Transactions on Engineering and Technology Research
ISSN: 2960-1797, eISSN: 2960-2246 | Volume 3
ICMEIT 2024

T-Learner Based on Machine Learning for Customer Conversion Prediction and Causal Effect Evaluation

Zhenming Liu[1, *], Yan Yang[1] and Xinyao Huang[1]

[1]School of Mathematics and Statistics, Nanning Normal University, Nanning, China

*Corresponding author:

Abstract. Increasing customer conversion rate is an important topic of concern for every business entity. Among them, promotions and offers are the most common ways to do so. Often, managers want to predict whether customers are likely to become repeat customers through their consumption behaviour and quantify the impact of coupon issuance or not on customer conversion rate to help them determine practical business strategies. In this paper, we focus on customer consumption data of commercial entities, and construct a repurchase prediction model based on three different machine learning algorithms, namely Random Forest, XGBoost and LightGBM, based on RFMA consumption behaviour characteristics. Meanwhile, using the repurchase prediction model combined with the T-learn evaluation method, we propose a quantitative indicator of AUUC for evaluating the impact of coupon issuance on customer conversion rate. The machine learning-based quantitative model for interpretable causal inference proposed in this paper has feasible guidance and value in helping decision makers adopt optimal business strategies.

Keywords: K-means clustering algorithm; machine learning; T-Learner; causal inference.

1. Introduction

E-commerce platforms with large amounts of data and platform algorithms are undoubtedly the home of machine learning. The aim of this paper is to explore the application of explainable machine learning and causal reasoning in precision marketing on e-commerce platforms. Firstly, data collection, preprocessing and exploratory data analysis are conducted through the e-commerce platform. Based on the classification and description of consumers with different consumption behaviours by RFMA, machine learning models such as Random Forests, XGBoost and LightGBM are constructed to predict consumers' repurchase behaviours. Subsequently, the repurchase prediction model is combined with the T-learn evaluation method to calculate the AUUC quantitative index to understand the impact of coupon issuance or not on customer conversion rate. Finally, the difference model allows causal inferences to be made about coupon issuance and appreciation.

2. Data Processing and Exploratory Analysis

2.1 Data Collection

This paper collects the online transaction order information generated by an e-commerce platform from January 2022 to June 2022, including 10 variables such as order ID, merchant ID, user ID, payment date, usage status, actual payment amount, postage, province, city, and quantity, with a total of 20,183 pieces of data.

2.2 Analysis Data

First, count unique values of order ID, merchant ID, and user ID and compare them. Merchants are few, competition is high, and the number of orders and users is similar, indicating low user retention. Coupon usage statistics reveal that few people purchase without using coupons. Analysis of paid amount, quantity purchased, average unit price, and postage shows a skewed distribution: most orders have low out-of-pocket amounts, are small in quantity, and have an average unit price of 50-100 yuan. Most orders are postage-free; few require postage. Orders peak in mid-January, late February, and late June, likely due to Chinese New Year, post-Spring Festival recovery, and mid-year promotions like "618". Purchase behavior varies by festival, analyzed using the Chinese calendar and matplotlib. Economically developed provinces (Shanghai, Guangdong, Beijing, Jiangsu) show higher out-of-pocket payments, indicating higher purchasing power, while central and western provinces (Qinghai, Tibet) show lower transaction amounts. Postage characteristics at the province level, including sum and average, were visualized in Fig. 1. Higher postage costs correlate with frequent economic activities (Guangdong, Shanghai). Higher average postage costs in remote areas (Chongqing, Qinghai, Hainan) may be due to logistics. To reduce costs in high-postage provinces, optimize logistics strategies. In provinces with high total but low average postage, analyze the order structure. For provinces with low total postage, increase marketing to boost order volume.

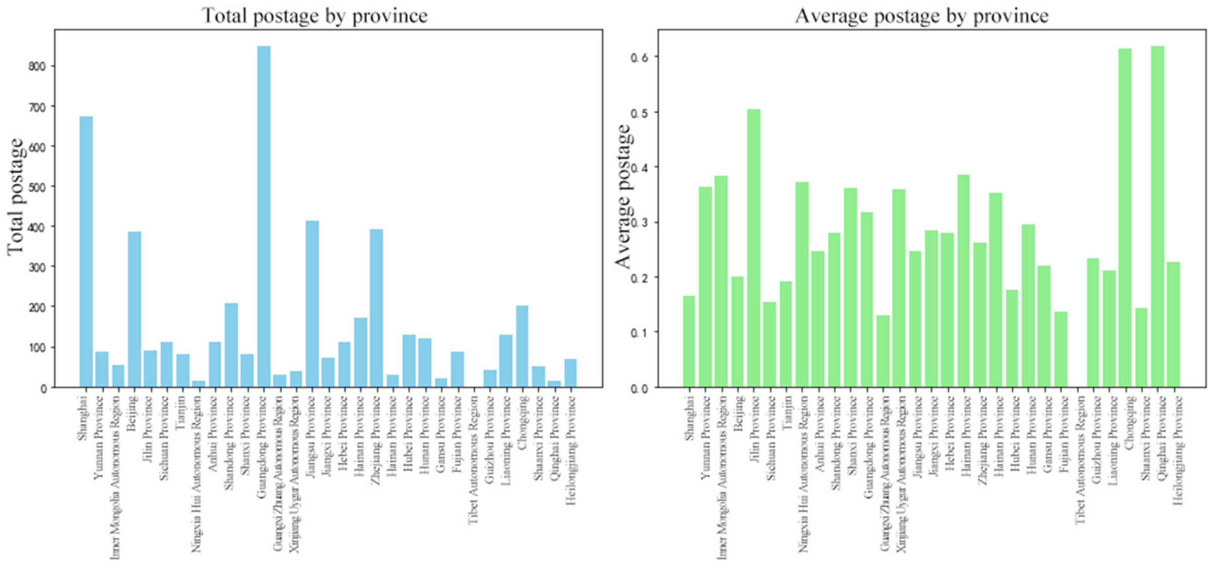

Fig. 1 Total and average postage by province

In summary, when formulating marketing strategies, platforms should consider how to improve user retention, optimize the coupon use mechanism, and adjust marketing activities according to order characteristics, time, and holiday distribution. At the same time, it is necessary to pay attention to the economic differences in different regions and formulate differentiated regional market strategies to better meet the needs of users in different regions and enhance the overall market competitiveness.

3. Customer Portraits

3.1 K-means Clustering Algorithm

The K-means clustering algorithm is a classic unsupervised learning algorithm that is used to divide data points into K clusters [1,2]. The goal is to minimize the impurity of the cluster, i.e., the sum of the distances from the point in each cluster to the center point of the cluster. The K value can be determined according to the elbow rule, the contour coefficient, and Calinski-Harabasz.

The elbow rule determines the optimal K value by observing the tendency of the SSE (Sum of Squares of Error) to decrease as the K value increases. SSE is the sum of the squares of the distance from a point in a cluster to its nearest centroid and is calculated as follows:

$$SEE = \sum_{i=1}^{K} \sum_{x \in C_i} \|x - \mu_i\|^2 \tag{1}$$

The contour coefficient measures the quality of clustering, and higher values indicate better clustering results.

$$s(i) = \frac{b(i) - a(i)}{max\{a(i), b(i)\}} \tag{2}$$

Calinski-Harabasz is a statistic that measures the effectiveness of clustering, and it is based on the ratio of variance between and within clusters. The higher the CH score, the better the clustering effect.

$$CH = \frac{Trace(B)}{Trace(W)} \times \frac{n-k}{k-1} \tag{3}$$

3.2 RFM Model

The RFM model is an important tool and means to measure customer value and customer ability to create benefits. It describes a customer's value profile through three metrics: recent purchases, overall frequency of purchases, and how much money they have spent.

In this paper, by integrating the average unit price indicator into the RFM model, we get an extended RFM model, called the RFMA model, which can help enterprises understand customer behavior in more granular terms.

3.3 Model building

By grouping and aggregating user IDs, the consumption interval (R), consumption frequency (F), total consumption amount (M) and average unit price (A) of each user were counted and standardized.

The K-means clustering algorithm was used to perform cluster analysis in the range of 2 to 8. clusters, and the Calinski-Harabasz index, Silhouette score and clustering inertia under different clusters were evaluated to determine the optimal number of clusters. The trend of these three evaluation indicators with the number of clusters was plotted as Fig. 2 to visualize the optimal number of clusters for your model.

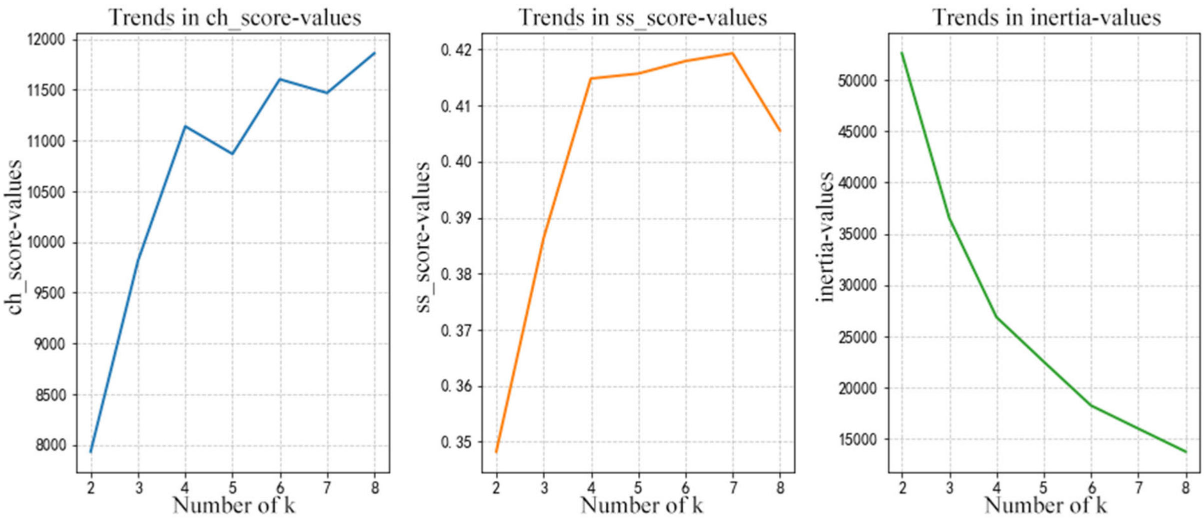

Fig. 2 Trends in ch index, silhouette score, and clustering inertia with k

Combining the three index curves, when $k = 4$ the image shows an obvious inflection point, indicating that the clustering effect is better, therefore, the customer group is divided into four categories, and the clustering center results are as follows Table 1：

Table 1. RFMA Customer Value Model Clustering Center

Labels	Count	R	F	M	A
2	6583	-1.0486	-0.2494	-0.4837	-0.5011
1	5687	0.028	-0.2494	0.7659	1.2104
0	5153	0.8712	-0.2494	-0.5636	-0.6190
3	1294	-0.3877	3.3588	1.4231	-0.1816
Mean		-0.1343	0.6526	0.2854	-0.0228

Based on the clustering results, draw a customer value radar chart of the RFMA model. Compare the features with the average to form a customer rating such as Table 2:

Table 2. Three Scheme Comparing

	Category	R	F	M	A	Priority	Customer ratings
0	5153	↑	↓	↓	↓	4	Low-value customers
1	5687	↑	↓	↑	↑	2	Customers with high unit price and low frequency
2	6583	↓	↓	↓	↓	3	Customers who have made frequent purchases in the near future
3	1294	↓	↑	↑	↓	1	High-value, high-frequency users

As shown in Table 2, Customer Group 0: The purchase frequency is low, the amount of each purchase is not large, and the last purchase time is relatively long, due to their relatively low contribution, they can be regarded as a group that needs to be activated or evaluated whether to continue to invest in resource maintenance. Customer group 1: The purchase frequency is not high, but due to the strong single consumption power, it should be regarded as a customer group with high potential value. Customer group 2: The amount and total value of a single consumption are not large, but they still have a certain value due to frequent purchases. Customer group 3: Not only is the purchase frequent, but the amount of each purchase is large, and the unit price is also high. This is the most valuable customer group and makes a huge contribution to the business.

The RFMA model can intuitively measure customer value, which is easy to understand and implement, and is suitable for rapid segmentation and basic customers, and divides customers into different groups such as high value, medium value and low value, which is convenient for enterprises to carry out differentiated marketing.

4. Precision Marketing Model Based on Machine Learning and Causal Judgment

4.1 Feature Engineering

From the original order data, a wealth of user behavior, time, region, and transaction attribute characteristics are extracted. Calculate the correlation of the above features and output a heat map. By setting the threshold of 0.7 to remove the autocorrelation, the variable pairs with correlation higher than the specific threshold were filtered out, and a total of 8 features were screened out, so as to identify and deal with the multicollinearity problem in the data. Delete features autocorrelated and redraw the feature correlation heat map for the remaining 20 features. Before and after feature screening, correlation heat maps are as follows: Fig. 3 shown:

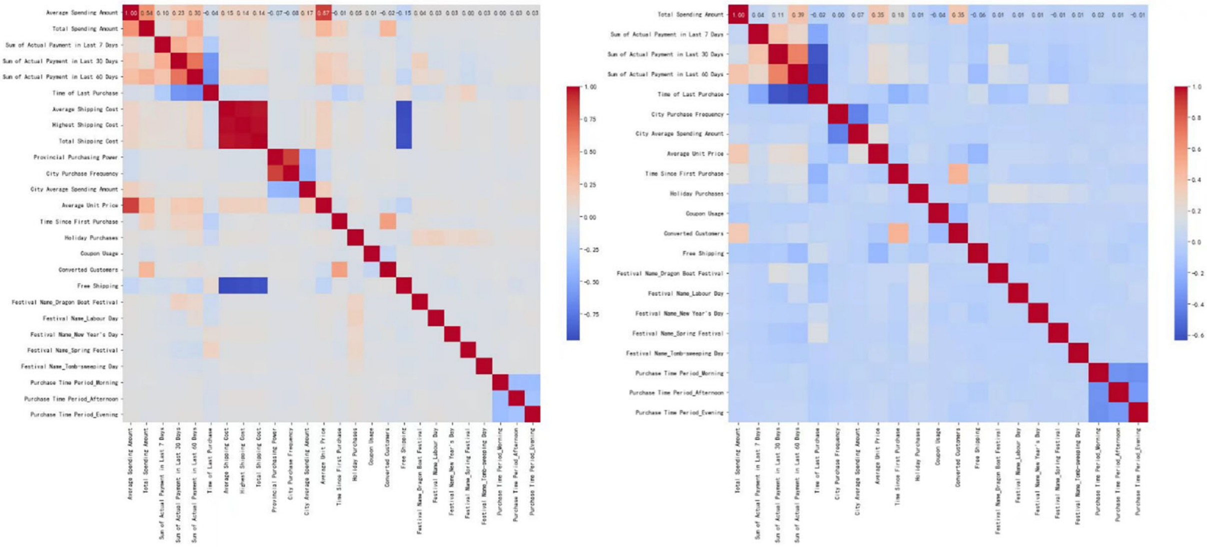

Fig. 3 Heat map before and after feature screening

4.2 Classification Model

Taking the remaining 23 characteristics as the independent variables and Y (converting customers, that is, whether there is repurchase behavior) as the dependent variables, the prediction models of Random Forest, XGBoost and LightGBM conversion customers were constructed.

4.2.1 Random Forest

Random Forests are an ensemble learning method that makes predictions by building and combining multiple decision trees. It is based on two core ideas: Bagging and Random Trait Selection [3]. For classification tasks, Random Forests usually use majority voting as the final prediction, that is, the mode of the prediction results of all trees is taken as the category label, and the prediction result of the Random Forest is:

$$\hat{y}(x) = argmax \quad {}_c \sum_{t=1}^{T} I\,(\hat{y}_t(x) = c) \tag{4}$$

Where I represents the indicator function and c represents the category labeling.

4.2.2 XGBClassifier

XGBoost (eXtreme Gradient Boosting) is an efficient Gradient Boosting Decision Tree (GBDT) implementation [4]. It introduces regularization terms and second-order Taylor expansions to minimize the loss function of weighted residuals by iteratively adding new trees. XGBoost optimizes the traditional GBDT, including efficient block approximation histogram algorithm, column sampling, regularization and other technologies, which improves the training speed and generalization performance of the model.

Let the current model be $F_m(x)$, and the goal is to$f_t(x)$ minimize the loss function by adding a new tree:

$$L(y, F_{m+1}(x)) = \sum_{n}^{i=1} l(y_i, F_m(x_i) + f_t(x_i)) + \Omega(f_t) \tag{5}$$

Where l is the objective loss function, y_i is the true label of the ith sample, n is the number of samples.

$\Omega(f_t)$ is a regular term that is used to control the complexity of the model.

In each iteration, the CART is constructed by solving for the optimal split point to maximize gain:

$$\text{Gain}=\frac{1}{2}[I_L - I_R - \gamma(T_L + T_R)] - \lambda|w| \tag{6}$$

4.2.3 LightGBM

Table 3. Three Scheme comparing

The name of the model	AUC	Precision	Accuracy	Recall	F1-Score
Logistic Regression	0.989	0.941	0.941	0.941	0.941
Decision Tree	0.969	0.970	0.970	0.970	0.969
Random Forest	0.999	0.981	0.981	0.981	0.981
Gradient Boosting	0.996	0.963	0.963	0.963	0.963
K-Nearest Neighbors	0.988	0.964	0.963	0.963	0.963
XGBClassifier	0.998	0.978	0.978	0.978	0.978
LightGBM	0.998	0.977	0.976	0.976	0.976

LightGBM is an efficient machine learning tool based on a gradient boosting framework designed to process large-scale data and reduce memory consumption. Compared with XGBoost, LightGBM introduces gradient-based unilateral sampling, which improves training efficiency and accuracy.

In this paper, we construct a transformation customer classification prediction model with seven different algorithms, including logistic regression, decision tree, Random Forest, gradient boosting, K-nearest neighbor, and the ensemble algorithms XGBoost and LightGBM. Each model was trained on oversampled training data and predicted on a test set, and the model performance was evaluated by 5-fold cross-validation, as Table 3shows.

After evaluating the model performance, we found that Random Forest, XGBClassifier, and LightGBM performed well in all evaluation metrics, especially on AUC, Precision, and Accuracy. These models not only perform well on individual performance metrics, but also exhibit consistently high levels of performance when all metrics are taken into account, so we chose these three models as meta-learners for the T-Learner.

4.3 T-Learner

T-Learnering is a machine learning method used to estimate individual causal effects or conditional average treatment effects. In this paper, three meta-learner prediction models were constructed to predict whether the customers in the intervention group (coupons were issued) to predict whether they were converted customers. Similarly, for the customers in the control group (no coupons issued), three meta-learner prediction models are built to predict whether they are converted customers.

For any customer on the platform, based on the characteristics of customer consumption behavior, the prediction value was obtained by using the meta-learner prediction model constructed by the intervention group, and then the prediction value was obtained by using the meta-learning period prediction model constructed by the control group, and the Uplift value was obtained by differential operation of the two prediction values, and the precision marketing strategy for customers on the whole platform was constructed according to the Uplift value.

The steps to build a T-Learner are as follows:

Construct a classification prediction model of conversion customers based on the characteristics of consumption behavior by intervening in the intervention group (issuing coupons) customers. Feature and label building model (classification model of three different algorithms):

$$Y = f_t(X) \tag{7}$$

Build a model (classification model with three different algorithms) using the characteristics and labels of the control group (no coupon issued) data:

$$Y = f_c(X) \tag{8}$$

For the consumption behavior characteristics of any customer on the platform, use the sum model constructed above, calculate the predicted value of label Y respectively, and differentially obtain the gain value of the predicted value, where is the Uplift value of the T-Learner.

$$\hat{\tau}(X) = \widehat{f_t(X)} - \widehat{f_c(X)} \tag{9}$$

4.4 Assessment Methods

The core idea of the cumulative gain curve is to rank users according to the response probability (or uplift score) predicted by the model, and then cumulatively calculate the total gain that users can bring to each percentage segment in the order in which they are sorted [5-7]. This gain can be positive, e.g. in marketing, indicating that the customer group predicted by the model will lead to more conversions or revenue than a Randomly selected customer group. The calculation formula is as follows:

$$\text{Cumulative Gain} = \sum_{N}^{i=1} \left(\frac{Y_i^T}{N^T} - \frac{Y_i^C}{N^C}\right)(N^T + N^C) \tag{10}$$

Where$N$is the total number of segments $Y_i^T$and Y_i^Crepresents the total number of responses in the experimental and control groups in the first segment $N^C$and N^Trepresents the total number of people in the experimental and control groups in the ith segment, respectively.

The cumulative gain curve can help decision-makers understand the additional value of the model at different user coverages.

The area under the cumulative gain curve is called the Area Under Uplift Curve (AUUC), and it measures the ability of a model to predict which individuals are more likely to respond positively to an intervention, such as a marketing campaign. The calculation formula is as follows:

$$\text{AUUC} = \int_0^N f(t)dt \tag{11}$$

Where $f(t)$ represents the cumulative gain curve.

4.5 Modeling Process

The dataset is divided into two groups based on whether the user used the coupon: the group that used the coupon and the group that did not use the coupon, and check if the categories are balanced, and if the number of positive and negative classes is not equal, the samples are oversampled to balance the data set.

The Bayesian optimization method was used to optimize the hyperparameters of the meta-learners in the intervention group and the control group, and the model was trained, and the optimization results were as follow Table 4.

Table 4. Three Scheme comparing

Model type	Hyperparameters	Corresponding values (intervention group)	Corresponding value (control group)
(RandomForest)	n_estimators	245	300
	max_depth	7	7
	min_samples_split	2	2
	min_samples_leaf	2	1
	max_features	0.9662222963492746	0.837448370202317
	n_jobs	-1	-1
	Random_state	42	42
LightGBM	bagging_fraction	1.0	0.8085396792511581
	bagging_freq	5	4
	feature_fraction	1.0	0.679511465960702
	max_depth	7	6
	min_child_samples	24	44
	min_child_weight	1	3
	n_estimators	300	230
	num_leaves	150	81
	n_jobs	-1	-1
	Random_state	42	42
XGBoost	objective	binary:logistic	binary:logistic
	alpha	0.01	0.17526374143768195
	colsample_bytree	1	0.7005577771458656
	gamma	0.5	0.5060977507260509
	learning_rate	0.1319309150058509	0.12042701259544326
	max_depth	7	4
	min_child_weight	2	5
	n_estimators	300	175
	min_delta	0.1	0.05891187021047896
	subsample	0.6	0.8414676504131005
	n_jobs	-1	-1
	Random_state	42	42
	reg_lambda	0.1	1.8304537275924477

The trained intervention group and control group models were used to predict the full test data and obtain their respective probability outputs. Calculate the difference between the probability predicted by the model in the treatment group and the probability predicted by the model in the control group to obtain the model gain value (uplift).

4.6 Results Discussed

The actual cumulative gain for each model is calculated and compare it with the Random Uplift and its cumulative gain, and plot the cumulative gain, such as: Fig. 4 show.

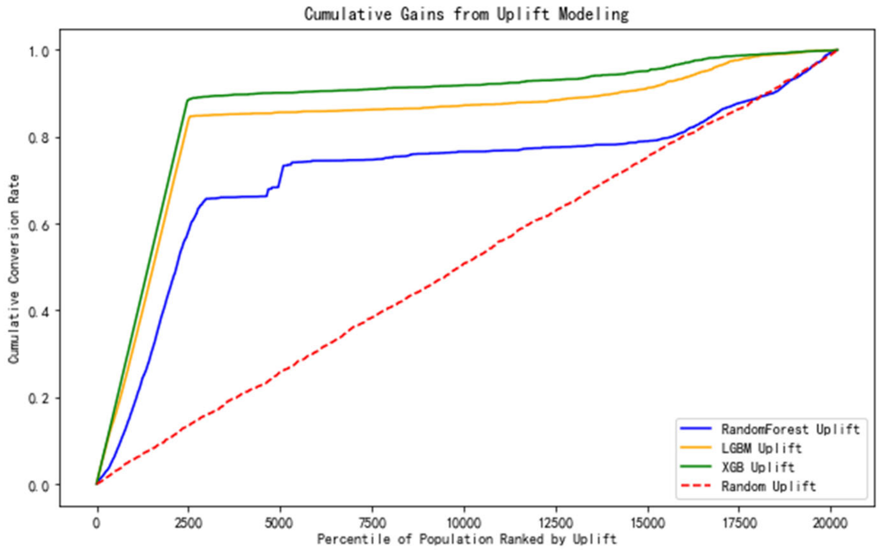

Fig. 4 Cumulative gain vs randomized intervention across models

In Fig. 4, the cumulative gain curves for four different models (Random Forest, LightGBMClassifier, XGBClassifier, and Random) are shown, and overall, the XGBClassifier model has the highest cumulative gain curve, indicating that it performs best in identifying individuals with high uplifts and provide the highest cumulative gain.

The gain effect of the three models can reach the maximum value when the top 20% of customers are circled, but the gain value of the XGBClassifier model is the largest, while the gain effect of Random Forest is negative when the top 20% of customers are circled.

The AUUC values of each model were calculated using the Simpson integral method and compared with the Randomized intervention results shown in The AUUC values of each model were calculated using the Simpson's rule and compared with the Randomized intervention results shown in Table 5.

Table 5. Three Scheme comparing

Model	AUUC	Randomized intervention amplification
RandomForest	14474.481884057972	41.47%
LightGBMClassifier	16912.100603864736	65.29%
XGBClassifier	17657.79577294686	72.58%

According to the AUUC value and the increase in Randomized intervention, XGBoostClassifier showed the strongest predictive ability in Uplift Modeling, followed by LightGBMClassifier, while Random Forest performed relatively weakly on this task.

5. Summary

As the economy enters a new stage of post-epidemic recovery and high-quality development, e-commerce platforms and precision marketing strategies in the context of digital transformation have become inevitable requirements. The aim of this paper is to construct a quantitative model for customer consumption behaviour prediction using machine learning and causal inference techniques to improve the precision marketing efficiency of e-commerce platforms. Firstly, the K-mean clustering algorithm and the improved RFMA customer value model are used to identify different user groups. Second, three classification models, namely Random Forest, XGBClassifier and

LightGBM, are used as meta-learners to construct a customer repurchase prediction model, and causal inference between coupon issuance or not and customer repurchase behaviours is carried out by combining the repurchase prediction model through T-Learner. The causal inference-based precision marketing model provides a more scientific basis for decision-making by identifying and quantifying the impact of different marketing coupon distribution on customer conversion rates, helping companies optimise their marketing investment and better respond to market changes.

References

[1] Qiu Ziyun. Research on precision marketing method of e-commerce platform based on cluster analysis[J]. Digital Communication World,2023(10):188-190.

[2] Dai Jinhui,Wang Mengen,Zhong Xuan. System analysis of e-commerce platform orders based on data mining[J]. Journal of Shangqiu Normal College,2023,39(12):4-8.

[3] Cui Anqi. Utility increment Uplift Tree algorithm and its application in precision marketing[D].Lanzhou University,2024.

[4] Song Xia. Research and application of O2O coupon use prediction based on XGBoost[D].Southwest Jiaotong University,2022.

[5] Wang Dechao. Credit card risk control management model and visualization based on causal inference[D].East China Normal University,2023.

[6] Wang Yunhua ,Deng Cuiyan. Research on the construction of customer portrait and precise marketing strategy based on big data[J]. Information System Engineering,2024, (07):141-144.

[7] Zhang Wenjin. Research on the analysis of enterprise value creation process of data-enabled e-commerce platform[D]. Inner Mongolia University of Finance and Economics, 2024.DOI:10.27797/d.cnki.gnmgc.2024.000422.