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Study on Psychological Crisis Evaluation Combining Factor Analysis and Neural Networks*

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Effective and rapid psychological crisis evaluation under emergency is the basis to carry out psychological crisis intervention (PCI). In this paper, based on existing research, an index system to evaluate the state of psychological crisis is established and the index system is simplified by the model combining factor analysis and neural networks. Experiments illustrate that the training times, training time and maximum error of the combination model are 1445, 20.476 (s), 0.0011 respectively while the general neural networks are 5581, 115.610 (s), 0.0090 with 92 samples and the final diagnosis by the combination model are also exact.

Keywords: Psychological Crisis, Evaluation, Index System, Factor Analysis, Neural Networks

Introduction

In 1964, American psychologist G. Gaplan originally brought up psychological crisis (PC). He defined psychological crisis as the status of psychological unbalance in which individuals could neither avoid nor cope with sudden or serious life events (Gaplan, 1964). Once the psychological crisis occurs, the psychological crisis intervention (PCI) is needed immediately to recalibrate the mental situation to normal level, in case the individuals fall into a status of suffering, anxiety, coupled with desperation, autonomic symptoms and behavior disorder. However, the effective crisis intervention is dependent on accurate evaluation. Through evaluation, the psychologist can understand the individuals' crisis situation and their reactions thus effective crisis intervention can be carried out as soon as possible.

Myer and Williams (1992) proposed a three-dimensional triage evaluation model which provides a framework for understanding individuals' reactions during a crisis. The model presumes that reactions to crisis events are seen in three domains: cognitive, affective and behavioral (Myer, William, Ottens & Schmidt, 1992). Brende (1998) presented an evaluation model of phases based on his research on unprecedented and destructive floods from 1987 to 1998 in USA. In this article he says that survivors' predictable emotional and physiological responses usually process through five phrases over a period of time toward either resolution or symptom development. To preclude more severe and chronic symptoms, survivors should be debriefed by trained professionals within 48 hours (Brende, 1998). Wilson (1999) brought up a person-envi- ronment interactional model to explain the typologies of traumatic events and stressor dimensions. This model pays attention to comprehension of stress and its factors as well as the diversity of traumatic events (Wilson, 1999).

In this article, we propose a novel and effective method to evaluate PC. Firstly integrating the core idea of Myer and Williams, we establish an evaluation index system for psychological crisis. Further, considering the evaluation should be effective and valid, we put forward an evaluation model combining factor analysis and back-propagation neural networks. Through factor analysis, the intrinsic relationships among indices are eliminated, and the dimension of these indices is compressed while enough information is maintained. Moreover, the structure of the neural networks is simplified. Overall, the accuracy of networks' output is improved and the evaluation time is reduced.

Establishing Evaluation Index System

Evaluation index system has monitoring function which adopts one or more rigorous theories to analyze the causal relationship between individuals and development of crisis according to the status of the individuals.

The three-dimensional triage evaluation model proposed by Myer and Williams is considered to be a simple and rapid evaluation system. While in a state of emergency, it also requires that the evaluation and the diagnosis should be accurate; therefore the article starts to establish an evaluation index system to evaluate the state of psychological crisis.

When individuals face a crisis, they will conduct a series of physical and psychological reactions, and the reactions to the crisis are mainly in physical, emotional, cognitive and behavioral domains. Accordingly, the psychological crisis evaluation index system can be established from these four domains. The index system is shown in Table 1.

Using a 90-item self-report symptom inventory (SCL-90) for reference, we divide each specific index of the evaluation index system into five levels: not at all, a little bit, moderately, quite a bit, extremely (Holi, 2003). Each level is assigned a score from

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Table 1.
Psychological crisis evaluation index system.

reactions	indices
physical	gastrointestinal discomfort or diarrhea, poor appetite C_{11}
	headache C_{12}
	Fatigue, insomnia, nightmares, easily startled C_{13}
	Difficulty in breathing or there is a sense of choking or infarct C_{14}
	Muscular tension C_{15}
emotional	scared or suspicious C_{21}
	Depressed or sad C_{22}
	Irritable C_{23}
	helpless, insensitive C_{24}
	negative or lonely C_{25}
	disturbed or nervous C_{26}
	self-condemned C_{27}
	Too sensitive or alert, unable to relax C_{28}
	Continuously concerns over the safety of family members, fear of death C_{29}
cognitive	Immersed in the grief of body and mind, leading to changes in memory and perception C_{31}
	Trouble concentrating and the relations experienced between things are ambiguous, leading the ability of making decisions and solving problems affected C_{32}
	Sometimes be afraid of being mad C_{33}
	Lack of confidence, easily forgetful, performance degradation, could not turn attention from crisis to other things C_{34}
behavioral	Can not concentrate on studies or work C_{41}
	Avoid other people or make oneself feel not lonely in a special way C_{42}
	Have implemented disruptive behaviors on oneself or around C_{43}
	Refused to help and it is weak to accept the help C_{44}
	Behavior is inconsistent with thinking and emotions C_{45}
	Appear typical behaviors which did not occur in the past C_{46}

one to five respectively. According to the research on reliability and validity of SCL-90 by Chen Shulin and Li Lingjiang (2003), the reliability of SCL-90 is good overall, the inter-item consistency reliability of the general scale is 0.97 and those of subscales are over 0.69, the test-retest reliability is over 0.73. The construct validity of SCL-90 is also good, the correlation coefficients between the general scale and subscales are 0.79-0.92, and correlation coefficients among subscales are 0.59-0.83 (Chen & Li, 2003).

In SCL-90, the final score is the sum of all scores gained from each item and the minimum score is 90. Once the final score is more than 160 points, the examinee requires psychological counseling or advice. In this evaluation system, we set the final score to be the average of total scores, lowest score is 1.0, and the highest is 5.0. If the critical average score is more than 1.77 (160/90), the examinee has a certain mental disorder and the PCI is required. When the final score is in the interval of [1.0, 1.77) or [1.77, 2.77) or [2.77, 3.77) or [3.77, 4.77) or [4.77, 5.0], which indicates the examinees' five states of psychological crisis.

Factor Analysis

Since the evaluation index system has been established, now the factor analysis (FA) will be introduced to index compression.

FA is a widely used method of multivariate statistical analysis. This method is used to describe variability among observed variables in terms of a potentially lower number of unobserved variables called factors. If Z_i is the standardized variable of X_i, Z_i can be expressed a linear combination of factor variables F_n and error variable μ_i, the weight coefficients of F_n and μ_i respectively are c_{in} and d_i, that is

$$Z_i = \sum_{n=1}^{m} c_{in}F_n + d_i\mu_i \qquad (1)$$

where c_{in} is a factor loading expressing the linear correlation between factor p and variable i. Estimating factor loadings are intended to interpret the variation of data as much as possible. The first main factor has the strongest explanatory power for variation, while the second main factor is inferior and so on.

We designed the questionnaires according to the evaluation index system and sent out 110 questionnaires in the Wenchuan Earthquake place, we randomly chose the local residents as our examinees. At last we collected 103 samples, among them only 92 samples are valid, so we use the 92 valid samples to conduct the data analysis.

Before implementing FA, we firstly adopt Kaiser-Meyer-

Olkin (KMO) test and Bartlett's test of sphericity to test the data whether they are fit for FA. The values of KMO statistic between 0.7 and 0.8 are good, values between 0.8 and 0.9 are great and values above 0.9 are superb (Hutcheson & Sofroniou, 1999). For these samples, the value is 0.732, which falls into the range of being good, so we are confident that the FA is appropriate for these data.

The Bartlett's test of sphericity measures the null hypothesis that the original correlation matrix is an identity matrix. For a satisfactory FA to proceed, some relationship between variables are needed, in other words, we want this test to be significant as a significant test tells us the matrix is not an identity matrix. For these data, Bartlett's test is highly significant ($p < .001$). Therefore, FA is appropriate (Field, 2005).

We adopt principal component analysis to extract factors and varimax rotation method to progress factor rotation. Eigenvalues, the percent of variance attributable to each factor and the cumulative variance of the first 14 factors are shown in Table 2. From Table 2, we can see that the cumulative variance of the first 14 factors has reached 91.129%. To ensure adequate information is maintained and the eigenvalue is greater than one, ultimately there are 12 factors to replace the original 24 variables and 88.769% of total information is guaranteed.

According to rotated component score coefficient matrix, every factor can be expressed by a linear combination of the original variables. The main indices (loadings are more than 0.2) explain the 12 factors are shown in Table 3. Further, if we use each factor's percentage of variance explained as weight and sum up these 12 factors, the composite score of each sample can be gained.

From the above analysis, only 12 factors can well reflect the 88.769% information of original 24 variables, thus greatly reducing the dimension of evaluation and the correlation between variables.

Back Propagation Neural Networks

Back propagation neural networks (BPNN) are multilayer feed-forward neural networks (NN) based on back-propagation algorithm. The nonlinear processing ability of BPNN can process cognitive judgments in various complex environments effectively such as vague, incomplete and conflicting information. It is the most widely used NN model.

BPNN is a supervised learning algorithm. It is necessarily a multilayer perception (with input layer, hidden layers and output layer). The network structure of BPNN is in Figure 1: input vector is x_1, $x_2, \cdots$, x_m and output vector is y_1, $y_2, \cdots$, y_n. The learning process can be divided into two phases: (a) the information flow goes through input layer, hidden layers, output layer; (b) error back propagation network process, if the NN model does not get expected output value in output layer, the error signal propagates backward along the original pathway layer by layer, and adjusts its weights and threshold value. Kolmogorov theorem of neural networks has proved that a full learning three-layer BPNN can approximate any functions. Therefore we choose a three-layer BPNN with only one hidden layer. There is no theoretical guidance in selecting the number of hidden layer nodes currently. Too many nodes will increase the training time and weaken the networks' generalization and predictive ability, while too few nodes cannot reflect the correlation between the follow-up value and previous value and the model is insufficient. The number of nodes in hidden layer can refer to the following formula: $m_1 = \sqrt{m+n} + a$, where m_1 is the number of hidden layer nodes, m_1 is the number of input layer nodes, n is the number of output layer nodes, a is a constant between one and ten (Rafael, 2004).

Sample Classification and Neural Networks Design

Choose 10 testing samples from 92 samples as a test set. In test set each of the five states (not-at-all, a little bit, moderately, quite-a-bit, extremely) has two samples respectively. The other 82 samples are as a training set.

To reflect the difference whether carrying out FA before BPNN or not, we design two BPNN structures. In particular, we name the former one as factor-analysis-back-propagation (FABP) neural networks, while name the latter one as non-factor-analysis-back propagation (NFABP) neural networks.

- FABP: after FA, 12 factors are gained. Take the values of 12 factors in training set as input, well then the number of input layer nodes is 12. Take the corresponding composite scores of training samples as output and then the number of output layer nodes is one. According to the formula $m_1 = \sqrt{m+n} + a$ and experiment results, we decide the number of hidden layer nodes is eight. The maximum training times are 1500.
- NFABP: take the original data of training samples as input, well then the number of input layer nodes is 24; take the corresponding composite scores of training samples

Table 2.
Main variance explained.

Factors	F_1	F_2	F_3	F_4	F_5	F_6	F_7
Eigenvalues	3.025	2.874	2.226	2.100	2.067	1.994	1.917
Variance explained %	11.882	11.016	9.531	8.885	8.123	7.337	7.089
Accumulative variance explained%	11.882	22.898	32.429	41.314	49.437	56.774	63.863
Factors	F_8	F_9	F_{10}	F_{11}	F_{12}	F_{13}	F_{14}
Eigenvalues	1.882	1.843	1.756	1.087	1.052	0.876	0.853
Variance explained %	6.782	6.275	6.368	2.931	2.550	1.224	1.136
Accumulative variance explained %	70.645	76.920	83.288	86.219	88.769	89.993	91.129

Table 3.
Factors explained by mian indices.

Factors	The main indices
F_1	C_{26} C_{29} C_{23} C_{28} C_{15} C_{21}
F_2	C_{42} C_{45} C_{41} C_{22} C_{46} C_{43}
F_3	C_{11} C_{14} C_{13} C_{44}
F_4	C_{31} C_{44} C_{34} C_{32}
F_5	C_{32} C_{33}
F_6	C_{24} C_{25}
F_7	C_{34} C_{31} C_{44} C_{25}
F_8	C_{12} C_{24} C_{33}
F_9	C_{27} C_{43} C_{13} C_{25} C_{46} C_{33}
F_{10}	C_{21} C_{23} C_{15} C_{34}
F_{11}	C_{24} C_{31} C_{27} C_{22}
F_{12}	C_{41} C_{44} C_{42}

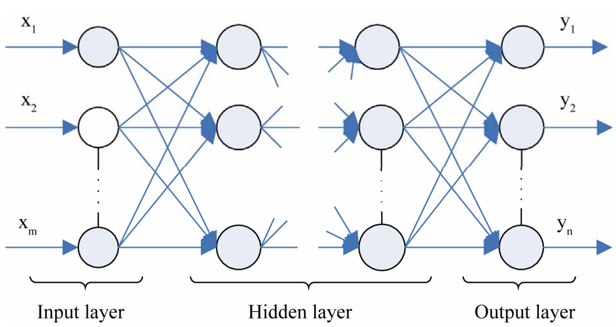

Figure 1.
Network structure of BP.

as output, and then the number of output layer nodes is one. According to the formula $m_1 = \sqrt{m+n+a}$ and experiment results, we decide the number of hidden layer nodes is 15. The maximum training times are 6000.

Now we determine other parameters in NN. Transfer function in hidden layer is "tan-sigmoid" while in output layer is "log-sigmoid". Make use of Levenberg-Marquardt back propagation algorithm to train the BPNN. Learning rate is 0.2 and momentum parameter is 0.8 with the training aim is 0.001. After training, two BPNNs are formed, one is FABP with structure of 12-8-1 and the other is NFABP with the structure of 24-15-1.

Results and Discussion

In order to compare the merits of FABP with the NFABP neural networks, record three parameters during the training phase: training times, training time and maximum error between the output and corresponding known composite scores. Arrange these results in Table 4.

From the above table, we can see that if we use raw data as input for NFABP, the training for the neural networks will take a long time and the test accuracy is not as high as FABP which has compressed the dimension of the input layer, and the maximum error of NFABP is larger.

Table 4.
Three parameters comparison between FABP and NFABP.

Types of NN	Training times	Training time(s)	Maximum error
FABP	1445	20.476	0.0011
NFABP	5581	115.610	0.0090

Table 5.
Comparison between the expected output and the actual output from FABP.

Expected output	Actual output	Error	Final diagnosis
1.00	1.0000	0.0000	Not at all
1.67	1.6696	0.0004	Not at all
1.96	1.9609	0.0009	A little bit
2.54	2.5398	0.0002	A little bit
3.06	3.0603	0.0003	moderately
3.29	3.2911	0.0011	moderately
3.88	3.8807	0.0007	Quite a bit
4.63	4.6297	0.0003	Quite a bit
4.92	4.9198	0.0002	extremely
4.86	4.8595	0.0005	extremely

Testing results of 10 testing samples by FABP is in Table 5. The results from FABP is almost accurate and the finally diagnosis is exact, so the FABP is a reliable evaluation method.

This paper proposes a novel and effective method which is the combination of FA and BPNN to evaluate psychological crisis statue. This combination model has the following advantages:

- FA can compress the dimension of the evaluation index system and eliminate the correlation between indices and factors.
- Taking 12 factors as input of the neural networks, this streamlines the structure of neural networks and reduces training costs and improves the output accuracy.
- The FABP neural networks model overcomes the subjectivity of traditional psychological crisis evaluation scale, which will give some ideas to psychological crisis evaluation.

In psychological crisis intervention, the evaluation is the prerequisites. Via evaluation, the psychologist can define the examinees' psychological condition, and then take steps to carry out the crisis intervention as soon as possible, such as to use the medicine or psychotherapy to adjust examinees' mental situation, to maximally release the negative impact on the examinees, physically and mentally, and then to lead them having a positive view of life.

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