DAliM: Machine Learning Based Intelligent Lucky Money Determination for Large-Scale E-Commerce Businesses

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Abstract. E-commerce businesses compete in the market by conducting marketing strategies consisting of four aspects: customers, products, marketplaces and intermediaries. One of the widely-used marketing strategies, called Lucky Money, is capable of encouraging customers to buy products from marketplaces. However, the amount of luck money for each customer is usually randomly determined or even manually determined and cannot fully achieve the business objectives. This paper proposes a machine-learning based lucky money determination approach, called DAliM, for e-commerce businesses to achieve their desired goals. We implement DAliM for the "Double 11 Global Shopping Festival 2017" initiated by Alibaba Group and evaluate it using a few hundred million real customers from all over the world. The experimental results demonstrate that our method manages to decrease the lucky money spent by 41.71% and increase the final purchase rate by 24.94% compared to the state-of-the-art baseline.

Keywords: Machine learning · Lucky money · E-commerce · Data mining
Price prediction · Price optimization

1 Introduction

Large-scale worldwide e-commerce businesses, such as Amazon, e-Bay and Alibaba Group, are always competing for marketing shares, and the number of target customers attracted by the business to a large extent determines its profits [1, 2]. Hence, the e-commerce businesses and companies have launched several marketing strategies which are related to four key aspects: customers, products, marketplaces and intermediaries [1]. Throughout the four aspects, intermediaries are the most special one because they are able to build a link between the providers and the customers who buy products at certain marketplaces [1, 2]. As such, one of the widely-used intermediaries for

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marketing plans is known as "Lucky Money", which is a certain amount of e-cash bonus given to the buyers and can be used to offset the original price to be paid by a customer [3]. In other words, with luck money, customers can buy products at a lower price. Hence, luck money is becoming increasingly popular among e-commerce companies and even other companies [4, 5].

The ways of determining the amount of lucky money for each customer used by e-commerce businesses are usually by assigning a random amount of money to the customer or by issuing a manually-determined amount of money to the customer [6–9]. However, there are several drawbacks with these existing methods: (1) the random amount may not be satisfactory to the customer; (2) the issued random amount for each customer does not fully satisfy the business objectives (e.g. cost optimization and targeted purchase rate) set by stakeholders; (3) it provides little reason to explain why the customer is assigned with the money [10]. The use of these methods is because it is not straightforward to determine the accurate amount of lucky money for each customer, in terms of three challenges: (1) the money should be issued on an ongoing basis; (2) the characteristics of each customer are difficult to be obtained; (3) the budget for lucky money is quite limited.

In this paper, we propose a novel and intelligent approach, called DAliM, for better determining lucky money for customers. DAliM is based on historical data analysis and machine learning techniques. We first analyze hundreds of million real historical data related to customer, transaction and lucky money usage, and then we rely on machine learning techniques to train the historical data to obtain a purchase rate prediction model, which is used for calculating the predicted purchase rate of a particular customer with a certain amount of lucky money. Next, we apply a smoothing regression algorithm to figure out each target customer's assigned lucky money that can drive the customer to buy products at the targeted purchase rate set by the stakeholders. According to our knowledge, it is one of the first kind to apply machine learning for lucky money determination.

We evaluate the feasibility and validity of DAliM in the "Double 11 Global Shopping Festival" initiated by Alibaba Group in 2017. In the experiment, we use an AB-Test strategy by simultaneously launching two sets of lucky money determination approaches: (1) Alibaba Group's existing random lucky money based approach; (2) our newly proposed approach: DAliM. These two approaches are applied on a few hundred million real target customers of the "2017 Double 11 Global Shopping Festival". We make a comparison between these two approaches, and the experimental results show that DAliM is able to decrease the lucky money spent by around 41% and increase the final purchase rate by 25% compared to the existing method, while satisfying the business objectives set by stakeholders.

The research contributions of this paper are: (1) we propose a novel and intelligent machine learning based approach for determining appropriate lucky money within e-commerce businesses; (2) we formulate the business objectives and requirements to be set by e-commerce business stakeholders; (3) we propose a methodology to evaluate the difference between two lucky money determination approaches, and demonstrate the applicability of the methodology.

The remainder of this paper is organized as follows: Sect. 2 introduces the background; Sect. 3 discusses the related work; Sect. 4 illustrates our proposed method of determining lucky money; Sect. 5 is the experimental evaluation; Sect. 6 provides the conclusions and our future work.

2 Background

We introduce the fundamentals of lucky money in e-commerce businesses, and discuss business requirements and objectives for lucky money.

2.1 Lucky Money in E-Commerce Businesses

E-commerce businesses, especially the large-scale ones such as Amazon and Alibaba Group, choose to use lucky money as one of their preferred marketing strategies, in order to compete for their marketing share and attract more customers [1, 2]. Lucky money is a type of e-cash bonus given to the customers by e-commerce corporations or product providers [3]. With the lucky money, customers can offset the original price they need to pay when they buy a particular product, which gives them a sense that they buy the products at a discounted price [3]. Normally, based on various business purposes, there are four types of lucky money: (1) visit-number oriented lucky money whose purpose is to increase the visiting number of users; (2) advertising oriented lucky money whose purpose is to publish and advertise a promotion activity; (3) purchase-rate oriented lucky money which aims at increasing the purchase rate of customers; (4) new-customer oriented lucky money which targets to attract more new customers who have never bought products from the e-commerce corporations. For instance, every year Alibaba Group launches a lucky money strategy called "Torch Red Packet" during big promotion activities, and launches the "Happy City Red Packet" lucky money strategy during the "Double 11 Global Shopping Festival" [3]. As for the "Double 11 Global Shopping Festival", it achieved a turnover of 18 billion dollars during 11 November 2016, and 25.5 billion dollars during 11 November 2017, so a reasonable lucky money strategy plays and will continue to play a significant role in e-commerce businesses' promotion activities like "Double 11 Global Shopping Festival".

2.2 Business Requirements and Objectives for Lucky Money

The above-mentioned four types of lucky money reflect the business requirements and objectives which are to increase visits, advertise a promotion activity, increase purchase potential, and attract new customers [11–14]. All of the four objectives are highly related to increasing the overall profits of e-commerce businesses either by increasing the number of customers or by increasing the possibility for each customer to buy products. Moreover, these requirements also aim to give those e-commerce businesses a larger exposure to the market. In this paper, we are mainly focused on the objective of increasing the purchase rate.

3 Related Work

Machine learning techniques are widely employed to solve many problems in financial and economic areas, and we discuss a few of them in this section. The lucky money determination problem addressed in this paper highly resembles several economic decision problems such as price determination [15–17].

3.1 Share Market Price Prediction Using ANN

The researchers from SUST proposed a price prediction mechanism for share market based on Artificial Neural Networks (ANN) techniques in 2011 [15]. This proposed method addressed the challenge with the insignificant relationship between the variables of the share market chaos system and the share price [15]. The traditional multiple layer perceptron (MLP) model was applied to the neural network and the back propagation (BP) mechanism was used to calculate and update the weights of the intermediate inputs and outputs [15]. There are several drawbacks with this mechanism: first, only two hidden layers were constructed in the neural network, and there is no explanation for it; moreover, there is no comparison between the predicted effect of using two hidden layers and that of using more hidden layers; second, the variables of share market used in the neural network only contain the information about the company's financial situation and do not consider other useful features such as the company's customer size or launch time [15]. In addition, the proposed method was evaluated using only one company coupled with two sets of input data, which decreases the validity of the method [15].

3.2 Financial Time Series Forecasting

The researchers from Bond University, Australia found that Artificial Neural Networks (ANNs) were identified to be the dominant machine learning technique in the area of predicting financial time series in the stock market [16]. While the other methodology used for such a prediction was based on evolutionary and optimization based techniques, there is a clear trend to use and enhance established ANN models with new training algorithms or combine ANNs with emerging technologies into hybrid systems [16]. However, how the real-world constraints can impact the accuracy of financial time series forecasting and stock index prediction remains a question, and whether the investors' risk-return tradeoff can be improved or not should also be studied [16].

3.3 Crude Oil Price Prediction with ANN-Q

The researchers from the University of Manchester proposed an Artificial Neural Network-Quantitative (ANN-Q) model based approach for predicting the price of crude oil in 2010 [17]. This research addressed a big problem with crude oil price prediction: the price of crude oil is related to a complex set of factors and any change of the factors may have an exclusive impact on the price, because crude oil is one of the world' major commodities with high volatility level [17]. An ANN-Q model was developed based on a total of 22 key factors that have an impact on the price of crude oil. In order to develop a better model, the data related to these key factors were further divided into three categories: large impact class, medium impact class and small impact class [17]. BPNN was used for training the input variables [17]. The simulation results showed acceptable accuracy of the proposed method since it was still in progress, and the improved accuracy could be achieved by better tuning the parameters or applying other machine learning models.

4 Our Proposed Method

Large-scale e-commerce businesses like Alibaba Group have their own business goals and objectives to fulfil when it comes to determining the lucky money for their customers. For example, with a fixed amount of lucky money budget, the corporation may demand that the max number of customers should receive at least a minimum amount of lucky money and the final purchase rate of those customers should be optimized or meet the purchase rate goal set by the stakeholder. Our proposed method is designed to be able to satisfy these business objectives. However, there are some challenges: (1) whether a customer will buy products with the given lucky money or not depends on a complex set of factors, not only on the amount of lucky money; (2) the characteristics of every customer are quite different from each other, and it is difficult to use a universal way to model different customers; (3) some customers are not sensitive to lucky money at all, and they would not buy any products no matter how much lucky money is given to them. As such, we define three research questions: (1) apart from lucky money amount, what are the other factors and features that impact the overall purchase rate of customers? (2) how to model the set of factors and features to represent the data of every customer? (3) how to develop the model that is able to correctly filter the customers sensitive to lucky money and assign the appropriate amount of lucky money to these selected customers?

Our proposed method, DAliM, answers all of the three research questions defined. When applied within Alibaba Group, DAliM is able to fulfil all of the business objectives set by the stakeholders of Alibaba Group. As far as we know, it is the first time that such a method is ever proposed. The problem can be defined in the following way:

Suppose the lucky money budget is C, and the number of customers who receive lucky money is D, each customer's lucky money is Q_i ($1 \le i \le D$), and each customer's purchase rate is P_i, then we need to determine Q_i based on the following formula:

$$\boldsymbol{Q} = \underset{Q_i}{\operatorname{argmax}} \sum_{i \in D} P_i \tag{1}$$

Subject to:

$$\sum_{i \in D} Q_i P_i \le C \tag{2}$$

Where:

$$P_i = g(\boldsymbol{X_i}), \mathrm{i} \in D \tag{3}$$

Where g(.) is the function that represents the machine learning model used for predicting the purchase rate and Xi denotes the set of customer features, including the feature of lucky money amount.

4.1 Overview of DAliM

The overview of DAliM is shown in Fig. 1.

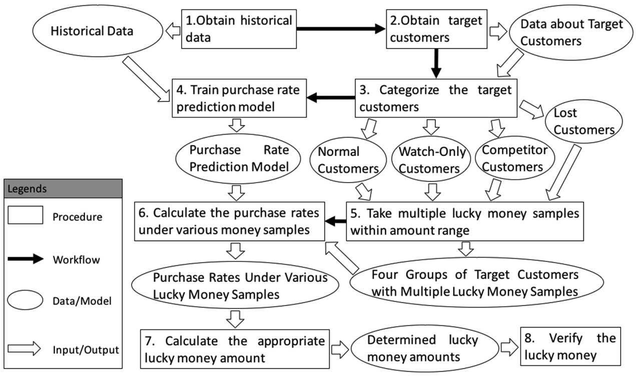

Fig. 1. Overview of DAliM.

The method consists of eight procedures: (1) we obtain the historical data about the past customers and their usage of the lucky money given to them (i.e. whether they have used the lucky money to buy products or not); (2) we obtain the target customers who will attend the promotion activity (i.e. "Double 11 Global Shopping Festival 2017"); (3) we then make categorization for those target customers based on the extent to which they will participate in the promotion activity, and they are categorized into four groups: normal customers, watch-only customers, competitor customers and lost customers; (4) next we use the historical data about customers and lucky money usage to train the machine learning model that is used for predicting the purchase rate (probability) of a particular customer; (5) we take samples of the lucky money by selecting several amounts of money that are within the lucky money range specified by the stakeholder, and for each customer group we attach each selected sample amount with all the customers inside that group, to form up a series of customer sets with different lucky money samples, yet all of the sets share the same set of customers. In total, there are four customer groups and each group is attached with several lucky money samples, and the money sample works as one of the data features. (6) With the obtained purchase rate prediction model and a series of target customer sets with multiple lucky money samples, we calculate the purchase rate for each customer in each group with attached sampled lucky money; (7) then relying on the information about each customer's different purchase rates under different lucky money samples, we calculate how much lucky money should be given to each customer so that the customer will buy products at the stakeholder-specified purchase rate, and the calculated money is the result assigned to that customer. We do this for each of the four groups. (8) Finally, we verify the predicted lucky money for all the target customers.

4.2 Training Data and Prediction Data

The historical data about the characteristics, natures and lucky money usage of all the past customers of the promotion activities is used for training the machine learning model. The data about the characteristics and natures of all the target customers of the current promotion activity ("Double 11 Global Shopping Festival 2017") is used as prediction data.

We obtain the training data from the data generated in last year's promotion activity, which is "Double 11 Global Shopping Festival 2016". There were hundreds of million items of data generated in 2016's "Double 11 Global Shopping Festival", and each data item included 275 features and 1 label that specified whether the customer made any purchase or not. These 275 features are all related to the label or the purchase status. These features could be classified into the following 8 groups: (1) purchase information; (2) membership information; (3) personal information; (4) shopping cart actions (e.g., adding items to the cart); (5) products collection action e.g., adding products into the favorite store); (6) products visiting action; (7) customer coupon sensitivity; (8) customer purchase capacity. These 8 groups are independent of each other.

For the labelling of the historical training data, we use the label 0 to represent a customer made no purchase and we use label 1 to represent a customer made any purchase. We obtain the prediction data by analyzing who will be the target customers of this year's "Double 11 Global Shopping Festival". The target customers of the promotion activity are determined by summarizing those who have made at least one purchase action or visiting action in the past 3 months prior to this year's "Double 11 Global Shopping Festival", because the expert knowledge has indicated that the customers being proactive in the past 3 months prior to an upcoming promotion activity will also be proactive in the upcoming promotion activity, and those who have accessed the e-commerce platform will also be valuable for the upcoming promotion activity. The number of such customers is a few hundred million. The lucky money that should be given to a customer is highly affected by the customer's proactivity in the promotion activity [3]. As such, in order to provide a better lucky money determination mechanism, we differentiate these customers by their proactivity in the promotion activity and categorize them into the following 4 groups: (1) Normal Customers, (2) Watch-Only Customers, (3) Competitor Customers and (4) Lost Customers. The definitions of these 4 groups of prediction data and the percentages of customers in each group are illustrated in Table 1.

We divide the big prediction dataset into 4 prediction sub-datasets. All the prediction sub-datasets share the same features as the big training dataset, and the percentage data inside each prediction sub-dataset will be passed to the trained machine learning model as its inputs for predicting the purchase probability of each target customer. We have also checked for the noise inside the prediction dataset and found

Table 1. Four groups of prediction data.

Group	Definition	Percentage
Normal customers	The customers who have made at least 1 purchase during the past 3 months	90.5%
Watch-only customers	The customers who only accessed the e-commerce platform and merely browsed products on the platform without making any purchase during the past 3 months	4.5%
Competitor customers	The customers who have bought products only from the competitors of Alibaba Group during the past 3 months	3.8%
Lost customers	The customers who haven't made any purchase or products browsing during the past 3 months	1.2%
Overall customers:		100%

no noise in it, since the noise was filtered out by the big data storing and processing engine provided by Alibaba Group.

4.3 Feature Engineering

If we use all of the 275 features in the training dataset for training the machine learning model, it may take relatively much time. Although all the features are related to the labelling, not all of them are of the same importance and only a subset of them have heavier weights and contribute more to the labelling. The remaining features are with light weights and some can even be negligible. Hence, in order to reduce the model training time while maintaining the validity of the model, we need to filter the heavily-weighted features, and thus we apply feature engineering. While feature engineering also includes feature generation and feature transformation, we are only concerned with feature filtering, because we argue that the features in use are already complete enough.

Feature filtering can be performed in several ways, such as by expertise, random sampling or relying on external feature engineering tools, and we determine to perform the feature engineering by using a combination of three ways: (1) relying on the feature importance determination library provided by popular SDKs (e.g. Python machine learning libraries); (2) calculating and ordering the entropy values and Gini indexes of all the features; (3) relying on the gradient boosting decision tree machine learning library. A combination of these three steps is more suitable than any single method for determining feature importance and thus results in a better outcome. For a specific feature, suppose its importance determined by the first step is denoted as W_1, and its importance determined by the second step is denoted as W_2, and its importance determined by the third step is denoted as W_3; we assume these three importance values are of the same weight since there is no apparent clue to indicate which one is more accurate than another one; then the final importance of this feature is calculated as $(W_1 + W_2 + W_3)/3$. We calculate this importance value for each feature and extract the top 50 important features. This answers our research question 1. Among the top 50 important features, their weights range from 0.005 (occupation) to 0.35 (lucky money amount), and they come from all the eight feature groups: 28 of them belong to the group of purchase information related features, 7 of them belong to the group of membership information related features, 5 of them belong to the group of personal information related features, 2 of them belong to the group of shopping cart actions related features, 4 of them belong to the group of products collection actions related features, 2 of them belong to the group of products visiting actions related features, 1 of them belongs to the group of customer coupon sensitivity, and 1 of them belongs to the group of customer purchase capacity related features.

4.4 Training Model Selection and Parameter Tuning

We determine to investigate four training model candidates and choose the best one among them, and they are: Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF) and Gradient Boosting Decision Tree (GBDT). In our pioneer study, we noticed that GBDT can provide better accuracy, precision and recall than the other three, and hence we choose GBDT as the training model. In order to confirm the validity of the selected GBDT training model and its parameters, we further investigate the GBDT model by using the first half of the historical data as the training dataset and the second half of the historical data as the prediction dataset, and the results show that the accuracy is 83.6%, the precision is 0.82 and the recall is 0.77. Although the accuracy is not very high, considering the huge amount of base data and the limited lucky money budget, we assume that the data with correctly predicted results is large enough for assigning lucky money properly. The machine learning model, denoted as G(F), can be represented as below:

$$G(\boldsymbol{F}) = g(x_1, x_2, \ldots, x_n), \mathrm{n} = 50(\textit{features count}) \tag{4}$$

Where g(.) is the function that represents the GBDT model used for predicting the purchase status and x_i denotes each feature of any customer inside both the training dataset and the prediction dataset. This answers the research question 2.

4.5 Data Prediction

We use the result returned by the GBDT model to calculate the purchase rate of each customer in the prediction dataset. The features of each customer in the prediction dataset are denoted as $\mathbf{X}_i$, and the GBDT machine learning model can be denoted as g ($\mathbf{X}_i$), so the purchase rate of the customer, denoted as P_i, is calculated as:

$$P_i = g(\boldsymbol{X_i}), \mathrm{i} \in T \tag{5}$$

Where T is the count of the target customers inside the prediction dataset.

When we make the prediction, the feature of lucky money amount does not use a fixed value. Instead, we use a set of sample lucky money amounts for this feature. The minimum lucky money amount must be in accordance with the requirements of the stakeholders (e.g. 1 RMB); the maximum amount should also satisfy the business requirements (e.g. 25 RMB); the average lucky money amount can also be determined according to the overall lucky money budget and the number of lucky money target customers. Suppose the minimum lucky money amount is 1, the maximum lucky money amount is 25 and the average lucky money amount is 8, then the lucky money samples used in DAliM could be 1, 5, 8, 10, 15, 20, 25. The purchase rate values returned when using all of these lucky money samples can be denoted as P(1), P(5), P (8), P(10), P(15), P(20) and P(25), respectively.

4.6 Lucky Money Determination

After we obtain each customer's purchase rate for each sample lucky money amount, we can determine how much lucky money can hit the intended purchase rate specified by the stakeholders. We define the stakeholder-specified purchase rate as R and for each customer we need to find the target lucky money amount, denoted as M, to make sure R and M can satisfy the following formula:

$$R \leq g\left(X_i', M\right), \mathrm{i} \in T \tag{6}$$

Where X_i' denotes the customer's features excluding the feature of the lucky money amount and g(.) is the function that represents the GBDT model used for predicting the purchase rate. Considering the rule that larger amount of lucky money results in a higher purchase rate, we argue that the final lucky money can be determined by making and analyzing the regression over the sample lucky money amounts and the corresponding purchase rates. Suppose the lucky money samples are denoted as set **S**, and the predicted purchase rates for all the lucky money samples are denoted as set **P**, we apply a smoothing regression algorithm to determine each customer's target lucky money amount, as shown in the below algorithm. The inputs are the lucky money samples set **S**, the purchase rates set **P** in response to **S** and the stakeholder-specified target purchase rate R. This algorithm is able to assign the appropriate money to the customers sensitive to lucky money, which answers our research question 3.

Algorithm 1: Lucky Money Amount Determination Algorithm

Inputs: the lucky money samples set ***S***, the purchase rates set ***P***,
the stakeholder-specified purchase rate *R*

Output: the final lucky money amount

```
function DetermineLuckyMoney (S, P, R) {
  for (i ← 1; i < |S|; i++) {//this is for smoothing the rates
    if (P[i] < P[i-1]) {
      P[i] ← P[i-1];}}
  for (j ← 0; j < |P|; j++) {//this is for regression of the rates
    if (P[j] >= R) {
      if (j == 0) {return S[j]; }
      else if (P[j] == R) {return S[j]; }
      else if (j > 0) {
        slope ← (P[j] - P[j - 1]) / (S[j] - S[j - 1]);
        amount_to_deduct ← (P[j] – R) / slope;
        lucky_money ← S[j] - amount_to_deduct;
        return lucky_money; }}}
  return 0; //if all the rates are smaller than R, return 0
}
```

5 Experimental Evaluation

We have implemented DAliM for the promotion activity called "Double 11 Global Shopping Festival 2017" initiated by Alibaba Group, as such, our experimental evaluation is based on a real-world large scale scenario. In the following subsections, we describe the experimental environment, illustrate the experimental procedure, analyze the experimental results and provide some discussion for the experimental results.

5.1 Experimental Environment

The experimental environment is shown in Fig. 2. The historical training data are stored in Alibaba Group's big data processing platform (ODPS), which provides distributed data storage services and big data processing services. This is where we warehouse all the training data and prediction data. Then, the training data and the prediction data are passed to the distributed machine learning platform.

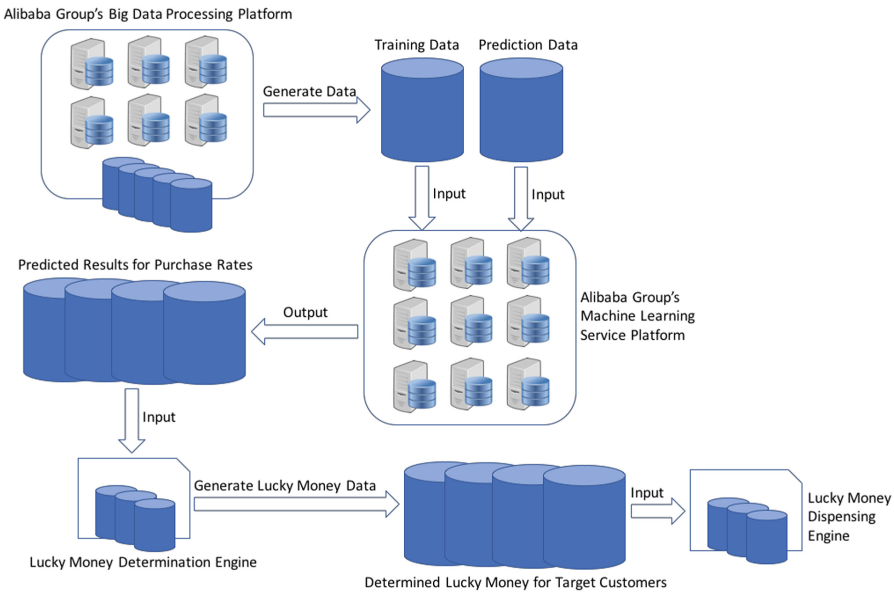

Fig. 2. Experimental environment

The machine learning model is derived based on the training data, and 4 groups of prediction data will be inputs of the machine model for purchase rates prediction. Next, we employ our lucky money determination engine to figure out the appropriate lucky money that can satisfy the stakeholder-specified requirements for each target customer. Finally, the lucky money will be dispensed to these customers through our lucky money dispensing engine. Alibaba Group is using a web service-oriented architecture for all of the services involved in the experiment, and we make use of these web services via front-end browsers.

5.2 Experimental Procedure

We run two sets of lucky money dispensing mechanisms simultaneously: the first one uses our proposed method and the second one uses the random lucky money based method. By using the random lucky money base method, the customers who should receive lucky money are randomly selected and the lucky money amounts given to them are also randomly determined, and the random amounts are within the threshold set by the stakeholders. The second method meets Alibaba Group's business standards and requirements, and hence it is used for comparison with our proposed method. For each prediction sub-dataset, we divide it into two sets, where the first set uses the old method and the second set uses our method. As such, these two methods are applied on two sets of customers for each of the 4 prediction sub-datasets, and these two customer datasets have the same statistical distribution because we control both of their volumes to be statistically large enough, though they are different in size. In this way, essentially we apply the AB testing. The customers whose lucky money is determined by our method are called the B-group, and the customers whose lucky money is determined by the existing old method are called the A-group. The experimental procedure is strictly following the lucky money dispensing and spending workflow executed in the promotion activity of "Double 11 Global Shopping Festival 2017". Hence, the experimental procedure is as below:

Step 1: determination of the A-group and the B-group of target customers. For each of the 4 prediction data groups, we randomly select 2% of the customers in the group as the A-group and select the remaining customers in the group as the B-group. By doing so, we can make sure that the distribution of the A-group is the same as the distribution of the B-group, and we can also to a large extent avoid the negative effects that are brought by the existing old method.

Step 2: making all the target customers receive the pre-arranged lucky money. The promotion activity takes place on 11 Nov 2017; between 1 Nov 2017 and 7 Nov 2017, it is the time for dispensing lucky money to customers. During these 7 days, every customer will receive the lucky money after he/she logins into the e-commerce web page and clicks on the promotion activity button. The customers in the A-group will receive the money determined by the existing method while the customers in the B-group will receive the money determined by our proposed method. However, the received lucky money is not allowed to be used until 11 Nov 2017 (Double 11).

Step 3: customers purchasing products with the given lucky money. On the day of 11 Nov 2017, all the target customers who have received lucky money will make a purchase with the given lucky money, and we record the details of all of these transactions, including whether each customer has made any purchase.

Step 4: obtaining purchase status data of the A-group and the B-group and making a comparison between them. For each of the 4 groups of prediction data, we compare the purchase rate of its A-group and that of its B-group.

5.3 Experimental Results

We obtain the experimental results for each of the 4 groups of target customers: normal customers, watch-only customers, competitor customers and lost customers. Each group consists of the A-group and the B-group, and for both the A-group and the B-group, we calculate the actual purchase (denoted as Ra) based on the formula below:

$$R_a = \frac{N}{M} \times 100\% \tag{7}$$

Where N is the number of those customers who have made any purchase with the given lucky money, and M is the number of all the customers who have been given lucky money.

We first show the results for the overall target customers and walk through the experimental results for the 4 groups of target customers one by one. The experimental results for the overall customers are shown in Table 2.

Table 2. Experimental results for overall customers.

Group	AB-group	Lucky money methods	Decreased average amount (B over A)	Increased purchase rate (B over A)
Overall customers	A-group	Existing old method	41.71%	24.94%
	B-group	DAliM		

We can see that the average lucky money amount for the B-group which uses DAliM has decreased significantly by 41.71% compared to the average lucky money amount for the A-group which uses the existing old method, and the actual purchase rate when using DAliM has increased by 24.94% compared to the actual purchase when using the existing old method. Hence, DAliM improves on the existing old method. On the one hand, DAliM is able to save money; on the other hand, DAliM is able to increase the actual purchase rate.

For the experimental results for the normal customers, we notice that the average lucky money amount for the B-group which uses DAliM has decreased by 43.56% compared to the average lucky money amount for the A-group which uses the existing old method, and the actual purchase rate when using DAliM has increased by 26.4% compared to the actual purchase rate when using the existing old method. The results show that normal customers make frequent online purchases regularly, and there is no need to attract them by giving them a relatively large amount of lucky money.

For the experimental results for the watch-only customers, we notice that the average lucky money amount for the B-group which uses DAliM has increased by 100.73% compared to the average lucky money amount for the A-group which uses the existing old method, and the actual purchase rate when using DAliM has increased by 18.4% compared to the actual purchase rate when using the existing old method. The fact that the average lucky money amount when using DAliM is more than the average amount when using the old method is in accordance with the stakeholder's expectation, because a good possible way to drive customers who show interest in buying products but do not actually buy them to make the purchase is to provide them with more price discount. Our suggested approach is able to find out this rule and take advantage of it. Nevertheless, we notice that both methods do not result in a very high purchase rate, and this is because making watch-only customers buy products is intrinsically a challenge. Anyhow, DAliM improves on the existing old method.

For the experimental results for the competitor customers, we notice that the average lucky money amount for the B-group which uses DAliM has increased by 105.03% compared to the average lucky money amount for the A-group which uses the old method, and the actual purchase rate when using DAliM has increased by 16.0% compared to the actual purchase rate when using the existing old method. The relatively higher expenditure on lucky money is because a good possible way to drive customers who only buy products from an e-commerce corporation's competitor is to provide them with better price offers, and a relatively large amount of lucky money is equivalent to a better price offer. Both methods yield relatively low purchase rates because making the customers who have got accustomed to our e-commerce business's competitors switch the loyalty to our e-commerce business is not that straightforward and requires many other conditions.

For the experimental results for the lost customers, we notice that the average lucky money amount for the B-group which uses DAliM has increased by 103.91% compared to the average lucky money amount for the A-group which uses the old method, and the actual purchase rate when using DAliM has increased by 17.5% compared to the actual purchase rate when using the existing old method. The results show that a potential way to drive customers who no longer buy products from our e-commerce business is to provide them with better price offers and more discounts.

5.4 Discussion

The experimental results are in accordance with the business requirements defined by the business stakeholders. It is requested that the minimum number of customers receiving lucky money should be reasonable, and the expected number of customers who will buy products during the promotion activity should be a relatively large number. So, the overall target purchase rate can be calculated based on this information. With the lucky money budget set by the stakeholders, the average lucky money per customer can be calculated. For the sake of business confidentiality, we do not show these numbers in this paper. As such, we compute the actual average lucky money amount per customer resulting from our method and can find that it is within the stakeholder-defined average amount; the actual purchase rate when using our method is also larger than the stakeholder-specified target purchase rate. Moreover, with DAliM, 28% more customers have received the lucky money compared to last year's promotion activity, which well satisfies the stakeholder-specified requirement about the number of lucky money target customers.

6 Conclusions and Future Work

E-commerce businesses compete for the market by several ways, one of which is called the Lucky Money strategy. Lucky money is a type of intermediary that is capable of encouraging customers to buy products from marketplaces. However, the existing ways of lucky money determination usually cannot fully satisfy the business objectives and goals set by the stakeholders, especially for large-scale e-commerce businesses like Alibaba Group. As such, this paper proposes a lucky money intelligent determination approach, called DAliM, for e-commerce businesses to achieve their predefined business objectives such as purchase rates. We design and implement DAliM based on a set of machine learning based techniques. It is able to issue an appropriate amount of luck money to each customer to make sure the customers can buy products at the stakeholder-defined purchase rate. We evaluate DAliM in a real promotion activity named "Double 11 Global Shopping Festival 2017" initiated by Alibaba Group. A few hundred million real customers' data from all over the world have been used for the evaluation. The experimental results show that our method can decrease the lucky money spent by 41.71% and increase the final purchase rate by 24.94% on average compared to the existing old method.

Our future work includes: (1) try applying DAliM on other promotion activities and research on how to readjust it to cater for these activities; (2) obtain more historical training data, train a more accurate prediction model and propose a better way of selecting the target customers of the promotion activity.

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