Estimation of Dominant Attributes of Product for Each Customer through Behavior Observation of Shopping

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Abstract: Our purpose is to make a personalized shopping support system in a retail store. In this study, we estimated dominant attributes for each customer through behavior observation of shopping to collecting decision-making data of them with various kinds of products. The dominant attributes are estimated by conjoint analysis of the product attributes and the degree of interest in the product estimated from customer's behavior. In the experiment with a trial retail store, we achieved success about estimations of 3 of 4 customers. The products recommended by our system also were shown to be better suit for customers.

Key words: Ubiquitous Sensing, Modeling of Customer Preference, Smart Shop, Online Shop.

1. Introduction

Current recommendation services are mostly based on social recommendation by collaborative filtering of huge number of shopping logs of many consumers. To perform personalized recommendation we need effective method for collecting decision-making data of each consumer with various kinds of products.

The purpose of our study is to quickly estimate the individual tastes of each consumer on products through observation of shopping behavior in a shop equipped with ubiquitous sensors. Personal taste can be described with dominant attributes and their attribute values.

2. System and Implementation

2.1 Smart Shop

We built an experimental shop, Smart Shop, with ubiquitous sensors to capture the passive observation of the each consumer's behavior such as "look", "touch", and "take" action to products [1]. The installed sensors are RFID readers and tags attached to customer cards and shirts and web cameras. The former is to locate and identify the customer and to sense which shirt is taken, and the latter is to sense customer's action.

Our Smart Shop also has digital signage devices with web camera for active observation of consumer's gaze as "watch" action to the computer coordinated signage.

2.2 Estimation of Dominant Attributes

We adopt conjoint analysis as to find the dominant attributes [2]. The sample products for the method are provided based on an orthogonal array. We analyze these products with quantification methods 1. The explanatory variables are the product attributes and the response variables are the degree of taste to the products estimated by the Smart Shop. As the result of the multiple regression analysis, the maximum |t| value of each attributes are considered as the degree of dominant attributes and the maximum degree is considered as the best dominant attribute.

2.3 Method of Recommendation Considering Dominant Attributes

The Smart Shop recommends products based on each customer's taste when they stand in front of a digital signage device. They are recommended by order having high score as follows:

$$Score_p = \sum_{(a,v)\in p} \frac{V_a \times S_v \times D_a}{S \times N_v},$$

where p, a, and v are a product, an attribute, and an attribute value. V_a is a number of total attribute values the attribute a has. S_v is a number of times a customer chose products which has the attribute value v. D_a is a degree of dominant attributes of the attribute a. S is a total number of times a customer chose products. N_v is a number of products which have attribute value v. The taste degrees of each attribute value are obtained by D_a and the number of times a customer chose v. The scores of each product p are obtained by the total of the taste degree of each attribute falling under p.

3. Experiment

We conducted an experiment to compare our implicit method by Smart Shop and previous explicit one by questionnaire. Subjects were 4 male students. The process is as follows.

1. A subject did shopping in Smart Shop. The products were 18 t-shirts selected randomly. The Smart Shop analyzed the subject's action data and estimated a formula of subject's action pattern.
2. The subject also did shopping in the Smart Shop. However the products were 18 t-shirts selected based on an orthogonal table. The Smart Shop estimated the taste degree of products and the degree of dominant attributes based on the action pattern formula.
3. The subject answered survey questions to evaluate the preference to the products with 5 phases (+2, +1, 0, -1, -2). We also estimated the degree of dominant attributes based on the answer.
4. Each recommendation products of the Smart Shop and the questionnaire data obtained by the degree of dominant attributes. Digital signage devices showed 5 of them based on the subject action for products. The subject evaluated the preference to the 5 recommendation products with 5 phases. This recommendation step was repeated 3 times and we got 15 product evaluations in total.

4. Results and Discussion

Table 1 shows the rates which evaluations estimated by Smart Shop was matched with another estimated by questionnaire. The evaluations were divided into likes and dislikes. We showed 2 cases that 0 is likes or dislikes because an evaluation is 0 on questionnaire may differ depending on subjects. The estimation accuracies of subject A and B were more than 61% in both case, however, it of subject C and D were less than 50% in case that 0 is likes.

Table 2 shows the degree of dominant attributes estimated by Smart Shop or with questionnaire. The dominant attribute estimated by Smart Shop were matched with another estimated with questionnaire about subject A and B. Particularly about subject A, the order of dominance were also matched with another. The decimal place's difference about subject B suggests that Smart Shop can estimate the degree of dominant attributes more correctly than questionnaire. However, the dominant attributes of 2 methods were matched about subject C and D. These results may be caused by Smart Shop's estimation or questionnaire.

Table 1. Estimated rate of taste by Smart Shop's behavior observation.

Subject	Like: +2 ~ 0 Dislike: -1 ~ -2	Like : +2 ~ +1 Dislike : 0 ~ -2
A	0.722	0.722
B	0.611	0.833
C	0.389	0.667
D	0.500	0.833
Average	0.556	0.764

Table 2. Dominant attribute rates of each subject (|t| value).

Subject	Method	Color	Design	Shape
A	Smart Shop	0.434	**2.288**	1.929
	Questionnaire	0.569	**3.128**	2.560
B	Smart Shop	1.691	**2.938**	1.756
	Questionnaire	3.232	**3.555**	3.232
C	Smart Shop	**2.084**	0.849	1.443
	Questionnaire	2.410	2.410	**8.677**
D	Smart Shop	2.932	**4.962**	2.039
	Questionnaire	6.978	3.806	**8.881**

Table 3. Good evaluation rate in the recommendation.

Subject	Smart Shop	Questionnaire
A	0.800	0.800
B	0.667	0.667
C	0.333	0.600
D	0.667	0.600

Table 3 shows the ratio which subjects liked the recommended products. All subject's results were more than 60%. The results suggest Smart Shop with this study's method can provide stable satisfaction to each subject.

Recommended Products for subject A and B by Smart Shop were the same as another by questionnaire because both estimated dominant attributes were the same. On the other hand, those for subject C and D were not the same as another. Subject C rated the products recommended by Smart Shop less by 30% than another although subject D rated them more by 6.7%. These results indicate the need for review of the action pattern formula by Smart Shop.

Therefore we reviewed and optimized the action pattern formula of all subjects to maximize adjusted R-square. Some of the formulas have had unnecessary variables. The action pattern formulas before and after the optimization are shown in Table 4. Table 5 shows the degree of dominant attributes estimated with optimized formulas of Smart Shop. The optimized formula of subject C made his dominant attributes, estimated by Smart Shop, agree with another by questionnaire. Those of subject A, B and D were not changed. We can consider the product recommendation by Smart Shop is able to satisfy subject C well as another by questionnaire.

Finally, these results presented Smart Shop with our method attained implicit estimation of dominant attributes in 3 of 4 subjects. These also presented that, in the case of estimated dominant attributes by Smart Shop and another by questionnaire did not fit, it satisfied a subject better than modeling by questionnaire.

Table 4. Regression equation of shopping behavior.

Subject		Fomula $y_{Item} = \cdots$	Adjusted R-square
A	Before	$-1.796 + 0.087x_{Look} + 0.618x_{Touch} - 0.007x_{Take}$	0.430
	After	$-1.274 + 0.587x_{Touch}$	0.505
B	Before	$-2.720 + 0.622x_{Look} + 0.626x_{Touch} + 0.0237x_{Take}$	0.497
	After	$-2.818 + 0.656x_{Look} + 0.682x_{Touch}$	0.532
C	Before	$-1.868 + 0.195x_{Look} + 0.109x_{Touch} + 0.219x_{Take}$	0.722
	After	$-1.952 + 0.221x_{Look} + 0.248x_{Take}$	0.741
D	Before	$0.202 - 0.216x_{Look} + 0.466x_{Touch} + 0.123x_{Take}$	0.712
	After	$0.202 - 0.216x_{Look} + 0.466x_{Touch} + 0.123x_{Take}$	0.712

Table 5. Dominant attribute rates of each subject (re-estimate).

Subject	Method	Color	Design	Shape
A	Smart Shop	0.283	**1.794**	**1.794**
	Questionnaire	0.569	**3.128**	2.560
B	Smart Shop	1.693	**3.093**	1.685
	Questionnaire	3.232	**3.555**	3.232
C	Smart Shop	1.659	0.857	**1.671**
	Questionnaire	2.410	2.410	**8.677**
D	Smart Shop	2.932	**4.962**	2.039
	Questionnaire	6.978	3.806	**8.881**

5. Conclusion

We suggested the estimation method of product dominant attributes for each customer through behavior observation in a retail store. Also, we implemented the product recommendation system for experiments which recommends products based on each customer's dominant attribute estimated using Smart Shop. The purpose was this system recommends more satisfactory products for each customer than another by questionnaire with 5 phases. Experiment led to a result this system accuracy is equal to or better than another by questionnaire. In addition, the result suggested the formula of each customer's action pattern needs optimization before attribute analysis.

A hypothesis in this paper was each customer’s dominant attribute are fixed. However, Smart Shop needs to understand each customer's taste changing actively. Further consideration will be needed to yield any findings about method Smart Shop analyzes a dominant attribute which is not fixed.

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