Research about Recommendation System by Attribute Relationship Matrix in Shopping

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Abstract – In recent years, more and more shops have been performing recommendations to the customers in order to guide the purchase motive and increase sales. We propose a mathematical programming model for the recommendation system. This technique utilizes data-mining, Analytic Hierarchy Process (AHP), conjoint analysis, and most notably, adds a learning function to handle changes in the tastes of the customers.

We examined this mathematical model in a functioning brick-and-mortar shop, with the result that both the customers and the owner of the shop were very satisfied.

Keywords: Recommendation System, Data-mining, Mathematical Programming , Analytic Hierarchy Process

1 INTRODUCTION

We propose a method that uses a mathematical programming model to recommend goods that are suited to consumer's tastes at the time of purchase. Previous research applied collaborative filtering [1] and contents analysis [2] using purchase history data. Although widely utilized in business, methods of recommending goods based on the similarity of purchase history data for every customer require great deal of data.

These methods are not applicable to recommendation of new goods. Moreover, a gap exists between the sales promoter's intuition and the recommendation made using a mathematical programming model that only depends on data analysis of each customer's tastes. In the present research, we propose a method of recommending goods that unites the sales promoter's intuition and a mathematical programming model, and apply it to a model shop. Using a collaborative filtering, extent to which particular goods matches customer's tastes is quantified for all individual goods contained in each commodity category.

A target customer usually has limited purchase history for a set of goods, thus we have to make assumptions when the customer has little or o purchase for a particular set of goods. Usually, sales promoters narrow the target customers to include only the most likely consumers and focus on the main goods when considering a sales strategy on the spot. If the amount of purchase history data in a specific period is relatively limited, collaborative filtering is applied, decreasing the presumed evaluation value gap and many of the resulting cases uniformly recommend goods which the customer has never purchased before. The current paper proposes a new method of identifying goods which can be recommended [3] [4] [5],[6],[7],[8],[9].

2 METHOD FOR RECOMMENDING GOODS

A method for recommending goods that unite the sales promoter's intuition and the mathematical programming model is explained below. The relationship between the taste characteristics of "customer attributes" and "goods attributes" is generated using the mathematical programming model. Furthermore, an "Attribute Relationship Matrix" which attaches weights to those taste characteristics is created. This method is our original logic of thinking that other examples do not have.

Moreover, the sales promoter evaluates the recommendation candidate goods that extracted using the mathematical programming model are narrowed to actual recommendation goods. "Analytic Hierarchy Process (AHP)" [10] which is a typical evaluation method is used.

The list of recommendation goods is narrowed down following the flow of selected goods illustrated in Figure 1, identifying the recommending candidate goods extracted by data-mining (mathematical programming model) as alternatives, and adding the subjectivity evaluation using AHP in the spot. A large-scale AHP which presupposes many alternatives and two or more evaluator is used in the present study. Attribute conversion is originality on the combination method of data- mining + AHP.

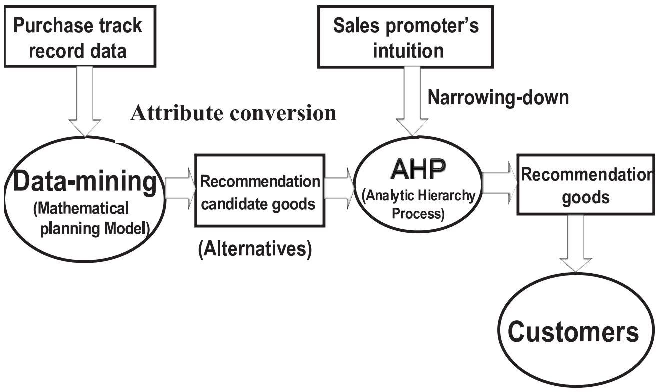

Figure 1: The flow of recommending goods selection

2.1 Analysis using Attribute Vector of Goods and Customers

We assume that each customer's taste in goods is based on the weight accorded to goods attributes (brand, type, specification, price, etc.). The characteristics of all goods are determined by some attributes and some levels and are expressed with an attribute vector. Similarly, all customers have attributes (area, age, sex, taste genre, etc.), and the customers are identified by some attributes and some levels. The goods profile is expressed with an attribute vector in the following equation (1).

$$G^d, d = 1 \sim m \in B^m \tag{1}$$

B^m : m dimensions binary vector

Here, m is the attribute number and level. The number of goods is shown as k in Table 1.The element of an attribute vector is "0" or "1". The attribute vector of the goods belonging to the goods set G_j purchased by customer c_i is set as I_c. For example, when four attributes and the level of each attribute are set at two, they can be expressed using the goods attribute matrix G shown in Table 1. The element of the matrix applicable to the attribute showing the feature of each goods is set as "1". This method is our original logic of thinking that other examples do not have.

Table 1: Example of goods attribute matrix G^T

goods	brand-1	brand-2	type-1	type-2	specification-1	specification-2	price-1	price-2
g 1	1		1		1		1	
g 2		1		1		1	1	
g 3	1			1		1		1
...								
g k	1		1			1	1	

(The number of goods k that refers to g_k in Table 1.)

A customer c_i is similarly characterized according to attributes. The customer profile is expressed with the attribute vector in the following equation (2).

$$C^d, d = 1 \sim n \in B^n \tag{2}$$

B : n dimensions binary vector

Also here, n is the number and level of attributes. The number of customers is shown as l in Table 1.The element of an attribute vector is "1" or "0". The attribute vector of the customer belonging to the customer set C_i that purchased goods g_j is set as I_g. For example, when four attributes and the level of each attribute are set at two, an attribute can be expressed with the customer attribute matrix C shown in Table 2. The elements of the matrix showing the level applicable to the attributes of each customer's features is set as "1".

Table 2: Example of customer attribute matrix

customers	location-1	location-2	age-1	age-2	male	female	genre-1	genre-2
c 1	1			1	1		1	
c 2		1	1		1			1
c 3	1			1		1	1	
...								
c l		1		1		1		1

(The number of goods l that refers to c_i in Table 2.)

2.2 Weight of Attributes

We generated the taste degree vector showing the weight (the element has a part-worth) of the customer's priority for each good's attribute using Conjoint Analysis. And, we generated the taste degree vector showing the weight prioritizing the customer's attribute that selects the goods.

The goods attribute taste degree matrix for all customers is defined as equation (3).

$$U \in R^{m \times l} \tag{3}$$

The goods part-worth vector for customer c_i serves as the next equation (4). The part-worth of the goods g_j for the customer c_i is shown as u_{ji}.

$$U_i^T = (u_{j1}, u_{j2}, \cdots, u_{jm}) \tag{4}$$

The taste evaluation value of goods g_j to customer c_i is expressed with equation (5).

$$E_{C_i} = U_i^T G_j \tag{5}$$

"Conjoint Analysis" presumes that part-worth reproduces the purchase history ranking of each good by customer c_i as much as possible in descending order of the taste evaluation values, and part-worth is given as a solution of a mathematical programming problem. Moreover, part-worth of a goods attribute without a purchase history cannot be decided. "Collaborative Filtering" decides the undecided part-worth value using the purchase history of the goods of a similar attribute, and a taste degree vector is generated for every customer. Part-worth presumption value is completed by adding. The taste evaluation value E_c of goods U_i is calculated using the completed vector U, and goods with high taste values are recommended out of the goods set g_j.

Goods without a history can also be recommended. Recommendations about new goods are also possible because goods are expressed by the attribute vector.

The taste degree matrix of a customer attribute toward the target goods g_j is defined as equation (6).

$$V \in R^{n \times k} \tag{6}$$

The customer part-worth vector of goods g_j is shown in equation (7). The part-worth of the customers c_i about the goods g_j is shown as v_{ij}.

$$V_j^T = (v_{i1}, v_{i2}, \cdots, v_{in}) \tag{7}$$

The taste evaluation presumption value of customer c_i toward goods g_j is shown in equation (8).

$$E_{g_j} = V_j^T C_i \tag{8}$$

Good g_j is a part-worth presumption value E_g so that the purchase history ranking for every customer may be reproduced as much as possible in descending order, by taste evaluation value. The customer with a high taste evaluation value is recommended out of the customer set. Since a customer's feature is expressed by the attribute vector, the recommendation about a new customer is also possible. The priority and part-worth value by the taste evaluation value of the goods as seen by the customer and should be recommended are expressed, and priority and part-worth value by the taste evaluation value of customers who perceive goods similarly and should be recommended are also carried out.

2.3 Attribute Relationship Matrix

The next matrix [which makes the customer attribute into a row and the goods attribute into a column] based on these part-worth values is defined as equation (9). This matrix is called "attribute relationship matrix".

$$W \in R^{n \times m} \tag{9}$$

Matrix W is expressed with equation (10).

$$W = \begin{bmatrix} w_{11}, w_{12}, w_{13}, \cdots, w_{1m} \\ w_{21}, w_{22}, w_{23} \cdots, w_{2m} \\ \vdots \qquad\qquad \vdots \\ w_{n1}, w_{n2}, w_{n3}, \cdots, w_{nm} \end{bmatrix} \tag{10}$$

This method is our original logic of thinking that other examples do not have.

The evaluation presumption value of the target goods g_j as seen by the customer c_i can be expressed with equation (11).

$$p_i = W^T C_i = U_i \tag{11}$$

Namely,

$$U = W^T C \tag{12}$$

Similarly, the receiving target customers' evaluation presumption value for the good g_j can be expressed with equation (13).

$$q_j = WG_j = V_j \tag{13}$$

Namely,

$$V = WG \tag{14}$$

Both sides are transposed from equation (15),

$$V^T = G^T W^T \tag{15}$$

In equation (16) both sides are multiplied.

$$V^T C = G^T W^T C = G^T U \tag{16}$$

However, generally, since W is not materialized from equation (16), the solution of the minimization problem to the matrix W is obtained from equation (17).

$$\left\| U - W^T C \right\|^2 + \left\| V - WG \right\|^2 \rightarrow \min \qquad st. \quad W \geq 0 \tag{17}$$

Moreover, as shown in Figure 2, the purchase results after recommendation are fed back to the next recommendation.

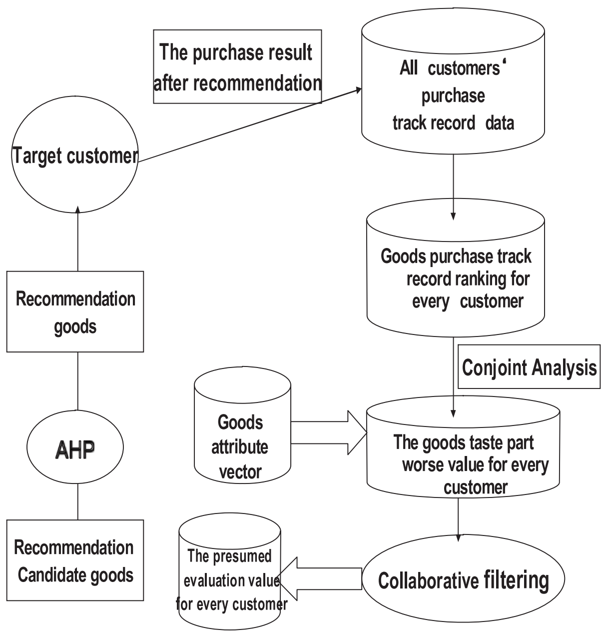

Figure 2: The learning function of recommending goods

The difference between a presumed value and the purchase history d after recommendation is set as s .

$$d = GW^T C - s \tag{18}$$

Adding the feedback function of the purchase results after the recommendation shows equation (19). Here,
n is the number of times feedback repetition occurs.

$$\left\| U - W^T C \right\|^2 + \left\| V - WG \right\|^2 + \sum_{n=1}^{k} \left\| d_n \right\|^2 \rightarrow \min \qquad st. \quad W \geq 0 \tag{19}$$

The solution of the minimization problem to the matrix W is obtained from equation (19). Generally, equation (19) is solved using at the method of least squares.

3 The SELECTION METHOD OF RECOMMENDING GOODS

By AHP, the recommendation goods are selected from many recommendation candidate goods by a one-pair comparison in the spot.

3.1 Selection Procedure

Recommendation goods are narrowed down using the procedure described below.

(1) A hierarchy diagram is generated for the recommendation candidate goods to be evaluated.

(2) The importance of evaluation items is calculated.

(3) The importance calculation for the recommendation candidate goods (as alternatives) is carried out using the pair comparison method or the absolute comparing method.

(4) Recommendation goods are selected according to the importance ranking of alternatives.

3.2 Weighting Importance Evaluation in Real Shop

Using the above-mentioned recommendation method, shown in Fig. 2, the recommendation candidate goods for a customer were selected and the evaluator of the spot set up a target and evaluation items for AHP. The target of the spot was considered to be a sales expansion.

Evaluation items, such as customer satisfaction, goods specification and profit, were considered. The AHP tool was utilized, comparing a pair of recommendation candidate goods. Customer satisfaction was most important, and given a high priority in the evaluation. Importance ranking was carried out at the time of order, giving a high weight value to the recommendation candidate goods of each customer, and recommendation goods were selected. After the goods recommendation for specific customers, the rates of purchase were compared, and the sale of goods was expanded.

4. Experiment in Model Shop

The application experiment was attempted in the model shop, treating miscellaneous goods. From customer purchase history data for the past two years, goods were extracted according to the recommendation target customers, and were entered as object data of 60,000 transactions.

(1) Candidate customers: 50 customers were selected from the purchase history top layer.

(2) Customer attributes: location (4), age (4), sex (2), and a taste genre (2).

(3) Goods attributes: brand (5), type (5), specification (2), and price range (2).

cf. ( ): indicates the number of levels.

4.1 Goods Taste Evaluation for Specific Customer

The taste evaluation value E_c for each good is calculated using the completed taste degree vector U, and goods with a high taste evaluation value are recommended. The goods taste evaluation value for the specific target customer using part-worth is shown in Table 3. It recommends the goods with the highest evaluation presumption value E_c .

Table 3: Example of a specific customer's goods taste evaluation value E_c

goods	brand-1	brand-2	type-1	type-2	specification-1	specification-2	price-1	price-1	Evaluation Value
g r1	0	4	0	3	0	2	0	1	10
g r2	1	0	5	0	1	0	1	0	8
g r3	0	1	0	3	0	2	0	1	7
...									
g rk	1	0	1	0	0	1	1	0	4

4.2 Extraction of Recommendation Goods

Next, extraction of the recommendation goods according to the "Attribute Relationship Matrix" is shown.

$$W \in R^{n \times m} \tag{20}$$

Customer C_j evaluation presumption value p for the target goods is shown by the equation (21).

$$p = W^T C_j \tag{21}$$

A target customer's evaluation point q estimates goods g_j using equation (22).

$$q = WG_j \tag{22}$$

Table4 shows a part-worth matrix. The customer and goods attributes for which part-worth serves as a large value in this matrix are assigned a high degree of recommendation.

Table 4: Example of a customer and goods attribute part-worth value matrix

	brand-1	brand-2	type-1	type-2	specification-1	specification-2	price-1	price-2
location-1	5	3	4	2	1	2	1	1
location-2	1	2	5	1	4	3	1	1
age-1	2	1	2	1	1	2	1	3
age-2	3	1	4	2	1	2	3	1
male	2	1	3	1	5	2	4	1
female	4	1	4	3	1	6	1	1
genre-1	1	4	2	2	3	3	2	1
genre-2	2	2	3	5	1	2	4	1

The attribute vector of customer c_i of "location-1, age-1, male, and genre-1" serves as equation (23).

$$C^T = (1,0,1,0,1,0,1,0) \quad (23)$$

The evaluation presumption value p of the target goods for customer c_i serves as equation (24).

$$p = U^T = W^T C = (10,9,11,6,10,9,8,6) \quad (24)$$

The taste evaluation value of the goods attributes in equation (24), "brand-1, type-1, specification-1, and price-1" is high. These goods attributes with high taste values are recommended out of the goods set.

4.3 Selection of Operation of Recommendation Candidate Goods by AHP

The experiment applied the selection method by AHP evaluation to the model shop where specific goods out of five classifications, "bag, wear, tableware, stationery, and accessories," are recommended as candidates for a goods group with high taste evaluation values, based on the strength of goods attributes (brand, type, specification, price) to a specific customer. Model shop management strategy data were changed to the general name of goods. As shown in Figure 3, the recommendation candidate goods for a specific customer were mentioned, and the target setup and evaluation items were identified by the evaluator of the spot. The targets identified were expansion of sales and the accomplishment of evaluation items such as customer satisfaction, goods specifications, and profits.

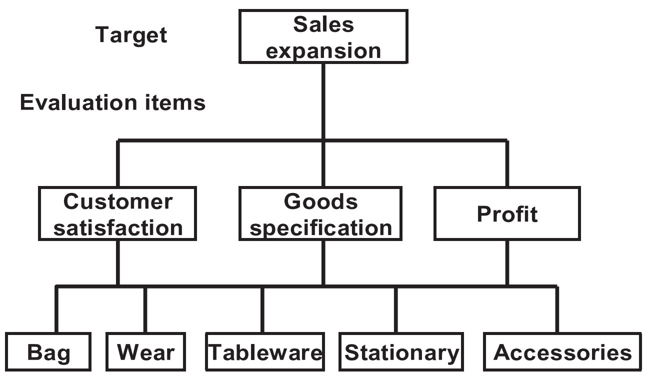

Figure 3: Example of recommending goods classification for evaluation

The large-scale AHP software was used to perform a one-pair comparison among the recommendation goods alternatives for every valuation basis.

An example of the results of the valuation-basis importance value calculation of the whole evaluator group is shown in Figure 4. The weight value of the valuation bases was highest for customer satisfaction, followed by goods specification, and then profits growth. This supports the recommendation goods suitable to customer taste, and the intention giving priority to customer specification.

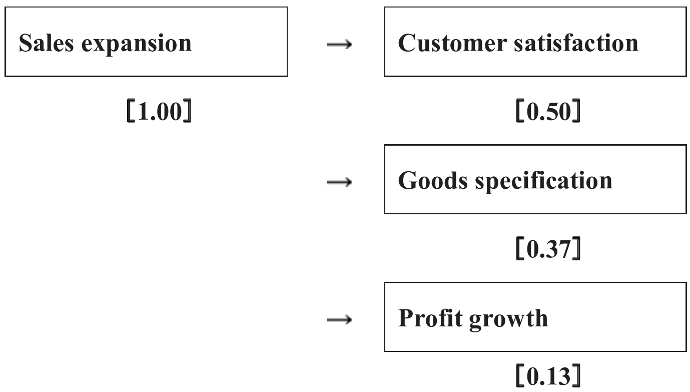

Figure 4: Example of the valuation-basis importance value for recommendation goods

Next, as an example, a one-pair comparison of the recommendation goods alternative set was performed, and its weighted values are summarized in Table 5. For the target customers, the highest weighted value was for "bag" among the recommendation candidate goods.

Table 5: Example alternatives weight values for recommending goods classifications

Alternatives of recommendation goods	Weight
Bag	0.34
Wear	0.31
Tableware	0.18
Stationery	0.06
accessories	0.11

4.4 Example of Recommendation

The application example of the recommendation method in a model shop are shown in Table 6. By the demand of the shop, I showed superiority than an existing method by the experiment of few customers of high-ranking regular customer.

(1)Recommendation goods were selected for specific customer, and the evaluation from the sales promoter was compared with the purchase results. Although the evaluation of stationery was "✕" (the customer did not purchase), the customer purchased the stationery("〇").

(2)Although the evaluation of accessories by the recommendation method was "✕", the sales promoter was recommended the accessories to the customer, but who did not purchase .

(3)Although the evaluation of tableware by the recommendation method was "〇", the sales promoter was recommended the tableware to the customer, that did not purchase.

Table 6: The result of recommendation system in the shop

No.	Goods	Recommendation method	Evaluation of the model shop	Customer's purchase
1	Wear ①	O	O	O
2	Stationery ②	O	x	O
3	Wear ②	O	O	O
4	Tableware ①	O	O	x
5	Stationery ②	O	x	O
6	Bag ①	O	O	O
7	Tableware ②	O	O	x
8	Accessories ①	x	O	x
9	Bag ②	O	O	O
10	Accessories ②	x	O	x

Below, we describe the results of our application of this method to a real shop.

The rate of purchase resulting from each recommendation method is compared in the rate comparison table 7. Our Attribute Relationship Matrix method showed a significantly higher rate of purchase other both the method currently used in the shop and the collaborative filtering.

Table 7: Rate of purchase by recommendation

Method of recommendation	Rate of Purchase (%)
Method currently used in the shop	56
Collaborative filtering	67
Attribute Relationship Matrix method	77

These results show that Attribute Relationship Matrix method successfully recommended goods which suited customer's tastes. Many new products were included in the pool of recommended goods. The promoter was extremely satisfied with the results of this experiment.

5 CONCLUSIONS

The proposed method of recommending goods on the spot has the following advantages. We showed a procedure for developing recommendations based on the attributes of both the customer and goods, even when we don't have a complete purchase history for that customer.

5.1 Consideration

(1) We have identified which attributes, including functions, performance, price, brand, etc. most influence customer's tastes.

(2) We can make recommendations that suit the customer's tastes, even for new goods.

(3) We have defined the strength of the correlation between the attributes of both goods and a customer in the "Attribute Relationship Matrix". Using this "Attribute Relationship Matrix", goods can be recommended to a customer with the appropriate characteristics, and target customers can be identified for goods with particular characteristics.

(4) Using AHP, we analyzed the goals and criteria used by those responsible for marketing, resulting in the evaluation weight value, allowing us to select the most effective goods for recommendation.

5.2 Effect of application

(1)We have shown that it is possible to recommend the goods effectively based on good and customer attributes, even when there is no purchase history data for goods. Using the Attribute Relationship Matrix method, the strength of the relationship between the characteristics of customer and the characteristics of goods is known.
The selecting goods which are candidate for the particular customer is easy.

(2)Recommendation system made on the spot by sales promoter ware used, but limited to the personal knowledge of the sales promoter about the individual customer or to the instincts that sales promoter way have developed. Furthermore, recommendation system made based only on purchase history are limited as well, and only by combining the two, as we have in this method, can we achieve the best possible sales and the highest degree of customer satisfaction.
The proof of our method was difficult on the shop, but the owner of the shop was extremely satisfied with the results of recommendations made to the top ten customers.

6. The next research subject

Further research on this subject should focus on the utilization of the goods recommendation method for practical use.

Corresponding to the needs in the shop at the time of applying a technique, a future subject is correspondence to a dynamic change. Since the taste evaluation value by the mathematical technique is presumed using the past purchase history data, change of the taste of the customer by change of fashion of goods is not supported. The dynamic learning function of the attribute relationship matrix method is examined.

In the future, research on utilization in the spot will be further advanced by the new method that recommends goods, which unite the intuition of the spot and the mathematical programming model. We are continuing improvement of the recommendation method, in order to gather the customer's rate of purchase more.

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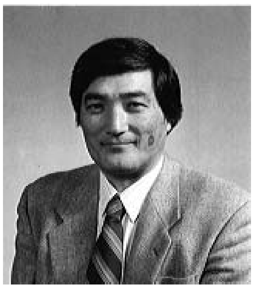

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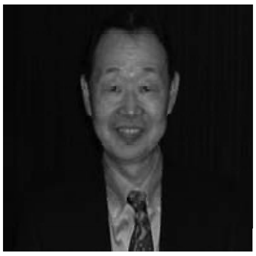

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