

# ANALYSIS OF CUSTOMER DEMAND TO CAPTURE CUSTOMER DEMAND KNOWLEDGE

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## KEYWORDS

Simulation in business, customer demand discrimination, knowledge capture

## ABSTRACTS

Customer demand discrimination is a well-established methodology for the analysis of customer relationship management systems. Based on the background of mobile industry, this paper makes a mobile customer demand analysis model and proposes ways to simulate customer value hierarchy and capture customer demand knowledge. Firstly, a contour model of customer value layers is gotten by investigation and specific interview; secondly, the significant attributes of customer value layers are screened out; finally, a customer demand discrimination model is built while making the customer demand objective layer as the output of the model and making customer demand attribute layer as the input of the model. Well-formed model could judge the classification of customer demand objectives dynamically from their demand attributes. This model is used in analysis of mobile customer samples. A contour model of mobile customer value layer is made, and 13 key variables of attribute layer are screened out. The results of customer demand discrimination reflect its outcome with the correct percentile over 80%. Compared with customer clustering analysis, it's precise and high in intelligence level. Besides that, the conclusion is easy to understand.

## 1. INTRODUCTION

Customer demand discrimination is a well-established methodology for the analysis of customer relationship management systems. The customer demand knowledge is descriptive information about customer consume preference and consume behavior that to identify customer demand. However, in the actual marketing, not only the preference cannot be defined by customers exactly, but also the preference is erratic. Especially in the telecommunication industry, the customers' demands are more variable and ambiguous because of various services and depressed switching cost, etc. Furthermore, there are some factors that potentially impact the

customer perceptive value, which are customer education background, market circumstance, customer emotion, etc (Boulton et al. 2000; Sharp 1997).

The complexity of customer demand discrimination is indicated in two aspects: firstly, a customer may belong to multiplex sorts that are simply classified by demand attributes. Secondly, there are uncertain relationships between the customer demand attributes and consume decision-making. So the customer demand discrimination is a subject of customer classification under uncertain condition.

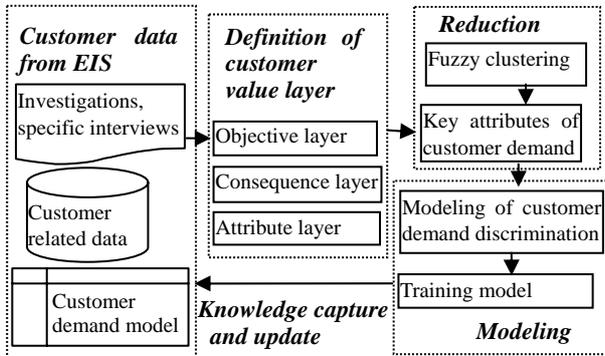
Previous studies mainly focus on these subjects: firstly, predicting customer preferences and repeat-purchase patterns by consume data analysis (Simpson et al. 2001; Shih et al. 2005); secondly, analyzing the antecedents and consequences of consume behavior and customer loyalty (Srinivasan et al. 2002; Inoue et al. 2003); thirdly, classifying customers by using clustering analysis (Wan et al. 2005). The shortage of this method is subjective with low intelligence level and large manual work.

Woodruff, Burns and Goodstein proposed the CVD (Customer Value Determination) and built the correlative relationships among the customer demand attribute layer, the consequence layer and the objective layer (Woodruff, 1997; Burns, 1990). However they did not present technical tools to implement the CVD knowledge capture.

Based on the background of mobile industry, this paper makes mobile customer demand analysis model and proposes ways to simulate customer value hierarchy and capture customer demand knowledge. Firstly, a contour model of customer value layer is gotten by investigation; secondly, the significant attributes of customer value layers are screened out; finally, a customer demand discrimination and analysis model is built. Well-formed model could judge the classification of customer demand objectives dynamically from their choices on demand attribute layer. This method is used to analyze the samples of 122 mobile telecommunication customers.

## 2. FRAMEWORK FOR CUSTOMER DEMAND DISCRIMINATION

The supporting framework for the process of mobile customer demand analysis is presented in Figure 1. The subsequent sections of this paper will explore it in detail.



Figures 1: Framework for Customer Demand Discrimination

**Definition of customer value**—According to Woodruff’s CVD theory, which suggested that customer demand hierarchy contains the objective layer, the consequence layer and the attribute layer, the mobile customer value hierarchy is defined.

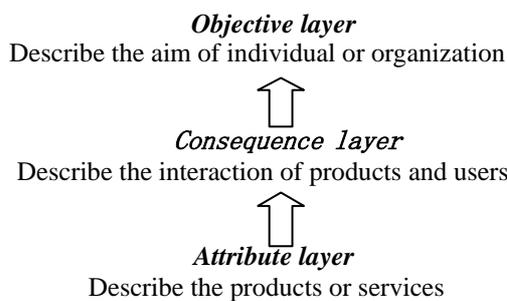
**Reduction**--This step is to find the significant attributes of customer value layers, which is a group of attribute layer variables that influence the customer demand objectives. That is solved by the fuzzy cluster analysis.

**Modeling**—a customer demand discrimination model is built. Well formed model could judge the classification of customer demand objective layer perfectly from their choices on demand attribute layer. This is achieved by adopting the neural network method.

## 3 MOBILE CUSTOMER DEMAND ANALYSE AND THE KNOWLEDGE CAPTURE

### 3.1 Contour Model of Mobile Customer Value Hierarchy

Woodruff advanced the CVD indicating that how customer consider product with hierarchy structure. The customer value hierarchy is presented in Figures 2.



Figures 2: Customer Value Hierarchy

From the bottom of customer value hierarchy, customers

firstly consider the attributes and availabilities of products. At the second layer, customers begin to make expectation according to these attributes. At the top layer, customers form expectation about the realization of their aim.

In this paper, the mobile customer value hierarchy consists of the customer demand objective layer, the consequence layer and the attribute layer.

**The objective layer**-- The objective layer means the ultimate motivations of customers engaging in mobile telecommunication services. Customers may have multiple motivations in the objective layer.

**Consequence layer**—The Consequence layer means the customer experience of mobile services.

**Attribute layer**—The Attribute layer means the usage of mobile services.

Based on the mobile customer interview that made in X city, this paper constructs the mobile customer value hierarchy presented in Table 1. The factors of objective layer and attribute layer are defined as the variable  $a_i$  ( $i=1, 2...29$ ).

Table 1: Mobile Customer Value Hierarchy

Objectives	Consequences	Attributes	
Communicative Object (a26)	Convenient communication,	short message service	a1
		call waiting call diversion	a2
		little secretary	a3
		voice mail box	a4
			a5
Business Object(a27)	High quality, knight service, high standing	U-net	a6
		Routine service	a7
		Ticket booking	a8
		Uni-colour E	a9
		E- bank	a10
		Stock exchange	a11
		Mobile purchase	a12
Recreational Object(a28)	Fashion, pleasure, selfhood, fun	Color ring back tone	a13
		mobile ring	a14
		mobile picture	a15
		E-game	a16
		chat	a17
		mobile movie	a18
Informational Object(a29)	knowledge, in time, information	News service	a19
		Weather info	a20
		Travel info	a21
		Finance info	a22
		Physical news	a23
		Entertainment info	a24
		U-map	a25

### 3.2 Significant Attributes Analysis of Customer Value Hierarchy

The significant attributes of customer value hierarchy mean the key attribute variables of the attribute layer which distinctly correlate with the objective layer.

Because of the large numbers of mobile telecommunication products/services and the relatively small percentage of the mobile services/products engagement, the original data of customer value hierarchy is high dimensional sparse feature data. Therefore, this step is mainly to decrease the data dimension in customer demand analysis. This paper adopts fuzzy cluster analysis method to find the significant attribute and accomplish reduction.

#### A. The Principles of Significant Attributes Analysis

According to the rough set theory, data of the customer value objective layer and attribute layer can be defined as  $S = (U, A, V, f)$ . Here:  $U = \{u_1, u_2, \dots, u_n\}$ : the set of customers where  $n$  is the total number of customer.  $A = \{a_1, a_2, \dots, a_m\}$ : the set of variables of the objective layer and the attribute layer.  $A = C \cup D$ , where  $C$  is the characteristics set of the attribute layer, and  $D$  is the characteristics set of the objective layer.  $V$  is the set of the customer attribute parameters. The value of  $f(u_j, a_i)$  indicates the value of  $u_j$  about  $a_i$ .

The significant attributes analysis is solved by fuzzy cluster. The process of the analysis is:

Step1. Partition customer set  $A$  into  $D$  and  $C$ . Consider the numerical character of attribute  $a_i$  in attributes set  $C$ , and represent attribute  $a_i$  as  $a_{ij}$  ( $j=1,2,\dots,k$ ). Here  $k$  is the number of incoordinate value of attribute  $a_i$ .

Step2. Calculate the fuzzy similarity matrix  $R$ . The paper adopts Equation (1) the Cosine distance measure as the method of similarity measurement of the study objects.

$$r_{ij} = \frac{\sum_{k=1}^m (a_{ik} a_{jk})^2}{\sqrt{(\sum_{i=1}^m a_{ik}^2)(\sum_{k=1}^m a_{jk}^2)}} \quad (1)$$

Step3. Calculate the fuzzy transitive closure  $t(R)$  of the fuzzy correlation matrix  $R$ . Use the cluster method to analyze  $t(R)$  with intercept  $\lambda$  and find out the significant attributes set.

#### B. The Process of Data Analysis

The investigation gave 150 pieces of questionnaire out to the mobile individual customers in X city. 122 effective sheets of questionnaire were retrieved. The rate of retrieving efficiency is 81.3%.

The questionnaire contains two parts: (1) questions about the importance of the customer objects in the objective layer. Five scores are adopted to fill out the questions: one score means the least important and five scores mean the most important. (2) Questions about whether the customers have engaged the services of the attribute layer. The questionnaire enumerate products/services of the attribute layers that corresponding to a given object of the objective layer. Then we transform the answer into data: 1 means the customer has engaged the products/services and 0 means the customer hasn't

engaged the products/services.

In order to be less costly and easily applied, 50 questionnaires are chosen as the analysis samples. By taking the business object related attribute layer as an example, the process of finding the significant attributes of attribute layer is illustrated.

Firstly, data of the customer business demand objective layer and attribute layer can be defined as  $S = (U, A, V, f)$   $A = \{a_6, a_7, a_8, a_9, a_{10}, a_{11}, a_{12}, a_{27}\}$ ,  $V = \{\tilde{1}, \tilde{0}, 5, 4, 3, 2, 1\}$ ,  $U = \{u_1, u_2, \dots, u_{50}\}$ , and,  $u_1 = (\tilde{1}, \tilde{1}, \tilde{0}, \tilde{0}, \tilde{0}, \tilde{1}, \tilde{0}, 5), u_2 = (\tilde{0}, \tilde{1}, \tilde{0}, \tilde{0}, \tilde{0}, \tilde{0}, 1), \dots, u_{50} = (\tilde{0}, \tilde{1}, \tilde{0}, \tilde{0}, \tilde{0}, \tilde{0}, 1)$ ,  $f(u_1, a_6) = \tilde{1}$ ,  $f(u_1, a_7) = \tilde{1}$ ,  $f(u_1, a_8) = \tilde{0}$ ,  $\dots, f(u_1, a_{27}) = 5$

If define the set of objective layer  $D = \{a_{27}\}$ , the set of attribute layer is  $C = \{a_6, a_7, a_8, a_9, a_{10}, a_{11}, a_{12}\}$ , and the numerical representation of attribute  $a_i$  ( $i = 6, 7, 8, 9, 10, 11, 12$ ) is  $a_{ij}$  ( $j = 0, 1$ ). The matrix of the numerical character is expressed as:

$$\begin{bmatrix} 42 & 11 & 50 & 44 & 48 & 49 & 49 \\ 8 & 39 & 0 & 6 & 2 & 1 & 1 \end{bmatrix}^T$$

Secondly, Calculate the fuzzy similarity matrix  $R$ . The result is expressed as Equation (2):

$$[R] = \begin{bmatrix} 1 & 0.447 & 0.982 & 0.999 & 0.989 & 0.986 & 0.986 \\ 0.447 & 1 & 0.271 & 0.399 & 0.311 & 0.291 & 0.291 \\ 0.982 & 0.271 & 1 & 0.991 & 0.999 & 1 & 1 \\ 0.999 & 0.399 & 0.991 & 1 & 0.996 & 0.993 & 0.993 \\ 0.989 & 0.311 & 0.999 & 0.996 & 1 & 1 & 1 \\ 0.986 & 0.291 & 1 & 0.993 & 1 & 1 & 1 \\ 0.986 & 0.291 & 1 & 0.993 & 1 & 1 & 1 \end{bmatrix} \quad (2)$$

Thirdly, calculate the fuzzy transitive closure  $t(R)$  of the fuzzy correlation matrix  $R$  with square method. If the fuzzy correlation matrix can be expressed as

$$R = (r_{ij})_{n \times n}, \text{ then } R \circ R = (t_{ij})_{n \times n}, t_{ij} = \max_{k=1}^n (\min(r_{ik}, r_{kj}))$$

If  $[R]^{2^k} \circ [R]^{2^k} = [R]^{2^k}$ , then the fuzzy transitive closure  $[t(R)] = [R]^{2^k}$ .

The result of calculation and the significant attributes of four objective layers are presented in table 2.

Table 2: Significant Attributes of Attribute Layer

objective layer	$\lambda$	attributes cluster	Significant attributes
Communicative Object	0.91	{a1}{a2,a3,a4}{a5}	a1,a2,a3,a4
Business Object	0.99	{a6,a9},{a7},{a8,a10,a11,a12}	a6,a7,a9
Recreational Object	0.99	{a13,a14}{a15}{a16}{a17,a18}	a13,a14,a15 a16

Informational Object	0.95	{a19},{a20} {a21,a22,a23,a24 a25}	a19,a20
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From total 25 products/services, 13 products/services were found that have distinct correlation with the customer demand objectives. This conclusion can help the operators to implement powerful marketing strategies. Therefore, the set of significant attributes  $C_c$  can be expressed as:

$$C_c = \{a_1, a_2, a_3, a_4, a_6, a_7, a_9, a_{13}, a_{14}, a_{15}, a_{16}, a_{19}, a_{20}\}$$

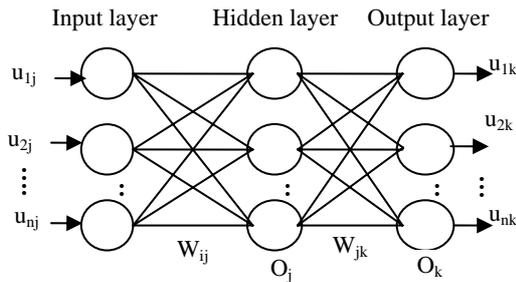
### 3.3 Mobile Customer Demand Discrimination Modeling

The customer demand hierarchy is applied into customer demand analysis modeling for concluding customer demand object by analyze customer demand attribute. This is achieved by adopting BP-neural network method.

#### A. The Principle of Modeling of mobile customer demand discrimination

Customer demand discrimination model is built while making the customer demand objective layer  $U = [u_{1k}, u_{2k}, \dots, u_{nk}]$  ( $k \in D$ ) as the output of the model and making significant attributes of the attribute layer  $U = [u_{1j}, u_{2j}, \dots, u_{nj}]$  ( $j \in C_c$ ) as the input of the model.

The structure of neural network is shown in Fig.3.  $w_{ij}$  is the weight from input layer to hidden layer;  $w_{jk}$  is the weight from hidden layer to output layer. The crunodes number of the hidden layer is set between 3 and 20.



Figures 3: the Model of BP-neural Network for Customer Demand Discrimination

#### B. The Process of Data Analysis

The process of data analysis is accomplished by using Clementine 8.0. This paper uses 61 customers as the training samples set and others as the contrastive samples set. The model is trained with  $\alpha = 0.9$  and  $\eta = 0.01$ , and finally when the number of hidden layer is 5, the best acceptable training result is achieved. The accurate percentage of forecast is 80.517%. The weight matrix from input layer to hidden layer  $W$  is described

as:

$$W = \begin{bmatrix} -0.9 & -0.04 & -0.63 & 0.51 & 0.34 \\ 0.67 & -0.73 & 0.32 & -0.22 & -0.72 \\ -0.82 & -1.18 & 0.06 & 0.44 & -1.02 \\ 0.26 & -0.94 & 0.68 & -0.20 & -0.70 \\ -0.37 & -0.06 & 0.21 & -0.03 & -0.70 \\ -0.33 & -0.26 & -0.35 & -0.21 & -0.26 \\ 0.02 & -0.62 & -0.56 & 0.16 & 0.39 \\ 0.14 & 0.86 & -0.43 & -0.58 & -0.15 \\ -0.02 & 0.06 & -0.70 & -0.48 & -0.29 \\ 0.35 & -0.45 & 0.27 & -0.79 & 0.59 \\ -0.79 & -0.08 & -0.73 & 0.04 & -0.35 \\ 1.26 & -0.42 & 0.16 & -1.02 & -0.19 \\ 0.53 & -0.1 & 0.15 & -1.48 & 0.75 \end{bmatrix}$$

And the weight matrix from input layer to hidden layer is expressed as:

$$T = \begin{bmatrix} 0.918 & 0.393 & 0.921 & 0.973 \\ 0.145 & -1.252 & 0.363 & -0.459 \\ 0.852 & 0.724 & -0.424 & 0.509 \\ 0.976 & -0.195 & -1.577 & -0.247 \\ 0.992 & -0.537 & -0.395 & 1.527 \end{bmatrix}$$

### 3.4 Customer Demand Knowledge Capture

Well-formed model could judge the classification of customer demand objectives dynamically from their demand attributes. 3 customers are randomly selected from samples and the comparison between the analytical conclusions and the actual demands is presented in Table 3. For getting obvious conclusion, we assume 3 as the dividing line.

Table 3: Comparison Between Analytical Conclusions and Actual Demands

customer		a26	a27	a28	a29	customer demand object
1	Actual demand	5.0	2.0	2.0	3.0	Communication object, Information object
	Analytical conclusion	4.9	3.1	2.6	3.8	Communication object, Business object, Information object
2	Actual demand	5.0	3.0	2.0	4.0	Communication object, Business object, Information object
	Analytical conclusion	4.9	3.	2.9	3.8	Communication object, Business object, Information object
3	Actual demand	5.0	3.0	3.0	5.0	Communication object, Business object, recreation object, information object
	Analytical conclusion	4.9	2.6	3.1	3.9	Communication object, recreation object, information object

It can be indicated that the model can discriminate the customer demand with high accurate percentage. The sort order of customer demand objects that discriminated

by the model are accordant to customer's actual object's sort order, even though the conclusion is not absolutely correct. That is because the conclusion is influenced by the dividing line of customer demand. Furthermore, the model can indicate a mensurable conclusion based on customer motivation that has the advantage of stability and reliability. The model advanced in this paper can help the mobile operators to efficiently carry out "one to one" customer service strategy

#### 4. CONCLUSIONS

Based on the background of mobile industry, this paper makes mobile customer demand analysis model and proposes ways to simulate customer value hierarchy and capture customer demand knowledge. The method is used to analyze the samples of 122 mobile telecommunication customers. We make a contour model of mobile customer value layer, and screen out 13 key variables of attribute layer. The results of customer demand discrimination reflect its outcome with the correct percentile over 80%. Compared with customer clustering analysis, it's precise and high in intelligence level. Besides that, the conclusion is easy to understand.

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#### REFERENCES

- Inoue, A.; S. Takahashi; K.Nishimatsu; and H. Kawano. 2003. "Service Demand Analysis Using Multi-Attribute Learning Mechanisms". In *the International Conference Integration of Knowledge Intensive Multi-Agent Systems (KIMAS '03)*. IEEE, 634-639
- Burs; M. Jane; R.B. Woodruff. 1990. "Value: An Integrative Perspective". In *Proceedings of the Society for Consumer Psychology*. Washington : American Psychological Association, 59-64
- Sharp, B. and A. Sharp, 1997. "Loyalty programs and their impact on repeat-purchase loyalty patterns". *International Journal of Research in Marketing*, No.14 , 473-486.
- Simpson. P.M; J.A. Siguaw; T.L. Baker. 2001. "Value Creation Supplier Behaviors and Their Impact on Reseller-Perceived Value". *Industrial Marketing Management*, No.30, 119-134
- Boulton, R.; B. Libert.; and S.M. Samek. 2000. *Cracking the Value code: How Successful Businesses Are Creating Wealth in the New Economy*. New York: Harper Collins

- Publishers Inc., 288
- Woodruff, R.B. 1997. "Customer Value: The next source for competitive advantage." *Academy of Marketing science*. Spring, Vol.25, Issue 2, 139
- Srinivasan, S.S.; R. Andeson; and K. Ponnaveolu. 2002, "Customer Loyalty in E-commerce: an Exploration of Its Antecedents and Consequences." *Journal of Retailing*, No.78, 41-50
- Shih, Y.Y.; D.R. Liu; Hybrid. 2005. "Recommendation Approaches: Collaborative Filtering Via Valuable Content Information." In *Proceedings of the 38<sup>th</sup> Hawaii International Conference on System Sciences*, 217
- Wan, Y.; Y. Qian; J. Li; and L. Cui. 2005. "The Analysis of Customer Value Dimensions' Difference of the Bank's Interacting Channel." In *The Second IEEE Conference on Service Systems and Service Management, Institute of Electrical and Electronic Engineer Inc*, 193-198

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