Methods for Estimating Customer's Product Preference in an Online Shopping System

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Abstract: Obtaining timely information on consumer preference is critical for the success of marketing and operations management. In a previous paper we proposed a method of estimating consumer preference by using their history of browsing among possible configurations of personal computer in an online shopping environment. It consisted of three steps: (1) collecting data on each consumer's browsing history regarding quotations and purchase requests, (2) converting requests for quotations and purchase order data into ordinal preference data, and (3) estimating consumer preference for product attributes by applying a multiattribute utility function. The underlying assumption with this method was that a product configuration that was quoted later would be preferred to those quoted earlier. Another assumption was that how many times a product configuration was quoted would not affect estimates for product preference as long as this was quoted at least once. Although these assumptions are critical in estimating consumer preference, their validity has not been examined. In this paper, we evaluate the validity of such hypotheses regarding the relationships between consumer preference and the sequence and frequency of quoted product configurations, and propose six methods of estimating consumer preference. We show through experiments that, for about 60% of examinees, all the proposed methods could approximate consumer preference obtained by conjoint analysis, and that the six methods have almost equal accuracy. We therefore concluded that any of the six methods could be used equally well for estimating consumer preference in a timely fashion.

Keywords: product preference, online shopping, multiattribute utility function, conjoint analysis

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1 Introduction

Obtaining timely information on consumer preference is critical for the success of marketing and operations management. Personal computer (PC) manufactures carefully control their inventories of components because their profit margins are rapidly declining [1], and the underage and overage costs of inventory may become prohibitively expensive. To keep such inventory related costs under control, these companies need to track shifts of consumer preference in a timely fashion.

Many methods of estimating consumer preference have been developed. One category of such methods is to estimate consumer behaviour such as preference and price sensitivity by constructing a marketing model based on buying information collected by tools such as a POS (point of sales) terminal [2][3][4].

Another is conjoint analysis [5][6], which is used to estimate the consumer preference for each of product attributes. Input data of conjoint analysis is collected by questionnaire that survey how consumers make trade-offs between attributes collects.

Methods that use POS data, however, fail to collect information on the preferences of the shoppers who do not make purchases, while methods that use elaborate questionnaires are expensive and time-consuming even if questionnaire survey can be conducted by online environment such as Internet [7]. When we are dealing with short-life-cycle products like PCs, we need an economical and fast means of tracking shifts in consumer needs in response to new product launches, price changes, and competitors' moves.

The widespread use of Internet has allowed companies to offer product information and prices in real time, and take purchase orders through online shopping systems [8]. Ono and Matsuo (2000) [9] focused on the browsing data of consumers who did not make purchases. The proposed method used data on consumer browsing history involving available product configurations in an online shopping environment. The information could easily and inexpensively be collected by the seller, reflecting individual consumer preference as well as her/his chosen set.

The proposed method consisted of three steps: (1) collecting data on individual consumers' browsing histories for quotations and purchase requests, (2) converting requests for quotations and purchase order data into ordinal preference data, and (3) estimating consumer preference on product attributes by applying a multiattribute utility function [10].

The proposed method assumed that that a product configuration quoted later would be preferred to those quoted earlier. It also assumed that how many times a product configuration was quoted would not affect estimates of product preference as long as it was quoted at least once. However, some consumers might prefer a configuration that was quoted earlier or one that was selected more frequently. In this paper, we evaluate the validity of several conceivable hypotheses regarding the relationships between product preferences and the sequences and frequency of quoted product configurations. We are not concerned with the wider issue affecting preferences such as choice of store, quality of on-line store and prior experience [11].

The rest of this paper is organized as follows. Section 2 describes the procedure for estimating product preference. Section 3 describes proposed methods of converting requests for quotation data into ordinal preference data. Section 4 reports our experimental evaluation of the proposed methods through experiments. Section 5 concludes the paper.

2 Estimating Product Preference

2.1 Definition of Product Preference

The product attributes of the PC we consider in this paper are its total price and the performance levels of its components such as the CPU, random access memory and hard disk drive. Product attributes have various levels. The random access memory level, for example, is measured by its storage capacity (e.g., 256 and 512 MB).

When consumers purchase a product, they decide whether some attributes are more important than others, and what levels for all attributes are required or preferred. A particular configuration that a consumer purchases is regarded as the configuration that has the largest total preference calculated from the preference for each product attribute. The product preference of each consumer can be expressed as an additive model of the multiattribute utility function (Green and Krieger, 1993):

$$U(x_1, x_2, \cdots, x_K) = \sum_{k=1}^{K} u_k(x_k) \tag{1}$$

where x_k is the level of attribute k, $U(x_1, x_2,\ldots,x_k)$ is the product preference for attribute levels equal to x_1, x_2, …, and x_k, and $u_k(x_k)$ is the preference for attribute k at level x_k.

As preference differs from one consumer to another, the attribute preferences are estimated for each consumer. When the preferences of all attributes are estimated, we can estimate the preference for a product that is represented by the combination of attributes.

2.2 Procedure for Estimating Product Preference

Ono and Matsuo's method proposed (2000) consists of three steps. This subsection describes each step in detail(Figure 1).

(1) Collecting requests for quotations and purchase order data

The consumer's series of requests for quotations and orders are collected using an online shopping system. Figure 2 shows a web screen for such a system. The consumer's operational procedure using online shopping system is as follows.

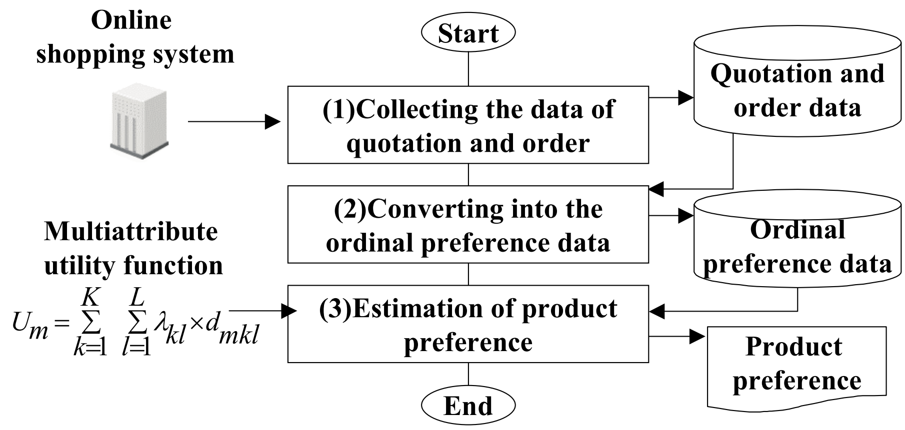

Figure 1: Methods for Estimating Product Preference

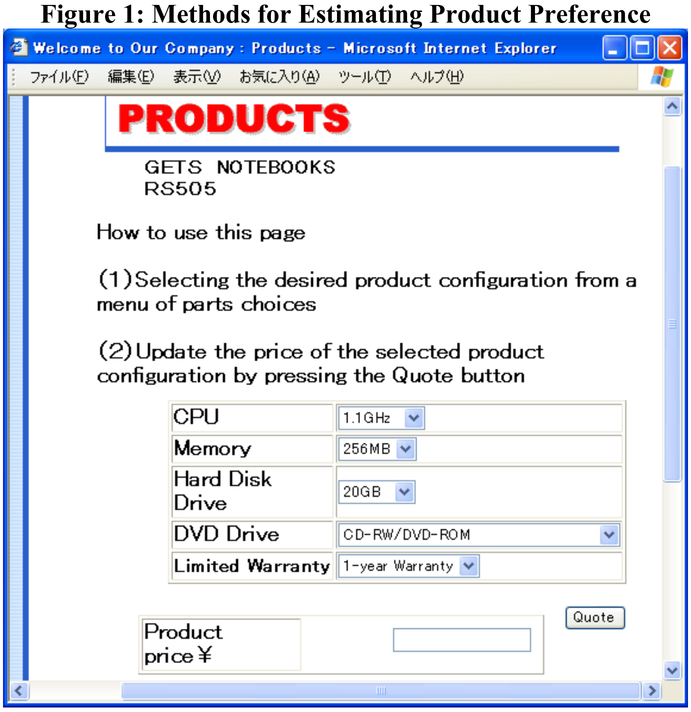

Figure 2: Screen for Online Shopping Service.

Table 1: Example Consumer Series of Requests for Quotations and Purchase Order Data.

#	Consumer ID	Time	Request	CPU	Memory	...
1	123.45.6.7	14:09:06	Quote	900 MHz	256 MB	...
2	123.45.6.7	14:09:59	Quote	1.1 GHz	512 MB	...
3	123.45.6.7	14:11:02	Quote	900 MHz	256 MB	...
4	123.45.6.7	14:11:35	Quote	1.1 GHz	256 MB	...
5	123.45.6.7	14:12:20	Quote	900 MHz	512 MB	...
6	123.45.6.7	14:13:20	Order	900 MHz	512 MB	...

(a) She/he selects her/his desired product configuration from a menu of component alternatives.

(b) The consumer sends a quotation request for the selected product configuration.

(c) The consumer receives the price for the selected product configuration.

(d) If the consumer decides to purchase the product with the configuration, then she/he sends her/his order to purchase it. Otherwise, she/he quits or repeats (a) to (c).

The online-shopping server system collects and stores a series of quotation requests (b) and purchase order information (d), if any.

Table 1 has an example of a consumer's series of requests for quotes and purchase order. Here, she/he first asks for a quote for a configuration comprised of a 900-MHz CPU and 256-MB memory. Then, she/he asks for a quote for a configuration comprised of a 1.1-GHz CPU and 512-MB memory. After five rounds of such requests for quotes, she/he finally places a purchase order for a configuration comprised of a 900-MHz CPU and 512-MB memory.

In this example, the consumer can be identified by her/his source IP address to access the Internet. We could also use a preliminarily registered consumer ID or a "cookie" [12], which is Internet technology to read and write in a file on the consumer's PC.

(2) Converting requests for quotes and purchase order data into ordinal preference data

Based on collected requests for quotes and purchase order data, we can attempt to rank configurations that have been requested for quotes by each consumer in the order of preference. The collected data contains purchasers' data and non-purchasers' data. The product configuration that is ordered to purchase should be ranked the highest in terms of preference. Product configurations that are not quoted should be ranked lower in the order of preference. However, the question is how configurations that are quoted and then not ordered should be ranked in each consumer's order of preference. We propose several rules for converting requests for quotation data into ordinal preference data in Section 3, and evaluate these in Section 4.

(3) Estimating product preference

Three models for measuring a consumer's multiattribute utility function are described in Green and Krieger (1993). The vector model assumes that the preference is linearly related to product attribute levels. The ideal-point model assumes that preference is inversely related to the weighted squared distance between the level of an attribute and the individual's ideal level of the attribute. The part-worth model assumes a function representing the discrete part-worth levels for each attribute.

Because the performance levels of components such as CPUs and random access memories are discrete, we use the following part-worth model:

$$U_m = \sum_{k=1}^{K} \sum_{l=1}^{L} \lambda_{kl} \times d_{mkl} \tag{2}$$

where U_m is a consumer's product preference for configuration m, d_{mkl} is an indicator that takes on value of one when attribute k is at level l for configuration m, and zero otherwise, and λ_{kl} are part-worth for attribute k at level l. The ordinal preference data and the configurations can be regarded as sample values of Um and d_{mkl} in Eq. (2), and the estimate of part-worth, λ_{kl} is calculated using linear regression analysis.

3. Proposed Methods of Converting Requests for Quotation Data Into Ordinal Preference Data

3.1 Hypotheses on Relationships between Consumer Preference and Sequences and Frequency of Requests for Quotation

In this subsection, we propose the following hypotheses on the relationships between the consumer preference for configurations and the sequence and frequency of configurations that appear in a consumer's series of requests for quotation, and propose methods of converting requests for quotation data into ordinal preference data. In Section 4, we attempt to verify the validity of these hypotheses.

(1) Ranking the configurations based on the sequence of quoted product configurations

Hypothesis 1a: Consumers prefer configurations quoted later.

– Configurations quoted later rank higher in the order of preference.

Hypothesis 1b: Consumers prefer configurations quoted earlier.

– Configurations quoted earlier rank higher in the order of preference.

Hypothesis 1c: Consumer preference is not reflected in the order of the sequence of requests for quotes.

– All configurations requested for quotes rank in the same order of preference.

(2) Ranking configurations based on frequency of appearance in sequence

Some consumers quote the same configuration many times. We propose the following hypotheses on the relationships between the ordinal preference for configurations and the frequency of appearance in the sequence.

Hypothesis 2a: Consumers prefer configurations more frequently requested for quotes.

– Configurations requested for more quotes rank higher in the order of preference.

Hypothesis 2b: Consumer preference is not reflected in the frequency of requests for quotes.

– All the configurations requested for quotes rank in the same order of preference.

3.2 Algorithm for Deriving the Ordinal Preference of Configurations

We propose the following algorithm to assign a positive integer to each configuration based on a sequence of configurations where a consumer requested a quotation. An integral number is assigned to each configuration that reflects the order of preference for the configuration. This integral number for each configuration is referred to below as the preference number. A preference number of one is assigned to the most preferred configuration. The smaller the preference number, the more preferred the configuration is.

Steps 1-7 are applied to each consumer's data.

Step 1: Set the preference number of n =1.

Step 2: If the collected data includes the product configuration that the consumer placed order to purchase, then a preference number of n=1 is assigned to the configuration that is ordered to purchase. Then, set n: =n+1, and proceed to Step 5. Otherwise, proceed to Step 3.

Step 3: Of the unprocessed request data in the consumer's series of requests for quotations,

(i) If Hypothesis 1a or 1c is applied, then select the latest configuration in the consumer's series of requests for quotations.

(ii) If Hypothesis 1b is applied, then select the earliest configuration in the consumer's series of requests for quotation.

Step 4: Consider one of the following three cases for the selected configuration,

(i) If the configuration selected in Step 3 has already been assigned a preference number, then proceed to Step 5.

(ii) If the configuration selected in Step 3 has not been assigned a preference number, then preference number n is assigned to the configuration

(ii-a) If Hypothesis 1a or 1b is applied, then set n: =n+1 and proceed to Step 5.

(ii-b) If Hypothesis 1c is applied, then proceed to Step 5.

Step 5: If been a configuration remains that has not been processed in the sequence of requests for quotations, then proceed to Step 3. Otherwise, proceed to Step 6.

Step 6: There are two cases for Hypotheses 2a and 2b.

(i) If Hypothesis 2a is applied, then do the following.

Apply the following Steps 6.1 to 6.7 for each configuration that has been requested for quotation many times.

Step 6.1: Select the configuration that has been requested for quotation many times.

Step 6.2: Count the frequency of quotations for the selected configuration.

Step 6.3: Set i: =1

Step 6.4:

(a) If the selected configuration has a preference number of 1, then preference numbers that have already been assigned to other configurations should be increased by one.

(b) If the selected configuration has a preference number of 2 and the configuration that has been ordered by the consumer has a preference number of 1, then the preference numbers that have already been assigned to other configurations should be increased by one.

(c) For any other cases, the preference number for the selected configuration should be reduced by one.

Step 6.5: Count up i = i+1

Step 6.6: If i is equal to the frequency of quotation for the selected configuration, then proceed to Step 7. Otherwise proceed to Step 6.4

(ii) If Hypothesis 2b is applied, then proceed to Step 7.

Step 7: Calculate the maximum value for the preference numbers assigned to the configurations in Steps 1 to 6. Assign the maximum value plus 1, as the preference number to the product configurations that do not appear in the sequence of requests for quotations and purchase order.

We evaluate six combinations of Hypotheses 1a-1c and 2a-2b and these are listed in Table 2.

Table 3 lists the preference numbers for the six methods, which were calculated from data on the sequence of requests for quotations and purchase order in Table 1.

Table 2: Methods of Deriving Ordinal Preference for Configurations.

	Quote-sequence hypothesis	**Quote-frequency hypothesis**
Method 1	Hypothesis 1a	Hypothesis 2a
Method 2	Hypothesis 1a	Hypothesis 2b
Method 3	Hypothesis 1b	Hypothesis 2a
Method 4	Hypothesis 1b	Hypothesis 2b
Method 5	Hypothesis 1c	Hypothesis 2a
Method 6	Hypothesis 1c	Hypothesis 2b

Table 3: Examples of Ordinal Preference Data

Consumer's data on quotation and purchase order				**Ordinal preference data by proposal methods**					
Request	**CPU**	**Memory**	**…**	**Method 1**	**Method 2**	**Method 3**	**Method 4**	**Method 5**	**Method 6**
Quote 1	900 MHz	256 MB	…			2	2		
Quote 2	1.1 GHz	512 MB	…	4	4	4	3	3	2
Quote 3	900 MHz	256 MB	…	2	3			2	2
Quote 4	1.1 GHz	256 MB	…	2	2	5	4	3	2
Quote 5	900 MHz	512 MB	…						
Order 6	900 MHz	512 MB	…	1	1	1	1	1	1
Rest of above configuration				5	5	6	5	4	3

3.3 Estimating Part-worth

Based on the preference numbers derived in Section 3.2, we estimate the part-worth coefficients in Eq. (2). Figure 3 has an example of a part-worth estimate. The Method 2 column in Table 3 has sample values for product preference $\underline{U_m}$ in Eq. (2), and corresponding configurations are represented by d_{mkl}. The estimate for part-worth, λ_{kl}, can be calculated by using linear regression analysis. Part-worth, λ_{kl}, expresses a consumer's preference for product attributes. Product preference U_m for configuration m can be estimated by the sum of the part-worths of corresponding product attributes.

$$
\begin{array}{lcccc}
 & U_m & & d_{mkl} & \lambda_{kl} \\
 & \textit{Preference} & & \textit{Product configuration} & \textit{Part- worth} \\
 & \textit{number} & & \begin{array}{ccccc} 900\ MH_Z & 1.1\ GH_Z & 256\ MB & 512\ MB & \cdots \end{array} & \\
\begin{array}{l} \text{Quote 2} \rightarrow \\ \text{Quote 3} \rightarrow \\ \text{Quote 4} \rightarrow \\ \text{Order 6} \rightarrow \\ \text{Other} \rightarrow \\ \end{array} &
\begin{pmatrix} 0 \\ 3 \\ 0 \\ 1 \\ 5 \\ \cdots \end{pmatrix} & = &
\begin{bmatrix} 1 & 0 & 1 & \cdots \\ 0 & 1 & 0 & \cdots \\ 1 & 1 & 0 & \cdots \\ 0 & 0 & 1 & \cdots \\ & \cdots & & \\ & \cdots & & \end{bmatrix} &
\begin{pmatrix} \lambda 11\ (900\ MHz) \\ \lambda 12\ (1.1\ GHz) \\ \lambda 21\ (256\ MB) \\ \lambda 22\ (512\ MB) \\ \cdots \\ \cdots \end{pmatrix}
\end{array}
$$

Figure 3: Example Part-worth Estimate.

4 Evaluation of Proposed Methods

4.1 Experimental Procedure

We designed an experiment and tested it on subjects, who were university students majoring in science and engineering, to evaluate the methods proposed in the previous sections. The product attributes and levels that we used are listed in Table 4. The total price of a product configuration is determined by the sum of the component prices in Table 4. We constructed the experimental system as a Web site on the Internet to mimics an actual online shopping system. Because it was an experimental system, we did not sell products or collect the data on requests for purchase.

To test the validity of the proposed methods, we compared our experimental results with those of the conjoint analysis. To do this, we conducted a questionnaire using the same set of subjects. We used orthogonal design, and asked each participant to rank eight configurations in their order of preference.

Table 4: Products Attributes in Experiment.

#	Attribute	Level No.	Level	Price
A	CPU	1	900 MHz	+0 yen
		2	1.1 GHz	+20,000 yen
B	Memory	1	256 MB	+0 yen
		2	512 MB	+23,000 yen
C	HDD	1	20 GB	+0 yen
		2	40 GB	+10,000 yen
		3	60 GB	+20,000 yen
D	DVD drive	1	CD-RW & DVD-ROM	+0 yen
		2	DVD-RAM & DVD±R/RW	+20,000 yen
E	Warranty	1	1-year warranty	+0 yen
		2	3-year warranty	+18,000 yen
	Base price			190,000 yen

(Note: Profile nos. of all 48 (2*2*3*2*2) kinds of product configurations were calculated by 24*(attribute A's level No.-1) +12*(attribute B's level No.-1) +4*(attribute C's level No.-1) +2* (attribute D's level No.-1) + (attribute E's level No.-1)

4.2 Results and Discussions

4.2.1 Results for preference estimation

The quotation data collected from 66 subjects with the experimental system described in Section 4.1 are listed in Table 5. We converted the collected data into ordinal preference data by using the six methods described in Section 3 and used the data to estimate part-worth λ_{kl} and product preference U_m for any m.

Figure 4 is a graph indicating the part-worth λ_{kl} estimated with Method 2 for five subjects. The estimated part-worth value was calculated from the corresponding preference number described in Section 3. By data conversion, the higher the part-worth is, the more the subjects preferred that level for product attribute. The average part-worth in the same attributes for each consumer is set to zero. Figure 3 shows that subject No. 1 preferred a 1.1-GHz CPU and 512-MB memory and that subject No. 5 preferred a 900-MHz CPU and 512-MB memory.

4.2.2 Discussions on results

We evaluated the accuracy of estimated product preferences Um with the questionnaires, which subjects had indicated the configurations they preferred. The data collected from these questionnaires is listed in Table 6.

Table 5: Collected Requests for Quotation Data.

Subject No.	Product profile of quote sequence
1	46, 22, 34, 46, 42, 45, 46, 48, 46
2	44, 48, 36, 48, 47
3	10, 48, 24, 22, 2 , 24 ,23, 19
…	…
66	29

(Note: Starting from left, product profile is quoted earlier)

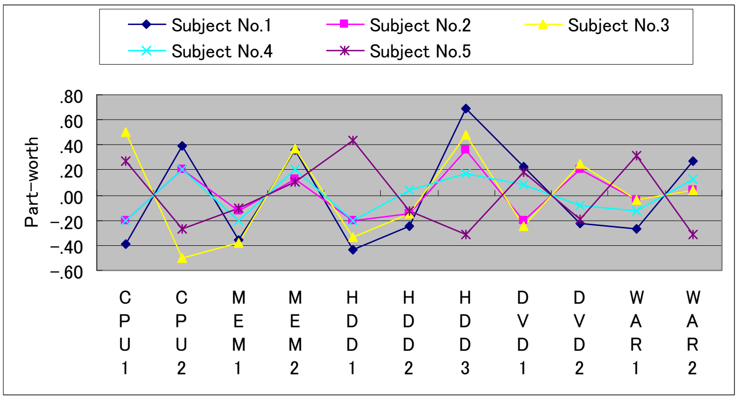

Figure 4: Part-worth of Five Subjects Estimated With Proposed Method 2.

Table 6: Preference Data Collected From Questionnaire.

Subject No.	Preference order for 8 product profiles (4, 7, 10, 16, 25, 28, 42, 47)
1	4, 7, 3, 8, 6, 5, 1, 2
2	7, 5, 4, 6, 3, 8, 2, 1
3	1, 8, 6, 4, 7, 5, 3, 2
…	…
66	3, 8, 6, 4, 7, 5, 2, 1

Table 7: Examples of Estimated Product Preferences and Correlation Coefficients.

Product No.	Product preference of subject No. 1 estimated with proposed methods						Preference on questionnaires
	Method 1	Method 2	Method 3	Method 4	Method 5	Method 6	
1	0.40	0.21	0.38	0.54	-0.33	-0.17	0.36
2	0.75	0.75	1.25	1.25	0.00	0.00	2.71
…	…	…	…	…	…	…	…
48	3.33	2.92	3.00	2.58	0.90	0.48	8.75
Peason's correlation	0.761	0.77	0.722	0.721	0.741	0.764	-
Significance probability of correlation	0	0	0	0	0	0	-

We calculated Peason's correlation coefficient between product preference estimated with conjoint analysis and product preferences estimated with the six proposed methods. The estimated product preferences and correlation coefficients for subject No. 1 are listed in Table 7. Figure 5 shows the percentages of subjects for whom the correlation coefficients between preference estimated with conjoint analysis and with the six proposed methods are statistically significant at the 5% and 1% levels. Note that 33 of the 66 subjects only requested one configuration for quotes. Therefore, these six methods generated the same ordinal preference data, and the same correlation coefficients results.

The number of subjects for whom there was a significant correlation between the preferences estimated with conjoint analysis and with the six proposed methods was greatest for Methods 3 and 4. For Method 3, the correlation coefficients of 42 of the 66 subjects were significant at the 5% level and the correlation coefficients of 39 subjects were significant at the 1% level.

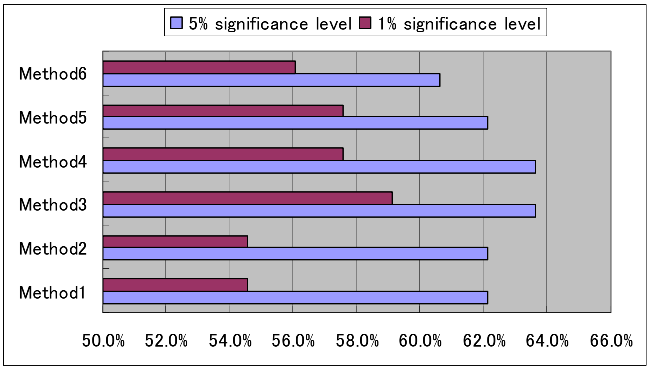

Figure 5: Percentage of Subjects for Whom Correlation between Preferences Estimated with Conjoint Analysis and Proposed Methods was Significant at 1% and 5% Levels.

In terms of ratio, the correlation coefficients for 63.6% of the subjects were significant at the 5% level and the correlation coefficients for 59.1% of subjects were significant at the 1% level. Even with the method that had the lowest correlation, 60.6% of the subjects had correlation that was significant at the 5% level, and 54.5% of the subjects had significant correlation at the 1% level. These results led us to conclude that any of the proposed methods could approximate preference obtained by conjoint analysis for about 60% of the subjects.

Figure 6 shows the percentages of subjects for whom the correlation are statistically significant, in case proposal methods assigned 48, the number of all configurations, not the maximum value of assigned configurations plus 1, as preference number to the product configurations in Step7. Compared Figure 5 with Figure 6, proposal methods and methods in case of assigning other preference number in Step 7 are almost the same, and none can be said to be better than another.

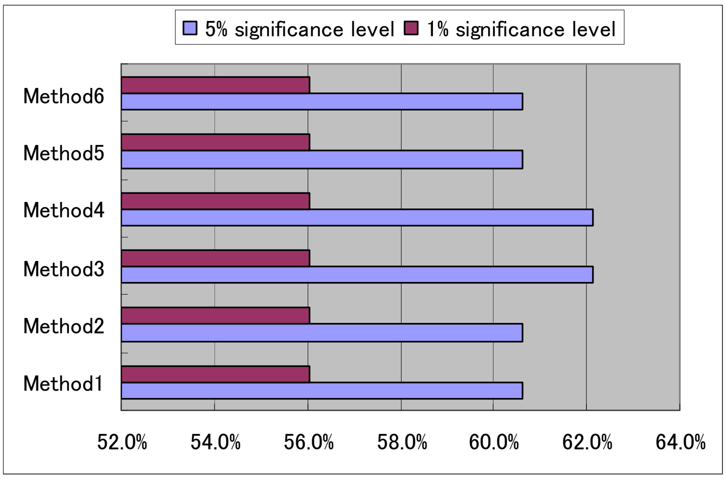

Figure 6: Percentage of Subjects for Whom Correlation was Significant in Case Proposal Methods Assigned Other Preference Number to the Product Configurations in Step7.

Outcome of the hypothesis test for difference of correlation coefficients among the proposed methods are listed in Table 8. Numeric data "4" in the table where the row is Method 2 and the column is Method 4 means that H0 is rejected in favor of H1 at the 5% significance level by "4" subjects from the outcome of testing the hypotheses.

H0 (null hypothesis): population correlation coefficients between Methods 2 and 4 are equal

H1 (alternative hypothesis): population correlation coefficient of Method 2 is greater than that of Method 4.

All six methods are almost the same, and none can be said to be better than the others.

From the viewpoint of computational effort, Method 6 (based on the hypothesis that quote sequence and frequency are not related to configuration preference) is the most efficient because Steps 4 and 6 for the algorithm described in Section 3.2 are not required to process for each consumer data.

Table 8: Outcome of the Hypothesis Test for Difference of Correlation Coefficients Among Proposed Methods

	Method 1	**Method 2**	**Method 3**	**Method 4**	**Method 5**	**Method 6**
Method 1	-	0	4	4	1	2
Method 2	0	-	4	4	1	2
Method 3	3	3	-	0	0	2
Method 4	3	3	0	-	0	1
Method 5	0	0	3	3	-	1
Method 6	0	0	3	3	0	-

5. Conclusions

We proposed and examined hypotheses regarding the relationship between preference for configurations and the sequences and frequency of requests for quotes. These hypotheses are critical in estimating individual consumer product preference from their browsing data. Ono and Matsuo (2000) assumed Hypotheses 1a and 2b. However, the validity of their assumptions over others that are conceivable has not examined, and it was the focus of this paper.

The experimental results indicated that, for about 60% of subjects, any of the six proposed methods was able to approximate explicit preference obtained by conjoint analysis. Therefore, any of these methods could be used to track shifts in consumer preference in a timely fashion.

The six methods had almost equal accuracy. From the viewpoint of computational effort, the method based on the hypothesis that there is no relationship between configuration preference and the quote sequences and frequency was the most efficient.

Our evaluation only used experimental data on requests for quotes, and thus did not include information on purchase order. Evaluation based on data that includes the order information from an actual online shopping system is an issue for further investigation.

The proposed methods can not only be applied to PCs but also other products consisting of several components. As long as we can collect data on the browsing history of individual consumers, the proposed methods may also be able to be applied to shopping systems that use multimedia kiosks in stores and on the street.

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