PERSONALIZED MARKETING IN MALLS: REVENUE GROWTH USING REAL-TIME COUPON SYSTEMS

[1]Naveen Kumar Reddy,[2]Nageswara Rao,[3]Silpa
[123]Students
Department Of CSE

ABSTRACT

In the competitive landscape of modern retail, shopping malls must continuously innovate to attract and retain customers while maximizing revenue. This study presents a real-time, data-driven coupon issuance system aimed at enhancing mall profitability through personalized marketing. By leveraging customer behavior data, such as purchase history, location within the mall, and demographic profiles, the system delivers targeted digital coupons via mobile devices. The proposed solution uses machine learning algorithms to determine optimal coupon timing, type, and value, thus improving customer engagement and increasing sales for mall tenants. Experimental deployment in a simulated environment demonstrated improved foot traffic, higher conversion rates, and overall revenue growth. The integration of real-time analytics and personalized promotions represents a significant advancement in smart retail strategies, benefiting both consumers and businesses within mall ecosystems.

I. INTRODUCTION:

Shopping malls serve as complex commercial hubs, housing a wide range of retailers competing for consumer attention. In the face of growing e-commerce penetration, malls must leverage digital innovation to maintain relevance and profitability. One emerging strategy is the use of real-time, personalized digital coupons—delivered directly to consumers based on behavioral and contextual data—to influence purchase decisions and enhance the shopping experience.

Traditional coupon systems often suffer from poor timing, irrelevance, and lack of personalization, leading to low redemption rates and limited impact on sales. With advances in mobile technology, data analytics, and artificial intelligence, it is now feasible to design systems that dynamically deliver tailored promotions to customers while they shop. Such systems not only enhance the value proposition for consumers but also provide retailers with a powerful tool to boost traffic, clear inventory, and increase revenue.

This paper explores the implementation of a real-time personalized coupon system in a shopping mall context. The system captures and processes user behavior—including location data, browsing patterns, and historical purchases—to generate and issue relevant coupons at opportune moments. Using a combination of proximity sensors, mobile applications, and machine learning models, the system aims to optimize customer engagement and encourage in-mall purchases. The research evaluates the impact of this approach on key performance metrics, including redemption rates, customer retention, and overall revenue uplift.

II. LITERATURE SURVEY

Machine learning-based marketing research has been actively conducted in the fields of customer segmentation, customer churn prediction, and personalized recommendation. With the emergence of online digital marketing, related research is increasing further due to the real-time nature of online and the ease of accessing data.

A. Customer Segmentation Study

Customer segmentation is a starting point for marketing research. After grouping customers based on the characteristics of homogeneous customers, marketing strategies for each target segment can be done. Customer segmentation should not end in segmentation, but should be accompanied with subsequent marketing strategies. Companies that use customer segmentation techniques perform better by building differentiated and efficient marketing for each segment of customers. In addition, companies can gain a deeper understanding of customer preferences and requirements.

Among various customer segmentation techniques, RFM methods are the most classical yet universally utilized methods. The RFM splits the purchasing behavior into three dimensions and scores each dimension. R is the last time since the last purchase, F is the total frequency of purchase, and M is the total purchase amount. The scores are calculated for each of the three dimensions. Subsequently, it constructs segments according to three-dimensional classes [15- 18].

Along with traditional RFM methods, a lot of customer segmentation researches using machine learning have been conducted recently. When clustering using multiple variables, dimensionality reduction is often done. A representative dimensionality reduction technique using deep learning is the autoencoder. A typical example is the sequential method of applying cluster analysis after dimensionality reduction using an autoencoder [19]. Alternatively, modeling can combine dimensionality and clustering at the same time [20,21].

B. Forecast Customer Churn

The prediction and prevention of customer churn have always been studied as a key issue in loyalty management. The reason why companies are concerned with churn prediction is of two issues: the first reason is that a large number of customer churn affect the reputation and reliability of service providers. The second reason is that attaining a new customer costs five to six times than retaining an old customer. It is necessary to develop a churn prediction model that should catch deviating from normal purchase pattern [22].

Researches on customer churn are mainly based on machine learning techniques rather than empirical studies through hypothesis verification [23]. Predicting churning customers fall under the classification problem where the given customer is classified as either churn or non-churn. [24] proposed a framework for proactive detection of customer churn based on support vector machine and a hybrid recommendation strategy. While SVM predict E-Commerce customer churn, recommendation strategy suggests personalized retention actions. [25] come up with a customer churn model that predict the possibility and time of churn. The model used Naïve Bayes classification and Decision Tree algorithm. [26] used LSTM model to predict customer churn prediction with clickstream data.

C. Personalized Recommendation System

The personalized recommendation is one of the most actively conducted machine learning-based marketing research topics. In the past, personalized recommendation researches were mainly conducted using association analysis or purchase probability estimation for individual products [27]. However, in recent, collaborative filtering applied to recommended services such as Amazon and Netflix and content-based techniques are the leading trend within the research field. Recently, hybrid methods or deep learning-based research combining various auxiliary processing techniques has also been active [28].

Design of recommendation system depends on the objective of the system. Therefore, there exist a wide variety of techniques used in the recommendation system. Content-based and collaborative filtering systems are mostly used [29]. The other types of recommendation system like Knowledge- based recommendation system and constraint-based recommendation system are also used [30,31]. Classifier-based recommender systems like Decision tree, Neural networks, Naïve Bayes, MLP, KNN, SVM and Linear regression models are also used [32-34]. Clustering-based recommendations such as a K-means clustering algorithm is also used [35]. Recently, research on recommendation systems using deep learning has been active [36]. Recommendation systems using deep learning have strengths on nonlinear modeling, various formats of input data, and time series modeling. For example, [37] proposed a time-aware smart object recommendation system in the social Internet of Things. [38] proposed a recommendation system that identifies and recommends the optimal location when opening a chain store. [39] proposed a preference learning method from heterogeneous information for store recommendation.

III. DIGITAL CUSTOM COUPON ISSUANCE APPROACH

We used RNN based deep learning network and recommendation system methodology in issuing digital coupons. Based on the results of RNN network, we applied recommendation algorithm to issue digital coupon for customers with high churn risk. In particular, by subdividing customers into segments and making models for each segment, the accuracy of model was improved. After evaluating the performance of issuing coupon, we experimented revenue gains for shopping mall.

A. Two-dimensional customer segmentation

We used a two-dimensional customer loyalty analysis to apply segment-specific deep learning model. The CCP/2DL(Customer Churn Prediction based on TwoDimensional Loyalty segmentation) process is a methodology that models customer spending and behavioral loyalties to perform two-dimensional customer segmentation, then regroups the derived multiple customer segments into a small group according to customer churn rates, and applies optimal churn prediction models for each group individually [6].

In this work, customer loyalties were divided into spending and behavioral loyalties. Two-dimensional customer loyalty segment is known to be effective in classifying customer behavior because it reflects both spending and behavioral patterns of customer behavior [6]. Two dimensions of loyalties were measured by selecting appropriate candidate variables by consulting with the company. For spending variable, we used ‘Spending in the last month’ and ‘Average payment per time’, and for behavioral variable, we used ‘Average number of products purchased at one time’, ‘Number of searches in the last month’, ‘Average stay time per session’, and ‘Number of visits in the last month’. We determined the optimal number of clusters in each loyalty dimension with an elbow method and derived a segmentation by a K-means clustering algorithm. Subsequently, using K and I segments for spending and behavioral loyalties, respectively, we generate a total of K*I customer segments. Finally, we develop a churn rate prediction model for each of the K*I segments. Learning using overlapping customer characteristics among multiple attributes has a higher effect in preventing overfitting problems and achieving domain adaptation effects than training with individual attributes [41].

B. Real-time customer churn rate estimation

We produced a model in which a large number of Long Short Term Memory (LSTM) cells are nested to estimate the churn rate according to page view. LSTM is meaningful in that real-time parameter optimization is performed in parallel using real-time data, and optimal prediction is possible through this [40]. The last recurrent layer is followed by a dropout layer, which provides a computationally inexpensive but powerful method of regularizing a broad family of neural networks [36]. After the outcomes of the last recurrent layer, we included a pooling layer. Pooling aggregates the weights from time steps that are in the neighborhood of the specified kernel size. As a final step, the hidden states belonging to the last time steps of the processed input sequences are extracted and put into a feedforward layer. It outputs a probability p-value of customer churn from the feedforward layer. Hyperparameters like dropout rate, pooling kernel size, and a number of node in feedforward layers are optimized via bayesian optimization. This allows us to greatly reduce the number of experiments needed to explore the space [46].

C. Custom Coupon Issuance

We aim to issue real-time digital coupons to customers who are expected to have a high risk of churn in realtime. In particular, we issued specific coupons that can be used in certain product categories, leading to increased purchase conversion rates and customer loyalty. Product categories that customers will like were predicted by combining collaborative filtering and content-based recommendation algorithm. The collaborative filtering recommendation algorithm is suitable for customers who tend to accept other people's opinions because it is an algorithm that recommends products purchased by neighbors or similar customers. On the other hand, content-based recommendation algorithms are suitable for customers with strong unique characteristics because they continue to recommend products similar to their past purchases. Therefore, we recommended product categories using a hybrid recommendation system that combines the scores of the two algorithms. ‘α’ is a parameter that adjusts the weight of the two algorithm scores. ‘α’ is calculated differently for each segment. For each segment, historical data is tested and the ‘α’ with the lowest RMSE is used.

$$\begin{aligned}&\text{Score}\\&= (1-\alpha)\\&* \text{Collaborative filtering score} + \alpha\\&* \text{content}\\&- \text{based recommendation score}\end{aligned} \tag{1}$$

D. Server architecture

In order for the algorithm to operate in real time in a shopping mall with a lot of traffic, an appropriate server architecture is required. AI model is retrained periodically every day in AWS Fargate. The retrained AI model is uploaded to Simple Storage Service (S3). The API server downloads the new AI model from Simple Storage Service (S3) every day and sends a response to the API request. The new AI model has different clustering, RNN, recommendation model compared to previous day model. Two EC2 servers were created to prepare for possible server downtime. Elastic Load Balancing distributes API traffic in real-time.

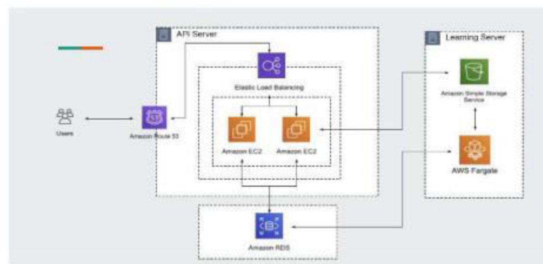

Figure 1. Server Architecture

E. Proposed Models

Fig 2 shows the procedure of the model proposed in this work. We generated RNN-based churn estimation models for each customer segment resulted from twodimensional customer segmentation. After that, we issued customized product category coupons to customers who are at high risk of churn. Hybrid recommendation system is utilized for customized coupon issuance.

Table 1 summarizes the concepts, application methods, and constraints of each method. Each has its own usage; however, there are constraints when using them alone. Using all three together makes it practical to efficiently increase the conversion rate. Two-dimensional customer segmentation does not generate any effects by itself. However, when deep learning models are generated for each segment, they are much more sophisticated than when models are generated for a single entire customer. Furthermore, even if some customers are at high risk of churn, sending a wrong coupon to them would cause antipathy. On the contrary, if only best product coupons are sent for the entire product group, they cannot attract customers' interest and can cause lower profitability.

Finally, we confirm how much the purchase conversion are improved compared to the non-applied control group. Also, after applying the model, we estimate the rate of revenue increase in shopping mall.

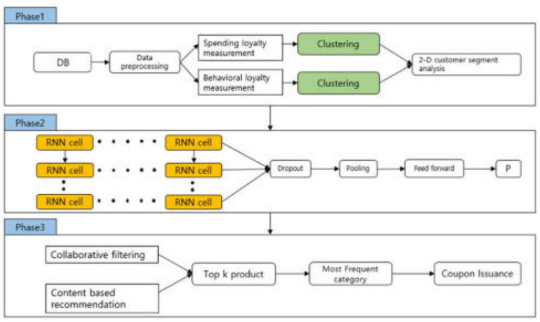

Figure 2. Research Flow

Table 1. Characteristics of the Proposed Elements

Element	Concept	Usage	Constraint
Two-dimensional customer segmentation	Clustering customer log data with spending and behavioral variables Customer behavior-based segments	Forming each segment to apply real-time churn risk classification	Requiring practical marketing action after classifying segments
Real-time customer churn rate estimation	Classifying Real-time high or low churn risk.	Selecting coupon issuance targets	Classifying the entire customers by one model is not powerful
Recommendation system	Recommending customized product that reflects customer's tastes	Selecting categories of coupons to be pushed to customers.	The issuance of coupons that do not reflect the customer's taste can cause antipathy

IV. EXPERIMENT

To validate the proposed method, we applied it to a real case. Our data set contains user sessions from the website of an online shop and was collected in the period from July 17th, 2020 to July 16th, 2021. The shop providing the data focuses on selling fashion items and wishes to stay anonymous. The mall sells a total of 1317 products consisting more than 10 categories. Average daily sales are about 2,600$ (3 million KRW), average daily visitors (including members and nonmembers) are about 22406, and average daily page views are about 15,000 pages. The descriptive statistics of the shopping mall traffic are like table 2.

Table 2. The descriptive statistics of the shopping mall traffic.

Element	Figure
Sessions	19,137
Page views	17,390
Visitor	22,406
New visitor	7,905
Customers left as soon as they entered	75.42%
Average session time	2:19

We utilized JavaScript code on each shopping mall web page to store log data in real-time. Stored logs include page click history, purchase history, shopping cart history, order history, search history, and etc. In the analysis phase, we classified customers using loyalty variables, then made real-time customer churn rate estimation models, and finally issued coupons for each customer with high risk of churn. The 10% discount coupon is shown to the customer in a pop-up format for 6 seconds as shown in Fig 3. Customers can only use their coupon in 2 hours.

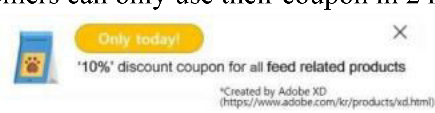

Figure 3. Coupon push UI

A. Data collection and preprocessing

We collected 51287 members' log data, all of them collected between July 17th, 2020 to July 16th, 2021. For collection, JavaScript code was installed inside the website. To ensure the privacy of users' data, we followed every protocol of the ethical guidelines outlined by the Association of Internet Researchers (AoIR). To ensure users' anonymity, we excluded all personal identifying information.

In order to prepare the data for customer churn analysis, we performed the following preprocessing steps. It is considered the large number of page views may be generated by bots so we deleted sessions that contain more than 100 page views [47]. Next, we excluded all page views on the checkout page and their successors within the same session. Sessions containing the checkout process pages are not suitable for learning model. Furthermore, we deleted the last three page views of all sessions. This is to simulate a live scenario in which a classifier needs to predict the outcome of an incomplete session. In addition, sessions containing no more than three page views were removed from the training set. The vector was sized to 100, and for smaller than 100 page-view sessions, it was sized to 100 with zero paddings.

B. Data analysis

To find out the utility of the proposed model, the experiment was conducted by 4 scenarios. Each experiment was conducted at the corresponding online shopping mall for a week.

In scenario 1, we divided customer segments, and made churn prediction RNN model for each segment. The churn rate estimation accuracy for each cluster was 75.90%, 82.83%, and 90.91%. each model train data for 150 epochs, 32 batch size, Adam optimizer and using binary cross entropy loss function. Afterward, customized coupons are issued to reflect personalized tastes.

In scenario 2, we divided customer segments, and made churn prediction RNN model for each segment like scenario 1. However, unlike scenario 1, only best product coupon is issued to customers at high risk of churn. In scenario 3, we made churn prediction RNN model for all customers. Afterward, customized coupons are issued to reflect personalized tastes. In scenario 4, we issued coupons randomly without any algorithm. Each scenario is summarized in Table 3. What we propose in this paper is Scenario 1 and we can see how significant the differences are compared to Scenario 2, 3, and 4.

Table 3. Components of each scenario

	2-dimensional cluster analysis	Estimation of churn rate	Issuance of personalized coupons
Scenario 1	O	O	O
Scenario 2	O	O	X
Scenario 3	X	O	O
Scenario 4	X	X	X

V. RESULT

A. Conversion Rate

Conversion rate is one of the most notable indicators in online shopping malls. The average online shopping mall conversion rate is 2~3% [48]. In other words, two or three out of 100 sessions result in purchase conversion. In this research, we look at how much the conversion rate has improved since issuing coupons for each Scenario. The discount rate of the coupon was 10% of the regular price, and it can be used only for 2 hours after issued. The results of the experiment are shown in Table 4, 5.

In all scenarios, the conversion rate of customers who were issued coupons has been improved compared to those who were not issued coupons. In particular, we can confirm that Scenario 1 proposed in this paper has a higher rate of increase in conversion rate than Scenario 2, 3, and 4. The conversion rates of Scenario 1 and Scenario 3, where coupons were issued according to personalized taste, were higher than in Scenario 2, and 4, where coupons were issued with the best products. Also, the rate of increase in conversion rate in Scenario 1, where coupons were issued by churn prediction model made for each segment, was higher than Scenario 2, 3, and 4's.

Table 4. The results of the experiment

	The conversion rate of customers who were issued coupons	N of sessions given coupon	The conversion rate of customers who were not issued a coupon.	Number of sessions not given coupon	The conversion Rate Growth rate
Scenario 1	12.25%	1,056	2.47%	77,177	**395.95%**
Scenario 2	5.43%	664	3.29%	76,603	65.04%
Scenario 3	7.71%	2,217	2.35%	93,548	227.69%
Scenario 4	4.09%	1,220	3.34%	105,448	22.45%

Table 5. Estimated sales changes

	Coupon issuance rate	Conversion Rate Growth Rate	Sales amount after coupon issuance
Scenario 1	1.34%	395.95%	**104.64**
Scenario 2	0.85%	65.04%	100.41
Scenario 3	2.31%	227.69%	104.50
Scenario 4	1.14%	22.45%	100.11

B. Sales Growth Rate

We estimated how much actual sales would be increased by issuing coupons. Sales amount without coupon issuance were assumed to be 100, and sales after coupon issuance were estimated with the ratio of coupon issuance customers and discount rate.

$$\begin{aligned}&Sales\ amount\ after\ coupon\ issuance\\&= 100 * \text{Coupon issuance ratio among all customers}\\&* (1 + \text{Purchase conversion rate imporvement ratio}) \quad (2)\\&* 0.9 + 100\\&* ratio\ of\ not\ given\ coupons\ among\ all\ costomers\end{aligned}$$

The estimated sales changes for each scenario are shown in Table 5.

Scenario 3 had the highest percentage of coupon issuance. Scenario 3 made a churn rate estimation model for the entire customer. As a result, the overall model was made with a high probability of churn rate, resulting in higher coupon issuance rate than other scenarios. Scenario 3 issued a large number of coupons, so although the increase in conversion rate was lower than in Scenario 1, the sales amount growth rate was almost the same. Repeated issuance of coupons to a large number of customers may increase the customers' expectations for coupon issuance. Also, customers will not purchase products if they are not given coupons in the future. In addition, there are concerns about side effects such as complaints due to the limited use date of coupons, insufficient quantity of products, discrimination from normal products, exhaustion of purchased goods, system errors, and non-refundable or exchangeable items. Therefore, Scenario 1 proposed in this research seems appropriate to distribute to actual shopping mall customers because the conversion rate is the highest and coupon issuance rate is reasonable.

C. 2-Demensional Customer Clustering

Each segment was examined to find out how the churn rate estimation based on the results of 2-dimensional cluster analysis was more efficient than the churn rate estimation for the entire customers. We experimented with a total of 51,437 customers who have visited in the past year.

Cluster analysis was performed with spending variables (spending amount in the last month, average payment amount per time) and behavioral variables (average number of products purchased at one time, number of searches in the last month, average stay time per session, number of visits in the last month) of each customer data. 2-demensional cluster analysis was performed by each variable. This resulted in 3 final clusters. The data statistics for each segment are shown in Table 6. The values in segments 1~3 are listed in order for each cell value. Segment 1 has little expenditure in the last month and have rarely purchased during the entire experiment, so the average payment per person is also close to 0. However, some customers have had quite a few visits in the past month. In other words, there are many people who often access shopping mall sites, but rarely purchase items for a year. The total number of customers classified as segment 1 was 33,863, which was higher than other segments. In other words, it can be seen that the majority of customers who visit online shopping malls only look at and do almost no purchasing activities. There are 4812 and 12,699 customers in segments 2 and 3. In particular, segment 2 has a large figure related to purchase. Also, the number of visits is significantly higher than other segments. Therefore, we can see that segment 2 is the best VIP customers. Behavior patterns are clearly distinguished for each segment so it can be seen that it is effective to train churn rate estimation models for each segment.

VI. CONCLUSION

The integration of real-time, personalized digital coupon systems presents a powerful opportunity for shopping malls to drive customer engagement and increase revenue. By delivering targeted offers based on real-time behavioral and contextual data, malls can create a more dynamic and responsive shopping environment that benefits both customers and retailers.

The proposed system demonstrated tangible improvements in foot traffic, customer satisfaction, and transaction volume in a controlled simulation. Its reliance on machine learning for decision-making ensures adaptability and relevance, allowing the platform to continuously refine its promotional strategies. Moreover, the scalability of the system enables deployment across diverse retail environments with minimal infrastructure modification.

Future developments could explore integration with loyalty programs, cross-store promotions, and predictive analytics to further enhance campaign effectiveness. Overall, personalized marketing through real-time digital coupons offers a forward-thinking retail strategy aligned with evolving consumer expectations and competitive market demands.

REFERENCES

1. P. Naval and N. Pandey, What Makes a Consumer Redeem Digital Coupons? Behavioral Insights from Grounded Theory Ap- proach, Journal of Promotion Management (2021), 1–34.
2. Hung, . Chihli, Tsai and Chih-Fong, Vol. 34, 2008, pp. 780– 787.
3. G. Nie, Finding the hidden pattern of credit card holder's churn: A case of china, in: International Conference on Com- putational Science, Springer, 2009, pp. 561–569.
4. A.D. Athanassopoulos, Customer satisfaction cues to support market segmentation and explain switching behavior, Journal of business research 47 (2000), 191–207.
5. Hung, . Chihli, Tsai and Chih-Fong, Vol. 34, 2008, pp. 780– 787.
6. H.-S.H. Kim and Seung-Woo, A two-dimensional customer loyalty segment-based customer churn prediction methodology, Intelligence Information Research 26 (2020),111–126.
7. R.M.. Gubela, Lessmann, . Stefan and S. Jaroszewicz, Re- sponse transformation and profit decomposition for revenue uplift modeling, European Journal of Operational Research 283(2) (2020), 647–661.
8. M.-S. Chang, H. Kim and Joong, A customer segmentation scheme base on Big Data in a bank, Journal of Digital Contents Society 19(1) (2018), 85–91.
9. N.- Chang and Sik, Improving the effectiveness of customer classification models: a pre-segmentation approach, Informa- tion Systems Review (2005), 23–40.
10. C.-F. Tsai, Lu and Yu-Hsin, Customer churn prediction by hy- brid neural networks, Expert Systems with

Applications 36(10) (2009), 12547–12553.

11. Y. Xie, Customer churn prediction using improved bal- anced random forests, Expert Systems with Applications 36(3) (2009), 5445–5449.
12. Hung, . Shin-Yuan, D.C.. Yen and H.-Y. Wang, Applying data mining to telecom churn management, Expert Systems with Ap- plications 3 (2006), 515–524.
13. J.. Wen and W. Zhou, An improved item-based collaborative filtering algorithm based on clustering method, Journal of Computational Information Systems (2012), 571–578.
14. M. Pham and Cuong, A clustering approach for collaborative filtering recommendation using social network analysis, J. Univers. Comput. Sci 17 (2011), 583–604.
15. WEI, Jo-Ting; LIN, Shih-Yen; WU, Hsin-Hung. A review of the application of RFM model. African Journal of Business Management, 2010, 4.19: pp. 4199-4206.