Construction and Coordination Mechanism of College Students' Employment and Labor Relations in the Internet+ Environment

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Abstract—Revealing the law of two-way selection between college students and employers is of great value to the proper construction of college students' employment and labor relations and the coordination of employment issues. So far, there has been little research on the feasibility testing of building a harmonious employment and labor relations network for college students and on the coordination countermeasures for employment issues. To this end, this paper studies the construction and coordination mechanism of college students' employment and labor relations in the Internet+ environment. Firstly, the spatial autocorrelation of the distribution of college students' employment and labor relations was checked based on Moran's I index, and a random effect spatial Durbin model was constructed based on the employment data of college students in the study region within the study period to study and analyze the spatial effects of colleges and majors on the construction of college students' employment and labor relations in the region. Then, based on the simple graph neural network theory, a representation learning method was put forward for college students' employment and labor relations network, and the employment and labor relations of college students was built through full utilization of the implicit structural similarity existing in the known employment and labor relations network of college students. The experimental results verified the effectiveness of the proposed construction method.

Keywords—Internet+ environment, college students' employment and labor relations, spatial Durbin model

1 Introduction

The rapid development of information technology in today's era has promoted the interconnections between people, between people and things, and even between things, and enabled long-distance communication and exchanges [1–10]. Under the Internet+ environment, college students' employment and labor relations can be defined as the bond between college students and employers and the key to the mutual understanding and two-way selection of the two sides [11–20]. Based on all college students and all employers, an employment and labor relations network can be constructed, where the college students and employers in the network can be analyzed to reveal the law of two-way selection between the two sides and identify the possible connection modes existing in the network structure. This is undoubtedly of great value to the proper construction of college students' employment and labor relations and the coordination of employment issues.

In light of the current uneven and inaccurate allocation of employment resources among college students, social network mining has been applied to the design of the employment resource allocation algorithm for college students. Qi [21] proposed a college student employment resource allocation algorithm based on social network mining. In terms of resource allocation, virtual machines can be simulated and placed through the established energy consumption model and performance loss model, so the status value can be obtained through the Monte Carlo method. Based on social network mining, and according to the constructed resource allocation model and the obtained status value, the employment resource allocation algorithm for college students was acquired. In order to make the employment of college students and enterprise recruitment more efficient, Zhang et al. [22] designed an "intelligent two-way recommendation system for employment of college students" through data mining and other means to achieve intelligent integration, reorganization and sharing of high-quality employment resources, and improve the employment services for college students. Yumoto [23] proposed a conditional relaxation method based on users' abilities and developed an employment location recommendation system for students using the decision rules in rough sets. When there are not enough searches, the system will simplify the criteria and search for additional employment locations, which are estimated based on normalized Euclidean distances and selected based on aptitude. Through practical experiments, it was found that the proposed system could recommend employment locations for students more effectively than the usual conditional search. Du [24] employed various methods such as education and psychological measurement, multivariate statistics and network technology, and established a multi-dimensional student information database and comprehensive talent portraits by building a data analysis model, which laid a quantitative analysis foundation for the accurate matching of talent supply and demand.

Through review of domestic and international research conclusions, it is found that domestic and foreign scholars study college students' employment and labor relations in an attempt to adapt them to the employment and entrepreneurship service system for college students implemented by the national government. The aim is to solve the problems that college students encounter in employment and entrepreneurship. Such studies mainly consist of theoretical research and quantitative analysis. Regarding the feasibility testing of building a harmonious employment and labor relations network for college students and the coordination countermeasures for employment issues, the existing research has been inadequate and needs to be further improved. Therefore, this paper studies the construction and coordination mechanism of college students' employment and labor relations in the Internet+ environment. First, Section 2 checks the spatial autocorrelation of the distribution of college students' employment and labor relations based on Moran's I index, and constructs a random effect spatial Durbin model based on the employment data of college students in the study region within the study period to study and analyze the spatial effects of colleges and majors on the construction of college students' employment and labor relations in the region. Then, Section 3 puts forward a representation learning method for college students' employment and labor relations network based on the simple graph neural network theory, and builds the employment and labor relations of college students by fully utilizing the implicit structural similarity existing in the known employment and labor relations network of college students. The experimental results prove the effectiveness of the proposed construction method.

2 Spatial autocorrelation analysis of employment distribution

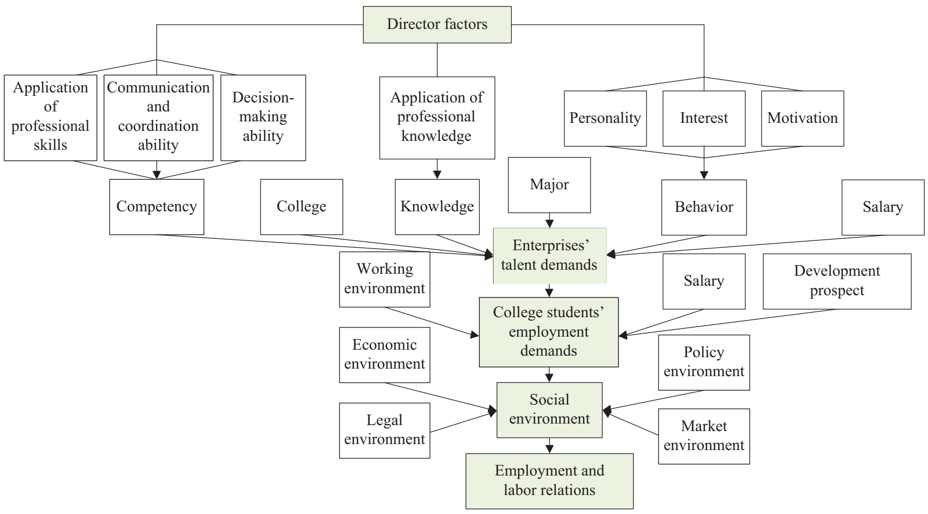

Fig. 1. Theoretical model of the influencing factors to college students' employment and labor relations

It is found in this paper that the main factors forming college students' employment and labor relations are enterprises' talent demands, college students' employment demands and social environment. Figure 1 shows the theoretical model of the influencing factors to college students' employment and labor relations. Enterprises' talent demands involve competence, college, knowledge, major, behavior and salary, while college students' employment demands involve working environment, salary and development prospect. Social environment involve economic environment, legal environment, policy environment and market environment.

The spatial autocorrelation of college students' employment and labor relations distribution was checked based on the Moran's I index. Suppose that the number of observation areas is represented by $\overline{a} = 1/m\Sigma_{i=1}^{m} a_i, m$, that the spatial weight matrix by q_{ij}, and that the observed values of observation areas i and j by a_i and a_j, respectively. Then the global Moran's I index, which tests the spatial correlation of the distribution of college students' employment and labor relations in the entire study area, and the local Moran's I index, which tests the spatial correlation of the distribution of college students' employment and labor relations in a local area, are calculated as follows:

$$Global\ Moran's\, I = \frac{m}{\sum_{i=1}^{m}(a_i - \overline{a})} \cdot \frac{\sum_{i=1}^{m}\sum_{j=1}^{m} q_{ij}(a_i - \overline{a})(a_j - \overline{a})}{\sum_{i=1}^{m}\sum_{j=1}^{m} q_{ij}} \tag{1}$$

$$Local\ Moran's\, I = \frac{m(a_i - \overline{a})}{\sum_{i=1}^{m}(a_i - \overline{a})} \cdot \sum_{i=1}^{m}\sum_{j=1}^{m} q_{ij}(a_j - \overline{a}) \tag{2}$$

The colleges and majors of college students have effects on the structure of their employment relations and the quality of employment. For example, graduates of engineering majors are more likely to find suitable jobs than graduates majoring in music or fine arts from vocational colleges. In order to scientifically measure the spatial effects of colleges and majors on the structure of college students' employment and labor relations in the study area, the following distance matrix Q_{ij} was constructed in this paper. Suppose that the geographical distance between a college student node *i* and an employer node *j* is denoted as δ_{ij}, then there is the following expression:

$$Q_{ij} = \begin{cases} 1/\delta_{ij}, i\ and\ j\ are\ adjacent\ and\ i \neq j \\ 0, i\ and\ j\ are\ not\ adjacent \end{cases} \tag{3}$$

The mismatch between students' majors and jobs is the biggest factor hindering the construction of college students' employment and labor relations. In order to solve the complex spatial interactions and spatial dependence between college students' majors and the jobs offered by enterprises in the employment and labor relations network of college students, the corresponding spatial econometric model was constructed in this paper. Suppose that the explained variable is represented by b_{io}, that the explanatory variable by a_{io}, that the element in the *i*-th row and the *j*-th column of the $M \times M$ order spatial weight matrix Q by q_{ij}, that the spatial effect by λ_i, that the time effect by ϑ_o, that the spatial disturbance term by ψ_{io}, that the interference term that obeys the independent identical distribution by ρ_{io}, that the spatial autocorrelation coefficient by σ, and that the coefficient to be estimated by γ, ω, and μ. The following formula shows the expression of the spatial panel model:

$$\begin{cases} b_{io} = \sigma \sum_{j=1}^{M} q_{ij} b_{jo} + \gamma a_{io} + \sum_{j=1}^{M} q_{ij} a_{jo} \omega + \lambda_i + \vartheta_o + \psi_{io} \\ \psi_{io} = \mu \sum_{j=1}^{M} q_{ij} \psi_{jo} + \rho_{io} \end{cases} \tag{4}$$

If there exists ω=μ=0, the above formula is the expression of the spatial lag model. If there exists ω=σ=0, the above formula is the expression of the spatial error model. If there only exists μ=0, the above formula is the expression of the spatial Durbin model.

In order to avoid omission of any important variable that hinders the construction of college students' employment and labor relations, 5 factors were selected as the control variables in this paper, which are economic structure, denoted as *CJ*, legal and policy environment, denoted as *KC*, labor market environment, denoted as *ZZ*, enterprise threshold, denoted as *DK*, and training policy of colleges, denoted as *WL*. Suppose that the colleges and majors of college students are represented by *HG*, and that the employment concept of college students by *ZZ*. Based on the employment data of college students in the region within the study period, a random effect spatial Durbin model was constructed to study and analyze the spatial effects of the colleges and majors of college students on the construction of college students' employment and labor relations. The specific expression of the constructed model is as follows:

$$\begin{aligned}\Omega_{io} &= \gamma_0 + \sigma\sum_{j=1}^{M} q_{ij}\Omega_{io} + \gamma_1 HG_{io} + \gamma_2 CJ_{io} + \gamma_3 KC_{io} + \gamma_4 ZZ_{io}\\ &+ \gamma_5 DK_{io} + \gamma_6 WL_{io} + \sum_{j=1}^{M} q_{ij} HG_{io}\omega_1 + \sum_{j=1}^{M} q_{ij} CJ_{io}\omega_2 + \sum_{j=1}^{M} q_{ij} KC_{io}\omega_3\\ &+ \sum_{j=1}^{M} q_{ij} ZZ_{io}\omega_4 + \sum_{j=1}^{M} q_{ij} DK_{io}\omega_5 + \sum_{j=1}^{M} q_{ij} WL_{io}\omega_6 + \lambda_i + \rho_{io}\end{aligned} \tag{5}$$

In order to further explain the effect estimation results of the constructed model, the total effect of the model was broken down into direct effect and indirect effect, respectively corresponding to the effects of explanatory variables on the explained variables in the study region and other spatially related areas. The following formula shows the vector expression of the spatial Durbin model:

$$B_o = (I_m - \sigma Q)^{-1}(A_o\gamma + QA_o\omega) + (UP_m - \sigma Q)^{-1}\rho \tag{6}$$

The partial differential matrix of the explained variables is expressed as follows:

$$\begin{aligned}\begin{bmatrix} \frac{\partial B}{\partial A_{1l}} & \cdots & \frac{\partial B}{\partial A_{Ml}} \end{bmatrix} &= \begin{bmatrix} \frac{\partial B}{\partial A_{1l}} & \cdots & \frac{\partial B}{\partial A_{1l}} \\ & \cdots & \\ \frac{\partial B}{\partial A_{1l}} & \cdots & \frac{\partial B}{\partial A_{1l}} \end{bmatrix}\\ &= (UP_m - \sigma Q)\begin{bmatrix} \gamma_l & q_{12}\omega_l & \cdots & q_{1M}\omega_l \\ q_{21}\omega_l & \gamma_l & \cdots & q_{2M}\omega_l \\ & & \cdots & \\ q_{M1}\omega_l & q_{M2}\omega_l & \cdots & \gamma_l \end{bmatrix}\end{aligned} \tag{7}$$

Based on the above two formulas, the direct effect, indirect effect and total effect of colleges and majors on the construction of college students' employment and labor relations can be further obtained through calculation.

3 Construction of employment and labor relations based on the spatial employment distribution network

In order to make full use of the implicit structural similarity of the known employment and labor relations network of college students to construct their employment and labor relations, a representation learning method was proposed in this paper for college students' employment and labor relations based on the simple graph neural network theory. The algorithm can complete the calculation of similarity between network nodes, and further obtain the transition probability in the local neighborhood space of the network through calculation. The semantic sequence of nodes containing the implicit similarity of network structure can be generated based on the property of Markov chain, and the obtained sequence can have an effective network representation through model learning. Figure 2 presents the algorithm framework.

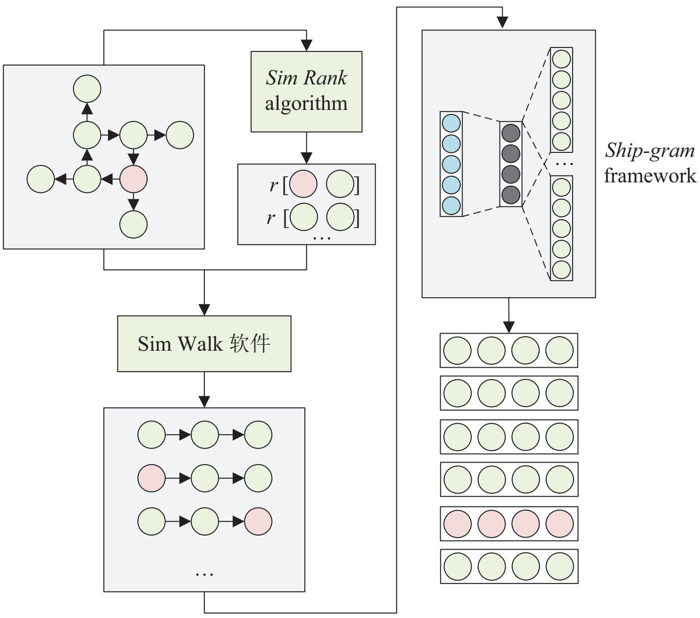

Fig. 2. Algorithm framework

For data such as college students' colleges and majors, and jobs offered by enterprises, in the calculation of the similarity between nodes in the employment and labor relations network of college students, what is considered is whether the nodes have similar contextual relationships, that is, two nodes are similar if the information provided for the two nodes is referenced by similar objects.

This paper applies the SimRank algorithm fill to iteratively calculate the similarity of nodes in the employment and labor relations network of college students. Suppose that the in-degree node sets of nodes e and f are represented by $UP(e)$ and $UP(f)$, respectively, that the index numbers of the in-degree nodes by i, j, that the number of nodes contained in the in-degree node set by $|UP(\ )|$, and that the constant by $D \in (0,1)$. If $UP(e)$ or $UP(f)$ is an empty set, then $r(e,f)=0$.

$$r(e,f) = \frac{D}{|UP(e)||UP(f)|} \sum_{i=1}^{|UP(e)|} \sum_{j=1}^{|UP(f)|} r(UP_i(e), UP_j(f)) \tag{8}$$

It can be seen from the above formula that when the similarity of the neighbor nodes of e and f is high, that is, the value of $r(UP(e), UP(f))$ is high, and the value of $r(e,f)$ is also relatively high, then the two nodes e and f are similar, and the relationship can be built. Through the above processing, the similarity between a node in the employment and labor relations network of college students and its neighboring node is quantified, which characterizes the implicit similarity in the local space where college students' employment and labor relations are distributed. The following section uses the software *SimWalk* to guide the network walk process based on the Markov chain by using the obtained similarity of the nodes in college students' employment and labor relations network.

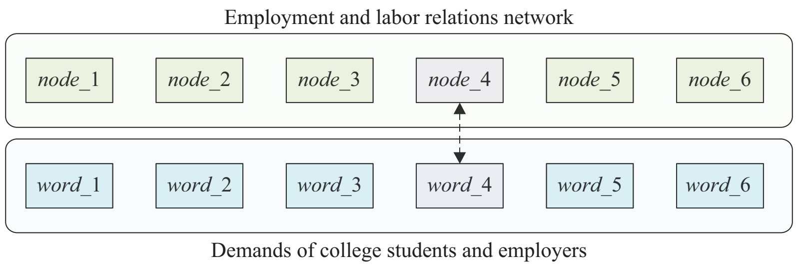

Fig. 3. Semantic sequence matching of nodes

In order to preserve the implicit structural similarity between the nodes in college students' employment and labor relations network to the greatest extent, the software SimWalk was adopted to ensure that the semantic sequence matching of nodes in the sequence samples is more in line with the demands of both college students and employers in the actual environment. Figure 3 shows the semantic sequence matching of nodes. Suppose that the set of the semantic sequence samples is denoted by B, that any node sequence by b, that the probability of u_i shifted to u_{i+1} by $RU(u_{i+1},u_i)$, and that the node pair form of u_i–u_{i+1} by b_i, then:

$$RU(B \mid U) = \sum_{b \in B} \prod_{i=1}^{|b|-1} RU(b_i \mid u_i, u_{i+1}) RU(u_{i+1} \mid u_i) \tag{9}$$

In order to ensure that the semantic sequence does not lose its generality, it is necessary to make b_i satisfy the following formula:

$$b_i = (u_i, u_{i+1}) \equiv (u_{i+1}, u_i) \tag{10}$$

And then there is:

$$RU(b_i \mid u_i, u_{i+1}) = \begin{cases} 0, (u_i, u_{i+1}) \notin S \\ 1, (u_i, u_{i+1}) \in S \end{cases} \tag{11}$$

The Markov chain can be regarded as a set of discrete random variables, in which all variables have the Markov property. Assuming that the state at time $o \in O$ in the random process is represented by A_o, then the state at time o+1 is independent of the past state when the current state at time o is determined, that is:

$$RU(A_{o+1} \mid A_o, A_{o-1}, \ldots, A_1) = RU(A_{o+1} \mid A_o) \tag{12}$$

If the traditional random walk model is used for network representation, it is assumed that the importance of the neighbor nodes in the network is the same to the target node. With the aid of the software SimWalk, based on the implicit structural similarity between nodes, the similarity in the neighborhood of the target node can be converted into probability distribution, so that the implicit structural similarity between nodes can be recorded through the network walk process, and finally the construction plan of the employment and labor relations with the optimal matching of the demands of college students and employers can be obtained. Assuming that the weight of the connecting edge (u_i,u_{i+1}) of the node is represented by $q(u_i,u_{i+1})$, and that the similarity of the node pair by $r(u_i,u_{i+1})$, there is:

$$RU(u_{i+1} \mid u_i) = \begin{cases} 0, u_{i+1} \notin M(u_i) \\ \dfrac{exp(e(u_i, u_{i+1}) \cdot q(u_i, u_{i+1}))}{\sum_{t \in M(u_i)} exp(e(u_i, t) \cdot q(u_i, t))}, u_{i+1} \in M(u_i) \end{cases} \tag{13}$$

The ultimate goal of SimWalk is to map the college student and employer nodes in college students' employment and labor relations network into a low-dimensional space. Assuming that the number of network walks starting from node u is represented by M, and that the i-th walk starting from node u by $Q_i(u)$, the following equation shows the objective function of the algorithm to generate network node representation:

$$\angle = \max_{\mu} \sum_{u \in U} \sum_{i=1}^{M} \log RU(q_i(u) \mid \mu(u)) \tag{14}$$

Assuming that the function that realizes the low-dimensional mapping of nodes is represented by μ, it can be obtained using the stochastic gradient descent method. The independence assumption is made on the conditional probability of the generated node semantic sequence as follows:

$$RU(Q_i(u) \mid \mu(u)) = \prod_{v \in Q_i(u)} RU(v \mid \mu(u)) \tag{15}$$

The following formula gives the optimization objective of maximizing the probability of similar nodes in SimWalk:

$$\angle = \max_{\mu} \sum_{u \in U} \sum_{i=1}^{M} log \prod_{v \in Q_i(u)} RU(v \mid \mu(u)) \tag{16}$$

The above formula characterizes the co-occurrence and correlation of similar node pairs in the node semantic sequence with the best matching of the demands of college students and employers, and finally the proper construction of college students' employment and labor relations and coordination of employment issues can be achieved.

4 Experimental results and analysis

In order to eliminate the impacts of dimensions, the five control variables, namely, economic structure, legal and policy environment, labor market environment, enterprise threshold, and training policy of colleges, were normalized in this paper. The processed variables passed the unit root test. Table 1 presents the descriptive statistical analysis results of the control variables.

Table 1. Descriptive statistical analysis of control variables

Variable	Group	Mean	Standard deviation	Min value	Max value
CJ	Overall	0.369	0.025	0.2381	0.528
	Inter-group		0.036	0.362	0.437
	Intra-group		0.069	0.274	0.581
KC	Overall	8.152	1.302	4.162	13.269
	Inter-group		1.692	6.295	11.275
	Intra-group		0.748	7.318	13.629
ZZ	Overall	0.296	0.137	0.025	0.614
	Inter-group		0.192	0.162	0.528
	Intra-group		0.028	0.085	0.316
DK	Overall	12.364	7.341	1.492	35.269
	Inter-group		7.629	4.312	31.025
	Intra-group		2.169	3.629	15.274
WL	Overall	9.152	1.528	4.513	10.529
	Inter-group		1.027	6.841	13.629
	Intra-group		0.692	7.625	11.208

Tables 2 and 3 show the analysis results of the direct effect, indirect effect and total effect of the spatial Durbin model, respectively. It can be seen that the coefficient of the direct effect of colleges and majors on the construction of college students' employment and labor relations in the region is significantly positive at the significance level of 0.01, indicating that improving the matching of college students' colleges and majors can facilitate the construction of college students' employment and labor relations in the region. College students' colleges and majors did not pass the significance test, which shows that although college students' colleges and majors do play a certain role in facilitating the construction of college students' employment and labor relations in spatially related regions, the spillover effect is not significant.

Table 2. Direct effect and indirect effect of the spatial Durbin model

Variable	**Direct Effect**						**Indirect Effect**					
	HG	***CJ***	***KC***	***ZZ***	***DK***	***WL***	***HG***	***CJ***	***KC***	***ZZ***	***DK***	***WL***
Coefficient	0.03	0.451	0.062	−0.215	−0.032	0.059	0.015	0.014	0.069	−0.025	−0.084	0.026
z value	5.16	6.29	9.37	−4.15	−0.95	6.37	1.37	0.58	1.16	−2.69	−1.36	2.58
p value	0.025	0.014	0.039	0.062	0.347	0.081	0.017	0.186	0.619	0.237	0.051	0.016

Table 3. Total effect of the spatial Durbin model

Variable	**Total Effect**					
	HG	***CJ***	***KC***	***ZZ***	***DK***	***WL***
Coefficient	0.047	0.461	0.058	−0.841	−0.027	0.05
z value	4.37	5.69	5.74	−3.69	−1.58	3.67
p value	0.095	0.037	0.051	0.025	0.015	0.037

Table 4. Performance of different network representation learning methods

Dataset	**Classifier**	**Precision**			**F_1 Value**		
		Decision Tree	**Logistic Regression**	**Naive Bayes**	**Decision Tree**	**Logistic Regression**	**Naive Bayes**
A	Proposed algorithm	0.52±0.02	0.56±0.01	0.43±0.03	0.52±0.07	0.58±0.01	0.54±0.05
	SDNE	0.58±0.06	0.51±0.03	0.39±0.07	0.54±0.01	0.41±0.03	0.38±0.06
	GraRep	0.52±0.01	0.56±0.09	0.31±0.02	0.52±0.06	0.46±0.05	0.36±0.02
	LINE	0.58±0.03	0.56±0.01	0.45±0.06	0.49±0.04	0.41±0.09	0.47±0.04
	DeepWalk	0.46±0.02	0.49±0.04	0.38±0.02	0.34±0.05	0.39±0.02	0.35±0.06
B	Proposed algorithm	0.69±0.04	0.63±0.12	0.58±0.03	0.52±0.07	0.63±0.15	0.57±0.02
	SDNE	0.6±0.02	0.67±0.14	0.56±0.02	0.52±0.01	0.69±0.27	0.41±0.03
	GraRep	0.65±0.06	0.62±0.27	0.59±0.08	0.54±0.02	0.61±0.06	0.54±0.01
	LINE	0.69±0.02	0.64±0.25	0.57±0.03	0.52±0.07	0.64±0.39	0.45±0.03
	DeepWalk	0.39±0.02	0.49±0.02	0.29±0.07	0.26±0.09	0.36±0.15	0.15±0.09

Taking the entrepreneurship of students majoring in music as an example, the proposed model was compared with four classic network representation learning methods, namely *SDNE*, *GraRep*, *LINE*, and *DeepWalk*, for the performance of the node relationship matching task in a real employment and labor relations network environment of college students. Table 4 presents the performance of different network representation learning methods with respect to different datasets, with detailed analysis. It can be seen that the proposed algorithm trained by the *Ship-gram* framework has stronger performance in network node representation, and the generated network node representation has higher precision and *F* value under three classifiers, namely decision tree, logistic regression and Naive Bayes. And different data sets have little impact on the two performance indicators – precision and *F* value, indicating the model is more stable. At the same time, compared with logistic regression and Naive Bayes, the decision tree classifier has better representation of network nodes with respect to the two datasets.

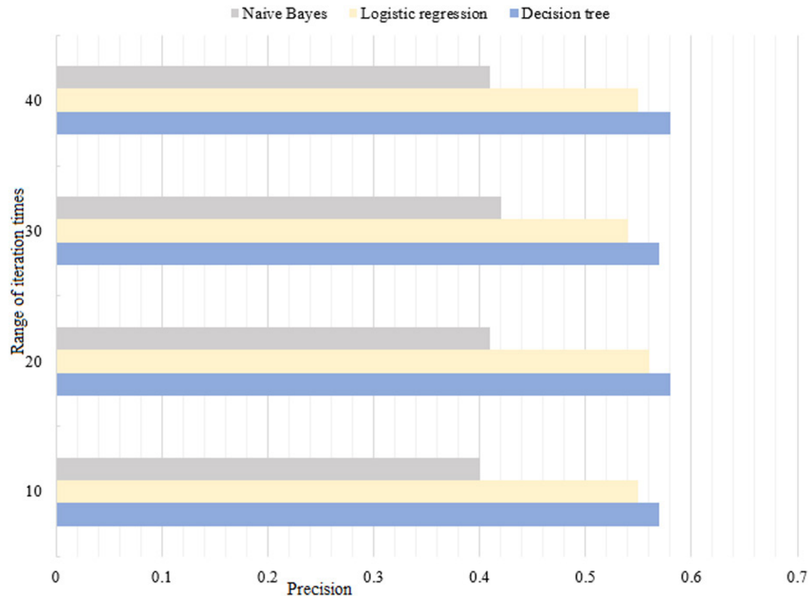

Fig. 4. Sensitivity test on the iteration times of nodes

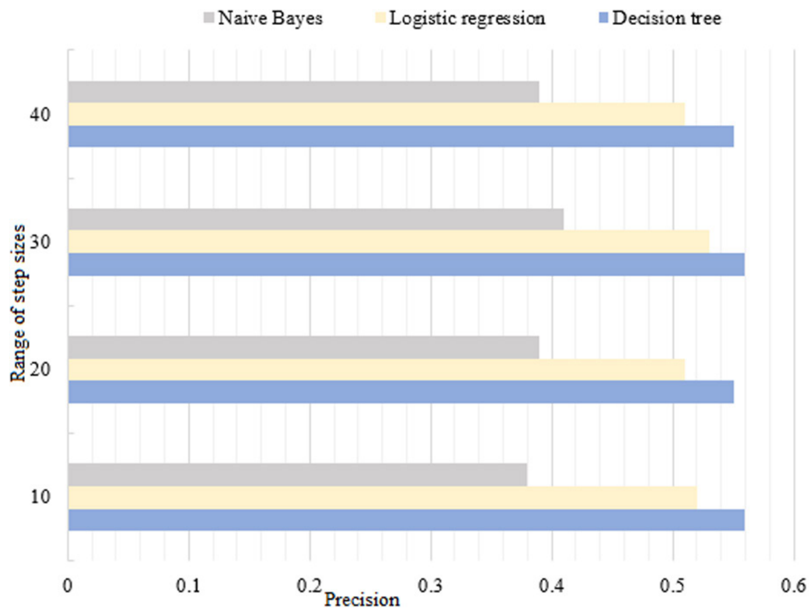

Fig. 5. Sensitivity test on the step sizes of nodes

Figures 4 and 5 show the validation results of network node relationship matching with different node iteration times and step sizes, respectively. It can be seen that the overall performance of the proposed algorithm is stable. In the range of different iteration times, the performance of the proposed algorithm did not change significantly with the increase or decrease of the number of node iterations, and was not significantly affected by the step size. Figure 6 presents the sensitivity test on the number of dimensions of network representation. It can be seen that as the number of dimensions increased, the overall performance of the proposed algorithm was slowly weakening.

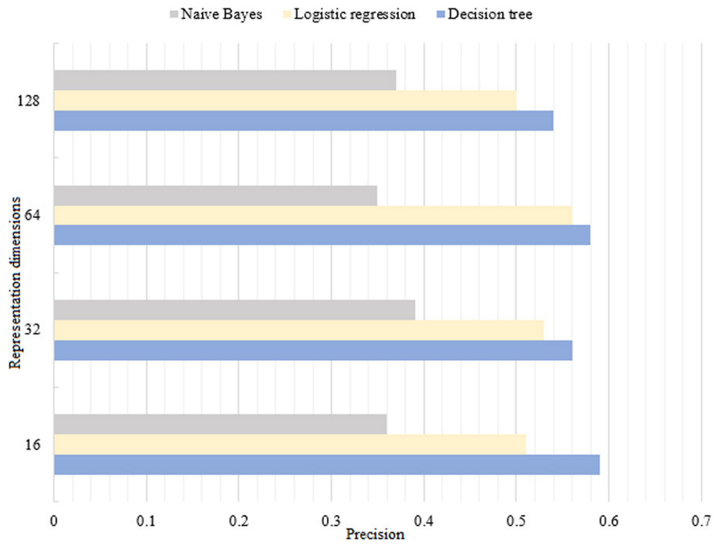

Fig. 6. Sensitivity test on the number of dimensions of network representation

5 Conclusions

This paper studied the construction and coordination mechanism of college students' employment and labor relations in the Internet+ environment. Firstly, the spatial autocorrelation of the distribution of college students' employment and labor relations was checked based on the Moran's I index, and a random effect spatial Durbin model was constructed based on the employment data of college students in the study region within the study period to study and analyze the spatial effects of colleges and majors on the construction of college students' employment and labor relations in the region. Then, based on the simple graph neural network theory, a representation learning method was put forward for college students' employment and labor relations network, and the employment and labor relations of college students was built through full utilization of the implicit structural similarity existing in the known employment and labor relations network of college students. The descriptive statistical analysis results of the control variables were summarized, and the analysis results of the direct effect, indirect effect and total effect of the spatial Durbin model were given through an experiment. It is verified that although colleges and majors play a certain role in promoting the construction of college students' employment and labor relations in spatially related regions, the spillover effect is not significant. The proposed model was compared with four classical network representation learning methods, *SDNE*, *GraRep*, *LINE*, and *DeepWalk*, which shows that the proposed algorithm has stronger performance in representation of network nodes. Finally, the validation results of network node relationship matching with different node iteration times, step sizes and numbers of dimensions were shown.

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