

APPLIED RESEARCH

Improving Shopping Mall Revenue by Real-Time Customized Digital Coupon Issuance

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ABSTRACT With the development of big data and deep learning technology, big data and deep learning technology have also been applied to the marketing field, which was a part of business administration. Customer churn management is one of the most important areas of marketing. In this paper, we proposed a method to prevent customer churn and increase purchase conversion rate by issuing customized discount coupons to customers with high churn rate based on big data in real time. After segmenting customer segments with two-dimensional segment analysis, a real-time churn rate estimation model based on clickstream data was generated for each segment. After that, we issued customized coupons to our customers. Finally, we tested the conversion rate and sales growth. A two-dimensional cluster analysis-based churn rate estimation combined with a recommendation system was found to be significantly more useful than the respective simple models. Using this proposed model, it is possible to increase sales by automatically estimating the customer's churn probability and shopping propensity without the burden of marketing costs in the online shopping mall.

INDEX TERMS Customer churn prediction, deep learning, digital marketing, ecommerce, recommendation system.

I. INTRODUCTION

With the development of big data and deep learning technology, big data and deep learning technology have also been applied to the marketing field, which was a part of management. Also, growth in internet adoption has made digital coupons a popular promotional tool [1]. Customized digital coupon issuance is a very important topic in online commerce. This is because maintaining existing customers is a more important business issue than acquiring new customers [2]. Also, retaining existing customers is much more economically advantageous than acquiring new customers [3]. In fact, the acquisition cost of new customers is known to be five to six times higher than the maintenance cost of existing customers [4]. Companies that have effectively managed customer churn by improving customer retention are known to have a positive effect not only on the company's profitability but also on improving brand image by improving customer satisfaction [5].

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Customized coupon issuance research has traditionally been active in highly competitive and urgent sectors such as telecommunications, finance, distribution, and game industries, and has focused mainly on developing predictive models using machine learning and artificial intelligence technology [6]. Also, recently, AI-based marketing using big data analysis and deep learning is emerging.

Such AI-driven targeting can save huge amounts of marketing costs and raise online sales provided that the targeting model succeeds in estimating customer responsiveness accurately [7].

In particular, in the case of online shopping malls, the average purchase conversion rate is around 2%. Online shopping malls have the advantage of being easily accessed through the PC web or mobile web, but on the contrary, this advantage can be a disadvantage that it is easy to see and leave quickly. Therefore, even the slightest reduction of customer churn rate can lead to high conversions, which can lead to huge profits.

Unlike offline shopping malls, online shopping malls are easy to collect data. All online behavioral characteristics of customers can be collected in real time in the shopping mall's

own DB. Therefore, it is possible to have a wealth of customer history data and to use it to understand customer tendencies. In conclusion, if you use rich customer historical data to infer behaviors and tastes, you can increase customer conversion rates without special promotions.

The easiest and most intuitive way is to issue personalized coupons to customers in real time. By selecting customers with a high risk of real-time churn and issuing real-time customized discount coupons, it is possible to increase sales by increasing the purchase conversion rate without burdening special expenses such as promotional events. And to put these strategies into action, you need an AI-powered strategy. After AI automatically learns the histories of customers, it is possible to properly issue coupons by identifying the behaviors and tastes of individual customers.

Among the AI methodologies, in particular, deep learning-based strategies can be implemented. Deep learning learns a large amount of data to make an optimal decision, and the more data, the better the result. By learning a large amount of real-time log data accumulated in an online shopping mall, it is possible to predict customer behavior and taste. In particular, it is possible to create a more sophisticated model every day by updating and re-learning the existing model with data that accumulates every day.

AI-based customized coupon issuance methods are largely divided into three: customer segmentation, customer churn prediction, and personalized recommendation.

Customer segmentation is an activity that categorizes customers according to their homogeneous customer characteristics, providing the basis for differentiated marketing activities by customer group [8]. Machine learning models used for customer segmentation were mainly used either supervised learning models such as decision trees or unsupervised learning models such as self-organizing maps (SOMs) or K-means models [9]. One of the key features of recent machine learning-based customer segmentation studies is that customer segmentation is being performed for related other marketing research purposes, such as customer churn prediction [10], [11]. Customer churn prediction is also one of the main marketing research topics based on machine learning. Not to mention the fact that effective churn prediction has been recognized as a critical research topic not only for marketing but also for enterprise-wide management strategy [4], with the increasing number of customer churn under a highly competitive modern business environment, many new model development studies have been conducted to successfully predict customer churn. In the past, there have been major studies to learn models using single algorithms such as decision trees, logistic regression, and artificial neural networks to predict customer deviations, however, in recent, more attempts have been made to develop ensemble models or hybrid models that interconnects different models [12]. Meanwhile, personalized recommendation systems are also one of the most active machine learning-based marketing research topics along with churn prediction [13]. Research on personalized recommendations applied to recommended

services such as Amazon and Netflix is increasing. Personalized recommendation studies have been dominated by model development studies to enhance predictive performance itself [13], [14].

On the other hand, customized coupon issuance can contribute greatly to online shopping malls. In the case of an online shopping mall, real-time performance is required compared to an offline shopping mall because a large number of users come and go in an instant. Therefore, it is inappropriate to apply the traditional offline discount coupon issuance strategy online. Also, in online, a lot of log data can be collected much more than offline. Therefore, if you use the marketing method using AI, you can establish effective marketing strategies such as discount coupon issuance strategy in real time.

In most studies, the entire customer group is regarded as a group and AI prediction models are developed at once. In fact, however, customers have different behavioral characteristics due to unexplainable and different transaction patterns, so it is unreasonable to assume the entire customer as a single customer group. It will be much more powerful if AI models are established for each group who are sharing similar tendencies according to customer behavior. In this study, applying deep learning techniques to real-time click stream data, we find customers with high chance of churning rates and issue a coupon that suits customers' preferences. This study has the following significance: First, we segmented the customer and develop a suitable model for customer churn prediction for each segmentation. Second, we made a clickstream-based real-time customer churn risk prediction model using deep learning models. Third, we improved the actual conversion rate by issuing customized coupons in real shopping mall website.

Unlike other studies, the scientific contribution of this study was to analyze customers in real time using data collected in real time as well as going through three steps to prevent customer churn. Also, we applied our model to the actual shopping mall, demonstrating the economic effectiveness and efficiency of the three steps of our model.

This paper is organized as different sections. Section II describes the various research work done in this field. Section III describes the methodology of this research. Section IV describes the process of applying the proposed methodology to the actual shopping mall. For comparative study, various scenarios were tested. Section V presents the experimental results and proves the validity of this research. Section VI consists of conclusions.

II. LITERATURE RESEARCH

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], [16], [17], [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. Reference [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. Reference [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. Reference [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], [33], [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. Reference [38] proposed a recommendation system that identifies and recommends the optimal location when opening a chain store. Reference [39] proposed a preference learning method from heterogeneous information for store recommendation.

D. APPLICATION OF DEEP LEARNING IN VARIOUS FIELDS

Advances in deep learning have solved many problems using deep learning in many industries. The method using deep learning was applied to the battery industry example. Reference [40] proposed deep learning-based prognostic method for lithium-ion batteries with on-line validation. Also, it applied machinery fault field. Reference [41] proposed an adversarial multi-classifier optimization method for cross-domain fault diagnosis based on deep learning. There are also cases where deep learning has been applied in the medical field. Reference [42] proposed a method to find out the name of a disease through the clinical note of patients using deep learning. Reference [43] proposed a method for predicting the deterioration of dementia based on medical records. In addition, deep learning was applied in the field of semantic analysis, which plays the biggest role in creating chatbots. Reference [44] proposed a method to measure the similarity between two sentences using deep learning. In addition, deep learning is widely used in the recommendation field. Reference [45] proposed an embedding method that understands the context and a method of recommending

tourist destinations using deep learning. There are many ways to solve problems using deep learning in so many industries.

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 Two-Dimensional 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 feed-forward 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 real-time. 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.

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

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.

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 two-dimensional customer

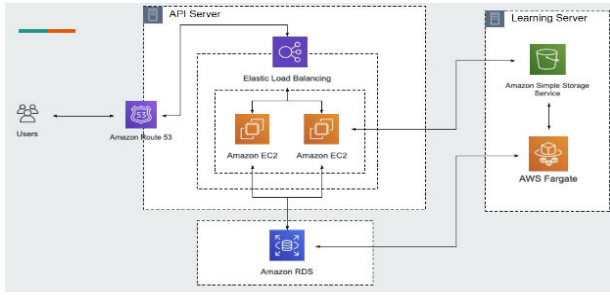


FIGURE 1. Server Architecture.

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.

TABLE 1. Characteristics of the proposed elements.

Element	Concept	Usage	Constraint
Two-dimensional customer segmentation	Clustering customer log data with spending and behavioral variables	Forming each segment to apply real-time churn risk classification on behavior-based segments	Requiring practical marketing action after classifying segments
	Customer behavior-based 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

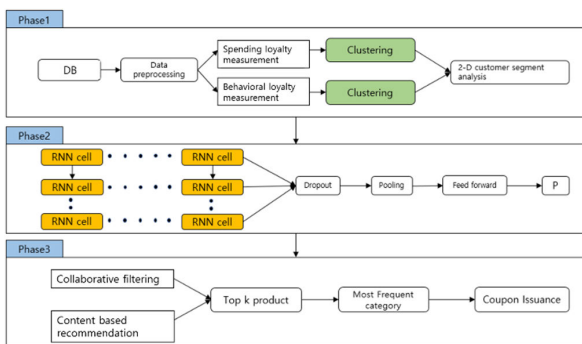


FIGURE 2. Research Flow.

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 non-members) 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.

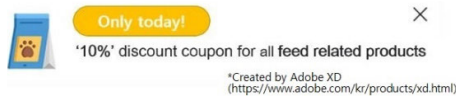


FIGURE 3. Coupon push UI.

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

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

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.

TABLE 6. Statistics for each segment.

	spending amount in the last month (\$)	the average payment per person (\$)	the average number of products purchased at one time	number of searches in the last month	average stay time per session time (second)	number of visits in the last month
Mean	(0.29, 45.03, 16.51)	(0.28, 40.53, 15.82)	(0.059, 4.10, 2.20)	(0.11, 0.40, 0.25)	(228.84, 460.85, 401.08)	(3.49, 8.53, 5.41)
Std	(1.29, 17.82, 6.71)	(1.28, 12.78, 6.24)	(0.27, 2.57, 1.32)	(3.58, 1.63, 1.17)	(779.71, 1088.87, 1012.87)	(35.29, 13.07, 9.98)
Min	(0, 29.56, 8.23)	(0, 9.54, 5.00)	(0,1,1)	(0,0,0)	(0,0,1)	(0,0,0)
25%	(0, 35.88, 9.94)	(0, 33.07, 9.94)	(0,2,1)	(0,0,0)	(38, 101.96,90)	(0,0,0)
50%	(0, 39.83, 15.62)	(0, 37.58, 14.53)	(0,4,2)	(0,0,0)	(80, 207.86, 176.75)	(0,3,0)
75%	(0, 44.44, 19.79)	(0, 4.08, 18.79)	(0,5,3)	(0,0,0)	(180.80, 442.29, 370.12)	(4,13,7)
max	(9.93, 323.07, 39.05)	(7.55, 145.23,27.25)	(7,22,12)	(647,56,30)	(21794.50, 21378, 21699)	(6378,163,132)

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.

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.

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

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

We identified previous e-commerce marketing approaches to derive user behavior prediction. A deep learning method for real time customer churn prediction showed an appropriate result. We applied our research to online shopping mall to raise conversion rate and sales. To check whether our experiment carry out monetary value, we developed a framework to measure the sales amount when used with segment model and personalized recommended digital coupon. We found that our model(scenario1) shows the best results. We found it is suitable for e-commerce online shopping mall to raise conversion rate and sales. Our study empirically showed that marketing, which was a field of management, could be solved more efficiently and quickly by applying big data and deep learning technology.

A. IMPLICATIONS

The experiment results have several implications for industry and academia. From an industrial perspective, First, our model can be used in online shopping mall in real-time. The model can be regularly trained from the server in batches, and the generated model can predict the probability of customer churn and issue coupons in real-time. Second, it all works automatically without the need for any human work. In general, marketing MD directly analyzes customers' tendencies and conducts events such as coupons. However, the more customers there are, the more difficult it is for people to look at everything, and it takes time and money. Our model can be huge cost-effective for shopping mall owner because the whole process proceeds automatically. Third, it can increase sales and conversion rate. By issuing customized coupons to customers at high risk of churn, the conversion rate was significantly increased. From the

perspective of customers, coupons will be issued considering their taste, so there is a high possibility that they will revisit the shopping mall more often.

From an academic perspective, First, our model proposed an ensemble form that sequentially combined 2-dimensional customer cluster analysis, RNN-based customer churn rate prediction, and a personalized recommendation system. Compared to other ensemble models that were removed one by one, our proposed ensemble model show that it is the best fit for online shopping malls. Second, 2-dimensional customer cluster analysis and RNN-based churn rate prediction results are interpreted to increase the reliability of our proposed model.

B. LIMITATIONS AND FUTURE RESEARCH

Our research has some limitations that open up opportunities for future research. First, the length of the clickstream varies across user sessions. Approaches to standardize or auto-tune

session length in the form of zero-padding and pruning can facilitate RNN model. Also, various thresholds on the maximum length of a session can be tried.

Second, the coupon discount rate was constantly 10%. The rate of conversion and increase in sales may vary depending on the discount rate. Therefore, it is necessary to find the optimal discount rate by applying various discount rates. In addition, the discount rate can be varied in real-time depending on customers and products by algorithms. Future research could seek richer ways to support marketing decision-making by identifying the optimal marketing action for each user.

Third, machine learning is an active field of research and new modeling approaches keep appearing. For example, given the success of CNNs in other applications [39], [40], it might be worth considering a convolutional layer to train a better feature representation before processing the sessions through recurrent layers. Combinations of CNN and RNNs can also be considered in the scope of computer vision. In addition, instead of sequentially performing cluster analysis and churn rate estimation, we can also consider integrating whole training process into one deep-learning model.

Fourth, three scenarios demonstrated the drop-off effect by comparing the results. Experimenting with more various combinations of model parameters will lead to more clear results. For this, the consent of the stakeholders in the shopping mall should be needed.

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