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Research on the Innovation and Intelligent System Integration of the Education Mode of Ideology and Politics Courses under Digital Education Environment

Yuanyuan Zhang[1,2,*] and Huining Guo[2]
[1] Shanxi College of Applied Science and Technology, Taiyuan, Shanxi, 030062, China
[2] Weinan Normal University, Weinan, Shaanxi, 714099, China
Corresponding authors: (e-mail: yyzhang9860@163.com).

Abstract The continuous development and maturity of digital teaching methods is a powerful boost for the intelligent development of Civics course teaching. This paper takes the establishment of an intelligent education system for the Civics course in colleges and universities as a research goal, takes the Civics teaching of computer majors as an entry point, and puts forward the online and offline mixed teaching model course Civics system. The system effectively integrates the elements of Civics and politics with the professional courses through the form of online and offline hybrid. Combining this system with the knowledge point Civics element mining model, the teaching design method of digital Civics courses is established. At the same time, the meta-path strategy is introduced, and the pre-set meta-path is guided to wander in order to obtain the characteristic representation of the data nodes and improve the mining quality and analysis effect of the teaching data of the Civics and Politics course. By implementing the teaching strategy of digital Civics course and using the data mining method based on Metapath2vec node embedding method to analyze the students' performance in Civics course, the construction of the intelligent system of Civics course is completed. The designed teaching method is applied in practice to assist students' Civics performance to improve up to 1.079, demonstrating a significant positive assistive effect.

Index Terms civics course instructional design, metapath strategy, intelligent system, Metapath2vec node embedding, cluster analysis

I. Introduction

With the high-quality development of society and economy, digitalization has become an important symbol of transformation in various industries, and so has education. Education is shifting from traditional education to education in the new era, which needs the opportunity of digital transformation [1]. The digitalization of education is an important breakthrough to open up a new track of education development and shape new advantages in education [2]. Promoting education digitization is the proposition of the times to build a strong education and talent country, a key initiative to respond to the national education development strategy, a key element and growth highlight to build a solid foundation for promoting high-quality development of education, and a forward coordinate for high-quality development of education on the new journey [3], [4].

Compared with traditional education, education digitization has higher flexibility and convenience, access to teaching resources anytime and anywhere, and improved learning efficiency [5], [6]. Teaching plans and teaching materials can be tailored to meet the individual needs of students based on their different levels and needs [7]. Through online communication between teachers and students, it can effectively promote thought provocation and knowledge sharing, enhance interactivity, and also improve students' social skills and cooperation ability [8]-[10]. It can also collect and master students' learning outcomes more effectively, and through intelligent learning achievement assessment and analyzing the data of students' learning behaviors, it can assess students' learning effects more objectively, as well as improve the efficiency of teaching evaluation [11], [12]. It can be seen that digitalization is a necessary path for educational reform, and it can really promote the high-quality development of schools in a comprehensive way.

The education of the Civics course in the digital education environment, the use of intelligent technology to change the traditional boring and inefficient teaching mode, is the first to take the lead in the core curriculum, keep pace with the times, constantly innovate and develop, and realize the magnificent turn from indoctrination to heuristic, from monolithic to diversified, which greatly enhances the depth and breadth of Civics teaching and thus the implementation of the action of the policy of high-quality development of education [13], [14].

This paper firstly takes the Civics course of computer majors as an example, respectively discusses the teaching methods of two modes of online teaching and offline teaching, and puts forward the online and offline hybrid teaching model course Civics system. It also designs the mining model of knowledge point Civics elements to form the teaching design method of digital Civics course. Then elaborate the method and process of obtaining heterogeneous node sequences by random wandering under the guidance of meta-path strategy, and establish the data mining method of Civics course based on node embedding. Meanwhile, K-Means clustering is selected as the cluster analysis method for students' performance in Civics course. Finally, 1,000 students of the Civics and Political Science course in University C are taken as the research object to cluster analyze their academic achievement performance. The proposed digital Civics course teaching design method is applied to Civics teaching, and the teaching effect is analyzed to verify the effectiveness of the proposed method.

II. Instructional Design of Digital Civics Courses

II. A. Online and Offline Hybrid Teaching Model Curriculum Civics System

Adopting online and offline mixed teaching mode, the structure of the Civics system of the computer hardware experimental course Civics through the integration of Civics elements in both online and offline is shown in Figure 1.

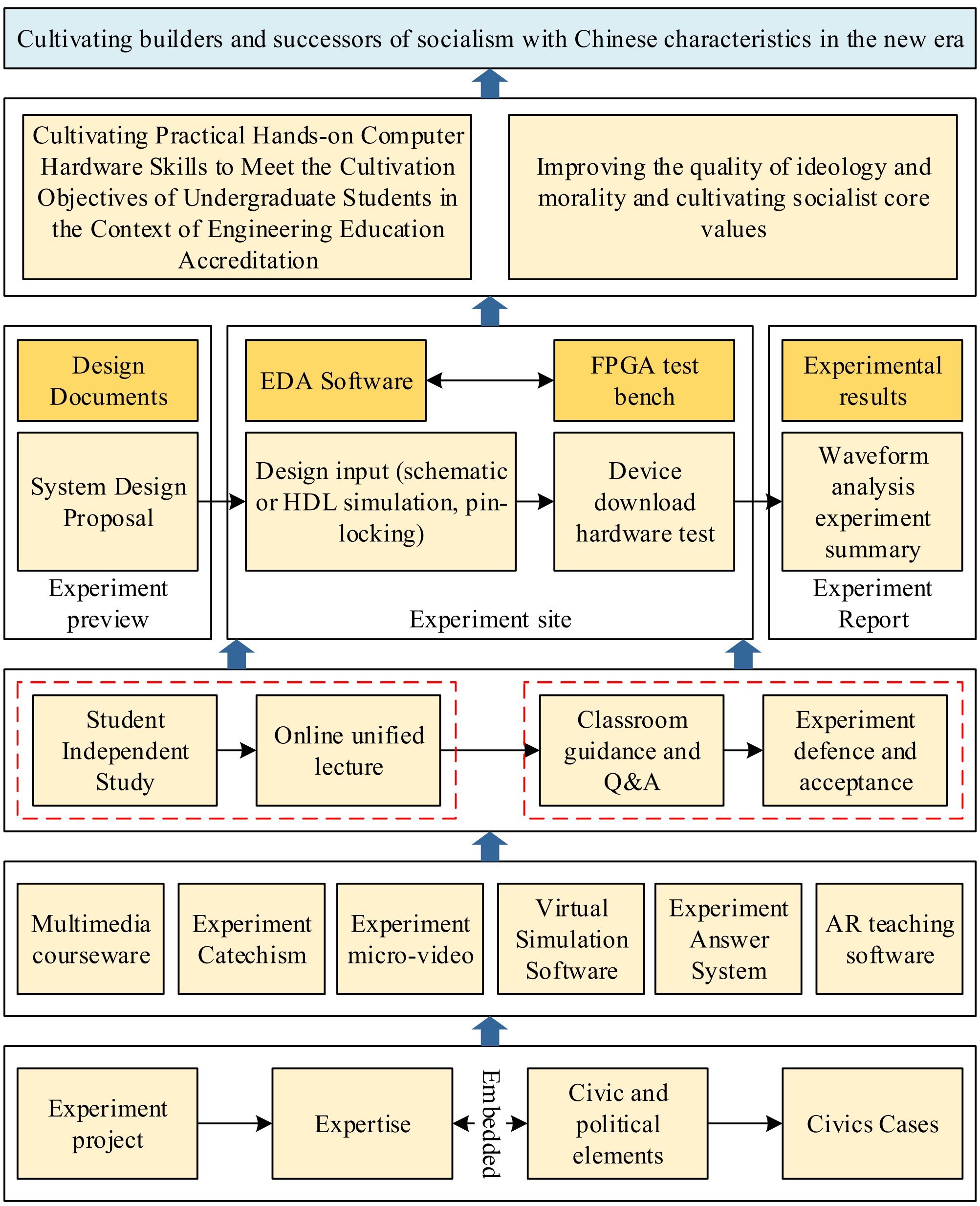


Figure 1: The architecture of ideological and political education in computer courses

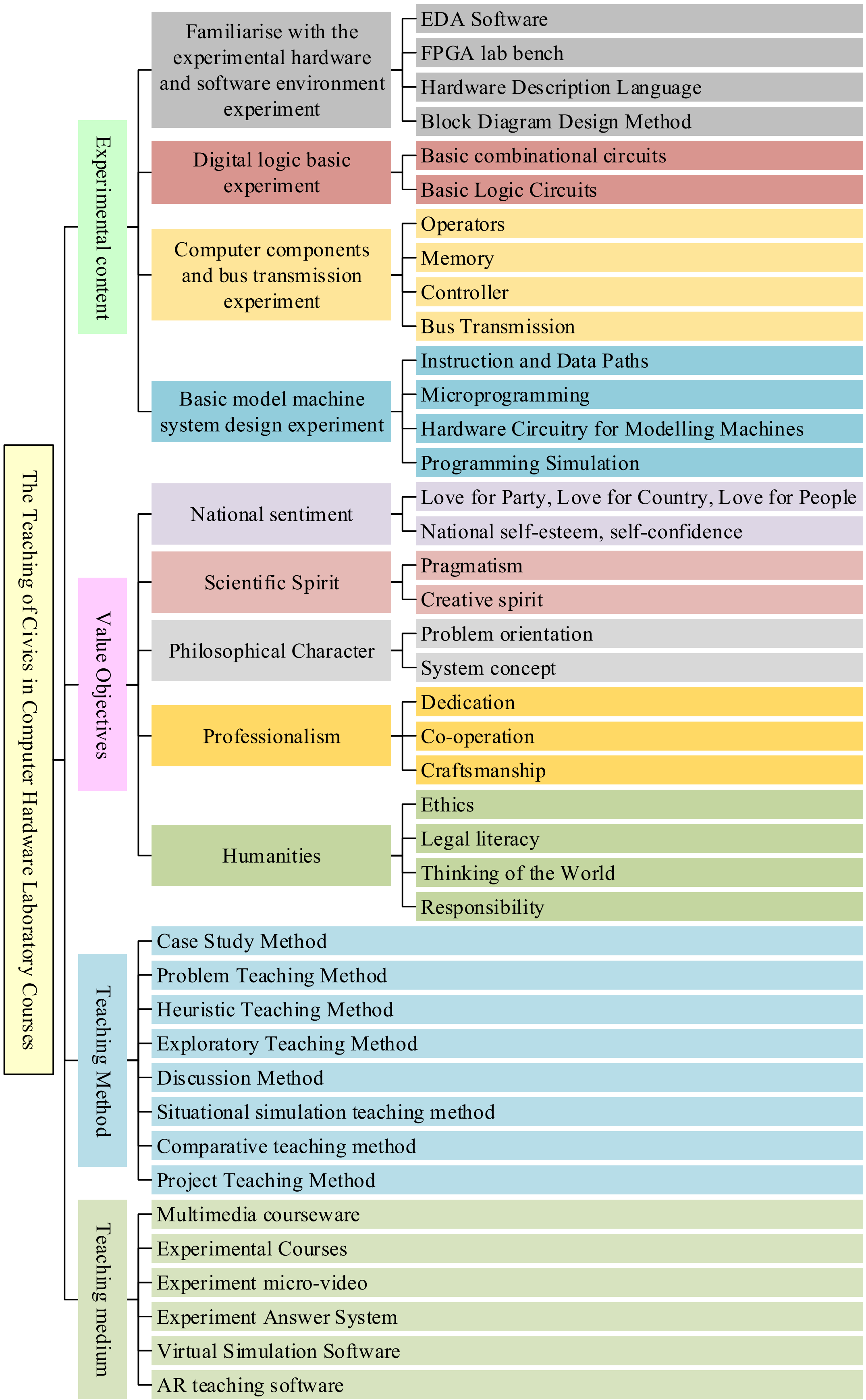


Figure 2: Teaching Ideas of Ideological and Political Education in Computer Courses

(1) Online teaching: complete students' independent learning and online unified explanation, which can be used in the teaching sessions of experimental preview and experimental report. Using experimental catechism, experimental micro-video, virtual simulation software, auxiliary teaching software and third-party educational platforms, integrating the case of Civics and Politics into various digital resources, and realizing the leadership of Civics and Politics value while completing the learning task online.

(2) Offline teaching: Completing students' on-site experimental operation and the use of experimental bench. Teachers will guide and answer questions on site, accept students' experimental results and record the whole process of experimentation and learning status. Classroom teaching is an important way to implement the Civics of the curriculum, and the goal of Civics education is realized through teachers' explanation, Q&A and teaching by example.

The mixed mode of online and offline makes full use of the advantages of modern educational technology and digital tools, realizes the whole process of educating people in the three stages of teaching: pre-laboratory preparation, on-site operation of the experiment and post-laboratory data analysis, and promotes the realization of the goal of educating people in the ideology and politics.

II. B.Mining Model of Knowledge Point Civics Elements

In order to be able to better mine the Civic and Political elements contained in the knowledge points of the course, the use of the mind map to show the Civic and Political teaching ideas of the computer hardware experimental course is shown in Figure 2.

Taking the knowledge points covered by the experimental content as the basic unit of Civic-Political integration, a five-element model is proposed for the mining and integration of Civic-Political elements through the analysis of Fig. 2, which is analyzed and organized to form a case of Civic-Political teaching in the course. The model is described as follows:

(1) Knowledge points: mainly refers to the knowledge points that contain Civic and Political elements in the experimental program. Digging deeper into the value of each knowledge point, it can effectively support the achievement of the goals of the course's civics.

(2) Civic-political cases: mainly refers to the case stories related to the knowledge points that can realize value leadership, including historical events, classic cases, traditional culture and current affairs reports.

(3) Value objectives: mainly the refinement of the five major categories of Civic and Political objectives, specifically including the spirit of patriotism, the spirit of truth-seeking, the spirit of innovation, the concept of system, the spirit of dedication, the spirit of craftsmanship and legal literacy.

(4) Teaching methods: mainly refers to the teaching methods in which the elements of Civics and Politics are integrated into the knowledge points, including the case teaching method, the problem teaching method, the heuristic teaching method and the project teaching method.

(5) Teaching media: it mainly includes multimedia courseware, experimental catechism, experimental micro-video, question-answering system, and auxiliary teaching software. It also includes classroom teaching, the teacher's board and teaching by example.

III. Instructional Data Mining and Cluster Analysis Based on Node Embedding

III. A. Obtaining Heterogeneous Node Sequences Based on Randomized Wandering of Metapaths

A graph is a type of structured data, which in essence is a collection of vertices or nodes connected together by edges. Typically, a graph is represented by $G=(V,E)$, where V and E denote the set of all nodes and the set of all edges, respectively. Then, by defining the node type mapping function $\varphi: V \to T_v$ such that $\forall v \in V, \varphi(v) \in T_v$, $\varphi(v) \in T_v$, and the edge type mapping function $\psi: E \to T_e$, $\forall e\, in E, \psi(e) \in T_e$ to characterize the types of nodes and types of edges in the graph, respectively. Where T_v is the set of node types and T_e is the set of edge types. Usually, graphs can be categorized into homomorphic and heteromorphic graphs by the types of nodes and edges. Homomorphic graphs are graphs that contain only one type of node and relationship, i.e., $|T_v|+|T_e|>2$, and usually the network structure of this type of graphs is simpler. Heterogeneous graphs, on the other hand, refer to graphs with more than one type of node or edge, i.e., $|T_v|+|T_e|>2$, which have richer semantic information, thus presenting a more complex and diversified relational network structure.

The acquisition of heterogeneous node sequences in Metapath2vec is essentially borrowed from the ideas of Deep Walk and Node2vec that use random wandering to acquire node sequences on homogeneous graphs. The difference is that a pre-set meta-path strategy is introduced to guide the direction of the random walk on the heterogeneous graph to generate paths that capture the semantic and structural correlations between different types of nodes, thus accomplishing the acquisition of heterogeneous node sequences. As shown in Equation (1), a metapath M can be formalized as:

$$V_1 \xrightarrow{M_1} V_2 \xrightarrow{M_2} \cdots V_t \xrightarrow{M_t} V_{t+1} \cdots \xrightarrow{M_{s-1}} V_s \tag{1}$$

where $M = M_1 \circ M_2 \circ \cdots \circ M_{s-1}$ denotes a composite relation between different types of nodes V_1 and V_s, $\circ$ denotes a combinatorial operator on the relation, and $V_1, V_2, \cdots, V_s$ then constitute a higher-order relation. Utilizing meta-paths M to guide the direction of random wandering on graph structures, transforming random wandering into biased wandering under the conditions of a predetermined system of meta-paths M captures more complex and rich semantic information than link (edge) based methods (i.e., first-order relations). The transition probability p of the random wandering at the n th step satisfies Equation (2):

$$p\left(v^{n+1} \mid v_t^n, M\right) = \begin{cases} \dfrac{1}{\left|N_{t+1}(v_t^n)\right|}, & \left(v^{n+1}, v_t^n\right) \in E, \varphi\left(v^{n+1}\right) = t+1 \\ 0, & \left(v^{n+1}, v_t^n\right) \in E, \varphi\left(v^{n+1}\right) \neq t+1 \\ 0, & \left(v^{n+1}, v_t^n\right) \notin E, \varphi\left(v^{n+1}\right) \neq t+1 \end{cases} \tag{2}$$

where $\varphi(v)$ is the node mapping function and v_t^n is a node of type V_t, i.e., $v_t^n \in V_t$. $N_t(v_t^n)$ denotes the set of nodes of type V_{t+1} that are neighbors of node v_t^n, in other words, $v^{n+1} \in V_{t+1}$ and the probability of the wandering is one fraction of the total number of all nodes that satisfy the condition. The metapath randomized wandering is schematically shown in Figure 3.

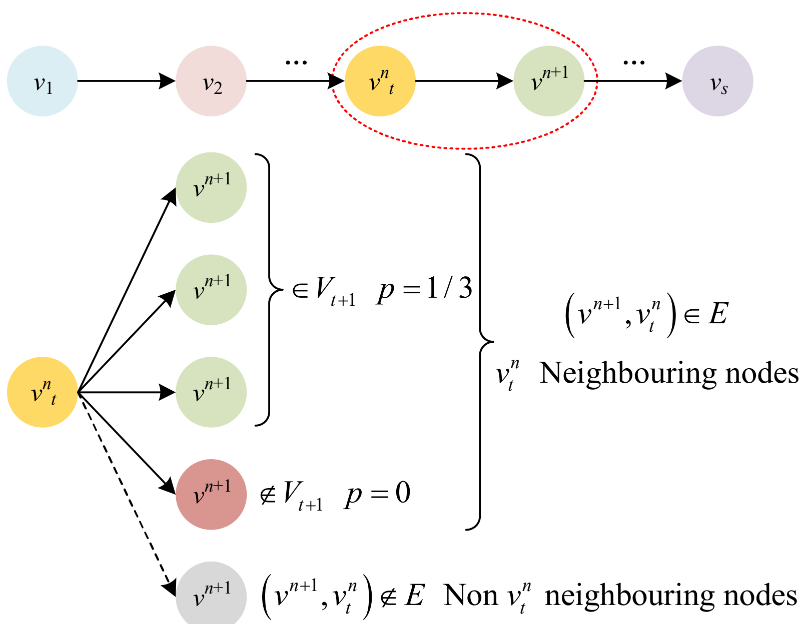


Figure 3: Random walk of meta-paths

Specifically, suppose the n th step of the randomized wandering captures a yellow v_t^n node, a node belonging to type V_t. The gray node in Figure 3 does not satisfy the $(v^{n+1}, v_t^n) \in E$ condition, i.e., it is not a neighboring node of v_t^n. In addition, there are four other neighboring nodes $v^{n+1}, v_t^n) \in E$ condition that satisfy the $(v^{n+1}, v_t^n) \in E$ condition, of which the three green ones are the ones that satisfy the $v^{n+1} \in V_{t+1}$ condition but the red ones do not satisfy the $v^{n+1} \in V_{t+1}$ condition. Then, the probability that the v^{n+1} node captured at the $n+1$ th step is $1/3$ under the current randomized wandering strategy M, and it must be a green node belonging to the type V_{t+1}. That is, the next node that wanders randomly is restricted to the range of nodes on the metapath strategy M, and the transfer occurs only if the next step is a node of type on the specified metapath location.

Therefore, when expressing the characteristics of heterogeneous network nodes, the use of meta-path based random wandering can be used to capture the semantic and structural information between heterogeneous nodes to ensure the correctness of the semantic changes, and also effectively avoid the statistical bias caused by the high percentage of the number of nodes of a certain type, so as to efficiently incorporate the heterogeneous information network into the subsequent model in order to complete the embedding of the vertices.

III. B. Selection of the number of clusters

The difficulty of the K-means algorithm is that the number of clusters needs to be given in advance, and the selection of the number of clusters in practical applications can have a large impact on the results. In order to solve this problem, some researchers have proposed the elbow rule and the contour coefficient method. These two methods can automatically determine the appropriate number of clusters according to the distribution of data points and the quality of clustering.

(1) Elbow rule

SSE (sum of squared errors) is one of the core indicators of the elbow rule. As the number of clustering clusters gradually increases, each sample can be more finely categorized and the value of SSE becomes smaller. At the same time, when the number of clustering clusters is not optimal, sample cohesion rises with the number of clusters, and the size of the sum of errors squares shrinks extremely quickly. When the number of clustering clusters exceeds the number of clustering optimal clusters, the change in SSE becomes smaller and the overall curve slows down. At this point, the graph of SSE versus the number of clustered clusters will look like an elbow, and its elbow point is the optimal number of clusters, hence the name of the elbow rule. In this case, the formula (3) for the error squared and SSE is as follows.

$$SSE = \sum_{i=1}^{K} \sum_{p \in C_i} \left| p - m_i \right|^2 \tag{3}$$

where K is the number of clusters, the i th cluster is denoted by C_i, the sample points in the cluster C_i are denoted by p, and the center of mass of the cluster C_i is denoted by m_i, and the selection of the center of mass is calculated by the method of maximum and minimum distance.

(2) Contour coefficient method analysis

The purpose of the contour coefficient (SC) law is to identify when the value of k maximizes the contour coefficient. The specific method is for any sample point X_i, whose cluster is C_i. The intra-cluster similarity of the sample point X_i is denoted as a_i, which is the average distance between the sample point X_i and other sample points X_j in the same cluster, and is calculated as in equation (4).

$$a_i = \frac{1}{|C_i| - 1} \sum_{C_j = C_i, X_j \neq X_i} dist(X_i, X_j) \tag{4}$$

The average distance between the sample point X_i and all sample points in the cluster is calculated by selecting a certain cluster C that does not contain the sample point X_i and calculating this value for all clusters, the smallest average distance is also referred to as the inter-cluster dissimilarity of the sample point X_i is notated as b_i, which is calculated as in equation (5).

$$b_i = \min_{C \neq C_i} \left\{ \frac{1}{num(C_q)} \sum_{C_q = C} dist(X_i, X_q) \right\} \tag{5}$$

The profile factor of the sample is denoted as s_i and is calculated as in equation (6).

$$s_i = \frac{b_i - a_i}{\max\{a_i, b_i\}} \tag{6}$$

The value of the contour coefficient s_i is generally set to $[-1,1]$, when s_i is closer to 1, it represents that the sample point is close to the rest of the sample points of the same clusters, and is far away from other clusters, and is suitable to be placed in that category. When s_i is closer to -1, it means that the sample point is far away from the rest of the sample points of the same clusters and close to the other clustered sample points, and is not suitable to be placed in that category.

If the total number of samples is n and the number of clusters is k, the average profile coefficient is denoted as S_k, which is calculated as in equation (7).

$$S_k = \frac{1}{n}\sum_{i=1}^{n} s_i \tag{7}$$

The value range of the average profile coefficient S_k is generally set to $[-1,1]$, the average profile coefficient is directly proportional to the clustering effect, the more prominent the clustering effect, the larger the value of the average profile coefficient.

In practice, the average profile coefficient and clustering effect is usually follow the above rules, but there are special circumstances. For example, when the number of clusters is taken as 2, although the average contour coefficient value is large, the SSE value will also be large. In this case, attention needs to be paid to comprehensive consideration, and the number of clusters in the average contour coefficient and SSE value are selected in the acceptable range of values.

IV. Application and Analysis of Civic Education Models

As can be seen from the above, this paper designs a digital Civics course teaching method, as well as a teaching data mining method based on node embedding, and an achievement analysis method based on the idea of cluster number selection. In this chapter, a total of 1,000 students of different majors and different grades within the Civics course of university C are randomly selected as research objects, descriptive statistics of students' professional and academic performance are conducted, and cluster analysis of students' academic performance is launched. At the same time, the feasibility of the proposed idea of selecting the number of clusters is tested in the form of comparing the effect of clustering. Finally, the teaching method proposed in this paper is applied to the teaching of Civics to 1000 students, and the teaching effect is evaluated from 6 dimensions.

IV. A. Basic student information

In this section, the statistics and descriptive analysis of students' basic information are unfolded. The distribution of students' majors is shown in Fig. 4, in which (M1) communication engineering students accounted for 25.9%, (M2) electronic information students accounted for 13.6%, (M3) Internet of Things students accounted for 18.4%, and (M4) digital media students accounted for 42.1%.

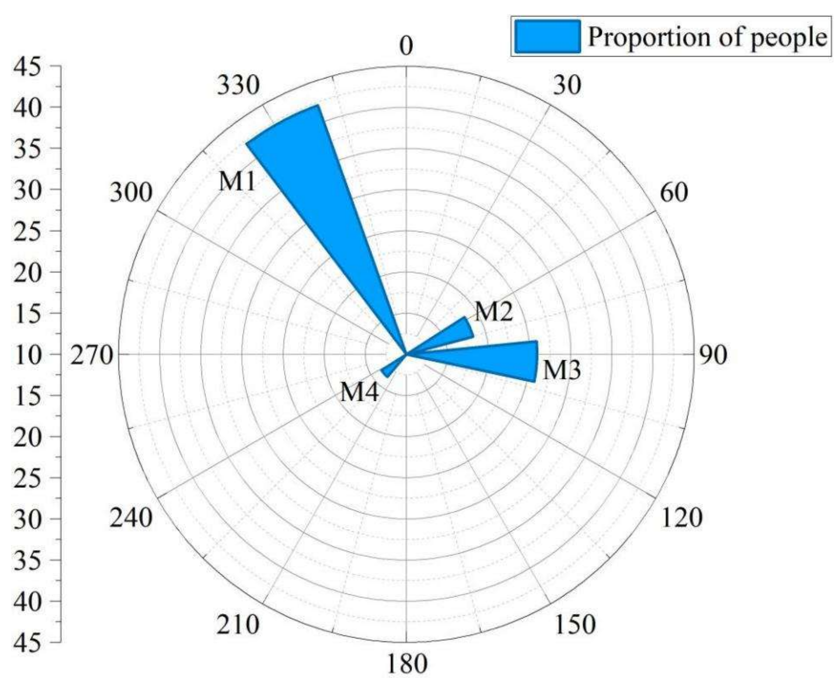


Figure 4: The proportion of students' major distribution

The performance status was categorized into the following five levels:(S1) poor, (S2) poor, (S3) fair, (S4) good, and (S5) excellent, and the distribution of the 1000 students' performance on different courses is shown in Figure 5.

The main course categories assessed were (L1) Civics, (L2) Foreign Language, (L3) Physical Education, (L4) College Language, (L5) Entrepreneurship, (L6) Health Guidance, (L7) Professional Foundations, and (L8) Professional Core, and it can be seen that over 600 students' performance was concentrated in the (L1) Civics and Physical Education courses at the (S2) Poor grade level, which is less than satisfactory. In other courses, the distribution of student performance was more consistent, with approximately 300-400 students clustered in the (S3) Fair, (S4) Good grades.

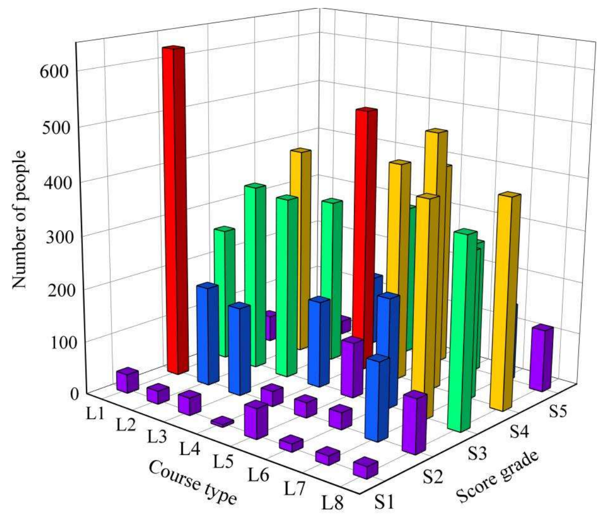


Figure 5: The distribution of students' grades in different courses

IV. B. Cluster analysis of students' academic performance

In this study, the academic data of 1000 students were grouped using clustering algorithm and the six student clusters generated were visualized and analyzed as shown in Figure 6.In the visualization results, these six student clusters showed different trends in academic performance. Students in student cluster cluster 2 excelled in academics and also excelled in practicals. Students in student cluster cluster 5 need to strengthen their theoretical knowledge in academics and participate in research competitions to improve their practical skills. Students in Student Cluster Cluster 1, Student Cluster Cluster 3, Student Cluster Cluster 4 and Student Cluster Cluster 5 need to strengthen their studies in the basic courses of their majors in academic performance.

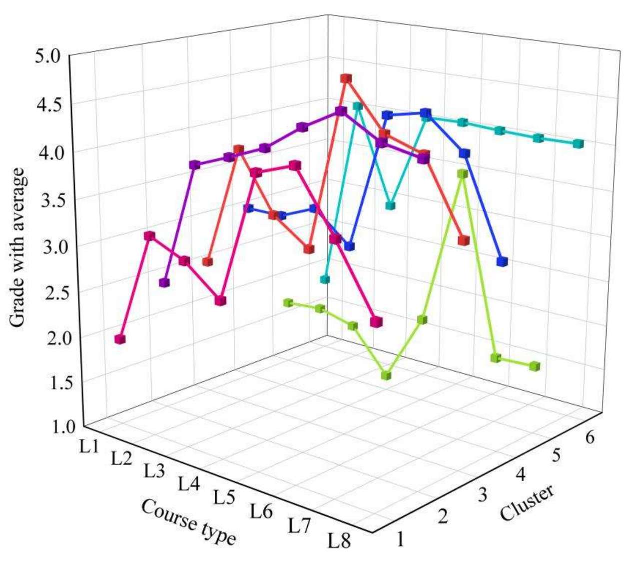
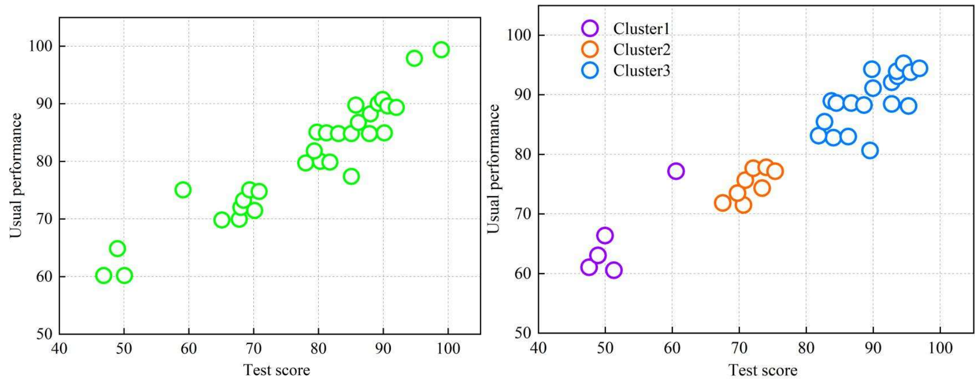


Figure 6: Visualization of group division based on students' performance

IV. C. Tests of cluster analysis methods

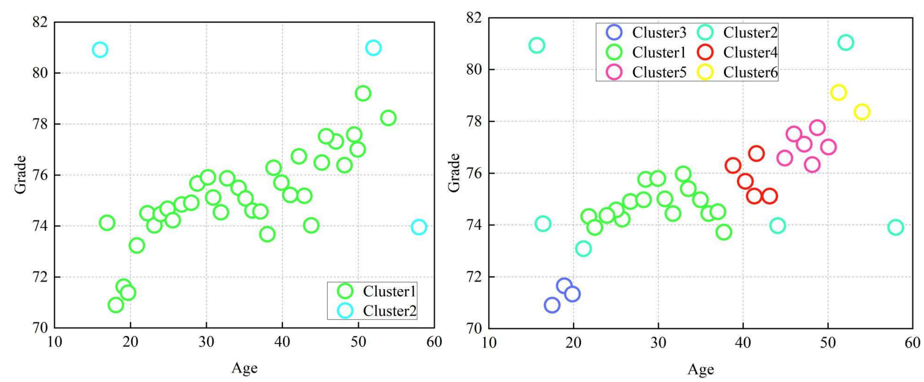
The before-and-after comparison of the clustering of students' usual grades and exam grades based on the K-Means clustering algorithm is shown in Fig. 7, which reveals that under the guidance of the idea of selecting the number of clusters, it can clearly classify the students into three different major cluster classes according to the density distribution. Such a classification method will not easily change the students' attributable grouping because of the change of the difficulty of the examination content. After analyzing, this paper's cluster number selection idea is a more reasonable method for grouping students' academic performance.



(a) Before clustering (b) After clustering

Figure 7: Comparison of student performance clustering results

The clustering of the relationship between students' independent learning age and achievement is shown in Figure 8, where Figure 8(a) is when the number of independent learning grids is 10 and Figure 8(b) is when the number of independent learning grids is 20. When students are in the state of independent learning, their grades show an increasing trend with age, and the grades of students between the ages of 19-30 years old are growing smoothly with age. Therefore, in the design of teaching strategies for students in colleges and universities, corresponding adjustments and optimization should be made in combination with the age of students.



(a) The number of autonomous learning grids is 10 (b) The number of autonomous learning grids is 20

Figure 8: Cluster analysis of Age and performance in autonomous learning

IV. D. Analysis of Teaching Effectiveness

A pre-test on the performance of the Civics course was conducted for 1,000 students, and the themes chosen for the test were: (A) scientific innovation, (B) pursuit of values, (C) responsibility, (D) traditional culture, (E) patriotism, and (F) socialist core values. Each theme corresponds to five questions, which are scored out of five. The experimental pre-test is mainly in the form of questionnaire to understand the basic literacy of students. The reliability Cronbach.α coefficient of the data of the experimental pre-test is 0.901, and the validity KMO value is 0.777, and the reliability Cronbach.α coefficient of the data of the experimental post-test is 0.892, and the validity KMO value is 0.689. The students' experimental pre-test and post-test are summarized in Table 1.

Table 1: Pre-experiment test and post-experiment test performance

Theme	Question number	Average value		Standard deviation	
		Pre-test	Pro-test	Pre-test	Pro-test
A	1	3.133	4.439	1.298	1.015
	2	3.175	3.875	1.03	0.335
	3	3.383	3.496	1.277	1.088
	4	2.794	3.022	1.647	0.436
	5	2.51	3.001	2.323	0.64
B	6	2.676	3.932	2.34	1.024
	7	3.888	4.535	1.09	1.18
	8	3.226	4.058	2.02	1.249
	9	3.079	4.075	2.173	0.402
	10	3.292	4.957	1.049	1.112
C	11	3.709	3.439	1.55	0.981
	12	3.601	4.193	2.202	0.691
	13	3.331	3.926	2.458	0.458
	14	3.117	4.199	1.257	1.054
	15	3.401	3.525	2.116	1.027
D	16	3.728	4.876	1.433	1.193
	17	3.721	4.477	1.15	1.081
	18	2.772	3.052	2.1	0.57
	19	3.806	4.548	2.04	0.367
	20	3.309	4.86	1.116	0.651
E	21	3.578	4.962	2.047	0.875
	22	3.118	3.574	1.887	0.984
	23	3.158	4.24	2.464	0.929
	24	2.512	4.298	1.237	1.292
	25	2.723	3.875	1.021	1.196
F	26	3.803	3.805	2.318	0.701
	27	3.07	4.089	1.11	0.542
	28	2.801	4.921	2.412	0.41
	29	2.711	3.507	1.293	0.521
	30	3.445	3.946	1.245	0.333

In the pre-test, the mean value of each topic is in the range of 2-4, which indicates that the students' ideological and political literacy is OK, and their ideological awareness is better overall, and there is still some room for improvement. The post-test data show that the mean value of the questions is between 3-5, and there are a lot of questions with the mean value of the scores close to 5. Combined with the value of the standard deviation, the standard deviation of the students' scores in the post-test is concentrated in the range of 0-1.5, and the standard deviation of the pre-experimental test data is concentrated in the range of 1-3. The fact that the standard deviation of the post-test data shrinks partially compared to the pre-test data indicates that the overall differences of the class students become smaller and the students' ideological literacy develops in a better direction.

The questions are divided into 6 groups according to the 6 integration points, and the mean values are taken respectively to compare the differences before and after the experiment, and the weights of the indicators are assigned to get the final weight scores of the pre-test questionnaire and the post-test questionnaire. The final scoring results of students' learning in the six Civics objectives are shown in Table 2.It can be seen that under the guidance of this paper's teaching method, students' Civics scores in the six dimensions have been improved, of which the improvement in the (B) value pursuit dimension is up to 1.079.It shows that this paper's method has a positive positive influence on the performance of Civics courses.

Table 2: The final scores of the six ideological and political goals

Serial number		A	B	C	D	E	F	Total
Weight		0.164	0.137	0.175	0.154	0.181	0.190	1.000
Quantitative scoring	Pre-test	2.999	3.232	3.432	3.467	3.018	3.166	3.219
	Pro-test	3.567	4.311	3.856	4.363	4.190	4.054	4.057
	Mean	3.283	3.772	3.644	3.915	3.604	3.610	3.638
	Difference value	0.568	1.079	0.425	0.895	1.172	0.888	0.838
Weighted score	Pre-test	0.492	0.530	0.563	0.569	0.495	0.519	0.528
	Pro-test	0.585	0.707	0.632	0.716	0.687	0.665	0.665
	Mean	0.093	0.177	0.070	0.147	0.192	0.146	0.137
	Difference value	0.538	0.619	0.598	0.642	0.591	0.592	0.597

V. Conclusion

This paper innovates the existing teaching mode of Civics course by designing the teaching method of digital Civics course, as well as the teaching data mining based on Metapath2vec node embedding, and the analysis method based on the idea of clustering number selection, to establish the intelligent system of Civics course education. The designed clustering number selection idea can reasonably guide the clustering grouping of students' academic performance, and provide effective theoretical guidance for analyzing students' performance in Civics and Political Science courses. In practical application, the designed teaching method of digitalized Civic and Political Science courses not only reduces the differences in students' Civic and Political Science achievements, but also has a significant positive impact on students' achievements in the teaching of the theme of “pursuit of values”.

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