topic words are more important in the network relationship, and they are the hotspots of the current research on interdisciplinary knowledge fusion.

The proximity centrality reflects the degree of proximity between a node and other nodes in the network, and from the value, it can be seen that the subject terms with higher proximity centrality are interdisciplinary, artificial intelligence, sustainable development, and intelligent manufacturing, which indicates that these subject terms are in the core position in the network, and the proximity centrality of information security, economic policy, and intelligent transportation is low, and so they are farther away from the center.

The mediation centrality degree as a measure of the node's mediating role in the network, the value of which directly reflects the significance of the subject terms' bridging role in the network. In addition to the popular subject words such as interdisciplinary and artificial intelligence, the mediated centrality degree of words such as big data, biomedical science, and health science also significantly exceeds the average mediated centrality degree value of 0.6881, and these words play a key pivotal role in the network of subject words, which effectively connects and facilitates the communication and integration with other subject words. Combining the three indicators of point centrality, proximity centrality, and mediated centrality, interdisciplinary, artificial intelligence, sustainable development, and intelligent manufacturing, which have relatively high indicators of the three centrality degrees of the theme words, play a more important role in the social network of interdisciplinary knowledge integration in dual colleges and universities.

Table 3: High frequency word center measure

Key words	Point center	Proximity center	Intermediate center
Interdisciplinary	100.000	100.000	1.227
Artificial intelligence	100.000	100.000	1.235
Large number	96.551	96.659	0.991
Biomedical science	96.545	96.665	1.090
Sustainable development	100.000	100.000	1.228
Intelligent manufacturing	100.000	100.000	1.232
New material	93.100	93.545	0.748
New energy	93.099	93.547	1.029
Health science	96.557	96.667	0.958
Environmental science	96.558	96.662	1.106
Digital art	72.413	78.381	0.313

Education technology	68.958	76.314	0.224
aerospace	68.971	76.315	0.264
Information security	51.729	67.436	0.080
Economic policy	51.728	67.447	0.025
Social network	75.867	80.562	0.166
Gene editing	68.965	76.317	0.265
Intelligent traffic	55.172	69.044	0.120
Cultural heritage protection	89.650	90.628	0.734
Ethics	93.102	93.546	0.726

V. Design of a system of interdisciplinary knowledge integration and pedagogical innovation in bi-universities

V. A. Clarify the positioning of course objectives

The correct positioning of curriculum objectives is the first prerequisite for the implementation of interdisciplinary education. Interdisciplinary courses are different from traditional single-discipline courses, with distinctive features such as problem orientation, knowledge synthesis and process innovation, which requires a broader perspective on the course objectives and highlights the leading and comprehensive nature of the objectives. On the one hand, the objectives of interdisciplinary courses should serve the fundamental task of establishing moral character, helping students establish a correct worldview, outlook on life and values, and leading the long-term development of students. They should fully embody the requirements of “three-pronged education”, organically integrate value shaping, knowledge imparting and ability cultivation, and focus on the overall development and lifelong development of students. On the other hand, the objectives of interdisciplinary courses should reflect the characteristics of the era of cross-disciplinary integration, comply with the needs of the cultivation of innovative and complex talents, and highlight the orientation of cultivating students' interdisciplinary awareness and thinking ability. Students should be guided to break the stereotypes of thinking, learn to analyze problems from a multidisciplinary perspective, understand the logic of thinking in different disciplines, master the intrinsic connection of disciplinary knowledge, and enhance the ability to transfer and apply knowledge.

V. B. Optimize course content selection

Based on the frontiers of the disciplines, core concepts, principles and research methods reflecting the latest developments in the disciplines are selected to help students update their knowledge structure in a timely manner and to enhance their forward-looking thinking and sense of innovation. At the same time, it is also necessary to emphasize the study of classical theories, to consolidate students' disciplinary foundation and to cultivate their logical thinking ability. The relationship between fundamentals and frontiers should be well handled, so that students can not only systematically master the basic laws of the discipline, but also broaden their academic horizons and grasp the latest trends of the discipline. Combined with the needs of economic and social development, the interdisciplinary problems closely related to real life and industrial applications are preferred as the important carrier of the curriculum, so as to enhance students' awareness and ability to analyze and solve complex problems. Teachers should actively expand school-enterprise and school-local cooperation channels, and work with industry and enterprise experts to select contemporary, applied and inspiring cases as important curriculum resources. Through the cases, students are guided to comprehensively apply interdisciplinary knowledge, propose solutions to problems, understand the general logic of knowledge generation and application, and realize the integration of learning and use, knowledge and action.

V. C. Rationalization of course structure

The rational layout of the curriculum structure is an important link in realizing the function of comprehensive interdisciplinary education. In the design of the overall framework of the curriculum, it is necessary to take into account the intrinsic logical connection between knowledge learning, practical application and problem exploration, so as to promote students' mobility and creativity in the learning process. A number of modules can be set up, such as basic theory module, cross-disciplinary module, application of practical inquiry module, etc., to take a ladder and spiral way of organizing teaching units, guiding students to deepen their understanding and application of interdisciplinary knowledge in the different modules of learning. In the time arrangement of teaching activities, the proportion of theoretical learning and practical application should be handled well. The important goal of interdisciplinary courses is to cultivate students' comprehensive ability to analyze and solve complex problems, which requires students to experience real-life situations and transform knowledge into lively practice and vivid experience. The course structure should provide students with a platform for social practice and innovative practice, such as through scientific research projects, thematic research, disciplinary competitions, etc., to provide students with opportunities to touch the front line and apply what they have learned, and to guide students to realize the integration of theory and practice and enhance their innovative practice ability in the process of solving practical problems.

VI. Conclusion

In this study, the interdisciplinary knowledge fusion and teaching innovation system of dual colleges and universities was constructed through artificial intelligence technology, focusing on analyzing the interdisciplinary knowledge network and its application in education. The experimental data show that among the 15 interdisciplinary themes analyzed based on the LDA model, the contribution degree of theme 2 “big data and artificial intelligence application” is 0.9878, indicating its dominant position in the cooperation between dual universities. In addition, the disciplinary knowledge network constructed by the graphical convolutional self-encoding model successfully reveals the knowledge correlation between different disciplines, in which “interdisciplinary” and “artificial intelligence” are the most central knowledge nodes.

In the social network analysis, through the comprehensive assessment of point centrality, proximity centrality and mediation centrality, it is found that the role of interdisciplinary, artificial intelligence and sustainable development is crucial in the knowledge network. These terms not only occupy a central position in interdisciplinary knowledge integration, but also play a bridging role in promoting research and teaching innovation in universities.

Therefore, an interdisciplinary knowledge fusion framework based on artificial intelligence not only helps optimize the allocation of disciplinary resources in dual colleges and universities, but also promotes the innovation of education and teaching methods. In the future, with the continuous development of technology, this framework will be applied in a wider range of disciplines, providing strong support for teaching reform and research innovation in universities.

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