Advance Journal of Food Science and Technology 9(8): 637-642, 2015
DOI: 10.19026/ajfst.9.1979
ISSN: 2042-4868; e-ISSN: 2042-4876
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Submitted: April 19, 2015 Accepted: May 10, 2015 Published: September 10, 2015

Research Article

Research on Food Network Marketing Performance Evaluation Based on Improved BP Algorithm

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Abstract: The study presents a new BP neural network algorithm to evaluate food network marketing performance. First, rough set is used to determine the attribute dimension of decision table and simplify the calculation structure of BP neural network algorithm; Second, genetic algorithm is modified to search the weights in BP algorithm calculation globally and optimize BP algorithm locally to avoid the network falling into the local extremes; Third, a new indicator system for evaluating food networking marketing performance is established focusing on enterprise value; Finally the improved algorithm is applied to evaluate food networking marketing performance and the experimental results show that the improved algorithm has great superiorities, such as simple algorithm process, fast convergence speed, get out local minimum easily and high evaluation accuracy.

Keywords: BP Algorithm, food network marketing, genetic algorithm, performance evaluation, rough set

INTRODUCTION

In the face of the opportunities and challenges brought by economic globalization, how to exploit network marketing to help food enterprises enhance their competitiveness and achieve sound and rapid development has become a universal concern of governments, enterprises and academic circles. Compared with the other industries, the network marketing performance of food electronic commerce enterprises is low and its effect is not very ideal. So how to evaluate and enhance the implementation effect of network marketing of food electronic commerce enterprises, including evaluation factor system construction and evaluation algorithm design, has become a hotspot for food enterprises and researchers related (Ray and Lesley, 2013).

Following methods are wildly used in network marketing performance evaluation:

- AHP (Analytic Hierarchy Process) effectively combines qualitative analysis with quantitative analysis, not only able to guarantee the systematicness and rationality of model, but also able to let decision makers make full use of valuable experience and judgment, so as to provide powerful decision-making support for lots of regulatory decision making problems. The method has such strengths as clear structure and simple computation, but due to its strong subjective judgment, the method also has shortcomings like low evaluation accuracy (Yueh, 2013).
- Data Envelopment Analysis (DEA), starting from the perspective of relative efficiency, evaluates each decision-making unit and the indicators selected are only relied on input and output. As it doesn't rely on specific production function, it is effective for dealing with the evaluation with various kinds of input and output indicators, suitable for the analysis of benefit, scale economy and industry dynamics. But it is complicated in computational method, subject to certain limitations in application (Shifei and Weikuan, 2011).
- BP neural network method; BP neural network learning algorithm adopts gradient search technology so as to minimize the error mean square value between actual output value and desired output value; the method is adept in the processing of uncertain information. If the input mode is close to training sample, the evaluation system is able to provide correct reasoning conclusion. The method has such advantages as wide applicability and high evaluation accuracy, but it also has some disadvantages like easy to fall into local minimum in the computation, low rate of convergence and etc (Sue and Raman, 2010).

BP algorithm are wildly used in food network marketing performance evaluation for its high

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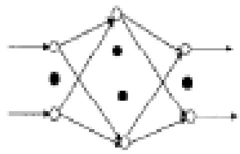

Fig. 1: Basic structure of three-layer BP algorithm

evaluation accuracy, but the algorithm also has its own defects in practice. Some actions are taken in the paper to overcome its own defects and bring its superiorities into full play. In doing so a new BP algorithm based on rough set and modified genetic algorithm for evaluating food network marketing performance is presented.

MATERIALS AND METHODS

BP Neural network algorithm: There are various artificial neural network models are presented from perspectives of various research views, in which multi-hierarchy feed forward error back propagation BP neural network is wildly researched and used in practice. Here take basic three-layer BP neural network for example, algorithm structure is given as Fig. 1.

From the Fig. 1, we can see that input layer, hidden layer and output layer are the main layers of three-layer BP neural network. ω is adjustable weight to connect different layers. There can be several hidden layers, forming multi-layer BP neural network. $x_i(k)$ and $y_j(k)$ means the input and actual output of BP neural network respectively, $Y_i(k)$ means the ideal output of BP network, the subscripts i, j are used to indicate the input layer nodes of BP network respectively and k means the running iterations of BP model. The approximation error of the BP model can be calculated by formula 1, in which L means the number of output layer nodes; the function characteristic of BP model can be shown as Formula 2 in this way:

$$E = \frac{1}{2}\sum_{j=1}^{L}(Y_j(k) - \gamma_j(k))^2 \tag{1}$$

$$\gamma_j(k) = f(x_i(k), \omega) \tag{2}$$

In formula 2, function f can be calculated through the composition of weights of each network layer and node function, generally being very complicated non-linear function BP neural network training is to dynamically adjust the connecting weight ω to make Formula 3 workable. The learning of weight ω adopts the fastest grads descent principle, i.e., the variable quantity of weights is in proportion to the negative gradient direction of approximation error E (Yohan, 2010):

$$\lim_{k\to\infty} E = \lim_{k\to\infty}\frac{1}{2}\sum_{j=1}^{L}(Y_j(k) - \gamma_j(k))^2 = 0 \tag{3}$$

OPTIMIZING BP NEURAL NETWORK STRUCTURE WITH ROUGH SET

BP neural network is the learning supervised by instructors and the learning rule is offered by a group of training set describing network behavior: $\{p_1, t_1\}$ $\{p_2, t_2\}$,…., $\{p_Q, t_Q\}$. In the rough set, the training set is the decision set. p_i is the condition attribute of decision table, expressed by C; t_i is the decision attribute of decision table, expressed by D. Generally, there is a certain degree of dependence between condition attribute and decision attribute, defined by the degree of dependence, see formula 4:

$$\gamma_C(D) = |pos_C(D)|/|U| = \left|\bigcup_{X\in U/D} C(X)\right|/|U| \tag{4}$$

In formula 4, $pos_C(D)$ is the C positive domain of D. $\gamma_C(D)$ makes a measurement on proportion that the objects in the decision table can be correctly partitioned in decision class based on the knowledge of attribute C.

Due to the dependence and relevance between condition attribute and decision attribute, as for decision attribute, not all the condition attributes are necessary, thus bringing the problem of attribute reduction, i.e., on the premise of unchanged classification ability, expressing the decision table in the simplest way.

While determining the attribute reduction of decision table, often used is the concept of attribute significance, the definition of which is $sig(\alpha, B; D) = \gamma_{\{\alpha\cup B\}}(D) - \gamma_{\{B\}}(D)$, showing the significance of attribute a, on attribute B with respect to decision attribute D.

Determining the attribute reduction of decision table: As the relative reduction of decision table includes core attribute and intersection is core, in the algorithm for determining relative reduction, we generally use definition first to determine the relative core of decision table.

As for $\forall R \in C$, if R meets the condition for satisfied $pos\{C\text{-}R\}(D) = pos_C(D)$, R is called D unnecessary in C, otherwise, R is called D necessary in C. All the sets constituted by D necessary original relationship in C are called the core of C with respect to D, recorded as $CORE_D(C)$ (Sue and Raman, 2010).

Some of the relative core of decision table is the relative reduction, so after determining relative core, we shall first decide it to be relative reduction or not. Judgment is made based on the following 2 conditions generally.

If the non-empty subset P of condition attribute C meets the condition of:

- $pos_P(D) = pos_C(D)$
- $pos_R(D) \neq pos_C(D)$ of R exists for any $R \subseteq P$, P is called the reduction of C with respect to D, recorded as $REDD(C)$.

Therefore, make $reduct = CORE_D(C)$ redundant attribute set $redundant = C\text{-}CORE_D(C)$. If $pos_{reduct}(D) = pos_C(D)$, it means the set *reduct* (relative core at this time) is the relative reduction of decision table; otherwise, add every attribute in the redundant attribute set to *reduct*, so as to determine the attribute α_i reaching the largest value according to the definition of attribute significance, making $reduct = reduct \cup \{\alpha_i\}$, $redundant = redundant \cup \{\alpha_i\}$, updating to be tested reduction set *reduct* and redundant attribute set *redundant*. Continue to cycle until $pos_{reduct}(D) = pos_C(D)$ satisfied; *reduct* at this time is the relative reduction of decision table.

Improving BP neural network structure with rough set: Determining the relative reduction is expressing original decision table in the simplest way, but making no changes on the classification ability. Hence, first make a judgment on whether training set has relative reduction via rough set so as to reduce its dimensionality, then input BP neural network model to carry out the training on learning rules. Besides, neural network can filter the random noise brought in the process of training sampling to certain extent, while rough set is sensitive to the noise. Combining such two can not only improve the real-time performance of system but also strengthen the fault-tolerant capability of system.

Specific steps for rough set improving BP neural network are as follows:

- Discretizing and normalizing original sample space to obtain original decision table
- Making use of the reduction algorithm of attribute significance to carry out reduction on the decision table to eliminate redundant condition attribute and obtain reduction decision table
- Deduction decision table inputting BP neural network training, successively updating weight and threshold, until meeting the given accuracy
- Testing the trained BP neural network with testing sample to obtain predictions, verifying the performance of improved BP network.

IMPROVING GENETIC ALGORITHM BY OPTIMIZING NETWORK PARAMETERS

Making use of global rough search of genetic algorithm and local detailing and optimizing of BP algorithm to look for the optimal weight and threshold of network, so as to conquer the defect that using BP algorithm only is easy to fall into local extreme point. Encoding the weight and threshold of network into the individual of genetic algorithm; first using genetic algorithm to optimize individual, until the sum of absolute value of BP network prediction error reaching the given accuracy; at this time, individual, after decoding, is the approximate solution of the optimal solution of weight and threshold. Based on this, local optimization is carried out with BP algorithm to find the optimal weight and threshold of network.

Individual encoding: There are generally two kinds of individual encoding in genetic algorithm: binary encoding or real number encoding. As the former needs to discretize continuous space while optimizing, which may cause a certain encoding error, while the latter has no discretization error, with intuitive description of problems and high solution accuracy, this thesis adopts the latter.

BP network adopts 3-layer network, comprised of input layer, hidden layer and output layer, so the individual consists of weight w_1 and threshold b_1 from input layer to hidden layer and weight w_2 and threshold b_2 from hidden layer to output layer. w_1, b_1, w_2 and b_2 are matrix or vector, each element being encoded as real number.

Fitness function: Training sample predicts system output after inputting BP network, taking the sum of absolute value of error between actual output and expected output as individual fitness value, see formula 5:

$$F = k\left(\sum_{i=1}^{n} abs\,(y_i - o_i)\right) \tag{5}$$

In formula 5, n is network output contacts number; y_i is the expected output of the i th node of BP network; o_i is the predicted output of the i th node; k is coefficient. The small the absolute value of error is, the better the predictive ability of network is. However, in the genetic algorithm, reciprocal is generally adopted as fitness value. The larger the fitness value is, the better the predictive ability is.

Selecting operation: Calculate selective probability according to the fitness value of each individual in the population and select excellent individuals from parent population pursuant to the selection strategy of "survival of the fittest" to form new population. This thesis adopts roulette selection, first calculating the selection probability of each individual, then generating one [0, 1] random number in each round according to population size iteration. After that, calculate cumulative probability; when the cumulative probability is larger than the generated random number, the pointed individual at this time is selected, cycling like this until meeting iteration number. Formula 6 is for selection probability calculation and Formula 7 is for cumulative probability:

$$P_i = \frac{(k/F_i)}{\sum_i^N (k/F_i)} \tag{6}$$

$$cumul_i = cumul_{i-1} + P_i \tag{7}$$

In the formula, F_i is the fitness value of individual i; as it is better to have small fitness value, reciprocal shall be determined on fitness value before individual selection; k is coefficient; N is population individual number (Fang *et al*., 2011).

Crossover operation: Arbitrarily select two individuals from new population and interchange part of genes according to certain way to generate two new individuals.

The value of crossover probability p_c in crossover operation exerts a direct impact on the convergence and effectiveness of genetic algorithm. The large the p_c is, the faster the new individual is generated, but the large the possibility that genetic algorithm is degenerated into random research algorithm; the small the p_c is, the slower the search speed is, even stagnating. Hence, crossover probability with self-adaption is adopted, as shown in the formula 8:

$$P_c = \begin{cases} \dfrac{(P_{c1} - P_{c2})(f^{'} - f_{avg})}{f_{\max} - f_{avg}}, & f^{'} \geq f_{avg} \\ P_{c1} & f^{'} \prec f_{avg} \end{cases} \tag{8}$$

In formula 8, f_{avg} indicates the average fitness value of each generation of population, $f_{\max}$ indicates the largest fitness value of each generation of population, $\acute{f}$ indicates the larger fitness value between 2 individuals to be crossed over. When $\acute{f}$ is equal to or greater than f_{avg}, reduce the crossover probability; otherwise, increase the crossover probability.

As the individual adopt real number encoding, crossover operation adopts the method of single-point crossover of real numbers. When meeting the crossover probability, the crossover operation algorithm of k th chromosome a_k and the l th chromosome a_l in the position of j is shown in Formula 9 and Formula 10, in which b is a random number among [0,1]:

$$a_{kj} = a_{kj}(1-b) + a_{lj}b \tag{9}$$

$$a_{lj} = a_{lj}(1-b) + a_{kj}b^{'} \tag{10}$$

Mutation operation: Arbitrarily selecting one individual from new population and substituting some gene values in the encoding string with other genes, thus forming a new individual. Similar to crossover probability, if the mutation probability p_{m} is too large, the genetic algorithm will be degenerated into random search algorithm; if it is too small, the algorithm is easy to be converged in local extreme point untimely, not easy to generate new individual gene. Therefore, mutation probability with self-adaption is adopted, as shown in the formula 11 (Lu *et al*., 2010):

$$P_m = \begin{cases} \dfrac{(P_{m1} - P_{m2})(f^{'} - f_{avg})}{f_{\max} - f_{avg}}, & f^{'} \geq f_{avg} \\ P_{m1} & f^{'} \prec f_{avg} \end{cases} \tag{11}$$

In the formula, the meanings of f_{avg}, f_{max} and $\acute{f}$ is the same as those in Formula 8.

When meeting mutation probability, randomly select mutation position. Select the j th chromosome a_{ij} of the i th individual to carry out the mutation; mutation operation is as formula 12:

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) * f(g) & r \succ 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) * f(g) & r \geq 0.5 \end{cases} \tag{12}$$

In the formula, $a_{\max}$ is the upper limit for the value range of chromosome a_{ij}, $a_{\min}$ is the lower limit of chromosome a_{ij}; $f(g) = r_2\ (1\text{-}g/G_{\max})^2$, r_2 is a random number; g is the current iteration frequency, $G_{\max}$ is total iteration frequency, r is the random number among [0, 1].

The improvement of genetic algorithm: Although genetic algorithm has a lot of advantages, there are also many problems, like easy to be converged in premature set. This thesis adopts the method of protecting elite individuals to improve the classic genetic algorithm, i.e., the individual with the best fitness in each round of iteration will be kept to the next generation of population without the operation of crossover or mutation operation. Besides, substituting the individuals with the worst fitness generated after crossover and mutation operation in the population with the optimal individual in current population, also able to improve classic genetic algorithm. After the genetic algorithm optimization is finished, optimal individuals are generated, i.e., roughly selecting optimal weight and threshold to be the initial structure parameter of BP network, then making use of the parameter of BP algorithm for locally optimizing network, so as to achieve more accurate mapping from input to output.

RESULTS AND DISCUSSION

Evaluation indicator system establishment: As performance evaluation of food network marketing to focus on enterprise value which makes the evaluation factors special and complicated, the similarity of

Table 1: Part evaluation results of three food network corporations

	Website design	Corporation management	Customer management	Final evaluation
Corporation A	4.038	3.962	4.223	4.108
Corporation B	3.076	3.993	3.589	3.629
Corporation C	3.336	2.985	3.321	3.201

Table 2: The evaluation performance of three algorithms

Algorithm	Improved BP algorithm	Ordinary BP algorithm	DEA Evaluation algorithm
Accuracy rate	94. 87%	84.11%	64.33%
Time consuming (s)	12	893	11

network marketing performance evaluation and the specialty of food enterprises shall be considered to establish the evaluation indicator system of its performance. Integrating the general idea of performance evaluation and taking existing research literature for reference (Ray and Lesley, 2013; Rian and Merve, 2013), from such four aspects as evaluation of internal and external performance of food enterprises, the paper establishes a new evaluation indicator system for evaluating food network marketing performance including 3 hierarchies, 3 categories, 9 second-grade indicators and 29 third-grade indicators; 3 first-class indicators are website design indicator, corporation management indicator and customer management indicator respectively, in which website design indicator includes website design, website properties, website popularization and website flow; enterprise management indicator includes financial performance and competition performance; customer management indicator includes customer service, customer satisfaction and food logistics distribution; the specific contents of three second-class indicators are omitted here because of limited paper page.

EXPERIMENTAL RESULTS AND ANALYSIS

Three typical food network corporations, called enterprise A, B and C respectively, are selected as research sample to collect experimental data and build experimental database. When collecting customer part data, 600 consumers of each food network corporation are investigated and the results is taken as the database for subsequent training and experimental verification, totally 1800 consumers' data are collected through practical visit and investigation. In order to make the selected data, representatives, 600 consumers (200 consumers from each corporation) with more than one and half years network food shopping experience, 600 consumers with one year food shopping experience, 600 consumers with less than one years food shopping experience.

In order to save paper space, here omits the intermediate evaluation results, only final comprehensive evaluation results and some secondary evaluation results and provided (Table 1).

As for the performance of the presented algorithm, the paper also realizes the application of the ordinary BP evaluation algorithm (Sue and Raman, 2010) and DEA evaluation algorithm (Shifei and Weikuan, 2011), evaluation performances of different algorithms are shown in Table 2. And the calculation platform as follows: hardware is Dell Poweredge R710, in which processor is E5506, memory 2G, hard disk 160G; software platform is Windows XP operating system, C programming language environment.

CONCLUSION

Based on modified genetic algorithm and rough set algorithm, the paper takes advantage of the high system evaluation accuracy of BP evaluation algorithm and overcomes the actual defects of original BP algorithm in poor calculation convergence, establishes an evaluation indicator system and presents a new BP neural network algorithm for food network marketing performance evaluation. The experimental results show that the algorithm has the following superiorities compared with original BP algorithm:

- Through self-study on samples involving in the comparison, genetic algorithm structure can be simplified, repeatedly iterating according to the criterion of optimal training, constantly adjusting ant genetic algorithm structure, until reaching a relatively stable status, thus, the utilization of that method eliminates many human factors, helping to ensure the objectiveness of the evaluation results
- High accuracy, able to make system error reach the requirement of any accuracy with convergence
- Good dynamics, self-study and dynamic tracking ability will be stronger with the progress of time and the increase of samples involved in comparison. Hence, there is certain practical application value in that method.

ACKNOWLEDGMENT

This study is supported by Jiangxi Academy of social science research of "The twelfth five year" planning project (2014) (No. GL02).

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