Analysis of College Curriculum Construction and Student Employment Based on Non-Smooth Association Rules

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Abstract: With the continuous expansion of the scale of the students in the job market, their behaviors are becoming increasingly complex. The behavior of some students will have a great influence on the job market. If this kind of unexpected job market status change cannot be treated in a timely manner, it will cause more serious consequences to the job market, such as the job market node abnormalities, or even the job market paralysis and so on. Therefore, in order to maintain the smooth operation of the job market, it is necessary to analyze and quantify the influence of the employment behavior of the students on the change of the job market in a timely manner after the unintended fluctuations in the job market occur, so as to help identify the students who cause the changes in the job market, control the situation, investigate and hold them responsible for their behaviors, so as to avoid the occurrence of more serious consequences, and achieve effective management on the employment behavior of the students and the refined management on the job market.

1. Introduction

With the continuous expansion of the scale of the students in the job market, their behaviors are becoming increasingly complex. The behavior of some students will have a great influence on the job market. If this kind of unexpected job market status change cannot be treated in a timely manner, it will cause more serious consequences to the job market, such as the job market node abnormalities, or even the job market paralysis and so on. Therefore, in order to maintain the smooth operation of the job market, it is necessary to analyze and quantify the influence of the employment behavior of the students on the change of the job market in a timely manner after the unintended fluctuations in the job market occur, so as to help identify the students who cause the changes in the job market, control the situation, investigate and hold them responsible for their behaviors, so as to avoid the occurrence of more serious consequences, and achieve effective management on the employment behavior of the students and the refined management on the job market [1,2].

Quantitative evaluation of the student employment behavior has been widely applied in a number of fields, such as the credible evaluation method for the student employment behavior based on the evaluation feedback data in the E-commerce field [3~6], in which the power law [3], fuzzy logic [4], semi-ring algebra [5], probability theory [6] and other tools are used to quantify and evaluate the credibility value of the students. However, such feedback data can only reflect the evaluation of the application on the student employment behavior, while cannot reflect the job market status, hence it cannot be directly used to quantify the level of the influence of the student employment behavior on the changes in the status of the job market. Typically, for example, the AHP hierarchy analysis and evaluation method, it is on the basis of the well-established evaluation criteria (such as the ISO 7498-2 standard) to build evaluation indicators and use the AHP hierarchy analysis method to determine the weight, evaluate and quantify the effect of the behavior attack of the students. However, due to the weight distortion caused by the fuzzy nature that is easily introduced by the AHP hierarchy analysis method for the weight determination [7], some researchers also introduce the knowledge mining technology to improve the rationality of the weight, such as the combination of the fuzzy logic and AHP hierarchy analysis method [8], the combination of the gray theory and

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AHP hierarchy analysis method [9], the method based on the information entropy [10,11] and the non-smooth association rules [12] etc. Although these methods have achieved quite good result in the quantification of the student attack effect, these methods still have the problem of subjectivity and static nature of the evaluation indicator when they are applied to evaluate the level of the influence of the student employment behavior on the change of the job market status. On the one hand, the evaluation indicators constructed by the experience based, expert advice or evaluation criteria and other methods will inevitably bring the subjective assumptions, thus affecting the precision of evaluation [7]. On the other hand, the indicators and weights of the evaluation methods for the evaluation of the attack effect are static after the setting, while the job market and student employment behaviors are in the dynamic changes. The student employment behaviors that lead to the change in the job market may be different from each other, and the levels of the influence of the same student employment behavior in different job market environment (such as in the idle and busy time period of the job market) on the changes in the status of the job market are also different. Therefore, to accurately evaluate the level of the influence of the student employment behavior on the changes in the status of the job market, it is necessary to further deepen the application of the knowledge mining technology, so that the construction of the student employment behavior evaluation method indicators and weights can be both on the basis of the analysis and mining of the actual data of the student employment behavior and job market status. In addition, the indicators and weights can be adjusted dynamically with the change of the job market environment and student employment behavior, thus overcoming the defects of the subjectivity and static nature of the existing evaluation methods.

If the unintended changes in the status of the job market are caused by certain behaviors of the students, the specific characteristics of such behaviors must have strongly relevance to the changes in the status of the job market. Therefore, the association mining on the student employment behavior data and the job market status data can be used to help quantify the influence caused by the students and their behaviors on the changes in the status of the job market. The traditional association mining methods (such as the correlation analysis, etc.) often require artificial preset thresholds (such as the confidence, etc.). Once set incorrectly, it will influence the analysis results, while the non-smooth association rules [13] do not require any priori knowledge, which can adaptively identify the correlation between the data. Therefore, an adaptive student employment behavior evaluation method based on the non-smooth association rules is put forward in this paper. Under the premise without the need to preset the evaluation indicator or the weight, by introducing the non-smooth association rule reduction and association rule importance method, the analysis and mining on the student employment behavior and the actual data of the status of the job market are carried out. On this basis, the evaluation indicator and weight are set and adjusted adaptively to quantify the level of the influence of the student employment behavior on the change in the status of the job market. The experimental results show that this method can quantify the level of the influence of the student employment behavior on the change in the status of the job market more accurately compared with the traditional evaluation methods of the preset indicator and weight. The evaluation results are conducive to identify the students who have affected the operation of the job market, so as to formulate the corresponding student control strategy, and provide support for the effective control on the student employment behavior.

2. College Student Employment Behavior Evaluation Model Based on the Influence

In order to accurately quantify the influence of the college student employment behavior on the change in the status of the job market, it is necessary for the student employment behavior evaluation method based on the influence to first fully collect the student employment behavior and job market status data. And then the non-smooth association rule method based on the actual data is used to analyze the correlation between the different student employment behavioral characteristics and the change in the status of the job market. Then the minimum student employment behavior characteristic set related to the status change is specifically selected as the evaluation indicator, and its weight is set according to the degree of association. And finally, the influence of the student employment behavior is calculated according to the evaluation indicator and weight, to quantify and evaluate the data of the student employment behavior. On this basis, this paper puts forward the student employment behavior evaluation model by on the influence, including four modules, that is, the data acquisition, data preprocessing, evaluation indicator and weight setting, and student employment behavior evaluation, as shown in Figure 1.

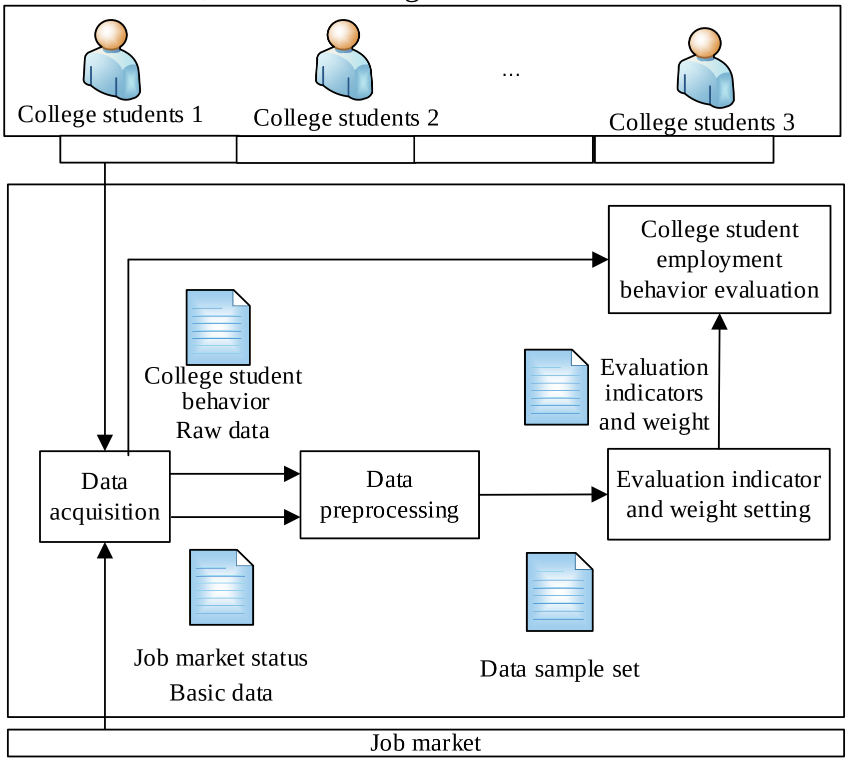

Fig.1 Student Employment Behavior Evaluation Model Based on the Influence

1) Data acquisition module: This module is only logically responsible to acquire the raw data of the student employment behavior and changes in the status of the job market, while in the implementation, the distributed third parties, such as NetFlowMonitor, Bandwidth Monitor and other collectors can be used for the construction.

2) Data preprocessing module: This module is responsible for the further standardization and discretization of the raw data generated by the acquisition module, and the construction of the data sample set used by the evaluation indicator and weight setting module. The specific treatment method is shown in Section 3.1.

3) Evaluation indicator and weight setting module: This module makes use of the association rule reduction and association rule importance method in the non-smooth association rules on the basis of the data sample set, to carry out mining and analysis on the correlation between the student employment behavior and the change in the status of the job market. Thus, it can identify the minimum student employment behavior characteristic set related to the change in the current status of the job market as the evaluation indicator, discard the irrelevant characteristics, and set the weight of the evaluation indicator according to the size of the correlation.

4) Student employment behavior evaluation module: The module carries out the quantification and evaluation on the student employment behavior data according to the evaluation indicator and weight. The evaluation value thus obtained can reflect the influence of the student employment behavior on the change in the status of the job market. The three modules including the data preprocessing, evaluation indicator and weight setting, as well as the student employment behavior evaluation can all be deployed in the central node of the job market management for the centralized processing. The data acquisition module is deployed in all the nodes of the job market. Therefore, in the system architecture, the evaluation model proposed in this paper can be effectively integrated with the existing job market management system, which has relatively strong feasibility.

3. College Student Employment Behavior Evaluation Method

3.1 Data Preprocessing

Setting up the evaluation indicator and weight is the core content of the evaluation on the influence of the student employment behavior, which depends on the mining and analysis of the actual data of the student employment behavior and the job market status. For the precision and convenience of the analysis, it is necessary to make preprocessing to the student employment behavior and job market status data that is acquired in the measurement. The preprocessing process can be divided into the following three steps.

Step 1 contruct the raw data matrix. That is, the measure data of the association job market status and the student employment behavior: Conduct sampling on the job market student employment behavior and the job market status, respectively. Assuming that within the time period t, the student employment behavior data collector obtains m student employment behavior raw data, in which each entry of the data $x_i = (i = 1, \cdots, m)$ is the vector $\{x_{i_1}, x_{i_2}, \cdots, x_{i_n}\}$ constituted by the measured values of the student under n characteristics of the behavioral characteristic set Craw. At the same time, the job market status collector acquires m' entries of the raw data of the job market status, in which, each entry of data $e_j(j = 1, \cdots, m')$ is the vector $\{e_{i_1}, e_{i_2}, \cdots, e_{i_n}\}$ constituted by the measured values of the employment market after standardized in the state factor set $\{D_1, D_2, \cdots, D_h\}$. Equation (1) is used to calculate and obtain the job market status value $d_j(j = 1, \cdots, m')$. For each x_i, based on the timestamp, the corresponding job market status data d_j is identified. Let it be y_i, coordinate x_i and y_i to constitute the m×(n+1) raw data matrix X within the time period t.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} & y_1 \\ x_{21} & x_{22} & \cdots & x_{2n} & y_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} & y_m \end{bmatrix}_{m \times (n+1)} \quad (1)$$

Step2 Standardization. The student employment behavior data in the raw data matrix is composed of the sampled values, which are usually dimension data or percentage data. To avoid the error caused by the range of values, it is necessary to conduct standardization (The job market state value y_i has been standardized upon the calculation, and no need to be processed herein). Let the maximum value of the j-th (j=1,···, m+1) in the matrix X be r_{max}^j, and the minimum value be r_{min}^j. Hence, the canonical data matrix B can be obtained as the following

$$b_{ij} = \begin{cases} x_{ij} & , x_{ij} \text{ Positive incremental percentage data} \\ 1 - x_{ij} & , x_{ij} \text{ Positive descending percentage data} \\ \left(x_{ij} - r_{min}^j\right) / \left(r_{max}^j - r_{min}^j\right) & , x_{ij} \text{ Positive incremental physical dimension data} \\ \left(r_{max}^j - x_{ij}\right) / \left(r_{max}^j - r_{min}^j\right) & , x_{ij} \text{ Positive descending physical dimension data} \end{cases} \quad (2)$$

Step3 Discretization. The range of values taken in the canonical data matrix B is continuous. Hence, there may be more values that are close but not equal to each other in each column, which is not conducive to the non-smooth association rule computation. Therefore, it is necessary to merge the values by a certain interval, that is, to conduct discretization on the data matrix B.

For the student employment behavior data, due to the complexity of the behavior, the range and distribution of the data measurement are unknown, which is not suitable to use the discretization methods that are oriented for the equal width, equal frequency interval with uniform distribution. In this paper, the discretization method based on entropy [17] is adopted. This method analyzes the distribution of the sample data by the information entropy, and achieves the optimization of the differentiation boundary by seeking for the optimum balance between the entropy loss and the appropriate interval values, so as to preserve the intrinsic knowledge information contained in the raw data distribution.

For the job market status data, the range of its values taken, distribution and evaluation criteria are usually fixed. Therefore, the interval boundary can be set in advance. In this paper, the five-level system is selected as the interval division standard. Then the job market status value y'_i after the discretization can be calculated by Equation (3) as the following.

$$y'_i = \begin{cases} 5, 0.8 \le y_i \le 1 \\ 4, 0.6 \le y_i \le 0.8 \\ 3, 0.4 \le y_i \le 0.6 \\ 2, 0.2 \le y_i \le 0.4 \\ 1, \ \ 0 \le y_i \le 0.2 \end{cases} \tag{3}$$

3.2 Adaptive Settings of the Evaluation Indicator and Weight

In the theory of the non-smooth association [13 ~ 16], “Knowledge” is regarded as the ability of the group division. And the classical set theory is extended by embedding the knowledge of the division set into the set itself. If the pre-processed student employment behavior and the corresponding job market status data are regarded as the entries of information to be analyzed and reasoned, the sample set obtained from the data preprocessing is the system decision table (hereinafter referred to as SDT for short) of the non-smooth association rules), and SDT={U,A,V,f}. In which, $U = \{x_1, x_2, \cdots, x_m\}$ is known as the domain, x_i stands for an entry of the evaluation data of the influence of the student employment behavior on the job market, $A = C \cup D$ stands for the union of the conditional association rules and decision making association rules. The conditional association rule C=Craw=$\{C_1, C_2, \cdots, C_n\}$, that is, the student employment behavioral characteristic set. The decision association rule D is the job market status, V is the domain element value field, and $f: U \times A \to V$ stands for the value taken for the element $x \in U$ on the association rule value $a \in A$.

The construction and adjustment of the evaluation indicator and weight of the student employment behavior depend on the analysis on the correlation between the student employment behavior and job market data, while the importance association importance in the non-smooth association rules has exactly reflected the correlation between the conditional association rules and the decision making association rules. Therefore, the correlation analysis can be carried out through the calculation of the association rule importance. Due to the inconsistency characteristic existing in the evaluation data of the student employment behavior, the job market status of the same timestamp often corresponds to the different behaviors of multiple students. So in this paper, the non-smooth association rule method under the information view is adopted, as shown in the literature [13]. Take the empty set as the initial set, and calculate the association rule importance by computing the degree of conditional entropy change of the set after the increase or decrease of the different behavioral characteristics, and use it as the minimum subset in the heuristic search behavioral characteristic with the maximum correlation to the job market status, to conduct association rule reduction. Hence, the student employment behavioral characteristics in the reduction results constitute the evaluation indicator set. And the association rule importance of each characteristic constitutes the weight of the evaluation indicator.

4. Precision Analysis

The evaluation value based on the method proposed in this paper can distinguish the target students who have influenced the job market. In this paper, the hierarchical clustering algorithm AGENES is used to distinguish the student evaluation values into two clusters. The clusters with high evaluation values are taken as the target students. And then the distinguished results are compared with the experimental arrangement. The following indicators are used to measure the precision of the distinction. Assuming that the number of target students involved in the experiment arrangement is N, and the number of ordinary students is T. Distinguish the students according to the evaluation value within each time period. Let the number of students being identified as the target students in the time period be TN, and the number of students who are actually the target students be N ', the evaluation indicator is as the following.

1) Precision: $P = \frac{N'}{TN}$, that is, the proportion of the real target students in the target students who are identified.

2) False negative: $FN = \frac{N - N'}{N}$, that is, the proportion of the target students who are not identified.

3) False positive: $FP = \frac{TN - N'}{T}$, that is, the proportion of ordinary students who are mistakenly identified as the target students.

On the basis of the student employment behavior data evaluation value in the four time periods, clustering method is used to distinguish the students. Compare with the experimental preset arrangement, the distinction results are shown in Table 1.

Table 1 Differentiation of the Results

Time period	Target students / persons	Identification results / persons	Correctly identified / persons	Mistakenly identified / persons
1	10	10	9	1
2	18	16	14	2
3	24	23	22	1
4	27	28	25	3

The precision, false negative and false positive rates are shown in Table 2.

Table 2 Precision, False Negative and False Positive Rates of the Distinction Results

Time period	Precision /%	Missing rate /%	False rate /%
1	90.0	10.0	3.3
2	87.5	6.7	8.0
3	95.7	8.3	6.3
4	89.3	7.4	23.1

It can be seen from Table2 that, the evaluation method can effectively distinguish the target students. The correct rate is up to 90% with the minimum up to about 87% in the experiment. As the evaluation method mainly aims to provide support for the identification of the students who lead to the changes in the status of the job market, on the basis of which, application identification method and so on can be further applied to identify and subdivide the students. Therefore, the false negative rate indicator is also very important, which can also reach the minimum of 6% in the experiment distinction result, with the maximum up to 10% and below.

For the comparison of the difference between the evaluation method proposed in this paper and the traditional evaluation method, the sampling of this paper adopts the AHP based hierarchy analysis method (hereinafter referred to as AHP for short) and the evaluation method based on the information entropy put forward in the literature [11]. The complete set of the student employment behavioral characteristics is used as the evaluation indicator of the control method. Similarly, the student employment behavior evaluation is carried out using the data of the above four time periods, and make distinction on the students according to the evaluation value clustering results. The results are shown in Figure 2 ~ 4.

It can be known from the comparison results that, the evaluation method proposed in this paper is superior to the AHP hierarchy analysis method and the evaluation methods based on entropy in the precision, false negative and false positive rate of distinguishing the target students who lead to the change in the status of the job market. The reason is that the method proposed in this paper can dynamically construct and adjust the evaluation indicators and weights through the analysis on the student employment behavior and job market status data, so as to more accurately measure the influence of the student employment behavior. While for the AHP hierarchy analysis method, as the evaluation indicator and weight cannot be dynamically adjusted according to the student employment behavior change, its effectiveness is the poorest. The evaluation method based on entropy can adjust its weight dynamically, hence its effectiveness is higher than that of the AHP hierarchy analysis method, but its indicator is still fixed, so the effectiveness is still inferior to the evaluation method proposed in this paper.

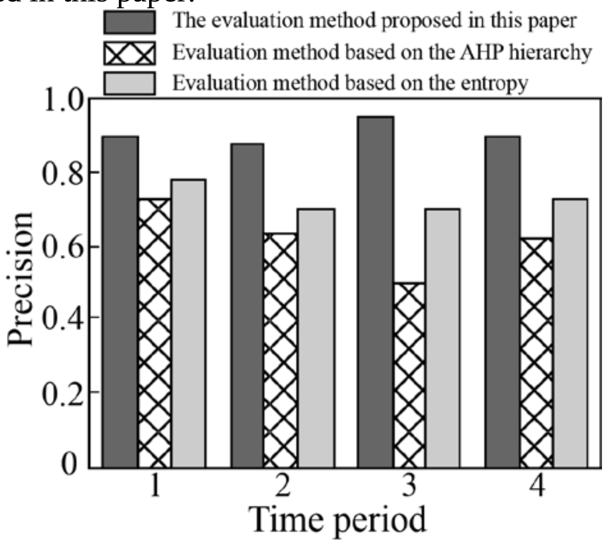

Fig.2 Precision Comparison Results

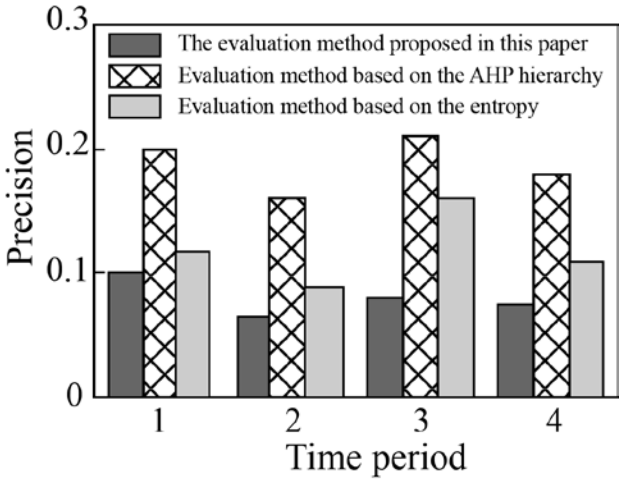

Fig.3 False Negative Comparison Results

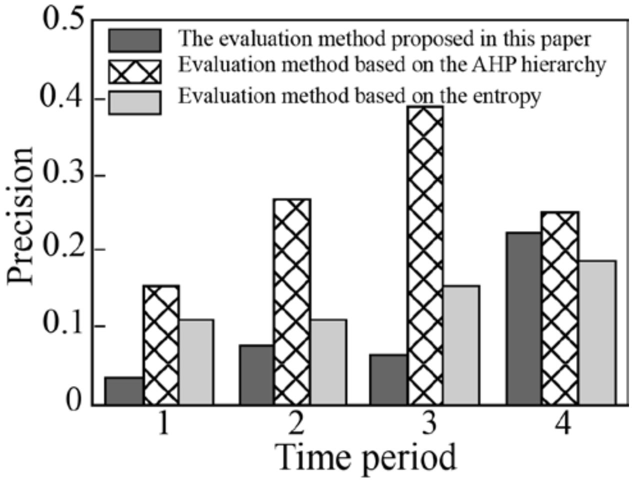

Fig.4 False Positive Comparison Results

5. Conclusion

The increasing scale and complex behavior of the students have had a huge influence on the normal operation of the job market. The evaluation on the level of the influence of the student employment behavior on the change of the job market can provide basis for the identification of the corresponding students and the control decision making upon the occurrence of the unexpected changes in the job market, so as to further help realize the controllability of the student employment behavior. The traditional student employment behavior evaluation methods have the defects of subjective and static nature in the settings of the evaluation indicator and weight, which has influenced the precision of the evaluation on the influence of the student employment behavior on the job market. In view of this, this paper introduces the non-smooth association rule theory, making use of its association rule reduction and association rule importance method to achieve the adaptive indicator selection and weight setting and adjustment, so as to avoid the defects of the traditional methods, and to accurately quantify and evaluate the influence of the student employment behavior on the changes in the job market status. On the basis of the student employment behavior evaluation, the next work is mainly to combine with the behavioral recognition, student clustering and other methods, to further study the student employment behavior control mechanism and methods, so as to achieve the predictability and controllability of the student employment behavior.

References

[1] LUO J Z, HAN Z G, WANG L M. Trustworthy and controllableetwork rchitecture and protocol framework [J]. Chinese Journal of Computer, 2009, 3(3): 391-404.

[2] LIN C, LEI L. Research on next generation internet architecture[J].Chinese Journal of Computers, 2007, 30(5):693-711.

[3] FUNG C, ZHANG J, AIB I, et al. Trust management and admission control for host-based collaborative intrusion detection[J]. Journal ofNetwork and Systems Management, 2011, 19(2):257-277.

[4] TAJEDDINE A, KAYSSI A, CHEHAB A, et al. Fuzzy reputationbased trust model[J]. Applied Soft Computing, 2011, 11(1):345-355.

[5] GOVINDAN K. Trust computations and trust dynamics in mobile ad hoc networks: a survey[J]. Communications Surveys & Tutorials, 2011,14(2):279-298.

[6] RAYA M, PAPADIMITRATOS P, GLIGOR V D, et al. On data-centric trust establishment in ephemeral ad hoc networks[A]. INFOCOM[C].2008. 13-18.

[7] XI Z Y, CHEN H, WANG X Z, et al. Evaluation model for computer network information security based on analytic hierarchy process[A].Intelligent Information Technology Application[C]. 2009.

[8] CAO Y, ZHANG L, WU H. An evaluation system for network attack effect based on fuzzy[A]. E-Business and Information SystemSecurity[C]. 2009.

[9] JIN F, LIU P, ZHANG X, et al. The evaluation study of knowledge management performance based on grey-ahp method[A]. Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing[C]. 2007.

[10] ZHANG Y R, XIAN M, WANG G Y. A quantitative evaluation technique of attack effect of computer network based on network entropy[J]. Journal on Communications, 2004, 25(11):158-165.

[11] WANG X, HE H, ZHANG H L, et al. Dynamic damage evaluation of network availability adjusted by indicator correlation[A]. Internet Computing for Science and Engineering (ICICSE)[C]. 2009.

[12] LI X Y, GUI X L, MAO Q, et al. Adaptive dynamic trust measurement and prediction model based on behavior monitoring[J]. Chinese Journal of Computers, 2009, 32(4):664-674.

[13] LIANG J Y, LI D Y. The Uncertainty and Knowledge Acquiring in Imformation Systems[M]. Beijing: Science Press, 2005.

[14] GONG Z H, ZHUO Y. Research on cyberspace situational awareness[J].Journal of Software, 2010, 21(7):1605-1619.

[15] JIANG Y, LIN C, WU J P. Integrated performance evaluationcriteriafor network traffic control [J]. Chinese Journal of Computers,2002, 25(8):869-877.

[16] MOORE A W, ZUEV D. Discriminators for Use in Flow-Based Classification[R]. Technical Report IRC-TR-04-028, 2004.

[17] LIN Z, FENG J. A rough set approach to feature selection based on relative decision entropy[J]. Lecture Notes in Computer Science, 2011,6954(2011):110-119.

[18] KIM H, CLAFFY K, FOMENKOV M, et al. Internet traffic classification demystified: myths, caveats, and the best practices[A].Proc of ACM CoNEXT’08[C]. New York, USA, 2008.1-12.