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A Study on the Efficient Estimation of the Payment Intention in the Mail Order Industry

Masakazu Takahashi[a]*, Hiroaki Azuma[b], Kazuhiko Tsuda[b,c]

[a]Graduate School of Innovation and Technology Management, Yamaguchi University, 2-16-1 Tokiwadai, Ube Yamaguchi 755-8611, Japan
[b]Graduate School of Systems and Information Engineering, University of Tsukuba, 3-29-1, Otsuka, Bunkyo, Tokyo 112-0012, Japan
[c]Graduate School of Business Sciences, University of Tsukuba, 3-29-1, Otsuka, Bunkyo, Tokyo 112-0012, Japan

Abstract

This paper presents investigating the customer payment intention prediction in the mail order industry. As the B2C market expands their market volume, the fraud transactions increase in number. The primary indicator for the detection are the shipping address, the recipient name, and the payment method. These information usually make use of the prediction in the Japanese mail order industry. Conventional detecting method for the fraud depends on the human working experiences so far. As the number of transaction becomes large, fraud detection becomes difficult. The mail order industry needs something new method for the detection. The result of the Google Flu Trends shows, accurate prediction needs the heuristics knowledge. For these backgrounds, we observe the transaction data with the customer attribute information gathered from a mail order company in Japan and characterized the customer with machine learning method. From the results of the intensive research, potential fraudulent transactions are identified. Intensive research revealed that the classification of the deliberate customer and the careless customer with machine learning. This result will make use of the customer screening at the time of order received.

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Keywords: Mail Order; Customer Analyses; Machine Learning; Weak learner; Risk Management; Service Science and Management Engineering

1. Introduction

Mail-order industry is a typical non-face-to-face sales system and to provide the goods or the services to the customers' hand directly. Since the nature of the business system, the time lag of the collecting money occurs. The mail order company usually requires the customers to pay by the credit card or cash on delivery for the first time transactions. A post-paid system will be accepted at the time of second trading. A post-paid system method is popular among the Japanese mail-order industry carries the risk arising from the distance and time difference knocks the customer's anxiety down.

However, even if the customer passed the credit screening from the mail order company, some of them forget the payment. These customers are distinguished the intentional forget and the careless forget. Most of the mail-order company usually tries to persuade to remit the bill. But the recipients of the intentionally reply answering in an indolent and evasive manner to put off paying the bill. Along with the mail-order market expansion, the amount of bad debt is also increasing. A survey from the Japan Direct Marketing Association says that the percentage of the credit losses in a mail order company is estimated about 0.5% of net

* Corresponding author. Tel.: +81-836-85-9066; fax: +81-836-85-9877.
E-mail address: masakazu@yamaguchi-u.ac.jp

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sales. This number is indicated after the intensive collection activities, such as delivering the notice of reminders or the phone calls. With regard to the shipping address, an exact shipping address is not required. This is because the purpose of delivery for the logistics company is made ill use of the guess correction to deliver the ordered items, while the delivery address is incomplete. After the completion of delivery, even if the payment is delayed, there is no single-mindedly way other than to encourage the payment. Therefore, the credit management before the shipping becomes important for the industry.

One of the conventional method for the detecting the fraud is making use of the working experience by the rank and file employees. They understand some keys for the fraud transactions heuristically. But as the mail order market size expands, since the conventional detecting skill for the fraud depends on their heuristics skill, some fraud transactions pass the screening. This is because those who make fraud transaction are well understand the function of the information systems. They well understand the function of information retrieval for the classification and make it hard to extract the vicious transactions. From the intensive observation of the transaction data in the mail order company, we found that the trend of high potential customers who turn into the bad debt situation.

In this paper, the feature analysis of the customer is made. We focus on the customer who are sent the reminder more than twice. We carry out data analysis of the customer classification as the decision support knowledge in the mail order industry with machine learning method and propose the method for the customer classification from the fraud transactions.

The rest of the paper is organized as follows: Section 2 discusses the backgrounds of the research and related work; Section 3 briefly summarizes the gathered data on the target mail order company; Section 4 describes the analytics of the data and presents analytical results; and Section 5 gives some concluding remarks and future work.

2. Background and Related work

Decision-making using data becomes an important business activity since the keywords of big data is in common. It becomes possible to get a great deal of data easily than used to be from the source of such as twitter, email, and Web access. As a result, the service from the data analysis result is provided in various phase on our life. For example, NetFlix and Amazon predict the programs expect the user broadcasting needs from the user logs of on-line video [1, 2].

In 2009, Google announced the Google Flu Trends from the analytical result of their search engine [3]. Schnberger described the algorithm of the Google Flu Trends [4]. Google assembled the algorithm with the five years web logs including the hundred billions of search results and then proposed the prediction influenza indicators with the 45 search words. They explained the model more effective than the government alert from the statistical data analysis that delays announce. However, the Google Flu Trends (GFT) was not able to predict the outbreak of the pig flu in 2009. The GFT predicted the epidemic of influenza excessively about 1.5 times occurred in the end of 2012 [5]. Moreover, the simple way same as the temperature prediction based on the temperature transition predicted the epidemic of the flu accurately more than the GFT. The GFT was overestimated the epidemic rate of flu in 100 weeks out of the past 108 weeks [5-7]. In other words, even if there is no such as big data, there is a mechanism to put out the results better than the GFT. We should consider what can be learn from such error. Primary issue for this error is overestimated the data validity.

Many big data is not obtained from the device that is developed for the purpose of data generation fit for the scientific analysis. We should think whether data is really useful for prediction. Because, we can get the huge data easily. In general, we decomposes the problem into the understandable unit. The GFT result shows the necessary of heuristics knowledge. Understanding of the problem is necessary for acquisition of knowledge [8]. Then, there is still in the territory of unresolved problem such as incomplete search for the wide search area or the human behavior model. Improvement of the machine performance and the development of algorithm can overcome.

According to the annual mail order industry sales survey, it was estimated amount to 61,500 billion yen in total of the 2014 fiscal year which increased in 4.9% raise compared with previous year [9]. As for the related work on the mail order industry, it separates into the activity of before the order and of after the order received, respectively. The related work of the before the order activities were focused on the elaboration of the order received in consideration of the time lag from customers such as the demand predictions and the advertisement effect [10-14].

Then, as for the after order received phase, most of the researches have been made for the customer analysis with the purchase record. There are lots of customer analyses with the data-mining methods [15, 16]. For example, the order history has been used for such as trend analyses of customers and sales promotion strategies as the retailers' decision support tools. As long as the reversionary system is adopted in the mail order industry, it is important to collect the payment from the customers as soon as possible, whereas the related work on the collecting the payment was less studied than that of customer analysis, especially collecting the bad debts.

As the study on the credit reminder, Customers' name identification [17-19], the credit reminder effect [23-25], characterization of the payment trends from the order received channels [24-25], and the profiling the customer characteristics [26-28] are made. Azuma et al. made study on the payment rate at the time of post-paid system [22]. In this study, it is to verify the effect of credit reminder compared with the natural payment rate. This company forgot sending the credit reminder to the customer. Payment rate after sending the credit reminder is being inspected. Compared with the credit reminder effect among 21 days passed after due date and 31 days, Although there is a difference in the payment rate at the time of credit reminder dispatched, but after the reminder shipping 20 days passed, the payment rate become approximately 98%. This means that the screening of bad customer is more important at the time of order-received than optimizing dispatch timing of credit reminder.

There are variety payment methods in the mail order industry. Credit card, Bank or Postal transfer, Cash on delivery, and remittance from Convenience store are the primary payment method in Japan. Among the variety of the payment system, Bank or postal transfer, they have two method such as the advanced payment and the post payment, respectively. However, most of the user employ the post payment system. These variety of payment system make the mail order company complicated in their accounting and credit management that comes from the different timing of payment.

Cressey described the fraud scheme named the fraud triangle from the investigation of the actual frauds. Opportunity, Motivation, and Justification to the fraud are made if all the elements are completed [29]. Based on his scheme, the Japanese mail order company adopts the post payment system include the requirement of the fraud with high potentiality. Aslaksen et al. described as follows; the subdivided science is insufficient as the knowledge base to compare or predict the impacts of the complicated systems however the subdivided science is wise.

The potential problems is confirmed to be predictable from the previous work to some extent. The final loss and profit should be considered if we take the preventive action or do not take. Especially, the importance of finding and pointing out the loophole and the lack among the scientific knowledge should be pointed out [35, 36]. Therefore, it is necessary to conduct the comprehensive frauds detection.

As for the study on the fraud detection in e-commerce, the efficient detection methods were made in accordance with the expansion of the transaction volume [30-34]. However, they were specialized for the credit card payment. Since post payment system is used in the transaction in Japan, those work dose not match completely. Based on the market condition in Japan, the study including the post payment transaction are required.

With regard to the study on the fraud detection, including the post payment, Takahashi et al. extracted the features of the transaction with machine learning. [37, 38] Change of payment method, delivery area characteristics and effects of reminder were examined.

From the result of analyses, Customer screening at the time of order received has led to be an effective defensive measure of preventing fraud transaction. For this reason, a powerful fraud screening method is required. Fraud detecting sense from the rank and file employees helps this kind of problem.

That is, as shown in the result of the Google flu, delivering knowledge only from the data, a robust algorithms fit this kind of issue better than the powerful algorithms. Suzuki proposed the cost-sensitive learning algorithms. [39, 40] This is the learning method to consider the practical cost, not to maximize the prediction accuracy. It's more important not to miss the fraud than the total accuracy rate.

3. Data summary

We make an intensive research from the transactional data gathered from the mail order company in Japan. Table1. shows the summary for the transactional results. Grand total of the transactions amount to 1,617,636 and composed of the 402,727customers. Among the customer, the 125,953 customer were used the post-paid transfer. Table 2. indicates the breakdown of payment methods. The about half of the customer from this company is use COD. Table 3. Shows the comparison of the payment method. Table 4. summarizes frequency of the reminder delivery. About 10% of the customer sent the reminder. The frequency of reminder is made by the transactional record and summarized. Table 5. shows the overview of the reminder frequency.

Table 1. Transitional Results Demography.

Term	2011/5/30 - 2013/9/30
Number of Transaction	1,617,636
Number of Customer (a)	402,727
Postpaid transfer user (b)	125,953
Postpaid transfer user in % (b) / (a)	31.28%

Table 2. Breakdown of Payment Methods.

Payment Method	Transaction	%
Credit Card	311,269	19.2%
Bank Transfer	8	0.0%
Post-paid Transfer	570,976	35.3%
Cash On Delivery	735,383	45.5%
Total	1,617,636	100.0%

Table 3. Monetary Comparison of the Total Transaction and the Postpaid Transfer Customer.

	Total	Post-paid Transfer
Average Order Price	¥5,090	¥5,674
Average Order Frequency	4.02	4.53

Table 4. Frequency of the Reminder Delivery.

Number of customer received the reminders more than twice (a)	12,982
Number of customer (b)	125,953
Potential fraud transaction in % (a) / (b)	10.31%

Table 5. Overview of the Reminder Frequency

	Count	%
Number of the Reminder #1	39,830	7.13%
Number of the Reminder #2	11,706	2.06%
Number of the Reminder #3	6,259	1.10%
Number of Customer	570,976	

Fig. 1. Payment Pattern Classification.

Usually, most of the mail order company send the reminder at least three time before they financially count into the bad debt account. Payment pattern classification by the customer types is summarized in Fig.1. The relationship between the timing of the order and payment is illustrated. Based on the concept of Fig.1, those who received the reminder more than two times are seemed to be fraud transaction. Thus, an efficient distinction method is considered.

4. Data analysis

Based on the above data, we made analysis with the target data. Fig. 2. indicates the relation between the order frequency and the reminder frequency. The x axis represents the order frequency by the customer ID and the Y axis represents the reminder frequency by the customer ID, respectively. Above the function indicated by y=x, the frequency of the reminder is larger than the frequency of the order. From this figure, most of the customer pay properly, but sometimes forget the payment carelessly. And the high frequency order customer is not the hotbed of the fraud. Therefore, the mail order company need to capture the customer of intentionally forgotten at the time of order received. Fig.3. indicates the relation of the order frequency and the monetary volume. Only the customer D was sent the reminder once. The customer from A to C were not sent the reminder. Then, Fraudulent transactions to exist under cover in the normal transactions, there is a possibility that it is too severe screening leads to estrange their customers from the order information. Therefore, risk scoring of transaction is needed in the target industry.

In this paper, the knowledge extraction by collective learning is performed. Ensemble learning is one of the machine learning method by integrating the multiple results to improve the accuracy. As a method for integrating and combining plurality of results, the classification is employed the majority, and the regression is decided the average. In the Ensemble learning, the simple model are made from the different weight or the different sample.

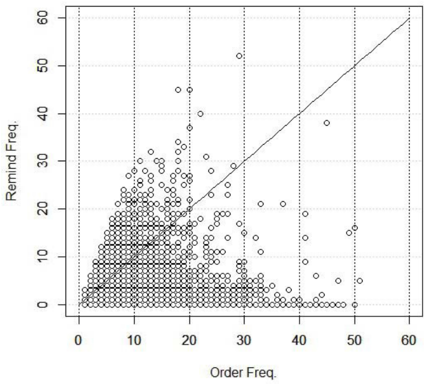

Fig. 2. Relation of the Order Frequency and the Reminder Frequency.

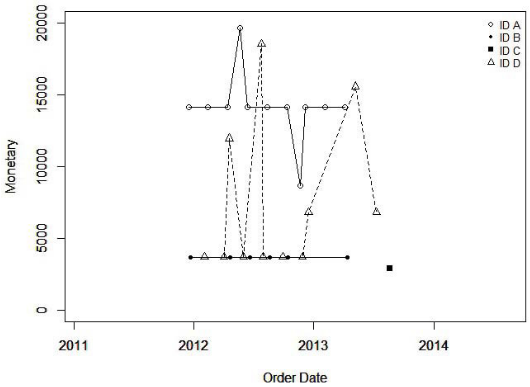

Fig. 3. Relation of the Order Frequency and the Monetary Volume.

Table 6. Experimental Result of Reminder Frequency

	0	1≤
0	484,956	28,225
1≤	740	57,055

Combining the model by certain method to achieve both accuracy and generalization. Ensemble learning contains bagging for regression and classification, boosting and random forest. Among them, Boosting performs learning using supervised data. By repeating sequentially adjusting the weight based on the learning result, the accuracy is improved by integrating and combining the results. Primary differences in the proposed methods are the given method of the initial value, the calculation method of reliability and weight update methods.

Xgboost (eXtreme Gradient Boosting) can achieve the high precision approach approaching comparable to Deep Learning by a comparatively low tuning cost [41-43]. However, since the Xgboost are originally from trees model, results for this algorithms ends in same as decision tree. Therefore, this algorithms fits linear inseparable pattern. This time, we use the R and Xgboost package. This time we examined the reminder frequency from the transactional records described in Table.5. They are all the customer who took the post-paid method. A customer is distinguished based on the information on the following figures; customer ID, Frequency of reminder, Monetary amount, and Duration of reimbursement. Table 6. indicates the experimental result. 4.10% of normal transaction are determined to be fraud transaction.

From the result of the analysis, payment intention of customers can be detected if we identify parameters. From the series of fraudulent transaction studies in the mail order industry, more accurate detection measure is possible to integrate with the following studies; such as the guess correction of delivery address analyses, the reminder delivery pattern analyses, the payment method change pattern analyses, the frequency of order, and the transactional pattern analyses.

Analyses of reminder effects, transcription in delivery address, paying method change, and normal transaction history are made separately, so far. Each research point is focusing on a single aspect, and the elements of fraudulent transaction are related complicatedly each other. And fraudulent transactions are aiming on exploitation for their purpose, their fraud methods evolve day by day.

For this purpose, it is necessary to predict what kind of fraudulent transaction is generated in the future. Even if it is controlled timing of reminder, it isn't possible to exclude fraudulent transaction completely from our series of study. In other words, customer's screening at order receiving phase is required to detect fraudulent transaction. Therefore, the precise or wise prediction at the time of order received is required.

In the mail order industry, since the reminder effect is restrictive from the result of our study, Identifying parameters to decrease fraudulent transactions at the time of order receiving phase, proposed method is available to find the functions for evaluation.

5. Concluding remarks

This paper presented investigating for analyzing customer characteristics from the reminder list of a mail order company which aims to understand the characteristics of the bad debt customers. We described research backgrounds, related wok, research method, and analytical results. Concerning to the screening of suspicious bad debt customers, it depends on the heuristic knowledge based on the rank and files staffs' working experiences. In order to expand of market size of mail order industry, such a bad debt customer is not only something of necessary evil but side-effect factor. In this paper, the frequency of reminder is focused. Both those who forget intentionally and carelessly are intermingled among the arrears customers. Then we make an intensive research to classify the arrears customers with weak learner algorithms. The analytical results suggested that making bad customers can be detected if we identify parameters. This result will make it use for the decision support knowledge for screening customer at the order received phase in the mail order industry.

Our future work includes; 1) parameter tuning for the accurate classification, 2) examine another machine learning method for the fraud detection and compare the methods for the accuracy, 3) generate new transactional patterns with meta-heuristic algorithms. These work will require practical experiments and further survey studies.

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