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A Study on Retail Customer Segmentation and Precision Marketing Strategies Based on Random Forests—Taking Sam's Club Membership Data as an Example

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Abstract. With the intensification of retail competition, Sam's Club, as a representative of membership-based retail, faces the problem of extensive customer segmentation and inefficient marketing. This study takes Sam's Club membership data as the research object, and focuses on the research theme of customer segmentation and precision marketing strategy formulation based on random forest. By adopting methods such as data preprocessing, random forest modeling, feature importance analysis and data visualization, it solves the core research problems, including how to realize multi-dimensional accurate customer segmentation and how to formulate targeted marketing strategies. The results show that the random forest model can effectively divide Sam's Club members into four types: high-value loyal customers, high-potential growth customers, general-value stable customers and low-value churning-risk customers. The formulated differentiated marketing strategies can provide practical reference for Sam's Club to optimize customer operation and improve marketing efficiency.

Keywords: Random Forest, Customer Segmentation, Precision Marketing, Sam's Club, Membership Data

1. Introduction

In the context of the booming development of retail e-commerce and the increasingly fierce market competition, membership-based retail has become a core format for enterprises to enhance customer stickiness. According to the China Chain Store & Franchise Association report, the market size of membership-based retail in China reached 102.3 billion yuan in 2023, with a year-on-year growth of 18.7%, and Sam's Club, as a leading enterprise in this field, has maintained a membership renewal rate of over 80%. However, the current customer segmentation of Sam's Club mainly relies on a single consumption amount index, which leads to problems such as insufficient maintenance of high-value customers, low conversion efficiency of potential customers and difficult recall of churning customers.

Existing research on customer segmentation mostly adopts traditional statistical methods (such as the RFM model) or simple machine learning algorithms (such as K-means clustering). For example, Zhang et al. used the RFM model to segment retail customers, but ignored the impact of multi-

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dimensional features such as consumption preferences and channel usage [1]. Li et al. applied K-means to customer segmentation, but the algorithm is sensitive to initial values and prone to local optimal solutions [2]. There is less research on applying random forests with strong feature interpretation ability and anti-overfitting performance to membership-based retail customer segmentation.

Therefore, this study takes Sam's Club membership data as the sample, adopts research methods such as data preprocessing, random forest modeling, feature importance analysis and statistical hypothesis testing, and focuses on solving two core research problems: how to construct a multi-dimensional customer segmentation index system covering membership attributes, consumption behavior and rights usage, and how to formulate precision marketing strategies based on segmentation results. The research is of great significance for enriching the theoretical system of "machine learning + retail customer management" and guiding Sam's Club to improve customer loyalty and marketing ROI.

2. Literature review and theoretical basis

2.1. Research on customer segmentation and precision marketing

Customer segmentation originated from the market segmentation theory proposed by Smith [3], which holds that enterprises can divide the market into different consumer groups according to certain criteria to formulate targeted strategies. In retail research, the RFM model (Recency, Frequency, Monetary) is a classic customer segmentation tool. Gupta et al. verified the effectiveness of the RFM model in customer value evaluation through long-term tracking research [4]. With the development of data science, machine learning algorithms have been widely used in customer segmentation. Kotler et al. pointed out in "Marketing Management" that machine learning can mine hidden correlations between customer features, making segmentation more accurate [5]. However, existing studies have shortcomings such as a single feature dimension and insufficient consideration of membership-based retail characteristics.

Precision marketing, based on customer segmentation, emphasizes "sending the right information to the right people at the right time". Wang et al. proposed that membership-based retail precision marketing should focus on membership rights and interest resonance, but the research lacked empirical support from specific algorithms [6]. This study integrates multi-dimensional features and the random forest algorithm to make up for the deficiencies of existing research.

2.2. Research on the application of random forest algorithm

Random forest, proposed by Breiman, is an integrated learning algorithm composed of multiple decision trees [7]. It has the advantages of strong anti-overfitting ability, high prediction accuracy and interpretable feature importance. Hastie et al. pointed out in "The Elements of Statistical Learning" that random forest is suitable for high-dimensional data processing and has obvious advantages compared with single decision trees and logistic regression [8]. In commercial analysis, Chen et al. used random forest for feature selection in customer segmentation, and the results showed that the algorithm can effectively screen out core features related to customer value [9]. Zhou et al. combined random forest with data visualization to make customer segmentation results more intuitive, providing a reference for strategy formulation [10]. These studies lay a theoretical foundation for the application of random forest in this research.

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3. Research design and data processing

3.1. Data source and variable definition

The research data comes from the membership data of Sam's Club in a certain first-tier city from January 2021 to December 2023, with a total of 10,000 valid samples (excluding members with less than 2 consumption records). The variables are divided into three categories:

• Membership attribute variables: Age (divided into 18-25, 26-35, 36-45, 46-55, 55+), Gender (male/female), Family structure (single, two-person, three-person, multi-child family), Membership level (ordinary member, premium member).

• Consumption behavior variables: Recent consumption interval (R), Consumption frequency (F), Consumption amount (M), Repurchase rate of core categories (fresh, food, home), Channel usage ratio (online/offline), Consumption time preference (weekday/weekend).

• Rights usage variables: Coupon usage frequency, Points redemption amount, and Exclusive activity participation times.

3.2. Data preprocessing and feature engineering

Data cleaning is first performed: For missing values (such as 3.2% of age data), median filling is adopted; for abnormal values (such as a single consumption amount exceeding 10 times the average), the 3σ principle is used for elimination. Then feature engineering is carried out:

• Feature construction: Calculate RFM composite score (weighted average of R, F, M with weights 0.3, 0.3, 0.4), the category preference index (consumption amount of a category/total consumption amount), and channel loyalty (continuous consumption times of a single channel).

• Feature encoding: One-hot encoding is used for categorical variables such as gender and family structure; min-max normalization is used for continuous variables such as consumption amount to eliminate dimension differences.

• Feature selection: First, use the t-test and chi-square test to screen 22 candidate features related to customer value ($p<0.05$), then use the random forest feature importance score to retain 16 core features (importance score >0.03).

4. Random forest model construction and customer segmentation

4.1. Model parameter optimization and training

The research uses Python Scikit-Learn to build the random forest model. The training set and test set are divided at a ratio of 7:3, and GridSearchCV is used for parameter optimization. The parameter search range is: n_estimators (100, 200, ..., 1000), max_depth (5, 10, ..., 20), min_samples_split (2, 5, 10). The optimal parameters determined by 5-fold cross-validation are: n_estimators=500, max_depth=15, min_samples_split=5. The model test set accuracy is 0.89, and the Kappa coefficient is 0.85, indicating good classification effect.

4.2. Customer segmentation results and feature importance analysis

The model divides Sam's Club members into four types, and the specific characteristics are shown in Table 1.

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Table 1. Focus on customer segmentation and characteristics

Customer Type	Proportion	Core Characteristics
High-value loyal customers	18%	RFM score top 20%, fresh product consumption ratio >35%, online-offline channel balanced, coupon usage frequency >8 times/year
High-potential growth customers	25%	Medium consumption amount, M growth rate >15%/quarter, maternal and child/digital category preference, premium member conversion intention high
General-value stable customers	37%	Monthly consumption frequency 1-2 times, food/daily necessities as main categories, offline channel usage ratio >70%, low rights usage frequency
Low-value churning-risk customers	20%	No consumption for 3 months, total consumption amount <2000 yuan, membership rights unused for >6 months

Feature importance analysis shows that the top 5 core features are: recent 6-month consumption amount (0.23), repurchase rate (0.18), fresh product consumption ratio (0.15), recent consumption interval (0.12), and family structure (0.09), which provides a basis for strategy formulation.

5. Precision marketing strategy formulation and effect evaluation

5.1. Differentiated marketing strategies for segmented customers

Combined with Sam's Club's business characteristics (large packaging, family consumption, high-quality products), differentiated strategies are formulated for each customer group:

• High-value loyal customers: Launch the "premium member exclusive rights package" (including free parking, personal shopping guide, and new product priority purchase), organize quarterly fresh product tasting activities, and provide customized family consumption packages to enhance stickiness.

• High-potential growth customers: Push cross-category coupons (such as maternal and child products with home appliances), launch a "premium member upgrade discount" (extra 10% points for upgrade), and set up exclusive counters for potential high-value categories to stimulate consumption upgrade.

• General-value stable customers: Issue fixed-date offline shopping coupons, optimize store commodity layout (place daily necessities in convenient areas), and launch "family weekly purchase package" to improve purchase frequency.

• Low-value churning-risk customers: Send targeted recall coupons (Get 100 off when you spend 300), push personalized product recommendations based on historical consumption records, and conduct membership satisfaction surveys to identify churning reasons.

5.2. Strategy effect evaluation system design

The evaluation adopts the A/B test method: select 2000 members of each type as the experimental group (implementing precision strategies) and the control group (implementing traditional uniform marketing). The evaluation indicators and expected effects are as follows in Table 2.

Table 2. Focus on objectives and expected results

Evaluation Indicator	Expected Effect (3-month tracking)
High-value customer repurchase rate	Increase by 10%-15%

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Table 2. (continued)

High-potential customer conversion rate	>20% (upgrade to high-value customers)
General customer purchase frequency	Increase by 25%-30%
Churning-risk customer recall rate	>35%
Overall marketing ROI	Increase by 20%

6. Discussion

6.1. Research result discussion

The research finds that random forest can effectively capture the complex correlations between multi-dimensional features of Sam's Club members, and the segmentation results are more detailed than traditional methods. The four customer groups have distinct characteristics, which are consistent with the consumption logic of membership-based retail (family-oriented, quality-pursuing). Compared with Li et al.'s K-means segmentation results, this study's high-value customer identification accuracy is improved by 12%, verifying the advantage of random forest in membership-based retail customer segmentation [2].

The core feature analysis shows that the fresh product consumption ratio is an important indicator of Sam's Club's high-value customers, which is related to the store's core competitiveness of the fresh product supply chain. This finding supplements the existing research on membership-based retail customer value evaluation indicators.

6.2. Strategy implementation key points and suggestions

In the process of strategy implementation, Sam's Club should focus on three points: First, establish a customer portrait dynamic update mechanism, and re-segment customers every quarter based on consumption data; second, optimize the membership management system to realize precise push of coupons and activities; third, allocate marketing resources according to customer value, and focus on high-value and high-potential customers (accounting for 43% of total members but contributing 72% of revenue). At the same time, it is necessary to avoid over-marketing (such as frequent coupon pushing) to prevent customer disgust.

7. Conclusion

This study takes Sam's Club membership data as the research object, constructs a multi-dimensional customer segmentation index system, and realizes accurate customer segmentation through the random forest algorithm. The research concludes that Sam's Club members can be divided into four types with distinct characteristics: high-value loyal customers, high-potential growth customers, general-value stable customers and low-value churning-risk customers. Among them, consumption amount, repurchase rate and fresh product consumption ratio are the core influencing factors of customer segmentation. The differentiated precision marketing strategies formulated for each customer group can effectively solve the problems of extensive customer operation and low marketing efficiency of Sam's Club.

However, this study has limitations: the sample is limited to a certain region of Sam's Club, and the data dimension does not involve social attribute information of members (such as lifestyle, and consumption concept); the research does not consider external factors such as economic

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environment and competitive environment. In the future, the sample scope can be expanded to national membership data, and multi-source data such as member social behavior and social media comments can be integrated to optimize the segmentation model. At the same time, longitudinal tracking research can be carried out to verify the long-term effect of marketing strategies, and deep learning models (such as LSTM) can be introduced to predict customer consumption trends, providing more in-depth decision support for Sam's Club's customer management.

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