Using Customer lifetime Value Model for Product Recommendation: An Electronic Retailing Case Study

Zahra Tabaei and Mohammad Fathian

***Abstract*—Electronic commerce has developed a lot in the last few years. Product recommendation helps to satisfy customers as one of useful applications of electronic commerce. Recommending right products to right customers enhances the customer's utility and firm profitability. Different types of customers have different interests, so firms should firstly segment customers in to groups and recommend right product to them. A very useful method for grouping customers is customer lifetime value model, which identifies the value of each customer by various parameters. The main purpose of this paper is to clustering customers based on customer lifetime value and then recommending product to different groups of customers with using association rule mining technique. We use one electronic retailing in our study. One useful result of this survey indicates that the rules which are generated for the most loyal customers have more confidence.**

***Index Terms*—Roduct recommendation; customer Lifetime Value; electronic commerce;data mining; customer loyalty.**

I. Introduction

With growing electronic commerce in all over the world, considering to customers and their needs and desires is so important. Customers attract to electronic retailing with high compliance with their desires [1]. So considering the voice of customers and providing right product for them is important. In electronic commerce because of not face to face relation with customers this subject is more important.

Customers with different interests in electronic shopping can't relate to the salesman, so there is not direct way to persuade customers to buy some special goods. Automated product recommendation system can help to provide appropriate product to right customers.

Different groups of customers prefer some special products. Customer's type recognition is one of the main aims of each business and firms know who want what. [2] So firms should try finding customer groups according to customer's behavior.

Recommender systems are so useful in one-to-one marketing [3]. As Reference [4] "Recommender systems rely on customer purchase history to determine customer preferences and to identify products that customers may purchase". So we should investigate all past customer purchases and provide the transaction record for each customer. With exposing these records and using association rule mining we can suggest suitable product to every customer and customers may buy the suggested products with high probability. As result both customers and retailers obtain profitability. [5]

Finding customer's behavior similarities is a useful method for product recommendation. Grouping customers with this method can help us to reduce the dimensions of issues and concentrate more to profitable group of customers and as result allocate them the proper portion of marketing resources.

Customer loyalty is a suitable feature for segmenting customers. Customers' past purchasing behavior can show their loyalty [6]. The customer is loyal, if he/she purchases more products in his/her lifetime, buys products recently and spending more money during the lifetime. But if a customer doesn't purchase recently, total number of his/her purchases is low and usually spends a little money in the lifetime, so he/she is disloyal customer.

Customer loyalty in different industries is so different. In some cases with expensive and valuable products, customers may refer few. But in some industries such as grocery customers refer several times in a week to provide the daily needs. So the importance of frequency and recency values are different in varied industries [7].

RFM model is one of customer lifetime value models that have been used for customer loyalty in a lot of studies ([4], [6], [8]-[12]). This model is easy. The parameters required for constructing this model almost are available. RFM is behavioral model and consider all past customer purchases to prospect the future customer behaviors. Considering this model in a lot of studies in varied issues can prove the usefulness of this model.

Some studies have developed the RFM model with adding some parameters to it. Reference [13] has added the Count item to this model and has constructed the RFMC model. Results showed that this parameter is not so useful and the result of RFM model was better than RFMC model. Cheng in 2009 added two parameters to RFM model: Time since first purchase, and churn probability, then developed RFMTC model [9].

Using CLV models for customer loyalty value and data mining techniques for customer segmentation according to CLV, we can recommend right products to right customers and provide individual marketing decision for each customer. So customers receive products according to their requirements, will been satisfied and purchase more at time and finally they will be loyal customers. On other words, firms spend lower cost for customer retention and can reach more profitability.

The organization of this study is as follows. In Section II, we review the related works in customer lifetime value models and recommendation systems. In section III, we propose our methodology for product recommendation which is based on CLV in conjunction with findings in our

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case study. Finally, a discussion on the study results is described in section IV.

II. LITERATURE REVIEWE

A. Customer Lifetime Value

Customer Lifetime Value models are used widely to identify customer loyalty and determinate marketing strategies for different groups of customers [14]. There are several models for CLV. Some of them are based on past behavioral models and some of are based on future customer revenue.

One of useful behavioral models for customer value is RFM model. RFM was constructed based on 3 variables [15]:

- Recency: refers to the duration time between last customer purchasing and present time.
- Frequency: refers to the total number of customer purchases during life time.
- Monetary: refers to the average money which is spent during past customer purchases.

In weighted RFM, each normalized variables multiply to their estimated weights which defined by experts. Experts define the weights according to their experiences [16]. Equation 1 shows the weighted RFM.

$$RFM = w_R \times R + w_F \times F + w_M \times M \tag{1}$$

where R, F and M refer to recency frequency and monetary value, and w_R , w_f and w_m refer to weight of R, F and M.

Khajvand et al. in 2011 added Count Item to RFM model and developed the RFMCI model. They compared the result of their proposed model with RFM model and emphasized that RFM model is better than RFMCI model. Figure 1 shows the framework of their model [8]. The modeling phase shows that they use weighted RFM model with AHP analysis and selected the more valuable model. They used this model in a health and beauty company and obtained useful results.

Some studies such as [9], after customer segmentation, have estimated customer value with distance between the center of each cluster and zero.

$$CV_i = \sqrt{(C_{ir} - 0)^2 + (C_{if} - 0)^2 + (C_{im} - 0)^2} \tag{2}$$

where C_{ir}, C_{if} and C_{im} are respectively the average of R, F and M value for segment i.

Past customer value (PCV) is another CLV model which is based on the past monetary value of customers. PCV extrapolate the past monetary spent by customers in past purchases into present time. This model doesn't consider the future expected customer value [17]. This model emphasizes that the previous monetary value of customers is a good scale for predicting the future value. Equation 3 shows one type of this model [18].

$$PCV = \sum_{t=0}^{T} PR_t \times (1+d)^t \tag{3}$$

where T is the total time period, RP_t is the customer profit in time period t and d is discount rate. Discount rate is the very important parameter of this model and depends on economical situation of each country.

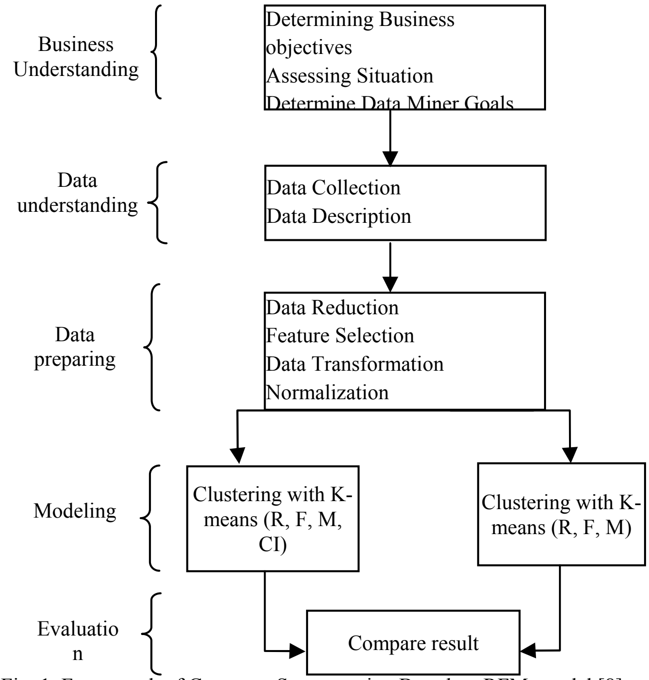

Fig. 1. Framework of Customer Segmentation Based on RFM model [8].

Some CLV models prospect the future monetary value of customers. These models extrapolate the future prospected monetary will spend by customer into present time [16]. In contrast of PCV, this model is prospective. There is a lot of formula for this model in literature for special industries and situations. Equation 4 shows the general form of LTV model [19].

$$LTV = \sum_{t=o}^{T} pp_t \times \frac{1}{(1+d)^t} \tag{4}$$

where pp_t is the predicted customer profit in time period t. d is the discount rate.

Some studies such as [20], [21] have prospected future customer acquisition profits and active time for each customer, then they have sued them to estimate the LTV.

Retention rate is an important factor in LTV estimation. If the firm identifies the right retention rate, it can estimate the valid LTV. Some studies such as [22], [23] have constructed the LTV according to the retention rate. Equation 5 shows the LTV with considering the retention rate and acquisition price [16].

$$LTV = \sum_{t=1}^{T} \left(\prod_{r=1}^{t} R_r \right) CM_t \times \left(\frac{1}{(1+d)^t} \right)^t - AC \tag{5}$$

where R_r is the retention rate, and AC is the acquisition cost. Acquisition cost is very important in marketing and almost is so high. So every business should try to retain former customers with providing some value for customers. Research shows that the cost of customer acquisition is so higher than retention cost.

Combining PCV and LTV model leads to complete model. This model considers both past and future behavior of customer for calculating customer value. Hwang in 2004 has applied CLV model to estimate customer loyalty value for a service provider industry. Equation 5 shows the proposed CLV model [24].

$$CLV = \underbrace{\sum_{t_i=1}^{N_i} \pi_p(t_i)(1+d)^{N_i-t_i}}_{\text{Past customer profit}} + \underbrace{\sum_{t_i=N_i+1}^{N_i+E(i)+1} \frac{\pi_f(t_i)+B(t_i)^t}{(1+d)^{t_i-N_i}}}_{\text{Expected future profit}} \quad (6)$$

where t_i is the time period the customer i has received the service, N_i is the total times the customer i has received the service, E(i) is the expected time periods the customer i will be active in future, $\pi_p(t_i)$ is the past profit by customer i in time t_i, $\pi_f(t_i)$ is the expected future profit by customer i in time t_i and $B(t_i)$ is the potential profit by customer i in time t_i. As Equation 6 shows, both PCV and LTV have been considered.

Buyer and seller's commitment is an effective factor has been considered in [25]. In fact, customer commitment builds the loyalty and seller's commitment leads to customer trust and as result CLV models can been constructed based on these commitments.

According to literature review about customer value we can understand that although CLV model is the best one, but prospect the acquired future revenue from customers and their lifetime are so difficult. But RFM model is a behavioral flexible model and can adapt itself to every business. The usefulness of RFM model in marketing and customer relationship management has confirmed in a lot of studies in different industries: service provider ([9], [12], [13], [24], [26], [27]) and retailing ([4], [28]-[30]). So we use weighted RFM model to estimate the loyalty value of each group of customers.

B. Recommendation Systems and Association Rule

According to reference [4] "Recommender systems are technologies that assist businesses to implement one-to-one marketing strategies". Recommender systems review the history of past customers purchasing and identify the customer desired products. Using recommendation systems leads to both customer and firm profitability [31].

For product recommendation first stage is to gather information about past customer's purchases. This information contains all data about any combination of products have been purchased by each customer group. With this information, recommendation system extracts the useful rules and can propose the right products to customers [32].

One of the useful data mining techniques which has been used in recommendation systems is association rule mining. This technique extracts useful patterns according to customer transaction records [33], [34].

Association rule mining is a very useful method to find the effective rules in every field of marketing. At first stage all data transaction of all customers in the past purchases should be gathered. After that all frequent itemsets (a set of some items) are generated and finally useful rules are accepted according to some metrics. There are some algorithms to create frequent itemset. In Brute-Force algorithm each itemset is a choice for frequent itemset. Using "support" metric can help to select actual frequent itemset. Support count refers to frequency of occurrence of an itemset. "An itemset whose support is greater than or equal to a min-support threshold is a frequent itemset"[35] the time complexity of this algorithm is exponential . So this method is so expensive. Another algorithm which is named Apriori algorithm uses anti-monotone property of support and reduces the candidate itemsets [36].

Another rule evaluation metric is 'confidence'. For every $x \rightarrow y$ rule, confidence measures how often items (products) in y appear in transactions that contain x [36]. So if the confidence value of the rule is equal or more than min-confidence threshold, it is selected as useful rule.

After rules extraction, recommendation system works according to the following method:

If x_c is the set of all product types have been purchased by customer c at past, for each $x \rightarrow y$ rules in RR_i, if $x \subseteq x_c$ then all $y - x_c$ product types were proposed to candidate customer. RR_i is the set of rules related to customer group i [4],[37].

III. Methodology with Findings

In our survey we have used weighted RFM model for customer loyalty estimation.

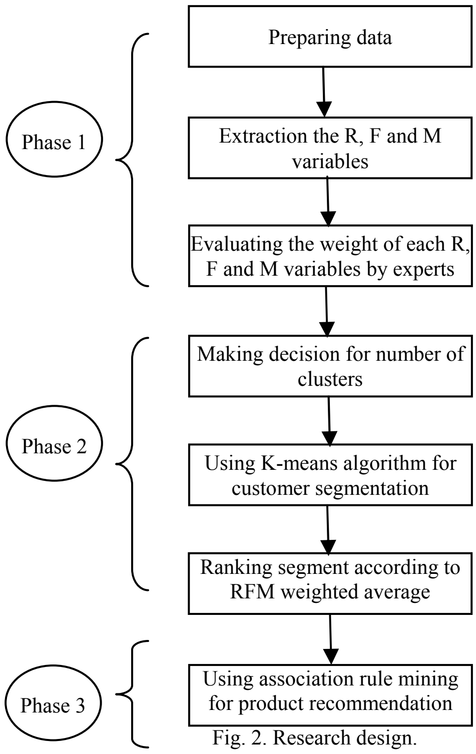

Fig. 2. Research design.

In the first stage after data preparing we used RFM model for customer value estimation. In the second stage customers have been segmented according weighted RFM and have been assigned ranking score to each groups. Finally we use association rule mining to extract useful rules for product recommendation. The brief stages of our methodology have been shown in Fig. 2.

A. Data Preparing

We use a data set from one electronic retailing in our study. This electronic retailing sells different types of CD (software, educational, film, game and music) as total 218 CDs to customers. Data set contains 65535 transaction records with 22086 customers. Each record contains customer ID, last purchase time, price of purchased product and product ID. The R, F and M value for each customer were extracted. In our survey the customers who purchase recently has higher R value.

B. Clustering Customers with Similar RFM Value

After evaluating the weight of each variable with AHP analysis, K-means algorithm has been used in order to customer segmentation. We set the number of clusters at 8, because each variable R, F and M is higher (↑) or lower (↓) than its average (2*2*2=8) [38]. TABLE I shows the result of customer segmentation according to normalized weighted R, F and M value.

TABLE I: 8 CLUSTER RANKING BY WEIGHTED SUM OF NORMALIZED RFM VALUE

cluster	No. of customers	Weighted Recency	Weighted Frequency	Weighted Monetary	Pattern Type	WRFM	Rank
1	13374	0.06	0.000	0.000	$R\downarrow F\downarrow M\downarrow$	0.060	8
2	3	0.728	0.164	0.058	$R\uparrow F\uparrow M\uparrow$	0.950	1
3	2127	0.586	0.004	0.001	$R\uparrow F\uparrow M\downarrow$	0.591	4
4	1	0.134	0.048	0.038	$R\downarrow F\uparrow M\uparrow$	0.220	7
5	1979	0.254	0.002	0.001	$R\uparrow F\downarrow M\downarrow$	0.257	6
6	71	0.708	0.037	0.012	$R\uparrow F\uparrow M\uparrow$	0.757	2
7	2462	0.692	0.006	0.002	$R\uparrow F\uparrow M\uparrow$	0.700	3
8	2069	0.438	0.003	0.001	$R\uparrow F\uparrow M\downarrow$	0.442	5
Overall average		0.236	0.0021	0.0011			

W_R=0.68, W_F=0.21, W_M=0.11

TABLE II: 4 CLUSTER RANKING BY WEIGHTED SUM OF NORMALIZED RFM VALUE

cluster	No. of customers	Weighted Recency	Weighted Frequency	Weighted Monetary	Pattern Type	WRFM	Rank
1	13937	0.065	0.000	0.000	$R\downarrow F\downarrow M\downarrow$	0.065	4
2	4856	0.638	0.005	0.002	$R\uparrow F\uparrow M\uparrow$	0.645	2
3	3284	0.336	0.002	0.001	$R\uparrow F\downarrow M\downarrow$	0.369	3
4	9	0.713	0.116	0.034	$R\uparrow F\uparrow M\uparrow$	0.863	1
Overall Average		0.236	0.0021	0.0011			

W_R=0.68, W_F=0.21, W_M=0.11

TABLE III: CLUSTER RANKING BY WEIGHTED SUM OF NORMALIZED RFM VALUE

cluster	No. of customers	Weighted Recency	Weighted Frequency	Weighted Monetary	Type	WRFM	Rank
1	13937	0.065	0.000	0.000	$R\downarrow F\downarrow M\downarrow$	0.065	3
2	4863	0.648	0.006	0.002	$R\uparrow F\uparrow M\uparrow$	0.645	1
3	3286	0.338	0.002	0.001	$R\uparrow F\downarrow M\downarrow$	0.369	2
Overall Average		0.236	0.0021	0.0011			

W_R=0.68, W_F=0.21, W_M=0.11

As TABLE I shows clusters 2 and 4 have few customers, they may be outliers. So with putting aside them only 4 cluster patterns ($R\downarrow F\downarrow M\downarrow$, $R\uparrow F\uparrow M\uparrow$, $R\uparrow F\uparrow M\downarrow$, and $R\uparrow F\downarrow M\downarrow$) have been identified. So it seems that we should decrease the number of clusters. We set number of clusters at 4 and perform K-means algorithm again. The results with 4 clusters have been shown in TABLE II.

Results show that with 4 clusters, 3 pattern types have been identified and cluster 4 with 9 members is outlier. So we repeat last stage again with 3 clusters. There is no outlier customers. The results with 3 clusters have been shown in TABLE III. Results show that with 3 clusters, 3 pattern types have been identified and there is no outlier customers. So the results are valid.

C. Product Recommendation

The association rule mining is used for extracting useful rules in each separate segment of customers and then propose desired products to customers.

TABLE VI: EXTRACTED RULES FOR LOYAL CUSTOMERS

Rule	Instances	Support (%)	Confidence (%)
$M23 \rightarrow F1$	3388	69.661	85.394
$G2, M7, E67 \rightarrow F3$	1545	31.778	85.198
$G5, M1 \rightarrow F18$	2052	42.199	85.046
$G2, M7, S2 \rightarrow F18$	1527	31.408	84.882
$G2, M8, S2, E8 \rightarrow F3$	1277	26.269	84.585
$S2 \rightarrow E34$	3395	69.805	84.069
$F7 \rightarrow M6$	3447	70.874	83.933
$E75 \rightarrow S2$	3404	69.99	83.847
$G2, M26, S3 \rightarrow E54$	1527	31.408	83.639
$G5, F2, S2 \rightarrow E81$	1581	32.518	83.565
$G1, M26, S2, F1 \rightarrow E30$	1296	26.66	83.346
$G5, E34 \rightarrow S2$	2090	42.98	83.166
$G4, E54, F11 \rightarrow S1$	1590	32.703	83.092
$S3, G2 \rightarrow E12$	2099	43.165	82.81
$G2, E3, F12 \rightarrow M26$	1590	32.703	82.778
$G5, M3, E54 \rightarrow S3$	1545	31.778	82.665
$G1, F3 \rightarrow M13$	2125	43.7	82.126
$G1, M12, E22, F8 \rightarrow S3$	1316	27.071	82.08
$S2, G1, F3 \rightarrow M2$	1581	32.518	81/985
$G2, S9, E74, F1 \rightarrow M3$	1321	27.174	81.77
$E2, M1 \rightarrow F3$	2264	46.557	81.589
$S6, M4 \rightarrow F9$	2228	45.817	81.202
$S7, M4 \rightarrow E3$	2228	45.817	80.709
$S2, F5 \rightarrow E5$	2268	46.639	80.608
$E5, F6 \rightarrow M12$	2295	47.194	80.488

Note: G=Game, E=Educational, F=Film, S=software, M=music

Some extracted rules from loyal customers and all rules from disloyal and new customers segments have been shown in TABLE IV, V and VI. We used Apriori algorithm from SPSS Clementine 12 for rule extraction.

As have been shown, the rules have been extracted from disloyal segment have low support (1%) and the maximum confidence is 74%. Reference [4] has proposed that for disloyal customers preference-based CF Collaborative Filtering (CF) method is useful and can improve the recommendation quality. But for loyal and new customers the minimum support and confidence are high so the results are reliable.

TABLE V: EXTRACTED RULES FOR DISLOYAL CUSTOMERS

Rule	Instances	Support (%)	Confidence (%)
$G27, E7 \rightarrow S4$	163	1.170	74.347
$G3, S2 \rightarrow E12$	175	1.256	69.714
$G3, M3 \rightarrow F21$	165	1.184	68.485
$G5, F3 \rightarrow M9$	169	1.213	66.864
$S5, M9 \rightarrow E4$	214	1.535	66.355
$E59, M3 \rightarrow S2$	222	1.593	63.964
$S2, F32 \rightarrow E67$	194	1.392	62.371
$F9, E32 \rightarrow M3$	201	1.442	60.697
$F10, E12 \rightarrow S4$	201	1.442	60.199

Note: G=Game, E=Educational, F=Film, S=software, M=music

TABLE VI: EXTRACTED RULES FOR NEW CUSTOMERS

Rule	Instances	Support (%)	Confidence (%)
$E75 \rightarrow S2$	1837	55.907	84.586
$S2 \rightarrow E28$	1854	56.425	83.81
$F7 \rightarrow M6$	1793	54.568	83.594
$M23 \rightarrow F1$	1793	54.568	83.595

Note: G=Game, E=Educational, F=Film, S=software, M=music

IV. CONCLUSION

In this survey product recommendation was studied. At first customers were segmented with CLV model. Three types of customers were identified: loyal, disloyal and new customers. Then association rule mining was used for extracting rules from each segment. Results show that the rule support and confidence for loyal and new customers is relatively high, so this method is useful and reliable for these groups. But because of low support for disloyal customers this method is not so useful and CF method may be applicable for the disloyal segment, as proposed in [38].

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