Chapter 4. Combining WRFM and purchased preference

A weighted RFM-based method (WRFM-based method) that integrates AHP and data mining to recommend products based on customer lifetime value. The WRFM-based method (described in Chapter 3) employs association rule mining to identify recommendation rules from customer groups that are clustered according to weighted RFM values. The experiments demonstrated that the WRFM-based method outperforms the typical KNN-based CF method, and can identify effective rules for making recommendations to customers with high lifetime value or loyalty. However, generating recommendation rules for less loyal customers is difficult. Similar to the WRFM-based method, a preference-based CF method can be derived that employs association rule mining to extract recommendation rules from customer groups which are clustered according to customers' purchase preferences. A pilot experiment of this study revealed that the preference-based CF method may suggest some useful recommendations that the WRFM-based method can not provide, and thus may improve the quality of recommendations to less loyal customers. Accordingly, this study proposed two hybrid recommendation methods that incorporate the advantages of the WRFM-based method and the preference-based CF method. The proposed hybrid recommendation methods are named hybrid1 and WRFMCP, respectively. Those are presented in Liu and Shih (2004) and are described as following sections.

4.1 Hybrid1 methods

The WRFM-based method is capable of identifying effective recommendation rules for customers with high lifetime value or loyalty. However, generating recommendation rules for less loyal customers is difficult because such customers typically have low purchase frequencies and spend less money; they are also unlikely to have made recent purchases. The preference-based CF method uses clustering to group customers with similar purchase preferences. A pilot experiment of this work yields a meaningful result that shows the preference-based CF method would improve the quality of recommendations for less loyal customers. Accordingly, the proposed $hybrid_1$ method incorporates the merits of the WRFM method and the preference-based CF method to recommend products, as shown in Figure 6.

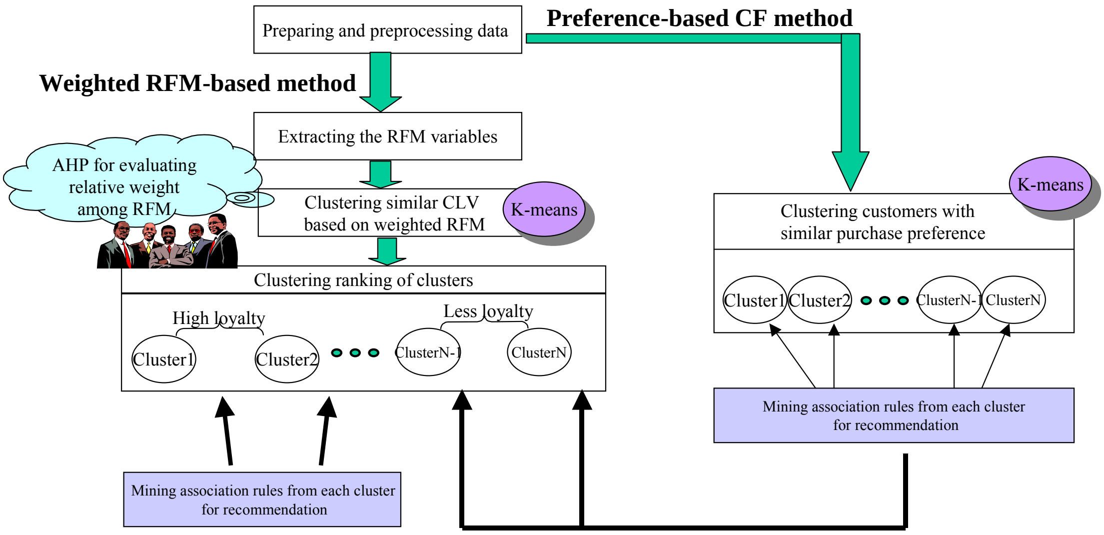

Figure 6. Hybrid_1 method for product recommendation

Two kinds of clustering are conducted to group customers into weighted RFM-based clusters (referred to Chapter 3.1.1) and Preference-based clusters (referred to Chapter 2.3.2.2), respectively. The weighted RFM-based clusters are created by grouping customers with similar lifetime value according to weighted-RFM value, while the preference-based clusters are created by grouping customers with similar purchase preferences. Notably, the CLV ranking of the weighted RFM-based clusters represent the loyalty ranking of customer groups (described in Chapter 3.1.4). The association rule mining approach is then applied to extract recommendation rules from each group of customers, derived separately from weighted RFM-based clustering and preference-based clustering. Finally, recommendation rules extracted from weighted RFM-based clusters are used to recommend product items to loyal customers; and recommendation rules extracted from preference-based clusters are used to recommend product items to less loyal customers. Recommendation phase of hybird1 method details in following section.

4.1.2 Recommendation phase

The association rule mining approach is employed to extract recommendation rules from each group of customers, derived separately from WRFM-based clustering and preference-based clustering. Let C^i_{WRFM} be the WRFM-based customer group *i*, generated by clustering customers based on WRFM values. Let C^j_p be the preference-based customer group *j*, generated by clustering customers based on customers' purchasing preferences. Association rule mining is used to extract the recommendation rule set RS^i_{WRFM} from customer transactions associated with each customers group C^i_{WRFM}. Similarly the recommendation rule set RS^j_p is extracted from customer transactions associated with each customer group C_p^j. Then, the top-*N* candidate products to be recommended to customer *u* are selected as follows. The customer group C_{WRFM}^i to which customer *u* belongs to must be identified before the top-*N* product items can be recommended to that customer. If the customer belongs to a high-loyalty group, then the recommendation rules (RS_{WRFM}^i), extracted from C_{WRFM}^i, are used to recommend the top-*N* product items; otherwise, the customer group C_p^j to which customer *u* belongs must be identified, and then the recommendation rules (RS_p^j), extracted from the C_p^j are used to recommend top-*N* product items.

Two feasible approaches are available to determine the high/low loyalty ranking of a customer group C_{WRFM}^i. One is to set the threshold *integrated_rating* to α. The *integrated_rating* is the weighted sum of the averaged normalized WRFM values. If the *integrated_rating* of C_{WRFM}^i exceeds α, then the loyalty ranking of C_{WRFM}^i returns high; otherwise, it returns low. The other approach is to observe analytical results on a small test data set by computing the recommendation quality of the WRFM-based method and the preference-based CF method. For each customer group C_{WRFM}^i, the WRFM-based recommendation quality is derived by using the WRFM-based recommendation rule set (RS_{WRFM}^i), while the preference-based recommendation quality is derived by using the preference-based recommendation rule set (RS_p^j). Notably, customers in the same WRFM-based customer group C_{WRFM}^i may belong to different preference-based customer groups. The recommendation rules (RS_p^j), extracted from customer transactions associated with the customer group C_p^j to which customer *u* belongs, are used to derive the preference-based recommendation quality. The F1-metric described in Chapter 2.5 can be used to measure the recommendation quality. If the value of WRFM-based F1-metric exceeds that of preference-based F1-metric, the loyalty of C_{WRFM}^i returns *high*; otherwise, it returns *low*.

4.2 WRFMCP approach

The hybrid$_1$ method cluster customers based on either the customer lifetime value or the purchase preferences separately. The method then uses the preference-based recommendation rule set to improve the quality of recommendations for less loyal customers, This work proposes another hybrid method, named WRFMCP method that clusters customers by integrating dimensions of customer lifetime value and customer preference, as shown in Figure 7. The relative weighting is adopted to adjust the importance of customer lifetime value and purchase preferences in clustering. The WRFMCP approach initially establishes a customer-WRFM matrix and a customer-item matrix. Then, the WRFM-based and preference-based correlation coefficients are computed using Eq. 2 (referred to Chapter 3.1.1) and Eq. 1 (referred to Chapter 2.3.2.2), respectively. Subsequently, K-means clustering is used to group customers with similar CLV and preferences based on weighted correlation coefficients, which is obtained from integrated dimensions of CLV and preferences. Finally, the association rule mining approach is applied to extract recommendation rules from each group derived from K-means clustering.

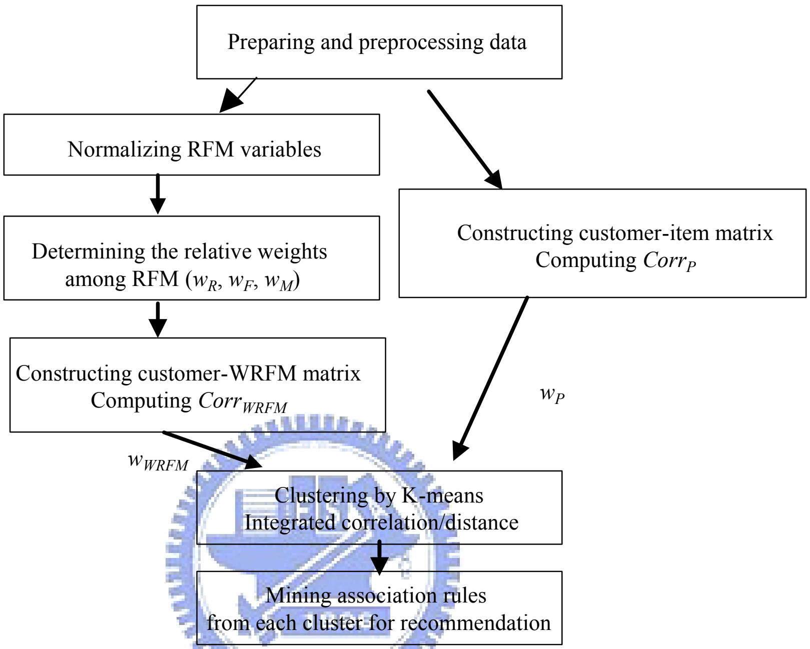

Figure 7. WRFMCP method for product recommendation

4.2.1 Grouping customers with similar CLV and purchase preference by K-means

Difference from the hybrid$_1$ method, the WRFMCP method clusters customers by integrating dimensions of CLV and purchase preferences. The customer-WRFM matrix and customer-item matrix are first established. For customer-WRFM matrix, the RFM values of customers are normalized and then multiplied by the relative importance of RFM variables. An element r_{ij} of the customer-item matrix represents whether the ith customer had purchased the jth product. Eq. 1 is used to compute the preference-based Pearson correlation coefficient, $corr_P$; while Eq. 2 is used to compute the WRFM-based Pearson correlation coefficient, $corr_{WRFM}$. The integrated correlation coefficient is then derived according to Eq. 3.

$$Corr_{\text{integrated}(c_i,c_j)} = w_{WRFM} \times corr_{WRFM}(c_i, c_j) + w_P \times corr_P(c_i, c_j) \tag{3}$$

w_{WRFM} and w_P represent the relative importance (weights) of the dimensions of CLV and purchase preferences, respectively. If $w_{WRFM} = 0$, then the method becomes preference-based CF method, that uses purchase preference to group customers. If $w_{WRFM} = 1$, then the method becomes WRFM-based method, that uses weighted RFM values to group customers.

K-means technique is employed to cluster customers based on the integrated correlation coefficients. In general, the integrated correlation coefficient between a centroid c_j of a cluster and a customer c_i is measured using Eq. 3. The centroid of a cluster is represented by both the average WRFM values and the average purchase preferences of customers within the cluster. Customers are assigned to a cluster with maximum integrated correlation coefficient.

The weights of parameters w_{WRFM} and w_P are used to yield an integrated correlation coefficient. The proper weighting values of w_{WRFM} and w_P can be determined by performing some experimental results to evaluate the quality of recommendations under different weight combination (for example, w_{WRFM} equals 0.8 and purchase preferences equals 0.2).

4.2.2 Recommendation phase

Association rule is used to extract recommendation rule set RS_j from transactions associated with each cluster. Each cluster is generated by grouping customers based on weighted correlation coefficients of CLV and purchase preferences. The cluster C_j to which a customer, *u,* belongs is first identified. Then, RS_j, the recommendation rule set extracted from C_j is used to select the top-*N* candidate products to be recommended to customer *u*. The F1-metric described in Chapter 2.5 can be used to measure the recommendation quality.

4.3 Experimental setup

Various experiments are conducted to evaluate the proposed hybrid1 and WRFMCP methods for product recommendation, using the hardware retailing data set described in Chapter 3. The proposed methods are compared with the WRFM-based method, the preference-based CF method, and the KNN-based CF method. The KNN-based CF method uses preferences for product purchases to compute similarities between customers, and then employs the *k*-nearest neighbor (KNN) approach to derive the top-*N* recommendations, as illustrated in Chapter 2.3.2.2.

The hardware retailing data were divided into a 75% data set for training and a 25% data set for testing to verify the quality of the recommendations. The training set includes product items purchased by customers in a specified period, and is used to extract recommendation rules from customer transactions. Moreover, a preliminary analytical experiment was conducted to determine the high/low loyalty ranking of customer groups in hybrid1 method and the proper weighting of w_{RFM} and w_P in WRFMCP method. The training set was also used as the analytical data set in the preliminary analytical experiment, where 65% data set was used for deriving recommendation rules and 10% for analyzing recommendation quality. In the experiments, the minimum confidence is set to 0.8, and the minimum support is set to 0.1. Identifying all frequent *itemsets* is difficult, since the average number of product items purchased by customers is 34. Hence, association rule mining explores only to frequent *itemsets* with sizes of less than or equal to three.

4.4 Experimental results

4.4.1 Evaluation of hybrid1 method

This experiment verifies that the proposed hybrid1 method is a feasible way to enhance the quality of recommendations for less loyal customers. Customers with similar CLV and similar preferences were separately grouped into WRFM-based customer groups (CLV groups) and preference-based groups. The hybrid1 method needs to determine the high/low loyalty ranking of customer groups, which is derived by conducting a preliminary analytical experiment, as described in Chapter 4.1.2. The analytical experiment used the training set as the analytical data set, where 65% data set was used for deriving recommendation rules and 10% for analyzing recommendation quality. The analytical result shows that the preference-based CF method improves the recommendation quality of customer groups with the seventh and eighth loyalty rankings.

To determine whether the hybrid1 method is effective, the training set was used to extract recommendation rules, and the testing set was used to verify the recommendation quality. Based on the analytical result, recommendation rules extracted from the WRFM-based customer groups (CLV groups) were used to recommend products to the top six loyalty ranking CLV groups, while the recommendations rules extracted from the preference-based customer groups were used to recommend products to the last two loyalty ranking CLV groups. The hybrid1 method is compared with the WRFM-based method, preference-based CF method and the KNN-based CF method. Table 13 lists the average F1-metrics for each cluster, obtained using various methods under $N = 20$ (top-20 recommendations) and k = 100 (100 nearest neighbors). The last row shows the overall average F1-metrics. The F1-metrics obtained by the hybrid1 method exceeds those obtained by the WRFM-based method, preference-based CF method, and the KNN-based CF method, implying that the proposed method, hybrid1 provides better recommendations than the WRFM-based method, preference-based CF method and the KNN-based CF method.

Table 13. F1-metrics of various methods under top-20

CLV Ranking	WRFM-based method	Preference-based CF	Hybrid1	KNN-based CF (K=100)
	F1-metric	F1-metric	F1-metric	F1-metric
1	0.645	0.636	0.645	0.634
2	0.608	0.586	0.608	0.596
3	0.553	0.545	0.552	0.545
4	0.473	0.471	0.473	0.456
5	0.458	0.453	0.458	0.422
6	0.412	0.419	0.412	0.408
7	0.387	0.415	0.415	0.377
8	0.310	0.335	0.335	0.308
Overall	0.524	0.518	0.528	0.515

4.4.2 Determine proper weightings of WRFMCP method

The WRFMCP method considered different weightings on the dimensions of CLV and purchase preferences. A preliminary analytical experiment was conducted to determine the proper weightings, w_{WRFM} and w_P (w_P = 1 - w_{WRFM}). The analytical experiment used the training set as the analytical data set, where 65% data set was used for deriving recommendation rules and 10% for analyzing recommendation quality. Figure 8 summarizes the recommendation quality (F1-metric) obtained using the WRFMCP method. If w_{WRFM} equals zero, then the WRFMCP method is the preference-based CF method; if w_{WRFM} equals one, then the WRFMCP method is the WRFM-based method. The WRFMCP method achieved the best recommendation quality when w_{WRFM} equals 0.8 and w_P equals 0.2. Overall, when w_{WRFM} exceeds w_P, the F1-metric of WRFMCP method exceeds that obtained using the WRFM-based method or the preference-based CF method alone. Based on the analytical result, further experiments (described in Section 4.3) were conducted to evaluate the WRFMCP method by setting w_{WRFM} = 0.8 and w_P = 0.2.

w_{WRFM}	Precision	Recall	F1-metric
0.00	0.4271	0.6308	0.5001
0.10	0.4365	0.6329	0.5067
0.20	0.4369	0.6361	0.5074
0.30	0.4452	0.6285	0.5117
0.40	0.4485	0.6294	0.5122
0.50	0.4436	0.6372	0.5121
0.60	0.4428	0.6401	0.5122
0.70	0.4413	0.6475	0.5129
0.80	0.4412	0.6564	0.5133
0.90	0.4388	0.6529	0.5131
1.00	0.4357	0.6473	0.5111

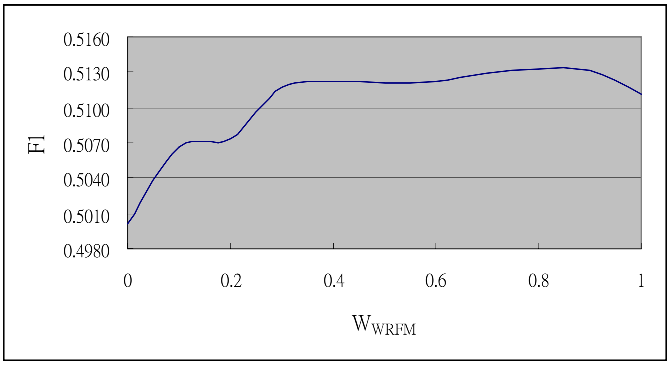

Figure 8. Analytical result of WRFMCP method under different weightings of $w_{WRFM.}$ (top-20)

4.4.3 Comparing various methods on top-*N* recommendations

Experiments were conducted to compare various methods by using the training set and the testing set. The methods were compared by varying the *N*, the number of recommendation items. Table 14 shows the F1-metrics of various methods under different top-*N* recommendations. In general, both the F1-metrics of the hybrid1 and WRFMCP methods exceed those of the WRFM-based method, preference-based CF method, and the KNN-based CF method. The result implies that the proposed hybrid methods provide better recommendations than other methods. Moreover, the WRFMCP method performs better than the hybrid1 method.

Table 14. F1-metrics of WRFM-based, preference-based, hybrid1, WRFMCP and KNN-based CF methods under different *N* (top-*N*)

Top-*N*	WRFM-based method	Preference-based CF	Hybrid1	WRFMCP	KNN-based CF (k=100)
Top-4	0.333	0.335	0.338	0.342	0.286
top-10	0.499	0.476	0.480	0.486	0.487
top-20	0.524	0.518	0.528	0.533	0.515
top-30	0.504	0.502	0.519	0.525	0.498
top-40	0.484	0.496	0.486	0.496	0.467
top-50	0.477	0.473	0.480	0.489	0.422

4.4.4 Experiments on three clusters of customers

Experiments were also performed on clustering customers into three clusters. Similarly, 75% data set was used as the training set, while 25% data set was used as the testing set. Moreover, the training set was also used as the analytical data set to determine the low/high loyalty ranking of hybrid1 method and the weightings of WRFMCP method. For hybrid1 method, the preference-based CF method can improve the recommendation quality of WRFM-based customer groups with the third loyalty ranking. For WRFMCP method, the best combination of w_{WRFM} and w_P is 0.7 and 0.3, respectively. Tables 15 and 16 present the experimental results on the testing set (25% data set), which exhibit trends similar to those results obtained in the experiments that used eight clusters.

Table 15. F1-metrics of WRFM-based, preference-based, hybrid1 and KNN-based CF methods for three clusters under top-30

CLV ranking	WRFM-based mehod	Preference-based CF	Hybrid1	KNN-based CF (k=100)
1	0.736	0.713	0.736	0.698
2	0.533	0.529	0.533	0.520
3	0.393	0.416	0.416	0.386
Overall average	0.510	0.508	0.514	0.498

The result also indicates that the proposed hybrid1 and WRFMCP methods provide better recommendations than the WRFM-based method, preference-based CF method and the KNN-based CF method. Additionally, the F1-metric of WRFMCP exceeds that of hybrid1.

Table 16. Comparisons WRFM-based, preference-based, hybrid1, WRFMCP and KNN-based CF methods under various *N* (top-*N*) for three clusters

top-*N*	WRFM-based method	Preference-based CF	Hybrid1	WRFMCP	KNN-based CF (k=100)
top-4	0.314	0.311	0.316	0.319	0.286
top-10	0.496	0.484	0.497	0.500	0.487
top-20	0.511	0.504	0.512	0.515	0.515
top-30	0.510	0.508	0.514	0.518	0.498
top-40	0.498	0.476	0.501	0.509	0.467
top-50	0.468	0.470	0.472	0.472	0.422

4.5 Discussions

This chapter presented two hybrid recommendation approaches. The hybrid1 method overcomes the drawback of WRFM-based method by using preference-based CF method to improve the quality of recommendation for less loyal customers. Furthermore, the proposed WRFMCP method integrated CLV and customer preferences to group customers and then extracted recommendation rules from each group to improve the quality of recommendation. The experimental results demonstrate that the proposed hybrid1 and WRFMCP methods outperformed the WRFM-based, preference-based CF and the KNN-based CF methods. The WRFMCP method outperformed the hybrid1 method, especially when the CLV was weighted more heavily than purchase preferences.

Furthermore, as mentioned previously, the hybrid1 method is proposed to make recommendations for highly loyal customers based on customer lifetime value (by setting the $w_{WRFM} = 1$; $w_P = 0$) and to make recommendations for less loyal customers based on customer preferences (by setting the $w_{WRFM} = 0$; $w_P = 1$). The WRFMCP method considers different weightings on the dimensions of CLV and purchase preferences for overall customers. A further improvement can be achieved by using a two-phase approach that integrates the hybrid1 and WRFMCP methods. In other words, we can derive high/low loyalty ranking of customer groups on the basis of customer lifetime value. The WRFMCP method can then be used to determine the different weightings of the dimensions of CLV and purchase preferences for either high or low ranking of customer groups, respectively. Such two-phase approach will be verified by further study.