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Product Recommendation Based on Analysis of Aesthetic Elements Used to Customer's Favorite Products

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Abstract. In recent years, recommendation systems have been widely used for product recommendation at EC sites and so on. Existing recommendation systems are mainly based on cooperative filtering, but this approach simply estimates the customer preferences from the information about other customers with similar purchase histories and doesn't take into account customer kansei, i.e., the degree of the impressions and preferences that they receive from the product, the design / aesthetic features of the product, and their corresponding relationships. For more accurate estimation of customer preferences, a new recommender system that takes into account customer kansei is proposed in this paper. The proposed system makes product recommendations by collecting information about the many different types of products that customers have purchased or preferred in the past and analyzing the correspondence relationships between the customer preferences and their design / aesthetics. In the case study, recommendation of a long wallet was made from the information about 6 types of customer's favorite products (backpack, smartphone case, sneaker, pencil case, tie and scarf) for 18 subjects and it was confirmed that the proposal system can make recommendations with a certain degree of accuracy.

Keywords: Kansei engineering, Product recommendation, Analysis of product aesthetics.
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1 INTRODUCTION

Due to maturation of science and technology, it becomes increasingly difficult to differentiate products in terms of performance, functional feature or price. Therefore, companies are required to differentiate their products in terms of subjective and abstract qualities such as aesthetic and comfort that are evaluated by customer's feeling, which is called "Kansei" in Japanese. The quality evaluated by customer kansei is called "Kansei quality" [17].

In the field of kansei engineering (referred to as affective or emotional engineering) [8],[9], the methods for measuring customer kansei or the impression of products have been developed and applied to many case studies. In these methods, semantic differential (SD) method [11] is widely used. In addition, various types of aesthetic design methods based on analysis of measured customer kansei have also been developed. These methods generate a new aesthetic design which a customer prefers best by revealing the relationships between the results of customers' kansei evaluation of the same type of existing products as the design target and their aesthetic features. In these methods, various analysis methods such as artificial neural network [4] [5], fuzzy set theory [3], interactive reduct evolutionary computation [16], multi-dimensional scaling [5], rough set theory [6] [7] [10] [13] [15], self-organizing map [5] etc. are used. In addition, methods for estimating customer preferences and generating product designs using deep learning [1], which has developed rapidly in the past few years, have been proposed [2] [12] [14].

A recommender system is to predict the "rating" or "preference" a user would give to an item. Recommender systems are widely utilized in playlist generators for video and music services such as Netflix, YouTube and Spotify, product recommenders at EC site and content recommenders etc. Various types of recommendation approaches such as collaborative filtering and content-based filtering have been developed. Collaborative filtering is a method of predicting user interests by collecting information about preferences or taste information of many users and analyzing their similarities. In the case of product recommendation, collaborative filtering matches the people with similar interests from purchase histories of many user and recommends the items which the similar users have purchased or rated highly. However, this approach simply estimates the customer preferences from the information about other customers with similar purchase histories and doesn't understand why customers prefer products, i.e., the corresponding relationships between the degree of the impressions & preferences that they receive from products and their design & aesthetic features. Since Kansei impressions that customers receive from product aesthetics vary greatly from person to person, customers tend to buy products that are different for a variety and might not always want "blue" products for example. Therefore, it is difficult for the collaborative filtering approach to accurately estimate the customer preferences for product aesthetics. In order to overcome such difficulty, a new recommendation system based on the analysis of the correspondence relationships between customer preference and product design / aesthetics is developed in this paper. Generally, products aesthetics consist of multiple aesthetic elements. Their impact on customer's preference is different. Therefore, when recommending a new product, the proposed system estimates customer's preference for candidate products for recommendation by summing up impact scores of aesthetic elements that make up candidate products and recommends the product which a customer is most likely to prefers best. The new feature of the proposed system is to calculate impact scores of aesthetic elements from evaluation results performed to various types of products different from candidate products for recommendation. This is because, although it is easier and more accurate to make product recommendations based on the evaluation results of the same type of products, it is impractical to collect sufficient evaluation results because customers rarely purchase the same type of products over and over again except purchasing commodity products. To overcome this dilemma, the proposed system estimates the customer preference for the candidate product based on the evaluation results for different types of products than the candidate product by defining a parameter called "Similarity" between aesthetic elements used in different types of products. This paper proposes a recommender system, which is expected to be developed into an aesthetic design system.

The rest of this paper is organized as follows. The details of the proposed method is explained in section 2. To confirm the effectiveness of the proposed method, it is applied to recommendation of a long wallet based on the information about 6 types of customer's favorite products: backpack, smartphone case, sneaker, pencil case, tie and scarf, as described in section 3. Finally, the results of this paper is summarized in section 4.

2 PROPOSED METHOD

In this paper, in order to provide more accurate product recommendations based on customer kansei, a new recommendation system to estimate the customer's preference for new types of products based on the correspondence between the results of the customer's past evaluations of various types of products and the design features of those products, instead of the information of other customers who have similar purchase histories, as in the existing recommendation approach is proposed.

Before explaining the proposed system, three technical terms are introduced here. "Aesthetic element" is a part of product design / aesthetic. Examples of aesthetic elements are "blue", "red", "metal", "leather", "zipper" and "button". Products consist of various aesthetic elements. "Aesthetic element type" is a set of similar aesthetic elements. Examples are "color", "material" and "fastener". Each aesthetic element type has several aesthetic elements as its option. For example, "blue" and "red" are options of "color" type. "Product type" is a set of products having same types of aesthetic elements. Examples of product types are "sneaker" and "backpack". In addition to the introduction of three technical terms, two parameters are also introduced. The first parameter is "similarity" of aesthetic element types between different product types. For example, since the colors of bag and wallet are quite similar, the customer's color preference of bag color can be estimated from the customer's color preference of wallet. In such case, "similarity" of color between bag and wallet becomes high. Figure 1 illustrates the concept of "similarity" between 2 product types. The second one is "priority" of aesthetic elements. Generally, products consist of many types of aesthetic elements. Some aesthetic elements have a great impact on customer's preference while others have a small impact on customer's preference. Therefore, degree of their impact is defined as "priority".

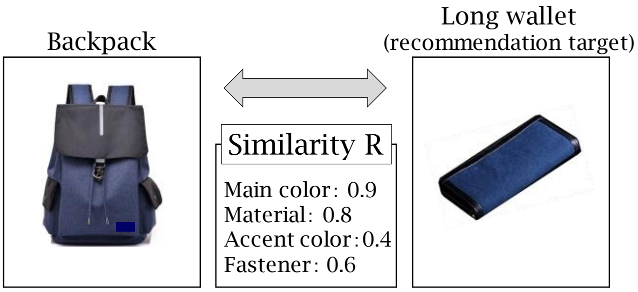

Figure 1: Concept of "similarity" between 2 product types.

The proposed method consists of the following advance preparation + 2 Steps. The rest of this section explains their details.

Advance preparation: Data collection

Step1: Calculation of contribution score

Step2: Estimation of customer's preference for candidate products

2.1 Advance Preparation: Data Collection

In order to make product recommendations using the propose system, it is necessary to collect as much information as possible about customer's favorite products. A customer has considered purchasing a variety of products in the past. Therefore, the products preferred by a customer are recorded at that time. The more records collected, the more accurately customer preferences can be estimated. At least, all aesthetic elements used in the candidate products for recommendation must be included in one of the recorded customer's favorite products. In the case study, since there is no information on customer's favorite products, subjects selected 3 favorite products out of 20 products for each of 6 product types by means of a questionnaire investigation.

2.2 Step1: Calculation of Contribution Score

In step1, contribution of aesthetic elements used in candidate products for recommendation to customer's preference is separately calculated. As described before, the basic concept of customer preference estimation is that aesthetic elements frequently used in various types of customer's favorite products are closely related to customer's preference. Based on this concept, contribution is calculated separately for all aesthetic elements that make up candidate products by the below equation. When the candidate product type consists of *n* aesthetic elements and information about customer's favorite products belonging to *l* product types are used for estimation, contribution score $S_{i,j}$ of aesthetic element *i* that belongs to aesthetic element type *j* is calculated by the below equations.

$$C_{i,j} = \sum_{k=1}^{l} N_{i,k} \times R_{j,k} \tag{2.1}$$

$$\text{Contribution score } S_{i,j} = \frac{W_j \times C_{i,j}}{\max_i C_{i,j}} \tag{2.2}$$

Where, $N_{i,k}$ is the number of times aesthetic elements *i* is used in the customer's favorite products belonging to product type *k*. $R_{j,k}$ is the similarity of aesthetic element type *j* between the candidate product type and product type *k*. W_j is the priority of aesthetic element type *j*. max $C_{i,j}$ is the largest *C* of aesthetic elements that belong to aesthetic element type *j*. This term is used for normalization.

Table 2 shows a calculation example of a contribution score. In the case of this figure, the contribution score is calculated from favorites products that belong to 3 produce types. Aesthetic element a1 that belongs to aesthetic element type A was used 2, 1 and 2 times in the products that belongs product types 1, 2 and 3 respectively. The similarities of aesthetic element type A between the candidate product type and product types 1, 2 and 3, $R_{A,1}$, $R_{A,2}$ and $R_{A,3}$ are 0.9, 0.4 and 0.7 respectively. In this case, $C_{a1,A}$ is calculated as 2*0.9 + 1*0.4 + 2*0.7 = 3.6. $C_{a2,A}$ and $C_{a3,A}$ are also calculated as 2.0 and 0.4. Based on them, max $C_{i,A}$ is calculated as 3.6. Finally, if the priority of aesthetic element type A, W_A is 0.9, the contribution scores of aesthetic elements a1, a2 and a3, $S_{a1,A}$, $S_{a2,A}$ and $S_{a3,A}$ is calculated as 0.9, 0.5 and 0.1.

2.3 Step2: Estimation of Customer's Preference for Candidate Products

Customer's preference of candidate products is estimated by summing up contribution score of aesthetic elements that make up them. Customer's preference P_l of candidate product *l* is calculated by the below equation.

$$\text{Preference score } P_l = \frac{\sum_{j=1}^{n} S_{i,j} \in product\ l}{\sum_{j=1}^{n} \max_i S_{i,j}} \tag{2.3}$$

Where the numerator is the sum of contribution scores of the aesthetic elements that make up candidate product *l*. The denominator is the sum of the maximum contribution scores for each aesthetic element type. The preference scores are calculated for all candidate products and the candidate product with the highest preference score is recommended.

Tables 2 and 3 show a calculation example of a preference score. In the case of figure, product 1 consists of a1, b4, c2 and d3. As show in Fig.4, the denominator of the preference score is calculated as 1 + 0.9 + 0.7 + 0.3 = 2.9 while the numerator is calculated as 1 + 0.4 + 0.3 +0.3 = 2.0. Therefore, the preference score of Product1 is calculated as 2.0 / 2.9 = 0.690.

Product type	Favorite product	Options of asthetic element A	Similarity
1	1	a2	0.9
	5	a1	
	12	a1	
2	2	a1	0.4
	4	a2	
	9	a3	
3	3	a1	0.7
	4	a2	
	11	a1	

Table 1: Calculation example of a contribution score.

	Aesthetic element type			
	A	B	C	D
Product 1	a1	b4	c2	d3

Table 2: Calculation example of a preference score.

Aesthetic element type							
A		B		C		D	
Aesthetic element	Score	Aesthetic element	Score	Aesthetic element	Score	Aesthetic element	Score
a1	1	b2	0.9	c1	0.7	d3	0.3
a3	0.8	b3	0.5	c2	0.3	d2	0.1
a4	0.5	b4	0.4	c4	0.2	d1	0
a2	0.3	b1	0.2	c3	0	d4	0

$$\Rightarrow \sum_{j=1}^{n} \max_i S_{i,j} = 1 + 0.9 + 0.7 + 0.3 = 2.9$$

$$\Rightarrow \sum_{j=1}^{n} S_{i,j} \in product\ l = 1 + 0.4 + 0.3 + 0.3 = 2.0$$

Table 3: Calculation example of a preference score.

3 CASE STUDY

To confirm the effectiveness of the proposed method, a case study was performed. Based on the information on 6 types of customer's favorite products: backpack, smartphone case, sneaker, pencil case, tie and scarf, a long wallet was recommended. 18 undergraduate students participated as subjects.

3.1 Preparation of the Case Studies

In order to collect information about customer's favorite products, 12 products (photos) were collected from each of 6 product type described above. 12 long wallets were also collected as candidate products. Participants selected 3 favorite products from each of 6 product types using questionnaire sheets illustrated in Figure 2. For discussion after the experiment, participants also select 3 favorite products from 12 long wallets. Table 4 shows the favorite products selected by 18 participants. A long wallet has 7 aesthetic element types (Main color, pattern, material, accent color, glossy, fastener type and zipper strap) while 6 product types have 3 to 5 aesthetic element types, as shown in Table 5. Table 6 shows the options of 7 aesthetic element types. As for Similarity and priority, Tables 7 and 8 show similarity *R* between a long wallet and 6 product types and priority *W* among 7 aesthetic element types respectively. Note that pencil cases, like backpacks and smartphone cases, have zippers, but that information cannot be used to estimate customer preference because all products that belong to "pencil case" have zippers and no other options. Therefore, no information is listed in the fastener columns of Tables 5 and 7.

Figure 2: Example of questionnaire sheets.

3.2 Results and Discussions

The contribution score for each design element is calculated from the information in Tables 4 to 8 and the customer preferences of the candidate products are estimated by summing the contribution scores which the aesthetic elements that belong to them have. Tables 9 shows the contribution score of each aesthetic element of subject 1. Table 10 shows the preference scores of candidate products of subject 1 and 2. This table also shows 3 favorite products pre-selected by subject 1 and 2. As for subject 1, 2 of 3 favorite products can be estimated by the proposed system while, as for subject 2, no favorite products can be estimated. Table 11 shows how many favorite products the proposed system can estimate. These results show that when the proposed system recommended 3 products, subjects preferred 1.22 products on average. On the other hand, when 3 products are randomly selected and recommended, 0.75 recommended products probablistically match subject's favorite products. t-test shows that there is a significant difference between them. These discussions show that the proposed system can recommend products based on past information on various types of customer's favorite products in a certain accuracy level but fall short of our expectations. The following points can be given as reasons. (1) Since the proposed system calculates contribution scores of aesthetic elements individually, the synergistic effect of the combination of aesthetic elements cannot be considered. (2) In the proposed system, similarity *R* and priority *W* need to be manually configured, but they may not have been configured appropriately in the case study.

Subject	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Backpack	4	1	6	2	6	12	4	4	4	1	2	4	6	3	5	6	3	12
	8	3	9	4	7	7	6	7	5	10	4	11	11	9	8	8	5	11
	11	9	11	7	11	6	11	11	7	11	11	8	12	12	11	10	8	9
Smartphone case	4	2	1	4	1	3	1	2	2	2	4	1	4	2	3	1	1	3
	9	3	2	10	5	1	2	9	5	4	6	9	6	7	4	3	3	1
	12	10	5	11	12	9	12	12	10	11	10	12	12	12	6	6	12	9
Sneaker	2	1	2	6	2	5	3	5	1	6	3	2	2	2	3	3	1	3
	9	3	6	8	8	6	5	10	3	10	8	8	5	6	5	9	5	1
	10	11	8	12	10	7	10	11	10	12	11	12	6	9	8	11	11	4
Pencil case	3	3	1	3	3	11	5	4	6	3	3	3	5	3	1	3	3	6
	9	4	5	5	6	10	6	6	10	6	4	6	11	8	3	4	4	8
	12	10	8	6	8	7	11	11	11	10	5	11	12	11	4	10	7	12
Tie	1	2	4	5	1	12	5	1	4	1	3	2	2	4	2	2	2	11
	4	5	5	7	6	7	7	2	9	7	6	4	7	10	5	4	6	4
	10	8	10	10	12	10	10	5	12	10	11	12	12	12	12	10	12	6
Scarf	2	3	1	6	2	1	5	5	2	2	5	2	1	2	3	1	6	10
	6	6	5	9	5	5	6	9	7	5	6	5	5	5	7	5	7	9
	9	11	9	11	7	2	9	11	8	8	7	8	9	9	11	10	11	5
Long wallet	1	2	3	2	1	5	7	1	3	3	3	3	1	1	3	2	1	12
	3	4	7	4	3	8	5	3	5	4	4	10	5	8	4	4	4	1
	5	11	12	5	8	4	12	7	12	5	11	12	8	12	7	9	5	7

Table 4: Favorite products selected by 18 participants.

	Main color	Pattern	Material	Accent color	Glossy	Fastener	Zipper strap
Backpack	✓	-	✓	✓	✓	✓	-
Smartphone case	✓	✓	✓	-	✓	✓	-
Sneaker	✓	-	✓	✓	✓	-	-
Pencil case	✓	-	✓	-	✓	-	✓
Tie	✓	✓	-	✓	✓	-	-
Scarf	✓	✓	-	✓	-	-	-

Table 5: Aesthetic element types which 6 product types have.

In addition, priority of aesthetic elements might have been better to be configured for each subject. This is because subjects have their own evaluation viewpoints when selecting favorite products. (3) Since the number of products and product types was limited in the case study, the information on subject's preferences for them may not be sufficiently collected. These points need to be considered in the future research.

	Main color	Pattern	Material	Accent color	Glossy	Fastener	Zipper strap
Options of aesthetic element types	Blown	Stripe	Leather	No accent color	Matte	Flap	Without strap
	Black	Check	Fabric	White	Glossy	Zipper	With strap
	White	Plain	Nylon	Blown			
	Blue	Damier		Black			
	Red			Red			
	Yellow						
	Green						

Table 6: Options of aesthetic element types.

	Main color	Pattern	Material	Accent color	Glossy	Fastener	Zipper strap
Backpack	0.9	-	0.8	0.4	0.6	0.6	-
Smartphone case	1	0.9	0.9	-	0.9	0.2	-
Sneaker	0.8	-	0.7	0.2	0.8	-	-
Pencil case	0.9	-	0.9	-	0.9	-	0.8
Tie	0.8	0.7	-	0.2	0.2	-	-
Scarf	0.6	0.7	-	0.4	-	-	-

Table 7: Similarity *R* of aesthetic elements between a long wallet and 6 product types.

Main color	Pattern	Material	Accent color	Glossy	Fastener	Zipper strap
1	0.8	0.9	0.3	0.3	0.6	0.2

Table 8: Priority *W* of 7 aesthetic element types.

Color		Pattern		Material		Accent color	
Blown	1.000	Stripe	0.800	Leather	0.900	No accent color	0.300
Black	0.849	Check	0.714	Facbic	0.636	White	0.120
White	0.509	Plain	0.457	Nylon	0	Blown	0.090
Blue	0.472	Damier	0			Black	0.030
Red	0					Red	0
Yellow	0						
Green	0						

Glossy		Fastener		Zipper strap	
Matte	0.300	Flap	0.600	Without strap	0.200
Glossy	0.171	Zipper	0.200	With strap	0.100

Table 9: Calculated contribution scores of subject 1.

ID of candidate products	Subject1		Subject2	
	Preference	Favorite products	Preference	Favorite products
1	67.1	✓	63.4	
2	54.3		85.7	
3	84.8	✓	70.7	✓
4	51.9		66.7	✓
5	90.0	✓	74.7	✓
6	69.9		72.9	
7	65.7		77.2	
8	71.2		79.7	
9	68.4		90.2	
10	76.3		77.8	
11	60.8		73.0	
12	57.0		86.4	

Table 10: Results of subject 1 and 2.

# of correct estimation	# of subjects
3	0
2	7
1	8
0	3

Table 11: Results of 18 subjects.

4 CONCLUSION

Different from product recommendation based on collaborative filtering like EC sites, a new stem that recommends products which a customer is most likely to prefers best by analyzing aesthetics of products which a customer evaluated as "favorite products" in the past. The proposed system takes aesthetics of candidate products for recommendation apart into aesthetic elements, calculate their contribution to customer's preference from information on how often aesthetic elements are used in customer's favorite products and estimates customer's preference for candidate products. In the proposed system, once information on customer's preference for various types of products are sufficiently collected, it becomes possible to recommend new types of products without additional information. In the case study, a long wallet was recommended based on information on customer's preference for products belong to 6 product types. 18 subjects participated the case study. The results show that the proposed system can recommend products in a certain accuracy level and clarify several points need to be considered in the future research.

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