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Customer Active Probability and Customer Lifetime Value Analysis in Internet

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Customer active probability and customer lifetime value analysis in Internet shopping

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Abstract

As the age of digital information, marketers are in information overload. A mass of customers' data is available but may be useless only if it can be turned into business intelligence and implement appropriate database marketing. This research aims to assist managers in discriminating and learning from their right customers that helps to serve high value customers and create successful marketing programs targeted at the prospected ones. Transaction data on the purchasing of VCD at an online retailer was used as empirical analysis; Pareto/NBD model and customer lifetime value model were applied to capture customer active probability and construct profitable customer profile. The results demonstrated four priority ranks of online customers for managers to choose the prospects that best match the profitable customer profile by observing their purchase behaviors.

Keywords: Database marketing, customer active probability, customer lifetime value

Research Issues

The rapid growth of information technology has made it easy for firms to collect enormous amount of customer data, such as transaction records, customer characteristics, and marketing activities. It allows firms to investigate customer's revealed preferences and choices instead of subjective measures like attitude and motivation. In this aim, customer research on survey sampling is no longer necessary since the majority of targeted customers can be tracked in the databases. But the flip side of this IT evolution is that marketing managers are constantly swamped with immense amount of data but starve for extracting useful information or knowledge into practice.

Overall, marketers are interested in predicting customers' future purchasing patterns from this great amount of information available from the customer transaction databases [3][8]. Through database marketing, firms can identify the most profitable customers and build long-lasting relationship with them [4][5]. To accomplish this task, accurate behavioral predictions are important in making profitable marketing decisions. Previous research has shown that the best predictor of future behavior is the past behavior [4]. It is common practice for firms to summarize customers' prior behavior in terms of recency (time of most recent purchase), frequency (number of prior purchases), and monetary value (average purchase amount per transaction), commonly called RFM analysis, in customer database [2]. This research follows this stream of analytical reasoning.

Individual customers have such disparate tastes and preferences that it is difficult for firms to group them into homogenous segments in implementing marketing strategy. In fact, each customer expects to be served according to his/her unique need and purchase behavior [8]. For instance, to accurately classify a unique purchase behavior, one who makes a large number of purchases early on and then makes no purchase for a long time afterward is likely to be identified as an inactive customer. Contrarily, if a customer has regular and frequent interactions with the firm, he/she is likely to be identified as an active customer in making repeated purchases. The ability in distinguishing customers who are becoming active or inactive allows firms to look over the purchase trends over time and to reconcile a customer's subgroup targeted with specific promotional effort. This research utilizes customer active probability as an abbreviated RFM measure to predict future purchase probability.

However, not all customers embrace the same value for a company. Analogous to financial assessment, customer lifetime value (CLV) is a common metric in database marketing to evaluate a customer's present and future values. It assesses the net present value of propagating cash flows from various degrees of active customers in the database. Following the financial calculation on future value, most CLV models lack customers' purchase behavior in the metrics. This research adopts a finite mixture model that links customers' past purchase behavior with customer lifetime value in analyzing the structural and statistical properties of profitable customers. The resulting profile would generate information on customer recruiting and retention strategy in attracting and building the most profitable customers and help marketers design customized marketing programs to keep them.

The research objectives of this study are threefold: (1) to assist marketers in identifying the most active and highest profitable customers from the database; (2) to help marketers discriminate between profitable and less-profitable customers with separate marketing efforts; (3) and to recommend an analogy growth plan by developing promotional activities designed to attract new customers who fit the profile of active and profitable customers; thereby expanding high value customers to the database.

The research is outlined as follows; customers' online purchase behavior based on RFM analysis framework is collected. Secondly, customer active probability derived from Pareto/NBD (Negative binomial distribution) model is proposed; individual's customer lifetime value by gamma-gamma distribution is calculated. Finally, various degrees of active and profitable segments are analyzed. This concludes with managerial implications and future research directions.

Research Models

This research probes customer's transaction information that base on RFM theory into knowledge about customers. The analyzed process includes identifying customers' active probability and customer lifetime value, and then construct the profile of profitable customers.

The Pareto/NBD model [7] is used to calculate customer active probability. The model assumptions are: (1) each active customer purchases χ, the number of VCDs, according to a Poisson process with the purchase rate λ; (2) probability of each customer remains alive for the lifetime period τ, which has an exponentially distributed duration with termination rate μ; (3) the purchasing rate λ for different customers is distributed according to a gamma distribution with shape parameter γ and scale parameter α across the cohort of customers; (4) customer's termination rates μ are distributed according to a gamma distribution with shape parameter s and scale parameter β across customers; (5) the purchasing rates λ and termination rates μ are distributed independently of each other.

Assume a customer who is active at a current time is observed up to time T. During the observation, the customer makes χ purchases with the last purchase coming at t_x, $0 < t_x \leq T$. Therefore, information on this customer contains three elements χ, t_x, and T. The purpose of Pareto/NBD model is to calculate the conditional probability that customer is still active at time T with purchase information (χ, t_x, T). For any individual chosen at random from the cohort, those purchases are made while the customer remains active has followed the NBD model:

$$P\left[X = x \middle| r, \alpha, \tau > T\right] = C_x^{x+r-1}\left(\frac{\alpha}{\alpha+T}\right)^r\left(\frac{T}{\alpha+T}\right)^x; \quad x = 0,1,2.... \tag{1}$$

In the meantime, for any individual chosen at random from the cohort, the lifetime period the customer remains in the data set has followed the Pareto distribution:

$$f\left(\tau \middle| s, \beta\right) = \frac{s}{\beta}\left(\frac{\beta}{(\beta+\tau)}\right)^{s+1}; \quad \tau > 0 \tag{2}$$

The combined purchase event and the lifetime duration model is called Pareto/NBD model. Four parameters (γ, s, α, β) can be estimated by maximizing the log-likelihood function of the Pareto/NBD model. If α > β, the following equation is applied to figure out customer active probability from a randomly chosen individual that having the purchases pattern (χ, t_x, T):

$$P\left[\tau > T \middle| r, s, \alpha > \beta, X = x, t_x, T\right] = \left\{1 + \frac{s}{r+x+s}\left[\begin{array}{l}\left(\frac{\alpha+T}{\alpha+t_x}\right)^{r+x}\left(\frac{\beta+T}{\alpha+t_x}\right)^s {}_2F_1\left(a_1, b_1; c_1; z_1(t_x)\right) \\ -\left(\frac{\beta+T}{\alpha+T}\right)^s {}_2F_1\left(a_1, b_1; c_1; z_1(T)\right)\end{array}\right]\right\}^{-1} \tag{3}$$

where ${}_2F_1(.)$ is the Gaussian hypergeometric function

$a_1 = r+x+s;\quad b_1 = s+1;$

$c_1 = r+x+s+1;\quad z_1(y) = \dfrac{\alpha-\beta}{\alpha+y}$

Given the estimates of the four Pareto/NBD model parameters, managers can easily derive each customer's active probability and calculate how many active customers the firm has. Adding up the entire individual customer probability would be the estimated number of active customers [7].

Concerning the CLV model, [2] have developed the RFM analysis with customer lifetime value under the non-contractual setting (where the time at which customer become inactive is unobserved). The model assumes that monetary (M) value is independent of the two other transaction processes, recency and frequency. The stochastic model that based on Pareto/NBD reasoning [7] has captured the flow (i.e., recency and frequency) of transactions, while the gamma-gamma model [1] has captured the monetary value of transactions. This mixture model can be written as,

$$\begin{aligned} CLV &= m\arg in \times \left(revenue/transaction\right) \times \mathrm{DET} \\ &= m\arg in \times \frac{(\gamma + m_x x)\, p}{px+q-1} \\ &\quad \times \frac{\alpha^r \beta^s \delta^{s-1} \Gamma(r+x+1) \Psi\left[s, s; \delta(\beta+T)\right]}{\Gamma(r)(\alpha+T)^{r+x+1} L\left(r, \alpha, s, \beta \middle| X = x, t_x, T\right)} \end{aligned} \tag{4}$$

DET (discounted expected transactions) can be computed from the observed purchase behavior (χ, t_x, T); parameters (γ, s, α, β) are derived from the Pareto/NBD distribution; ψ(·) is the confluent hyper-geometric function of active periods; and L (·) is the Pareto/NBD likelihood function.

Calculating each customer's lifetime value could help marketers to identify the profitable customers to the firm; additionally, constructing customer profile reveals what characteristics and purchase behavior that their profitable customers have. This profile is useful for identifying which new customer look like current profitable customer. This research applies analysis of variance (ANOVA) to analyze the results of regression analysis involving both experimental and observational data.

Empirical Findings

Sample Description

The customer transactions data set was provided by an online music and movie VCD/DVD vendor that covers a complete cycle period of January 2006 to December 2006 on the weekly basis totaled 51 weeks. This research focuses on one single cohort of 508 customers who made purchases of VCD movies in the first four months; some of them repeat the orders at the end of 2006. Two research questions will be addressed: (1) what proportion of the 508 customers will repeat the order at the end of the year? (2) What level is this cohort of customers worthy of?

Table 1 shows the observation time, it is depends on the initial purchase that each customer made. For example, customers make the initial purchase during 1/15 to 1/21, the purchase behavior is observed for 49 weeks until the end of year 2006, and their observed time is specified as 49. There are 23 customers make their initial purchase during this period.

Table 1 Observed time period

Initial purchase date			Observed time (T)	Number of customers
1/8	to	1/14	50	24
1/15	to	1/21	49	23
1/22	to	1/28	48	37
1/29	to	2/4	47	55
2/5	to	2/11	46	56
3/26	to	4/1	39	28
4/2	to	4/8	38	28
4/9	to	4/15	37	31
4/16	to	4/22	36	26
4/23	to	4/30	35	27

This research database provides individual customer's purchase behavior information containing number of transaction, average transaction value, and average interpurchase time; shows how often and how much customers buy the online VCD products. The mainly demographic characteristic is the region of residence.

Figure 1 exhibits a histogram of the number of transactions for the 508 observed customers. There are 198 customers made no repeat purchases in the end of 2006 which occupies 39% in total customers. In the remainder 310 customer, 106 customers made one repeat purchase.

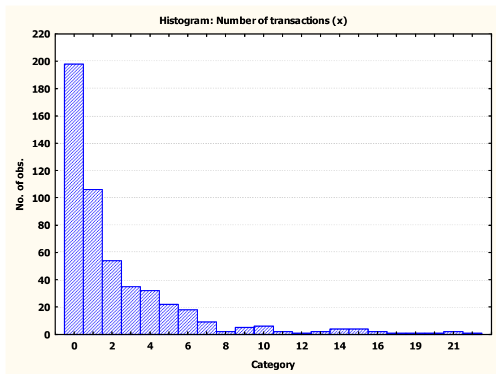

Figure 1 Histogram of Number of transactions

Those customers who did not make repeat purchase are not assuming permanently out of the market. They are separated and we then conduct the descriptive statistical analysis on number of transactions for the remaining 310 customers who made at least one repeat purchases. The mean of transactions is 3.89, with minimum 1 and maximum 50. The skewness value is 4.41; its distribution is skewed to the right. Based on the assumption of Pareto/NBD model that supposes the number of transactions follows a Poisson distribution is suitable.

In part of average transaction value, since there are

198 customers do not made repeat purchases after their initial purchase occasions, these average transaction value is zero. Observing the histogram of the average transactions in Figure 2, it demonstrates that the majority of customers' average transaction value is less than NT $1882.

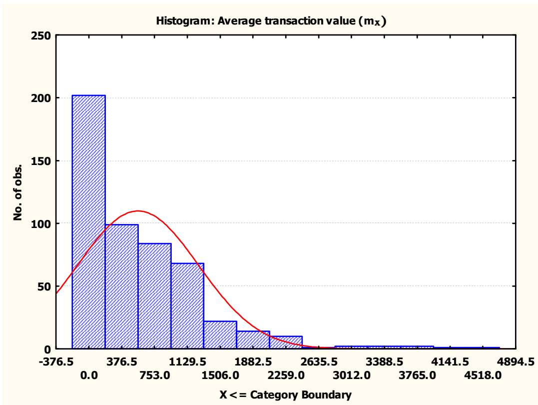

Figure 2 Histogram of average transaction value

Only account for the 310 customers, the mean transaction value is NT $ 923, reveals the transaction value across all customers and transactions. In addition, the skewness is 2.09, indicating that the distribution is skewed to the right. This research adopts the gamma-gamma model that originally proposed to calculate customer expected transaction value [1]. The gamma is a flexible distribution and can capture the spirit of most of the reasonable distributions. The sample skewness proves that the average transaction value is fit to gamma distribution.

In this online database, we got each customer's purchase volume in each transaction. Through adding all purchase volume and then dividing it by the number of transaction, the average purchase volume can be derived. Exception for the 198 customers having no repeat purchase, the 310 customers whose average purchases volume is less than 6 VCDs occupies 39% in total. The minimum volume is 1 and maximum is 33.67, mean value is 6.03.

This research further divides customers into four groups. The 198 customers are categorized as the first group occupying about 40% in total customers, and then the remainder 60% customers are divided equally into three groups, coding as UR 1, UR2, and UR3, summarizes the transaction volume in Table 2.

Table 2 Average purchase volume per transaction in each customer group

Average purchase volume (Unit)	Number of customers (Percentage)	Code
0	198 (39%)	UR0
1 to 3	95 (19%)	UR1
3.01 to 6	102 (20%)	UR2
6.01 and more	113 (22%)	UR3

Finally, we observe the average interpurchase time which is meaningful for market managers. Firms can base on individual customer's average interpurchase time to make new product promotion and enhance the effect of direct marketing to stimulate repeat purchase.

The interval time between transactions for repeated purchasing customers is depicted in Figure 3.

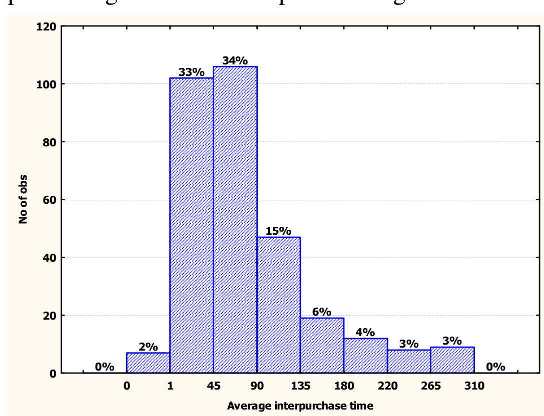

Figure 3 Histogram of average interpurchase time

Customers are also divided into four groups for discussion. The 198 customers who did not make repeated purchase are categorized as the first group, the remainder 60% customers are divided equally into three groups, specifying as IT1, IT2, and IT3, shown in Table 3. In the whole, the mean of average interpurchase time in 310 customers is 80 days.

Table 3 Average interpurchase time in each customer group

Average interpurchase time (Day)	Number of customers (Percentage)	Code
Cannot be counted	198 (39%)	IT0
1 to 45	109 (21%)	IT1
46 to 90	106 (21%)	IT2
91 and above	95 (19%)	IT3

The zip code are gained in the database. The 508 customers are divided into 5 groups according to their region of residence. Most of customers live in region 1 and region 2. Table 4 shows the code table of region of residence.

Table 4 Region of residence

Region of residence	Number of customers (Percentage)	Code
Keelung City, Taipei County, and Taipei City	171 (34%)	R1
Taoyuan, Hsinchu, and Miaoli County	113 (22%)	R2
Taiching, Changhua, Yunlin, and Nantou County	82 (16%)	R3
Chiayi, Tainan, Kaohsiung, and Pingtung County	106 (21%)	R4
Yilan, Hualien, and Taitung County	36 (7%)	R5

Parameter Estimation

For this online vendor case, the parameters (γ, s, α, β) were estimated by maximizing the log-likelihood function of the Pareto/NBD model; it yields γ = 0.6728, s = 0.0655, α = 10.8113, and β = 2.4551.

As the CLV analysis, assuming annual discount rate of 7% which yields a continuously compounded rate of δ = 0.001301128, and combines it with the estimates of parameters (γ, s, α, β), DET can then be derived. Likewise, the parameters of gamma-gamma model (p, q, γ) can be obtained by maximizing the log-likelihood function, p = 3.701, q = 3.478, and γ = 639.963.

Customer Active Probability

Given the estimates, the customer active probability for a randomly chosen individual having purchases pattern can be derived, shown in Table 5.

Table 5 Customer active probability in online shopping

ID	Number of transaction	Recency	Observed time	Customer active probability
36	1	8	50	0.7259
42	0	0	50	0.6757
43	1	5	50	0.6312
99	1	1	49	0.4384
114	1	2	49	0.4993
152	2	5	48	0.4040
355	9	27	44	0.7655
383	2	27	44	0.9503

To consider the purchase information of ID 36 ($T=50, x=1, t_x=8$), the observed time $T=50$ implies this customer make his first purchase during 1/8 to 1/14 in 2006. Over this time period, he made $x=1$ repeat purchases, with this repeat purchase occurring during 3/5 to 5/11 in 2006 $(t_x = 8)$. Active probability is 0.7259 represents that this customer has 72.59% probability to make repeat purchase.

To aggregate individual customer's probability as the estimated number of active customers, the sum of the 508 customers' active probability is 419.8. This translates to 82.6% of the vendor's active customer rate.

Firms can base on individual active probability as the criteria of marketing resource allocation, even delete the highly inactive customers from mailing list to reduce marketing cost.

Figure 4 is a 3D plot. The X-axis is recency, Y-axis is number of transactions, and Z-axis is customer active probability. Some phenomena are emerged.

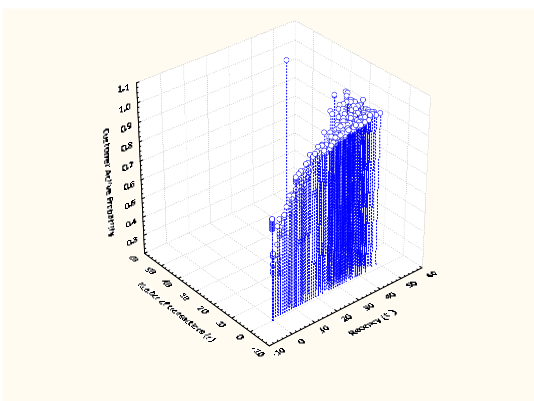

Figure 4 Three dimensions plot of customer active probability

(1) Although a customer does not make repeat purchase yet, it does not mean that his active probability is equal to zero. For instance of ID 42, active probability is 0.6757, even though he does not make repeat purchase.

(2) If customers have the same observed time and number of transaction, when the elapsed time $T-t$ since last observed transaction is lower, the customer active probability is higher. Compare ID 36 with ID 43, they have the same observed time $(T = 50)$ and number of transaction $(x = 1)$, but ID 36 with the elapsed lower time $(T - t = 42)$, thus has higher active probability.

(3) To compare ID 355 with ID 383 customer, they have the same observed time $(T = 44)$ and recency $(t_x = 27)$. By intuition we would expect ID 355 customer to have a greater active probability, given the higher number of transactions $(x = 9)$. However, the active probability of ID 383 is higher than ID 355. This phenomenon is "increasing frequency paradox". Customers with many purchases (x) in a small period (t_x) followed by a long elapsed time $(T-t)$ have probably become inactive. In general, for people with low recency, higher frequency seems to be bad.

(4) Scholars pointed out a phenomenon that the individual doing nothing $(x = 0)$ is more likely still active than a customer making one or more purchases [8]. Such as ID 99, 114, and 152, customers with low number of transaction and very long elapsed time $(T-t)$. Even they make one or more purchases; their active probability is less than some customers who do not make repeat purchase have.

According to the rule proposed by [6], they established a cutoff threshold $P(Active) = 0.5$. If the probability is above 0.5, they are assigned the status active. 44% of customers' active probability is between 0.9 and 1 in this online dataset. We can categorize them into loyal customers who have high probability to make repeat purchase, and 46% customers' active probability between 0.6 and 0.8. There is only 2% customers' active probability is below 0.5, have low probability to make repeat purchase.

Customer Lifetime Value

Given the estimates in gamma-gamma model, Table 6 is the DET result for 20 sample customers. In order to more easily calculation, we round off the DET to two decimal point.

Table 6 DET result

ID	Number of transaction	Recency	Observed time	L(r,α,s,β | x, tx,T)	DET
46	2	29	50	8.50E-05	26.65
47	21	45	47	3.72E-19	245.23
48	0	0	47	4.13E-01	4.94
49	2	35	50	8.26E-05	27.42
51	6	38	42	3.92E-09	81.21
52	3	44	46	4.52E-06	41.62
53	0	0	50	4.03E-01	4.65
54	3	47	50	3.51E-06	39
57	0	0	50	4.03E-01	4.65
58	5	45	46	2.38E-08	64.8
180	0	0	47	4.13E-01	4.94
181	7	47	47	2.43E-10	86.64
182	10	47	47	8.08E-13	120.83
183	1	10	47	4.04E-03	14.59
184	1	32	47	3.32E-03	17.78
185	4	42	47	2.69E-07	52.01
186	5	36	47	2.22E-08	61.88
188	1	39	47	3.26E-03	18.08
189	0	0	47	4.13E-01	4.94
190	4	47	47	2.67E-07	52.45

Figure 7 is a 3D plot for 508 observed customers. The X-axis is recency, Y-axis is number of transactions, and the Z-axis is DET. Some phenomena are emerged from Table 4 and Figure 7:

(1) Although a customer do not make repeat purchase, it does not mean that their DET is equal to zero. For example, the DET of ID 48 is 4.98, even though he does not make repeat purchase.

(2) If customers have the same observed time and recency, high number of transactions will cause higher DET. For instance, ID 181, 182, and 190 have the same observed time $(T=47)$ and recency $(t_x=47)$. The transaction of number of ID 182 customer is the highest in the three customers so he has the highest DET.

(3) In Figure 7, we found an outliner whose DET is obvious large. The customer is ID 122, his number of transactions is 50 and DET is 567.66.

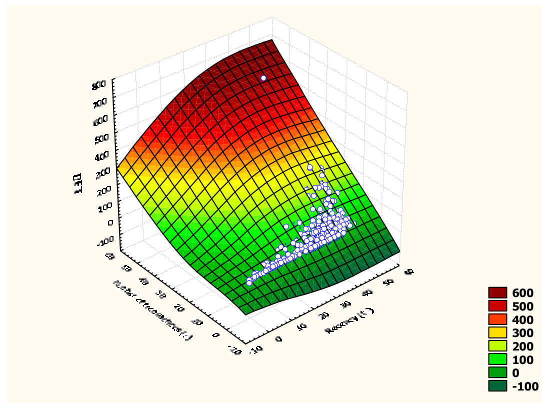

Figure 7 Three dimensions plot of DET

Given the parameters of gamma-gamma model obtained by maximizing the log-likelihood function in Excel add-in Solver, the expected CLV on each customer were calculated. Table 7 is 10 sample customers' CLV.

Table 7 Expected transaction value and CLV

ID	DET	$E(M\|p,q,\gamma,m_x,x)$	CLV
99	7.96	1030.1232	2460
104	185.55	1176.7459	65504
107	9.04	497.0830	1348
108	26.4	1352.2145	10709
113	28.66	973.8903	8374
114	9.04	1191.8320	3232
115	49.06	507.9512	7476
118	15.99	952.2634	4568
120	39.47	918.3293	10874
122	567.66	633.3170	107853

Profitable Customer Profile

After figuring out each customer's CLV, this research conducts the profitable customer profile. The best way for profiling is by customers' demographic characteristics and purchase behavior. According the classification of average usage and interpurchase time, use the sample results to test the following three hypotheses by one-way ANOVA to test for the equality of population means. The three null hypotheses are:

$H_{01}: \mu_{UR1} = \mu_{UR2} = \mu_{UR3}$

$H_{02}: \mu_{IT1} = \mu_{IT2} = \mu_{IT3}$

$H_{03}: \mu_{R1} = \mu_{R2} = \mu_{R3} = \mu_{R4} = \mu_{R5}$

Table 8 exhibits the CLV of each category and testing results.

Table 8 CLV and ANOVA Result $(\alpha = 0.05)$

Independent Variables	Code	CLV Mean	F Value	p
Usage rate	UR1	5895.87	27.3412	<0.001***
	UR2	11285.99		
	UR3	24558.87		
Average interpurchase time	IT1	22484.38	15.5892	<0.001***
	IT2	12354.03		
	IT3	7643.23		
Region of residence	R1	16504.07	0.5355	0.7098
	R2	12548.19		
	R3	14522.78		
	R4	12523.02		
	R5	15246.32		

Hypothesis 1 and hypothesis 2 are rejected that expresses that the CLV of each population are not all equal. Hypothesis 3 is not rejected, individual region of residence is not significant independent variable to affect CLV mean.

Since the usage rate and average interpurchase time are significant independent variables to affect CLV mean, they are applied to profile profitable customers. According to the three categories of usage rate and three categories of average interpurchase time, the 310 customers are divided into nine profiles and t arrayed form high to low CLV in order as following Table 9 and Figure 8.

The highest CLV mean is profile 1 customers whose usage rate is UR3 (average purchase number is more than 6.01 units) and average interpurchase time is IT1 (average interpurchase time is between 1 to 45 days). The lowest CLV mean is in profile 9 customers whose usage rate is UR1 (average purchase number is between 1 to 3 units) and average interpurchase time is IT3 (average interpurchase time is more than 91 days). If customer's average purchase number is higher and make repeat purchase with short interpurchase time, we expect that they have higher CLV mean as profile 1. Contrariwise, if the average purchase volume is lower and customers make repeat purchase with long interpurchase time, we expect that they have lower CLV mean as profile 9.

Table 9 Customer profile

Profile	Usage rate	Average interpurchase time	Number of customers	CLV Mean
1	UR3	IT1	38	42595.34
2	UR2	IT1	32	17494.75
3	UR3	IT2	44	17478.70
4	UR3	IT3	31	12498.90
5	UR2	IT2	35	10524.40
6	UR1	IT1	39	6983.13
7	UR1	IT2	27	6374.44
8	UR2	IT3	35	6371.00
9	UR1	IT3	29	3988.14

After ordering the CLV mean of nine profiles, whether the CLV means of nine profile customers are equal were tested. Figure 9 shows clearly the nine profile customers' CLV mean with three categories of usage rate and three categories of average interpurchase time.

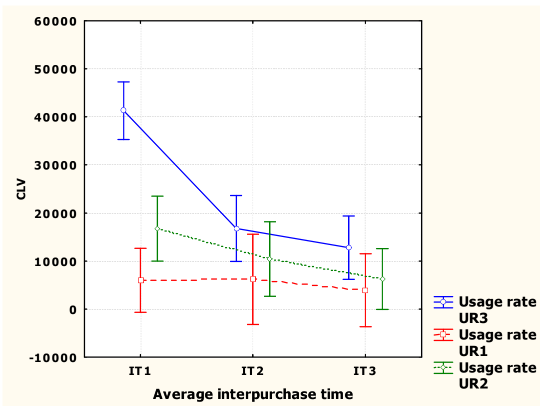

Figure 8 Customer profile plot

Supposing significant level as 0.05, ANOVA method was applied to examine whether the means of nine profiles are equal ($H_{04}:\mu_{p1}=\mu_{p2}=\mu_{p3}=\mu_{p4}=....=\mu_{p9}$). The result shows F value is 17.42 (p<0.001), hypothesis 4 is rejected that allows us to conclude that the population means are not all equal.

Go a step further and determine where the difference occurs. Fisher's least significant difference (LSD) procedure can be used to determine where the differences occur. It is based on the *t* test statistic presented for two population cases as following hypotheses 5.

$$H_{05}:\mu_{pi}=\mu_{pj} \quad i,\, j=1\sim 9,\ i\neq j$$

This procedure makes 36 pairwise comparisons in this research. The results indicate that the CLV mean of profile 1 customer is significant different from the other 8 profile customers; profile 2 and 3 customers' CLV mean are significant different from profile 1, 6, 7, 8, and 9; profile 4 and 5 customers' CLV mean are significant different from profile 1; profile 6, 7, 8, and 9 customers' CLV mean are significant different from profile 1, 2, and 3. According to the Fisher's LSD procedure results that exhibits that profile 2 and 3 customers have same pattern; profile 4 and 5 customers have same pattern, profile 6, 7, 8, and 9 have the same pattern.

Consequently, we conclude that there are four priority ranks of profitable customer. The most profitable customer for this online retailer is profile 1, their usage rate is heavy (UR3) and make repeat purchase with short interpurchase time (IT1). The second profitable customer is profile 2 and 3 customers, profile 2 customers' usage rate is medium (UR2) and make repeat purchase with short interpurchase time (IT1) and profile 3 customers usage rate is heavy (UR3) and make repeat purchase with medium interpurchase time (IT2).

Although profile 2 and 3 customers have different usage rate and average interpurchase time, those two profiles have the same importance. This phenomenon also occurs in third profitable customer (profile 4 and 5 customers) and least profitable customer (profile 6, 7, 8 and 9 customers).

Through the profitable customer profile, managers can observe customer's purchase behavior to choose the prospects that best match the profile of company's profitable customers. For example, there are three new customers, their purchase behavior as following: average purchase number of Customer A is 7 units (UR3) and his average interpurchase time is 30 days (IT1); average purchase number of Customer B is 4 units (UR2) and his average interpurchase time is 60 days (IT2); average purchase number of Customer C is 5 units (UR2) and his average interpurchase time is 95 days (IT3). And then check with Table 9, Customer A is classified to first profile; Customer B is classified to fifth profile; Customer C is classified to eighth profile. The result demonstrates that marketer should allocate more resource to acquire and maintain Customer A rather than Customer B or C.

Summary and Conclusion

By observing customer active probability and customer lifetime value, this research proposes several major findings. First, although some customers do not make repeated purchases, it does not mean that their active probability and customer lifetime value are equal to zero. Second, if a customer has shorter elapsed time ($T - t$), the active probability will be higher. Third, for the customer with the lowest level of recency, the high frequent transaction number is likely to turn out to be the lower active probability – the scenario of increasing frequency paradox is existential.

For further clarification on the importance of weights in RFM elements, this study divides the cohort into various segments according to its behavior information and demographic characteristics. The ANOVA result shows that usage rate and average interpurchase timing significantly affects CLV means. There are four priority ranks of profitable customers. The most profitable customer is the segment with heavy usage rate and short interpurchase timing. The second most profitable segments are medium usage rates with short interpurchase timing and heavy usage rates with medium interpurchase timing. This priority enables managers to gain a deeper understanding of their most profitable customers, improving their customization programs, and developing promotional activities that can attract the same profile of new customers.

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