Research on the Key Influencing Factors of Network Marketing

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Abstract

How to mine key influencing factors and calculate their action intensity of food network marketing plays an important role for food enterprises to improves their operating performance in Internet age. This paper presents a new influencing factor system and modified BP neural network for analyzing the influencing factors of food network marketing. First, a new influencing factor system of food network marketing is designed based on the specific characteristics and requirements of the food network marketing and with references to the present literatures; Second the paper uses a simultaneous analysis and design algorithm and immune genetic algorithm to improve BP neural network algorithm to simplify its calculation structure and improve its calculation efficiency; Finally, the presented BP algorithm are realized by the data from ten food network enterprises, and according to the calculation results 14 factors are selected as key influencing factors of food network marketing, and the experimental results show the effectiveness and validity of the presented influencing factors and improved BP model.

Keywords

Network marketing, influencing factors analyzing, BP neural network algorithm, immune genetic algorithm, simultaneous analysis and design algorithm.

1. Introduction

With the development of Internet, network marketing becomes a new marketing model for many industries, and food enterprises can not be avoided from the trend also. So more and more food enterprises have begun to try to use network marketing to expand its sell scale and build its product brand. Network marketing has brought both opportunities and challenges to food enterprises which is closely linked with people's life enterprise. For the food enterprises, how to effectively mine the key influencing factors and calculate their action intensity to the food network marketing is becoming a key means to build brand reputation and earn much more economic benefit in network age. Although researching on key influencing factors is a research hotspot in the field of food network marketing, it is still in the initial stage of exploration and there is still no systematic research system, because lots of practical characteristics of food such as freshness, safety, taste and nourishment of different foods are involved in it. Therefore the research on mining key influencing factors and calculating their action intensity of food network marketing are of important theoretical and practical significance.

Currently, the frequently-used methods of mining key influencing factors and calculating their action intensity of food marketing in the world at present are linear curve fitting method(such as least square method, Chebyshev algorithm), linear regression algorithm, and BP neural network method. The method of mining key influencing factors and calculating their action intensity of food network marketing is a multi-factor and multi-indicator complicated calculation process, and lots of uncertainties are involved in the calculation; thus it cannot be simply distinguished which methods is good or bad. So the former two methods (including linear curve fitting method and linear regression algorithm) have such advantages as simple algorithm structure, easiness to understand, high algorithm efficiency and sassiness to operate, but these two methods also have such defects as low in calculation accuracy. The third method (i.e. BP neural network method) adopts the strong non-linear information processing capability of neural network, shows its unique advantage in processing multi-factor and multi-indicator system; thus its calculation has favorable calculation accuracy, and it is favored by many researchers in the industry. But BP neural network algorithm also has the defects like complicated in model structure, low in rate of convergence, and etc.

The paper improves BP neural network algorithm by a simultaneous analysis and design---SAND algorithm and immune genetic algorithm to overcome the defect of slow convergence speed of original BP neural network algorithm. Through doing so, not only does the defects of convergence speed of BP algorithm have been solved, but also the simplicity of the model structure and the accuracy of the calculation are ensured, then a new BPNN model for calculating the action intensity of influencing factors of food network marketing is presented.

2. Mining Influencing Factors of Network Marketing

It is found from the research on mining influencing factors of food network marketing in the world at present that the perspective of research differs greatly. The influencing factors of food network marketing constructed by foreign researchers is mainly for e-commerce selling website, and what it calculates is the marketing website itself. However, researchers in China conducts researches on mining influencing factors of food network marketing in a more deep and abstract way, and influencing factor system is perfecting. The paper, combining literatures at abroad and home, considering the specific characteristics of food network marketing, constructs an scientific and extensive influencing factor system of food network marketing based on the factor properties and the system 35 influencing factors and they belong to 4 first-class properties and 7 second-class properties respectively, showing in Table 1 for details.

3. Derivation of Algorithm

3.1 Simultaneous Analysis and Design.

De Castro indicated that there were similarities among the quality of weight value initialization of back-propagation neutral network and the relationship of network output and the quality of antibody instruction system initialization in the immune system and the quality of immune response. A simultaneous analysis and design---SAND algorithm was advanced to solve the problem regarding the weight value initialization in the back-propagation network[6]. In SAND algorithm, each antibody corresponds to a weight value vector of neuron given in one of several layers of neural networks, the length is l, and the affinity $aff(x_i, x_j)$ between antibody x_i and antibody x_j is shown by their derivative of Euclidean distance function $D(x_i, x_j)$ in Formula 1. In which, ε is a positive of value adoption 0.001. The definition of Euclidean distance function $D(x_i, x_j)$ is shown in Formula 2.

$$aff(x_i, x_j) = \frac{1}{D(x_i, x_j) + \varepsilon} \tag{1}$$

$$D(x_i, x_j) = \sqrt{\sum_{k=1}^{l} (x_{ik} - x_{jk})^2} \tag{2}$$

SAND algorithm aims to reduce the similarities between the antibodies and produce the antibody repertoire to cover the entire form space with the best, so energy function is maximized. The energy function is shown in Formula 3.

$$E = \sum_{i=1}^{N} \sum_{j=i+1}^{N} D(x_i, x_j) \tag{3}$$

In the method of Eculidean form space, the energy function is not percentage. With a view to the diversity of the vector, SAND algorithm has to define the stop condition. Given vector $x_i, i = 1,2,\ldots N$, its standardization is unit vector $I_i, i = 1,2,\ldots N$, $\bar{I}$ shows to calculate the average vector. Therefore, Formula 4 shows the diversity of unit vector, in which, $\left\|\bar{I}\right\|$ means the average vector distance from the origin of coordinate. Formula 5 shows the stop condition U of SAND algorithm.

$$\left\|\bar{I}\right\| = (I^T I)^{1/2} \tag{4}$$

$$U = 100 \times (1 - \left\|\bar{I}\right\|) \tag{5}$$

Table 1 Influencing Factor System of Food Network Marketing

Target Hierarchy	First-class Properties	Second-class Properties	Influencing Factors
Influencing Factor System of Food Network Marketing	Food Properties	Food Properties	Food Safety
			Retaining Freshness
			Food Taste
			Food Nourishment
			Comprehensive Food Information
	Webpage Properties	Webpage Design Properties	Website Address Design
			Retrieval Function
			Timeliness of Information
		Webpage Performance Properties	Timeliness of Information
			Necessity of Information
			Function Comprehensiveness
			Webpage Security
			Browse Speed of Webpage
			Interactivities with Costumers
			Number of the Effective Links
			Effectiveness of Links
		Online Advertising Properties	Convenience of Food Choosing
			Convenience of Purchase Operation
			Online Food Product Diversity
			Food Price
		Management Properties	Food Quality Control
			Customer Participation
			Traceability of Food Information
	Customer Service Properties	Customer Service Properties	Webpage Ranking
			Customer Recommendation Rate
			Customer Return Rate
			Online Transaction Rate
			Website Reputation
			Feedback Efficiency of Customer Complaint
			Solving Efficiency of Customer Complaint
			Service Response Speed
			Customer Feedback Evaluation
		Food Transportation Properties	Time for Transportation Foods
			Package Quality of Received Foods
			Quality Control in Transportation

3.2 BP Neural Network Design Based on Immune Genetic Algorithm.

According to the actual application, providing that both the input and output number of node and the input and output values in BPNN have been confirmed, activation function adopts S type function. The following steps show BP neural network design based on immune genetic algorithm.

(1) Every layer of BPNN carries on the weight value initialization separately by SAND algorithm.

(2) Antibody code. The initial weight value derived by SAND algorithm constructs the structures of BPNN. Each antibody corresponds to a structure of BP neural network. The number of hidden node and network weight value carry on the mixture of real code. Each antibody serials are shown in Fig.1.

Table 2. Antibody Code

Number of hidden node	Weight value corresponding to the first hidden node	Weight value corresponding to the second hidden node	…	Weight value corresponding to the N hidden node

(3) Fitness function design. Fitness function $f(x_i)$ is defined as the mean value function of squared error of neural network in Formula 6, in which, $E(x_i)$ is shown by Formula 7. In Formula 7, p is the total training sample, o is the number of node of output layer, T_j^n and Y_j^n are the n training sample's expected output and actual output in the j output node separately, and ξ is the constant larger than zero.

$$f(x_i)=\frac{1}{E(x_i)+\xi} \tag{6}$$

$$E(x_i)=\frac{1}{2p}\sum_{N=1}^{p}\sum_{j=1}^{o}(T_j^n-Y_j^n)^2 \tag{7}$$

operation so as that each antibody decoding is the corresponding network structure and change the network weight value as shown in Formula 8, in which, x_i and x_i^m are the antibodies before and after the variation, μ $(0,1)$ shows that the mean value is zero and squared error is normal distribution random variable of l, and $\partial\in(-1,1)$ is the individual variation rate. It is seen in Formula 8 that the variation degree varies inversely as the fitness, i.e. the lower the fitness is (the less the fitness value of objective function is), the higher the individual variation rate is, or vice versa. After the variation, all the hidden node and weight value components constitute a new antibody again.

$$x_i^m=x_i+\partial\exp(-f(x_i))\times\mu(0,1) \tag{8}$$

(5)Group renewal based on density. In order to guarantee the antibody diversity, improve the entire searching ability of the algorithm, the model adopts the Euclidean distance and the fitness based on the antibodies to calculate the similarity and density of the antibody. Providing that there are x_i and x_j antibodies, and $\eta\succ 0$ and $t\succ 0$, given constants, the fact that Formula 9 is satisfied indicates that x_i and x_j antibodies are similar, the number of antibody similar to the antibody x_i is the density of x_i marked by C_i. The probability of selecting antibody x_i is $p(x_i)$ as shown in Formula 10, in which, α and β is the adjustable parameters between (0, 1), and $M(x)$ is the maximum fitness value of all the antibodies. It is seen in Formula 10 that while the antibody density is high, the probability of selecting the antibody with high fitness is low, and conversely high. Therefore, excellent individual is not only retained, but the selection of similar antibodies is reduced, and the individual diversity is guaranteed.

$$\begin{cases} D(x_i, x_j \le \eta \\ \left|f(x_i)-f(x_j)\right| \le t \end{cases} \tag{9}$$

$$p(x_i) = \alpha C_i[1 - \frac{f(x_i)}{M(x)}] + \beta \frac{f(x_i)}{M(x)} \tag{10}$$

4. Results and Discussion

The proposed influencing factors and intensity calculation model is realized with C language. This paper takes certain 10 food network enterprises for experimental examples and investigates theirs practical operating data in 5 years from 2010-2014 according to the influencing factors designed in the paper to carry out model application and intensity calculation of each factor. Taking into account the actual accuracy of the demand，the paper takes 2 power cut-off for the fitting curve of every influencing factors, i.e. the expression of the fitting curve is as Formula 11.

$$y = a_0 + a_1 x + a_2 x^2 \tag{11}$$

In Formula 11, x means each influencing factor and y operation performance of network enterprises. So the proposed BP neural network model is used to fit the intensity curve between each influencing factor and operation performance of food network enterprises. Specific calculation results see Table 2 and Table 3 In order to save the paper page, Table 1 only shows calculation results of 14 the influencing factors, and the comprehensive influencing intensities of these 14 factors are the most significant and we defines these 14 factors as key influencing factors of food network marketing.

Table 3 The Calculation Result of the 14Key Influencing Factors

	a_0	a_1	a_2
Food Safety	-2.2894	5.4108	-0.6287
Retaining Freshness	1.2649	2.1365	1.2782
Comprehensive Food Information	-1.1458	3.1221	1.6586
Website Address Design	-1.3554	2.4842	-0.4239
Necessity of Information	1.4562	2.0446	-0.2677
Interactivities with Costumers	-2.2867	2.3581	-0.4346
Food Price	-2.7220	4.5255	-0.7972
Food Quality Control	-3.2568	2.2314	-0.4554
Traceability of Food Information	-1.2545	2.2156	-0.3824
Customer Recommendation Rate	-1.3048	2.2519	-0.4687
Website Reputation	-1.2296	2.5527	-0.3589
Solving Efficiency of Customer Complaint	-0.9669	2.0548	-0.4267
Customer Feedback Evaluation	7.0258	-2.5669	0.2748
Time for Transportation Foods	7.3369	-2.5254	0.2567
Comprehensive Food Information	-1.1458	3.1221	1.6586

Table 3 shows the calculation result comparison among least square method [6], original BP neural network[9] and improved algorithm in the paper in the practical application and the experiment is conducted through PC. PC configurations are as follows: P4 2.5G CPU and 512M memories and the population number of genetic algorithm is supposed to be 60, the largest evolutionary generations is 80, crossover probability is 0.9, mutation rate is 0.01, target function takes the minimum total costs sum.

Table 4. Calculation performance comparison of different algorithms

Algorithm in the paper	Least square method	Least square method
94%	74%	88%
14	13	689

5. Conclusion

Based on the specific characteristics of food products of network marketing and with reference of the presented research results in the world, the paper designs a new influencing factor system. And based on the analysis the advantages and disadvantages of BP neural network model used in calculating the action intensity of the influencing factors, the paper uses a simultaneous analysis and design---SAND algorithm and immune genetic algorithm to improves the original BP neural network algorithm and takes corresponding measures to simplify the algorithm structure and improve calcultion accuracy and speed up calculation speed. The experimental results show that the algorithm presented in the paper can realize above purposes when used in calculating the action intensity of the influencing factors for food network marketing.

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