Extraction of Behavioral Features Based on Customers’ Point Use History

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Abstract. To analyze features of customers’ point use behavior, we define and classify a unit based on five feature values to extract the behavioral features. Our results will contribute to the construction of a customer-specific measurement system through visualizing time-series transitions of customer point use behavior.

Introduction

Many retailers now use frequent shopper programs (FSPs) to improve customer loyalty and obtain identification (ID) point-of-sale (POS) data. A retailer using an FSP issues a point card to each customer. The customer can present points corresponding to a purchase amount using the point card, and can receive services, such as discounts, according to the amount of points at the next purchase. Thus, an FSP that gives a reward to customers in the form of points is a type of sales promotion. An FSP has two advantages. First, it may increase customer loyalty. Although discounts and coupons lose their effect after a single purchase, points accumulated must be used for subsequent purchases, which may lead to the customer’s next purchase. Second, customer attribute data can be acquired and linked with purchase history. Customers who want to benefit from an FSP must use a point card. When the point card is issued, the customer must enter details, such as their name, address, gender, and age, which can be used as customer attribute data. Furthermore, because the customer must present their point card at the time of purchase, it is possible to identify who made the purchase. The data stored by FSPs are ID-POS data.

However, as the number of companies using FSPs increases, the effect of improving customer loyalty diminishes. If competitors have introduced similar programs, it is difficult to terminate an existing FSP even if a company’s profits are suffering. Therefore, it is necessary to use a current point service and propose measures to encourage effective point use that leads to an increase in customer loyalty. However, it is impossible to propose such measures at present because customers do not know how to effectively use points.

Verhoef [1] has shown that FSPs have a positive effect on the customer retention rate and the development of customer share. Ishigaki et al. [2] classified customers by probabilistic latent semantic analysis [3] of ID-POS data. However, few studies have analyzed point use behavior quantitatively, proposed measures to make better use of point services, and focused on point history to classify customers.

In this study, focusing on these gaps in the literature, we construct a model to analyze the point use behavior of customers, and we propose a measure for using point services more effectively. First, the point use behavior pattern of customers is extracted and the feature value is specified. Next, a classification model based on feature quantities is constructed to visualize time-series transitions of customer point use behavior.
Classification and Visualization of Feature of Point Use

First, we provide definitions for terms. Point history data are data that contain information about acquisition and use of customers’ points. POS data are data that contain information about customer purchases. This research uses point history data and POS data from large home appliance retailers in industry-academia collaboration. The analysis flow of the research is divided into first extracting feature quantities of point use behavior and constructing a customer classification model, and then analyzing use behavior by visualizing time series of points use.

In the point history, the point use behavior is a repetition of actions such as “save” and “use”. Thus, the “save” and “use” actions are included in a single unit, and the point history of each customer is divided into units to design the feature value (Figure 1). Based on the data, there are five feature values used for classifying one unit (Table 1).

![Figure 1. Separation of units.](image)

**Table 1. Feature values used to classify a unit.**

| Feature value                                                                 | Value                                                                 |
|------------------------------------------------------------------------------|----------------------------------------------------------------------|
| Number of purchases before using points                                       |                                                                      |
| Acquisition ratio of maximum points at all acquisition points                |                                                                      |
| Percentage of all usage points in the sum of unit balance and all acquisition points |                                                                      |
| Percentage of balance of unit in sum of balance of unit and all acquisition points |                                                                      |
| Point balance when using points for the first time of unit                   |                                                                      |

Classification of Point Use Behavior for One Unit

The five-dimensional feature vectors based on the feature values in Table 1 are classified by the $k$-means method [4]. The number of clusters, $c$, is determined by the elbow method. According to this classification, cluster numbers $c_{p,j}(=0,\ldots,c)$ are linked to all purchases in one unit $j$ of customer $p$. A point history $b_{p,i}$, linked to purchase $i (=1,\ldots,n_p)$ of customer $p (=1,\ldots,m)$ corresponding to one line of point history data is defined by Equation 1.

$$b_{p,i} = (g_{p,i}, u_{p,i}, r_{p,i})$$  \hspace{1cm} (1)

- $g_{p,i}$: Acquisition point amount at the time of the $i$-th purchase of customer $p$
- $u_{p,i}$: Amount of point use at the time of the $i$-th purchase of customer $p$
- $r_{p,i}$: Amount of points accumulated at the time of the $i$-th purchase of customer $p$

However, $r_{p,i}$ satisfies Equations 2 and 3.

$$r_{p,i+1} = r_{p,i} + g_{p,i} - u_{p,i}$$  \hspace{1cm} (2)
Using Equations 2 and 3, one unit data, \( S_{p,j} \), of the point history of unit \( j (= 1, ..., k_p) \) of customer \( p (= 1, ..., m) \) is determined by Equation 4.

\[
S_{p,j} = (b_{p,s_{p,j}}, b_{p,s_{p,j}+1}, ..., b_{p,t_{p,j}}, ..., b_{p,s_{p,j}+n_{p,j}-1})
\]

\( s_{p,j} \): First purchase in segment \( j \) of customer \( p \) is the number of purchases made by customer \( p \)

\( t_{p,j} \): First purchase using points in segment \( j \) of customer \( p \) is the number of purchases made by customer \( p \)

\( n_{p,j} \): Total number of purchases in segment \( j \) of customer \( p \)

However, in \( S_{p,j} \), points are used at \( t_{p,j} \) and subsequent purchases. That is, Equations 5, 6, and 7 are satisfied.

\[
u_{p,t_{p,j}} > 0, ..., u_{p,s_{p,j}+n_{p,j}-1} > 0
\]

\[
u_{p,s_{p,j}+n_{p,j}} = 0
\]

\[
g_{p,s_{p,j}+n_{p,j}} > 0
\]

**Classification of Point Use Behavior in a Customer's Designated Period**

To see the chronological change in the customer cluster, classification based on the point use behavior of customer \( p \) for specified period \( y \) is performed according to Equation 8.

\[
h_{p,y} = \left( \frac{n_{p,y}}{n_{p,y}}, \frac{n_{1,y}}{n_{p,y}}, ..., \frac{n_{c,y}}{n_{p,y}} \right)
\]

\( n_{c,y} \): Number of purchases in cluster \( c \) during period \( y \) for customer \( p \)

\( n_{p,y} \): Number of purchases made in period \( y \) for customer \( p \)

**Analysis of Time Series Point Use**

A cluster number, \( d_{p,y} (= 0, 1, ..., c) \), based on the point use behavior feature is linked to the point use behavior for period \( y \) for customer \( p \). Visualize a matrix that contains the probability of transitioning from cluster \( c_1 \) to cluster \( c_2 \) between period \( y \) and period \( y + 1 \). The \( c_1 c_2 \) component of the transition probability matrix \( T \) between period \( y \) and period \( y + 1 \) is \( T_{y,c_1,c_2} \) and is defined in Equation 9.

\[
T_{y,c_1,c_2} = \frac{N_{y,c_1,c_2}}{N_{p,c_1}}
\]

\( N_{y,c_1,c_2} \): Number of people transitioning from cluster \( c_1 \) to cluster \( c_2 \) during period \( y \) to period \( y + 1 \)

\( N_{p,c_1} \): Number of people belonging to cluster \( c_1 \) in period \( y \)

This makes it possible to see the transitional context of the cluster transitions.

**Verification with Actual Data**

The verification data are point history data from April 1, 2013 to May 20, 2018 from large home appliance retailers participating in industry-academia collaboration, and use the \( k \)-means model classification method. In the time series point use behavior analysis, point use history and purchase history data for all customers who opened a point card from April 1, 2013 to March 31, 2014 are used.

Figure 2 shows that the intra-cluster sum of squared errors (SSE) decreases at around 5 to 8 clusters; thus, verification is performed with 8 clusters.
Figure 2. SSE as a function of the number of clusters used in the elbow method.

Clustering is performed by the $k$-means method. Figure 3 shows a cluster transition diagram of customers who flowed into cluster 3 in the first half of the first year. About 36% of customers flowed out and about 16% of all customers left by the second half of the first year. In other words, this point service is disadvantageous to the company.

Conclusion

We analyzed the features of the customer's point use behavior, defined a unit for extracting features, and designed the feature quantity to construct a model to classify customers based on point use behavior. In a case study, we classified the features of customer behavior based on point use history, making it possible to consider measures to improve customer loyalty and retention.

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