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Evaluation of Graduate Student Innovation Capability Cultivation Based on Self-Organizing Networks

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Abstract: Cultivating graduate students' innovative capabilities is an essential goal of graduate education. The evaluation of innovative capabilities helps identify students' unique abilities and potential, promotes the adjustment of educational methods, guides universities to optimize curriculum settings and training strategies, thereby enhancing graduate students' practical application capabilities and research levels. This paper establishes an evaluation model for the cultivation of academic graduate students' innovative capabilities based on the Self-Organizing Feature Map neural network. Relevant data is collected through survey questionnaires, and the Self-Organizing Map neural network model is implemented using MATLAB, with appropriate input data and features selected, and the structure and parameters of the Self-Organizing Network are determined. Finally, the Self-Organizing Network model is used to classify and score academic graduate students at a university in Sichuan.

1. Introduction

Cultivating graduate students' innovative capabilities is an important means and content to improve the quality of graduate training and to help build a university's independent innovation system. The effectiveness of graduate students' innovative capability cultivation needs to be evaluated through appropriate methods and evaluation models. Scholars at home and abroad have conducted extensive research in this area[1].

At present, there are still some issues in the cultivation and evaluation of graduate students' innovative capabilities in China, lacking evaluation perspectives and methods that are multi-angle, dynamically changing, and open and inclusive[2]. Evaluating the cultivation of graduate students' innovative capabilities based on self-organizing neural networks can fully reflect the multi-dimensional and multi-level aspects of graduate students' innovative capability cultivation. It not only focuses on the performance of graduate students in their degree theses but also pays attention to scientific research projects, academic papers, patent inventions, entrepreneurial practices, and other aspects. It is a dynamic evaluation model carried by self-organizing networks, with tutors as nodes and graduate students as users, which analyzes behaviors such as academic exchanges, knowledge sharing, and collaborative task completion between teachers and students. It comprehensively measures factors such as the guidance level of tutors, the learning outcomes of graduate students, and academic contributions, achieving a comprehensive, objective, and effective evaluation of the process and results of graduate students' innovative capability cultivation.

2. Improvement of SOM Learning Algorithm

The commonly used learning methods for SOM are sequential algorithms and batch learning algorithms, both of which are unsupervised and have the problem of excessive learning iteration times[3][4]. Drawing on the fuzziness characteristics of human brain thinking and based on fuzzy set theory, a fuzzy learning method is proposed for SOM. The basic idea is to construct a fuzzy entropy criterion as the learning criterion for SOM. Obviously, the learning goal under the fuzzy entropy criterion is to find appropriate feature weights so that the fuzziness of classification is minimized, and the difficulty lies in how to reasonably choose the membership function of the fuzzy set[5].

Drawing on the fuzziness characteristics of human brain thinking and based on fuzzy set theory, a fuzzy learning method is proposed for SOM. The basic idea is to construct a fuzzy entropy criterion as the learning criterion for SOM. The fuzzy entropy criterion function is constructed as

$$H = \frac{1}{p}\sum_{j=1}^{p} H(B_j) \tag{1}$$

In the formula: $B_j(j=1,\Lambda,p)$ is a fuzzy subset of the input mode set $A=\{A_1,A_2,\Lambda,A_m\}$, representing p fuzzy classifications of A,In other words, $f_j(j=1,\Lambda,p)$, and $H(B_j)$ is the fuzzy entropy of the fuzzy subset B_j.

$$H(B_j) = \frac{2}{m}\sum_{k=1}^{m} | X_{B_j} - \mu_{B_j}(A_k, W_j) | \tag{2}$$

In the formula: $\mu_{B_j}(A_k,W_j)$ is the membership degree of the input pattern A_k to the fuzzy subset B_j, and X_{B_j} is the characteristic function of the ordinary subset that has the minimum distance to the fuzzy subset B_j. Clearly, the learning objective under the fuzzy entropy criterion is to find appropriate feature weights that minimize the fuzziness of the classification.

At the same time, the concept of attribute variance is introduced into the SOM model, replacing the elements of the U-matrix with attribute variance. Assuming a rectangular SOM display S has p rows and q columns, as follows:

$$S = \begin{pmatrix} s_{11} & s_{12} & \Lambda & s_{1q} \\ s_{21} & s_{22} & \Lambda & s_{2q} \\ \Lambda & & & \\ s_{p1} & s_{p2} & \Lambda & s_{pq} \end{pmatrix} \tag{3}$$

In the formula: $s_{ij}(i = 1,2,\Lambda\ , p, j = 1,2,\Lambda\ , q)$ represents the weight vector associated with the corresponding SOM node. Each weight vector contains m elements, where m is the number of attributes in the input matrix M_2. The s_{ij} contained elements can be represented as $w_{ij1}, w_{ij2}, \Lambda\ , w_{ijm}$.

The attribute variance matrix has p rows and q columns, as follows:

$$AM = \begin{pmatrix} a_{11} & a_{12} & \Lambda & a_{1q} \\ a_{21} & a_{22} & \Lambda & a_{2q} \\ \Lambda & & & \\ a_{p1} & a_{p2} & \Lambda & a_{pq} \end{pmatrix} \tag{4}$$

Element a_{ij} reveals the variance of all elements in s_{ij}.

3. Evaluation Indicator Set

The formation of graduate students' innovative capabilities is a complex dynamic system influenced by many factors. Among these factors are the graduate students' own knowledge, abilities, psychology, attitudes, as well as the guidance of tutors, the environment of the school, and the demands of society[6]. In recent years, many scholars have adopted an evaluation method based on three dimensions: "Innovative Basic Abilities," "Innovative Knowledge Abilities," and "Innovative Practice Abilities."[7][8][9] This study draws on the above methods and borrows the SLA model from the field of information service evaluation to construct the following set of indicators:

Table 1. Graduate Student Innovative Capability Evaluation Indicator Table

First-level Indicator	Second-level Indicator
Innovative Basic Ability	The number of Chinese journals read a
	Course grades b
	Evaluation by professional tutors c
	The number of English journals read d
Innovative Knowledge Ability	The number of academic papers published e
	Project contribution ranking f
	Number of scientific research projects g
	Number of academic exchange meetings attended h
Innovative Practice Ability	Days of enterprise internships i
	Number of participations in scientific and technological competitions j
	Number of awards in scientific and technological innovation competitions k
	Duration of social practice l

4. Data Collection

4.1 Questionnaire Design

The questionnaire is designed based on the indicator system. The basic information part mainly collects information such as the respondent's gender, grade, master's type, discipline affiliation, consistency between undergraduate and graduate majors, and the number of students guided by the tutor. This is to classify and analyze the respondents to explore the similarities and differences in scientific and innovative capabilities among different types of respondents. The part on graduate students' participation in scientific and innovative activities mainly collects information on the respondents' extracurricular reading, course grades, tutor evaluations, academic papers, scientific research projects, academic exchange meetings, enterprise internships, scientific and technological innovation competitions, and social practice. This is to quantify and assess the respondents' scientific and innovative capabilities and to explore the extent and mechanism of influence of different activities on scientific and innovative capabilities. The overall statistics of graduate students' innovative capabilities mainly collect the respondents' self-assessment of their scientific and innovative capabilities, including seeking help, work quality, exceeding expectations, using new methods, proposing new ideas, being rigorous, observant, having strong memory, rich association, being praised, pioneering fields, being independent, integrating theory with practice, focusing on related disciplines, discovering problem links, thinking from multiple angles, exchanging results, and dealing with emergencies. This is to qualitatively and comprehensively explore the composition and contribution of different dimensions to the scientific and innovative capabilities of the respondents. The open-ended question part mainly collects the respondents' suggestions or opinions on improving the scientific and innovative capabilities of graduate students. This is to understand their needs and expectations in scientific and innovative capabilities from the respondents' perspective, providing references and basis for proposing effective enhancement strategies.

4.2 Questionnaire Sample Statistics

The survey questionnaire was distributed online, and the main target of the survey was academic master's degree graduate students at a finance and economics university in Sichuan. A total of 391 questionnaires were collected, of which 357 were valid and 34 were invalid. The effective recovery rate of the questionnaire was 92%. The coverage of the valid samples is shown in the table below:

Table 2. Survey Questionnaire Valid Sample Characteristic Distribution

Variable	Category	Number of People	Percentage
Gender	Male	178	50.28%
	Female	179	49.72%
Grade	First year of graduate	117	33.33%
	Second year of graduate	110	30.56%
	Third year of graduate	130	36.11%
Master's Type	Academic Type	357	100%
	Professional Type	0	0%
Discipline Affiliation	Economics	78	22.50%
	Public Administration	65	18.06%
	Business administration	79	21.94%
	Other	135	37.50%
Consistency between Undergraduate and Graduate Majors	Yes	142	39.44%
	No	215	60.56%
Number of Students Guided by	1-2	116	32.22%

Tutors	3-4	177	50.00%
	More than 5	64	17.78%

From the table, the following characteristics of the sample can be seen:

The gender distribution is relatively balanced, with the male-to-female ratio being close to 1:1, indicating that there is no obvious gender bias in the recruitment of academic master's degree graduate students.

The grade distribution is relatively uniform, with the proportions of the first, second, and third years of graduate study being 33.33%, 30.56%, and 36.11%, respectively. This indicates that the training cycle of academic master's degree graduate students is basically three years, and there are not many cases of early graduation or delayed graduation.

The discipline affiliation distribution is relatively diverse, with the "Other" category having the highest proportion, reaching 37.50%. This indicates that the sample covers a variety of different academic fields and has a certain degree of representativeness. The proportions of Economics, Business Administration, and Public Administration are similar, at 22.50%, 21.94%, and 18.06%, respectively, indicating that the scale of academic master's degree graduate students in these three academic fields is quite similar.

The distribution of consistency between undergraduate and graduate majors shows that 60.56% of graduate students' undergraduate majors are inconsistent with their graduate majors, and only 39.44% of graduate students' undergraduate majors are consistent with their graduate majors. This indicates that the phenomenon of professional conversion among academic master's degree graduate students is quite common, which may be related to personal interests, employment prospects, enrollment policies, and other factors.

5. Model Construction

5.1 Network Structure and Hierarchical Settings

This study uses the MATLAB programming language to construct a Self-Organizing Map (SOM) neural network model and trains and tests the research model based on the evaluation indicators and dataset.

The SOM network consists of two layers: one is the input layer, and the other is the competitive layer. The input layer receives an input vector and transmits it to the competitive layer. The competitive layer is composed of multiple neurons, each with a weight vector identical in dimension to the input vector. When a data sample is input, the neurons in the competitive layer compete to become the winning node, i.e., the nearest neighbor node, based on their distance to the input sample. The winning node and the nodes within its neighborhood update their weight vectors to be closer to the input sample. The termination condition is set to a maximum of 200 iterations or an error less than 0.01. The network structure settings in the MATLAB program are shown in the following figure:

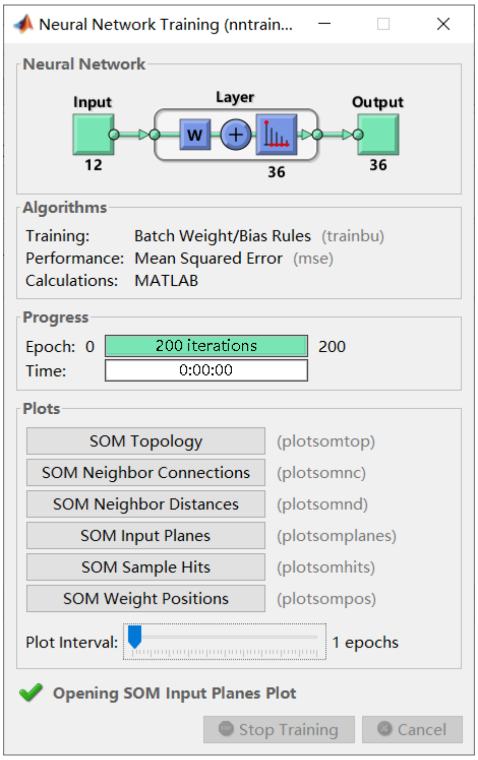

Figure 1. Network Structure Diagram

Since the indicator system includes 12 indicators, the number of neurons in the input layer of the SOM network is set to 12. The input vector is divided into 4 categories, called Class 1 to Class 4. To enhance classification capabilities, the number of neurons in the competitive layer is set to 36, in a 6x6 grid formation.

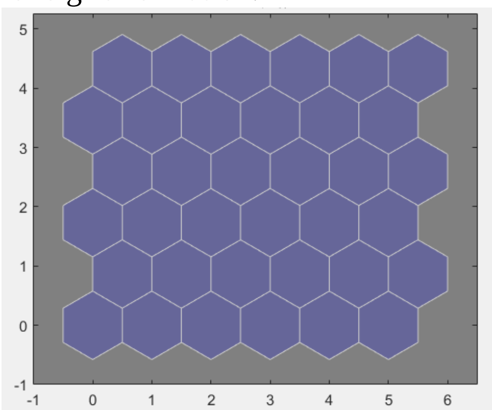

Figure 2. SOM Topology Diagram

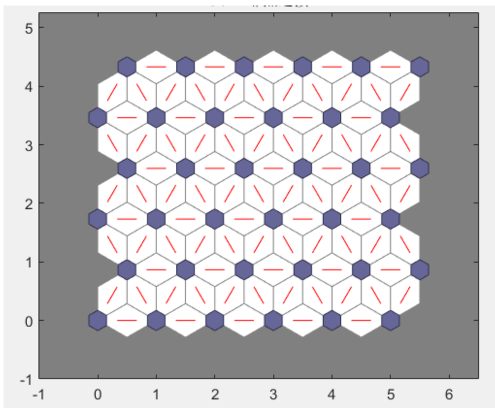

Figure 3. SOM Neighbor Connection Diagram

The above two figures represent 36 neurons, showing the position and connection relationships of the 36 neurons in the output layer. Each neuron is represented by a circle, and each connection is represented by a line. The distance between neurons reflects their similarity; the closer the distance, the higher the similarity. The color between connections reflects their strength; the darker the color, the stronger the strength. The topology diagram helps us visually observe the relationships between neurons and clustering results.

5.2 Parameter Training

When training the SOM network, some parameters need to be set and adjusted, including the distance function, neighborhood function, learning rate, neighborhood radius, decay function, and termination conditions. This paper uses the mean-variance normalization method for preprocessing of indicator data; the Euclidean distance is used as the distance function; the Gaussian function is used as the neighborhood function; the initial value of the learning rate is set to 0.1, and an exponential decay function is used to gradually reduce the learning rate; the initial value of the neighborhood radius is set to 5, and an exponential decay function is used to gradually reduce the neighborhood radius. The exponential decay function is multiplied by a constant less than 1, such as 0.99, after each iteration.

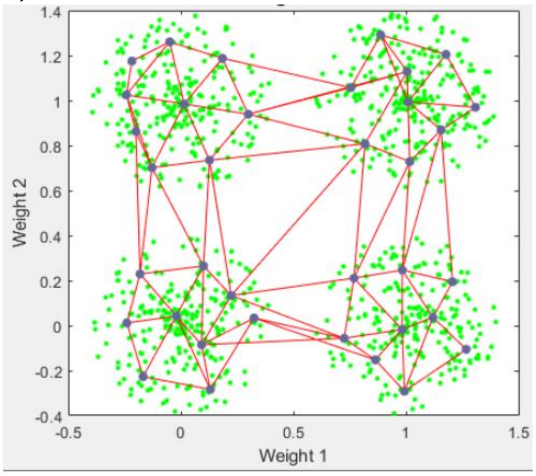

Figure 4. SOM Weight Position Diagram

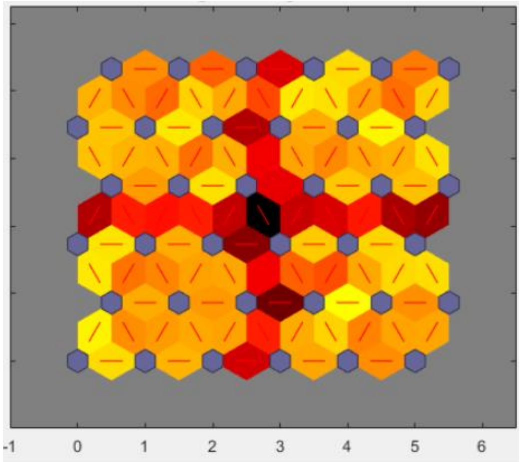

Figure 5. Distance Between Neighboring Neurons

After training is completed, four sets of light-colored line segments have appeared in Figure 45, which can be bounded by some darker line segments. This indicates that the grid has clustered the data into four groups. The situation of these four groups can be seen in the previous SOM weight position diagram.

From the weight position diagram, we can find that the weight vectors of neurons within each group are relatively close, while the weight vectors of neurons between different groups are relatively far apart. Further analysis of the characteristics and differences of each group can also be made by observing the number of samples and feature means within each group.

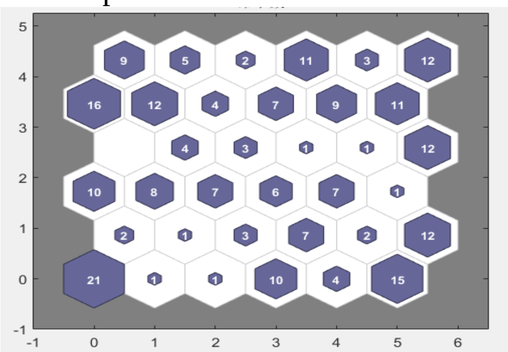

Figure 6. SOM Sampling Hit Count

The above figure shows the number of data points associated with each neuron. The data is more uniformly distributed around the neurons and sparser in the center. The overall distribution is relatively uniform.

5.3 Clustering Results

After clustering each cluster, the obtained average values are as follows:

Table 3. Average Values After Clustering

Cluster	1	2	3	4	5
Reading the number of Chinese journals	4.19	5.15	3.7	5.2	0.1
Reading the number of English journals	6.2	3.2	2.1	2.5	0
Course grades	92	87	83	85	76
Project contribution ranking	1.4	2.3	3.5	6.5	8.7
Evaluation by tutors	95	92	85	83	85
Number of academic papers published	6	2	1.5	1	0.3
Number of scientific research projects	3	2	2.1	1.3	0.5
Number of academic exchange meetings attended	15	12	14	10	6
Duration of enterprise internships	187.25	188.6	165.3	212.2	258.1
Number of awards in scientific and technological innovation competitions	8.6	7.3	6.6	2	0
Number of participations in scientific and technological innovation competitions	8	6.53	5.3	3.45	0.65
Duration of social practice	53.1	42.1	30.2	24.5	18.1

After classification by SOM, the following information is obtained:

Table 4. Sample Information After Clustering

Cluster	Excited Neuron Number	Comprehensive Evaluation Value of Independent Innovation Capability for Each Cluster
1	4	97.21
2	5	87.96
3	3	76.54
4	8	69.24

Based on the above table, the levels of each cluster can be defined. Cluster 1's innovative capability is defined as "High Innovative Capability," followed by Cluster 2 "Upper-Medium Innovative Capability," Cluster 3 as "Lower-Medium Innovative Capability," and Cluster 4 is defined as "Low Innovative Capability."

5.4 Model Verification

To evaluate the clustering effect of the Self-Organizing Map network, this paper first uses two methods: one is to use quantitative error to measure the network's fit to the input data; the other is to use the silhouette coefficient to measure the network's separation of the input data.

Quantitative error refers to the average value of the distance between the input samples and their corresponding winning nodes. It reflects the network's reconstruction capability for input data. The smaller the quantitative error, the higher the network's fit to the input data. The silhouette coefficient is an indicator to evaluate the quality of clustering results. It comprehensively considers the similarity of each sample to other samples within the same category and the dissimilarity to other samples in different categories. The larger the silhouette coefficient, the better the clustering result.

Using the test set to test the well-trained Self-Organizing Map network, the following results are obtained:

Table 5. Results of the Test Set

Indicator	Value
Quantitative Error	0.133
Silhouette Coefficient	0.577

From the results, it can be seen that the Self-Organizing Map network has good fitting and separation capabilities for the test set, indicating that the model is effective.

6. Conclusion

Through unsupervised clustering of the collected data using the SOM model, graduate students can be divided into five categories: High Innovative Capability, Upper-Medium Innovative Capability, Medium Innovative Capability, Lower-Medium Innovative Capability, and Low Innovative Capability. The differences among these types are as follows:

High Innovative Capability Category: Graduate students in this category show a high level in all dimensions, especially in innovative thinking, knowledge, and outcomes, which are significantly better than those in other categories. These graduate students have a strong sense of innovation and motivation, are good at using various innovative methods and skills, have mastered a wealth of innovative knowledge and skills, and can produce high-quality innovative outcomes in scientific research practice, such as academic papers, patents, awards, etc.

Upper-Medium Innovative Capability Category: Graduate students in this category show a good level in all dimensions, but there is still a certain gap compared with the High Innovative Capability category. These graduate students have a certain level of innovation awareness and motivation, have mastered some innovative methods and skills, have basic innovative knowledge and skills, and can produce some valuable innovative outcomes in scientific research practice, but the quantity and quality are not yet prominent.

Lower-Medium Innovative Capability Category: Graduate students in this category show an average level in all dimensions, which is comparable to the overall average level. These graduate students have an average level of innovation awareness and motivation, understand some innovative methods and skills, have basic innovative knowledge and skills, and can produce some ordinary innovative outcomes in scientific research practice, but lack breakthroughs and influence.

Low Innovative Capability Category: Graduate students in this category show a lower level in all dimensions, below the overall average level. These graduate students lack a clear sense of innovation and motivation, lack effective innovative methods and skills, lack the necessary innovative knowledge and skills, and find it difficult to produce meaningful innovative outcomes in scientific research practice, or they merely repeat the work of others.

Using a random forest to further analyze the impact of each cluster attribute feature, the following feature weight diagram is obtained.

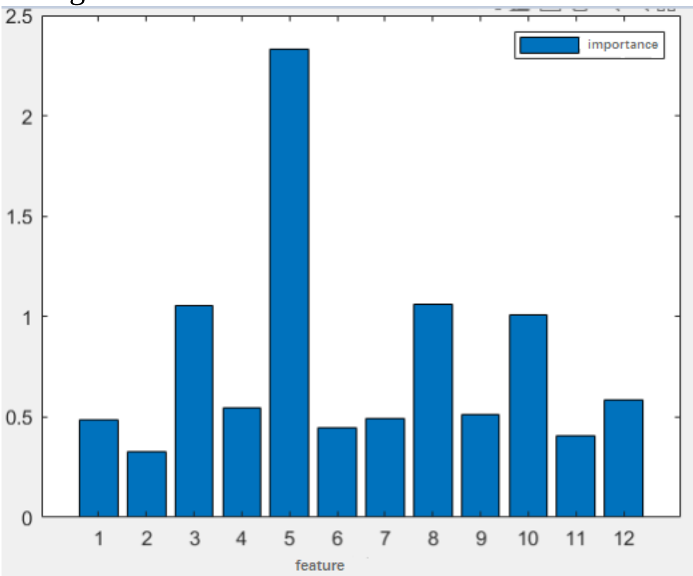

Figure 7. Feature Weight Diagram

The diagram has 12 features, with the horizontal axis representing the feature number, ranging from 1 to 12. It can be seen that: the weight of the 5th feature is the highest, at 2.43, indicating that thisfeature has the greatest impact on the innovative capabilities of graduate students. This feature represents the number of academic papers published, indicating that the number of academic papers published is an important indicator for measuring the innovative capabilities of graduate students, reflecting their knowledge innovation and academic communication abilities. The weights of the 3rd, 8th, and 10th features are next, at around 1, indicating that these features also have a significant impact on the innovative capabilities of graduate students. These features are the evaluation by professional tutors, the number of academic exchange meetings attended, and the number of awards in scientific and technological innovation competitions, respectively. They reflect the innovative foundational capabilities, innovative practical capabilities, and innovative outcomes of graduate students. The weights of other features are around 0.5, indicating that their impact on the innovative capabilities of graduate students is average. These features include the number of Chinese journals read, the number of English journals read, project contribution ranking, the number of scientific research projects, the duration of enterprise internships, and the duration of social practice. This suggests that while these features are related to the innovative capabilities of graduate students, they are not decisive factors. The weight of the 2nd feature is the lowest, at around 0.25, representing course grades, indicating that its impact on the innovative capabilities of graduate students can be almost neglected, possibly because the course assessment methods are not sufficient to reflect the innovative thinking and methods of graduate students.

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