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Research Article

Comprehensive Evaluation Model for Academic Quality of Food Journals Based on Rough Set and Neural Network

Mei-Jia Huang, He Nie, Chen Ye and Li Zhang
School of Electrical and Information, Jinan University, Zhuhai 519070, China

Abstract: In order to evaluate food journals efficiently and reasonably, this study puts forward a comprehensive evaluation model for academic quality of food journals based on rough set and neural network. Firstly, we reduce evaluation indicators of journals based on discernibility matrix in rough set theory, removing the miscellaneous indicators and form the core evaluation indicator system, so as to have a more effective training for BP neural network. Then, we use methods defined in our study to generate enough training samples for the neural network modeling based on the core evaluation system. Lastly, with the help of BP neural network algorithm to rank journals, thereby we establish a comprehensive evaluation model for academic quality of journal. Instance analysis of food journals shows that the principle of generating the sample is feasible and effective and the modeling process is reliable and reasonable. What' more, the model established can be used for comprehensive evaluation for academic quality of food journals.

Keywords: Academic evaluation of food journals, BP neural network, rough set

INTRODUCTION

Academic evaluation plays a growing important role in Academic journals. About the effect of academic evaluation, different people have different views. But it's true that many people attach importance to the academic evaluation of journals increasingly. The so-called academic evaluation function of academic journals means during academic evaluation, academic journal become an important indicator and tools to judge the academic level (Hu and Fu, 2008). Therefore, establishing a reasonable journal evaluation system and evaluation method is very crucial. It can not only promote the development of the journal itself, but also strongly promote scientific research and the construction of the university teaching staff.

Academic evaluation of journals is a complicated systematic project, how to reasonably and objectively evaluate journals is one of hot issues in present research (Lou *et al*., 2009). Currently there are some methods and models, such as, principal component analysis (Chen, 2004), Attribute interval recognition model (Yan, 2006), normalization method (Liu *et al*., 2006), grey correlation degree method (Liu and Zeng, 2013) and some other methods (Wang and Yu, 2012; Lv *et al*., 2012). The common feature of these methods is that human (experts) to determine the weight of each evaluation indicator, the evaluation result is inevitably affected by the presence of man-made factors and objectivity and comparability of these methods are poor.

Rough set theory is proposed by professor Pawlak (1982), which is a mathematical tool can quantitative analyze imprecise, inconsistent and incomplete information and knowledge (Pawlak, 1982). Through knowledge mining, rough set can discover the rule of implicit knowledge and potential rule. We can do an effective indicator reduction by discernibility matrix in rough set, without prior information and the impact of any human factors can be avoided. Li and Yun (2010) made a research on the construction of indicator system and comprehensive evaluation method based on Rough set. He *et al*. (2014) constructed an evaluation model based on rough set and TOPSIS.

On the other hand, Artificial neural network technology with the ability of self-learning and self-organization, especially suitable for nonlinear modeling (Statsoft, 1999). It also works well in nonlinear evaluation can. Cai *et al*. (2014) did a research on establishment of food safety evaluation model based on neural network. Silva *et al*. (2015) used artificial neural network to make an evaluation of extra virgin olive oil stability.

This study proposes an evaluation model based on Rough sets and neural network to evaluate the academic level of food journals. We take advantage of rough sets and neural networks, in order to obtain a more objective and reliable evaluation results of the journals, more

Corresponding Author: He Nie, School of Electrical and Information, Jinan University, Zhuhai 519070, China

finely characterize and differentiate academic level of journals. By using the model to validate data in reference (He *et al*., 2013), it shows that the model has good accuracy and applicability.

COMPREHENSIVE EVALUATION MODEL FOR ACADEMIC QUALITY OF JOURNAL

Algorithm of indicator reduction based on discernibility matrix: Rough set theory extends classical set theory, the knowledge, which is used for classification, is embedded in set as a part. There are some key definitions as follows:

Definition 1: Comprehensive evaluation of information systems decision table can be expressed as $S=(U,C,D,V,f)$, where U is the set of evaluation objects; C is the evaluation indicator system; D is a set of comprehensive evaluation result. Comprehensive evaluation result is commonly described as grade or score, or described as the clustering results of comprehensive evaluation object.

Definition 2: The evaluation indicator system is C, $C=\{a_i\}(i=1,2,3,...,m)$, the evaluation object set is U, there are n evaluation objects, $|U|=n$, the corresponding discernibility matrix is $d(x,y)=\{a\in C \mid f(x,a)\neq f(a,x)\}$, $d(x,y)$ able to distinguish the between indicator set of objects x and y and $d_{ij}=d_{ji}, d_{ii}=\varphi, d_{ij}\neq\varphi$. The core indicator set is the collection of all individual indicators in discernibility matrix.

Let Boolean variables to represent the relation of indicator set, if we can distinguish between the indicator set of objects x and y, the Boolean function is $a_1\vee a_2\vee...\vee a_k$, with representation is $\sum a(x,y)$; if $a(x,y)=\varphi$, the Boolean constant is 1. The discernibility function corresponding to the indicator system is $f(C)=\prod_{(x,y)\in U\times U}\sum a(x,y)$.

The element value of discernibility matrix can distinguish indicator set of two evaluation objects. In discernibility matrix, the indicator with high frequency shows a strong distinguishing ability, however the indicator with low frequency shows a weak distinguishing ability. In the extreme situation, the indicator does not appear in discernibility matrix, in fact, it can be directly deleted. Therefore, the times appears in the matrix are as a criterion to judge the importance degree of an indicator. That is, if one indicator appears the more times in the discernibility matrix, indicating that it has the strong distinguishing ability and the higher its importance.

According to the above definition and description of rough set, we know that, if the attribute combination value of an indicator in discernibility matrix is 1, it shows that the indicator is core indicator, must be retained. And some other indicator can be achieved from these indicators whose attribute combination values are not 1, but they have high frequency.

Thereby, heuristic algorithm of indicator reduction based on discernibility matrix can be established as follows (Li and Yun, 2010):

Denote $RED(\mathrm{A})$ is the indicator system after reduction and B is the set of core indicators.

Step 1: Calculating to obtain discernibility matrix and then we put the core indicator into reduced indicators system $RED(\mathrm{A})$, namely, $RED(\mathrm{A})=\mathrm{B}$

Step 2: The combination items with core indicators in discernibility matrix should be removed.

Step 3: Calculating the frequency of each indicator of all the rest combination items in discernibility matrix, select the indicator with highest frequency, denoted it as a, so $RED(\mathrm{A})=RED(\mathrm{A})\cup\{a\}$. And then we delete combination items with indicator a.

Step 4: Checking whether discernibility matrix is empty or not. If the matrix is not empty, then go to Step 3, or the end. $RED(\mathrm{A})$ is the final indicator system after reduction.

Obviously, this method can effectively make to reduce the complexity of solution and the method is simple. What's more, we can obtain the smallest reduction of the indicator system in most cases.

Generation of sample data: According to Lou *et al*. (2009), it shows that journal evaluation grade is decided by the upper and lower limit of evaluation indicator, that is, one certain indicator c_i of the evaluation system should meet:

$$c_{i1}\le c_i\le c_{i2}$$

where,

c_{i1} = The lower limit of evaluation indicator

c_{i2} = The upper limit of evaluation indicator

Since we obtain the core indicator system, the importance degree of each indicator is quite high. To a certain extent, in order to simplify the model, we can consider the weight of all the indicators in the core indicator system is almost the same.

Therefore, in order to reasonably expand the training sample data, we believe that, if the two indicators of journal evaluation system up and down reversely 10%, the grade of the journals evaluation is the same and the generated data can be relatively well training for neural network. Thus, as defined herein, when a two indicator $c1$, $c2$ of the core indicator system B of journals meet:

$$c3=(1\pm10\%)c1,\quad c4=(1\mp10\%)c2\quad c1,c2\in\mathrm{B}$$

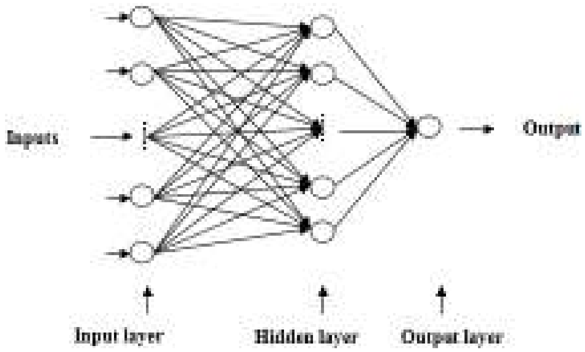

Fig. 1: Structure of a three-layer feed forward neural network

That is, when indicator data $c1$ increases (or decreases) 10% to generate a new indicators data $c3$, at the same time and indicator data $c2$ decreases (or increases) 10% to a new indicators data $c4$ and other indicators of the core indicator system do not change. In this way, we believe that the grade of the journal is in the same level.

Model structure of BP neural network: In this study, we use a three-layer feed forward BP neural network structure as shown in Fig. 1 to map the nonlinear relationship between academic journal indicators and its grade.

In the neural network, the input unit is corresponding to journal indicators and the output unit is corresponding to journal evaluation grade. The hidden layer neurons use Logarithmic sigmoid transfer function and the input layer and output layer neurons use pure linear transformation function. The selected network training evaluation function is a function of the mean squared error:

$$SSE = \frac{1}{2p}\sum_{j=1}^{p}\sum_{i=1}^{n}(t_i - o_i)^2$$

where,
o = The network predicted output
t = The desired network output
SSE = Normalized total error of neural network learning
n = The number of the output unit,
p = The number of samples

After determining the structure of a feed forward BP neural network model, using the sample data to have training, after training and we obtain the evaluation model. And then we input the indicator data to get an output value, with the output value to judge journals' rankings.

Instance analysis: In this part, we selects a part of journals and the data of some common evaluation indicators of food journals in references (He *et al*., 2013), as well as search the ranks of relevant journals in references (RCCSE, 2013). We use evaluation model based on rough set and neural network to evaluate the academic level of food journals and compare the results obtained with the searched rankings to verify the reasonableness of the model.

Reduction of evaluation indicators based on based on discernibility matrix in rough set: This study selects 23 food journals from CHINESE S and T JOURNAL REPORTS (Expanded Edition) as research objects. Let denote J1, J2, J3, J5, J6, J7, J8, J9, J10, J11, J12, J13, J14, J15, J16, J17, J18, J19, J20, J21, J22 and J23 as these research journals: Food Science, Food Science and Biotechnology, Chinese Institute of Food Science, Food Industry, Chinese Cereals and Oils Association, Food Science, Food Science and Technology, China's dairy industry, China oil, Chinese mushroom, Food and machinery, Chinese spices, Food research and development, Dairy Science and Technology, Chinese food additives, Chinese food and nutrition, Food and medicines, Preservation and processing, Salt and Chemical Industry, Food industry, Packaging and food machinery, Chinese animal quarantine, Food engineering.

We use 11 evaluation indicators from A Report on Chinese Academic Journals Evaluation and all of them are the maximum indicator. Let A1, A2, A3, A4, A5, A6, A7, A8, A9, A10, A11 respectively represent: extended total cited frequency, extended number of citing journals, extension immediacy index, extended cited rate, extended impact factor, expand discipline impact indicators, expand discipline diffusion index, extended H index, literature sources amount, average number of citations and fund citations number.

The evaluation indicator set A = {A1, A2, A3, A4, A5, A6, A7, A8, A9, A10, A11}, thereby we establish journal evaluation system. We divided all the selected journals into four levels based on these journals in academic journal ranking. Denote R as a rating score, with the number of 0.6, 0.7, 0.8 and 0.9 and the greater the score, the higher ranking. The raw data obtained are shown in Table 1.

Due to the different dimensions of evaluation indicators, we need to eliminate the dimension of the data to compare it. In order to make the data in [0, 1], we adopt the range transformation method to obtain normalization matrix $X = (x_{ij})_{m\times n}$, that is:

$$x_{ij} = \frac{r_{ij} - \min_i\{r_{ij}\}}{\max_i\{r_{ij}\} - \min_i\{r_{ij}\}}, i = 1, 2, ...m; j = 1, 2, ..., n$$

where, r_{ij} is the value of the corresponding journal indicators, x_{ij} is the dimensionless value and also $x_{ij} \in [0,1], i = 1, 2, ..., m; j = 1, 2, ..., n$.

Table 1: Evaluation indicators of food journals

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	R
J1	16408	1243	0.085	0.85	1.047	0.77	20.72	13	1685	20.98	0.69	0.9
J2	1634	448	0.068	0.86	0.846	0.62	7.47	7	205	19.04	0.83	0.9
J3	1581	390	0.068	0.92	0.917	0.68	6.5	7	380	19.25	0.81	0.8
J4	7017	791	0.115	0.8	0.709	0.78	13.18	9	2467	16.82	0.59	0.8
J5	2543	403	0.068	0.88	0.849	0.65	6.72	7	311	17.2	0.68	0.8
J6	4820	741	0.072	0.95	0.55	0.7	12.35	8	871	10.98	0.7	0.8
J7	2675	509	0.126	0.75	0.914	0.7	8.48	8	463	11.57	0.53	0.8
J8	1299	240	0.051	0.9	0.544	0.55	4	7	196	12.43	0.42	0.8
J9	2755	454	0.098	0.89	0.858	0.65	7.57	9	264	11.36	0.54	0.8
J10	1063	248	0.095	0.91	0.562	0.28	6.2	5	147	8.97	0.687	0.8
J11	2128	411	0.167	0.78	0.913	0.72	6.85	7	420	14.76	0.59	0.7
J12	1705	303	0.075	0.82	0.622	0.58	5.05	6	371	11.12	0.28	0.7
J13	4744	751	0.082	0.94	0.717	0.73	12.52	11	803	11.42	0.537	0.7
J14	391	133	0.029	0.94	0.595	0.38	2.22	4	71	16.9	0.3	0.7
J15	1846	426	0.097	0.95	0.567	0.68	7.1	8	207	13.74	0.43	0.6
J16	1974	598	0.109	0.96	0.679	0.63	9.97	7	265	11.51	0.44	0.6
J17	976	415	0.048	0.98	0.643	0.5	6.92	7	251	10.48	0.167	0.6
J18	721	169	0.105	0.91	0.936	0.09	15.36	5	76	18.53	0.67	0.6
J19	419	143	0.01	0.75	0.276	0.19	0.81	4	204	4.52	0.13	0.6
J20	1132	268	0.052	0.95	0.41	0.62	4.47	5	594	9.4	0.406	0.6
J21	601	158	0.255	0.63	0.877	0.5	2.63	5	110	14.38	0.37	0.6
J22	1093	229	0.174	0.7	0.465	0.56	2.2	5	426	4.52	0.183	0.6
J23	486	223	0.08	0.99	0.543	0.58	3.72	5	75	6.6	0.187	0.6

Table 2: The results (portion) of normalized indicators

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11
J1	1.000	1.000	0.306	0.611	1.000	0.986	1.000	1.000	0.674	1.000	0.800
J2	0.078	0.284	0.237	0.639	0.739	0.768	0.335	0.333	0.056	0.882	1.000
J3	0.074	0.232	0.237	0.806	0.831	0.855	0.286	0.333	0.129	0.895	0.971
J4	0.414	0.593	0.429	0.472	0.562	1.000	0.621	0.556	1.000	0.747	0.657
J11	0.108	0.250	0.641	0.417	0.826	0.913	0.303	0.333	0.146	0.622	0.657
J12	0.082	0.153	0.265	0.528	0.449	0.710	0.213	0.222	0.125	0.401	0.214
J13	0.272	0.557	0.294	0.861	0.572	0.928	0.588	0.778	0.306	0.419	0.581
J14	0.000	0.000	0.078	0.861	0.414	0.420	0.071	0.000	0.000	0.752	0.243
J15	0.091	0.264	0.355	0.889	0.377	0.855	0.316	0.444	0.057	0.560	0.429

Table 3: The discrete result (portion) of evaluation indicators

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	R
J1	4	4	2	3	4	4	4	4	3	4	4	0.9
J2	1	2	1	3	3	4	2	2	1	4	4	0.9
J3	1	1	1	4	4	4	2	2	1	4	4	0.8
J4	2	3	2	2	3	4	3	3	4	3	3	0.8
J11	1	2	3	2	4	4	2	2	1	3	3	0.7
J12	1	1	2	3	2	3	1	1	1	2	1	0.7
J13	2	3	2	4	3	4	3	4	2	2	3	0.7
J14	1	1	1	4	2	2	1	1	1	4	1	0.7
J15	1	2	2	4	2	4	2	2	1	3	2	0.6

There, we adopt the range transformation method to do with the data in Table 1 and the results (portion) are shown in Table 2.

Then we discretize the data of evaluation indicators in Table 2 by equidistance division method. As the journals selected are divided into 4 grades, so in our study, the range between the minimum and maximum is also divided into 4 intervals. The integers from 1 to 4 are assigned to 4 intervals from small to large. The discrete results (portion) are shown in Table 3.

According to algorithm of indicator reduction based on discernibility matrix, we write programs to solve the problem and obtain five core evaluation indicators after reduction: extended number of citing journals, extended impact factor, expands discipline impact indicators, extended H index and average number of citations. The grade of evaluation according to the core evaluation indicators can fully consistent with the results according to the all evaluation indicators.

According to Li *et al*. (2007), it shows that the impact factor, H index, citations are all common core indicators, so the five core indicators herein after reduction obtained are reasonable.

Table 4: The training sample data (portion)

	B1	B2	B3	B4	B5	R
J	1.100	0.900	0.986	1.000	1.000	0.9
J	0.312	0.665	0.768	0.333	0.882	0.9
J	0.255	0.748	0.855	0.333	0.895	0.8
J	0.652	0.505	1.000	0.556	0.747	0.8
J	0.612	0.515	0.928	0.778	0.419	0.7
J	0.000	0.372	0.420	0.000	0.752	0.7
J	0.290	0.340	0.855	0.444	0.560	0.6
J	0.461	0.470	0.783	0.333	0.425	0.6
J	0.279	0.428	0.594	0.333	0.362	0.6

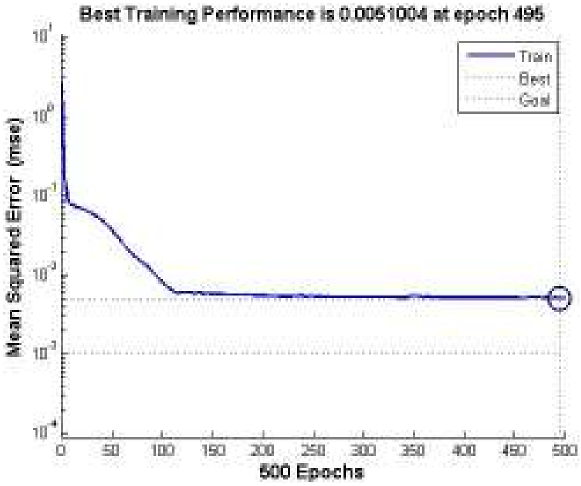

Fig. 2: The sample training results of the best hidden layer nodes

Thus, after reduction, we can extract core evaluation indicators of journals, so we denote B1, B2, B3, B4, B5, respectively as extended number of citing journals, extended impact factor, expand discipline impact indicators, extended H index and average number of citations. The indicator set B = {B1, B2, B3, B4, B5, B6}. Thus, we established a core evaluation system of food journals.

Generation of training sample: The establishment of reliable and efficient BP neural network model requires a lot of training samples and necessary test samples (Lou *et al*., 2009). It is obviously that we cannot just use the result of normalized indicators in Table 2 as training samples. On the other hand, according to the above section, we can know that the different grades of academic journals are determined by the upper and lower limit of 11 evaluation indicators. In this study, we reduce the indicator to obtain core indicators and the different grades of academic journals are also determined by the upper and lower limit of 5 evaluation indicators.

We use the method in the above section to deal with indicator in the core indicators system, any two indicators of five core indicators up and down reversely 10% and the remaining indicators unchanged. In this way, we believe that the evaluation grades of journals are the same. With the help of the approach to deal with all the indicators, we can get 460 training samples, part of the training sample data are shown in Table 4.

Comprehensive evaluation of food journals based on BP neural network:

Determination of number of hidden layer nodes: We use all samples as training samples, while the hidden layer has 1 to 8 nodes, the MSEs of training samples are greater than 0.005 and the training is not effective. When the hidden layer has 9-12 nodes, the MSE of each training samples were 0.00531, 0.00510, 0.00524 and 0.0051. And after 12 hidden nodes, the MSEs are around 0.005. Thus, taking into account the efficiency of the training, 10 hidden layer nodes of the neural network are reasonable and this is the most compact.

Evaluation results of neural network: With the help of MATLAB 7.0 neural network toolbox, we use training function of momentum back propagation algorithm of gradient descent. In the training figure, the vertical coordinate represents all the error level of parameters and the abscissa represents the *n*-th iteration steps in the iterative training process forward. The curve describes the error performance trend and straight line is the desired error target. In the training process, we use 460 samples data, 10 hidden layer nodes, the minimum error of training objective is set to 0.001, the training times are set to 500 times and the learning rate is set to 0.05. The sample training results are shown in Fig. 2.

In Fig. 2, in accordance with the expected error level of 0.001, after about 120 times of iterations to achieve the desired target error. After the training is completed, we can input evaluation indicators of 23 food journals selected and we can get the output value (*BP-o* for short). Taking into account all the training indicators are the maximum indicator. So the greater output value, the higher ranking. According to the output values, we can rank the food journals. We compare the ranking results with the rankings in A Report on Chinese Academic Journals Evaluation (*R* for short). In this way, we can verify the reasonableness of this model. Comparative results are shown in Table 5.

From Table 5, overall, the comprehensive evaluation result of food journals based on rough sets and neural network obtained and the rankings in A Report on Chinese Academic Journals Evaluation, is relatively close, especially the rankings of the top seven are almost the same, indicating that the model used herein is reasonable. Because different evaluation systems use different evaluation principles and evaluation indicators, the result is a little bit different. But the overall ranking trend is consistent.

But a few individual rankings in Table 5 have a larger deviation, for example, the ranking of J17 has a big difference. Since the weights of the core indicator system are the same in this study, maybe one or two of core indicators could have a larger impact on the evaluation results of J17. So the methods we used make a larger deviation to some extent.

In summary, in the process of evaluation of food journals, the core indicator system after reduction is reasonable, the principle of generating the sample is feasible and effective and the modeling process of BP

Table 5: Comparative comprehensive ranking result

Journal-NO.	*BP-o*	Ranking	*R*	Journal-NO.	*BP-o*	Ranking	*R*
J1	0.920	1	1	J13	0.704	12	13
J2	0.818	2	2	J14	0.675	15	14
J3	0.797	4	3	J15	0.675	16	15
J4	0.807	3	4	J16	0.671	17	16
J5	0.784	5	5	J17	0.722	10	17
J6	0.782	6	6	J18	0.653	18	18
J7	0.771	7	7	J19	0.634	19	19
J8	0.743	9	8	J20	0.618	20	20
J9	0.682	14	9	J21	0.607	22	21
J10	0.689	13	10	J22	0.599	23	22
J11	0.758	8	11	J23	0.612	21	23
J12	0.716	11	12				

neural network is reliable and reasonable. Hence, the model has a certain practicality and applicability.

CONCLUSION

Based on rough set theory and neural network for journals evaluation can have a fully data mining, providing a model for a more efficient and reasonable academic evaluation of journals.

We take the advantage of rough set in dealing with imprecision and uncertainty of the data sample and use it to make a pretreatment to obtain core indicator system, reducing properties of sample, reducing dimension of sample. On this account to map the core indicator to the training samples of neural network, we can build the number of hidden layer and hidden layer neurons and in this way, making the network more logical and reducing the training time of neural network, enhancing accuracy and generalization of training. We compare the results of the model and the rankings in A Report on Chinese Academic Journals Evaluation and we find that the results of the model are reasonable.

The modeling process is credible, but because we do not take into accounts the specific weight of each indicator of the core indicator system, just suppose they are approximately the same, the further research in the future we can optimize the model on this point.

Rough set theory and neural network are widely used in the field of academic evaluation, but they can also be applied to other aspects such as mine ventilation system evaluation (Hong Tu *et al*., 2011) and enterprise credit assessment (Yu *et al*., 2013). And in the future, we can have an in-depth study. A hybrid of these two methods can be applied not only evaluation studies, also be to other fields, such as pattern recognition (Xia *et al*., 2010; Qin *et al*., 2014).

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