Analysis of Customer Preference through Unforced Natural Passive Observation

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Abstract. In our former research, customer's preference has been estimated by passive observation of shopping behavior, e.g. customer's "look" and "touch". It takes much time to understand their preferences form the log. We need quickly to build up the preference model to perform suitable recommendation for a new customer. For this reason, we will propose an active observation mechanism that detects customer's unforced natural behavior to information through ambient devices such as speakers and electric displays. This mechanism also analyzes customer's preference on features and their values of commodities, which enables the system to estimate the rate of preference to an unknown product. We have experimented on ten university students. We had them evaluate the thirty-six Shirts. We used these evaluations for precision evaluations in naive Bayes classifier. We used the leave-one-out cross-validation. As the result, we have achieved the average precision in the estimating preferences by naive Bayes classifier is 71%.

Keywords: Passive and active observation, Recommendation system, Machine classifier, Digital signage, Decision making support

1 Introduction

Customer's preference has been analyzed on shopping logs in a real shop as well as page view logs in web shopping sites [1][2][3][4][5]. These approaches require mass data for each individual to build personal preference model, otherwise the analysis is just on the mass market as an average preference of customers. We have developing a smart shop system that analyzes each customer's preference to commodities observing his unforced natural behavior in the shop [6]. We have adopted passive observation of the customer's behavior, such as "look", "touch", and "take" a commodity in a shelf, which requires some period to save log. We will also adopt active observation of the customer's response to the digital signage, such as gaze and ignore, to capture log more quickly without forcing him to answer the messages.

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2 Discussion on Passive Observation

In our former research, customer's preference has been estimated by passive observation of shopping behavior, e.g. customers "look" or "touch". As this observation can only be captured their behavior without forcing replies, it takes much time to understand their preferences form the log. Quickly we have to build up the mechanism of preference model to perform preferable recommendation for a new customer. For this reason, we will propose on active observation mechanism that detects customer's unforced natural behavior to information through ambient devices such as speakers and electric displays. This mechanism also analyzes customer's preference for features and their values of commodities, which enables the system to estimate the rate of preference to an unknown product.

3 Active Observation

The aim of our research is to propose active observation system that can estimate customers' preferences from small load. This section explains three things. First is a way of observing behaviors that enables us to estimate customer's preferences. Second is a method to estimate customer's preferences from behaviors. Third is a method to understand customers' preference from small load. We described the overview process of active observation in Fig. 1.

3.1 A Way of Observing Behaviors

As devices of the active observation system, we adopted ambient display as digital signage devices with a function to detect a human face and its direction.

3.2 Estimating a Preference from Behaviors

Our former research found correlation between the gaze time and the rate of preference. It considers the subjectivity of gaze behavior by customer analysis [7]. The gaze time is the total duration of watching information on the ambient device. This observation system captures gaze time of each customer. Thereby, we estimate the customer's preference, "like" or "dislike", to be compare the mean and the variance of gaze time. For example, Fig 1 (a) (a') shows that the system estimates red polo shirt "like" and blue turtleneck shirt "dislike".

3.3 Analyzing Customer's Preference

We enable the system to estimate the rate of preference to unknown products. For that analyzing and learning algorithm, we have embedded content based filtering to system. We have used the naive Bayes classifier. Thereby, we can get an evaluation for the product which a customer hasn't evaluated. For example, Fig 1 (b) (b') shows that the system computed a posterior probability with product property of polo shirt and turtleneck shirt. Thereby, it estimated rates of preference the similar products in the database. On the other hands, content based filtering is recommending only similar products which customer evaluates as high. However, the customer's over all preference cannot have been analyzing.

We explain model making and a classification by naive Bayes. The way of calculating naive Bayes probabilistic model wants you to refer to documents [8]. The probability model for a classifier is a conditional model. Conditional model is dependent class variable, Class, and feature variables, sample, by eq. (1).

$$P(Class \mid sample) \tag{1}$$

Furthermore, using Bayes' theorem, we obtain the following expression (2).

$$P(Class \mid sample) = \frac{P(Class)P(sample \mid Class)}{P(sample)} \propto P(Class)P(sample \mid Class) \tag{2}$$

The feature variable, sample, is a set of the several feature variables $word_1$ through $word_n$. Each feature $word_i$ is conditionally independent of every other feature $word_j$ for $j \neq i$ given the class variable. We obtain the following expression (3).

$$P(sample \mid Class) = P(word_1 \wedge .... word_i \mid Class) = \prod_i P(word_i \mid Class) \tag{3}$$

Thus, we had classified unknown samples by eq. (4).

$$Class_{map} = \arg\max_{Class} P(Class) \prod_i P(word_i \mid Class) \tag{4}$$

We have embedded a metric based on entropy to estimate rates of recommendations. For example, Fig 1 (c) (c') shows that the system computes posterior probability of property on product (P (red|like), P (red|dislike)). Entropy, H, are calculated from posterior probability, P, by eq. (5).

$$H = -P \log_2 P - (1-P) \log_2 (1-P) \tag{5}$$

Therefore, we calculated the entropy of each product and decided a next candidate for recommendation from entropy. We combine entropy with naive Bayes classifier. Thereby, we can analyze the customer's preference with short duration and a small load.

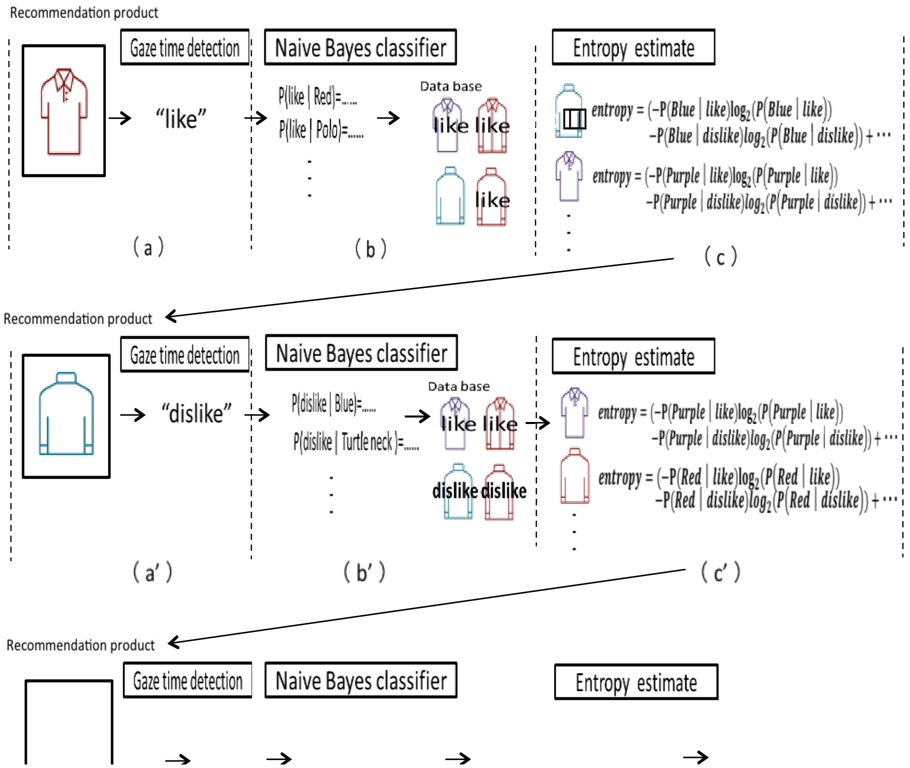

Fig. 1. Image of the flow to estimated customer's preference

(a)(a') … We estimated the customer's preference, "like" or "dislike", to compare the mean and the variance of gaze time.

(b)(b') … We computed a posterior probability with product property and estimated similar product in the database.

(c)(c') … We calculated the entropy of each product and decided a next candidate for recommend from entropy

4 Experiment

We had been experimenting on the effectiveness of the two processes. First is effectiveness of the estimated precision of the customer's preference by naive Bayes classifier. Second is effectiveness of the customer's preference estimate number of times by the entropy.

4.1 Estimating a Preference by Naive Bayes Classifier

We have experimented on ten university students (21- 24 years-old, in Tokyo). We had them look and touch thirty-six Shirts. Also, we had them evaluate the Shirts. We used these evaluations for precision evaluations in naive Bayes classifier. We used the leave-one-out cross-validation.

4.2 Reduction of the Estimate Duration by Entropy

We have experimented on three university students (21- 24 years-old, in Tokyo).

We had them look one hundred and four Shirts. Furthermore, we had subjects evaluate one hundred and four Shirts. We used these evaluations in analysis and precision evaluations. We compared the number of times to preference estimate when using the entropy with does not use it.

5 Result

5.1 Estimating a Preference by Naive Bayes Classifier

The result is as follows (Table1).

Table 1. Precision by naive Bayes classifier

Subject No	Precision(%)
1	61.1
2	75.0
3	69.4
4	72.2
5	61.1
6	66.7
7	80.7
8	80.6
9	80.6
10	72.2
average	71.1

As the result, the average precision in the estimating preferences by naive Bayes classifier is 71%. Therefore, we think that the estimating preferences by naive Bayes classifier are effective. Hence, we think that we enable the system to estimate the rate of preference to the unknown products.

5.2 Reduction of the Estimate Duration by Entropy

First of all, we explain the figure of this chapter in Fig. 2.

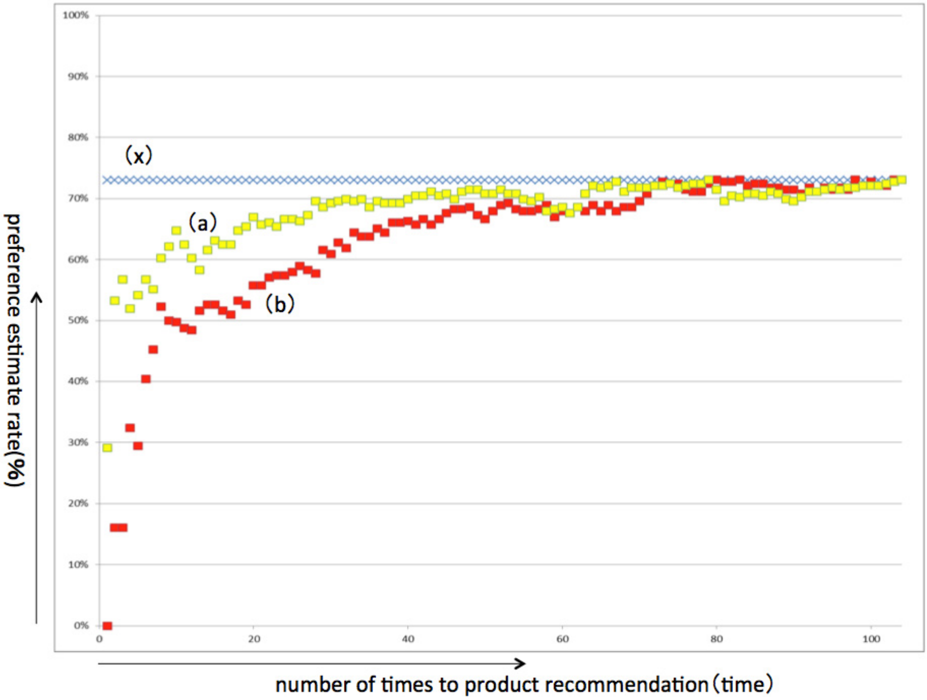

Fig. 2. Example of the figure

(x) … The upper bound that we can preference estimate in naive Bayes

(a) … Relationship between the number of times to product recommendation and preference estimate rate when using the entropy.

(b) … Relationship between the number of times to product recommendation and preference estimate rate when to not use the entropy.

The result is as follows (Fig. 3, Fig.4 and Fig. 5).

As analysis, we analyzed the change of the preference estimate rate when a product recommended by evaluation of the subject. We applied the analysis three times and averaged the results every subject.

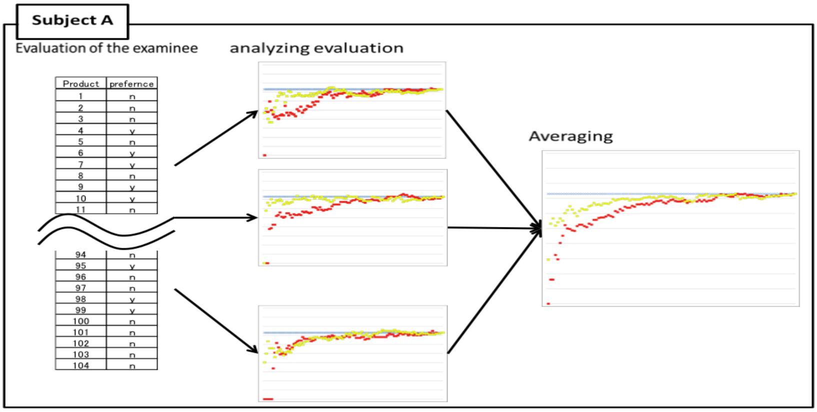

Fig. 3. Analysis result of subject A

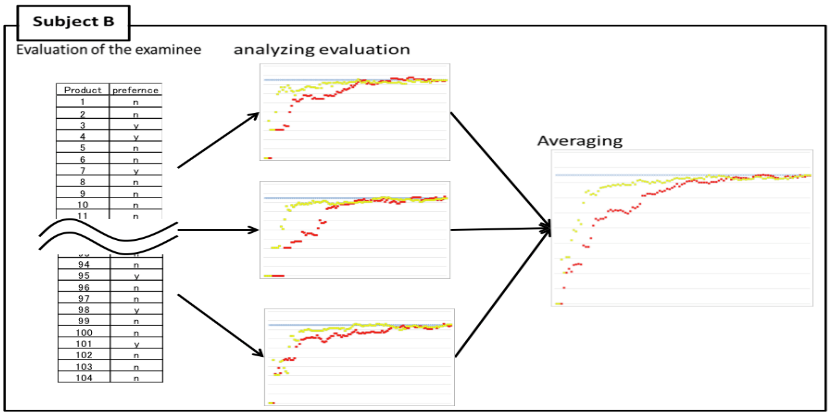

Fig. 4. Analysis result of subject B

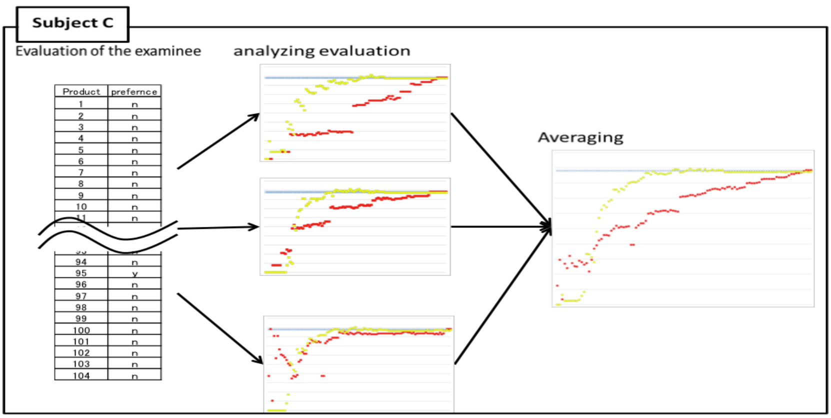

Fig. 5. Analysis result of subject C

Furthermore, we gathered up all the results of the subject in Fig. 6.

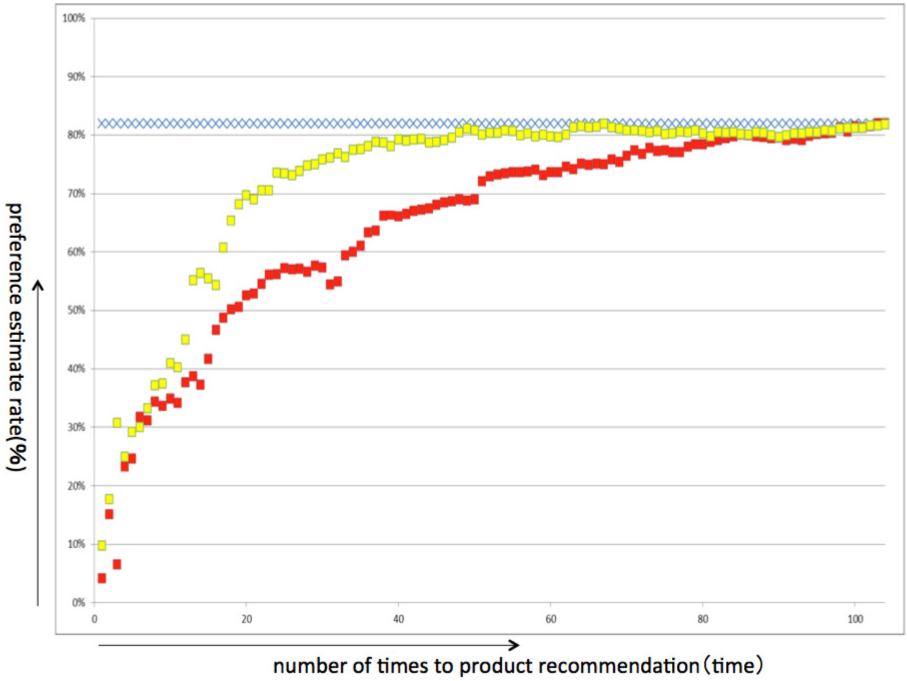

Fig. 6. Preference estimate when using the entropy with does not use it (united in subjects)

As the result, the learning using the entropy may achieve a high preference estimate rate in a short duration. As much analysis results, the learning to use the entropy is shorter than learning not to use. Hence, we think that we can analyze the customer's preference with short duration and a small load.

6 Conclusion

Our purpose has developing a smart shop system that analyzes each customer's preference to commodities observing his unforced natural behavior in the shop. In our former research, customer's preference has been estimated by passive observation of shopping behavior, e.g. customer's "look" and "touch". It takes much time to understand their preferences form the log. We need quickly to build up the preference model to perform suitable recommendation for a new customer. For this reason, we proposed an active observation mechanism that detects customer's unforced natural behavior to information through ambient devices such as speakers and electric displays. This mechanism also analyzes customer's preference on features and their values of commodities, which enables the system to estimate the rate of preference to an unknown product. We had been experimenting on the effectiveness of the two processes. First is effectiveness of the estimated precision of the customer's preference by naive Bayes classifier. Second is effectiveness of the customer's preference estimate number of times by the entropy. As the result, we have achieved the average precision in the estimating preferences by naive Bayes classifier is 71%. We can expect to analyze that we can analyze the customer's preference with short duration and a small load by using the entropy.

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