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Deep Learning-Based Hotel Customer Behavior Prediction and Precision Management Strategies

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Abstract The rapid development of data technology provides technical support for hotels to enhance their competitiveness. This paper combines customer behavior, customer value, word-of-mouth reliability and Boston matrix to construct a three-dimensional variance Boston matrix to achieve customer segmentation. The category gradient is introduced to address the overfitting limitations of the Random Forest algorithm (RF) in terms of both effective handling of category features and ranking enhancement. A two-stage group prediction model is constructed using improved RF and support vector machine (SVM) to accurately predict hotel customer behavior. The results show that the churn rate is extremely high or extremely low when the length of time since the last order in a year is within the range of [0,50000]. In the model performance comparison, the RF-SVM model achieves ROC values of 0.993, 0.997, and 0.999, and the average values of the 3 indicators of G-mean, F-measure, and AUC are all greater than 0.90, with variance less than 0.01, which is better than the comparison model. After adjusting the hotel strategy according to the behavioral prediction results, higher profitability is obtained.

Index Terms boston matrix, hotel management, random forest algorithm, support vector machine, customer behavior prediction

I. Introduction

The hotel industry has always been one of the most important parts of the service industry. In the past decades, the hotel industry has become part of the world's largest tourism industry, with more and more people choosing hotels as a place to stay for tourism or business trips [1]. At the same time, the hotel industry is gradually facing unprecedented challenges and opportunities due to digital transformation, and hotel companies need to understand their customers' behaviors and needs, and keep abreast of the changes in their purchasing habits and needs [2], [3].

With the rapid development of information technology and communication technology, customer behavior is actively or passively generating and creating data. Big data brings great changes to human life, and under the trend of increasing market saturation, how to mine the value of customer-related data, capture customer behavior trends, formulate strategies early and intervene reasonably is of great social and economic significance to the development of hotels [4]-[6]. The intensification of business competition has prompted hotels to pursue sustainable development, focusing on the use of digital technology and the ability to adapt to the environment, so that when customers' expected consumption changes with the market environment or other factors, hotels can identify and develop customer-centered marketing strategies and management modes in a timely manner, which promotes the strengthening of the hotel's competitiveness [7]-[10].

As one of the most effective business solutions in hotel marketing operations, customer behavior management usually provides reference information or decision support for hotel decision makers [11], [12]. Customer management has been proved to be an important tool in the process of digital transformation, which can effectively improve the ability of hotels to develop and manage their customers, and provide innovative exploration potential for hotel marketing [13]. The core objective of management is to increase customer satisfaction and loyalty to the hotel by developing, expanding, and maintaining reliable customer relationships, and to fully utilize the profitability of the hotel's precision marketing. Therefore, predicting and managing key information in customer behavior data is crucial for decision makers [14]-[16].

In this paper, for the dynamic conversion characteristics of hotel customers, we introduce the Boston matrix and three first-level behavioral influences to construct a three-dimensional three-dimensional model based on the variational Boston matrix to realize the classification of customer groups. Integrate random forest and category gradient boosting algorithm. On the basis of Random Forest categorization behavior prediction, reduce the gradient bias and prediction offset by feature category computational transformation and sample classifier sorting training.

Establish the fusion model of improved random forest algorithm and support vector machine to make two successive predictions based on sample customer behaviors to improve the accuracy of behavior prediction. Combine with several experiments to verify the practical application effect of the prediction model.

II. Deep learning algorithm based hotel customer behavior prediction implementation

II. A. Three-dimensional stereo model construction based on the variational Boston matrix

Boston matrix is one of the most commonly used methods of product strategy combination, this type of method for the enterprise's actions and strategic choices, allocation of resources and so on are of great significance. In order to find out whether there are valuable customers in the churned customers who deserve to be strategically recovered by the enterprise, the valuable customers in the churned customers can be recovered by utilizing this analytical principle, treating the churned customers as the products of the Boston Matrix, and carrying out the management of the customer segmentation portfolio. Customer value and customer behavior as the basis for measurement of two factors, so as to form the Boston Matrix based on customer value and customer behavior. Figure 1 shows the Boston Matrix based on customer value and customer behavior.

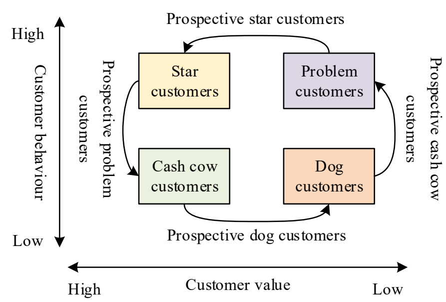


Figure 1: Boston Matrix based on customer value and customer behavior

In the original Boston Matrix of star customers, problem customers, golden calf customers, thin dog customers, the enterprise based on its own revenue and reputation reliability will be positively oriented to the customer, in the Boston Matrix based on the value of the customer problem customers for the star customers in the backup force, in the conversion of the star customers in the middle of the star customers will be the emergence of quasi-star customers of this type of customer groups, similarly, for the conversion from the star customers to the golden calf customers will be the emergence of quasi-golden calf customer groups on the way from the golden calf customers to thin dog customers will be the emergence of quasi thin dog customers. Similarly, for the conversion from star customers to golden bull customers there will be a group of quasi-golden bull customers, for the conversion from golden bull customers to skinny dog customers there will be quasi-skinny dog customers, and for the conversion from skinny dog customers to problem customers there will be quasi-problem customers.

Under the orientation of word-of-mouth reliability, the Boston matrix based on customer value and customer behavior is converted into a three-dimensional three-dimensional model, and the three first-level indicators of customer value, customer behavior, and word-of-mouth reliability are used as three-dimensional axes to construct a three-dimensional variant Boston matrix in the variant Boston matrix. The three-dimensional variant Boston matrix is constructed on the basis of the original Boston matrix. Figure 2 shows the three-dimensional variance Boston matrix.

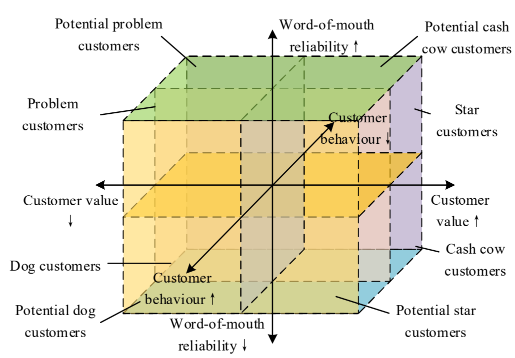


Figure 2: 3t Variation Boston Matrix

Table 1 shows the classification of the eight types of customer groups for the reclassification of the three-dimensional variance Boston matrix.

Table 1: Customer segmentation based on three-dimensional variant Boston matrix

Word-of-mouth reliability	Customer behavior	Customer value	Customer type
High	High	High	Star customer
Low	Low	Low	Thin Dog customer
High	High	Low	Problem customer
Low	Low	High	Taurus customer
Low	High	High	Prospective star client
Low	High	Low	Prospective thin dog customers
High	Low	Low	Prospective problem customer
High	Low	High	Prospective Taurus customers

II. B.Integration members of the Fusion Integration Framework

In this study, Random Forest and Category Gradient Boosting algorithms are used to construct a fusion integration framework to achieve simultaneous reduction of variance and bias in hotel customer behavior prediction. This section describes the modeling mechanisms of both.

Random Forest (RF) is an algorithm that integrates the prediction results of multiple decision trees through a bagging mechanism, and its main advantages are that it is not easy to overfitting, extremely noise-resistant, and fast computational speed. The construction process of random forest is:

(1) Assuming that the sample capacity is N, bootstrap self-help method is used to have put back from the original sample N times, each time to extract 1, and finally form a new training set containing N samples. This process is repeated k times to form k new self-help sample sets, and k new training sets are used to train the decision tree to obtain k decision trees $h_1(x), h_2(x), \cdots, h_k(x)$ as integrated members. Out-of-bag data consisting of samples that are not drawn each time are used to evaluate the prediction error.

(2) Assuming that each sample has M features, m features $(m \ll M)$ are randomly selected from these M features when each node of the decision tree needs to be split. The node is split using the best feature (maximizing the information gain) among the m feature dimensions.

(3) Maximize the growth of each tree without pruning.

(4) Construct a random forest using the generated multiple trees and use the random forest to classify new samples. The classification method is based on the classification results of k decision trees using the simple majority voting method, and the category in which the majority vote is obtained is the category to which the predicted sample belongs, and its mathematical expression is:

$$H(x) = \arg\max_{Y} \sum_{i=1}^{k} I(h_i(x) = Y) \tag{1}$$

$H(x)$ is the random forest classifier; $h_i(x)$ represents the base learner; Y is the categorical output variable; and $I(\cdot)$ is the indicative function, $I(\cdot) = 1.0$ when $h_i(x) = Y$ holds, otherwise, $I(\cdot) = 0.0$.

The category gradient boosting algorithm (CatBoost) is the boosted integrated classification algorithm.CatBoost makes two main enhancements based on the gradient boosting decision tree algorithm, i.e., the effective handling of category features and the introduction of a ranked boosting strategy to solve the gradient bias and prediction bias problems.

(1) Effective processing of category features

CatBoost randomly sorts the samples, subsequently calculates the labeled mean of the same category samples for a feature, and converts the category-based features into numerical features. Assuming that $\delta = (\delta_1, \delta_2, \cdots, \delta_n)$ is the sequence of samples after randomly sorting, the conversion formula for converting category-type variables to numerical variables is:

$$x_{\delta p,k} = \frac{\sum_{j=1}^{p-1} \left[x_{\delta j,k} = x_{\delta p,k} \right] Y_{\delta j} + \alpha P}{\sum_{j=1}^{p-1} \left[x_{\delta j,k} = x_{\delta p,k} \right] + \alpha} \tag{2}$$

P is the a priori value and α is the corresponding weight. The inclusion of the a priori value helps to weaken the noise caused by the low-frequency categories.

(2) Introducing Sort Boosting Strategy

Gradient boosting decision tree algorithm based on biased point-by-point gradient is prone to overfitting problems, so in CatBoost to introduce the sorting boosting strategy, on the sample x_i training classifier M_i (the data of the training classifier M_i does not contain the sample x_i), based on the M_i estimation of the sample gradient, and the use of this gradient to train the integrated members so as to obtain the final classifier.

II. C.RF-SVM two-stage group prediction method

Random Forest RF and Support Vector Machine SVM are both commonly used prediction algorithms in the field of machine learning, and they have their own advantages and disadvantages. Random Forest is an algorithm with a decision tree as the underlying support. It can usually give good prediction results without filtering the feature values or standardized conversion of metric scales. The support vector machine algorithm, on the other hand, requires fewer feature values and is not limited by the level of data dimensionality. It is very suitable for solving nonlinear binary classification problems. Its classification performance has some advantages over other basic prediction models. However, it does not perform well on the metric scaling of sample values and requires preprocessing of the dataset to ensure that the eigenvalues are within a similar distribution.

Considering the respective advantages and disadvantages of the Random Forest and Support Vector Machine algorithms, as well as combining different probability intervals in which different prediction models may have different calibrations, this paper proposes a hybrid model that combines the Random Forest and Support Vector Machine algorithms. The combination of these two methods is used to achieve the effect of complementary advantages, so as to improve the prediction performance. The specific operational steps are:

1) Random Forest prediction phase (RF phase). First, the original customer behavior data are preprocessed to remove useless feature values and missing data items. And the customer behavior data are standardized and centered to obtain normally distributed data with a mean of 0.0 and a variance of 1.0. Then use the random forest algorithm for initial prediction to get the predicted probability that all sample customers produce a certain behavior; secondly, group all samples between [0.0,1.0] according to a specific step, for example: [0.95,10], [0.90,0.95), according to the predicted probability; compare the prediction results of the sample data in each grouping.

2) Support vector machine prediction stage (SVM stage). Carrying on the previous step, for the groups with poor prediction results, use the support vector machine algorithm to make a second prediction to get the new prediction probability of a certain behavior produced by the sample customer individuals in these groups; combine the results of the behavior probability of the two predictions as the final prediction results. Set the decision threshold of the hybrid model, for example, for a binary prediction, set the threshold as 0.55, then the predicted probability ≥ 0.55 that the individual will occur a certain behavior, < 0.55 that the individual will not occur a certain behavior.

In summary, the original behavioral data can be used to make a model-based determination of what kind of behavior will happen to all individual customers, which can be used to help hotels formulate corresponding response strategies in advance.

In addition, it should be noted that when programming in Python, the interface of the scikit-learn module can be used directly to obtain the probability of classification. In general, outputting the probability is more convincing than outputting the decision result. Both the decision-function and predict-proba functions in the scikit-learn module can be used to get the probability determination of classification. We just choose to use one of these functions to obtain the behavioral probability. In the above two-stage prediction method, the predicted probability of a certain behavior for a sample customer individual is calculated by the above two function modules.

III. Deep Learning-based Hotel Customer Behavior Prediction Practices

III. A. Customer Churn Tendency of Hotel Booking Platforms

III. A. 1) Customer churn propensity based on customer price sensitivity

Based on customer price sensitivity behavior, the churn propensity of customers with different characteristic information is predicted using the prediction model of this paper. Table 2 shows the prediction results of customer churn propensity based on customer price sensitivity. Based on customer price sensitivity, customers with low price sensitivity and a length of time within one year from the last order in the range of [0,50000] are the least likely to churn, with a churn rate of only 14.84%. Customers with high price sensitivity and within the range of [0,50,000] from the last order in a year are the most likely to churn, with a churn rate of 59.65%. When the customer within a year from the last order length in the range of [0,50000], price sensitivity is at the two extremes, that is, high and low customer churn tendency is also at the two extremes, need to specifically analyze the customer behavioral patterns, looking for the corresponding optimization program.

Table 2: Customer churn tendency based on customer price sensitivity

Customer price sensitivity	Duration since the customer's last order within one year	Not lost	Loss
High	[0,50000]	40.35%	59.65%
High	(50000,100000]	79.12%	20.88%
High	(100000,+∞)	78.69%	21.31%
Higher	[0,50000]	76.52%	23.48%
Higher	(50000,100000]	83.17%	16.83%
Higher	(100000,+∞)	79.86%	20.14%
General	[0,50000]	80.15%	19.85%
General	(50000,100000]	81.52%	18.48%
General	(100000,+∞)	79.45%	20.55%
Lower	[0,50000]	85.16%	14.84%
Lower	(50000,100000]	79.71%	20.29%
Lower	(100000,+∞)	80.65%	19.35%
Low	[0,50000]	80.55%	19.45%
Low	(50000,100000]	79.63%	20.37%
Low	(100000,+∞)	77.68%	22.32%

III. A. 2) Customer churn propensity based on the customer spending power index

Based on the behavior of customer spending power index, the prediction model of this paper is used to predict the churn propensity of customers with different characteristic information. Table 3 shows the results of predicting the churn propensity of customers based on the customer consumption ability index. Based on the customer consumption ability index, the customers with average consumption ability index and the length of time within one year from the last order in the range of (100000,+∞) are the least prone to churning, and the churn rate is 17.54%. While the consumption ability index is low, and within one year from the last order length in the [0,50000] range of the customer is the most easy to lose, the churn rate of 61.72%, need to focus on this part of the customer's behavior pattern.

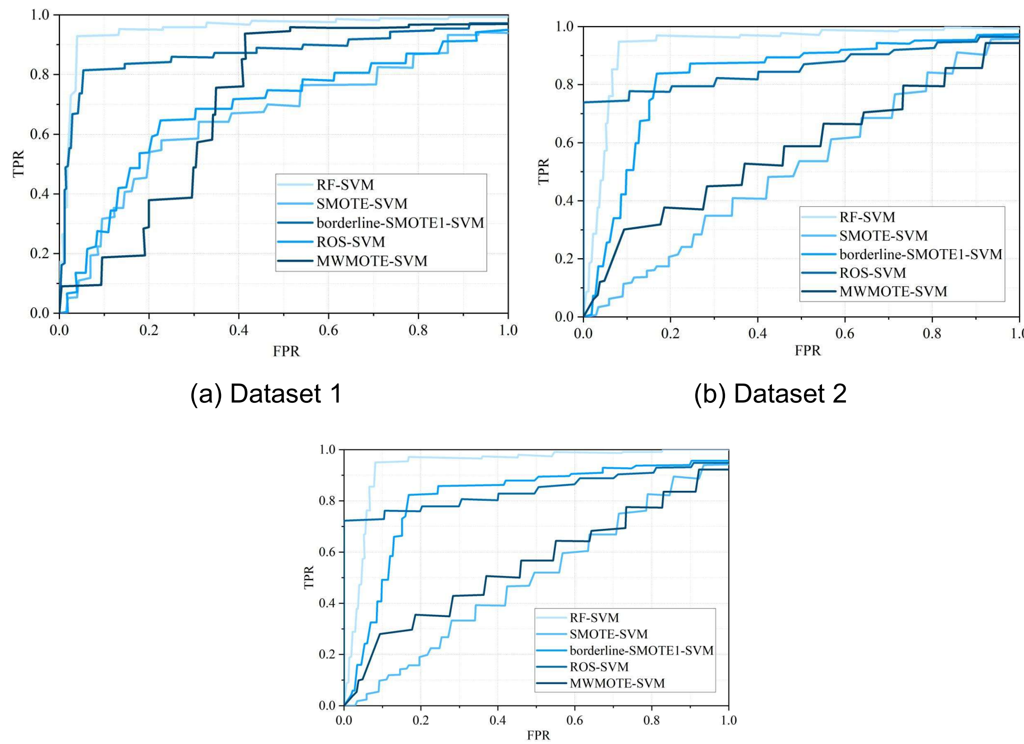
Table 3: Churn tendency based on customer consumption capacity index

Customer price sensitivity	Duration since the customer's last order within one year	Not lost	Loss
High	[0,50000]	70.35%	29.65%
High	(50000,100000]	72.13%	27.87%
High	(100000,+∞)	76.51%	23.49%
Higher	[0,50000]	64.17%	35.83%
Higher	(50000,100000]	70.26%	29.74%
Higher	(100000,+∞)	73.48%	26.52%
General	[0,50000]	69.11%	30.89%
General	(50000,100000]	76.63%	23.37%
General	(100000,+∞)	82.46%	17.54%
Lower	[0,50000]	40.17%	59.83%
Lower	(50000,100000]	70.37%	29.63%
Lower	(100000,+∞)	73.16%	26.84%
Low	[0,50000]	38.28%	61.72%
Low	(50000,100000]	70.81%	29.19%
Low	(100000,+∞)	75.36%	24.64%

III. B. Model Performance Comparison

III. B. 1) Comparison of ROC curves

Compare the prediction accuracy of this paper's RF-SVM behavioral prediction model with four behavioral prediction models, SMOTE-SVM, borderline-SMOTE1-SVM, ROS-SVM, and MWMOTE-SVM, in three hotel customer sample behavioral datasets. To determine the behavioral prediction advantage of the models in this paper. Figure 3 shows the variation of ROC of different models on multiple datasets. In the three datasets, the ROC values of this paper's model are the largest, and finally reach 0.993, 0.997, 0.999, respectively, which is very close to 1.000. And among the five model comparisons, this paper's RF-SVM behavioral prediction model is the fastest and stable to reach more than 0.900. Thus, it is judged that the model in this paper has efficient and accurate behavioral prediction ability, due to the other four models of the same type of comparison.



(a) Dataset 1 (b) Dataset 2

(c) Dataset 3

Figure 3: The ROC changes of different models on multiple datasets

III. B. 2) Comparison of the prediction results of different SVM-based models

Compare the behavioral prediction performance of the same type of algorithms of RF algorithm and SVM algorithm in groups, so as to analyze the reasonableness of the fusion of RF-SVM in this paper. Table 4 shows the comparison of the prediction results of different SVM-based models in the above three datasets. In the three performance indicators of G-mean, F-measure, and AUC, the average values of RF-SVM are 0.9526, 0.9659, and 0.9314, respectively, which are all greater than 0.90, and it is the only model with an average value of greater than 0.90 among all the compared models. In the variance comparison, the variances of RF-SVM are 0.0061, 0.0063, and 0.0022, which are all less than 0.01, and are the smallest variance among all compared models. In the comparison of the prediction results of different SVM-based models, RF-SVM has a significant advantage.

Table 4: Comparison of prediction results of different models based on SVM

Model	G-mean		F-measure		AUC	
	Average value	Variance	Average value	Variance	Average value	Variance
RUS	0.7602	0.0501	0.5049	0.0135	0.7147	0.0381
ROS	0.8198	0.0072	0.4511	0.0323	0.8413	0.0118
SMOTE	0.4778	0.0617	0.3556	0.0325	0.8772	0.0238
BLI	0.5996	0.0176	0.6431	0.0241	0.8113	0.0128
BL2	0.6907	0.0177	0.6991	0.0291	0.8063	0.0173
RF-SVM	0.9526	0.0061	0.9659	0.0063	0.9314	0.0022

III. B. 3) Comparison of different RF-based model prediction results

Table 5 shows the comparison of the prediction results of the different RF-based models in the three datasets. In the three performance metrics of G-mean, F-measure, and AUC, the different models based on RF have the same performance pattern as the different models based on SVM.The mean values of RF-SVM are 0.9904, 0.9762, and 0.9683, respectively, which are all greater than 0.90; and the variances are 0.0029, 0.0074, and 0.0049, which are all less than 0.01, is the best behavioral prediction performance among all the different RF-based comparison models.

Table 5: Comparison of prediction results of different models based on RF

Model	G-mean		F-measure		AUC	
	Average value	Variance	Average value	Variance	Average value	Variance
RUS-RF	0.8301	0.0239	0.4572	0.0311	0.7414	0.0116
ROS-RF	0.4881	0.0604	0.3765	0.0313	0.7773	0.0136
SMOTE-RF	0.6099	0.0162	0.7664	0.0229	0.8114	0.0226
BL1-RF	0.7031	0.0167	0.6772	0.0279	0.8064	0.0171
BL2-RF	0.8029	0.0448	0.5868	0.0551	0.7115	0.0352
RF-SVM	0.9904	0.0029	0.9762	0.0074	0.9683	0.0049

III. C. Comparative Analysis of Hotel Profitability Results

Based on the customer behavior prediction results of the RF-SVM model, we adopt targeted adjustment strategies for different customer groups and analyze the profit reports after the strategies have been implemented for a period of time. At the same time, the profitability reports before the strategy adjustment are compared to determine the reliability of the adjustment based on the behavioral prediction results of the RF-SVM model. Table 6 shows the comparison of profitability results. Providing different hotel ordering strategies for three types of customers with different lengths of time since the last order in a year, it can be seen that the optimized overall profitability increased by 37.24%, 15.56%, and 18.46% over the traditional profitability; the cost per capita decreased by 27.59%, 18.35%, and 13.61%; and the profitability per capita increased by 22.52%, 33.60%, 24.75%. Strategic adjustments based on the results of behavioral predictions can ultimately lead to higher hotel operating revenues.

Table 6: Comparison of profitability results

Project(Unit)	Customer type		
	[0,50000]	(50000,100000]	(100000,+∞)
Traditional profit margin (%)	45.97	60.16	55.49
Optimize profit margin (%)	83.21	75.72	73.95
Profit margin difference rate (%)	37.24	15.56	18.46
Traditional per capita cost (yuan)	189.25	173.92	162.48
Optimize per capita cost (yuan)	137.02	142.04	140.37
Per capita cost variance rate (%)	27.59	18.35	13.61
Traditional per capita profit (yuan)	198.76	300.17	295.63
Optimize per capita profit (yuan)	243.52	401.05	368.79
Per capita profit difference rate (%)	22.52	33.60	24.75

IV. Conclusion

In this paper, we combine the variational Boston 3D matrix and RF-SVM prediction model to predict the behavior of hotel customers and optimize the hotel management strategy in a targeted way.In the 3 dataset experiments, compared with the comparison model, the ROC value of the RF-SVM model is closest to 1, and the fluctuation is the most gentle. In the three performance indicators of G-mean, F-measure, and AUC, the mean values of RF-SVM model are 0.9526, 0.9659, 0.9314, 0.9904, 0.9762, 0.9683, and the variances are 0.0061, 0.0063, 0.0022, 0.0029, 0.0074, 0.0049. The performance is better than the comparison model. The overall profitability of the strategy-adjusted hotels increased by 37.24%, 15.56%, and 18.46% to obtain better revenue levels. In the future, the behavioral classification of customers can be refined to improve the targeting of management strategy adjustment for higher profits.

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