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A study of university student's entrepreneurial intention based on influence factors

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ABSTRACT: In recent years, university student's entrepreneurship has been in a prosperous rise. Hence, there're more and more important functions in studying university student's entrepreneurial intention. With sufficient understanding of university student's entrepreneurial intention, we are able to provide timely and appropriate guidance and assistance which can have great reference value on university students, universities, and state policies. At present, qualitative research is the focus of related studies at home and abroad. The development of quantitative research is slow. In order to solve the influence and functions that influence factors have on university student's entrepreneurial intention, this thesis established mathematical models according to the relations among those influence factors. However, there's certain complexity in solving the influence factors of university student's entrepreneurial intention. In many cases, a single algorithm cannot well solve the problems of evaluation accuracy and fault-tolerant capability. By optimizing fuzzy comprehensive evaluation algorithm, this thesis introduced neural network into complex models and had training on the parameters of neural network in the introduced ant colony algorithm; thus obtained university student's entrepreneurial intention study model based on influence factor and a new thought on solution. With organic combination of algorithms, this thesis has innovated and improved the existing algorithms and their applying reliability and accuracy. Quantitative analysis and explanation about the influence factors in study of university student's entrepreneurial intention will be shown in this thesis.

Keywords: university student's entrepreneurship; fuzzy algorithm; influence factor; neural network; ant colony algorithm; entrepreneurial intention

1 INTRODUCTION

With steady upsurge of entrepreneurship in our society, university students have formed the major part of entrepreneurial groups. Starting their own business has become an effective method to solve university students' employment problems. Therefore, related policies have been issued by the state to encourage and support university students to have their own business. The main reason of studying university student's entrepreneurship is to find out their potential entrepreneurial intention. Only scientific study that mainly focuses on university student's entrepreneurial intention can better help set up scientific and effective policies and plans to manage and promote university student's entrepreneurial development in a reasonable and effective way. So far, there're many qualitative studies about the influence factors of university student's entrepreneurial intention in China. Although there're certain related quantitative studies, they are low in model precision and evaluation accuracy. Firstly, this thesis applied documentary summary to conduct classified studies on the influence factors of university student's entrepreneurial intention. By establishing related models, this thesis confirmed the weight relations among those influence factors. Then, it did detailed explanation on model solution. At last, this thesis demonstrated the scientificity and effectiveness of the method based on concrete example proof. It can offer us important reference about the influence factors of university student's entrepreneurial intention. [3] To sum up, mathematical models can help decide the influence factors of university student's entrepreneurial intention to some extent. Due to the subjectivity in fuzzy comprehensive evaluation, there'll be certain influence left on the accuracy of related model rating. By introducing neural network, this thesis did training on the evaluation matrix of fuzzy comprehensive evaluation algorithm. With various kinds of self-learning accomplished through network, the model for studying the influence factors of university student's entrepreneurial intention can have higher robustness and accuracy. Besides, this thesis introduced ant colony algorithm to optimize the cost function of neural network, so as to ensure the convergence and stability of the algorithm. In the meantime, the accuracy of the algorithm can be improved in order to obtain a model to study university student's entrepreneurial intention strategy based on the influence factors in an objective and just way.

2 PROBLEM DESCRIPTION AND ALGORITHM FLOW

2.1 *Description of fuzzy comprehensive evaluation algorithm*

In fact, many factors may leave different influences on the same thing at the same time. Therefore, comprehensive evaluation is needed. As there'll always be some fuzzy influence factors, a fuzzy mathematical method can be used to evaluate the fuzzy relation.

(1) Confirmation of comment collection. Use X to represent all possible comments. All comments constitute a comment collection.

$$X = \{x_1, x_2, \dots x_n\}$$

In which, each x_i, i=(1,2,…,n) refers to various possible results in evaluation. The most reasonable evaluation results of all factors can be obtained based on fuzzy comprehensive evaluation. Thus, we are able to get the most scientific and reasonable evaluation results for the evaluation objects. [4].

(2) Confirmation of factor collection. U refers to factor collection:

$$U = \{u_1, u_2, \dots u_n\}$$

In which, each u_i refers to all factors which may have influence on evaluation result.

(3) Single factor fuzzy evaluation. In one factor collection, there are i factors of u_i (1,2…,m) which need corresponding evaluation; and there are j factors in comment collection u_i (1,2…,m). Membership degree of x_j is r_{ij} (j=1,2,…,n). Thus, the influence evaluation collection of No. i factor u_i is $r_i = (r_{i1}, r_{i2}, \dots r_{in})$.

While doing criterion layer evaluation, firstly use each criterion layer to evaluate m schematic layers under the indexes. Evaluation matrix is consisted of the evaluation collections of indexes in schematic layers [3]

$$R_i = \begin{bmatrix} r_1 \\ r_2 \\ \cdots \\ r_m \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}$$

(4) Fuzzy comprehensive evaluation. In evaluation matrix R_i : No.i row of R_i can reflect the influence degree that No.i factor has on evaluation object. No.j series of R_i represents the membership degree that all factor influence evaluates. When there are weight set W and evaluation matrix R_i, fuzzy comprehensive evaluation method shall be used to evaluate:

$$A_i = W_i \bullet R_i = (w_{i1}, w_{i2}, \dots w_{im}) \bullet \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{mi} & r_{m2} & \cdots & r_{mn} \end{bmatrix} = (a_{i1}, a_{i2}, \dots a_{in})$$

$$A = W \bullet R = (W_1, W_2, \dots W_i) \bullet [A_1, A_2, \dots A_i]^T = (a_1, a_2, \dots a_n)$$

In which, "•" refers to specific function calculation. A_i refers to the evaluation matrix that No.i criterion layer evaluation index has on comment. A refers to the overall evaluation result matrix of evaluation object while being evaluated by comment in object layer.

(5) Establishment of weight set [5]. w_i refers to the weight value confirmed by the influence u_i of different factors; and the collection of w_i constitutes weight set W. Use analytic hierarchy process to confirm the weight between different influence factors and different weights.

$$W = \{W_1, W_2, \dots, W_i\}$$

$$W_i = \{W_{i1}, W_{i2}, \dots, W_{im}\}$$

Use W_i to represent criterion layer weight and set schematic layer weight as w_{im}. The constraint condition of weight number in each layer can be expresses as:

$$\sum_{n=1}^{n} w_i = 1,\ w_i \geq 0$$

Fuzzy comprehensive evaluation can analyze quantification from multiple angles; however, its algorithm is based on certain human factor's training. It is impossible to remove the human factors. Thus, this thesis introduced neural network to improve the algorithm of fuzzy comprehensive evaluation. By training weight matrix of fuzzy comprehensive evaluation, reverse evaluation can be made on risk rating, so as to have actual risk rating result better matching fuzzy comprehensive evaluation result. Besides, the learning process and knowledge structure can be stored in the neural network through the learning while fuzzy comprehensive evaluation alone can only have one-time input and output. If no neural network is introduced, fuzzy comprehensive evaluation cannot accomplish a two-step recognition. In this case, a new model must be constructed to solve the problem.

2.2 *Description of neural network*

Neural network is usually constructed through $m \times n \times l$ mode in which vector quantity is entered in m layer;

matrix is computed in the middle of n layer; and vector quantity is printed in l layer. Set parameter matrix dimensions: the first array is θ_1, the second is θ_2, and the rest can be done in the same manner. Thus, parameter $\{\theta_1, \theta_2, \ldots \theta_n\}$ corresponds to the linkage coefficient between enter vector and middle calculation matrix and the linkage coefficient between middle calculation matrix and printing vector. [6]

After constructing the neural network, do forward calculation on the network and print out cost function. By cancelling bias options, the cost function can be simplified as:

$$J(\theta)=\frac{1}{m}\sum_{i=1}^{m}\sum_{k=1}^{K}[-y_k^{(i)}\log((h_\theta(x^{(i)}))_k)-(1-y_k^{(i)})\log(1-(h_\theta(x^{(i)}))_k)]$$

It can be seen that the linkage between $h_\theta(x^{(i)})$ and each element can be computed, in which K=6 refers to the tagged value of the global mapping and $h_\theta(x^{(i)})= a_k^{(3)}$ to No.k trigger function of print vector. For calculation convenience, map the original tag and discriminate by {0,1}value.

$$y=\begin{bmatrix}1\\0\\\vdots\\0\end{bmatrix}, y=\begin{bmatrix}0\\1\\\vdots\\0\end{bmatrix}, y=\cdots, y=\begin{bmatrix}0\\0\\\vdots\\1\end{bmatrix}$$

In the original matrix, if the mapping value of $x^{(i)}$ is label 5, the corresponding $y^{(i)}$ (computed by cost function) shall correspond to the vector in the dimension of category number, in which y_5=1. Other elements shall be expressed as $y_i = 0$.

By forward mapping, each example that is focused in training can be mapped and output for summary. [7]

Bias is usually added while calculating the network. The cost function will be converted into:

$$J(\theta)=\frac{1}{m}\sum_{i=1}^{m}\sum_{k=1}^{K}[-y_k^{(i)}\log((h_\theta(x^{(i)}))_k)-(1-y_k^{(i)})\log(1-(h_\theta(x^{(i)}))_k)]$$
$$+\frac{\lambda}{m}[\sum_{j=1}^{25}\sum_{k=1}^{400}(\theta_{j,k}^{(1)})^2+\sum_{j=1}^{10}\sum_{k=1}^{25}(\theta_{j,k}^{(2)})^2]$$

Start reverse calculation after forward mapping. Reverse calculation is the core for the network to study. Through reverse calculation, we are able to obtain the gradient of the network. By gradient calculation, we can realize minimized setting on the network.

Applicable algorithms include {fmincg, GA, AP}. In order to obtain partial derivative of parameter, remove bias firstly, so as to obtain the right derivative calculation value by calculating gradient verification. Then, add bias into training.

In which, set mapping function as sigmoid() which can be expressed as follows in details:

$$sigmoid(z)=g(z)=\frac{1}{1+e^{-z}}$$

Then, start calculation for partial derivative. The solution equation for partial derivative is given below:

$$g'(z)=\frac{d}{dz}g(z)=g(z)(1-g(z))$$

By forward calculation, we can obtain $J(\theta)$ and cost function. Then, start reverse calculation and randomly initialize influence factors in order to break the symmetry inside the matrix. The idea of reverse calculation is: for one set of data ($x^{(t)}$, $y^{(t)}$) in the training matrix, the stimulation of the whole network and $h_\theta(x^{(i)})$ can be obtained by calculating forward spread value. After calculation is completed, start calculation layer by layer and point by point in $j \subset l$ so as to obtain the difference value $\delta_j^{(l)}$ which represents the explanation element scale of the overall erroneous evaluation degree.

For the output value corresponding to the last array of vector, we can calculate $\delta_j^{(l)}$ to obtain it. For the linkage node in the middle, we can obtain the $\delta_j^{(l)}$ of current layer by doing weighted calculation on the next layer, that is:

$$L+1 \mapsto L$$
$$R^{L+1} \Rightarrow R^L$$

After completing the cost mapping matrix calculation of the network, we shall start gradient calculation and verification. Use the above algorithm to complete the calculation; and then we shall start the learning of network parameters. Select fmincg function for learning can always get very good parameter collections. However, for quantitative evaluation, typical algorithms cannot well solve the problems of fault tolerance and robustness. This thesis introduced ant colony algorithm into neural network. By applying biological searching algorithm appropriate for solving discrete problem so as to obtain extreme value of cost function, we are able to realize high algorithm adaptability. [8]

2.3 *Ant Colony algorithm and its combination with neural network*

During the cost function optimization search process of ant colony algorithm, there are three main steps. First, disperse the solution space into continuous areas, where is n spaces, by inputting elements (ants) to do iterative search. During each time of iterative search, implement the set-up rules after screening all the elements, so as to update the solution. See Figure 1 for the dynamic deployment diagram of ant colony algorithm.

In ant colony algorithm, communication occurs between set-up information message receiving elements and elements. The self-learning of message receiving element can update the success rate for the algorithm to realize optimization search on the whole route and the influence factors which have major efficiency. Take three-dimensional structural point set as the basis of message receiving elements. Each point of the set carries information of a receiving element. By setting influence threshold value, we can express the attraction degree that message receiving elements have to elements. After element passes through all the points, message receiving elements will update self-learning. By setting related rules, we can set two layers as update mapping layer and the first layer as partial self-update layer. After element passes through all the message receiving elements, the information nodes carried by the receiving elements will decrease. Thus, we can obtain the probability of the missed points to be passed. The self-learning formula is as follows:[9]

$$\tau_{ijk} = (1-\varsigma)\tau_{ijk}$$

In which, τ_{ijk} refers to the message element of some point within the three-dimensional area, and ς refers to attenuation factor.

The second layer is global inside self-update, which means taking the bound norm of a path as dependent variable after element passes the whole path. Screen out the minimum norm value from the collection to obtain extra path element information. See the update model as follows:

$$\tau_{ijk} = (1-\rho)\tau_{ijk} + \rho\Delta\tau_{ijk}$$

$$\Delta\tau_{\mathrm{ijk}} = \frac{K}{\min(length(m))}$$

In which, *length*(*m*) refers to the number of the norms which have been passed by element, ρ refers to element update proportion, and K refers to global balance coefficient.

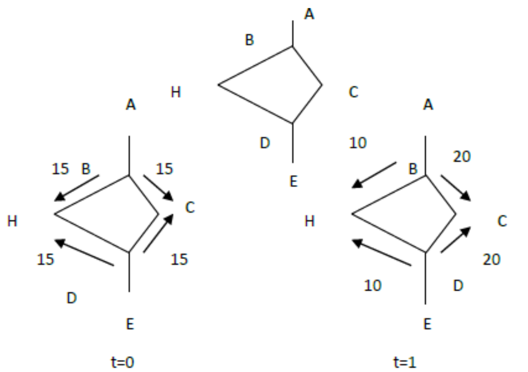

Figure 1. Dynamic deployment diagram of ant colony algorithm

3 ANALYSIS PROCEDURES AND CONCLUSIONS

Each factor that influences university student's entrepreneurial intention showed a complicated nonlinear status and there was intercoupling between variables. It is very hard to precisely describe a dynamic function or a describing function. However, neural network can well fit complicated nonlinear coupled functions and is very strong in decoupling. This thesis selected the influence factors which can influence university student's entrepreneurial intention as fuzzy evaluation factors and mapped the neural network. By using ant colony algorithm to seek optimum of extreme value among the cost functions in neural network, this thesis ensured the convergence and speed of iterative process. It selected the risk kinds and corresponding countermeasures. Through fuzzification, this thesis derived rating matrix and used the matrix as training data to do network training by normalization processing. Through training, the network learned about the data and established a model structure to ensure the hereditary characters of following actions. Thus, when similar engineering risk evaluation is needed, risk evaluation and strategy implementation can be started without any training. When a new problem occurs, the network just need to start topology of which the process is similar to human brain's continuous knowledge learning, knowledge conversion, and knowledge application. During the process, error correction and mapping are self-consistent without any requirement for human interference. See Figure 2 for the construction graph of fuzzy function network.

Select each influence factor for training. Set the number of training factor as *N*. This thesis selected 20 samples for training. By empirical analysis, data collections were obtained and introduced into the neural network for training. The structure of the network was set as seven layers as input layer, 10×12 matrix as intermediate hidden layer, and five layers as output layer. See the training process of cost function as follows:

Set a random initial point and a midpoint. Set the trigger function while element passes through all the points [10]:

$$H(i,j,k) = D(i,j,k)^{w_1} \bullet S(i,j,k)^{w_2} Q(i,j,k)^{w_3}$$

Set $D(i,j,k)$ as bound norm. Select the minimum

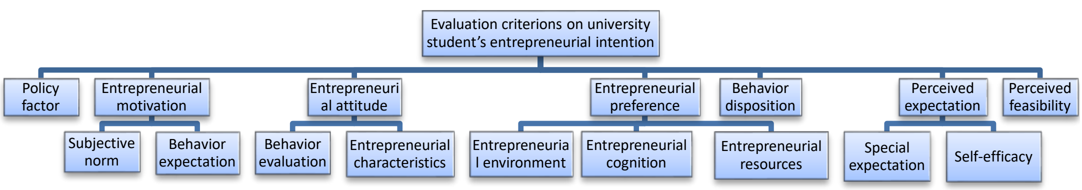

Figure 2. Construction graph of fuzzy function network

values of elements as priority. Set $S(i,j,k)$ as element safety evaluation index and $Q(i,j,k)$as the bound norm of the object in the next length.

Formula of $D(i,j,k)$:

$$D(i,j,k)=[(x_a-x_b)^2+(y_a-y_b)^2+(z_a-z_b)^2]^{\frac{1}{2}}$$

Formula of $S(i,j,k)$:

$$S(i,j,k)=\frac{N-M}{N}$$

Formula of $Q(i,j,k)$:

$$Q(i,j,k)=[(x_b-x_d)^2+(y_b-y_d)^2+(z_b-z_d)^2]$$

The search steps are as follows: [11]

(1) Map the discrete points of slice and decide point set.

(2) Calculate the trigger information between two adjacent points according to trigger functions.

(3) The extraction probability $p(i+1,u,v)$ of any point on slice is given below:

$$p(i+1,u,v)=\begin{cases}0, whenpossible=0\\ \dfrac{\tau_{a+1,u,v}H_{a+1,u,v}}{\sum\tau_{a+1,u,v}H_{a+1,u,v}}, whenpossible=1\end{cases}$$

(4) Start point set selection by roulette.

(5) Start parameter training through neural network. Obtain parameter collections and start iterative solution.

Compile MATLAB program and start neural network training. Convergence can be obtained after 27 times of training. See Figure 3 and 4 for the three-dimensional diagrams of the parameter selection process:

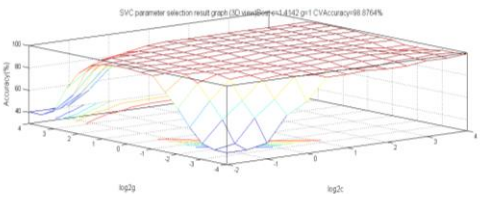

Figure 3. 3D result map of parameter selection

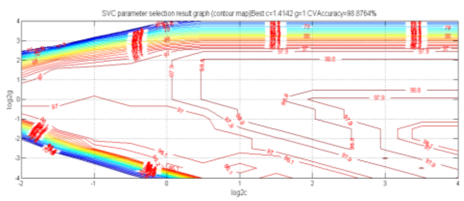

Figure 4. Isogram of parameter training

It can be seen from the above figures that parameter training mostly concentrated on edges. For data mapping, it can reflect the features contained in the applied evaluation strategy. By selecting and correcting parameters, we are able to improve the evaluation accuracy and robustness of the model.

For ant colony algorithm, see Figure 5 for the algorithm fitness changes.

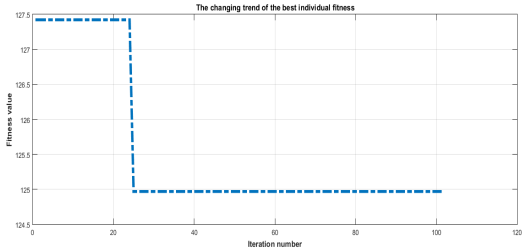

Figure 5. Algorithm fitness curve

Verification is needed after the network is well trained. This thesis divided the sets into training set, cross verification set, and verification set. It randomly selected five samples from the verification set for verification and simulation. See Figure 6 for the simulation result.

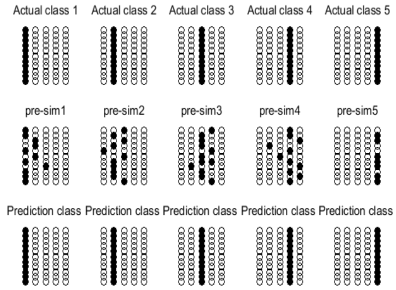

Figure 6. Simulation result figure

From the simulation result, we can see that for an actual rating project, we are able to obtain the maximum probability value corresponding to the right solution by dispersion and learning of the simulation layer. By evaluating randomly selected intention, we can prove the generalization ability and precision of the network.

4 DISCUSSION AND OUTLOOK

This thesis introduced ant colony algorithm in the model to study university student's entrepreneurial intention. As a representative of intelligent colony effect, ant colony algorithm has extremely expanded scientific researchers' thinking and exploration range. It has gradually become a research hotspot in each area. By realizing deep optimization on intelligent algorithm, this thesis succeeded in improving algorithm robustness and accuracy. By introducing ant colony algorithm into the complex model and realized optimization and training on neural network, this thesis obtained an efficient model for rating and a solution thought. The thorough application of ant colony algorithm has helped promote and enlighten related work. Through the path analysis in the model, we can know the most influential factor of university student's entrepreneurial intention at present is the right cognition of entrepreneurship. Therefore, enhancing university students' cognition on entrepreneurship during their campus life can greatly improve their entrepreneurial intention. Establishment of a systematic cognition system for university students can be an effective support for current university students. Meanwhile, cultivating university student's entrepreneurial spirit and creating good entrepreneurial policy environment constitute an important factor that has great influence on university student's entrepreneurial intention. Based on the study results mentioned above, certain enhancement can be given on university student's entrepreneurial cultivation, entrepreneurial protection, and entrepreneurial support in the future. The innovativeness of this thesis lies in its introduction of mathematical algorithm into research model. With the organic combination of research model and mathematical algorithm, innovation and improvement can be realized on current algorithm, so as to improve its applying reliability and accuracy.

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