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Influence of College Students' Social Development on Education of Entering College

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Abstract. To improve accuracy of predictive analysis of college students'social development impacts, a method of predictive analysis of college students'social development impacts based on ant colony optimization self-organization neural network is put forward. Firstly, establish predictive analysis index system of college students'social development impacts by using social development rating scale, overall well-being scale and social support rating scale based on subjective well-being index; Secondly, introduce self-organization neural network to realize the construction for predictive analysis model of college students'social development impacts by using fuzzy similar matrix and ant colony optimization; and finally, the validity of algorithm is verified and the influence factors of college students'social development are commented and analyzed through instance anlysis, used for guiding the practical work.

Key words. Ant colony algorithm, Self-organization neural network, College students, Social development, Predictive analysis, Subjective well-being index.

1. Introduction

Pursuit of happiness is the objective of everyone, and subjective well-being (SWB) refers to an overall evaluation of quality of life made by individuals according to their standard set by themseves, which is an important psychological index weighing people's quality of life, including life satisfaction (cognition of SWB), positve emotional experience and negtive emotional experience (emotion of SWB).

Social development of college students is an important subject of development at university level, and at the same time contemporary college students are 'semi-social man' who face multiple pressures from academic work, employment and life etc., affected by two-sided from schlool and social. Improvement of college students'

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SWB needs to take students'social development situation into account. A research of Yan Biaobin et al found social support of college students is an important predictive factor of SWB, different aspects of social support have an effect on different aspects of SWB. Meanwhile, many scholars have conducted researches to the relations between social support and SWB, among which the majority are about researches of the aged, also about SWB of stay-at-home children conducted by Zhang Lifang. Ma Donghui and Li Yi thought, the main influence factors of college students' social development are education and teaching system, teachers and peer groups, affected by mass media such as the Internet, television, newspaper and magazines etc, among effects of the Internet shall be paid more attention, for which it is in the virtual world of Internet that people are easily to obtain social support and self-worth. Thus it can be seen that there may be relations between social development and social support, SWB of individuals. The relationships between the level of the social development of contemporary college students and social support as well as SWB need to be studied for discussion.

The study starts with SWB and social support, a method of predictive analysis of college students'social development impacts based on ant colony optimization self-organization neural network is put forward. Establish predictive analysis index system of college students'social development impacts and predictive analysis model of self-organization neural network by using social development rating scale, overall well-being scale and social support rating scale. Provide references for the psychological healthy education of college students through empirical study on relations of the three factors.

2. Object and method

2.1. Object

Seclect 240 college students with different grade, major, and gender in the school though method of stratified random sampling for questionnaire survey, collect 226 valid questionnaires (94%). Grade: freshman 50 (22.1%), sophermore 56 (24.8%), junior 62 (27.4%), senior 58 (25.7%); Department type: science department 107(47.2%), Arts 119 (52.7%), Gender: male 105 (46.5%), Female 121 (53.5%).

2.2. Method

(1) Rating scale for social development level. *Rating Scale for Social Development Level of College Students* is prepared by Liu Jianrong, with 58 questions in total, including 3 subscales - subscale for cognition, subscale for emotion and subscale for behavior. In total points of subscale, 3-6 points represent severe sluggish development, 6-9 points representsluggish development, 9-12 points representmedium development and above 12 points representgood development. Test the restest reliability and internal consistency reliability are conducted in the scale, internal consistency coefficient of each subscale and total scale is between 0.83$\sim$0.94, which represents the scale has good reliability; Goodness of fit index (GFI) of each subscale and to-

tal scale is above 0.9 through analysis of construct validity and criterion relevance validity, which represents the scale has good validity.

(2) General Well Being (GWB). It contains two parts: Satisfaction with life scale (SWLS), Positive and Negative Affect Schedual(PANAS-R), 9 items in total. Consistency of PANAS-Rand SWLS is 0.55, internal consistency of general SWB is 0.56. Total scores of the scale is 14.7.

(3) Social support scale Adopt the*Social Support Rating Scale* revised by Xiao Shuiyuan in 1990 as measurement of individual social support situation. The scale contains 3 dimensions such as subjective support, objective support and support availability, 10 items in total, and for single choice, scoring is marked according to the serial number of choice question, while for multiple choice, according to the quantity of gerneral options; the scale has good reliability and validity for testing in domestic.

3. Fuzzy clustering method based on self-organization neural network model

3.1. Calculation of fuzzy similar matrix

For fuzzy clustering based on fuzzy similarity relation, establish fuzzy similar matrix at first, for which the key is to calibrate similarity coefficient. The similarity coefficient reflects similar degree of samples relative to certain attribute. There are many ways to determine the similarity coefficient, such as dot product method, included angle cosine method, correlation coefficient method, max-min method, arithmetic mean min method, geometric mean min method, absolute value index method, index similarity coefficient method, absolute counting backward method, absolute subtractive method, non-parametric method, close degree method, expert scoring method etc.

Assumed that $s = \{x_1, \cdots, x_N\}$ is the whole of sample objects, characteristic data of each sample x represented by $(x_{i1}, \cdots, x_{iN})$. Fuzzy similar matrix is $F_{(r_{ij})n\times n}$, similarity coefficient r_{ij} represents similar degree of sample i and j. The paper calibrates the similarity coefficient by adopting max-min method, namely:

$$r_{ij} = \left[\sum_{k=1}^{m} (x_{ik} \wedge x_{jk})\right] \Bigg/ \left[\sum_{k=1}^{m} (x_{ik} \vee x_{jk})\right]. \tag{1}$$

Where: $\wedge$ represents the minimum value to be taken, while $\vee$ represents the maximum value to be taken.

After treatment of calibration, elements in similar matrix R have been compressed into closed interval [0, 1], which can be directly usded as the input value of self-organization neural network.

3.2. Structure of self-organization neural network model

Self-organization neural network model is a network structural model with multu layer arborescence, which consists of the input layer and competitive layer (namely the output layer). In order to achieve non-linear dimensionality reduction mapping of the input signal and keep topology invariance when mapping to the similar neural tree, each input node of the model is associated with all neural trees and nodes though weight. The number of neuron of input layer is the number of row or column of fuzzy similar matrix (namely the number of sample in sample set), as shown in Fig. 1. Such structure can capture mode characteristic contained in each input mode and conduct self-organization to it by learning input repeatedly, show the classification result in competitive layer. When the Internet accpets an input similar to the memorial mode, the Internet will recall the mode and make correct classification. For the mode inexistent in the memory of Internet, self-organization neural network will memorize the mode without affecting the existing memory.

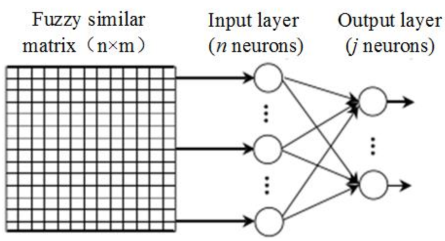

Fig. 1. Structure of self-organizaiton neural network model

Model learning sample consists of samples with N classification index, assumed that category of those dots in $N-$dimensional space is obviously same or some samples with similar characterisitc are close to each other in $N-$dimensional space, those samples will constitute one category, form a colony in $N-$dimensional space. When the input sample belongs to multi types, $N-$dimensional space will show a feature of multiple colony distribution. Each colony represents one type, center of the colony is the cluster center of type. The distance between samples belong to one type and the cluster center of such type shall be close. The distance can be measured by Euclidean distance.

$$D_j = \sqrt{\sum_{i=1}^{N} (x_i - W_{ij})^2} \,. \tag{2}$$

Where: x_i is the classification index, W_{ij} is the cluster center of dynamic type of class j, D_j is Euclidean distance.

3.3. Algorithm steps

Self-organization neural network learning algorithm dose not need teachers' signal, which uses the Euclidean distance between sample and cluster center to judge the type of sample, the algorithm steps are as follows:

Step 1: threshold β is given, which is used for controlling thickness of classificaiton, the bigger β is the thicker the classification is, and the fewer number of type is; when smaller β is, thinner theclassification is, and the more the number of type. Thus, tentative calculation shall be carried out to confirm β value according to the specific condition.

Step 2: the number of initial neuron in output layer is 1(namely $j = 1$), and a learning sample selected at ramdom is given the initial value, the connection weight W_{ij}.

Setp3: a new learning sample is input to calculate the Euclidean distance D_j between it and cluster center W_{ij} of each dynamic type.

Step 4: Output neuron with the minmum Euclidean distance D wins the competition.

$$D_j^* = \min\{D_j\} \,. \tag{3}$$

Step 5: if $D_j^* < \beta$, the current input sample belongs to the dynamic type represented by output neuron, adjustments to the connection weight W_{ij} will be made are as follows:

$$W'_{ij} = (x_i - W_{ij})/h_j \,. \tag{4}$$

Where: W'_{ij} is the adjusted value of W_{ij}, h_j is the number of current samples belong to class j. Then shift to the third steps.

Step 6: if $D_j^* \geq \beta$, which indicates that the output neurons win in the competition, however, the current input samples which can not be regarded as a dynamic type represented by the output neurons, belong to a new type, thus $j = j + 1$ shall be added in the output neurons to represent a new dynamic type, and the input sample shall be regarded as the initial value of $W_{i(j+1)}$. Then shift to step 3.

Step 7: Such circulation shall be carried out until all samples learning is finished. The output neurons of final network model are the number of type for all samples, and the connection weight is the cluster center value of each dynamic type.

The learning algorithm above shows self-organization neural network has the characteristics of plasticity and self-organized. Meanwhile, process of learning training of network is the process of dynamic classification for testing data, nework model established after training is the disaggregated model. A new testing data is obtained, network model can be input, and the dynamic type represented by output neurons and that wins in the final competition is the type of sample, which is the dynamic process of a new data recognized by model.

4. Parameter of ACO optimization self-organization neural network

4.1. Ant colony algorithm

Ant colony algorithm (ACO) is an intelligent algorithm raised for the discrete optimization problems at first, thus parameter of self-organization neural network is a continuous optimization problem, and corresponding improvement [31] must be made to ACO. Assumed that the following continuous optimization problems are taken into account:

$$y = \min f(x), X = (x_1, x_2, \cdots, x_d)\,. \tag{5}$$

The pheromone of ant in ACO reflects in the path of each discrete point, in this study, ant colony chooses the next marching approach according to the pheromone in certain region, the pheromone leechs on to the individual of colony, which represents the attraction degree of the individual to ants, the ants will release pheromone on the individual after leading them for optimizing.

4.2. Relevant settings on ACO algorithm optimization BP neural parameter

$knot(x_i, y_{i,j})$ is used to represent a node, x_i is the abscissa of segment $L_i, y_{i,j}$ is the ordinate of node j on segment L_i. Assumed that $\tau(x_i, y_{i,j}, t)$ representing the remaining pheromone in node $knot(x_i, y_{i,j})$ at moment t, pheromone on each node at initial moment is equal, namely $\tau(x_i, y_{i,j}, t) = \gamma(\gamma$ is the constant), the increasment of pheromone at initial moment is zero, namely $\tau(x_i, y_{i,j}, t) = 0$. η_{ij} represents the expectation degree of $knot(x_{i-1}, y_{i-1,j})$ to $knot(x_i, y_{i,j})$, which can be determined according to the heuristic algorithm and condition of questions, and the value is related to the objective function on last circulation. Assumed that $P_k\,(x_i, y_{i,,j}, t)$ representing the creeping probability of the k ant from $knot(x_{i-1}, y_{i-1,j})$ point to $knot(x_i, y_{i,j})$ at moment t, then:

$$P_k(x_i, y_{i,j}, _t) = \frac{\tau^{\alpha}(x_i, y_{i,j}, _t)\eta^{\beta}(x_i, y_{i,j}, _t)}{\sum\limits_{j=0}^{9} \tau^{\alpha}(x_i, y_{i,j}, _t)\eta^{\beta}(x_i, y_{i,j}, _t)}\,. \tag{6}$$

Assumed that all ants locate the origin of coordinates O at the initial moment $t = 0$, then, all ants creep to the terminal point from the starting point after n monment, then amount of information on each path point can be adjusted according to the following formula:

$$\tau\,(x_i, y_{i,j}, t+n) = \rho\,(x_i, y_{i,j}, t) + \Delta\tau\,(x_i, y_{i,j})\;, \tag{7}$$

$$\Delta\tau\,(x_i, y_{i,j}) = \sum_{k=1}^{m} \Delta\tau_k\,(x_i, y_{i,j})\,, \tag{8}$$

$$\Delta\tau_k\,(x_i, y_{i,j}) = \begin{cases} \dfrac{Q}{E_k}, & knot(x_i, y_{i,j}) \\ 0, & otherwise \end{cases} \tag{9}$$

Where, Q is the constant, E_k represents the cross validation error.

4.3. Steps of ACO algorithm optimizaiton self-organization neural network parameter

(1) Assumed that the number of ant is m, and each ant $k(k = 1\sim m)$ is defined one dimensional array $path_k$ with n elements. The longitudinal coordinates of the N nodes passed by the k ant are stored in sequence in $path_k$, which can be used to represent the crawling path of the k ant, and n is the total sigificance bit of optimized parameter.

(2) Assumed that the number of circulation $N = 0$, time counter $t = 0$, and the maximum number of circulation N_{max} and value of the amount of information $\tau(x_i, y_{i,j}, 0)$ on each node at initial moment isγ, aussumed that $\Delta\tau(x_i, y_{i,j}) = 0$, all ants are placed in the starting point O.

(3) Set variable $i = 1$.

(4) Use formula (15) to calculate the probability of each node transferred by those ants on segment L_i; roulette wheel selection method is adopted to choose a node for each ant k(k $= 1\sim m$) on segment L_i, and transfer the ant k to the node. At the same time, longitudinal coordinates of the node is stored into the i^{st} element of $path_k$.

(5) Set $i = i{+}1$, if $i \leq n$, then skip to step (4), or skip to step (6).

(6) Calculate the parameter of corresponding self-organization neural network of the path according to the path crawled by ant k, namely the array $path_k$.

(7) Divide the training sample on average into k subsets S_1, S_2, ..., S_k, which are mutually uncorrelated.

(8) Calculate $k-$fold cross validation error according to the calculated parameter training of self-organization neural network.

①Initialization $i = 1$.

② Subset S_i is remained for test set, and the union set of rest subsets for training set to train self-organization neural network.

③Calculate the generalization error $e_i = mean(s_i - \widehat{s}_i)^2$ of the subset i, assumed that $i = i + 1$ and repeat step ② until $i = k + 1$.

④ Calculate the average value of the k generalization error to obtain $k-$fold cross validation error.

(9) Take $k-$fold cross validation error as adaptive value to record the optimal path of this circulation.

(10) Assumed that $t = t + n$, $N = N + 1$, update the amount of information on each node and reset all elements in $path_k$.

(11) If $N < N_{max}$, and whole ant colony have not converged to walk on the same path, all ants shall be placed on the starting point O again and skip into step (3); if $N < N_{max}$, and whole ant colony have converged to walk the same path, then the algorithm is over, and calculate parameter of corresponding self-organization neural network by using optimal path.

5. Experimental analysis

5.1. Overall condition for social development lever of college students

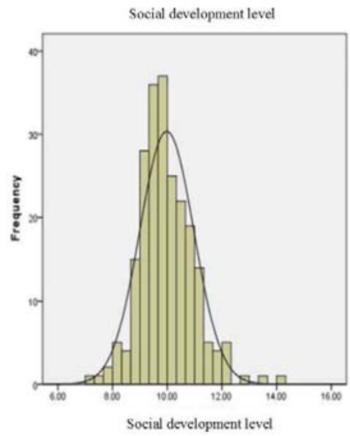

Fig. 2. Histogram for total points of college students' social development

Seen from Fig. 2, most of social development level of college students is in the range of 9 to 12 points, namely the social development level of college students is at the middle level.

5.2. Condition of college students'SBW

See table 1. It is shown from the statistical analysis of college students' SWB that average point of college students' SWB is (11.06±1.91), total points of the scale is 14.7 points, under 9 points is 18.9%, and above 11.5 points is 46.1%, above 13 points is 7.5%, college students' SWB is at the middle level.

Table 1. Conditons of college students'SWB

factor	$\bar{x} \pm s$
General emotion index	5.19 ± 0.84
Life satisfaction	5.87 ± 1.32
Subjective well-being(SWB)	11.06 ± 1.91

Table 2. Test for gender difference of college students' social support

Item	Gender	$\bar{x} \pm s$	t	P
Subjective support	Male	5.193 ± 0.883	-0.779	0.437
	Femal	5.277 ± 0.737		
Objective support	Male	2.978 ± 0.669	-2.070	0.040
	Femal	3.152 ± 0.593		
Support utilization	Male	2.609 ± 0.544	-4.806	0.000
	Femal	2.953 ± 0.529		
General social support	Male	10.742 ± 1.985	-2.724	0.025
	Femal	11.261 ± 1.634		

5.3. Results of gender difference in college students social support

Seen from Table 2 thatthere is no significant difference between male and female college students in subjective support, however there are significant differences in gender on 3 aspects such as objective support, support utilization and general social support, among them, female college students are significantly higher than male (P<0.05).

5.4. Correlation between college students'SWB, social support and social development level

See Table 3. Correlation analysis shows that both college students'SWB and social support, social development level of college students and social support , SWB and social development level are significantly correlated. Taking social support as the control variable, whether the key factor of analyzing the relation between social development level and SWB of college students by partial correlation is social support, whether two variables can still keep high correlation without social support? The result shows coefficient of partial correlation is 0.317, which represents there is a real correlation between social development level and SWB, and there is a direct relationship between social development level and SWB. According to the correlation analysis and partial correlation analysis mentioned before, relationships between social development level of college students, social support and SWB can be seen in Fig. 2

Table 3. Correlation of college students'SWB, social support and social development level(r)

Item	Subjective support	Objective support	Support utilization	General social support	Social development level
SWB	0.142*	0.163*	0.150*	0.207**	0.352**
Social development level	0.259*	0.138*	0.083	0.252**	–

6. Discussion

Social development level of college students in this study is at middle level, overall distribution is the range of 9 to 12 points, which indicates that our college students have fundamentally accquired relevant skills to participant in social life, and accepted values, ideological content, and social norms and other related behavior patterns which are advocated by society. In addition, they can successfully act as the role desired by the society; all those are related to family and school education, self-choice and growth of college students, as well as social support etc. At the same time there is a large capacity for growth of college students'social development level, and there is a certain distance to achieve a good level.

College students'subjective well-being is at upper middle level. Li Yinping's study found that level of college students'SWB is at upper middle level too. Studies of Yan Biaobin, Zhen Xue et al. also indicated college students'SWB is at middle level, which is related to broader horizon provided to college students by today's rapid development of Chinese economy and improvement of living standard, and the state'emphasis on education and psychological work actively carried at the university, all of which provide a better life, learning and entertainment environment for college students' healthy development.

There is a gender difference between college students in general social support and objective support, social support utilization, among them female college students are significantly higher than male, however, there is no difference between them in subjective support dimensionality, which consistent with the result of Yan Biaobin's research. Reasons for differences are related to the society and individual expectation of themselves to gender role. Compared with female college students, the male bears greater social pressure, and they are stricter to themselves, and at the same time, bearing responsibilities and to be a tough man are the expected goal put to man by society while the female is required to be tender and virtuous. Such expected difference caused stronger achievemement motivation, and stronger competitive awareness of male who are not easy to give the impression of weakness, and more independent when they getting in troubles. Emotion of the female is delicate and explosure to outside, more external supports are needed mentally, and more independent on external, they prefer to seek some supports from their friends, intimate person when they getting in troubles.

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