Social Experience Guidance for College Students' Entrepreneurship in the Social Network

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Abstract—The low success rate of entrepreneurship is quite common for contemporary college students, and its main reason can be attributed to their lack of social experience and entrepreneurial guidance, thus, it's of certain practical significance to study the social experience guidance for college students' entrepreneurship and this paper aims to explore this problem based on social network. At first, this paper introduced the formation mechanism of the social experience guidance for college students' entrepreneurship, proposed a novel Social Network Representation Learning (SNRL) method for college students' entrepreneurship, which could attain more information of social experience guidance from networks with isomorphic substructures. Then, in the social network of college students' entrepreneurship, this paper discussed the extraction method of structural subgraph of neighborhood space of college students and other entrepreneurial subject nodes, and proposed a method for building sub-networks similar to the scale and development state in the social network of college students' entrepreneurship, and realized the information sharing of social and entrepreneurial experiences among sub-networks. At last, this paper constructed a Social and Entrepreneurial Experience Guidance (SEEG) model, and verified its effectiveness in experiments.

Keywords—social network, college students, entrepreneurship, social experience, guidance, information sharing

1 Introduction

Entrepreneurship is an activity with high risk and high failure rate, especially the new startup business [1–8]. In the business running process, many factors can affect entrepreneurship, such as external factors of policy and market, and internal factors of manpower, experience, and resource [9–13]. As the saying goes, "experience is the best teacher", so among these factors, the entrepreneurial experience of entrepreneurs is a more important factor that closely related to the opportunity identification, strategic development, and enterprise performance of the newly created business [14–18]. The prior experience and knowledge of entrepreneurs gained from their entrepreneurial and social experience mainly include clear goals, opportunity identification, and effective choices when encountering problems, compared with those without any entrepreneurial experience, entrepreneurs with such prior experience and knowledge have a better chance to succeed in entrepreneurship [19–21]. For college students, the low success rate of entrepreneurship is quite common, and its main reason can be attributed to their lack of social experience and entrepreneurial guidance, they need some entrepreneurial guidance for starting a new business, so it's of certain practical significance to study the social experience guidance for college students' entrepreneurship.

At present, the value of entrepreneurs in the labor market is still unclear to us, theoretical studies and empirical evidences give varying conclusions. For instance, Merida and Rocha [22] believe that the timing of entrepreneurial experience is very important, they conducted follow-up surveys on many employers and employees in Denmark for fifteen years and attained a large amount of sample data, according to the time and type of entrepreneurial experience, they compared the labor market results of early-stage entrepreneurs, late-stage entrepreneurs, and those without entrepreneurial experience. Morehouse and James [23] used both quantitative and qualitative methods to survey recruiting employers of the Rose-Hulman Institute of Technology, a top undergraduate engineering school in Indiana of the United States, the Likert scale used by the researchers mainly focused on perceptions with employers as this may be related to the entrepreneurial experience students introduced in their resumes. Their preliminary results suggested that students who expressed entrepreneurial intentions during their undergraduate years tend to leave the company earlier than common engineering graduates, and this finding provided important insights for educators, entrepreneurship program directors, career services, and employer departments. Wang et al. [24] proposed that entrepreneurial orientation has become the core of enterprises' adaptation, competition, and development in the increasingly competitive environment at present, the writers took Chinese listed companies on growth enterprise market as samples and empirically analyzed the influence of entrepreneurs' prior experience on the venture capital investment of start-ups from the perspectives of the imprinting theory and the moderating role of opportunity innovation, and their findings suggest that the width of an entrepreneur's prior experience is positively related to his/her entrepreneurial intention, while the depth of prior experience is negatively related to entrepreneurial intention. Yang and Hahn [25] investigated how entrepreneurs learn from prior experience from microscopic perspectives and viewed this phenomenon dynamically, drawing on the organizational learning theory, the authors gave a theoretical analysis on learning effect from multiple empirical dimensions: direct vs. indirect experiences, successful vs. failed experiences, the relatedness, richness and diversity of prior experiences. Shyti and Paraschiv [26] proposed an experiment to investigate the vague attitudes of entrepreneurs and non-entrepreneurs in evaluating entrepreneurial projects, their attained results are consistent with the prospect theory, that is, entrepreneurs are ambiguity-averse, but they systematically exhibit more optimistic attitudes than non-entrepreneurs, who are ambiguity-neutral; the ambiguity aversion decreases with the increase of entrepreneurial experience, and serial entrepreneurs are more optimistic than novice entrepreneurs.

By reviewing and summarizing existing literatures, we found that present world field scholars have studied the topics of the generation of college students' entrepreneurship and how to promote their entrepreneurial performance from varying perspectives, although their findings have verified that rich social and entrepreneurial experience has an active role in promoting entrepreneurship, still less concern has been paid to the guidance strategies of social experience for college students' entrepreneurship. Therefore, in order to bridge this gap, this paper aims to study the social experience guidance for college students' entrepreneurship in social network. The second chapter introduced the formation mechanisms of social experience guidance for college students' entrepreneurship, proposed a novel SNRL method for college students' entrepreneurship, which could attain more information of social experience guidance from networks with isomorphic substructures. The third chapter discussed an extraction method for the structural subgraph of neighborhood space of college students and other entrepreneurial subject nodes in the social network of college students' entrepreneurship. The fourth chapter proposed a method for building sub-networks similar to the scale and development state in the social network of college students' entrepreneurship, and realized the information sharing of social and entrepreneurial experiences among sub-networks. At last, this paper constructed a SEEG model and verified its effectiveness in experiments.

2 Generation mechanism of social experience guidance for college students' entrepreneurship

Complex network analysis methods with small-world characteristics have attracted much attention from world field scholars. Since the social networks of student entrepreneurs also contain complicated interpersonal relationships and resource supply-demand relationships, conventional complex network analysis methods can no provide give effective analysis results.

Combining with the construction process of the social networks of student entrepreneurs, it's found that, the different social experience guidance required by student entrepreneurs at different stages is accompanied by the formation and maintenance of network relationships and the formation of new network relationships. Table 1 shows the generation mechanism of social experience guidance for college students' entrepreneurship. Because this research aimed at not only to explore the generation mechanism of the social experience guidance for college students' entrepreneurship, but also to figure out how such guidance affects the opportunity identification, strategic development, and enterprise performance of college students' entrepreneurship, this paper proposed a novel SNRL method for college students' entrepreneurship, so as to attain more information of social experience guidance from networks with isomorphic substructures.

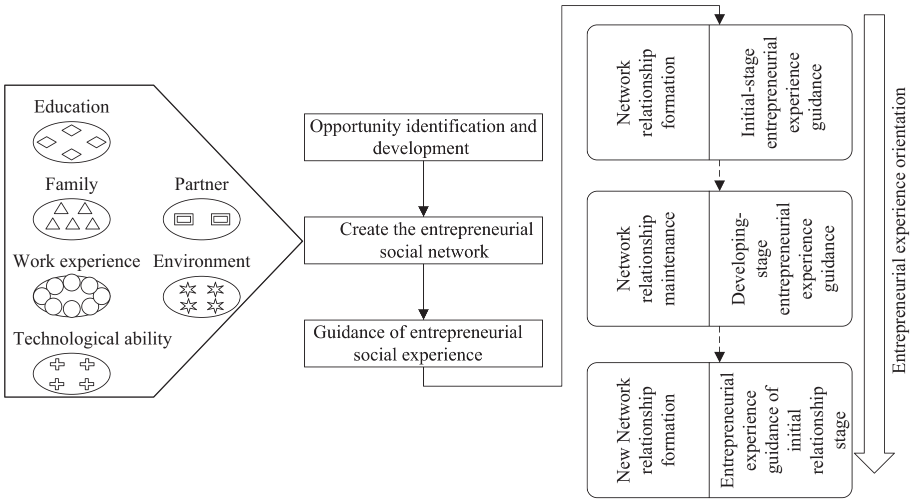

Fig. 1. The generation mechanism of social experience guidance for college students' entrepreneurship

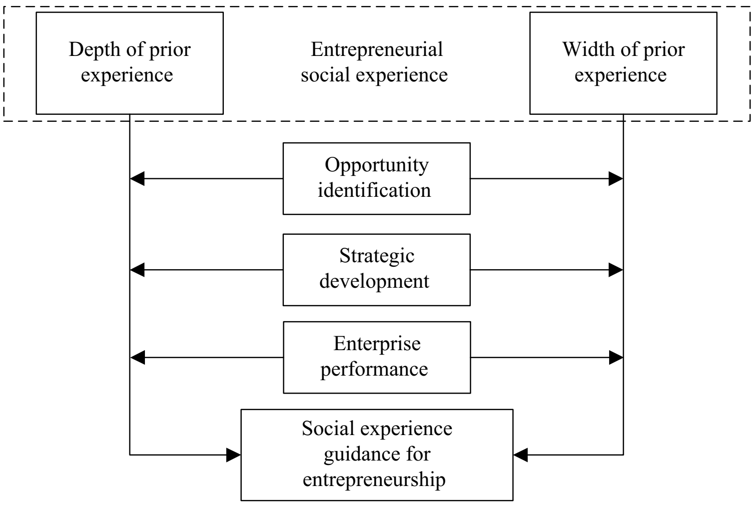

Fig. 2. Architecture of the conceptual model

Based on existing research results and research hypotheses, a conceptual model was established in this paper, and its architecture is given in Figure 2.

3 Extraction of social network structural subgraph of college students' entrepreneurship

At first, this paper introduced a method for extracting structural subgraphs of the neighborhood space of college students and other entrepreneurial subject nodes in the social network of college students' entrepreneurship. Assuming: $H = (U,O)$ represents the network structure subset when $d = \{1,2,...,l,l+1,...xl\}$; $m = |U|$ represents the number of nodes in graph H, and there is $\forall\theta\in\Omega$, wherein θ represents any structure subset; $\theta_v = (U_v, O_v)$ represents geometric features of node v, and there are $x>1$, $x\in Z^+$, then the node-based explicit topological structural subgraph network set Φ can be expressed as:

$$\Phi = \{\theta_1, \theta_m, ..., \theta_m\} \tag{1}$$

The core idea of this structural subgraph extraction method is to ensure that Φ can be extracted when the network achieves steady division.

The initialization of structural subgraph $\theta_v(|U_v| = xl)$ based on node v is to gradually introduce the neighborhood space nodes around the starting node $v\in U$ until neighborhood space nodes with p steps have been covered. The starting node here is a college student entrepreneur node, and the neighborhood space nodes are other entrepreneurial subject nodes that can give certain social experience guidance. Assuming: $\Psi_n(v)$ represents the set of neighborhood space nodes that are n steps away from node v, then there is:

$$\theta_v = v\bigcup_{n=1}^{p}\Psi_n(v) \tag{2}$$

Since v is the central starting point of θ_v, so in each iteration of the structural subgraph extraction algorithm, the label of v is always 1 in the case of any steady network division, that is, $d(v)$ is equal to 1.

This structural subgraph extraction method updates the attribution of neighbor space nodes via iterations. In detailed steps of the structure network attribution process of nodes, if there're nodes with the same attribution but their single-step neighborhood space nodes have different attributions, the update of steady network division is realized by calculating the structure network attribution sequence of θ. Specifically, in the update process of the i-th iteration, the structure network attribution of node u in θ_v is $d^i(u)$, assuming $M(u)$ represents the neighborhood space nodes that are single-step away from node u; <…> represents multi-set, then during the update process of i+1-th iteration, the update method of the structure network attribution of u is given by the following formula:

$$d^{i+1}(u) = \left(d^i(u), \left\langle d^i(e) : e\in M(u)\right\rangle\right) \tag{3}$$

Assuming: $f(u)$ represents the hash value of node u in the update process of each iteration; (.) represents the prime number set, then the formula of multi-set structure network attribution update is:

$$f(u) = d(u) + \frac{1}{\left[\sum_{e' \in U_v} log(T(d(e')))\right]} \cdot \sum_{e \in M(u)} log(T(d(e))) \tag{4}$$

Before actual application, the above formula needs to be verified for whether it meets the requirements for retaining the structure network attribution sequence, that is, whether it satisfies the two conditions for retaining and generating the structure network attribution sequence.

Retaining a network structure requires that two nodes have equal hash value and same attribution, and the one-step neighborhood space nodes contain the same structure network attribution and the same cardinality. Assuming: there are nodes x and y, if $d(x) = d(y)$, and $<d(x)> = <d(y)>$, then according to above formula, we can get $f(x) = f(y)$; if $f(x) = f(y)$, then there are:

$$\begin{aligned}
& f(x) = f(y) \\
& \Rightarrow d(x) - d(y) = \frac{\sum_{e \in M(y)} log(T(d(e))) - \sum_{e \in M(x)} log(T(d(e)))}{\left[\sum_{e' \in U_v} log(T(d(e')))\right]} \\
& \Rightarrow d(x) - d(y) = \frac{log \prod_{e \in M(y)} T(d(e)) - log \prod_{e \in M(x)} T(d(e))}{\left[\sum_{e' \in U_v} log(T(d(e')))\right]} \\
& \Rightarrow exp\left(\left[\sum_{e' \in U_v} log(T(d(e')))\right] \cdot (d(x) - d(y))\right) = \frac{\prod_{e \in M(y)} T(d(e))}{\prod_{e \in M(x)} T(d(e))}
\end{aligned} \tag{5}$$

According to above formula, the left and right sides of the equation are respectively the exponential function and rational numbers, to ensure that the equation holds, the following formula need to be satisfied:

$$\left[\sum_{e' \in U_v} log(T(d(e')))\right] \cdot (d(x) - d(y)) = 0 \tag{6}$$

Further, we can get:

$$\begin{aligned}
& d(x) - d(y) = 0 \\
& \Rightarrow d(x) = d(y)
\end{aligned} \tag{7}$$

If exp(0) is equal to 1, then there is:

$$1 = \frac{\prod_{e \in M(y)} T(d(e))}{\prod_{e \in M(x)} T(d(e))} \tag{8}$$

According to above results, the serial multiplication result of prime values of one-step neighborhood space nodes corresponding to node x is equal to the serial multiplication result of prime values of one-step neighborhood space nodes corresponding to node y, and the structure network attribution and cardinality of the neighborhood space nodes are also the same.

In the update process of the i-th iteration, the structure network attributions of nodes x and y are represented by $d^i(x)$ and $d^i(y)$, respectively, without loss of generality, it's assumed that $d^i(x) < d^i(y)$. Since the structure network attribution values of the nodes are all greater than or equal to 1, there is:

$$d^i(x) + 1 \leq d^i(y) \tag{9}$$

Given $|U_v|>|M(x)|$ and $|U_v|>|M(y)|$, then there is:

$$\frac{\sum_{e \in M(x)} log(T(d(e)))}{\left\lceil \sum_{e' \in U_v} log(T(d(e'))) \right\rceil} < 1 \tag{10}$$

By combining with Formula 4, there are:

$$\begin{aligned} f^i(x) &= d^i(x) + \frac{\sum_{e \in M(x)} log(T(d^i(e)))}{\left\lceil \sum_{e' \in U_v} log(T(d^i(e'))) \right\rceil} \\ &< d^i(x) + 1 \\ &\leq d^i(y) \\ &\leq f^i(y) \end{aligned} \tag{11}$$

Because $f^i(x) < f^i(y)$, it's known that the hash values of nodes can be sorted and mapped in ascending order, and the structure network attribution sequence can be generated and updated, that is, in the update process of the next round of iteration, $d^{i+1}(x) < d^{i+1}(y)$ should be satisfied.

After realizing steady network division, the subgraph needs to be pruned, assuming θ represents the geometric features and structure network attribution sequence features extracted from the subgraph, then, retaining the topological structure formed by the first l nodes in the attribution sequence of the structure network can be expressed as:

$$\theta = \theta \setminus \theta\left[l+1, \beta l\right] \tag{12}$$

4 Extraction of the topological features of subgraph and similarity analysis

If the potential sub-structures of the subgraphs attained in the previous chapter are similar, it means that the construction scale and development status of the social networks of college students' entrepreneurship are similar, and the entrepreneurial and social experience information can be shared between two subnetworks. Generally speaking, the process of proving two subnetworks are isomorphic is quite complicated. Assuming: $R = \{\theta_1,\theta_2,...,\theta_m\}$ represents the node-based structural subgraph set; $V(H)$ is a set of isomorphic units in $H = (U,O)$, if we want to verify whether there are substructures with similar geometric features in $\Phi = \{\theta_1,\theta_2,...,\theta_m\}$, then it is equivalent to verify the existence of isomorphic structural units self-embedded in the subgraph set.

Assuming: there are nodes x and y, the corresponding subgraphs $\theta_x = (U_x,O_x)$ and $\theta_y = (U_y,O_y) \in \Omega$. According to the extraction process of subgraphs, it can be known that $l = |U_x| = |U_y| > 0$, and $|O_x| > 0$, $|O_y| > 0$.

(1) When $l = 1$ or 2, apparently there is $\theta_x \approx \theta_y$, that is, there's a G that makes $G(U_x) = U_y^{\,3}$, therefore θ_x and θ_y are isomorphic units to each other, and there is θ_x, $\theta_y \in V(H)$;
(2) When $l = \delta(\delta>2)$, assuming there're V_i, $V_j \in V(H)$ and $V_i \in (U_i,O_i)$, $V_j \in (U_j,O_j)$, $V_i \approx V_j$, then there are $V_i \subset \theta_x$, $V_j \subset \theta_y$;
(3) When $l = \delta + 1$, assuming there're v, $u \in U$ that make $U_x = U_x \cup \{v\}$, $U_y = U_y \cup \{u\}$, then update side sets $O_x = U_x \times U_x$ and $O_y = U_y \times U_y$. Let $\kappa = \{v\} \times U_i$ and $\psi = \{u\} \times U_j$ represent the newly-added structural information related to V_i and V_j; $U(\kappa)$ and $U(\psi)$ represent the node sets of κ and ψ; and $O(\kappa)$ and $O(\psi)$ represent the side sets of κ and ψ.

If $O(\kappa)$ and $O(\psi)$ are both empty sets, since $V_i \approx V_j$ and $V_i \subset \theta_x$, $V_j \subset \theta_y$, there are V_i, $V_j \in V(H)$, so there are isomorphic units in θ_x and θ_y; if both $O(\kappa)$ and $O(\psi)$ are not empty sets, let $\alpha_i = U(\kappa)\backslash\{v\}$ and $\alpha_j = U(\psi)\backslash u$, then we can get $\xi_i = \alpha_i \cup G^{-1}(\alpha_j)\backslash\alpha_j \cup G^{-1}(\alpha_j)$, $\xi_j = G(\xi_i)$; further, we can attain $V_i' = V_i \backslash \xi_i$, $V_j' = V_j \backslash \xi_j$, assuming $V_i' = (U_i',O_i')$, $V_j' = (U_j',O_j')$. Since $V_i \approx V_j$, then $D(V_i) = D(V_j)$.

Moreover, because $V_i' \subset V_i \backslash \xi_i$ and $V_j' \subset V_j$, so $<M(t) \subset U_i' : t \in U_i'>$ is approximately equal to $<M(w) \subset U_j' : w \in U_j'>$. Therefore, $D(V_i')$ is equal to $D(V_j')$, then $V_i' \approx V_j'$, so V_i', $V_j' \in V(H)$. Since $V_i' \subset \theta_x$ and $V_j' \subset \theta_y$, there are isomorphic units in θ_x and θ_y.

For the potential substructure similarity of the social network of college students' entrepreneurship, assuming there are similar structures θ_x and θ_y, there are $V_i \approx V_j$, $V_i \subset \theta_x$, $V_j \subset \theta_y$. Since $D(\theta_x) = D(\theta_y)$, assuming ϕ represents the topological distance generated by isomorphic units during the network division process, then the isomorphic units in subgraph can be expressed as $<d(t):t \in U_i> \approx <d(w)+\phi:w \in U_j>$.

During the subgraph extraction of the social network of college students' entrepreneurship, $R = \{\theta_1,\theta_2,...,\theta_m\}$ has a structure network attribution sequence set $W = \{w_1,w_2,...,w_m\}$. The presentation of network structure features can attain more accurate social experience guidance through the learning of convolutional neural network (CNN).

Formally, if $u \in U$ is satisfied, assuming O_u represents the node embedding matrix containing the semantics of the neighborhood entrepreneurial social experience information; X_u represents the adjacency matrix containing the geometric features; K_u represents the label or category of the nodes; then data samples could be expressed as:

$$\Delta = \left\{ < \left\langle (O_u, X_u), K_u \right\rangle : u \in H \right\} \tag{13}$$

Assuming $l = |r_u|$; c represents the dimensionality of the pre-trained network; r_u represents a known structure network attribution sequence; $a_{ru(i)}$ represents the pre-trained network; *Concat* is the vector splicing operation function, then the arrangement method of all nodes in the subgraph can be expressed as:

$$O_u = a_u Concat_{i=1}^{l}(a_{r_u(i)}) \tag{14}$$

Assuming: $x_{i,j}$ represents the link form of the i-th node and the j-th node in r_u; $q(r_u(i), r_u(j))$ represents the weight of the side; under normal circumstance, if $q(r_u(i), r_u(j))$ is equal to 1, then it indicates there's a link between the nodes, then the feature data of the adjacency matrix X_u can be formalized based on r_u as follows:

$$x_{i,j} = \begin{cases} q(r_u(i), r_u(j)), (r_u(i), r_u(j)) \in O_u \\ 0, (r_u(i), r_u(j)) \notin O_u \end{cases} \tag{15}$$

5 Modelling of social experience guidance for college students' entrepreneurship

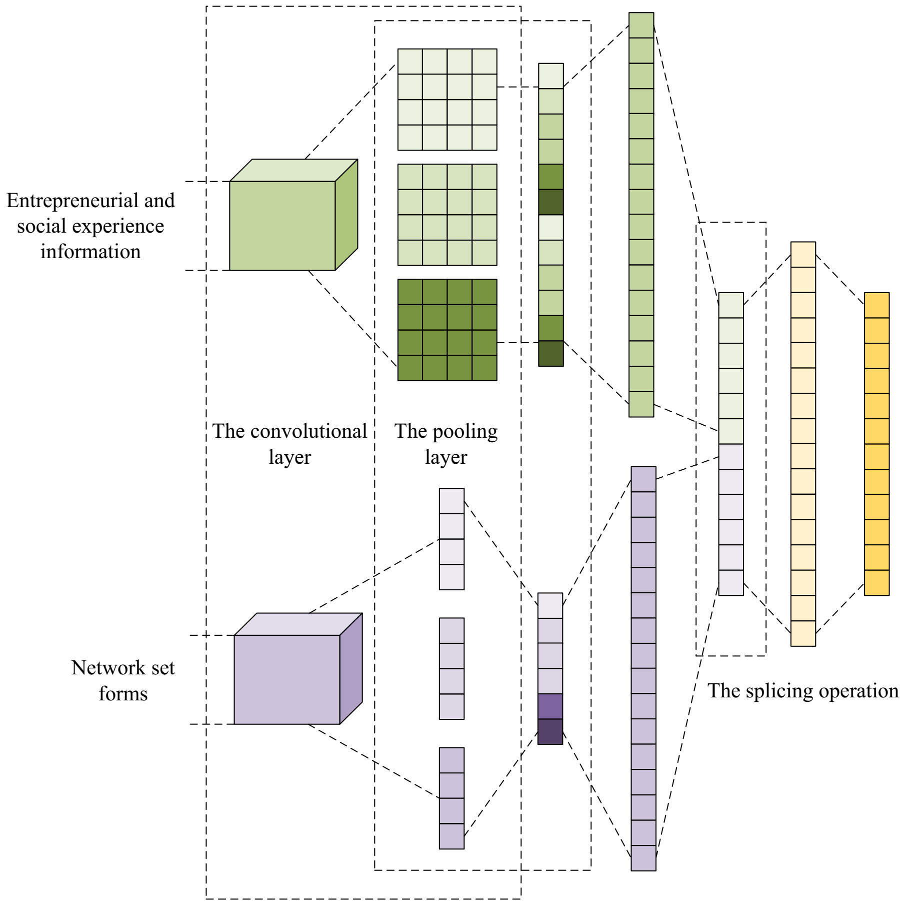

Fig. 3. The structure of SEEG model

Since the Social Network Representation Learning (SNRL) method for college students' entrepreneurship has combined the semantics of neighborhood entrepreneurial social experience information and the form similarity of network sets, it's necessary to embed the corresponding two convolution kernels into the constructed Social and Entrepreneurial Experience Guidance (SEEG) model, the structure of the model is given in Figure 3.

Let the width of the convolution kernel be the same as the dimensionality represented by the pre-trained CNN, assuming: convolution kernel receives m adjacent row vectors each time, $g(\cdot)$ represents the activation function of the CNN; φ_O represents the bias, then when the kernel slides to $O[i{:}i+m-1]$, the generation method of feature d_i is:

$$d_i = g(q_O \cdot O\left[i : i + m - 1\right] + y_O) \tag{16}$$

The adjacent convolution kernel receives the substructure link information of m nodes each time, that is, $q_X \in R^{m\times m}_{+}$, m<l. Therefore, when the kernel slides to $X[i{:}i+m-1]$ $[j{:}j+m-1]$, the feature valence $d'_{i,j}$ can be calculated by the following formula:

$$d'_{i,j} = g(q_X \cdot X\left[i : i + m - 1\right]\left[j : j + m - 1\right] + \phi_X) \tag{17}$$

The feature map attained from the convolution operation of the node embedding matrix based on the semantic similarity of entrepreneurial social experience information can be written as:

$$d_O = \left[d_1, d_2, \ldots, d_{l-m+1}\right]^T \tag{18}$$

The feature map attained from the convolution operation of the adjacency matrix based on the form similarity of network sets can be expressed as:

$$d_X = \begin{bmatrix} d'_{1,1} & \cdots & d'_{l-m+1} \\ \vdots & \ddots & \vdots \\ d'_{l-m+1,1} & \cdots & d'_{l-m+1,l-m+1} \end{bmatrix} \tag{19}$$

UO and UX could be attained after going through the pooling layer and the fully connected layer. Assuming $\oplus$ represents the splicing operation, then the social network of college students' entrepreneurship guided by entrepreneurial social experience can be expressed as:

$$u = g({q_D}^T \cdot (u_O \oplus u_X) + \phi_D) \tag{20}$$

At last, the CNN was optimized by the cross entropy loss function.

6 Experimental results and analysis

In terms of a same sample set, Figure 4 shows the guiding effect of entrepreneurial social experience under the conditions of different convolution kernels. As can be seen from the figure, with the increase of the convolution kernel, no matter which classifier was adopted, the performance of the proposed SNRL method declined significantly. The adopted classifiers included the support vector machine (SVM), the decision tree, and the K-nearest neighbor. According to the experimental results, if the convolution kernel is too large, the amount of subnetwork information received from the social network of college students' entrepreneurship will be too much, which would lead to failure of the convolution sliding operation of the model, and it will be difficult to attain valuable memory information, and the internal relationships of the network structure cannot be fully learnt by the model.

The experiments compared the proposed SNRL method with other four methods including *DeepWalk*, *LINE*, *node2vec*, and *SDNE* using a same sample set, and the results of the entrepreneurial social experience guidance under different network dimensionalities and classifiers are given in Table 1, which has intuitively showed the effectiveness of the proposed method in classifying the entrepreneurial social subnetworks and providing entrepreneurial social experience guidance.

Table 1. Results of entrepreneurial social experience guidance under different network dimensionalities and classifiers

	Dimensionality	Classifier No.	The Proposed Model	DeepWalk	LINE	node2vec	SDNE
Accuracy Rate	30	1	0.61±0.01	0.26±0.09	0.36±0.01	0.16±0.08	0.25±0.06
		2	0.59±0.04	0.21±0.03	0.25±0.04	0.09±0.01	0.17±0.02
		3	0.71±0.07	0.29±0.02	0.28±0.01	0.07±0.03	0.13±0.08
	60	1	0.69±0.01	0.24±0.01	0.39±0.04	0.17±0.05	0.27±0.05
		2	0.63±0.07	0.36±0.04	0.15±0.02	0.07±0.01	0.15±0.02
		3	0.42±0.02	0.15±0.01	0.35±0.06	0.05±0.03	0.17±0.01
	120	1	0.59±0.05	0.29±0.03	0.37±0.09	0.18±0.05	0.26±0.09
		2	0.67±0.01	0.34±0.01	0.15±0.02	0.05±0.01	0.17±0.03
		3	0.53±0.04	0.13±0.07	0.24±0.08	0.04±0.03	0.19±0.01
Weighted F_1-value	30	1	0.69±0.01	0.26±0.05	0.22±0.03	0.09±0.01	0.36±0.05
		2	0.56±0.02	0.22±0.02	0.14±0.09	0.05±0.03	0.14±0.09
		3	0.74±0.06	0.15±0.08	0.27±0.01	0.07±0.01	0.18±0.02
	60	1	0.61±0.02	0.27±0.02	0.29±0.05	0.09±0.05	0.28±0.04
		2	0.57±0.09	0.23±0.09	0.15±0.03	0.07±0.01	0.14±0.02
		3	0.63±0.04	0.14±0.06	0.26±0.01	0.08±0.04	0.17±0.05
	120	1	0.61±0.01	0.28±0.01	0.14±0.06	0.16±0.01	0.39±0.08
		2	0.42±0.08	0.16±0.07	0.27±0.02	0.08±0.04	0.18±0.02
		3	0.51±0.06	0.25±0.02	0.21±0.08	0.06±0.01	0.15±0.04

To further verify the effectiveness of the proposed SEEG model in giving entrepreneurial and social experience guidance, this paper plotted curves of the density function of college students' entrepreneurial intention scores. By observing Figure 5, it can be seen that, the overlapping interval of the entrepreneurial intention scores of college students with and without entrepreneurial social experience guidance was attained, which could describe the sample loss during the experience sharing process of student groups with and without entrepreneurial social experience guidance, and it could reflect the efficiency of the social network of college students' entrepreneurship in providing entrepreneurial social experience guidance. In Figure 5, the overlapping range of the entrepreneurial intention scores was relatively large, indicating that the efficiency of entrepreneurial social experience guidance was ideal.

Table 2 shows the impact of entrepreneurial social network on entrepreneurial opportunity identification. As can be seen in the table, the F-value is 21.052, P-value is less than 0.01, and the $Adj.R^2$ value of the constructed model is 0.47, indicating that the joint explained variance of the entrepreneurial social network for the identification of college students' entrepreneurial opportunities is 47%, indicating that the entrepreneurial social network has a significant positive impact on the identification of college students' entrepreneurial opportunities.

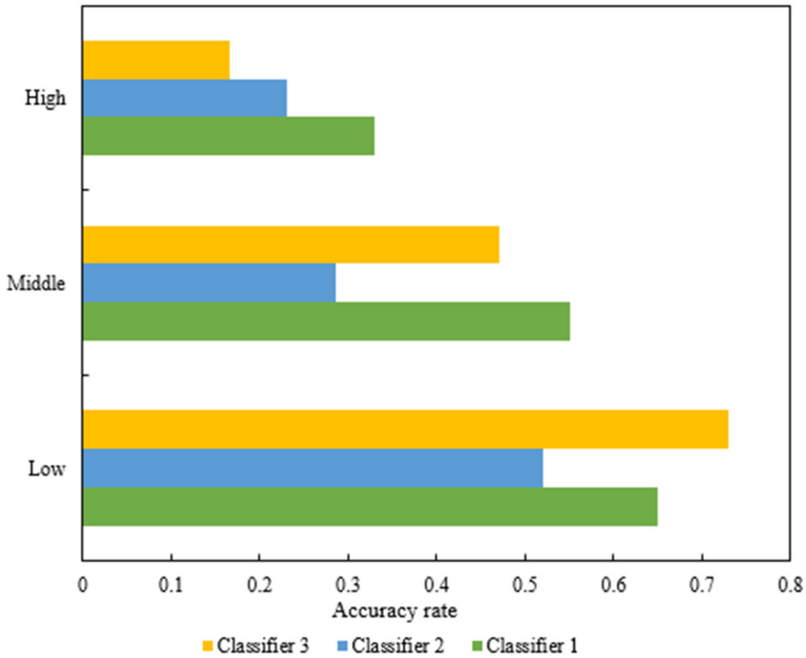

Fig. 4. The guiding effect of entrepreneurial social experience under different convolution kernels

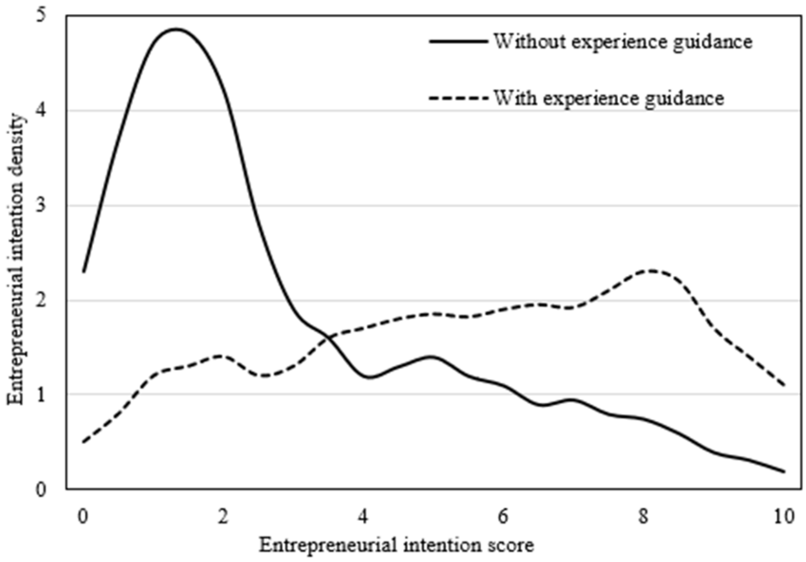

Fig. 5. Curve of the density function of entrepreneurial intention score

Table 3 shows the moderating effect of entrepreneurial social experience guidance on the relationship between strategic development and entrepreneurial performance. As can be seen from the data in the table, the β values of the interaction term are –0.036 and –0.037 (p<0.01). With the increase of college students' entrepreneurial and social experience, the impact of entrepreneurial and social experience guidance on strategic development and entrepreneurial performance is weakened, and it's verified that the less the entrepreneurial social experience college students have, the greater the positive impact of entrepreneurial social experience guidance on strategic development and entrepreneurial performance.

Table 2. Impact of entrepreneurial social on entrepreneurial opportunity identification

	Dependent Variable: Entrepreneurial Opportunity Identification	
	Beta	***Sig***
Independent variable		
Entrepreneurial social network	0.425	0.017
Control variable		
Attribute	0.035	0.428
Year limit	0.014	0.716
Scale	0.039	0.319
Connectivity	0.047	0.785
R^2	0.413	
$Adj.R^2$	0.470	
F	21.052***	

Table 3. The moderating effect of entrepreneurial social experience guidance on the relationship between strategic development and entrepreneurial performance

	Dependent Variable: Strategic Development		**Dependent Variable: Entrepreneurial Performance**	
	Beta	***Sig***	***Beta***	***Sig***
Independent variable				
Entrepreneurial social network	0.537***	0.011	0.751***	0.062
Entrepreneurial social experience	0.512*	0.014	0.629*	0.037
Moderating variable				
Entrepreneurial social network*Entrepreneurial social experience	–0.036	0.015	–0.037*	0.035
Constant	0.182	0.039	–0.461	0.027
R^2	0.937		0.938	
$Adj.R^2$	0.905		0.916	
F	352.182*		326.174***	
ΔR^2			0.02	

7 Conclusion

This paper studied the social experience guidance for college students' entrepreneurship based on social networks. At first, this paper introduced the formation mechanism of social experience guidance for college students' entrepreneurship, proposed a SNRL method for college students' entrepreneurship which could attain more information of social experience guidance from networks with isomorphic substructures. Then, this paper discussed the extraction method for structural subgraph of the neighborhood space of college students and other entrepreneurial subject nodes in the social network of college students' entrepreneurship, proposed a method for building sub-networks similar to the scale and development state in the social network of college students' entrepreneurship, and realized the information sharing of social and entrepreneurial experiences among sub-networks. After that, this paper constructed the SEEG model. Combining with experiments, this paper showed the guiding effect of entrepreneurial social experience under different convolution kernels, compared the performance of the proposed method and other four methods including DeepWalk, LINE, node2vec and SDNE on a same sample set, which intuitively exhibited the effectiveness of the proposed method in classifying the entrepreneurial social subnetworks and providing entrepreneurial social experience guidance; moreover, the curves of density function of college students' entrepreneurial intention scores were plotted, which further verified the effectiveness of the constructed SEEG model in providing entrepreneurial social experience guidance. At last, combining with data, this paper described the impact of entrepreneurial social network on entrepreneurial opportunity identification and the moderating effect of entrepreneurial social experience guidance on the relationship between strategic development and entrepreneurial performance.

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