Transforming E-commerce Operations: An Intelligent Business Intelligence Approach for Improving Customer Transaction Management

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Abstract

In the fast-paced world of e-commerce, understanding customer behavior is essential for success. Business intelligence (BI) tools provide valuable insights into customer transactions and can be used to model and predict customer behavior. This paper explores the use of BI techniques for modeling customer transaction behavior in e-commerce. We discuss the various types of BI tools available and their use in analyzing customer data. We then outline a framework for using BI to develop a customer transaction behavior model, including data collection, preprocessing, feature selection, and model selection. Finally, we present a case study in which we apply this framework to a real-world e-commerce dataset and demonstrate the effectiveness of our approach in predicting customer behavior. Our results show that BI techniques can be an effective tool for modeling customer behavior in e-commerce, providing valuable insights for businesses looking to optimize their operations and increase customer satisfaction.

Keywords: E-commerce; Intelligent Business; Intelligence Approach; Customer Transaction; BI

1. Introduction

In the highly competitive world of e-commerce, understanding customer behavior is essential for success. One way to gain this understanding is through modeling customer transaction behavior. By analyzing patterns in customer transactions, businesses can gain insights into customer preferences, habits, and needs. These insights can then be used to improve the customer experience, increase sales, and optimize operations [1-3]. Modeling customer transaction behavior involves using statistical and machine learning techniques to analyze customer data. This data may include information such as purchase history, browsing behavior, demographics, and other relevant factors. By identifying patterns and trends in this data, businesses can develop models that predict future customer behavior. These models can then be used to personalize marketing campaigns, recommend products, and optimize pricing and inventory management [4-7].

Business intelligence (BI) tools are widely used for customer transaction modeling in e-commerce. BI tools provide a range of techniques, including data mining, machine learning, and predictive analytics, to analyze customer data and generate insights. By modeling customer transactions in e-commerce, businesses can gain a better understanding of their customers' needs and preferences, optimize their marketing strategies, and improve their overall customer experience. Effective customer transaction modeling can provide businesses with a competitive advantage in the crowded e-commerce market, allowing them to stay ahead of the curve and meet their customers' evolving needs [8-11].

This work proposes a framework for modeling customer transaction behavior in e-commerce, which involves exploratory data analysis, data preprocessing, and Light GBM modeling. We conducted extensive exploratory data

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analysis to gain insights into the distribution and relationships of various features, which can help e-commerce businesses better understand their customers and optimize their marketing strategies. Extensive experimentation validated the promise of our approach for improving the management of business transactions for customers in a way that optimizes the operations and increases customer satisfaction.

2. Related Works

In this section, we review the relevant literature on modeling customer transaction behavior in e-commerce. We will likely summarize and critique previous work and discuss how their approach differs from existing research. For example, the authors [4] contribute to the field of e-commerce by proposing a ML approach to predict customer quality in social networks. They collected data from a Spanish e-commerce platform and used machine learning algorithms to analyze customer behavior and identify patterns related to customer quality. They defined customer quality as the likelihood of a customer making a high-value purchase in the future, and identified features that were highly correlated with this measure. In [5], the authors proposed a reinforcement learning approach to improve search engine ranking in e-commerce platforms. They formulated the search ranking problem as a Markov decision process (MDP) and used reinforcement learning to learn an optimal ranking policy. They evaluated their approach on a large-scale e-commerce search engine dataset and found that their proposed method outperformed traditional ranking methods. They also analyzed the convergence and stability of their approach and provided insights into the impact of different hyperparameters. In [6], the authors developed chatbots and conversational agents by providing a bibliometric analysis of the research landscape in this area. They collected data on publications related to chatbots and conversational agents from various academic databases and analyzed the resulting dataset using bibliometric methods. They identified trends in publication output, research topics, and influential authors and institutions. They also analyzed the citation network of the dataset to identify the most influential publications and to visualize the intellectual structure of the field. In [8], the authors proposed a reinforcement learning approach to optimize long-term user engagement. They formulated the problem of optimizing user engagement as a Markov decision process and used reinforcement learning to learn an optimal policy for recommending items to users. They evaluated their approach on a large-scale dataset from a popular e-commerce platform and found that their proposed method outperformed traditional recommender system algorithms in terms of long-term user engagement. In [12], the authors argued that ML can enable service organizations to extract value from large, complex datasets and to gain new insights into customer behavior and preferences. They provided a conceptual framework for understanding the role of ML in service innovation and design and discussed several applications of ML in service contexts, including personalized recommendations, customer segmentation, and predictive maintenance. In [15], the authors explored investigating the relationship between user-generated content (UGC) and stock performance of business-to-business (B2B) firms in industrial marketing management. They employed ML methods to analyze a large dataset of UGC from a popular online business review platform and linked this data with firms' financial data to examine the impact of UGC on stock performance. They found a positive relationship between UGC and stock performance, suggesting that UGC can serve as a valuable source of information for investors and that firms can benefit from actively managing their online reputation. In [16], the authors developed a deep learning architecture called Behavior Sequence Transformer (BST) for predicting user behavior in the context of online shopping. They argued that existing recommendation models that rely on simple sequential models or matrix factorization may not capture the complex relationships between user behaviors and product features. They demonstrated the effectiveness of the proposed model on a large dataset of user behaviors from the Alibaba e-commerce platform. In [18], the authors presented a web search and online advertising by proposing a method for detecting online commercial intent in user queries. They argued that online commercial intent is an important factor for search engines and advertisers to understand, as it can help to improve the relevance of search results and increase the effectiveness of online advertising. In [17], the authors proposed an approach to recommendation systems by treating the recommendation task as a link prediction problem in bipartite graphs. The authors argue that traditional approaches to recommendation systems suffer from the cold-start problem, where new users or items have insufficient data to make accurate recommendations. Their approach involved using graph kernels to measure the similarity between users and items and then applying a machine learning algorithm to predict missing links. They evaluated the proposed approach on several datasets and showed that it outperformed several state-of-the-art recommendation methods.

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3. Methodology

This section describes the proposed approach to model customer transaction behavior, and it includes a detailed description of the data collection and preprocessing steps, feature selection, and model selection. We also likely discuss any assumptions or limitations of their approach.

In our framework for modeling customer transaction data, we apply several data preprocessing techniques to prepare the data for analysis. The first step is data cleaning, where we remove any duplicates, missing or irrelevant data, and outliers [12-16]. We then perform feature selection to identify the most important features for predicting customer behavior. This helps to reduce the dimensionality of the data and improve the model's performance. We also apply feature engineering to create new features that may be more informative and help the model to capture more complex relationships in the data [16-19].

After performing these preprocessing steps, we then normalize the data to ensure that all features are on a similar scale. This is important because some machine learning algorithms are sensitive to the scale of the input features, and normalization can help to improve the model's accuracy and stability. Finally, we split the data into training and testing sets, with the training set used to train the model and the testing set used to evaluate its performance. This helps to ensure that the model is not overfitting to the training data and can generalize well to new, unseen data. By applying these data preprocessing procedures (in Algorithm 1), we can improve the quality of the data and increase the accuracy of our model for predicting customer transaction behavior.

Algorithm 1. Preparing Customer Transaction Data
Input: Customer Transaction Data, $D_{commerce}$
Output: Training sets, Testing sets
1. //data cleaning
2. $D_p \xleftarrow{remove\ null/missing} D_{commerce}$
3. $D_p \xleftarrow{remove\ duplicate} D_p$
4. X_{train}, X_{test} = split (D_p, size = 0.3)
5. //data standardization
6. **for** col in X_{train}.cols
7. $col_{max} = max(X_{train}.iloc[:, col])$
8. $col_{min} = min(X_{train}.iloc[:, col])$
9. $X_{train}.iloc[:, col] = (X_{train}.iloc[:, col] - col_{min}) / (col_{max} - col_{min})$
10. $X_{test}.iloc[:, col]$ = (X_{test}.iloc[:, col] – col_{min})/(col_{max} – col_{min})
11. **end for**
12. return X_{train}, X_{test}

Light GBM (Light Gradient Boosting Machine) is a gradient boosting framework that uses tree-based learning algorithms (See Figure 1). It is applied here to handle large-scale datasets and as it has been proven to be effective in various BI applications, including customer transaction modeling in e-commerce. In customer transaction modeling, LightGBM is used to predict customer behavior, i.e., likelihood of a customer making a purchase or the probability of a customer returning to make another purchase. It can also be used to identify important features that drive customer behavior, such as the frequency of transactions, the amount spent, and the type of products purchased. Given the customer transaction training data $\{(\mathrm{x_i}, y_i)\}_{i=1}^{N}$, we apply LightGBM to optimize the following regularization function.

$$Opt = \sum_i l(y_i, \hat{y_i}) + \sum_k \Omega(f_k) \tag{1}$$

In our case, we used cross-entropy function to compute the difference between the prediction $\hat{y_i}$ and the ground truth y_i.

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$$l(y_i, \hat{y}_i) = y_i \log\left(1 + e^{-\hat{y}_i}\right) + (1 - y_i) \log\left(1 + e^{\hat{y}_i}\right) \tag{2}$$

Followingly, the regression tree is applied as follows:

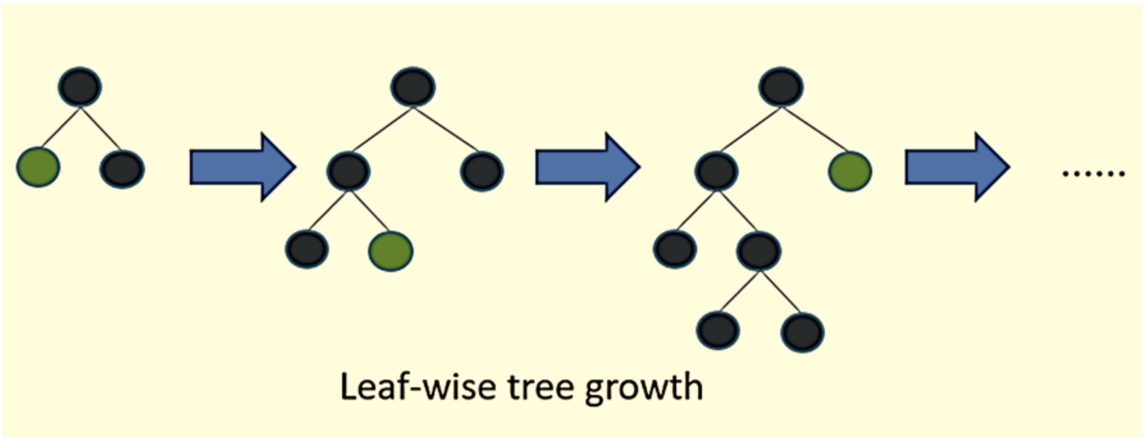

Figure 1: Illustration of LightGBM.

$$F_T(X) = \sum_{t=1}^{T} f_i(x) \tag{3}$$

This can be denoted in another formula, in which , w, and q denote the count of leaf nodes, sample weight, and determination. Then, newtons method is integrated to approximate the objective function, as follows:

$$opt^{(t)} \cong \sum_{i=1}^{n} [g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \sum_{k} \Omega(f_k) \tag{4}$$

4. Results and Discussions

This section will present the results of analysis of the e-commerce dataset. We present various metrics and visualizations to demonstrate the effectiveness of their approach. The discussion will also provide an interpretation of the results, highlighting the key findings and their implications. In this work, we provide an anonymized customer transaction dataset as a case study for our BI approach. The data containing numeric feature variables, the binary target column, and a string. In particular, we have a total of 200,000 samples of consumer data, each composed of 202 features.

Descriptive statistics are applied to customer transaction data, in which a set of measures are provided as a summary of the data, such as its central tendency, variability, and distribution (See Table 1). These statistics help our approach to understanding the behavior of customers in terms of their purchasing patterns and preferences. The measures of variability include range, variance, and standard deviation. The variance and standard deviation provide estimation of the spread of the data around the mean. These measures can be used to identify outliers or unusual patterns in customer transactions.

Table 1: Descriptive statistical analysis for our customer transaction data.

	count	mean	std	min	25%	50%	75%	max

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target	200000.00	0.10	0.30	0.00	0.00	0.00	0.00	1.00
var_0	200000.00	10.68	3.04	0.41	8.45	10.52	12.76	20.32
var_1	200000.00	-1.63	4.05	-15.04	-4.74	-1.61	1.36	10.38
var_2	200000.00	10.72	2.64	2.12	8.72	10.58	12.52	19.35
var_3	200000.00	6.80	2.04	-0.04	5.25	6.82	8.32	13.19
var_4	200000.00	11.08	1.62	5.07	9.88	11.11	12.26	16.67
var_5	200000.00	-5.07	7.86	-32.56	-11.20	-4.83	0.92	17.25
var_6	200000.00	5.41	0.87	2.35	4.77	5.39	6.00	8.45
var_7	200000.00	16.55	3.42	5.35	13.94	16.46	19.10	27.69
var_8	200000.00	0.28	3.33	-10.51	-2.32	0.39	2.94	10.15
var_9	200000.00	7.57	1.24	3.97	6.62	7.63	8.58	11.15
var_10	200000.00	0.39	5.50	-20.73	-3.59	0.49	4.38	18.67
...	...	...	...	...	...	...	...	...
var_195	200000.00	-0.14	1.43	-5.26	-1.17	-0.17	0.83	4.27
var_196	200000.00	2.30	5.45	-14.21	-1.95	2.41	6.56	18.32
var_197	200000.00	8.91	0.92	5.96	8.25	8.89	9.59	12.00
var_198	200000.00	15.87	3.01	6.30	13.83	15.93	18.06	26.08
var_199	200000.00	-3.33	10.44	-38.85	-11.21	-2.82	4.84	28.50

Exploratory data analysis (EDA) is presented to analyze and summarize the main characteristics of a data set to gain insights and understand the customer transactions. As a common way of performing EDA for customer transaction data, we visualize the density plot of each feature to envisage the distribution of the data, as shown in Figure 2. However, due to the large number of features, we show the density plot for only the first 100 features in our case study. It could be noted that there is a considerable set of features with a substantial distinct distribution for the two target values. This, in turn, necessitates careful choice of features during the modeling of customer transactions.

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Figure 2: The density plot for each feature on our case study of customer transactions

Class distribution analysis is performed as an important step to understand distribution of customer transaction, especially in BI where it is critical to have a balanced class distribution for accurate model training. Both bar charts and histograms are presented in Figure 3 to provide useful insights into class distribution, but they are best suited to different types of data. It is notable that the proposed system suffers from considerable class imbalance.

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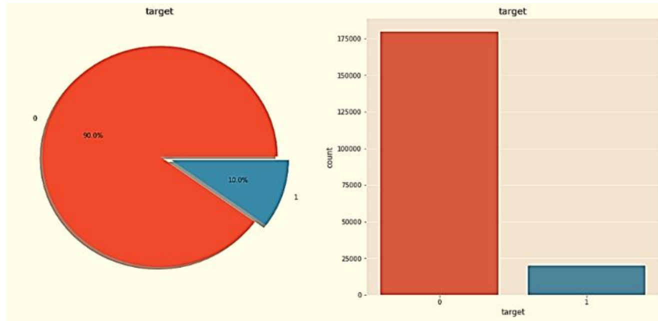

Figure 4: class distribution analysis for our case study of customer transactions

Feature importance analysis is applied to understand which features have the greatest impact on the model's predictions. In our study, we used the LightGBM algorithm to analyze the importance of features for modeling customer transaction behavior in e-commerce. LightGBM provides a feature importance metric that calculates the contribution of each feature in predicting the target variable. The feature importance score is calculated by summing up the number of times a feature is used in the construction of decision trees, weighted by the gain of each split. The higher the score, the more important the feature is for predicting the target variable. Based on our analysis using LightGBM (See Figure 4), we found that var_108 was the most important feature for predicting customer transaction

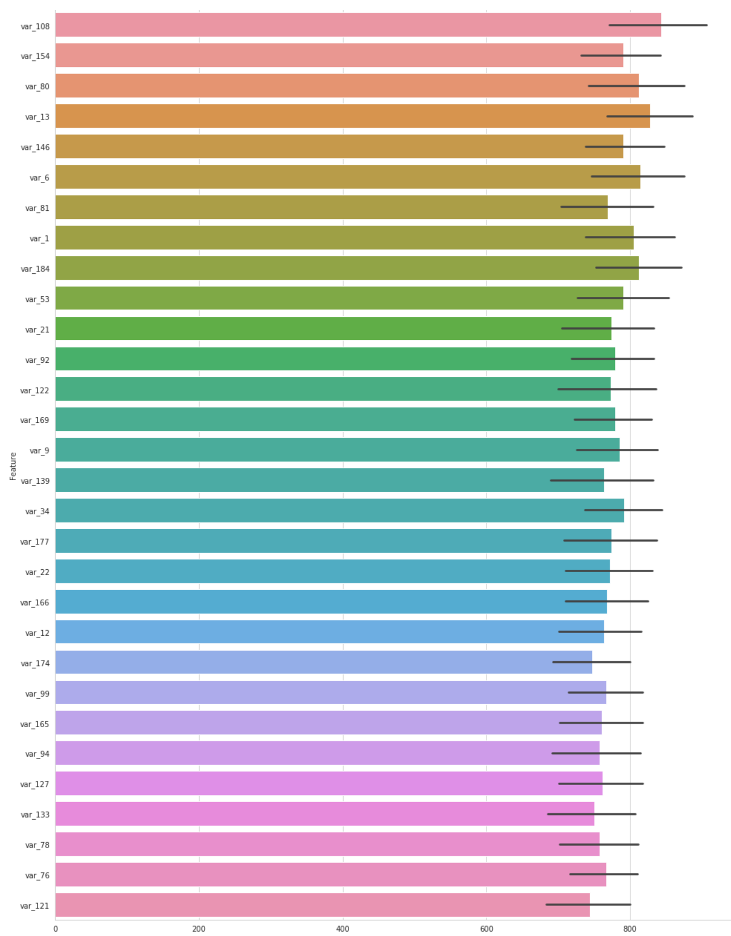

Figure 3: Visualization of the feature importance for our model on case study of customer transactions

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behavior in e-commerce. This was followed by var_154 and var_80. Other features, such as customer age and gender, had a lower importance score, indicating that they were less important for predicting transaction behavior.

5. Conclusion

This work introduces BI technique to model customer transaction behavior in e-commerce. We explored the use of descriptive statistics, exploratory analysis, class distribution analysis, and the LightGBM algorithm for this purpose. Through our analysis, we identified important features that contribute to customer transaction behavior. Our study demonstrated the usefulness of machine learning for understanding and predicting customer behavior in e-commerce. The results suggest that businesses can leverage machine learning models to gain insights into customer behavior and develop targeted marketing strategies to improve customer engagement and satisfaction. However, further research is needed to improve the accuracy and interpretability of machine learning models in the context of e-commerce.

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