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Customer Profitability Segmentation for SMEs Case Study: Network Equipment Company

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A B S T R A C T

It is important to segment the most profitable customers of a company. Many CRM researchers have been performed to calculate customer profitability and develop a comprehensive model of it. This paper with the aid of data mining tools tries to customer segmentation based on kind of RFM. Customers are clustered using K-means and finally calculated CLV. This approach is essential for an SME to be able to provide a personalized service to each customer and to reach customer satisfaction.

Keywords :
Customer Relationship management, Customer lifetime value, Data mining, RFM, SMEs.

1. Introduction

Customer relationship management (CRM) comprises a set of processes and enabling systems supporting a business strategy to build long term, profitable relationships with specific customers [1]. Customer data and information technology tools form the foundation upon which any successful CRM strategy is built. In addition, the rapid growth of the Internet and its associated technologies has greatly increased the opportunities for marketing and has transformed the way relationships between companies and their customers are managed [2, 3]. As corporations increasingly come to see customers as important assets, methods for estimating Customer Lifetime Value (CLV) have been developed as an important strategic marketing tool. CLV, which appears elsewhere in management literature as "customer equity "and" customer profitability" helps firms quantify customer relationships, illustrate the profitability of its customers and provides references for the allocation of marketing resources to customers and market segments [4]. In addition to long term customers buy more and less costly to serve whereas replacing existing customer by 'new' ones is known to be a more expensive [5]. Marketing managers can develop long-term and pleasant relationships with customers if they can detect and predict changes in their consuming habits [6]. Most previous studies are based on RFM model [7-10]. RFM incorporates three variable including Recency, Frequency, and Monetary to model customer's

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tendency of purchasing. Kind of RFM such as RF*M*, WRFM, LRFM, GRFM is expressed in different articles. Although these methods have been utilized in customer segmentation and behavior analyzing but preference of them are not apparent. In other word if our purpose is profitable customers clustering, It isn't clear which of models is suitable. This approach surveys all kind of RFM and compares techniques in case study for SMEs.
The rest of paper is organized as follows. Section 2 outlines the background and reviews CLV definition and RFM model and K-means technique. Section 3 describes the research methodology. Section 4 is implementation of study. Section 5 analyzes the result of customer segmentation and finally section 6 draws conclusions.

2. Literature Review

One important marketing concept in running today's business is the recognition of value of each individual customer. This concept is guiding today's business in developing personalized and value-added products and services. The value of a customer is defined as the profit resulting from payment of a transaction [11, 12]. Traditional customer segmentation models were based on demographic, attitudinal, and psychographic attributes of a customer .They gave too simple results and poor accuracy for today's complicated business environment. Recently, the customer segmentation based on customer transactional and behavioral data (e.g. purchases type, volume and history, call center complaints, claims, web activity data, etc.) collected by various information systems is commonly used. Customer profitability is a customer-level measure that refers to the revenues less the costs which one particular customer generates over a given period of time and has been studied the name of Customer value, customer valuation [13] , CLV, LTV, and Customer Equity [14]. RFM model is famous to CLV calculation.

2.1.RFM model

The RFM analytic model is proposed by Hughes. Recency (R) of the last purchase is the interval between the last purchase and a present time reference, so the lower recency is more valuable. Frequency (F) of the purchases is the number of transactions in a particular period, so the higher frequency is more valuable. Monetary (M) value of the purchases is the total amount of money paid by the customer over a particular period, so the higher monetary is more valuable. [9] Table1 is shown RFM definition and how it implemented.
In addition to traditional RFM, is presented method such as:

- WRFM: It dedicated weights to R, F, and M. For example, the highest weighting on the Frequency, followed by the Recency, with the lowest weighting on the monetary measure. To determine importance (weight) of RFM parameters, AHP method is exploited. [15]
- LRFM: It consists of four dimensions: relation length (L), recent transaction time (R), buying frequency (F), and monetary (M), to carry out customer clusters [16].

Table 1. RFM definition & implementation [11]

	Recency	Frequency	Monetary
Definition	The number of days between the last purchase and the time of analysis. The smaller the number, the higher the probability of next purchase	The number of purchases during a period of time. The higher the frequency, the higher the loyalty and value of a customer	Total amount of purchase during a period of time. The higher the amount, the higher the value of a customer Implementation
Implementation	Divide the sorted purchase dates into five equal intervals; then assign a weight 5 to the first 20%, 4 to the next 20%, and so forth	Divide the highest purchase count into five equal intervals; then assign a weight 5 to the first 20%, 4 to the next 20%, and so forth	Divide the total purchase amount into five equal intervals; then assign a weight 5 to the first 20%, 4 to the next 20%, and so forth

- GRFM: It emphasizes customers' purchasing behavior regarding different products. Chang and Tsai [17] propose new measure method takes into account the characteristics of the purchased items so that the calculated the RFM value for the customers are strongly related to their purchased items and can correctly reflect their actual consumption behavior.
- RF*M* : In cases such as Bank survey, because of numerous transactions , Bizhani and Tarokh [9] introduce new definition of R, F , M as fallow :
  F* = F / D: number of transactions per day
  M*=M / F: monetary unit value per transaction

According to previous studies, kind of RFM is shown in Table2**.**

As is mentioned, method of RFM had been used in several cases but each of them run one method. In this study, we perform all method to understand which method is suitable for case study.

2.2.K-means

Clustering is the process of grouping a set of physical or abstract items into classes of similar items where the groups are meaningful, useful, or both. A cluster is a collection of data items that are similar (or related) to one another within the same cluster and are dissimilar (or unrelated) to the objects in other clusters, so a cluster of data items can be treated collectively as one group and so may be considered as a form of data compression, which helps us easily annotate all the data items [9]. One of well- known data mining clustering technique is k-means [10]. The "K" in its name refers to the fact that the algorithm looks for a fixed number of clusters which are defined in terms of proximity of data points to each other the version described here was first published by J. B. MacQueen in 1967. For ease of explaining, the technique is illustrated using two-dimensional diagrams. Bear in mind that in practice the algorithm is usually handling many more than two independent variables. This means that instead of points corresponding to two-element vectors ($x1$, $x2$), the points correspond to n-element vectors ($x1$, $x2$, …, xn).

Table 2. Distribution of article according to RFM method

Technique	RFM Element	References	Case study
RFM	Recency Frequency Monetary	[18]	Retailer
		[19]	-
		[20]	-
		[21]	Service Company
		[22]	-
		[10]	Bank
		[23]	-
		[24]	Network Service
		[8]	Bank
		[25]	3G Mobile Company
RF*M*	R=Recency F*=Frequency /Day M*=M/F	[9]	Bank
GRFM	Group RFM (According to Purchase Item)	[17]	Amazon
LRFM	relation Length Recency Frequency Monetary	[16]	textile manufacturing
WRFM	Weithed RFM	[26]	hardware retail
		[27]	-
		[28]	-
		[29]	Car Manufacture
		[30]	Beauty Company
		[15]	Bank

The procedure itself is unchanged [31]. One advantage of k-means clustering is that distance in formation for the items and clusters becomes readily available [32].

3. Methodology

3.1.Crisp methodology

There are different methodologies for implementing data mining projects but one of the powerful methods is CRISP (CRoss-Industry Standard Process for Data Mining) .As a process model ,CRISP provides an overview of the data mining life cycle. CRISP uses six phases to describe the process from gathering business requirements to deploying the: Business Understanding; Data understanding; Data preparation; Modeling; Evaluation; Deployment. [10]

3.2.Research methodology

According to CRIPS methodology the framework of article is shown in Figure 1.

4. Implementation

4.1.Business & data understanding

The case study of this article is about the SME Company that sells network equipment (such as switch, cable, modem, …) . This company implemented CRM to use for registration of purchase information of customers. Purchase Data that is available in database, contains date, name and number of product , net price , discount and total price .for analyzing , we selected all purchases during one year (from 2010/03/21 to 2011/03/18 **).** The Company has 351 customers and 1277 purchase records.

4.2.Data preparing

First of all, we should minus the refund of purchases from records to get accurate data for analyzing. For extracting R, F, and M parameters of each customer we aggregate records based on customer ID. In each aggregated record, there is a unique customer with her/his number of monetary transaction as F parameter, latest transaction date as R parameter and total amount of money in all of her/his deposit account at the end of the certain period (1 years) as M parameter. Then we scale each of these three parameters in five scales. For the scaling R parameter, first sort the data based on R attribute by ascendant order then partition the customers transaction dataset into 5 partitions.

Customers in the first partition have lowest value of Recency and their Recency value named 1, second partition named 2, third partition named 3, fourth named 4 and finally fifth partition named 5 . For the scaling F and M parameters the same procedure must be done. For LRFM, we need date that customer account is created on. Unlike Recency, if relation Length is older, it has more score. Table 3 is shown LRFM score.

4.3.Modeling & Evaluation

According to customer segmentation based on profitability, we must use clustering technique in this part. K-means is most popular in cases. To finding optimum k (count of cluster), we need to calculate Dunn Index parameter. The main goal of this measure is to maximize intercluster distances (distance between different clusters), while minimizing intracluster distances (distance between members of a cluster). For any partition $C = \{C_1, C_2, \dots, C_k\}$, where C_i represents the i^{th} cluster of such partition, the Dunn indices, D, is defined as in equation (1):

$$D(C) = \frac{\min_{i,j=1,\dots,k,\ i\neq j} \delta(C_i,C_j)}{\max_{i=1,\dots,k} \Delta(C_i)} \qquad (1)$$

where $\delta(C_i, C_j)$ defines the distance between clusters C_i, C_j (intercluster distance), and $\Delta(C_i)$ represents the intracluster distance of cluster C_i or the size of the cluster C_i, and k is the total number of clusters. In this study:

$$\delta\left(C_i, C_j\right) = d(\overline{C_\iota}, \overline{C_j}) \qquad (2)$$

$$\Delta(C_i) = \max_{x\in C_i}\{d(x, \overline{C_\iota})\} \qquad (3)$$

where $\overline{C_\iota}$ and $\overline{C_j}$ are the centroid of cluster C_i and C_j. Thus large Value of *D* corresponds to good clusters. Therefore, the number of cluster that maximizes *D* is taken as the optimal number of clusters [15]. According to D in Chart1, number of clusters (K) is 5 for customers in both RFM and LRFM clustering.

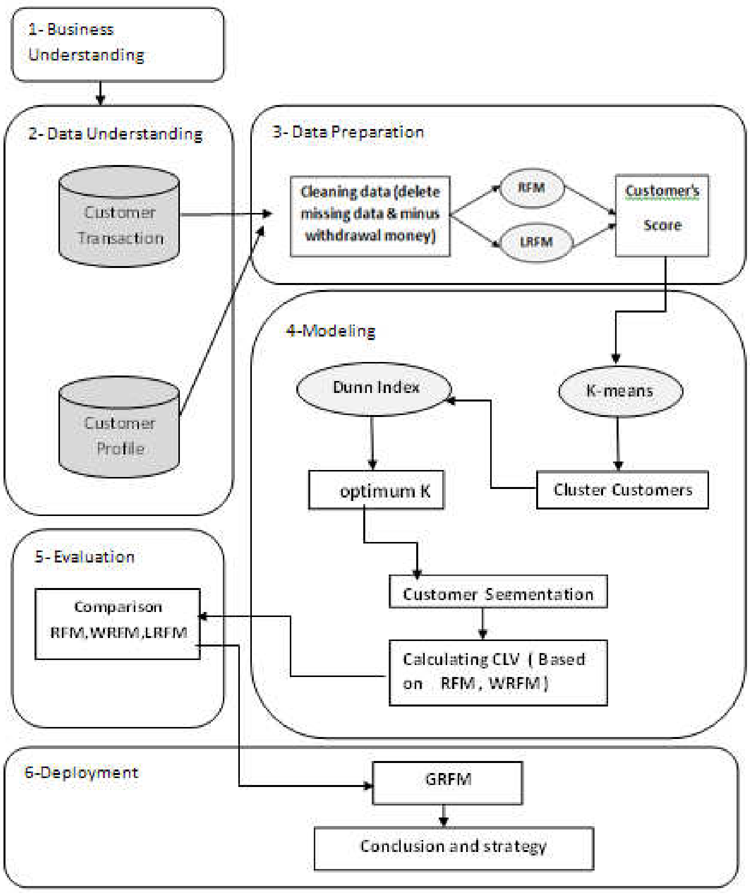
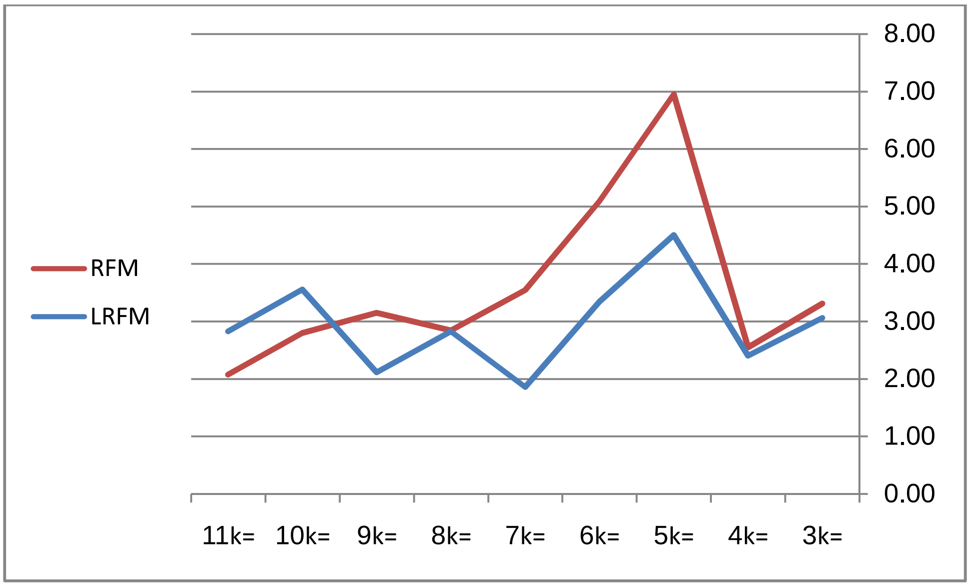


Figure 1. Research methodology

Table 3. Customer RFM score

Score	1	2	3	4	5
Relation Length	[1 ‹156]	[157 ‹301]	[302‹554]	[555‹625]	[626‹663]
Recency	[256 ‹364]	[171 ‹256]	[98‹170]	[39‹97]	[1‹38]
Frequency	[1‹1]	[2‹2]	[3‹4]	[5‹8]	[9‹32]
Monetary	1 - 777500	777501 - 3051200	3051201 - 8174000	8174001 - 22880000	22880001 - 202559560

Chart 1. Dunn Index



We use the K-means method of SPSS to cluster the data .Table 4 is shown RFM clustering, Table 5 is shown LRFM clustering.

Table 4. RFM Cluster

Cluster	Number	R	F	M
c1	5	90	13	199985782
c2	268	159	2	4724449
c3	54	110	5	33955250
c4	7	78	9	166896814
c5	17	85	7	85301459

Table 5. LRFM Cluster

Cluster	Number	L	R	F	M
c1	4	222	52	10	192,134,025
c2	164	212	158	2	6,240,174
c3	142	624	147	2	8,932,326
c4	33	313	94	6	68,426,722
c5	8	626	98	11	174,958,814

The RFM score is calculated as follows,

RFM Score= α* Rscore + β* Fscore + γ* Mscore (4)

where α, β, γ are the weights of R,F,M respectively , and they mention the relative importance of the three variables. In traditional RFM and LRFM, we propose α=β=γ=1 then calculate scores in Table 6, 7.

Table 6. LRFM Cluster

Cluster	L Score	R Score	F Score	M Score	LRFM
c1	2	4	5	5	16
c2	2	3	2	3	10
c3	4	3	2	4	13
c4	3	4	4	5	16
c5	5	3	5	5	18

Table 7. LRFM Cluster

Cluster	R Score	F Score	M Score	RFM
c1	4	5	5	14
c2	3	2	3	8
c3	3	4	5	12
c4	4	5	5	14
c5	4	4	5	13

After that , we calculate CLV that is similar to RFM score formula as follow :

$$CLV_{ci} = NR_{ci} \times \alpha + NF_{ci} \times \beta + NM_{ci} \times \gamma \quad (5)$$

where NR_{ci} refers to normal recency of cluster ci, NF_{ci} is normalized frequency, NM_{ci} is normalized monetary . In this study, min-max normalization method is used for normalizing data. Min-max normalization performs a linear transformation on the original data .Suppose that min_A and max_A are the minimum and maximum values of an attribute, A. Then min-max normalization maps a value, v, of A to $\boldsymbol{v}'$ in the range of $[newmin_A, newmax_A]$ by computing [30]:

$$\boldsymbol{v}' = \frac{v - min_A}{max_A - min_A}(newmax_A - newmin_A) + newmin_A \quad (6)$$

So first, we normalize R, F, M of table 4,5 and calculate CLV. Because of setting α=β=γ=1 for RFM scoring, also put 1 in weight in CLV formula. The result is shown in table5.

Table 8. CLV- RFM Based

Cluster	Normal R	Normal F	Normal M	CLV	Rank
c1	0.755494505	0.387096774	0.987293722	2.13	1
c2	0.565934066	0.032258065	0.023323752	0.62	3
c3	0.700549451	0.129032258	0.167630943	1.00	3
c4	0.788461538	0.258064516	0.823939458	1.87	2
c5	0.769230769	0.193548387	0.421117912	1.38	2

Table 9. CLV- LRFM Based

Cluster	Normal L	Normal R	Normal F	Normal M	CLV	Rank
c1	0.333837	0.85989	0.290323	0.948531	2.43	1
c2	0.318731	0.568681	0.032258	0.030807	0.95	3
c3	0.941088	0.598901	0.032258	0.044097	1.62	2
c4	0.471299	0.744505	0.16129	0.33781	1.71	2
c5	0.944109	0.733516	0.322581	0.86374	2.86	1

In WRFM, we do same work but according to the assessments obtained by the AHP method with regard to experts, the relative weights of the RFM variables are mentioned in table 10.

Table 10. Weights of RFM parameters

Parameter	R	F	M
Weight	0.105	0.258	0.637

Now we calculate CLV with these weights:

Table 11. CLV- WRFM Based

Cluster	α *R	β *F	γ *M	CLV	Rank
c1	0.079327	0.099871	0.628906	0.81	1
c2	0.059423	0.008323	0.014857	0.08	3
c3	0.073558	0.03329	0.106781	0.21	3
c4	0.082788	0.066581	0.524849	0.67	1
c5	0.080769	0.049935	0.268252	0.40	2

4.4.Evaluation

Hitherto we present three methods for CLV calculation: RFM, WRFM, LRFM. The main goal of study is to find the best method to clustering profitable customers. By comparing the descriptive statistics quantity of RFM and LRFM clustering with the statistics for whole date set, in Chart 2 and 3, we find that when we have steady data, LRFM is better than RFM to **clustering** data. As is shown in charts, 76.4 % from whole of customer is clustered in one group by RFM modeling but LRFM can divided data approximately in two cluster 46.72 % and 40.46 %.

Chart 2. NO Of Customer RFM

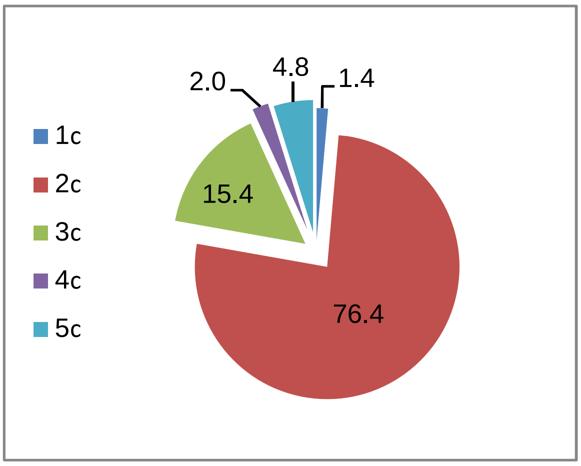
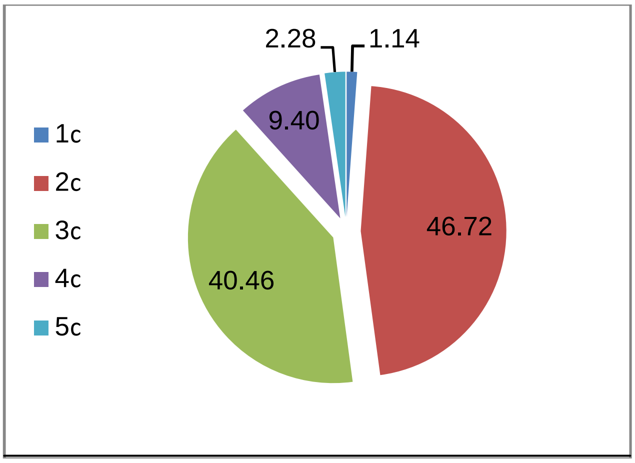
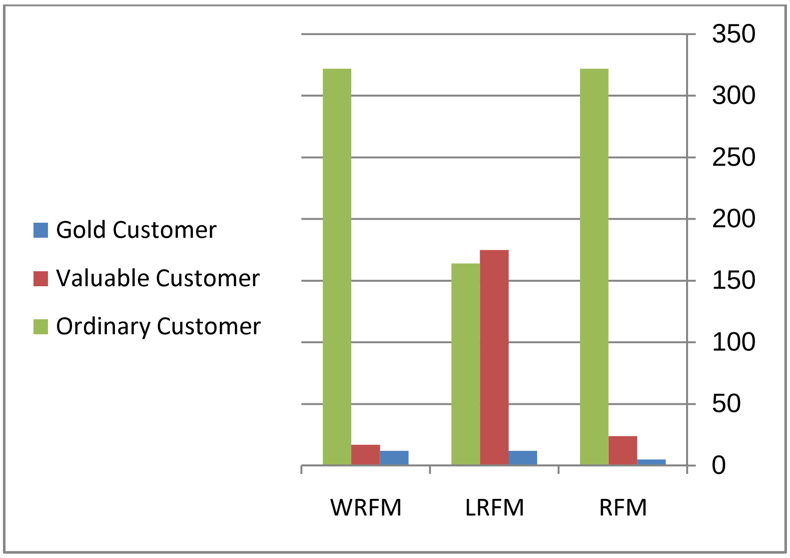


Chart 3. NO Of Customer LRFM



Also we segmented result of CLV in three methods to 1, 2, 3 ranking where 1 is Gold customer, Valuable Customer, Ordinary Customer in chart 4. Ranking in RFM and WRFM is similar, but LRFM is precision. According to different clustering, LRFM has better customer segmentation.

Chart 4 . CLV Ranking with RFM methods



Although we present the differences between RFM methods, it isn't enough to take decision about profitable customer group. We use GRFM to add products as a supplement in segmentation.

4.5.Deployment

Chang and Tsai [17] point out that RFM don't consider customers' purchasing behavior regarding different products while it is important because for example the frequency that a user buys a new notebook is very different from that of buying a new cloth. Moreover the amount of money spent on the above tow items is very different. They propose the framework as follow steps: It first transforms each transaction record in the transaction dataset into an integer. It then creates n ORPA (ORiginal PAtterns) table to store each integer and its occurrence frequency. The second phase follows to perform clustering over the ORPA table. Finally, the third phase calculates a (R, F, M) value for each customer in each cluster.
Although this method really consider customers' purchasing behavior in RFM , but it isn't more suitable for profitable customer segmentation. In other word it is good to find customer consumption behavior since a customer may belong to more than one cluster, a customer may be associated with different (R, F, M) values but our study focuses in finding profitable customers segmentation which only each customer can belong to one segment. So we consider product purchase items in new three steps:

- In according to product purchase records, find top ten products that have most price toward all purchases (Table 12)
- Consider which customer purchases these products from Gold customer in RFM, WRFM, and GRFM.
- Finally each customer has belonged to one of three groups and purchase at least one product is shown in table 12, is profitable customer (Table13). It means:

  Gold Customers = $\cup(Gold\ Customer_i \cap Purchase\ \text{Product}_i)$

  where i = RFM, WRFM, LRFM (7)

First we find Top 10 product based on total price of all products that is shown in table 12.

Table 12. Top 10 products

Product	Unit Price	Price	Percentage
A	7,951,160	405,509,159	2.53
B	5,728,142	463,979,486	2.90
C	1,352,911	465,401,405	2.91
D	3,388,880	474,443,219	2.96
E	507,760	480,341,428	3.00
F	2,350,519	498,310,000	3.11
G	2,536,110	507,222,000	3.17
H	3,401,513	517,030,000	3.23
I	4,654,034	544,522,000	3.40
J	625,296	622,169,739	3.89

Table 13. Top 10 products

Customer ID	A	B	C	D	E	F	G	H	I	J
192										
285										
349										
30										
252										
174										
139										
34										
247										
43										
105										
170										
200										

In order for comparison, according to customers of Gold segmentation in Chart4 and their purchase, is filled table 13 that is shown union of three group of customers that purchase top10 product. So between 351 customers only 13 customers are profitable that 30% income of company is result of their purchases. In addition to finding profitable customer by GRFM, it is specifies which products is purchased to each other such as C and E usually is bought together.

5. Discussion and Conclusion

One of the key purposes of marketing is to identify the target profitable customers and analyze it. Information is essential for an SME to be able to provide a personalized service to each customer and to make the customer feel valued by business. It is important that only implementation of CRM in SME isn't enough, It is essential to use dada mining tools for analyzing customer purchase behavior to run strategies such as price discrimination, that lead to service improvement and customer satisfaction.

In this paper, we presented the compilation RFM that integrated RFM, WRFM, LRFM and consider customers' purchasing behavior regarding products. As case study, we used SMEs that sells network equipments. This company has 351 customers and 1277 purchase records during one year (from 2010/03/21 to 2011/03/18**)**. At first we modeled purchase date with kind of RFM techniques and clustered customers by using k_means. Then was calculated CLV and compared results . In our case RFM and WRFM had similar outcome. For clustering LRFM was better toward another because the frequency of most customers was 1 and 2, LRFM can divided them according relation length. Although customers were segmented in Gold, Valuable and Ordinary groups but we used top 10 products (according to whole of purchase price) to revised gold customer in 3 methods and union of them. Finally we found 13 customers as gold customer.

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