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International Conference on Electronic Business (ICEB)

Winter 12-4-2016

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THE EFFECT PREDICTION OF ACQUIRING NEW CUSTOMERS BASED ON GONGTIANXIA'S DUTCH AUCTION[1]

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ABSTRACT

With the development of the Mobile Internet, many E-commerce sites are using mobile applications to promote marketing and to acquire new customers, mobile marketing activities has become one of the best ways to expand market share. Therefore, it's very concerned to study how to acquire new customers effectively in the early stage of entering the market. Gongtianxia's WeChat public platform is committed to attract new customers through Mobile Internet. Gongtianxia adopted two kinds of Dutch auctions, '7-day auction' and '15-minute auction' respectively, which can effectively acquire new customers. This study collected more than 80000 of records, 738 pieces of auction data from June 2015 to December 2015 in Gongtianxia's Dutch auctions, by collecting, sorting and analyzing the auction data, and established a BPNN simulation and prediction model. The prediction model for each auction data can be used to predict the customer number, cost and blowout price in advance of the auction. This study can improve customer-attracting effect of mobile application and make a theoretical complement for Dutch auction as Mobile Internet sale, and enriches the research for acquiring new customers through Mobile Internet.

Keywords: Dutch Auction, Acquiring New Customers, Prediction Model, BPNN

INTRODUCTION

With the popularity of smart phones, mobile commerce becomes a new trend. At the end of June, 2016 China's mobile phone users reached 656 million (CNNIC, 2016). A lot of traditional enterprises are transforming their business to mobile internet, and want to acquire new customers through mobile devices. More and more traditional enterprises have recognized that their customer base is their valuable asset[1][2]. Previous studies have proved that the cost for developing a new customer is 5 to 9 times of that maintaining an existing one, thus new customers consume more business costs than loyal clients. However, gaining new customers is the first step to occupy a certain market share. So, how to develop new customers effectively and efficiently is very worthy of study. Conventional customer developing methods are diverse, such as manual dialing, messages, leafleting and hosting promotional events. These methods required huge capital and time costs but missing the expected customers responses. Enterprises urgently require to explore an effective marketing mode with more customer engagement to attract new customers [3].

Potential customers exploring is a significant activity for enterprise development [4]. Mobile Ecommerce has diverse methods to attract new customers including creating hot topics, advertising through Weibo and WeChat[5]. WeChat Subscription has become to a popular platform for mobile commerce enterprises to attract new customers since WeChat users has been rapidly increasing. However, existing models of data integration, data capturing, cost estimation and prediction performance of attracting customers can not address the need for varied marketing mode of mobile Ecommerce[6][7][8].

Gongtianxia is a B2C E-commerce website was built in 2011, devoted to providing high-quality agricultural products for customers[9][10]. GonTianxia platform classified the agricultural products according to the location such as Shanxi, Yunnan,

[1] Supported by NSFC No.91546125,No.71072147
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Hainan, and Guangxi, which are all Chinese provinces, providing nearly 5000 kinds of local products including snack food, dairy, meat, poultry, grain, condiments, nuts, vegetables and seafood. With the fast development of Wechat, Gongtianxia realized that the use of Wechat platform was a tremendous opportunity to attract new customers. In the end of 2014, Gongtianxia established a WeChat public platform and launched Dutch auctions, which are '7-day auction' and '15-minute auction'[11]. '7-day auction' and '15-minute auction' are both descending price auctions with fixed total items number in which the auctioneer begins with a market price which becomes lower as time goes on according to the established rules, until the total items sold out. In '7-day auction' the price will be decreased to next auction price in 10 pm everyday, at the last day the auction price will be decreased to 1 RMB. Likewise, the auction price will be decreased every 15 minutes during 105 minutes, at the last 15 minutes the auction price is 1 RMB in '15-minute auction'. But the total items number is fixed, when the items sold out, the auction automatically stop. During an auction, some participants would be willing to accept a certain price if there are still items available until the predetermined bottom price (1 Yuan in this case) is reached. However, blindly waiting for lower prices can lead to missing out on the auction given the limited availability of items. The average deal prices are usually lower than the regular price on the market. Gongtianxia's Dutch auction lost hundreds and thousands of money, but it acquires almost 300 thousand new customers.

This study of Gongtianxia lays a strong emphasis on how to attract more customers with minimum cost on one auction. Theoretically, this research focuses on comprehensive analysis of online Dutch auction, WeChat marketing and new-customer attracting cost which is effective supplement for previous studies. Existing researches of online auction mainly emphasized particularly on pricing strategy and bidding strategy, ignoring the fact that Dutch auction, as a carrier of network marketing, can help bring new customers[12][13].

The rest of the paper is organized as follows. The next section (Section 2) is a literature review. This is followed by the research methodology in Section 3. We describe our research design and data analysis in the fourth section, and present the research discussion in the fifth section. We conclude the paper in Section 6 with contributions, limitations and directions for future research.

LITERAL REVIEW

Dutch Auction

Descending price auction is also known as Dutch auction, which is named for its best known event, the Dutch tulip auctions. Dutch auction is a type of auction in which the auctioneer begins with a relatively high asking price which is lowered until some participants are willing to accept the price[14]. Dutch auction is also used to describe online auctions where several identical goods are sold simultaneously to an equal number of high bidders[15]. In traditional Dutch auction, bids of increasing value are made until a final selling price is reached, because due to ever-decreasing bids buyers must act decisively to name their price or risk losing to a lower offer [16].

Most current researches on Dutch auction focus on mathematical calculation and experiment analysis. Guerci E. and Kirman A. (2014) proposed an original model of bounded rational behavior for wholesale buyers' behavior incorporating learning to improve profits [17]. Artyom Shneyerov (2007) found that for optimal revenue-maximizing clock in a slow Dutch auction, where the clock falls over time, the clock is genuinely dynamic and the auction involves delays since the buyers are less patient than the seller [18].

Based on the basic theory of auction, we summarize the characteristics of Dutch auction as follows:

(1) Dutch auction helps allocate market resources reasonably.
(2) Dutch auction is conducive to buyers under the information asymmetry between buyers and sellers.
(3) Dutch auction is a better decision for risk-averse buyers and sellers.

(4) Price methods of Dutch auction can prevent undesirable price discrimination that lessens competition or injures a small competitor.
(5) Dutch auction is a time-saving auction since the auction is concluded once the bidder makes an offer [19][20][21].

Online Auction Marketing
Online auction is defined by some scholars as ‘an auction in which both sides can bargin on the online platform offered by internet service providers ’[22].

Current domestic and international research of online auction was mainly conducted focused on following aspects:

Legal risks. Online auction is a new concept in China, at present there is no explicit laws and regulations as the basis, so it is particularly urgent to do research on the arising legal risks and countermeasure.

Credit evaluation. Yang J. (2007) proposed a new Credit Evaluation Index System based on users’ satisfaction survey, trying to compensate the deficiencies of early studies [23]. Zhou L A. demonstrated the huge effects of sellers’ reputation on transaction outcomes in online auction marketplace [24].

Bidding strategy. Existed literatures mainly analyzed the dominant strategy in bidding based on the English auction[25].

However, this paper lays emphasis to how online auction attract new customers as a novel network marketing mode. Online auction is a relatively successful form of e-commerce. Both English auction and Dutch auction appeal to customers with low price. Therefore, online auction can easily lead to high-quality traffic and more effective trades, since new entrants in e-commerce market tend to promote their commodities in an online auction. [26].

In the aspect of the fundamental research, most scholars hold that online auction theory has the same foundation as the classic auction theory. Based on economic game theory, data analysis and field experiments are popular as a way of analyzing specific issues of auction. This study concentrates on how Dutch auction, as a marketing tool, brings in new customers. This topic is roughly classified as an auction revenue problem.

One of the major finding of auction theory is the celebrated Revenue Equivalence Theorem(RET) proposed by William Vickrey in 1961[27]. The Revenue Equivalence Theorem states that any allocation mechanism/auction which meets the benchmark auction model will lead to the same expected revenue for the sellers. This theory is an applied branch of economics which deals with how people act in auction markets. However, it cannot be directly applied to online auctions. This study attempts to address this research gap through the case of Gongtianxia [28].

The Dutch auctions on Gongtianxia WeChat platform can attract customers and turn potential customers to valid ones, and has instructional significance to Customer acquisition management, which is worthy of study.

Generally, most researches on Dutch auction focused on analysis of gaming behavior between bidders and sellers, also expounded bidding strategy based on game theory. Dutch auction as an online marketing tool has been poorly studied; Moreover, most of the researches are only restricted in marketing modes and costs. This paper, based on online Dutch auction as an novel marketing approach, establishes a prediction model of per-customer attracting cost, new-customer quantity and blowout price through the analysis of how quickly new clients are added. Based on this model, it becomes possible for Gongtianxia to attract more customers and minimize the cost at the same time.

RESEARCH METHODOLOGY

Using BP Neural Network for Prediction

The current prediction methods which are comparatively popular and commonly used in academic circles include the following aspects: Causal analysis, such as Regression analysis. Judgment analysis is a qualitative research method that experienced management and operation personnel or experts can make sales forecasts over a certain time horizon relying on experience. SVM (Support Vector Machine) . In machine learning, SVM is a supervised learning model that analyzes data used mainly for classification. It requires full labeling of input data and is only directly applicable for two-class tasks [29].

Several factors have to be considered when selecting an appropriate neural network model. The dependent variables are numerical, thus SVM is inappropriate. Also, we make the correlation analysis by using the statistical analysis software SPSS as a tool, and found no obvious linear correlations between the independent variables. Thus regression analysis is also inappropriate.

Since Gongtianxia provides with available data, training of a neural network model could be supervised. Furthermore, the vector lengths and training set sizes were relatively small. This alleviated pressure to find quick and approximate methods for training. These considerations led to the selection of BPN, popularly called back propagation networks. It can be seen as a device which imitates the brain’s functions. During the training process, the network will learn to ignore any inputs that don't contribute to the output. Thus, back propagation can minimize output error by iteratively descending the steepest gradient of the error surface. This is suitable for this case since the variables have multiple data types. Though it cannot reveal the relationships between the independent and dependent variables, repeated tests proved its acceptable error range.

Creating a model which relates input variables to output results has several uses. First, the management can take actions based on the effects that the auction conditions have on selling. Second, we can adopt a piece-wise analysis of input variables for their impact on the final product. Third, the relationship can be inverted so that desired customer-attracting effect can dictate certain auction conditions.

Data Processing and Analysis for Descending Price Auction Introduction for Two Kinds of Auction

Gongtianxia has two different types of auction: ‘7-day auction’ and ‘15-minute auction’, the daily number of new auction is about 1-3.

“7-day auction” form:

(1) Each auction lasted for 7 days, the price will drop at 22 o'clock everyday, and for 6 times. For each time the price reduction gradient is different, and the price will drop to 1 RMB at the seventh day (also the last day) of the auction.

(2) The total number of items is fixed for each auction, the number of remaining items displayed in the top of the auction, to show customers the real-time auction merchandise surplus, to gradually reduce the number of items to encourage customers to make a purchase, until the time the auction ends or merchandise sold out.

‘15-minute auction’ is similar to ‘7-day auction’:

(1) ‘15-minute-auction’ start at 20:00 o'clock everyday and last for 105 minutes, and the price will drop every 15 minutes for 6 times in total with a different price gradient each time. Until the last time the price will drop to 1 RMB.

(2) The presentation of the number of remaining items and the end of the auction mode is the same as ‘7-day-auction’.

AUCTION DATA COLLECTION AND PROCESSING

Data Collection

This paper focuses on the study of descending price auction's pulling effects on new customers, acquired a 191-day auction data from June 2, 2015 to December 9, 2015 for "7-day-auction", 253 times in total, and a 106-day auction data from June 1, 2015 to September 14,2015 for "15-minute-auction", 485 times in total. Two kinds of auction data collection fields include product name, product information, starting price, starting quantity of a commodity, whether shipping, freight price and every auction price from the beginning of each, the sales records including a purchase of customer name, purchase quantity, the purchase price and the purchase time, a total of about 90,000 auction records. The amount of data is shown in table 1.

Table 1. Two kinds of auction data

Auction type	Auction time	Lasted days	Auction times	Auction records
7-day-auction	2015/6/1~2015/12/9	192	253	24840
15-minute-auction	2015/6/1~2015/9/14	106	485	63446

Independent Variable Selection

Two kinds of auction data collection fields include product name, product information, goods starting price, starting quantity of a commodity, whether shipping, freight, price and every auction price from the beginning of each, the sales records including a purchase of customer name, purchase quantity, the purchase price and the purchase time. While the product name and product information belongs to a text message. All the auction goods are local products, most of which are the food, beverage and supplemented, belonging to the same category of goods. Also, the price differences is not big. Therefore, this study will not consider the situation of divided types of goods.

(1)Auction type

According to Artyom Shneyerov (2014)'s research in the Slow Dutch Auction (SDA), lasting longer is more benefit to business, because business is more patient than consumers in the descending price auction[18]. This paper acquired two different auction types, "7-day-auction" and "15-minute-auction", lasting for different duration, and making the auction type as an independent variable to research.

(2)Starting price

Since this study cannot directly get the cost price of each auction item, and per-customer attracting cost is the cost of capital relative to the normal sale of goods, the price lower than the normal selling price of the auction will be treated as per-customer attracting cost. This study selects starting price as a reference, as the normal selling price, used to calculate the cost to pull new.

(3)Starting quantity

Number of auction items is a very important factor in a descending price auction. Oversupply of certain auction commodity can lead to the redundancy of goods at the end of the auction. If the quantity of an auction commodity is too small, the termination of the auction may occur in advance. How to set up an appropriate number of auctions, in order to ensure the normal auction and motivate consumers to make a purchase is very worthy of study.

(4) Shipping freight

Commodity prices during the descending price auction is tempting, but rational consumers will usually regard commodity transportation as an important reference standard, to decide whether to make a purchase[30]. Thus, whether the goods is "free shipping," or how much freight has also become an important reason for consumers to measure the value of the goods, which affect consumer willingness to buy.

(5) Price reduction gradient

Each auction has a total of the price reduction gradient for seven times, but each time the gradient of the price reduction are different, and at the last time price will be unified down to 1 RMB. The price of each auction after the price reduction will directly affect the cost of pulling new customer purchase behavior. Therefore, setting a reasonable price gradient can effectively improve the auction results. In this study, in order to make the price reduction gradient unified data visualization, For each auction price statistics have been processed, the i^{th} price reduction gradient is as follows：

$$G_i = \frac{P_i}{P_1} \tag{1}$$

(While $P_i$epresents the price after the i^{th}price reduction, P_1represents the starting price of the commodity.)

(6) Starting date

According to the starting date and the three dependent variables' scatter plot analysis, we found that there is no clear upward or downward trend between the date and the dependent variable, and the selected data range is small, therefore, this paper does not include date variable as an independent variable to analysis. But some studies show that, for agricultural' regressive auction, there is a phenomenon called "Calendar Effect", existing "iconic point of time", like promotional factors can make the same volume of goods changed significantly. Based on this, whether the starting date is weekend or not is also important.

Dependent Variable Selection

(1) Blowout price

Blowout price is the price that brings the maximum volume of sales for each auction. The forecast for blowout price can guide businesses to push auction information or do other promotions to new customers, in order to improve the success rate of the customer's purchase. Meanwhile, blowout price affects the new customer attracting cost. The higher blowout price is, the lower new customer attracting cost is.

(2) New customer quantity

The customer who purchase on the Gongtianxia platform for the first time is a new customer. The data is collected from June 1st, 2015, so we save the original customer database to May 31, 2015, and there has been a total of 10,293 customers by then. We investigate new customer information from June 1, 2015 appears in every auction for both "7-day auction" and "15-minute auction", and then update the new customer to the original customer database. The second day's investigation will use the updated database, and in the next day the new customers' data calculation methods is the same. In this paper, we use Java program to achieve new customer daily calculation.

(3) Per-customer attracting cost

In this study, we use the starting price as the original price. A price gap due to the descending price mechanism can be considered as marketing expense for every sale. It aims to attract more new customers to buy successfully and maintain old customers to become loyal customers. We use the calculation formula for per-customer attracting cost to calculate every auction's cost as following.

$$C = \sum_{i=0}^{n}(P_1 - P_i) \times m \tag{2}$$

(While C represents auction cost, m represents every auction's quantity.)

According to the definition of independent and dependent variables, the data need calculation processing, shown in Figure 1.

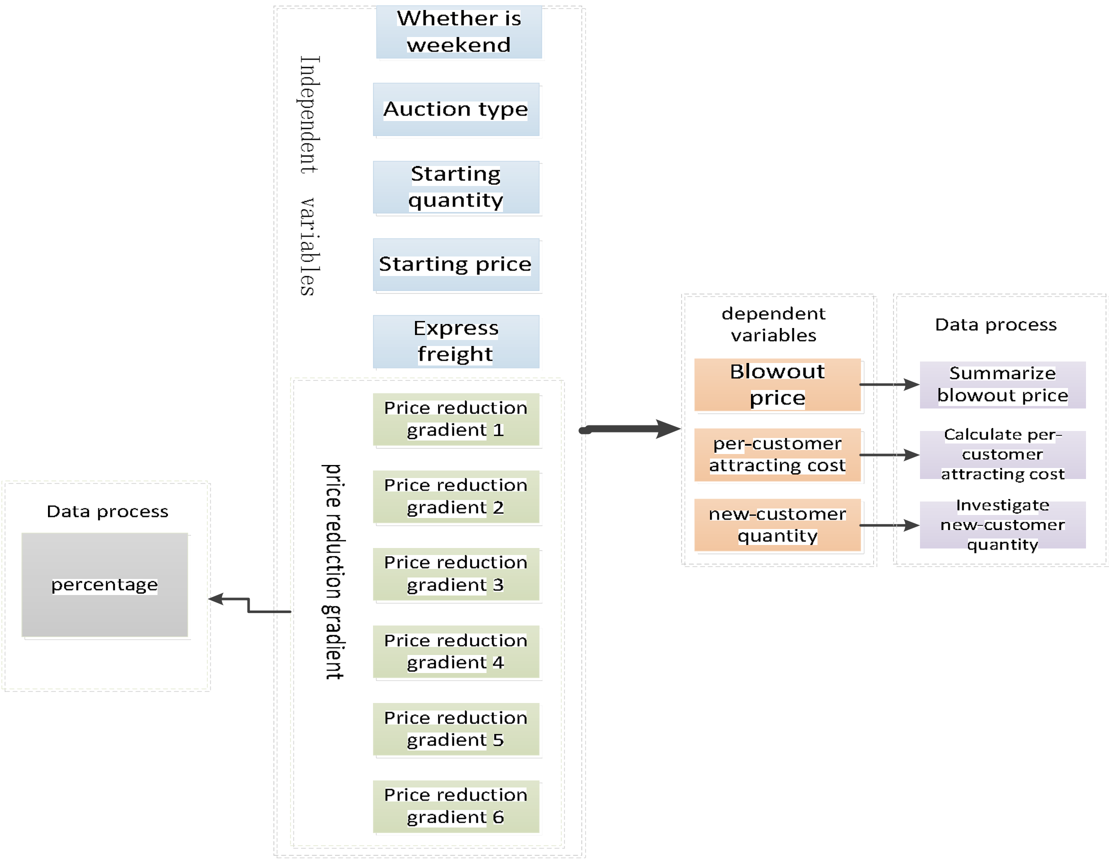

Figure 1. Model Variables

Auction data analysis

"7-day Auction" is Better Than "15-minute Auction"

In a slow Dutch auction, if the auction last longer, the sellers can get more profit, since businesses are more patient than customers[18]. Therefore, this paper use auction data to compare these two types of auctions' per-customer attracting cost and new-customer quantity.

Table 2. Analysis of Per-customer Attracting Cost and New-customer Quantity for Two Auctions

Auction type	Auction times	Total new-customer quantity	Total customer attracting cost	Average of new-customer quantity	Average of new-customer attracting cost	per-customer attracting cost
7-day auction	253	4316	660494	17.0593	2610.648	153.5675
15-minute auction	482	8277	1775729	17.1722	3684.085	214.191

Currency Unit:RMB

From the table, the average of new-customer quantity for "7-day auction" and "15 minutes beat" is nearly same, in the second half of 2015, each auction has pulled around 17 new customers, which shows that two kinds of auctions' pull new effect is approximately the same. But in the case of new-customer pulling effects, 7-day auction's average customer attracting cost and per-customer attracting cost is less than "15-minute auction", that is, "7-day auction" can help businesses save the cost of capital, which is same with Artyom Shneyerov's conclusion.

Free Shipping Has Positive Effects on Auction Effect.

Commodity prices during the auction is tempting, but rational consumers will usually use if shipping goods as an important reference standard, to consider whether to make a purchase [30]. So this paper will use if free shipping as an argument for a more detailed analysis. To make data analysis more regularity, two kinds of auction data integration, increase the amount of data to enable analysis persuasive. Now integrate two auction's data to analyze and calculate.as shown in table 3.

Table 3. Data Analysis for Free Shipping(1)

	Average of new-customer attracting cost	Average of new-customer quantity	per-customer attracting cost
All auctions: 735	3314.59	17.13	196.46
Free shipping auctions:381	2927.74	16.61	176.28
Not free shipping auctions:354	3730.94	17.70	210.81

Currency Unit: RMB

From the table, free shipping has almost no impact on the average of new-customer quantity, Average of new-customer quantity is 17, but per-customer attracting cost is reduced and form polyline. A brief description is that free shipping can reduce per-customer attracting cost.

The starting price of goods usually has some effects on whether the customer to make a purchase. If the starting price is high and the price drop by a big margin, customers will feel encouraged to buy because of the greater perceived benefits for customers. In order to explain the number of free shipping's new-customer quantity is unchanged, and per-customer attracting cost reduction issue, we calculate some other variables, as average starting price, average blowout price, average of purchase times and new customer proportion. As the table 4 below:

Table 4. Data Analysis for Free Shipping(2)

	Average of new-customer attracting cost	Average of new-customer quantity	per-customer attracting cost	Average starting price	Average blowout price	Average of purchase times	New customer proportion
All auctions: 735	3314.59	17.13	193.46	37.55	12.81	149.39	8.57%
Free shipping auctions:381	2927.74	16.61	176.28	44.39	17.81	109.93	16.20%
Not free shipping auctions:354	3730.94	17.70	210.81	30.19	9.60	191.85	5.00%

Currency Unit: RMB

Starting price of free shipping auction is 44.39 RMB for 381 times on average, and is 30.19RMB of not free shipping auction for 354 times on average. This result demonstrate that the starting price of free shipping goods are usually higher, although the starting price is higher but because of the free shipping promotion that the average of new-customer quantity is not significantly reduced, but maintained the same with the level of no free shipping auction. Therefore, free shipping can contribute to new customers to buy higher starting price of commodities.

Variable Correlation Analysis

In this study, we define 11 independent variable: whether is weekend, auction type, starting price, starting quantity, express freight, price reduction gradient 1, price reduction gradient 2, price reduction gradient 3, price reduction gradient 4, price reduction gradient 5, price reduction gradient 6; and 3 dependent variable, per-customer attracting cost, new-customer quantity, and blowout price. This paper uses SPSS to analyze the correlation between the independent variables and the dependent variables.Correlation analysis is associated with two or more of the variable element analysis to measure how closely two variables related.

This study respectively analyzes the relevance between independent variables and the dependent variables for both “7-day auction” and “15-minute auction”, to see if their relevance is high. The results of correlation analysis of independent variables and dependent variables are shown in the following table.

Table 5. Correlation Analysis Summary Table

R value	Whether weekend	Auction type	Starting price	Starting quantity	Express freight	Gradient 1	Gradient 2	Gradient 3	Gradient 4	Gradient 5	Gradient 6
blowout price	0.003	0.061	0.833	0.261	0.287	0.317	0.403	0.463	0.523	0.569	0.652
per-customer attracting cost	0.195	0.024	0.470	0.677	0.153	0.444	0.479	0.485	0.456	0.415	0.272
new-customer quantity	0.082	0.210	0.067	0.565	0.022	0.394	0.375	0.346	0.328	0.305	0.055

(Categorical variables’ correlation analysis use Spearman correlation coefficient. The correlation coefficient with the classified nature is the same with Pearson coefficients.)

The above table shows that the most independent and dependent variables is moderately or weakly correlated, and the significance is not obvious, so this paper use BPNN(BP neural network) model, which doesn’t require high correlation to do experiment to find higher accuracy rate for forecast model.

BP NETWORK PREDICTIVE MODEL

Modeling Steps

This study selected BP neural network algorithm to build predictive model, BP neural network (back propagation neural network) is a Multi-layer feedforward neural network. The network topology diagram is shown as following, auction type, Starting price, Starting quantity, Shipping freight, Price reduction gradient and starting date is the input of BPNN, blow out price, new customer quantity and per-customer attracting cost are the predictive value of BPNN. For the forward pass, the input signal coming from the input layer goes through the hidden layer and receives processing until it reaches the output later. The states of neurons in each layer only affects the next level. If the output layer does not output the desired result, then enter the back-propagation phase of errors, adjusting the network weights and thresholds based on the prediction error, to make the BP neural network output closer to the desired output.

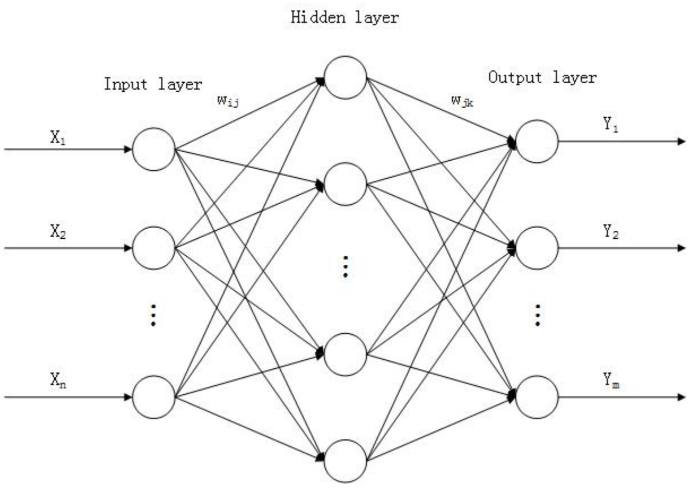

Figure 2. BP network topology

BP neural network can be seen as a non-linear function, the network input and predicted values respectively represent the independent and dependent variables of the function. and are the BP neural network weights, when the input node number is n,output node number is m,BP neural network is expressed from the n independent variables to the m dependent variable function mappings.

BP neural network training process includes the following steps.

Step 1: Network initialization. According to the system's input and output sequence (X,Y) to determine the network nodes in the input layer n, hidden layer l,and output layer m, to initialize the connection weights between the input layer, hidden layer and output layer and , to initialize the threshold of hidden layer a and the output layer threshold b, given the learning rate and neuronal excitation function.

Step 2: Hidden layer output calculation. According to the input variable X, the connection weights between the input layer and hidden layer, and hidden layer threshold a, to calculate hidden layer's output H.

$$H_j = f(\sum_{i=1}^{n} w_{ij}x_i - a_j) \qquad j = 1,2,...,l \tag{3}$$

While l is the number of the hidden nodes; f is hidden layer activation function.

$$f(x) = \frac{1}{1+e^{-x}} \tag{4}$$

Step 3: Calculate the BP neural network prediction output O.

$$O_k = \sum_{j=1}^{l} H_j w_{jk} - b_k \qquad k = 1,2,...,m \tag{5}$$

Step 4: Error calculation. Calculate the gap between predicted output and the desired output e.

$$e_k = Y_k - O_k \qquad k = 1,2,...,m \tag{6}$$

Step 5: Update the weights. The network update the connection weights w_{ij} and w_{jk}, according to the prediction error .while η is the learning rate.

$$w_{ij} = w_{ij} + \eta H_j(1-H_j)x(i)\sum_{k=1}^{m} w_{jk}e_k \qquad i = 1,2,\mathrm{L}\ ,n; j = 1,2,...,l \tag{7}$$

$$w_{jk} = w_{jk} + \eta H_j e_k \qquad j = 1,2,...,l; k = 1,2,...,m \tag{8}$$

Step 6: The threshold updating. According to the network predict error e to update the new network node threshold a, b.

$$a_j = a_j + \eta H_j(1-H_j)\sum_{k=1}^{m} w_{jk}e_k \qquad j = 1,2,...,l \tag{9}$$

$$b_k = b_k + e_k \qquad k = 1,2,...,m \tag{10}$$

Step 7: Determine whether the end of the iterative algorithm, if not finished, return to step 2.

Hidden Layer Node Selection

The selection of the number of the hidden layer node in BP neural network has a great impact on the prediction accuracy: if the number of nodes is too small, it will lead to increased training times, so the network is not very good at learning; if there are excessive number of nodes, the training time will increase, and it will be easy to produce the phenomenon of over-fitting. The optimal number of hidden layer nodes can be determined with reference to the following formula:

$$l < n - 1 \tag{11}$$

$$l < \sqrt{(m+n)} + a \tag{12}$$

$$l = \log_2 n \tag{13}$$

While n is the number of input nodes, l is the hidden layer nodes, m is the output layer nodes, a is an arbitrary constant between 1 and 10. Firstly, referring to experiment formula to determine the approximate range of the number of nodes, and then use trial and error method to determine the real number of the best node.

Performance Function

This paper use the Mean Squared Error (MSE) to describe the prediction accuracy, because the Mean Squared Error is better than The Mean Absolute Error (MAE) to measure the accuracy of the prediction value. The prediction error variance formula is:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n} e_i^2}{n} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2 \tag{14}$$

y_i represents the desired output, $\widehat{y_i}$ represents the actual output.

Model Data and Network

Experimental Data

Experiment uses 735 times ("7-day auction" 253 times, "15-minute auction" 482 times) auction data as the experimental data, select 90% of the data (660 times auction) as training data set, 10% data (75 times auction) as the test data set, each experimental data are randomly selected and normalized process to improve the accuracy of the experiment. The normalized process formula is as following:

$$x_k = (x_k - x_{\min}) / (x_{\max} - x_{\min}) \tag{15}$$

Input Variables

In order to improve the accuracy of prediction models, the experiment will use different combinations of variables. One group of all 11 variables as input variables, which is named as a full-variable model. Another group selects variables that have a weak correlation and above weak correlation with output variables, called variables related models. Thereby selecting a set of minimum error combination of variables as a predictive model input variables is namely the most appropriate combination of input variables to determine the network model.

Each output variable corresponding to the input variables is uncertain and cannot be predicted through using the same BP neural network. As for three different output variables, we establish BP neural network to predict them separately. In this paper, we use per-customer attracting cost forecasting model as an example and do experiments use Matlab R2014a software.

New-customer Attracting Effects Forecast

For per-customer attracting cost forecast model, use the full-variable model and the related variables model to do the experiments separately. We select "trainlm" as training function. And the network hidden layer neurons and output layer neuron transferring function is "tansig". Because the data is processed after normalization, the input vector and the target vector elements are located in [-1,1], so the transferring function can meet "tansig" output requirements. Codes are as follows:

net=newff(input_train,output_train,s(i),{'tansig','tansig'},'trainlm');

Network training parameters are as follows:

net.trainParam.show = 100; display the number of steps between the two training, every 100 cycles.

net.trainParam.mc = 0.9; network momentum factor.

net.trainParam.epochs = 10000; training times.

net.trainParam.lr = 0.05; learning rate.

net.trainParam.goal = 0.001; desired target minimum error.

The comparison situation of 2 sets of variables predictive model is shown in Table 6:

Table 6. Per-customer Attracting Cost Network Structure Comparison Table

per-customer attracting cost	Hidden node	Training function	MSEvalue
full-variable model	6	Trainlm	0.0028
related variables model	3	Trainlm	0.0016

MSE for related variable model has a value 0.0016, less than full-variable model, so we select the related variables and set the number of nodes as 3. The training function "trainlm" is the per-customer attracting cost's network prediction model. Fig 3, fig 4 are respectively the error curve and prediction model comparison chart for this model.

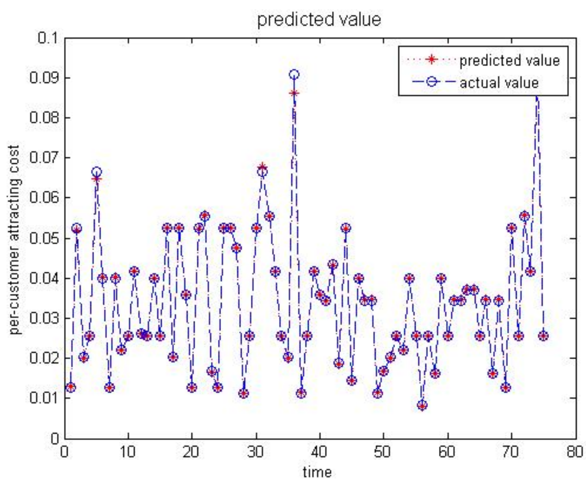

Figure 3. Model Error

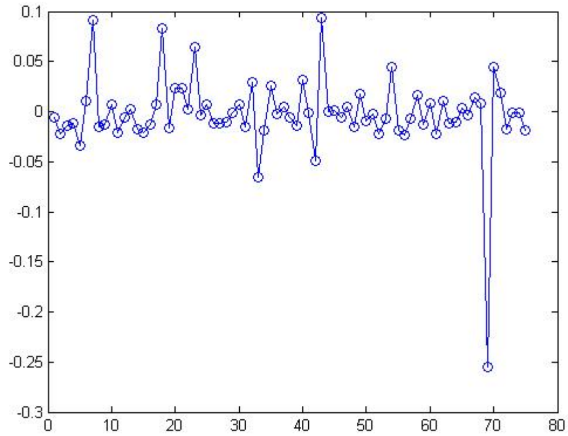

Figure 4. Comparison of Model Predictions and Actual Results

The red markers represent predicted value in fig 4, and blue markers represent the actual value. It can be seen from Figure 4, the prediction results and the actual value are highly fitting, so the prediction error is small. In fig 4, in addition to individual extreme external value, the prediction error is between the basic -0.05-0.05. We guess the reason of extreme values is the amount of data involved in the training of the network is too small.

Related variables model's regression model diagrams are shown in Figure 5, wherein the abscissa is the target value, the vertical axis is the output of the network. In the Figure Training, Validation and All map, data fits very good, because the curves are basically on the diagonal and there is no over-fitting phenomenon. Figure Test has some errors, but the errors are still within an acceptable range. Therefore, using related variables model to predict per-customer attracting cost is better.

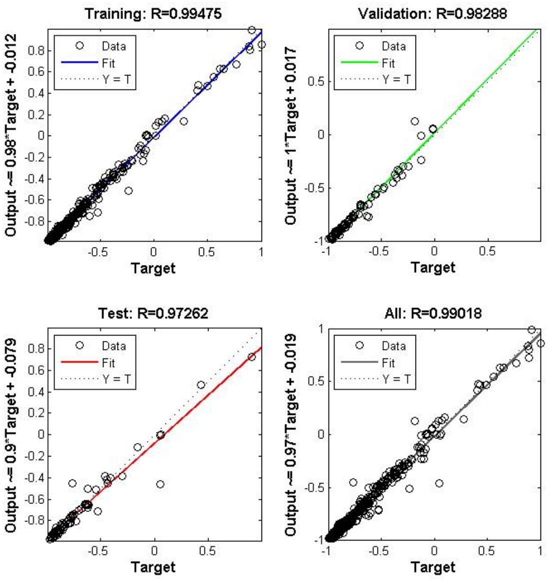

Figure 5. Per-customer Attracting Cost Regression Model

Use the same way to predict the new-customer quantity and blowout price. The results are as follows:

Table 7. Results

Model type		Hidden node	Training function	MSE value
blowout price	full-variable model	5	Trainlm	0.0013
	related variables model	7	Trainlm	0.0031

new-customer	full-variable model	7	Trainlm	0.0162
quantity	related variables model	3	Trainlm	0.0022

Blowout price forecast should use full-variable model, because the number of hidden layer nodes is 5 while MSE is 0.0013. New-customer quantity prediction model should use the related variables model, so the number of hidden layer nodes is 3.

Comparative Experiment

In order to verify the accuracy of BP neural network model to predict the effect, we used multiple linear regression, RBF neural network and SVM regression to do the comparing experiment. The results of MSE are in the following table.

Table 8. Different models prediction error

MSE value	per-customer attracting cost	new-customer quantity	blowout price
BP neural network	0.0016	0.0022	0.0013
Multiple linear regression	0.0849	0.0526	0.0391
RBF neural network	0.1054	0.0192	0.0271
SVM regression	0.0672	0.0456	0.0309

By comparing the experimental discovery, the error of BP neural network prediction model is much smaller than the other three comparison model. The multiple linear regression and SVM regression models are also able to achieve a certain precision, but the nonlinear fuzzy mappings forecast is not as effective as BP neural network. RBF neural network prediction model has larger errors, and its prediction results are easily affected by the number of expansion function and the number of neurons. Thus, the BP neural network prediction model is more accurate and stable.

Conclusion

The auction of Gongtianxia specialty network micro-channel public number use marketing campaign of low price that below cost price to attract a large number of potential customers to make purchase to become sticky customer. this paper use the auction data of Gongtianxia's micro-channel public number from June to December in 2015,to analyze the influencing factors of Dutch auction's pull new effects, include per-customer attracting cost, new-customer quantity, and blowout price. At the same time, we use SPSS software to do the correlation test, and do a more comprehensive analysis of the impact of factors on the auction time and free shipping for pull new effects, the following conclusions:

(1) The average of new-customer quantity for "7-day auction" and "15-minute auction" is nearly same, but 7-day auction's average per-customer attracting cost is much lower, and new customer's purchase number is much more. this is because network purchase's sensible reasons have more proportion than emotional reason, customers need more time to analyze the cost of goods, and thus make a choice when they make purchase on the internet. This means Slow auction or auctions of longer duration are more likely to attract new customers to make purchasing decisions to help businesses reduce the cost of capital, to get more benefit.

(2) Free shipping is almost no effect on the average number of new-customer quantity, but it can decrease the average of per-customer attracting cost, it means free shipping is easier to attract new customer, because free shipping can satisfy customer's expect of network shopping's low price, and make customer more likely to make purchase decision, so free shipping can help businesses reduce the cost of capital, and get more profit.

In this paper, we use BP neural network model to predict blowout price, new-customer quantity, and per-customer attracting cost respectively. These three variables are a measure of the effect of pulling new customer. By changing the number of nodes in the hidden layer and input variable combinations to do comparative tests, we find the minimized error and get the best effect prediction models. Through comparative experiment to verify the accuracy of BP neural network model, we determine the network structures shown in Table 9:

Table 9. Predictive Model Network Structure for Three Dependent Variables

Prediction variables	variable combination	Hidden node	Training function	MSE
blowout price	all-variable model	5	Trainlm	0.0013
per-customer attracting cost	related variables model	3	Trainlm	0.0016
new-customer quantity	related variables model	3	Trainlm	0.0022

Blowout price, per-customer attracting cost, and new-customer quantity, these three variables predictive value can effectively predict every auction's new pull effect and guide businesses to make reasonable designs about auction type and marketing strategy, in order to improve the ability to attract new customers and effectively lower the cost of capital caused by the descending price auction.

The research of this paper can complement for Dutch auction as Mobile Internet sale, and enriches the research for acquiring new customers through Mobile Internet. The conclusion of this paper can help the companies improve their acquiring new customer strategies in Mobile Ecommerce.

There are also some limitations in this paper, such as limited independent variables, due to the diversity of auction items included in the experimental data. Considering the ability to attract new customers is different, if business wants to improve the accuracy of the prediction, the effect of different commodities can be added into research, which means the auction data can be divided by type of goods. Meanwhile, the auction title's incentive and product images' colors will also have a certain impact to customers. In addition, different auctions have different proportions of new and old customers. Different products and different design of auction type also have different attracts to customer. A more detailed analysis of the kind of merchandise and type of auction will improve the pull-new-customer effect more obviously.

Acknowledgment

This paper support by National Natural Science Foundation of China(No.91546125).

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