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**INTERNATIONAL JOURNAL OF APPLIED
SCIENCE ENGINEERING AND MANAGEMENT**

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.

1. INTRODUCTION

With the development of big data and deep learning technology,big data and deep learning technology have alsobeen applied to the marketing field, which was a part ofmanagement. Also, growth in internet

adoption has madedigital coupons a popular promotional tool [1]. Customizeddigital coupon issuance is a very important topic in onlinecommerce. This is because maintaining existing customersis a more important business issue than acquiring newcustomers [2]. Also, retaining existing customers is muchmore economically advantageous than acquiring new customers[3]. In fact, the acquisition cost of new customers isknown to be five to six times higher than the maintenance costof existing customers [4]. Companies that have effectivelymanaged customer churn by improving customer retentionare known to have a positive effect not only on the company'sprofitability but also on improving brand image by improvingcustomer satisfaction [5].

.Customized coupon issuance research has traditionallybeen active in highly competitive and urgent sectors such astelecommunications, finance, distribution, and game industries,and has focused mainly on developing predictivemodels using machine learning and artificial intelligencetechnology [6]. Also, recently, AI-based marketing using bigdata analysis

and deep learning is emerging.Such AI-driven targeting can save huge amounts of marketingcosts and raise online sales provided that the targetingmodel succeeds in estimating customer responsive nessaccurately [7].

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

Unlike offline shopping malls, online shopping malls areeasy to collect data. All online behavioral characteristics ofcustomers can be collected in real time in the shopping mall' sown 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 conversionrates 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. AfterAI automatically learns the histories of customers, it is possibleto properly issue coupons by identifying the behaviorsand tastes of individual customers.

Among the AI methodologies, in particular, deep learning based strategies can be implemented. Deep learning learns alarge 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 everyday 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 modelsused for customer segmentation were mainly used either supervised learning models such as decision trees or unsupervisedlearning 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 oneof 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 modelsor hybrid models that interconnects different models [12].Meanwhile, personalized recommendation systems are alsoone of the most active machine learning-based marketingresearch topics along with churn prediction [13]. Researchon personalized recommendations applied to recommendedservices such as Amazon and Netflix is increasing. Personalizedrecommendation studies have been dominated bymodel development studies to enhance predictive performanceitself [13], [14].

On the other hand, customized coupon issuance can contributegreatly to online shopping malls. In the case of anonline shopping mall, real-time performance is required comparedto an offline shopping mall because a large number ofusers come and go in an instant. Therefore, it is inappropriateto apply the traditional offline discount coupon issuance strategyonline. Also, in online, a lot of log data can be collectedmuch more than offline. Therefore, if you use the marketingmethod using AI, you can establish effective marketingstrategies such as discount coupon issuance strategy in realtime.

In most studies, the entire customer group is regarded as agroup and AI prediction models are developed at once. In fact,however, customers have different behavioral characteristicsdue to unexplainable and different transaction patterns, so itis unreasonable to assume the entire customer as a single customergroup. It will be much more powerful if AI models areestablished for each group who are sharing similar tendenciesaccording to customer behavior. In this study, applying deeplearning techniques to real-time click

stream data, we findcustomers with high chance of churning rates and issue acoupon that suits customers' preferences. This study has thefollowing significance: First, we segmented the customer anddevelop a suitable model for customer churn pre- diction for each segmentation. Second, we made a clickstream-basedreal-time customer churn risk pre- diction model using deeplearning models. Third, we improved the actual conversionrate by issuing customized coupons in real shopping mallwebsite.

Unlike other studies, the scientific contribution of thisstudy was to analyze customers in real time using datacollected in real time as well as going through threesteps to prevent customer churn. Also, we applied ourmodel to the actual shopping mall, demonstrating the economiceffectiveness and efficiency of the three steps of ourmodel.

Customer segmentation is a starting point for marketingresearch. After grouping customers based on the characteristicsof homogeneous customers, marketing strategies foreach target segment can be

done. Customer segmentationshould not end in segmentation, but should be accompaniedwith 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 utilizedmethods. The RFM splits the purchasing behaviorinto three dimensions and scores each dimension. R isthe last time since the last purchase, F is the total frequencyof purchase, and M is the total purchase amount.The scores are calculated for each of the three dimensions. Subsequently, it constructs segments according to threedimensionalclasses [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 auto encoder. A typical example is the sequential method of applying cluster analysis after dimensionality reduction using an auto encoder [19]. Alternatively, modeling can combine dimensionality and clustering at the same time [20], [21].

The prediction and prevention of customer churn have alwaysbeen studied as a key issue in loyalty management. The reason why companies are concerned with churn prediction is of twoissues: 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 fiveto 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 thegiven 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 click stream data.

2. 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], [16], [17], [18].

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B. Forecast Customer Churn

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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.

3. EXISTING SYSTEM

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Disadvantages

• The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets to detect Improving Shopping Mall Revenue.

• Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.

• Incorrect labeling: The existing machine learning modelsare only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.

3.1 PROPOSED SYSTEM

In this study, applying deep learning techniques to real-time click stream data, we find customers with high chance of churning rates and issue acoupon that suits customers' preferences. This study has the following significance: First, we segmented the customer and develop a suitable model for customer churn pre- diction foreach segmentation. Second, we made a clickstream-basedreal-time customer churn risk pre- diction model using deeplearning

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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.

Advantages

The proposed system generated RNN-based churn estimation models for eachcustomer segment resulted from two-dimensional customer segmentation. After that, we issued customized product categorycoupons to customers who are at high risk of churn. Hybrid recommendation system is utilized for customized coupon issuance.

4. OUTPUTSCREENS

	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	(0.20, 43.03, 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)	(3.50, 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, 37.38, 14.55)	(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)

	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

	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%

5. 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.

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