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Reputation system of E-commerce based on artificial neural network

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Abstract: With the fast development, E-commerce is more and more popular in our daily life. To be successful in the E-commerce system, it is essential to keep a good reputation, which can help to get more customers. In this paper, we employ the Back error propagation neural network to balance weight between difference service components. Taobao as the most famous online mall is selected as the data resource. 1000 data sets as the training examples are obtained from Taobao. We get the gain value of each component. The training time for the 1000 data sets is 5.732 second and the overall accuracy is 96.8%.

Keyword: Neural Network; Reputation; E-commerce

1. Introduction

With sales estimated to rise from $3.3 billion in 1999 to $8.5 billion in 2001 [1, 2], online auctions are one of the fastest growing and most profitable segments of e-commerce [3], traditional commerce theory [4] and practice is challenged by the electronic commerce [5]. Electronic commerce, commonly known as e-commerce, refers to the buying and selling of products or services over electronic systems such as the Internet and other computer networks [6]. Electronic commerce draws on such technologies as electronic funds transfer, supply chain management, Internet marketing, online transaction processing, electronic data interchange (EDI) [7], inventory management systems, and automated data collection systems. Modern electronic commerce typically uses the World Wide Web at least at one point in the transaction's life-cycle, though it may encompass a wider range of technologies such as e-mail, mobile devices and telephones as well [8].

The challenge for the both side traders is the reputation and integrity. As we know, for the tradition business transaction, we can get all the information by face to face, such as the holder, the quality and so on. So both product providers and guests can regulate the business based on law and business regulations [9]. For the e-commerce, all the traders should achieve good integrity and reputation to gain the gain acceptance and trust of their participants. It proposes big challenge to both side traders to keep a good integrity and distinguish the identity based on fake or false initial trust. Customers often hesitate to make transactions with internet-based traders because of the potential risk of privacy, authentication and confidentiality [10].

M. Ekmekci [1] proposed a central mechanism which observed all past signals, and made public announcements every period. The set of announcements and the mapping from observed signals to the set of announcements was called a rating system. They showed that, absent reputation effects, information censoring could not improve attainable payoffs. However, if there was an initial probability that the seller was a commitment type that played a particular strategy every period, then there existed a finite rating system and an equilibrium of the resulting game such that, the expected present discounted payoff of the seller was almost his Stackelberg payoff after every history. This was in contrast to Cripps, You *et al.* [11] regarded that in consumer-to-consumer (C2C) markets, sellers could manipulate their reputation by employing a large number of puppet buyers who offered positive feedback on fake transactions. We presented a conceptual framework to identify the characteristics of collusive transactions based on the homo economics assumption. They hypothesized that transaction-related indicators including price, frequency, comment, and connectedness to the transaction network, and individual-related indicators including reputation and age could be used to identify collusive transactions. The model was empirically tested using a dataset from Taobao, the largest C2C market in China. The results showed that their proposed indicators were effective in identifying collusive traders. Tafreschi *et al.* [12] presented a system architecture enabling market participants to carry out bilateral and multi-attributive electronic negotiations with each other. Since the system used open and anonymous communication networks, market participants had to cope with much higher amount of uncertainty about the quality of products and the trustworthiness of other participants. Therefore, they presented a reputation system, which facilitated trust building among business partners who interacted in an ad-hoc manner with each other. The system enabled market participants to rate the business performance of their partners as well as the quality of offered goods. These ratings were the basis for evaluating the trustworthiness of market participants and the quality of their goods. The ratings were aggregated using the concept of Web of Trust. The approaches lead to robustness of the proposed system against malicious behavior aiming at manipulating the reputation of market participants.

In this paper, we use the error back-propagation neural network [13, 14] to analysis which factors can affect and contribute more to the integrity. The paper is organized in the following way: the first section is the introduction of the basic knowledge of the reputation of the e-commerce, and the current research about the reputation system. The second section introduces the basic method of the error back propagation neural network. The third section introduces the experiment including the dataset and examples of experiment results. The last section is the conclusion of this paper and our future work.

2. The Error Back-Propagation Neural Network

The BP is a type of supervised learning neural network [15, 16]. The principle includes using the steepest gradient descent method to reach any small approximation. A general model of the BP has a structure as shown in Figure 1.

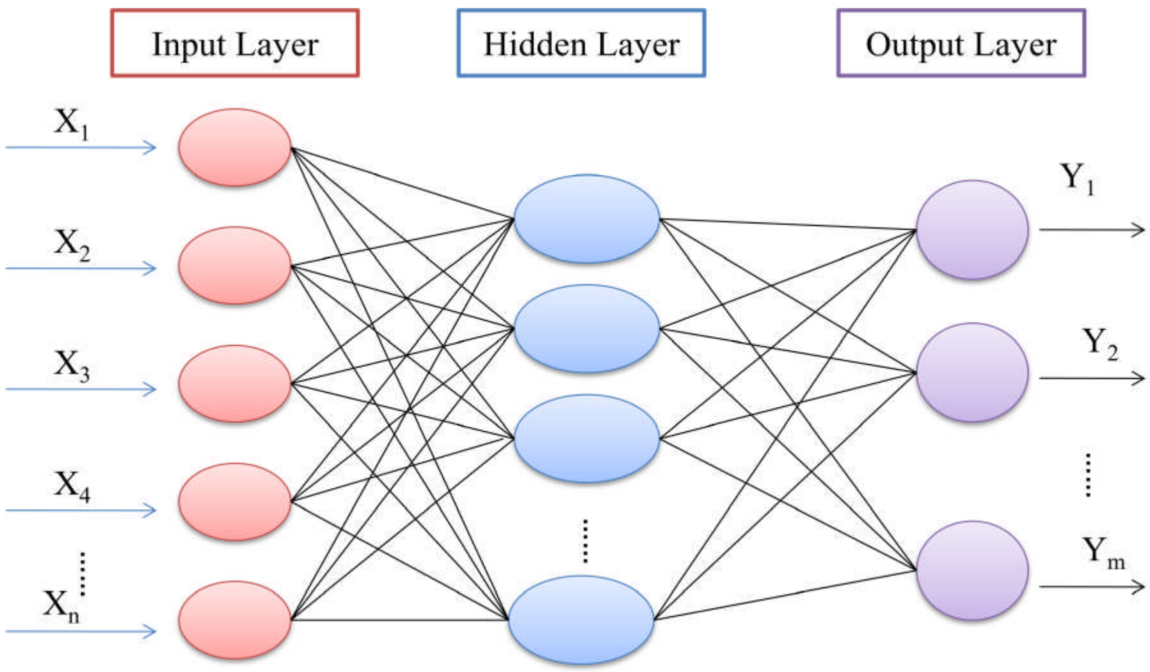

Figure 1. The architecture of Back Propagation Neural Network

From Figure 1 we can find that there are three layers contained in BP: input layer, hidden layer, and output layer. Two nodes of each adjacent layer are directly connected called as a link [17]. Each link has a weighted value presenting the relational degree between two nodes. Assume that there are n input neurons, m hidden neurons, and one output neuron [18-20], we can infer a training process described by the following equations to update these weighted values, which can be divided into two steps:

1) Hidden layer stage: The outputs of all neurons in the hidden layer are calculated by following steps:

$$net_j = \sum_{i=0}^{n} v_{ij} x_i \quad j = 1, 2, \cdots, m \tag{1}$$

$$y_j = f_H(net_j) \quad j = 1, 2, \cdots, m \tag{2}$$

Here net_j is the activation value of the jth node, y_j is the output of the hidden layer, and f_H is called the activation function of a node, usually a sigmoid function as follow [21]:

$$f_H(x) = \frac{1}{1 + \exp(-x)} \tag{3}$$

2) Output Stage: The outputs of all neurons in the output layer are given as follows:

$$O = f_O(\sum_{j=0}^{m} \omega_{jk} y_j) \tag{4}$$

Here f_o is the activation function, usually a line function. All weights are assigned with random values initially, and are modified by the delta rule according to the learning samples traditionally [22]

3. Reputation Model

In order to manage the service quality, the initial score to judge the service quality and model to build service quality is important. We suppose a initial score for all kinds of service. When the score is less than the initial value, it will be recovered to the lower limitation. We suppose S_0 is a new service's initial score, and $\overline{S}$ after k times of deals. Furthermore, we regard the reputation score of *i*th deal is consisted by its components which is different between websites. In this paper we take the Taobao as an example which is popular in china as the most famous online shopping mall.

$$\overline{S} = S_0 + \sum_{i=1}^{k} U_i \sum_{j=1}^{j=m} \alpha C_i \qquad (5)$$
$$k = 2,3,...,n,\ \text{j=1,2,.....m}$$

In this paper, we suppose the service is consisted of *m* main features. In the different application field, the feature number can be different, and meanwhile it could be different kinds of features. In this paper, we name all the features in a simple way as f_1 to f_i as shown in equation (6)

$$features = \{ f_1, ... f_i \}, i = 2,3,......m \qquad (6)$$

As we take the Taobao as the data resource, the feature is scored by numbers of starts as shown in Table 1. Five stars indicate the best service and one star stands for the bad service.

Table 1. Comments of the service of Taobao

Five stars	Four stars	Three stars	Two stars	One star
Best service	Good service	Average service	Low	Extreme bad

4. Experiment

The experiments are carried on a computer with a 2GBHz processor and 1GB memory. The proposed algorithm is implemented in Matlab code.

4.1. Dataset

We collect the data from the Taobao which is a famous online shopping mall in china. The entire reputation score consisted of customer service, description of the product, delivering efficiency, Security of the customer's privacy, easy degree of returning or changing products. Some data examples are shown in Table 2

.

Table 2. Data examples obtained from Taobao

Service Time	C_1	C_2	C_3	C_4	C_5	S_i
1	5	4	5	2	5	4
2	4	5	3	5	2	4
3	5	5	5	5	4	3
4	4	5	2	3	2	3
5	5	5	4	3	3	4
6	5	5	4	3	5	4
7	5	3	3	2	3	3
8	5	4	3	5	5	4
9	5	4	3	4	5	4
10	5	4	2	4	5	4
11	5	3	2	5	4	4
12	3	4	4	3	2	3

4.2. Experiment results

In this paper, we get 1000 data sets as the training data from Taobao. In the input layer of BP neural network, we have 5 neurons and in the output layer we get 5 output neurons as the predicted classes. The classification result is shown in Table 3.

Table 3. Confusion Matrix

	1	**2**	**3**	**4**	**5**
1	46	2	0	0	0

2	0	92	3	0	3
3	2	5	173	2	0
4	2	1	3	426	5
5	0	0	1	2	232

The accuracy of the classification reaches 96.8% which means that 969 data sets are correctly classified from 1000 datasets. The computation time for 1000 datasets is 5.732 seconds.

5. Conclusion and our future work

We focus on the development of the reputation system based on service ratemaking [23]. We employ the BP neural network as the development tool. We simulate the algorithm based on 1000 data sets from Taobao, and we finally get the weight values of each component of the entire score

In our future research, we are supposed collect more data and collect data from different application field, such as Amazon, Newegg, Bestbuy and so on. Furthermore we should optimize our algorithm for the future using. It is also necessary to build a user interface which can help the system to be widely used and for the trader of the E-commerce.

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