Research on the Quality Evaluation System of University Library Electronic Resources Based on RBF Neural Network

Dongzhe Wang, Haiyan Xie, Gaohu Meng and Zhiqi Liu

July 18, 2019

Research on the Quality Evaluation System of University Library Electronic Resources Based on RBF Neural Network

Dongzhe Wang
School of Science
Dalian Maritime University
Dalian, China
wangdongzhe334@163.com

Haiyan Xie
School of Science
Dalian Maritime University
Dalian, China
winteriscoming@sina.com

Gaohu Meng
School of Science
Dalian Maritime University
Dalian, China
kq59486@gmail.com

Zhiqi Liu
School of Science
Dalian Maritime University
Dalian, China
l17640317962@163.com

Abstract*—*In order to solve the problem that the evaluation system of library electronic resource quality is not comprehensive and objective at present, we use RBF network to model the electronic resource quality evaluation system of university library. And compared with BP network modeling method. The experimental results show that the evaluation system model of university library's electronic resources quality based on RBF neural network has more advantages than BP neural network model, and its results are more objective and comprehensive. This provides a new method and train of thought for the evaluation of electronic resources in university libraries.

Key words*— *RBF neural network ,BP neural network，library electronic resources ,quality evaluation system

I. Background Introduction

In recent years, the application of electronic information technology in libraries has become more and more in-depth, more and more intelligent. The proportion of electronic resources in the library collection resources is also increasing year by year, and readers' requirements on electronic resources are becoming more and more strict[8].In this context, how to make a reasonable and effective evaluation of the quality of library electronic resources has become an important research topic[1].At present, there are fuzzy analytic hierarchy process (AHP), analytic hierarchy process (AHP) and BP network model[2][3][4].The weight of the index system of AHP needs to be set in advance, and the RBF neural network can complete the self-fitting adjustment of the weight through the sample training. However, the nonlinear problem analytic hierarchy process cannot be solved. The successfully trained RBF neural network can automatically output the correct judgment value when calculating a new sample, and the user's satisfaction level is also high, which is more in line with the expert's judgment[7].The analytic hierarchy process is very cumbersome in actual operation, and it is mixed with higher personal emotional factors, which may lead to the final result not being objective and comprehensive[3][4].Moreover, the subjective arbitrariness of AHP is strong, often with strong personal subjective factors, and the accuracy in the process and results of the assessment is not enough.

It is a good idea to establish the prediction model by BP network, but it is troublesome to determine the parameters in the programming of BP network, and the result precision is not high enough. The RBF network is more convenient, efficient and accurate in practical operation. Therefore, this paper applies RBF neural network theory in the construction of quality evaluation of electronic resources in the library, by means of neural network model is established to evaluate the quality of the electronic resources, the traditional evaluation model of fuzziness and subjectivity, for quality evaluation of electronic resources in university library provides a new method and train of thought.

II. Introduction of RBF Theory

The RBF neural network belongs to a multilayer forward neural network. It is a three-layer forward network, the input layer is composed of signal source nodes; the second layer is the hidden layer, the number of hidden units is determined by the problem described, and the transformation function of the hidden unit is radial to the center point symmetric and attenuating non-negative nonlinear function; the third layer is the output layer, which responds to the effects of input patterns.

In the hidden layer of the RBF neural network, the radial basis function is used to process the data. Let $\phi : R^d \to R$ is a nonlinear function, $\phi(\|x - x^\alpha\|), \alpha = 1,2,\ldots,N$ is called the radial basis function. Neraly, there are several choices of the function, they are Gaussian RBF function; two-dimensional Gaussian RBF function; multiple quadratic functions; inverse multi-quadratic function ;linear function and so on. .

The basic idea of the RBF neural network is to use the radial basis function (RBF) as the "base" of the hidden unit to form the hidden layer space. The hidden layer transforms the input vector and transforms the low-dimensional mode input data into high-dimensional. Within the space, the output is obtained by weighted summation of the hidden cell outputs.

The RBF neural network is simple in structure, simple in training, and fast in learning convergence, and can approximate any nonlinear function. Therefore, the RBF network has a wide range of applications. Such as time series analysis, pattern recognition, nonlinear control and image processing. As long as there are enough hidden elements, the RBF network can approximate any nonlinear function [5] from arbitrary precision. Fig. 1,shows the basic structure of the RBF network[5][6].

In this paper, the RBF network model is used to model the library electronic resource quality evaluation system. Several different aspects of the library electronic resources will be evaluated separately, and a comprehensive evaluation will be obtained through the operation of the RBF network. What is ultimately obtained is the final result of the model we built. According to the principle of the RBF network model, we can approximate the objective evaluation with high enough precision.

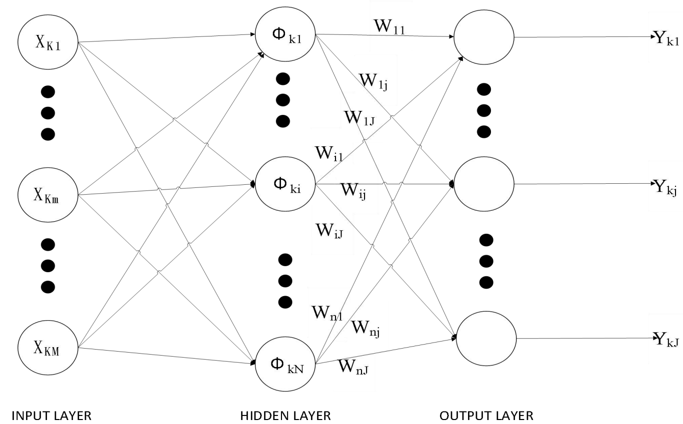

Fig. 1. RBF network structure

III. RBF NEURAL NETWORK EVALUATION SYSTEM MODEL

A. Building an Indicator System

In order to comprehensively evaluate the quality of library electronic resources, we use the evaluation system of reference [2] to classify the library electronic resource quality evaluation system into four first-level indicators in the following table, and then proceed to the first-level indicators.

TABLE 1 E-RESOURCE QUALITY EVALUATION INDICATORS BASED ON USER SATISFACTION

Primary indicator	Secondary indicator m	Introduction to secondary indicators
Content of electronic resources	Total coverage of resources M1	Covers the scope of subject resources to meet user satisfaction
	Updated rate M2	Whether the update speed of the resource meets the user's needs
Retrieval system	Search function M3	Retrieve the entry, search path, and search skill to meet the user's requirements
	User experience M4	Investigate the user experience
Electronic resource usage	The recall rate of the retrieved content M5	Is the search information comprehensive and accurate?
	Search accuracy of search content M6	The degree of stability of the system during operation
Data provider service	System stability M7	The degree of stability of the system during operation
	Pre-sales, after-sales service effect M8	Whether the effect of pre-sales training and after-sales service meets the requirements of users

B. Network Structure

According to the currently constructed evaluation index system, our RBF network model can be constructed with 8 input neurons, which are the total coverage of the resource M1, the updated rate M2, the retrieved function M3, the user experience M4, and the search content. The full rate M5, the precision of the search content M6, the stability of the system M7, the pre-sales, after-sales service effect M8. The output neurons are RBF neural networks with comprehensive evaluation indicators. According to the RBF network theory, we can get the network model as shown in Fig. 2:

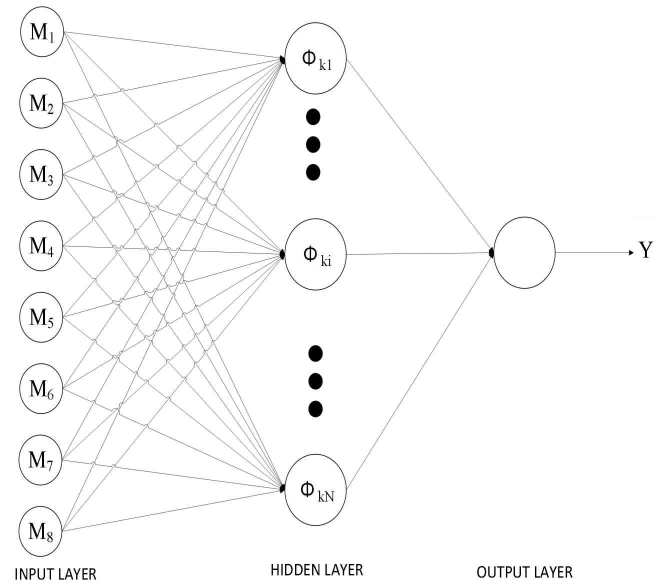

Fig. 2. RBF network evaluation model structure

IV. DATA EXPERIMENT

A. Input Data

The actual training of the RBF network requires objective and realistic actual data to train the network. Through the literature [2], as well as our survey of users. We can get a set of real valid and normalized data in Table 2.

TABLE 2 NORMALIZATION OF ELECTRONIC RESOURCE QUALITY EVALUATION

Name	M1	M2	M3	M4	M5	M6	M7	M8
CNKI	0.87	0.94	0.79	0.8	0.86	0.83	0.82	0.72
Springer Link	0.94	0.91	0.85	0.54	0.45	0.71	0.75	0.57
APS	0.91	0.94	0.45	0.96	0.6	0.67	0.73	0.87
Wan Fang	0.97	0.84	0.87	0.86	0.69	0.85	0.86	0.66
ACS	0.92	0.86	0.81	0.87	0.57	0.75	0.89	0.69
Nature	0.85	0.86	0.9	0.93	0.79	0.83	0.97	0.98
Science Online	0.55	0.88	0.56	0.71	0.8	0.62	0.74	0.94
EBSCO	0.53	0.97	0.72	0.54	0.7	0.87	0.75	0.58
EI	0.71	0.88	0.93	0.87	0.82	0.96	0.94	0.69

Name	M1	M2	M3	M4	M5	M6	M7	M8
Open Access	0.92	0.9	0.92	0.8	0.87	0.85	0.77	0.69
IEEE/IET Electronic Library	0.91	0.95	0.91	0.89	0.87	0.9	0.89	0.87
Engineering Village	0.78	0.92	0.94	0.76	0.76	0.86	0.78	0.65
CSCD	0.93	0.94	0.95	0.92	0.89	0.93	0.9	0.86
Superstar	0.75	0.92	0.89	0.91	0.9	0.91	0.9	0.96
ASCE	0.78	0.88	0.85	0.85	0.78	0.75	0.78	0.86
ASME	0.75	0.86	0.86	0.83	0.8	0.78	0.86	0.73
Hein Online	0.69	0.88	0.7	0.79	0.6	0.86	0.89	0.52
Bagel Digital Library	0.78	0.87	0.75	0.57	0.76	0.86	0.82	0.86
Shipping Intelligence Network	0.56	0.85	0.52	0.68	0.83	0.83	0.75	0.67

Experts make 16 electronic resources in the library such as CNKI, Springer Link, APS, Wan Fang, ACS, Nature, Science online, EBSCO, EI, Open Access, IEEE/IET, EV, CSCD, Superstar, ASCE, ASCM. The objective and comprehensive evaluation is shown in Table 3.

TABLE 3 EXPERT EVALUATION VALUE

Name	Expert evaluation
CNKI	0.9541
Springer Link	0.5419
APS	0.915
Wan Fang	0.8568
ACS	0.7965
Nature	0.9891
Science Online	0.9433
EBSCO	0.8314
EI	0.9738
Open Access	0.9362
IEEE/IET Electronic Library	0.9874
Engineering Village	0.8668
CSCD	0.9679
Superstar	0.9863
ASCE	0.9413
ASME	0.9332

B. Distribution Density (spread) σ Selection.

We use MATLAB R2016a to train the RBF network model. The 16 electronic resource samples after expert evaluation are the training samples of the RBF network to establish the RBF network model. The main code used by the program is:

```
L={'CNKI', 'Springer', 'APS', 'Wan Fang', 'ACS', 'Nature', 'Science Online', 'EBSCO', 'EI', 'Open Access', 'IEEE/IET ', 'EV', 'CSCD', 'Superstar', 'ASCE', 'ASME'};

n=size(L,2);

X=1:1:n;

% Establish a RBF network with a distribution density of 0.9, and find the error with the sample, write it into the table.

net1=newrb(P,T,0,0.9,12,1);

R1=abs(sim(net1,P)-T);

xlswrite('data.xls',R1,5,'B2');
```

The distribution density σ of the radial basis function can affect the accuracy of the RBF network model we established. If the σ setting is too large, it means that a large number of hidden layer neurons are needed to satisfy the rapid change of the hidden layer function; Small, it means that a lot of hidden layer neurons are needed to satisfy the slow change of the hidden layer function. In this case, the performance of the network is very bad. So here we set σ to 0.1, 0.3, 0.5, 0.7 and 0.9 to see how they affect the accuracy of the network. The prediction error distribution of the RBF network model when σ takes different values is shown in Table 4 and Fig. 3

TABLE 4 ERRORS AT DIFFERENT INDEX DENSITIES

Name	spread=0.9	spread=0.7	spread=0.5	spread=0.3	spread=0.1
CNKI	9.23E-05	0.001875	0.003973	0.017487	0.150769
Springer Link	0.001147	0.00012	0.003325	0.001897	0.194275
APS	0.000717	0.000292	0.000517	0.001455	1.36E-09
Wan Fang	0.001414	0.003414	0.005915	0.003894	0.001536
ACS	0.002406	0.002578	0.00296	0.002515	0.000101
Nature	0.000773	0.005294	0.002863	0.000962	0.000585
Science Online	0.000183	0.000152	0.000114	0.000778	5.05E-09
EBSCO	0.000749	1.87E-05	0.00275	0.002144	6.47E-07
EI	0.009953	0.00669	0.016993	0.007905	0.001128
Open Access	0.003823	0.006482	0.002204	0.0038	0.033861
IEEE/IET Electronic Library	0.011905	0.007248	0.010201	0.001128	0.028869
Engineering Village	0.008355	0.002502	0.006583	0.022143	0.092578
CSCD	0.011659	0.017766	0.007074	0.005293	0.036015
Superstar	0.005791	0.000797	0.013962	0.00306	0.000836
ASCE	0.010467	0.004092	0.003587	0.000292	0.001083
ASME	0.011026	0.012741	0.000124	0.000924	0.020133

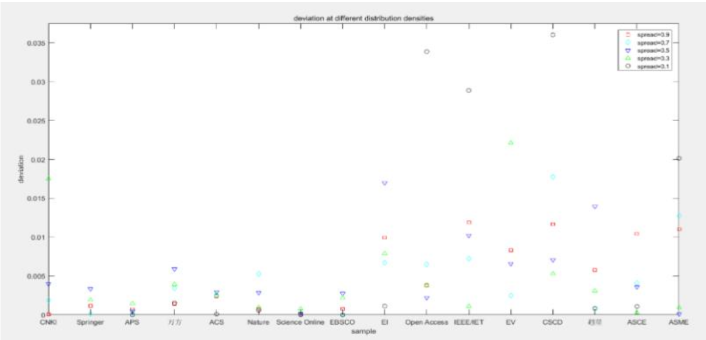

Fig. 3. Errors at different distribution densities

Through the comprehensive analysis of Table 4 and Figure 3, we can know that the error at the distribution density σ = 0.5 is the smallest. Therefore, we establish an RBF network with a target error of 0, a distribution density of σ=0.5, and a maximum number of neurons of 50, for each additional neuron showing a result.

C. Comparison with BP Network Results

The BP network has the same function as the RBF network. We compare the results obtained by the BP network model and the RBF network model to obtain the results as shown in Table 5.

TABLE 5 ERROR COMPARISON BETWEEN RBF NETWORK AND BP NETWORK

Final error:	RBF error	BP error
CNKI	5.55E-15	0.004213
Springer Link	8.88E-16	0.233567
APS	2E-15	0.004787
Wan Fang	4.44E-16	0.003322
ACS	2.66E-15	0.017003
Nature	1.67E-15	0.012605
Science Online	2.44E-15	0.060777
EBSCO	1.89E-15	0.003243
EI	1.11E-15	0.019324
Open Access	1.89E-15	0.009335
IEEE/IET Electronic Library	2.44E-15	0.024153
Engineering Village	1.78E-15	0.017741
CSCD	1.55E-15	0.003941
Superstar	1.55E-15	0.017618
ASCE	2.66E-15	0.005086
ASME	1.11E-15	0.041859

The main code of the BP network is as follows:

```
% establish a single hidden layer BP network, requiring 6 neurons in the hidden layer, sigmoid function for output and hidden layer, logsig for transfer function, expected error of 0.0001, learning rate of 0.1, initial weight at (0,1) between.
netBP =newff(P,T,[6],{'tansig','logsig'});
netBP .IW{1}=rand(6,8);
netBP .trainParam.goal=0.0001;
netBP .trainParam.lr=0.1;
netBP .trainParam.epochs=2000;
% training on BP network
netBP =train(net BP,P,T);
```

From the error comparison in Table 5, we get that the error of the RBF network is much smaller than the error of the BP network, and there is no error. The RBF network's evaluation of the quality of library electronic resources is also better, closer to reality.

D. Analysis of Results

We evaluated the remaining six electronic resources using the established RBF evaluation model and obtained the evaluation results shown in Table 6.

TABLE 6 EVALUATION RESULTS

	Wan Fang	ACS	Nature	Science Online	EBSCO	EI
Evaluation results	0.856854	0.796663	0.989074	0.943477	0.831534	0.97382

Analysis of the evaluation results of the RBF network, we can know that in the RBF network evaluation, the comprehensive evaluation results obtained by RBF are more affected by m1 and m2, and the indicators m1 and m2 account for a larger proportion in the network.

V. CONCLUSION

This paper establishes a model of electronic resource quality evaluation system based on RBF neural network in college library, and compares it with BP network model. It can be seen from comparison and analysis that the electronic resource quality evaluation system model of university library based on RBF neural network has more Advantages, this provides a new idea for the quality evaluation of library electronic resources.

ACKNOWLEDGMENT

This work was financially supported by the Fundamental Research Funds for the Central Universities under grant 3132018226 and National Natural Science Foundation of China under grants 51509030 and 61803065.

REFERENCES

[1] Marguerite E. Horn, E-Metrics for Library and Information Professionals: How to Use Data for Managing and Evaluating Electronic Resource Collections, Serials Review, 2007, pp.65-66

[2] Wang Junguang, Study on the Construction of Electronic Resources' Quality Evaluation System in University Libraries, New Century Library, 2017, (03), pp.30-33

[3] Zhao Rufiji, Comprehensive Evaluation of Electronic Resources Based on Analytic Hierarchy Process , Research on Library & Information Work of Shanghai Colleges & Universities,2008(3) , pp.24-27.

[4] Zhao Liangying, Li Lihua, Li Yimeng, Study on Evaluation Index System of Hybrid Library Informati on Resources Based on Multi-level Fuzzy, Library Work and Study,2011(3), pp.24-28.

[5] Deng Mingchun, Li Gang, The Comparison and Analysis of Some Typical Structure of Neural Networks, Information Technology and Informatization, 2008(6), pp.29-31

[6] Yin Zhengmei,Zhang Handong. Study on University Library E-resources Evaluation Basing on RBF Neural Network., Information Research, 2016(1) , pp.38-41.

[7] Li Jiacheng Research on the Adaptive Operation Mechanism of the User-network-oriented Logistics Network, Beijing Jiao tong University,2012.

[8] Tan Mingjun,The Scientific Evaluation of Electronic Resources in Library , Library Development,2008(1),pp.37-39