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The Code of Consumer Minds: Decoding E-Commerce User Behavior Through Advanced Models

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Abstract

E-commerce platforms must make decisions with significant financial and human resource implications, it is essential to comprehend consumer behavior. Finding patterns in vast amounts of user data is still quite difficult. This project demonstrates a data-driven pipeline that analyzes and forecasts user behavior using data mining techniques. The data comes from two weeks of activity in 2017 on Alibaba's Taobao website. Data preprocessing and exploratory data analysis (EDA) with visualizations are part of the workflow. Customer segmentation is done using K-means clustering and RFM analysis. User behavior is modeled and predicted using Long Short-Term Memory (LSTM) models and Recurrent Neural Networks (RNN). These forecasting methods offer insightful information about user behavior. The findings help e-commerce companies make well-informed, economical judgments. This method improves behavioral data-based strategic planning.

Keywords: E-commerce User Behavior; Data Mining; Customer Segmentation; K-Means Clustering; RFM Analysis; Predictive Modeling; Long Short-Term Memory (LSTM); Recurrent Neural Networks (RNN); Exploratory Data Analysis (EDA); Conversion Rate Optimization

How to Cite This Article

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Introduction

” The exponential evolution of the internet in the 21st cen-tury has boosted the fast growth of the online shopping indus-try and e-commerce platforms” [2]. ”Information about user behavior is stored in the web server logs in a structured way.” In contrast with traditional offline shopping, online shopping provides customers with a much more convenient and flexible shopping experience. E-commerce platforms offer a vast array of products across various categories, providing users with the freedom to explore, compare, and make purchases. [8] This shopping mode brings online shopping to a much higher profitable place.

However, gaining useful information in customer behavior data is a complex and challenging task. Each user behavior on the website, like clicks and purchases, can be collected and recorded in an extremely fast manner, thus generating a large amount of data each minute. Another challenge is data cleaning, as auto-collected data may have high noise, which will greatly interfere with the analysis process [8]. on the website, like clicks and purchases, can be collected and recorded in an extremely fast manner, thus generating a large amount of data each minute. Another challenge is data cleaning, as auto-collected data may have high noise, which will greatly interfere with the analysis process [8]. Nowadays, as the market is getting increasingly competitive and each business decision takes much financial and human resource costs, how to find what each user needs and make efficient marketing strategies are essential.

Facing a vast amount of raw data recording rich information about customers, there are several research questions worth delving into:

1) What are the peak activity times in purchasing?

2) What are the top-selling products or categories, and are the products with high sales also the ones that receive the most views?

3) Can we predict when a user is likely to stop using the platform or reduce their engagement? What are the warning signs of churn?

4) What is the next interaction of a user towards one item?

To solve the problems, ”data mining techniques” have been widely utilized ”to discover patterns” in user data. There has been a lot of research done in the field of e-commerce. ”Brijendra Singh et al.” defined the user behavior analysis of the web as ”web usages mining”, where user data is analyzed to personalize the information to individual users [14]. Previous research has studied and applied approaches like association rules, classification, clustering, and sequence modeling [14], [18].

In this project, a user data mining pipeline is proposed to help e-commerce platforms gain valuable insights into their customers, resulting in adjusting marketing and sell- ing strategies to enhance user behavior as well as improve sales revenues. The whole pipeline is shown in Figure 1. The original data was randomly collected from records of 1 million users from Taobao who have behaviors like clicking, purchasing, adding an item to the cart, and favoring an item [19]. As the actual data collected may have redundant and invalid information, data preprocessing is essential. With the processed data, exploratory data analysis can be conducted, generating useful statistics and visualizations for intuitive findings. Then, ”customer segmentation” is implemented to divide customers into distinct groups with different needs and behavior characteristics [5]. Finally, user sequential modeling is conducted to predict the next user action, which the market believes is important to their revenue [4].

Literature Survey

User behavior analysis is an important field of study in e-commerce understanding how users interact with online platforms. *Carmona et al. (2012)* argued that Web Usage Mining can increase the effectiveness of the design of e- commerce websites by studying user behavior to achieve greater personalization in their experience [2]. *Herna´ndez et al. (2017)* discuss the user behavior of well-structured e- commerce websites, and in doing so, reveal the complexities of such action-derived data in terms of users’ clicks and purchases. [6]

The work by *Bholowalia and Kumar (2014)* presents the Ebk-means clustering technique, which combines the elbow method and k-means clustering by the user behavior in wireless sensor networks. It will be applied to e-commerce scenarios as well. Surveying web data mining research, *Singh and Singh (2010)* remark on the evolution of techniques employed for the analysis of web usage patterns that includes classification and clustering methods. [14]

Effective customer segmentation is key to successful mar-keting strategies and improving user engagement. *Cooil et al. (2008)* presented different methods of customer segmentation, placing more emphasis on the RFM (Recency, Frequency, Monetary) model as a basic approach. [5] The application of the RFM model, integrated with clustering techniques such as k-means, to segment customers based on their purchasing behaviors is what was demonstrated by *Maryani et al. (2018)* [10].

This discussion was extended by *Wu and Chou (2011)* with a soft-clustering approach in customer segmentation across multiple product categories in e-commerce, leading to a nuanced understanding of customer needs. This segmentation is what would allow e-commerce platforms to target users with effectively personalized marketing strategies. [16]

This was first proposed by *Hochreiter and Schmidhuber (1997)*: the Long Short-Term Memory networks. Nowadays, it has become a benchmark standard for modeling sequential data, comprising sequences such as user behavior. In the context of this application, it has been helpful in predicting future user actions based on the history of their actions. [7]

User behavior forecasting is integral to e-commerce applica-tions. Therefore, as stressed by *Kohavi (2001)*, in the presence of noisy data, there is a need for effective data cleaning procedures for e-commerce environments to be able to extract meaningful information. Insights are directly proportional to the quality of the available data, which calls for more extensive preprocessing. [8] quality of the available data, which calls for more extensive preprocessing.

Methodology

Data Preprocessing EDA

1) Data Preprocessing: After sampling the original data, data processing techniques are employed to ready it for subsequent analysis. The steps are outlined below:

1) Clean the data to remove possible null values and duplicated records.

2) Filter data within an appropriate time range; modify the column ”Behavior” names to be more descriptive.

3) Convert the original timestamps into datetime format and extract time features like the corresponding date, hour, and day-of-week for time-series analysis.

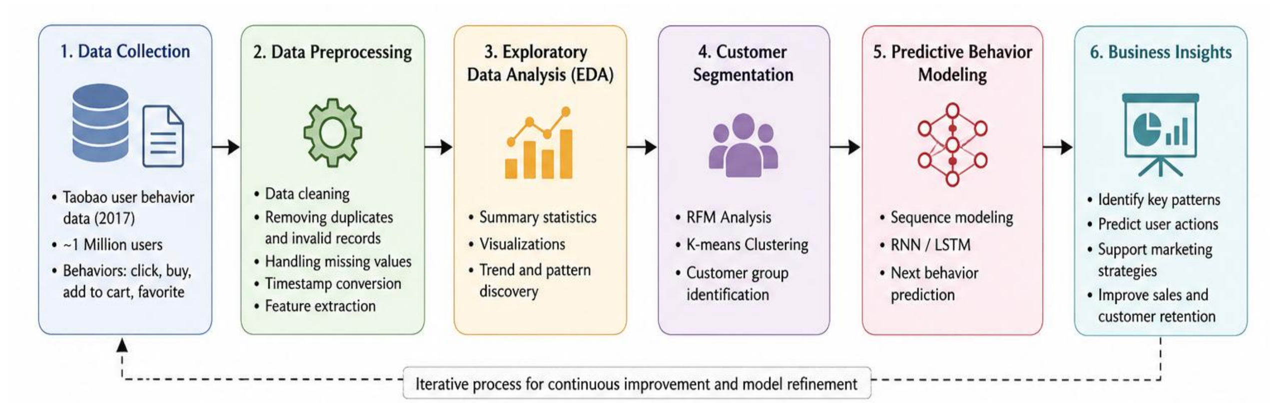
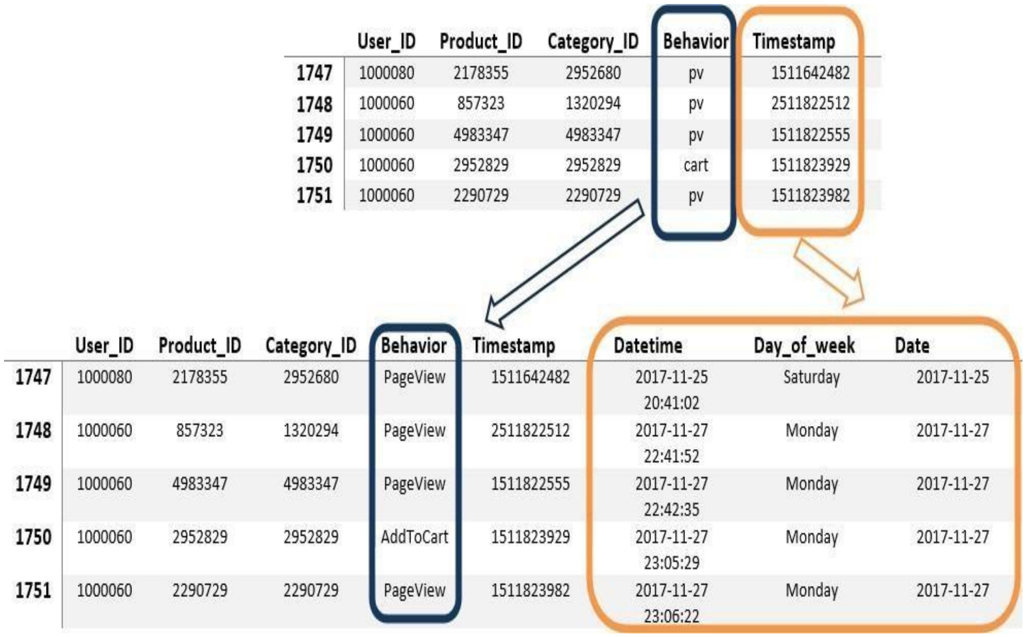


***Fig. 1.** The block diagram of the project pipeline*

2) Exploratory Data Analysis: To gain comprehensive in- sights from the dataset, I conducted exploratory data analysis, employing visualizations to uncover patterns. Figure 3 presents user interactions with the website, segmented by the ”hour of the day” and ”day of the week”. Notably, user activity peaks from 12 am to 2 pm, which is usually a midday break commonly observed during work hours. The trend remains relatively stable from midnight to 10 am, with a gradual increase in user interactions starting at 11 am. After 2 pm, interactions gradually decrease, reaching their lowest point between 6 pm and 9 pm with less than 1% of overall user activity. Furthermore, a consistent trend is observed from Monday to Friday, while user engagement increases during the weekends.

In Figure 4, I calculated the cumulative count of ”Buy” behavior and plotted the data based on each day and day of the week. The left plot distinctly shows an increase in customer



	User_ID	Product_ID	Category_ID	Behavior	Timestamp
1747	1000080	2178355	2952680	pv	1511642482
1748	1000060	857323	1320294	pv	2511822512
1749	1000060	4983347	4983347	pv	1511822555
1750	1000060	2952829	2952829	cart	1511823929
1751	1000060	2290729	2290729	pv	1511823982

	User_ID	Product_ID	Category_ID	Behavior	Timestamp	Datetime	Day_of_week	Date
1747	1000080	2178355	2952680	PageView	1511642482	2017-11-25 20:41:02	Saturday	2017-11-25
1748	1000060	857323	1320294	PageView	2511822512	2017-11-27 22:41:52	Monday	2017-11-27
1749	1000060	4983347	4983347	PageView	1511822555	2017-11-27 22:42:35	Monday	2017-11-27
1750	1000060	2952829	2952829	AddToCart	1511823929	2017-11-27 23:05:29	Monday	2017-11-27
1751	1000060	2290729	2290729	PageView	1511823982	2017-11-27 23:06:22	Monday	2017-11-27

Fig. 2. *The cleaned dataset after data processing techniques*

purchases from Friday to Saturday, maintaining a high count on Sunday, which indicates a preference for weekend buying. Meanwhile, the right plot visualizes the daily purchasing behavior over a two-week period. It is notable that a significant spike in user purchases occurred on December 2nd, 2017. This surge might be caused by the announcement of the Al- ibaba shopping carnival in December, with substantial product discounts. In addition, as November 25th and December 2nd were both Saturdays, the significant differences in the count of purchase behavior suggest that the carnival has a great influence in stimulating customer purchases. In summary, sales events and weekends appear to boost customer purchases, thus it's efficient to implement marketing campaigns and product advertisements during these periods.

Besides time series analysis, I also delved into the conver- sion situation for the products. The conversion rate measures the proportion of users who make a purchase compared to the total unique users visiting the platform [11]. Although the number of interaction records on e-commerce platforms is unaccountable, only 2.3% of visits end with purchasing products as of September 2023, according to Statista [17]. That is to say, the increase in conversion rate is undoubtedly essential for a company's revenues. To check the analysis, I first calculated the conversion rate of "PageView" to "Buy" for each category, and then I displayed the conversion rates of the 10 best-selling categories. The result is presented in Figure 5.

From the result above, it can be seen that even among the top-selling categories, the conversion rates remain exceed- ingly low. Most categories have rates below 4%, with only the second highest-selling category (1464116) and the ninth highest-selling category (4159072) exceeding this threshold. This suggests that the specific recommended items by the platform do not meet users' purchasing preferences, leading to low conversion rates after users click on the items. To gain comprehensive insights from the dataset, I conducted exploratory data analysis, employing visualizations to uncover patterns. Figure 3 presents user interactions with the website, segmented by the "hour of the day" and "day of the week". Notably, user activity peaks from 12 am to 2 pm, which is usually a midday break commonly observed during work hours. The trend remains relatively stable from midnight to

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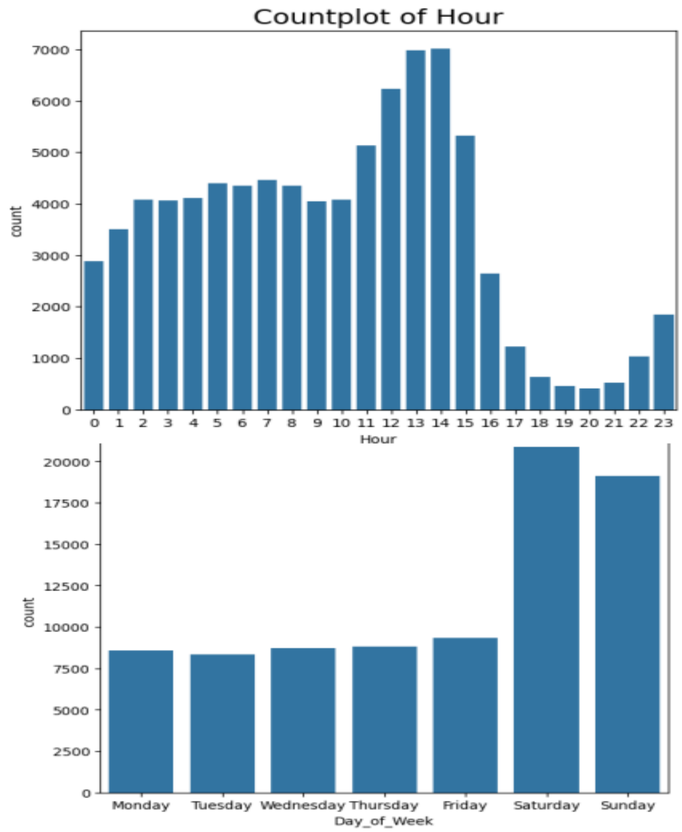

Fig. 3. *User behavior of each day and day of week*

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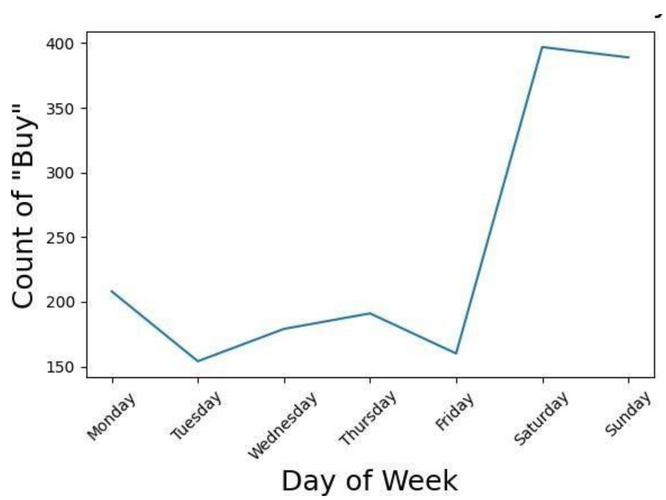

Fig. 4. *The cumulative count of "Buy" behavior over date and day of week*

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Customer Segmentation

Each customer has their own habits during online shop-ping. From this perspective, it's important for an e-commerce platform to understand its customers' shopping habits and not attempt only to develop one marketing strategy for all. Instead, they need to know the shopping behaviors of different customer types and develop personalized strategies for each segmented market. Applying clustering techniques to segment customers into subgroups or market segments can be used to analyze the relationship between customers and e-commerce platforms [16]. The results of such analyses can offer the

Behavior Category_ID	Buy	PageView	Conversion_Rate
2735466	1793.0	57013.0	0.030490
1664116	1722.0	34721.0	0.047252
4145813	1578.0	153557.0	0.010172
2885642	1546.0	48395.0	0.030957
4756105	1378.0	219062	0.006251
4801426	1306.0	91667.0	0.014047
982926	1193.0	138090.0	0.008565
2640118	965.0	37397.0	0.025221

Fig. 5. *The conversion rates of the 10 best-selling categories*

company insights into customer expectations when purchas- ing products on the website. By taking personalized actions based on these outcomes, companies can enhance customer engagement by improving their satisfaction.

The "RFM model" is one of the most common models used by researchers and companies to understand customers' pur- chasing patterns. This model measures three dimensions of a customer: "recency", "frequency", and "monetary". "Recency" is defined as days since the last purchase, "frequency" is the total number of purchases, and "monetary" is the total money this customer spent [12]. In this project, as monetary value is not provided in the dataset, I only calculate the recency and frequency of each user's purchase behavior. The scores are then standardized for a better comparison of the relative performance of customers, as shown in Figure 6.

	User_ID	Recency	Frequency
0	20	2	1
1	50	0	19
2	66	0	4
3	76	3	1
4	101	0	7

Standardization

	User_ID	Recency	Frequency	R_score	F_score
0	20	2	1	3	1
1	50	0	19	4	4
2	66	0	4	4	3
3	76	3	1	2	1
4	101	0	7	4	4

Fig. 6. *The samples of calculated and standardized RFM scores*

To group customers based on their "recency" and "frequency scores", I applied the K-means algorithm, an unsupervised clustering approach, to identify customers with similar behavior patterns. With the chosen value of k, k

cluster centers (centroids) are initialized arbitrarily. Next, each data object is assigned to the nearest center using the ”Euclidean distance”. Then, the average of the clusters is calculated. The iteration repeats until convergence [13]. The formulas for the cluster assignment and center update are as below, where n denotes each data sample while k denotes each cluster.

Regarding the number of clusters k, researchers have proposed to use the ”elbow method”. ”The elbow method” measures the proportion of variance explained as a function of the number of clusters. The optimal value of ”k” is selected where an additional cluster doesn’t significantly enhance the data modeling [1]. To implement the elbow method, I used KElbowVisualizer, a tool to fit the model with a range of values of k and select the one with the best performance.

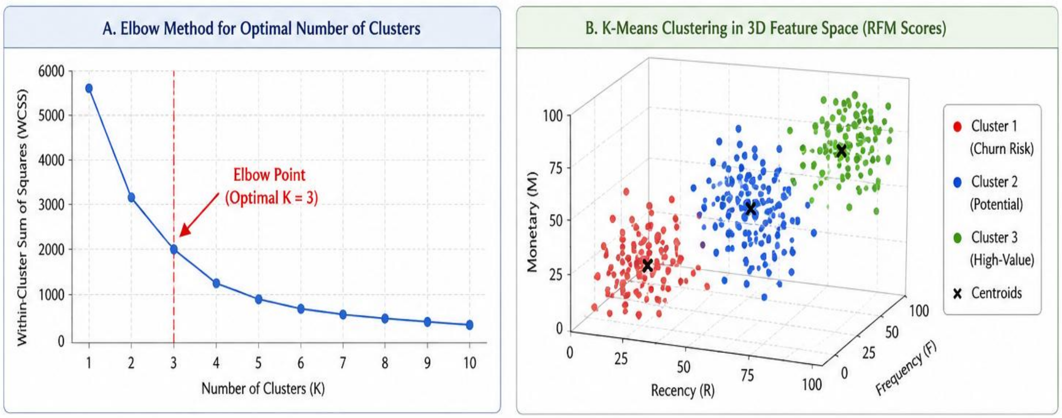

Fig. 7. *The samples of calculated and standardized RFM scores*

From Figure 7, the elbow method divides the customers into 3 groups based on their recency and frequency scores.

From the summary of clustering results shown in Figure 8, the customers can be categorized into the following groups:

• **Churn Risk Customers** (high recency and low fre-quency): They have relatively low interactions or pur-chases. They could be at risk of churning or reducing their engagement.

• **Potential Customers** (moderate recency and frequency): They have interacted recently but don’t have a high fre- quency of purchases. They could be potential customers exploring or making occasional purchases.

• **High-Value Customers** (low recency with high fre-quency): They have both recent purchases and a signifi- cantly higher frequency of transactions. They are highly engaged and loyal customers, contributing frequently to the e-commerce platform.

From Figure 9, the majority of customers are potential customers, with a percentage of 56.7%. is also a good sign that high-value customers also take a large portion, nearly three times the portion of churn-risk customers. For the 11.9%

	Recency	Frequency	Cluster_pred
count	10546.000000	10545.000000	10546.0
mean	5.698464	1.810449	0.0
std	1.399015	1.132397	0.0
min	4.000000	1.000000	0.0
25%	4.000000	1.000000	0.0
50%	6.000000	1.000000	0.0
75%	7.000000	2.000000	0.0
max	8.000000	8.000000	0.0

Cluster 0

	Recency	Frequency	Cluster_pred
count	19076.000000	19076.000000	19076.0
mean	1.218180	2.44800	1.0
std	1.090888	1.272697	0.0
min	0.000000	1.000000	1.0
25%	0.000000	1.000000	1.0
50%	1.000000	2.000000	1.0
75%	2.000000	3.000000	1.0
max	3.000000	5.000000	1.0

Cluster 1

	Recency	Frequency	Cluster_pred
count	4012.000000	4012.000000	4012.0
mean	1.091226	8.44800	2.0
std	1.341617	5.272697	0.0
min	0.000000	6.000000	2.0
25%	0.000000	6.000000	2.0
50%	1.000000	7.000000	2.0
75%	2.000000	10.000000	2.0
max	7.000000	175.000000	2.0

Cluster 2

Fig. 8. *K-Means results of the 3 clusters*

offers or send tailored communications to reduce the potential loss. Keeping high-value customers may involve VIP benefits and exclusive offers to foster loyalty. As the largest segment, potential customers may benefit from personalized recom- mendations aligned with their browsing history to enhance conversion rates.

Predictive Behavior Modeling

As user behavior is tracked alongside timestamps, it is intuitive to organize user behavior into a sequence of ac- tions. Previous research has found that developing models for predicting the next user actions is of significant benefit for marketers in enhancing user experience [3], [9]. Different users exhibit varying shopping habits—users view a product detail page just once before purchasing directly, others frequently favorite items without completing transactions, and some add items to their shopping carts in a regular manner.

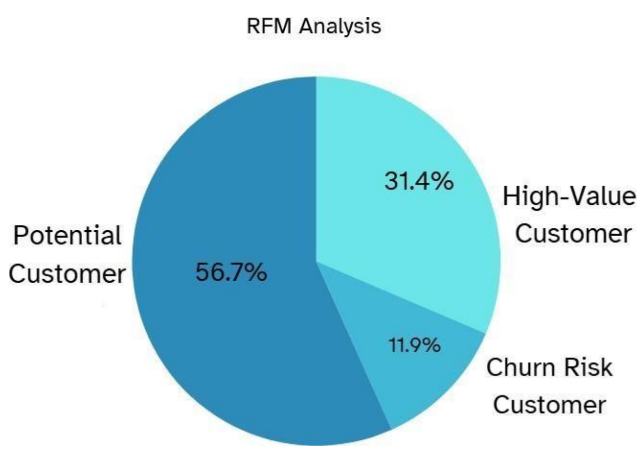

Fig. 9. The percentage of each customer group

Recurrent neural network (RNN) with its temporal structure has been widely used to capture sequential dependencies in data. The process involves computing a new state based on the input and the old state [15]. Although vanilla RNNs are simple, the backward flow of gradients in RNN can explode or vanish, resulting in poor performance. Therefore, it's common to use its variant, long short-term memory (LSTM), with additive interactions to improve gradient flow [7]. The method overview in this part is illustrated in Figure 10, and the model is implemented using PyTorch. Each user behavior towards one item is input in order and calculates the current state. By maintaining block states and utilizing gating mechanisms, LSTM layers learn to model sequential relations and output the predicted event.

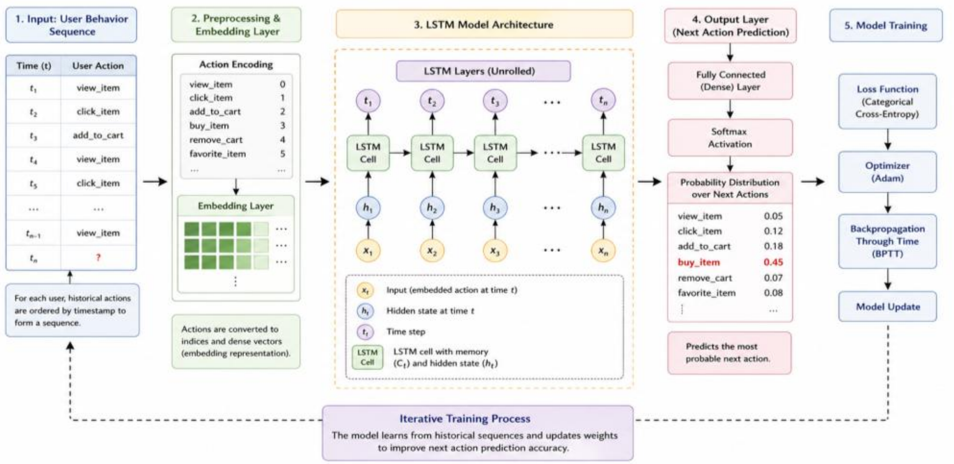

Fig. 10. The overview of the method used in the project

" The training loss curve" is shown in Figure 11, which provides a visual representation of how the loss of the LSTM

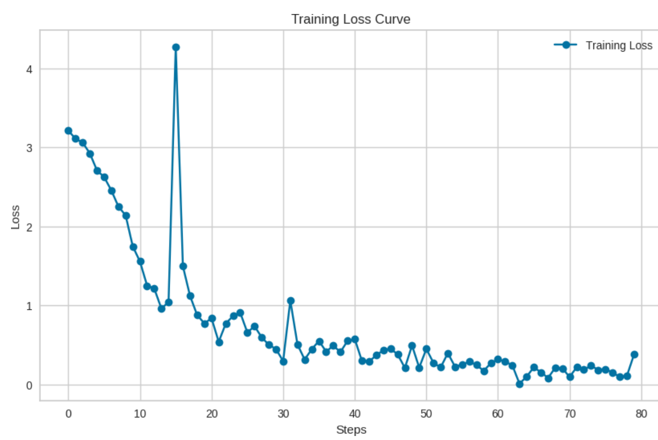

Fig. 11. *The training loss curve of lstm*

model changes over the training process. The curve has a clear decreasing trend throughout the whole steps, indicating the model is learning and improving its ability to predict user actions.

Conclusion

In this project, how to mine user interests and extract useful information through a large amount of user data on e- commerce platforms has been researched. Given the raw data, companies are eager to discover user behavior patterns and customer groups to adjust their marketing strategies. To help solve the problem, a pipeline has been designed, which is a full investigation of data processing and analysis, customer segmentation, and predictive behavior modeling.

The research questions mentioned in Section 1 Introduction can be answered as follows:

- The interest of user purchasing greatly increases during weekends and also boosts when there are shopping festi- vals with large discounts. In terms of each day, the peak activity hours are from 12 am to 2 pm, usually a midday break during work hours.

- The top-10 best-selling categories are shown in Figure

5. After investigating the conversion from page views to purchases, it's surprising that even among the top-selling categories, the conversion rates remain exceedingly low, mostly below 4%. This suggests that the recommended items by the platforms do not meet users' purchasing preferences, and the corresponding algorithms need to be improved.

- The RFM analysis combined with "K-means clustering" is applied to group customers. The metrics measured are the recency and frequency of a user's historical purchase behaviors. The warning signs of churn are high recency and low frequency. Through this method, the result shows around 11.9% of users are churn-risk users, who were in-active and would likely stop using the platform. Tailored strategies are required to avoid the loss. Fortunately, the high-value customers and potential customers still take up a very large portion, which can contribute positively to Taobao's operations.

- To predict the next interaction of a user towards one item, their past activities can be converted into a sequence. Then, the sequential patterns inside can be learned and discovered automatically through recurrent neural net- works. The LSTM model predicts the next user behavior with an accuracy of 95%, which presents the feasibility of the model.

Future Study

Although the project has conducted some research on the pipeline of user behavior analysis, there are still some limi- tations and practical problems to be further studied. They are listed as follows:

1) Due to the limitations of local computer resources, only 5% of the original dataset is sampled; thus, the data analysis may encounter some bias and information loss. Distributed computing frameworks like Spark and computing resources like GPUs can be used to process the whole dataset for a more comprehensive analysis.

2) Regarding predictive behavior modeling, this project only considers predicting the next user action towards one item. However, the RNN and LSTM models can be further applied with recommendation systems to predict the user preferences of different products and categories.

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