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Research of Customer Cross-selling Capability Based on Neural Network

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Abstract: With increasing market competition, enterprises have come to realize the importance of achieving profit by cross-selling services to existing customers. In this study, the author investigates customers' demographic data, studies how to quantify purchasing behavior and sets up mathematical method to calculate customers' cross-selling capability. Then, the model of customer cross-selling capability is set up based on counter propagation network, from which we can predict customers' cross-selling capability according to customers' demographics data---gender, age, educational level and income. The model will show us which products the customers should purchase. The predicting result from the model provides support for enterprise to evaluate customers' value and gives help to draw up the following targeted marketing strategy. At the same time, the author also points out the limitations of the research and lays out some directions for future research.

Key words: Cross-selling, counter propagation network, demographics data, direct marketing

INTRODUCTION

Customer resource is the core resource in market competition and is the competition focus for enterprises. It is the vital factor for enterprise to grasp a great deal of customer resource if they want to have a competitive advantage (Liu, 2007). Enterprise can gain more profits by the process of discriminating important customers and non-important customers, valuable customers and non-valuable customers, extending customers' lifetime to let customers purchase more products during their lifecycle (Hwang *et al*., 2004; Fader *et al*., 2007). The cost of winning a new customer is five times that of retaining an old customer and the profit achieved by winning over 10 new customers cannot offset the expense of losing a valuable customer (Verhoef and Donkers, 2001). Therefore, it is necessary for enterprise to know how to grab potential valuable customers firmly.

It is easier to maximize profit by cross-selling service to existing (Kaishev *et al*., 2013; Thuring *et al*., 2012) customers than to attract new customers. We often observe customers purchasing multiple products or services from the same provider. Cross-selling is a kind of marketing philosophy which persuading customers into purchasing product A after having purchased product B from the same enterprise (Kamakura *et al*., 2003). Cross-selling can provide personalized service for customers by using of finding out potential customers and knowing their needs and purchasing pattern (Zboja and Hartline, 2012). Research of cross-selling is focused on how to set up relationship between customers' purchasing pattern and customers' demographic data and then recommend products to customers (Li *et al*., 2005; Li *et al*., 2011). So, possibility recognition is the key issue cross-selling research.

The purpose of this study is set up cross-selling model to predict the relationship between and customers' demographic data and their purchasing behavior. Our research will resolve the issue of cross-selling recognition and provide support for enterprise to classify customers, predict customer value and distinguish the customer value.

The rest of this study is organized as follows. The second section introduces the structure of the Counter Propagation Network (CPN), presents demographic data and explains these research variables. In third section we set up the cross-selling model using the CPN. Finally, fourth section discusses our findings, points out the limitations of our research and lays out some directions for future research.

STRUCTURE OF CPN AND DESIGN OF NUMERICAL VALUE

Structure of CPN and simulation rule: A neural network model has the advantage in identifying relationships between variables of rather large and complex data bases. More and more researchers devoted themselves to study issues by using of neural network.

A CPN is founded by Hecht-Nielsen (1987). CPN consists of an input layer, a competition layer and an output layer. As shown in Fig. 1, from the input layer, the victorious nerve cell in the competition layer comes into being according to the learning rule; the connection weight between the input layer and the competition layer is adjusted according to the same learning rule. From the

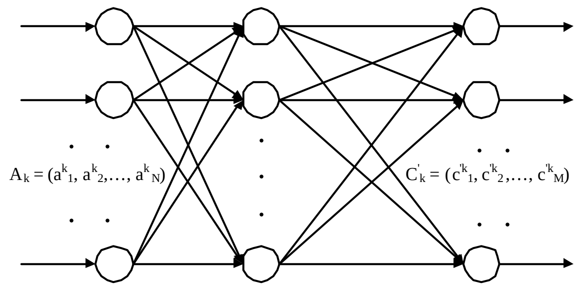

Fig. 1: Structure of the CPN

competition layer to the output layer, the network engenders the actual value of the output layer nerve cell based on the learning rule of a Competition Network (CN) and the connection weight between the competition layer and the output layer is revised accordingly. After repeated study, an arbitrary input pattern can be translated into a corresponding output pattern (Hecht-Nielsen, 1988). A corresponding network configuration is illustrated in Fig. 1.

We supposed an input layer has N nerve cells and the input pattern $A_k = (a^k_1, a^k_2,..., a^k_N)$, k = 1, 2,..., p. The competition layer has Q nerve cells and the corresponding output vector $B_k = (b^k_1, b^k_2,..., b^k_Q)$, k = 1, 2,..., p. The output layer has M nerve cells and the consecutive output vector $C'_k = (c'^k_1, c'^k_2,..., c'^k_M)$, k = 1, 2,..., p. The output vector of the targeted value $C_k = (c^k_1, c^k_2,..., c^k_M)$, k = 1, 2,..., p. The connection weight vector value between the input layer and the competition layer $W_j = (w_{j1}, w_{j2},..., w_{jN})$, j = 1, 2,..., Q, The connection weight vector value between the competition layer and the output layer $V_l = (v_{l1}, v_{l2},..., v_{lQ})$, l = 1, 2,..., M. The process of network study and the learning rule can be explained as follows (Zhang *et al*., 1998):

- In initialization, the connection weight vectors w_j and V_l are evaluated with stochastic values between 0 and 1 and input pattern A_k is changed into its normalized form
- The kth input pattern is introduced into the input layer
- The connection weight vector w_j is changed into its normalized form
- The weighted input summation in every nerve cell of the competition layer is calculated
- The vector W_g has a nearest distance to A_k for all the connection weight vectors W_j; the values of the output nerve cells are then evaluated-where the value of output g is 1 and the rest are 0
- Connection weight vector w_g is amended

Table 1: Brief description of the independent variables

Variables	Definitions
Age	1: The account owner's age is between 19 and 30
	2: The account owner's age is between31 and 40
	3: The account owner's age is between 40 and 49
	4: The account owner's age is above 49
Gender	1: The account owner is a male
	0: Otherwise
Education	1: Senior high school
	2: Junior college
	3: University
	4: Post-graduate
Income	1: <RMB1,000
	2: RMB1,000~RMB1,500
	3: RMB1,500~RMB2,000
	4: RMB2,000~RMB3,000
	5: RMB3,000~RMB5,000
	6: >RMB5,000

- The connection weight vector (v_l) that connects the competition layer with the output layer is modified according
- The weighted input of every nerve cell in the output layer is calculated as the actual output value of the nerve cell
- Going back to step 2, another input pattern is introduced into the input layer until all of the P input patterns have been introduced into the network
- When t = t+1, the input model A_k is introduced into the network and begins to operate until t = T

Design of numerical value of CPN: The related research show that customers' demographic variables has correlation with customer retention, customer profitability, customer life cycle and customer potential value. Customers' demographic variables and the stage of customers' lifetime can influence customers' purchasing sequence. Among these variables, gender, age, educational level and income level are the most important factors deciding customers' purchasing behavior. So, we choose these four variables as the input variables of CPN in this study. The design of numerical value of input layer of CPN is shown in Table 1. Number 1, 2, 3 and 4 signify four different age stages (between 19 and 30; between 31 and 40; between 40 and 49; above 49), respectively. Number 1, 2, 3 and 4 signify four different educational levels (senior high school; junior college; university; post-graduate). Number 1 and 2 signify male and female. Customers' income level has been classified into six different numbers.

MODEL OF CROSS-SELLING

Numerical of cross-selling capability: Products and services provided by bank include bank card, collection of taxes and fees, home loan, automobile loan, individual consumption loan, acting insurance or securities, internet banking and so on. Bank card, collection of taxes and fees, home loan, automobile loan and internet banking which have high purchase frequency are chosen as our research objects. The above five products are numbered from one to five. The purpose of this part is to analyze the relationship between customers' variables (gender, age, educational level and income level) and customers' purchasing behavior (purchasing these five products).

Due to the profit difference of these five products and the difference of possible purchasing number, we can evaluate customers' cross-selling capability according to profits achieved by purchasing products from enterprise, which will be different with the number and combination of products. We use value of product combination to signify number of customers' cross-selling capability. As shown in Table 2, there are thirty-two types of products combinations for the five products. Taken the maximum value of cross-selling capability as the base line value, we get the numerical values of cross-selling capability of every product combinations by comparing with the base line value.

Model of cross-selling capability: We design the numerical value of input layer of CPN according to Table 1. There are four nerve cells of the input of the model, which are gender, age, educational level and income level. The output layer has one nerve cell, the customers' cross-selling capability. Part of numerical value of input and output are shown in Table 3. In MATLAB 7.0, we input the numerical value for gender, age gender, educational level and income level into CPN, adjust the number of neural cell of the competitive layer and number of iterations in the process of simulation. When predicting result is within the margin of error and the predicting value is about to the actual value, the training process is ended. And then we get the neural network model of cross-selling capability. We can estimate the numerical number of customers' cross-selling capability and customers' cross purchasing behavior according to the result of the output of the model.

Table 2: Result of cross-selling capability of products

List	Numerical value	Cross buying	List	Numerical value	Cross buying
1	1	[1 2 3 4 5]	17	0.488	[1 2 5]
2	0.936	[2 3 4 5]	18	0.460	[1 2 4]
3	0.900	[1 3 4 5]	19	0.423	[2 5]
4	0.825	[3 4 5]	20	0.402	[1 2 3]
5	0.773	[1 2 4 5]	21	0.396	[2 4]
6	0.715	[1 2 3 5]	22	0.377	[1 5]
7	0.709	[2 4 5]	23	0.350	[1 4]
8	0.687	[1 2 3 4]	24	0.337	[2 3]
9	0.663	[1 4 5]	25	0.313	[5]
10	0.650	[2 3 5]	26	0.291	[1 3]
11	0.623	[2 3 4]	27	0.285	[4]
12	0.604	[1 3 5]	28	0.227	[3]
13	0.598	[4 5]	29	0.175	[1 2]
14	0.577	[1 3 4]	30	0.110	[2]
15	0.540	[3 5]	31	0.060	[1]
16	0.512	[3 4]	32	0	none

Table 3: Numerical design of cross-selling model

Age	Gender	Education level	Income	Numerical value	Cross buying
2	1	4	4	0.540	[3 5]
2	0	3	4	0.402	[1 2 3]
3	1	2	2	0.175	[1 2]
2	1	4	5	0.715	[1 2 3 5]
1	1	4	4	0.577	[1 3 4]
3	1	4	5	0.377	[1 5]
4	0	3	2	0.291	[1 3]
3	0	2	5	0.313	[1 2 3 4 5]
2	0	2	3	0.285	[4]
…	……	………	………	………	………
1	1	3	5	0.623	[2 3 4]

CONCLUSION

We set up cross-selling capability model based on CPN, which can predict the numerical number of cross-selling capability according to customers' demographic variables. The model can predict which products would be purchased by customers who possess certain gender, age, educational level and income level. The result of the model can provide support for marketing tactics. Enterprise should try to persuade the customers into buying the un-purchased products and provide the products to the right customer according to the output of the model. In this way, enterprise can get the most profit at the least cost.

Our research about prediction of the numerical number of customers' cross-selling capability has made beneficial exploration in the field of evaluating customer value, setting up customer classification system. The limitation of the research lies in unable predicting the time sequence of purchasing products. We hope that this research takes one step in that direction.

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